Universidad de Oviedo

Escuela de Ingeniería Informática

Metaheurísticas para el diagnóstico precoz de ictus cerebral basado en las anomalías en los movimientos.

Tesis presentada por Silvia González González
para obtener el grado de Doctorado Ingeniería Informática

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Departamento de Informática

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RESUMEN (en español)

La década actual ha sido testigo de la rápida evolución de la tecnología wearable. Hasta ahora no había evolucionado, tanto como para pensar en su uso con fines médicos. El uso de esta tecnología en la detección precoz de ciertas enfermedades aumenta las posibilidades de una buena recuperación y, por ende, una reducción de los costes hospitalarios. Estas posibilidades han sido los detonantes de este estudio.

Basándonos, por una parte, en la propuesta de D. José María Trejo mediante la aplicación de acelerómetros triaxiales para la detección de los movimientos anómalos propios de un episodio de ictus; y, por otra parte, en los dispositivos wearables desarrollados para este fin por el Instituto Tecnológico de Castilla y León, esta investigación ha profundizado en el diseño de un sistema para la detección precoz del ictus. Por reconocimiento precoz se conoce la detección de un episodio de ictus a lo largo del mismo, con lo que –generando la oportuna alarma- el paciente recibiría el tratamiento oportuno en el menor plazo posible.

Por lo tanto, se recopiló información sobre los efectos y consecuencias producidos en las distintas actividades por los episodios de ictus. Este estudio se centró en identificar las anomalías en la situaciones más comunes cuando acontece un episodio de ictus: debido al propio proceso degenerativo, un paciente raramente puede realizar otras tareas diferentes de caminar o estar tumbado –consciente o inconsciente-. Para estas situaciones se identificaron las anomalías en los movimientos.

Esta investigación tuvo dos objetivos claros, por un lado estudiar de forma pormenorizada todos los trabajos existentes sobre dicho tema y por otro lado generar un sistema capaz de reconocer entre distintas actividad e identificar los movimientos anómalos. El sistema está conformado por tres etapas fundamentales que se interrelacionan entre sí. La primera es la selección de características; la segunda está referida al proceso de reconocimiento de actividades humanas por medio de dos sistemas las máquinas de estados y el análisis de series temporales; y la última identifica las anomalías en dichos movimientos.

Los resultados de este estudio revelaron que la combinación de sistemas embebidos y los acelerómetros, era una solución eficaz para la identificación de patrones anómalos en los movimientos.

La investigación sustenta, entre otras implicaciones, la necesidad de encontrar un sistema que permita detectar precozmente los episodios de ictus, lo que supondría una actuación más rápida y una reducción de los efectos de esta enfermedad en términos de una disminución de la rehabilitación requerida por parte de los pacientes.

Descriptores clave: reconocimiento de actividades humanas, anomalías en los movimientos, máquinas de estados, series temporales, ictus.

RESUMEN (en Inglés)

The last decade has witnessed the fast evolution of the wearable technology, a technology that, so far, had not evolved enough to be suitable of being taken into consideration for medical purposes. Its use in early diagnosis of certain illnesses increases the possibilities of a successful recovery and, therefore, entails a reduction of hospital costs. These possibilities triggered the development of the present study.

Based, on one hand, on D. José María Trejo's proposal of triaxial accelerometers for stroke anomalous movements detection; and, on the other hand, on the wearable devices that had been developed for that purpose by the Instituto Tecnológico de Castilla y León, this research has delved into the design of an early ictus detection system. An ictus episode early detection is achieved while the episode is still ongoing so that, by means of the consequently triggered alarm, the patient would be able to received the suitable treatment with the least possible delay.

Therefore, information on the ictus effects and consequences on different activities was gathered. The study focused on the identification of the anomalies in the commonest circumstances when a stroke takes place: due to the degenerative process itself, a stroke patient can rarely perform any tasks but walking or laying down – consciously or unconsciously. So anomalies for those situations were identified.

This research had two clear objectives, on one hand, to study in depth every existing work on the matter and, on the other hand, to develop a system capable of recognising the different tasks and identifying their anomalous movements. The system consists of three main interrelated stages. The first one is feature selection; the second relates to the human activities recognition by means of two state machine systems; and the last one identifies the movement anomalies.

The results of the study revealed that the combination of embedded systems and the accelerometers was an effective solution for movement anomalous patterns.

The research supports, among other implications, the need for the finding of a system that enables the early detection of ictus episodes, which would mean a faster action and a reduction of the consequences of this disease in terms of a decrease in rehabilitation needs by the patients

Keywords: human activities recognition, movements anomalies, state machines, time series, ictus.

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Capítulo 1

Introducción

En estos últimos años la esperanza de vida ha aumentado considerablemente; sin embargo, no todos los años de vida ganados son de buena salud, sino vividos con discapacidad y necesidad de ayuda. Existen muchas enfermedades que reducen nuestra capacidad para la realización de las actividades diarias, tanto las tareas para el autocuidado básico como las habilidades necesarias para ser independientes. En este contexto, añadir calidad a los años que nos quedan por vivir se ha convertido en una necesidad.

Las enfermedades cerebrovasculares son todas aquellas alteraciones encefálicas secundarias a un trastorno vascular. Su manifestación aguda se conoce con el término ictus. El ictus cerebral es una disrupción violenta en la circulación sanguínea del cerebro que interfiere en la funcionalidad normal del mismo. El ictus tiene un gran impacto en nuestra sociedad, según los datos publicados por la Organización Mundial de la Salud (OMS) sobre la mortalidad global producida por las enfermedades cardiovasculares en el año 2002, el 32 % (5,5 millones de muertes) se debieron a ictus. Se considera que es una de las principales causas de mortalidad y de discapacidad en el mundo y la primera causa de incapacidad y coste económico [37, 44]. En España es actualmente la segunda causa de muerte en la población general y la primera causa de muerte en la mujer. Además supone la primera causa de discapacidad y genera un gasto muy elevado para los servicios sanitarios y sociales [40]. Por lo que, reducir las secuelas producidas por dichas enfermedades se ha convertido en una necesidad en la sociedad actual.

El ictus es una emergencia médica que requiere atención médica inmediata. Está comprobado que una de las claves para el éxito en la atención del ictus es la rapidez con la que se detectan los síntomas iniciales y se contacta con los sistemas de emergencias médicas para comenzar a actuar con la mayor celeridad posible y acortar el tiempo que transcurre desde que el paciente sufre un ictus hasta que se toman las medidas adecuadas en cada caso. Se mejoran las posibilidades de una buena recuperación, con una rápida actuación médica. Así que, el reconocimiento de los signos de accidente cerebrovascular es crucial. En caso de discapacidad, la rehabilitación es un proceso a largo plazo que no garantiza alcanzar el estado de normalidad anterior al episodio.

Se han encontrado vínculos epidemiológicos entre el ictus y múltiples factores de riesgo. Algunos de ellos están bien documentados, mientras que otros aún deben ser confirmados [40]. Algunas personas tienen más riesgo de sufrir un derrame cerebral si tienen otras condiciones médicas como por ejemplo: presión alta, colesterol alto, fibrilación auricular y diabetes entre otras. Además, el riesgo de sufrir un derrame cerebral es mayor entre las personas de ciertos grupos étnicos, incluidos los del sur de Asia, África y el Caribe. Esto es en parte debido a que la presión arterial alta y la diabetes son más comunes en estos grupos. También hay factores de estilo de vida que pueden aumentar el riesgo de sufrir un derrame cerebral. Ellos incluyen: fumar, sobrepeso, dieta pobre, la falta de actividad física [20, 46, 49]. En los últimos 20 años ha existido una tendencia decreciente en las cifras de mortalidad, frente al aumento de morbilidad, debido a la detección y el control de los principales factores de riesgo, en particular la hipertensión arterial.

Los métodos actuales de diagnostico se basan en la observación de la respuesta del paciente ante requerimientos posturales o de actividad concretas [20, 37]. Sin embargo, se ha demostrado que los efectos de un episodio se reducen si realiza un diagnostico temprano de ictus [37]. Por ello, detectar la disfuncionalidad en los movimientos de un paciente en el momento de ocurrencia de un ictus, es un reto en el diagnostico precoz del ictus. Otro punto de importancia que es necesario destacar es la importancia de utilizar modelos generales, que permitan cubrir una gran variedad de población sin mayores ajustes.

Por otro lado se ha demostrado que las actividades humanas se pueden caracterizar perfectamente por medio de sensores o de la computación visual. La mayor parte de los estudios se han realizado analizando series de video [9, 18, 27, 28, 37, 42, 43, 47, 60–62, 68]. En estos casos se usan cámaras de video instaladas en los escenarios a estudiar. Esta aproximación se centra en las pruebas de laboratorio, pero falla en entornos reales, debido a los cambios en el contraste e iluminación. A su vez los sujetos de estudio consideraban este sistema altamente intrusivo, aparte del coste computacional añadido al trabajar con las señales de video.

Desde hace varios años han ido apareciendo sistemas miniaturizados emplazados en la ropa o en los complementos. Se les denomina *wearable devices*. Podemos datar los orígenes de la tecnología wearable en la década de 1970 [66], pero no ha sido hasta la década actual cuando esta tecnología ha evolucionado lo suficiente para poder atraer un amplio abanico de consumidores. La evolución de los dispositivos electrónicos a sistemas más eficientes, potentes y pequeños, además de baterías de gran capacidad y flexibilidad permiten el desarrollo de sistemas complejos de gran potencia que se pueden acoplar en nuestra ropa o en cualquier complemento que se nos ocurra. Los ámbitos de uso de estos dispositivos son la navegación, deporte, vigilancia de la salud [33], comercio, videojuegos o redes sociales entre otros. [48] es un ejemplo claro de producto funcional con el fin de recopilar las constantes vitales en el ámbito deportivo, entre muchos otros dispositivos. Estos dispositivos ofrecen conectividad y servicios específicos sin necesidad de tener que utilizar un ordenador convencional y con el añadido de que el sistema está siempre conectado e interactuando con el usuario o con el ambiente que le rodea. Entre algunos de estos dispositivos que nos permiten transformar nuestras vidas se encuentran los acelerómetros.

Recientemente, el uso de los acelerómetros tri-axiales ha recibido la atención por parte de los investigadores por su aplicación en la medicina debido a la reducción de los costes de diagnóstico, a la posibilidad de realizar análisis de datos y la ubicuidad, ente otros [50, 53]. La posibilidad para detectar la actividad humana de manera automática y su viabilidad han decantado la balanza hacia el uso de estos dispositivos como los sensores más utilizados para la detección de la actividad humana [52]. Se han desarrollado diversas técnicas para la detección de la actividad humana basadas en el uso de acelerómetros, como pueden ser redes neuronales [67], árboles de clasificación binarias [38] y jerárquicos [4], funciones radiales fuzzy [15], reglas de activación por umbrales [35], Modelos Ocultos de Markov - Hidden Markov Models (HMM) [63], o Máquinas de Estados Finitos Difusos aprendidos mediante Algoritmos Genéticos - Genetic Finite Fuzzy State Machine (GFFSM) [8]. En todas ellas, se utiliza uno o más acelerómetros triaxial, bien en la cintura, bien en la muñeca del brazo dominante. De entre las posibles actividades a reconocer, la de caminar es la que ha sido estudiada más en profundidad [45], pudiendo determinar todas las secuencias de movimientos de brazos y piernas asociadas.

La idea de encontrar un nuevo método capaz de realizar la detección temprana del ictus surgió del neurólogo José María Trejo. Así mismo el Instituto Tecnológico de Castilla y León estaba trabajando en la división de Inteligencia Artificial con acelerómetros. La combinación de ambos derivó en la propuesta de diseño de un sistema para la detección precoz del ictus, lo que supondría una actuación más rápida y una reducción de los efectos de esta enfermedad en términos de una disminución de la rehabilitación requerida por parte de los pacientes.

Está demostrado [29] que un sujeto durante un episodio de ictus o bien colapsa o bien sufre una asimetría de movimientos respecto al eje longitudinal. A modo de ejemplo, en una actividad como puede ser andar esta asimetría se manifiesta por medio de diferencias al realizar giros y en los movimientos de las caderas, por otro lado puede sufrir un colapso y quedar tendido en el suelo. Este estudio se centra en los movimientos que cambian una vez se ha sufrido el ictus (donde las anomalías de los movimientos son más acentuadas), es decir durante la actividad de caminar y la de estar tendido (durmiendo o inconsciente).

Es así como esta idea se convirtió en la base de todos los trabajos presentados en esta tesis; experimentando tanto con la selección de características como con el reconocimiento de movimiento y con las técnicas SAX sobre series temporales. Vale la pena mencionar que los algoritmos propuestos se pueden transferir fácilmente a los sistemas embebidos y pueden beneficiarse de los reducidos costos de aprendizaje.

En esta memoria presentamos el desarrollo realizado sobre estas tres técnicas. Una vez finalizada la introducción, continuamos con los objetivos propuestos (Capítulo 2), el estado del arte actualizado (Capítulo 3), le sigue el planteamiento (ver Capítulo 4) y la discusión de resultados (ver Capítulo 5) en la cual se desarrolla la justificación, descripción y resultados por cada una de las técnicas propuestas.

Capítulo 2

Objetivos

En base a lo expuesto en la introducción y lo indicado en el plan formativo al comienzo de la realización de esta tesis, el objetivo general de la presente tesis doctoral es el de encontrar y desarrollar nuevos métodos o técnicas para la detección precoz del ictus.

La idea subyacente es detectar los diferentes tipos de actividades basado en la señal proveniente de un acelerómetro triaxial por medio del uso de diversas técnicas de soft-computing. Esta solución podría eventualmente implementarse en dispositivos móviles/smartphones, por lo que los diferentes modelos deben ser computacionalmente acotados. En las siguientes etapas ya con la actividad claramente establecida, se dispondría de modelos para detectar la anormalidad en los movimientos.

Los principales objetivos de este estudio son:

- *Realizar una revisión del estado del arte en meta-heuristícas para la detección y reconocimiento de movimientos.* Dados los numerosos métodos existentes en la literatura para realizar la detección y reconocimiento de movimientos, nos planteamos realizar un estudio de estas metodologías, y la selección que sea más acorde a nuestras intenciones.

- *Diseño e implementación de diferentes aproximaciones novedosas para el reconocimiento de la actividad humana. La simulación de las distintas actividades se ha realizado en un ambiente no hospitalario.*

- *Diseño e implementación de diferentes aproximaciones novedosas para el reconocimiento de movimientos humanos normales. La simulación de movimientos anómalos debidos a episodios de ictus serán realizados acorde* *a la literatura pero lamentablemente la experimentación con casos reales no se ha podido llevar a cabo.* Dada la dificultad de adquirir datos de pacientes sanos durante un episodio de ictus, ha sido necesario la creación de una batería de pruebas realistas.

- *Adaptar los algoritmos y técnicas de los pasos anteriores para su explotación en aplicaciones móviles.* De entre todos los métodos basados en la detección y reconocimiento de movimientos, aquellos basados en técnicas fácilmente embebibles han sido los seleccionados, al facilitar la posterior integración con aplicaciones móviles.

Capítulo 3

Estado del arte

En este capítulo se revisa brevemente las aplicaciones más importantes e interesantes para la detección de los movimientos humanos, los métodos más comunes para la recogida de datos y el preprocesado de la señal, entre otros.

No hay nada en el estado del arte enfocado en el reconocimiento de episodios de ictus, por lo menos, en nuestro conocimiento. Por lo tanto la atención se centra en las técnicas de detección por medio de dispositivos *no intrusivos* que sean adecuados para el seguimiento a largo plazo y sobre todo en los métodos similares a los presentados en las publicaciones (ver apartado 7.2).

La caracterización del movimiento humano, especialmente mientras se camina, está bien documentado en la literatura [45]. Sin embargo, acontecimientos no previstos, como las caídas modifican la forma de moverse de los pacientes [2]. Por esta razón, y también porque caminar es una de las actividades más sensibles se ha estudiado ampliamente la cinemática durante la marcha [2].

Se han divido los estudios con fines médicos en varios apartados según los dispositivos utilizados (Wearable Devices, Smartphones), por otro lado existen estudios que utilizan Reconocimiento de la Actividad Humana - Human Activity Recognition (HAR) con otros fines, estos se ha referenciado en el apartado Otras áreas.

Wearable Devices Para hacer frente al creciente envejecimiento de la población, es preferible utilizar los recursos existentes para tratar de ayudar a prevenir o retrasar la entrada en las instituciones geriátricas. El HAR se puede utilizar con el fin de ayudar a las personas mayores a permanecer en su casa el mayor tiempo posible. En este escenario [16] estudia la combinación de siete tipos de sensores diferentes, además de explorar la contribución de cada sensor en el reconocimiento de las actividades.

El estudio [36] desarrolla un framework centrado específicamente en el reconocimiento de la actividad utilizando en combinación acelerómetros, técnicas de Selección de Características - Feature Selection (FS) y métodos de clusterizado como K-Means, Affinity Propagation, Mean Shift y Spectral Clustering.

A su vez [67] presenta un enfoque por el cual mediante redes neuronales, realizan el HAR utilizando un acelerómetro triaxial. Mediante una estrategia de divide y vencerás que separa las actividades dinámicas de las actividades estáticas y reconoce estos dos tipos diferentes de actividades por separado.

El problema del HAR en [14], se plantea a través de la segmentación de los datos de aceleración, medidos utilizando acelerómetros. El enfoque propuesto se basa en un modelo de regresión múltiple. El modelo aprende en un contexto no supervisado y no requiere de una etapa de previa de procesamiento FS. En el estudio se realizó la comparación de los rendimientos de los clasificadores supervisados y HMM.

Aunque los métodos de reconocimiento de actividades tradicionales han demostrado ser eficaces se plantean algunas preocupaciones tales como la privacidad, el consumo de energía y los costos de implementación. En los últimos años, ha aparecido un nuevo enfoque basado en la utilización de transceptores inalámbricos para lograr una alta precisión de reconocimiento, reducir los costos de energía y preservar la privacidad del usuario. En [65], realiza una comparativa de varios métodos: ZigBee, Wi-Fi, RFID, y otros.

Smartphones Cabe destacar la importancia de la aparición de los teléfonos inteligentes en nuestra vida diaria. Su versatilidad y flexibilidad ha dado pie a la utilización de éstos en el HAR [1]. Los sistemas de HAR automático pretenden capturar el estado del usuario y su entorno mediante la explotación de sensores heterogéneos conectados al cuerpo del sujeto, además permiten el control en tiempo real de numerosas señales fisiológicas. Por ello los Smartphones son una alternativa viable en la resolución de la problemática HAR.

El trabajo publicado en [51] se centra en la clasificación en tiempo real por medio de un conjunto de sensores inerciales, proponiendo dos escenarios en los cuales las transiciones entre actividades se consideren o no actividades desconocidas. Esto se logra mediante la combinación de la salida probabilística de las predicciones de actividad consecutivas por medio de las Máquinas de Soporte Vectorial - Vector Machine Support (SVM) con un enfoque de filtrado heurístico. Por otro lado [13], gracias al uso de los acelerómetros de los dispositivos móviles, utilizan un modelo de predicción de la actividad basado en el aprendizaje automático de clasificadores. Este enfoque utiliza los árboles de decisión J48, Perceptron Multicapa - Multi-Layer Perceptron (MLP) y las técnicas de regresión logística, además combina estos clasificadores por medio de reglas de probabilidades. El conjunto de datos utilizado fue Wireless Sensor Data Mining (WISDM), que incluye información publica de treinta y seis usuarios. Siguiendo con la utilización de los sensores inerciales de los Smartphones [17] propone la utilización de clasificadores Random Forest (RF), ensembles y Lazy Learning. En [24], los autores describen un método para detectar con precisión la actividad humana mediante un Smartphones y un sensor de pecho dedicado, además realiza la comparación de los algoritmos de aprendizaje automático; C4.5, CART, SVM, MLP y Naive Bayes.

En la actualidad existen sistemas que permiten el HAR, por ejemplo Centinela [55]. Centinela es un sistema que combina los datos de aceleración con los signos vitales. Es capaz de reconocer cinco actividades: caminar, correr, sentarse, subir y bajar. El sistema incluye una plataforma de recogida de datos en tiempo real, que sólo requiere un único dispositivo de detección y un teléfono móvil. Los resultados indican que los signos vitales también son útiles para discriminar entre ciertas actividades.

Existen varias problemáticas que dificultan las tareas de HAR. Una de ellas es la dificultad de determinar el número de actividades que se desean reconocer. Por ello [32], mediante los datos recogidos del acelerómetro de los teléfonos inteligentes, propone un método de aprendizaje no supervisado para su resolución. El estudio permite seleccionar automáticamente un valor adecuado del número de actividades por medio de los modelos de combinación de funciones Gausianas.

Otro factor que puede afectar a los sistemas HAR es la ubicación de los dispositivos. Los datos recogidos por los sensores de aceleración en los teléfonos inteligentes generan resultados diferentes dependiendo de la ubicación del teléfono inteligente. En [41], se propuso un sistema de HAR utilizando el algoritmo AdaBoost, para ello se utilizan diferentes transformadas de la aceleración además de la posición del teléfono inteligente.

El trabajo [12] proponen la utilización de clasificadores y de filtros digitales de paso bajo con el fin de aislar las componentes de aceleración de la gravedad y de la aceleración. Además investigan sobre la integración de múltiples clasificadores para optimizar la precisión de los modelos.

Con el fin de solucionar el problema de la personalización de los modelos para los distintos sujetos [19] propone un modelo de HAR rápido y preciso, conocido como Transfer learning Reduced Kernel Extreme Learning Machine (TransRKELM); este método se aplica para actualizar el modelo inicial y adaptar el modelo a los nuevos usuarios de manera eficiente.

Otras áreas En el marco de los hogares inteligentes y con el avance de la investigación robótica, se prevé que en un futuro cercano los robots sean capaces de adaptarse a entornos complejos y desconocidos e interactuar con los seres humanos para ayudar en diversas tareas de la vida diaria. La convivencia de los seres humanos en el mismo entorno podría proporcionar información valiosa sobre los comportamientos humanos, que pueden ayudar a los robots a entender mejor el medio ambiente y proporcionar un mejor servicio a los seres humanos. Con este fin [56] propone la utilización de acelerómetros y algoritmos de reconocimiento jerárquico, para la identificación de obstáculos en los hogares inteligentes mediante el reconocimiento de las actividades humanas.

Así mismo [30] propone una metodología de fusión de sensores múltiples utilizando la teoría de pruebas temporales para la detección de la actividad en los hogares inteligentes. Dos conjuntos de datos de casas inteligentes se utilizan en los experimentos sobre el reconocimiento de actividad en la que los datos se registran a través de una serie de sensores pasivos.

Los sistemas HAR tienen otros posibles usos por explotar por ejemplo en el ámbito de la Construction Engineering and Management (CEM). Debido a la naturaleza compleja y dinámica de muchos proyectos de construcción, la capacidad de detectar y clasificar las principales actividades realizadas en el campo por los diversos equipos puede mejorar la calidad y fiabilidad de los proyectos. El objetivo de [3] es estudiar la posibilidad de utilizar los sensores de los teléfonos inteligentes como recopilación de datos con el fin de detectar las actividades de los distintos equipos de construcción. En la metodología se extraen ciertas características clave de los datos recogidos mediante el acelerómetro y el giroscopio, y un subconjunto de características son utilizadas para entrenar los clasificadores del tipo supervisado.

Capítulo 4

Propuesta de solución

La tecnología de adquisición de datos seleccionada fueron los acelerómetros triaxiales. El estado del arte realizado sobre estos sensores generó un gran número de estudios orientados a la medicina, mas específicamente relacionados con la detección de las actividades cotidianas en un ambiente no hospitalario. En la mayoría de los estudios se consideraron insuficientes los datos recogidos directamente de los acelerómetros (a^x, a^y y a^z), por ello llevaron a cabo un procesamiento previo de los mismos, por medio de la transformación, combinación y computo a partir de los datos de aceleración originales.

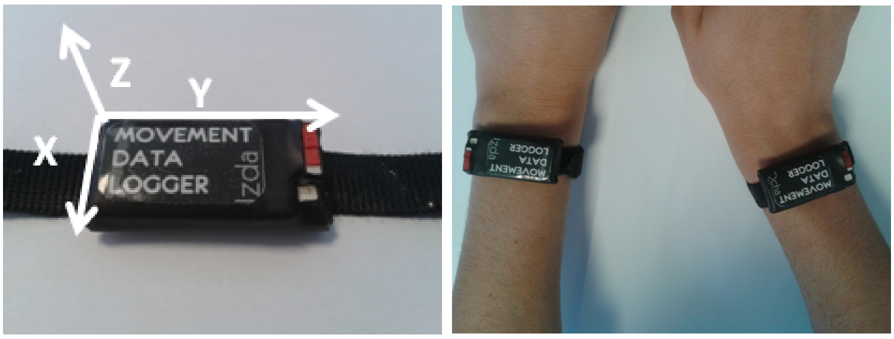
Este preprocesado de la señal está ampliamente documentado y es posible debido a la existencia de sistemas de procesamiento potentes que permiten la transformación de estos datos en tiempo real, incrementando la efectividad de las metodologías implementadas.

El estudio de la literatura en lo referente a la utilización de acelerómetros para la detección de actividades dio como resultado que a partir de los datos proporcionados por el sensor, se pueden extraer hasta 126 nuevas características.

Una vez seleccionada los mejores subconjuntos de características, se han desarrollado dos modelos para el reconocimiento de movimientos. Las dos metodologías son: Máquinas de Estados Finitos Difusos - Finite Fuzzy State Machine (FFSM) (ver apartado 4.4) y análisis de Serie Temporal - Serial Time (TS) utilizando la representación Symbolic Aggregate approXimation (SAX) (ver apartado 4.5).

4.1. Recogida de datos

Este estudio se centra en reconocer la asimetría existente en los movimientos de las extremidades superiores, por ello se creó un dispositivo *data logger* que a través de un acelerómetro registra, para cada muestra el tiempo con precisión de ms y los datos de la aceleración de dichas extremidades superiores con una frecuencia de 16 Hz y los guarda en la memoria interna de cada dispositivo. Los *data logger* se colocan en la cara anterior de cada muñeca del sujeto, la disposición de los ejes es tal y como se ve en la Figura 4.1.



(a) (b)

Figura 4.1: (a) Dispositivos *data logger* de recogida de datos. (b) Colocación de los dispositivos *data logger*.

Con el fin de sincronizar y etiquetar correctamente todos los datos recogidos, se desarrollo una aplicación .apk para Android. La aplicación y los *data logger* están sincronizados al milisegundo. La aplicación crea un fichero en el que se guardan los valores de cada una de las actividades y el milisegundo exacto del registro realizado, estos registros se emparejan con los valores recopilados con los *data logger*.

Es necesaria una batería de pruebas sobre la que validar las propuestas planteadas en este estudio. El estudio se realizó con dos sujetos de prueba de diferentes sexos y edades, ambos fuera de la población de riesgo y no sufrían de ninguna patología relevante para este estudio. La batería de pruebas utilizada en este trabajo se creó mediante la repetición de 10 series formadas por un conjunto de movimientos bien definidos y secuenciales. A partir de ahora se denominada *dataset original* a las 10 series recopiladas de la mujer, por otro lado las 10 series correspondiente al hombre se denominará *dataset validación*.

Los movimientos realizados por los sujetos de estudio son los siguientes, inicialmente permanecen sentados durante un periodo de tiempo t1, a continuación, se pone de pie en la misma posición durante un período de tiempo t2, y luego caminan 10 metros en línea recta, dan media vuelta y vuelven a recorrer otros 10 metros, volviendo a la posición original de pie y permanecen allí por otros t2 segundo, y finalmente se sienta y descansa otros t1 segundos (ver figura 4.2).

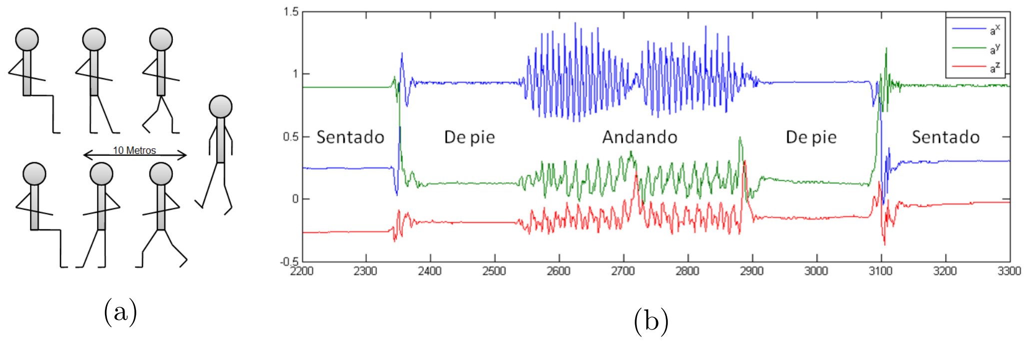


Figura 4.2: (a)Definición de los movimientos correspondientes a una serie de la batería de pruebas. (b)Valores de la aceleración obtenidos con el acelerómetro durante la recogida de datos de una serie.

4.2. Preprocesado de datos

Es difícil analizar y reconocer movimientos directamente de los valores de la aceleración, sin realizar un procesamiento previo de estos datos. Por ello en este trabajo se utilizan dos técnicas de preprocesado de la señal:

- Ventanas. Al recortar las secuencias de aceleración en varias ventanas superpuestas de la misma longitud las características calculadas proporcionar información más relevantes para la clasificación [15]. El tamaño de ventana utilizado en este trabajo es de 10 muestras, mientras que el desplazamiento es de 1 muestra.

- Filtrado de la señal. Ciertas características requieren que se descomponga la (RD) a_i^x, a_i^y y a_i^z en la aceleración de la gravedad (G) g_i^x, g_i^y y g_i^z y la aceleración del cuerpo (BA) b_i^x, b_i^y y b_i^z. Esto se realiza por medio de dos filtros de paso bajo y de paso alto respectivamente [10] (ver Tabla 4.1).

El proceso de filtrado aplicado sobre los valores de a^x recogidos durante la ejecución de una serie de la batería de pruebas, se puede ver en la Figura 4.3.

	Low pass filter	High pass filter
Order (n)	3	3
Passband ripple (Rp)	0.1	1
Stopband attenuation (Rs)	100	80
Cutoff (Wp)	0.3	0.25

Tabla 4.1: Parametrización de la función de Matlab ellip() [39].

La b^x es prácticamente nula mientras se esta sentado y de pie, mientras que la g^x y a^x son casi idénticas. Por otro lado durante la actividad de andar se puede observar una variación considerable en la b^x.

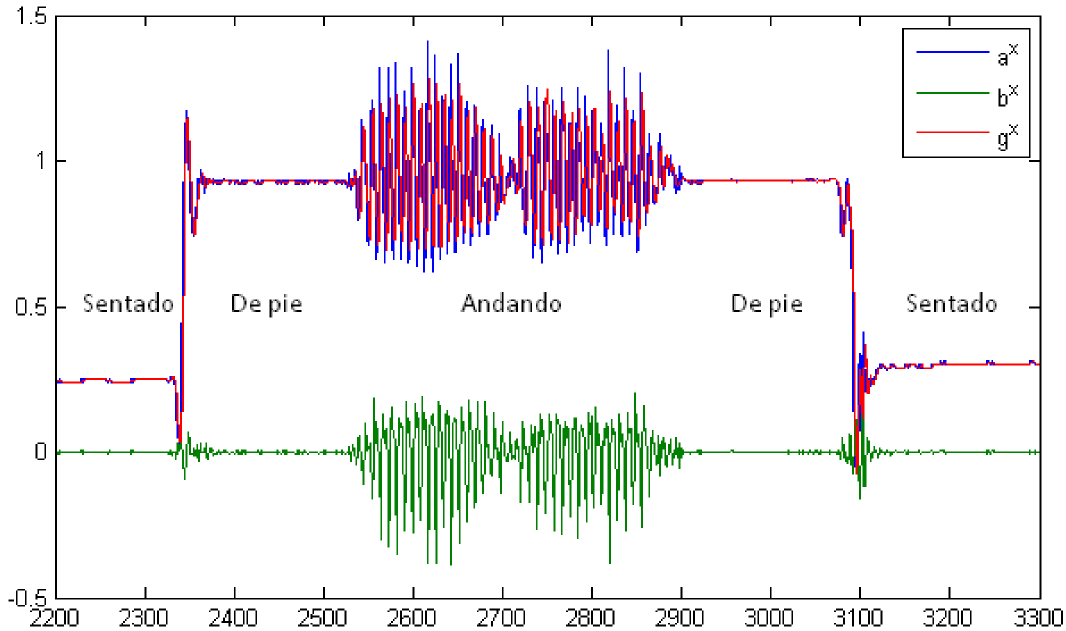


Figura 4.3: Descomposición de a^x por medio de los filtros paso bajo y paso alto del conjunto de datos correspondiente a la ejecución de una serie.

4.2.1. Transformadas de las aceleraciones

Una vez realizado el paso previo del filtrado de la señal, se obtienen las tres características principales (Aceleración - Raw Data (RD), Gravedad - Gravity. (G) , Aceleración del Cuerpo - Body Aceleration (BA)), las cuales se utilizan para el cálculo de las transformadas. Las transformadas recopiladas en la literatura y desarrolladas en este trabajo se encuentran en la Tabla 4.2.

Bloque.	Características	Cálculo
T1	Mean, standard deviation and higher momentum statistics values for the RD[31] or for the BA[64, 67]	Well known statistics.
T2	Intensity of the movement [25]	$InMo_t^{j\in\{x,y,z\}} = \frac{1}{w}\sum_{i=0}^{w-1} \cdot \lvert a_{t-i}^j - a_{t-i-1}^j\rvert / \Delta x_t$
T3	Root Mean Square [15]	$RMS_j = \sqrt{\frac{1}{w}\sum_{i=1}^{w} \lvert a_{i,j}^2\rvert}$
T4	Signal magnitude area[4]	$SMA = \frac{1}{w}\cdot\sum_{i=1}^{w}(\lvert b_i^x\rvert + \lvert b_i^y\rvert + \lvert b_i^z\rvert)$
T5	Sum of the absolute values [22] for the BA	$sBA_i = \frac{1}{w}\sum_{t=i}^{i+w}\sum_{j\in\{x,y,z\}}\lvert b_{t,j}\rvert$
T6	Amount of movement [8]	$AM_i = \sum_{j=\{x,y,z\}} \mid max_{t=i+1}^{i+w}(b_t^j) - min_{t=i+1}^{i+w}(b_t^j) \mid$
T7	Correlation between axes[11] for each signal RD, G y BA	$corr(x,y) = \frac{cov(x,y)}{\sigma_x\sigma_y}$
T8	Shifted Delta Coefficients for the BA[4]	$\Delta b_{t+i\cdot P}^{\{x,y,z\}} = \frac{\sum_{d=-D}^{D} d\cdot b_{t+i\cdot P+d}^{\{x,y,z\}}}{\sum_{d=-D}^{D} d^2}$
T9	Mean absolute deviation [15, 31]	$MAD_j = \frac{1}{w}\sum_{i=1}^{w}\lvert a_{i,j} - m_j\rvert$
T10	Vibration of the sensor [64]	$\Delta_i = \frac{1}{w}\sum_{t=i}^{i+w}\sum_{j\in\{x,y,z\}} a_{t,j}^2 - g_{t,j}^2$
T11	Average energy [11, 64, 67]	$Energy = \frac{\sum_{i=1}^{\lvert W\rvert}\lvert F_i\rvert^2}{\lvert W\rvert}$
T12	Time between peaks[31]	Different algorithms in the literature, Ref. [31] is among them
T13	Tilt of the body [8]	$sBA_i = \frac{1}{w}\sum_{t=i}^{i+w}\lvert a_i^y\rvert + \lvert a_i^z\rvert$
T14	Delta coefficients for the G [4]	$\Delta g_t^{\{x,y,z\}} = \sum_{d=-D}^{D} d\cdot g_{t+d}^{\{x,y,z\}} / \sum_{d=-D}^{D} d^2$
T15	Binned distribution, relative binned distribution and absolute binned distribution [31, 67]	Statistical count of TS values within each of the window range subintervals.

Tabla 4.2: Características recopiladas del estado del arte.

Las características englobadas en el Bloque T1 añaden 15 nuevas transformadas al conjunto final, tres por cada calculo estadístico utilizado, por otro lado T14 añade 15 características, mientras que T15 aporta en total 60 características extras, 30 correspondientes a *relative binned distribution* y 30 correspondientes a *absolute binned distribution.* Además T4, T6, y T10 aportan 1 cada una, y el resto (T2, T3, T7, T8, T9, T11, T12 y T13) de referencias aportan 3 transformadas nuevas cada una, de esta forma se obtienen 114 características. El conjunto final estaría formado por estas 117, además de las 9 correspondientes a RD, G y BA.

4.3. Selección de características

A pesar del gran de número de transformadas recopiladas durante la realización del estado del arte, se procedió a la implementación de todas ellas. Esto derivo en otro problema, el gran coste computacional asociado al análisis de 126 diferentes características, con el fin de seleccionar aquellas más relevantes para este estudio. La solución adoptada fue la FS para realizar la extracción de la información relevante.

La posibilidad de almacenar grandes cantidades de datos a bajo coste ha permitido la aparición de técnicas de selección de los mismos. La FS es un término usado en minería de datos para describir las herramientas y las técnicas disponibles para reducir las entradas a un tamaño apropiado para su procesamiento y análisis. La necesidad de técnicas de FS se deriva de que los datos no aportan valor por sí mismos, es la información que se extrae de ellos, la que aporta valor añadido. Las técnicas de FS implican tanto la reducción de cardinalidad como la elección de atributos, por lo que la selección o el descarte de los atributos debe realizarse en función de la utilidad para el posterior análisis.

La capacidad de aplicar la selección de características es esencial para un análisis eficiente, ya que los conjuntos de datos suelen contener información redundante o con ruido o simplemente innecesaria para la generación del modelo. Se usan técnicas de FS para detectar automáticamente las mejores características y excluir los valores estadísticamente no significativos. La FS ayuda a resolver el problema de tener demasiados datos de escaso valor o muy pocos datos de mucho valor.

Los métodos de FS realizan una búsqueda de nuevos subconjunto de características, con la finalidad de minimizar o maximizar la medida de evaluación de cada subconjunto. Se trata de una búsqueda exhaustiva en el espacio, y es computacionalmente intratable. Las técnicas a utilizar son:

- Filtrado. Selecciona las características de forma independiente del modelo, usando un criterio de "relevancia". Utiliza medidas con poco gasto computacional para determinar la idoneidad del subconjunto. Entre ellas se encuentran:

  * Información Mutua - Mutual Information (MI). Mide la dependencia mutua de las características X e y. Donde las $p(x)$ representan las probabilidades de los sucesos.

  $$MI(X,Y) = \int\int p(x,y) \cdot \log(\frac{p(x,y)}{p(x) \cdot p(y)})dxdy \qquad (4.1)$$

  * Coeficiente Correlación de la Información - Coefficient Correlation Information (ICC). Mide como de independientes son dos características entre sí. Cuanto mayor es el valor, mayor es la relevancia. Donde $H(X,Y)$ es la entropía de las características.

  $$ICC(X,Y) = \frac{MI(X,Y)}{H(X,Y)} \qquad (4.2)$$

- Extracción. Realiza una reducción de la dimensionalidad del conjunto original.

  * Análisis de la Componente Principal - Principal Component Analysis (PCA). Trata de encontrar un nuevo conjunto de ejes ortogonales en el que la varianza de los datos sea la máxima en alguna dirección. Esta técnica retiene aquellas características del conjunto de datos que contribuyen más a su varianza.

- Encapsulado (Wrapper). Selecciona los subconjuntos de características en función del desempeño de un modelo. Cada nuevo subconjunto se utiliza para entrenar un modelo. La tasa de error del modelo, es el valor de adecuación del subconjunto. Es un sistema con alto costo computacional. Necesita estrategias de búsqueda para explorar en forma eficiente el espacio de subconjuntos.

La selección de características se lleva a cabo en dos etapas. En la primera se realizan el filtrado con ICC y una modificación de PCA (PCA-Vote) y en la segunda se procede a la ejecución del método wrapper, con la finalidad de obtener el subconjunto óptimo de tres características (ver Figura 4.4).

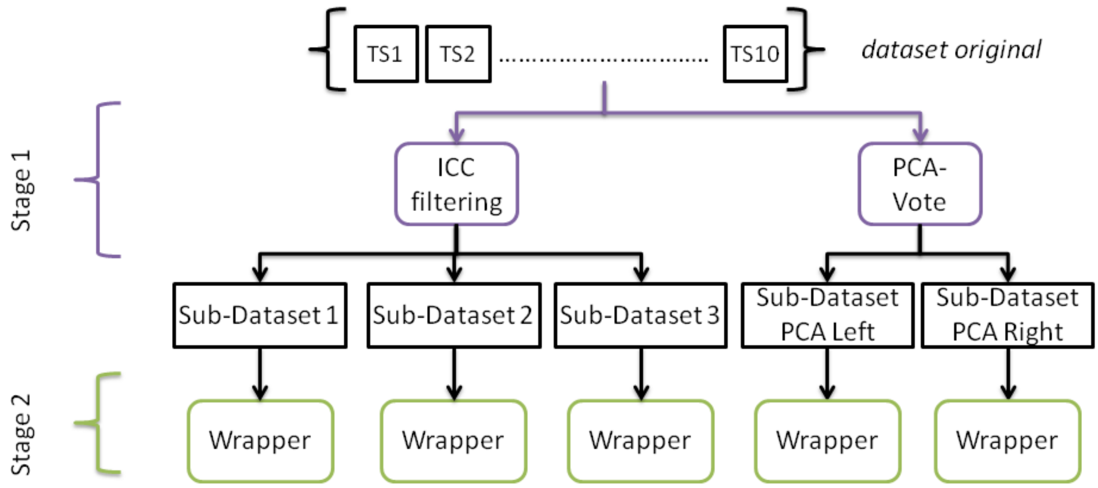


Figura 4.4: Vista general de la selección de características [21].

A continuación procedemos a la descripción de estas técnicas.

4.3.1. Selección de características por medio del filtrado

En la Figura 4.5 se observan las distintas agrupaciones llevadas a cabo sobre el *dataset original*, para la FS con ICC y MI.

El *Dataset 1* corresponde al conjunto de las 10 series temporales obtenidas del *dataset original* definido en el Capítulo 4.1. Se calculan los valores de ICC y MI, para cada una de las características (ver Capítulo 4.2) con respecto a la actividad que está desarrollando el sujeto. Tal y como se indica en [58] y en el Capítulo 5.1.1 el *Dataset 1* se escala previamente en el intervalo [0,1].

Partiendo de lo observado después de realizar el análisis de ICC y MI sobre el *Dataset 1* se plantean dos nuevas divisiones del dataset, con el fin de validar la propuesta planteada. En los dataset *Dataset 2* y *Dataset 3*, sólo se utiliza ICC debido a que MI no es capaz de discriminar entre las características [58].

El *Dataset 2* propone la división del *dataset original* en 10 subconjuntos diferentes. Para ello el *dataset original* se divide en dos subconjuntos, cada uno de los dos subconjuntos esta formada por 5 de las series (ver Figura 4.2). Esta operación se repite 5 veces, al estilo de la validación cruzada 5x2.

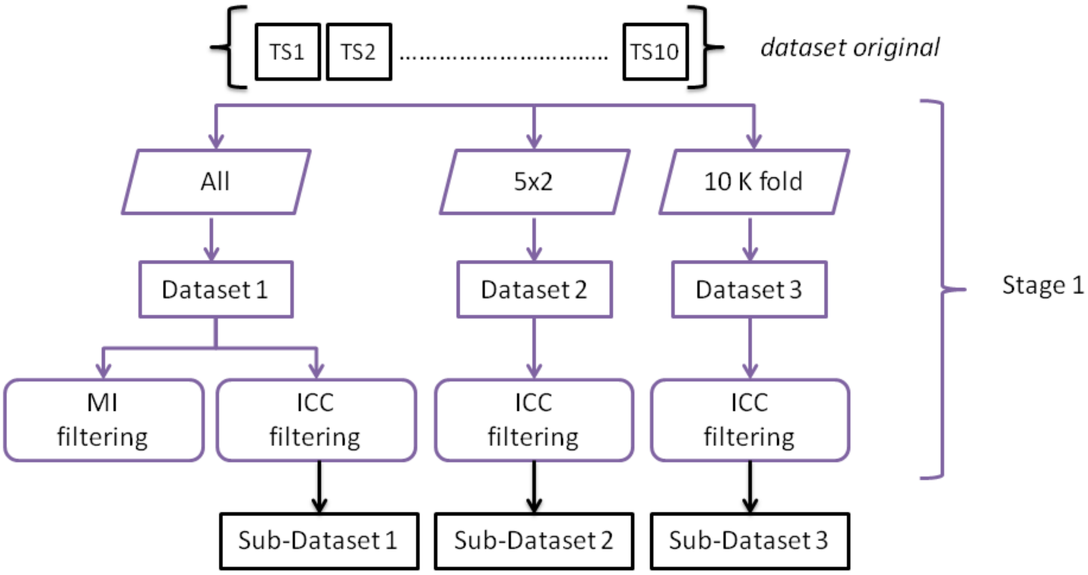


Figura 4.5: Vista general de la selección de características [21].

Para generar el *Dataset 3* de divide el *dataset original* en 10 subconjuntos diferentes que coinciden con cada una de las 10 series (ver Figura 4.2).

En el caso del *Dataset 1* se aplica ICC a todo el conjunto, y se seleccionan las 20 mejores características, mientras que en el caso de los *Dataset 2* y *Dataset 3*, se aplica ICC para cada uno de los subconjuntos y se seleccionan las 20 mejores características de cada subconjunto. Los subconjuntos de características seleccionadas se denominaran *Sub-Dataset 1*, *Sub-Dataset 2* y *Sub-Dataset 3*, respectivamente.

Para mas información ver el artículo [21] y el Capítulo 5.1.

4.3.2. Selección de características por medio de PCA-Vote

Para realizar la selección de características por medio de PCA, se plantea un método en 2 partes, ambas partes con la misma relevancia en el resultado final (50 %/50 %). En la primera parte se divide el *dataset original*(ver Capítulo 4.2) en 10 subconjuntos, cada subconjunto corresponde a la definición de una serie (ver Figura 4.2b). En la segunda parte se utiliza un solo conjunto de datos, es decir se agrupan las 10 ejecuciones de la serie. En ambos casos se aplican los siguientes pasos (ver Figura 4.6):

- El conjunto de datos se normaliza usando la media y la desviación estándar de los datos.

- Se seleccionan un número M de transformadas de PCA que expliquen el 95 % de la varianza de los datos.

- Las transformadas se ordenan ascendentemente según el porcentaje de representación, la transformada con el mayor porcentaje le corresponde el valor M/M, y a la segunda el valor(M-1)/M, etc.

- Cuanto mayor sea la suma de los votos, mayor será la relevancia de la característica.

- Finalmente se unen los resultados de las dos partes, cada una de ellas tiene un peso en el resultado final del 50 %/50 %.

Estos pasos se realizan sobre los datos de ambas manos, izquierda y derecha, con ello se obtienen dos grupos de características uno para cada mano, *Sub-Dataset PCA Left* y *Sub-Dataset PCA Right*, respectivamente. Para una mayor información sobre el método ir al artículo [59].

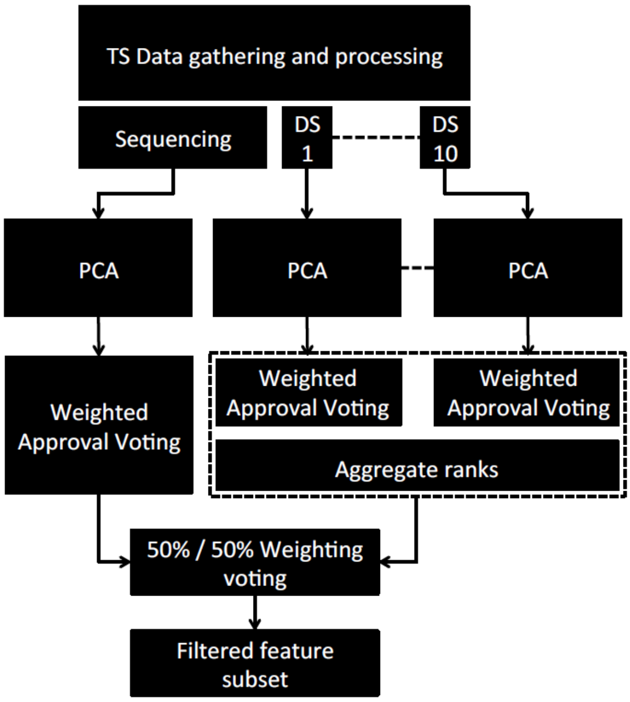


Figura 4.6: Vista general del sistema PCA-Vote [59]. Se llevan a cabo dos partes con el mismo peso en el resultado final.

4.3.3. Selección de características por medio del Wrapper

Con el fin de reducir el dataset de entrada se desarrolla un algoritmo genético de selección de características (ver Figura 4.7). Este método utiliza un dataset de entrada y selecciona un subconjunto óptimo de varias características. Los individuos serán evaluados por medio de un modelo GFFSM (ver apartado 4.4.1). La selección del subconjunto óptimo se realizará en función de la tasa de error del modelo GFFSM, el cual es el valor de adecuación del subconjunto.

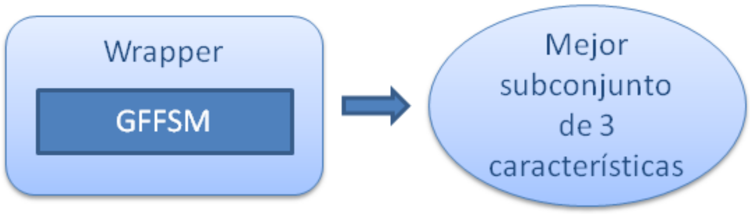


Figura 4.7: Wrapper.

Se aplicó a los diferentes GFFSM analizados en esta tesis, para ello se consideraron como dataset de entrada los siguientes 5 subconjuntos de características *Sub-Dataset 1*, *Sub-Dataset 2*, *Sub-Dataset 3*, (ver apartado 4.3.1 *Sub-Dataset PCA Left* y *Sub-Dataset PCA Right* (ver apartado 4.3.2). Los resultados obtenidos fueron tres conjuntos diferentes formados cada uno de ellos por tres características, que serán descritos en el Capítulo 5.

4.4. Reconocimiento de actividades

Una vez seleccionado un conjunto de características considerablemente inferior al inicial, nos planteamos la elección del modelo para realizar el HAR.

Tal y como se mencionó anteriormente los cambios que se producen en la forma de andar después de sufrir un episodio de ictus esta demostrada y documentada [29].

Debido al fuerte dolor de cabeza que sufre el paciente durante el episodio de ictus las actividades que este puede llevar a cabo están prácticamente limitadas a caminar, estar de pie, y sentarse. Evidentemente en caso de colapso también se producirá una caída, si bien esto no es una actividad. Por lo tanto este estudio plantea el reconocimiento de las tres actividades planteadas. Por si misma cada una de las actividades tiene un patrón de movimiento característico. En este contexto se reconocen las máquinas de estados difusos como método de modelado válido [8].

En [6] se implemento un sistema FFSM con el fin de determinar la actividad que se esta llevando a cabo dentro de una oficina. Este sistema pretende diferenciar entre: trabajando, caminando, tomando un café, visitando a un compañero, o estar en una reunión. Para ello utiliza por un lado la señal wifi para determinar la posición dentro de la oficina y por otro lado FFSM y un acelerómetro para diferenciar entre las actividades; sentado, de pie y andando. Mientras que en [7, 8] se utiliza la combinación de los sistemas GFFSM y acelerómetros. En todos estos estudios el acelerómetro se sujetó con un cinturón a la altura de la cintura en la parte media de la espalda.

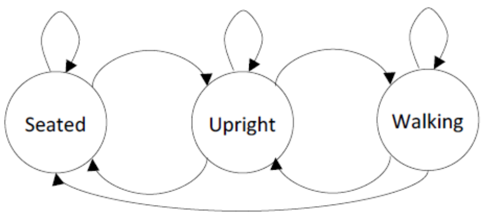
Los artículos [7, 8] se han estudiado en detalle por un lado [7] utiliza el sistema GFFSM con el fin de modelar la forma de andar de los seres humanos centrándose en las 4 posibles posiciones de los pies durante el ciclo de andar. En este caso las variables de entrada utilizadas son a^x y a^y. Por otro lado en [8] se ha utilizado este mismo sistema (GFFSM) con el fin de reconocer tres estados bien diferenciados; sentado, de pie y andando. En este caso las variables de entrada utilizadas son a^x, $T6$ y $T13(y, z)$.

4.4.1. Máquinas de estado difuso con aprendizaje en estilo Pittsburgh

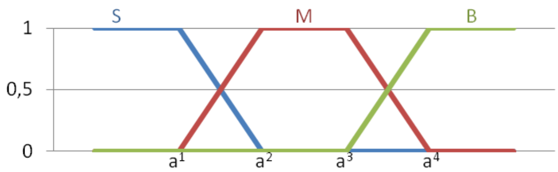
Los FFSM son un sistema de máquinas de estado con un número finito de entradas y salidas, en donde las salidas dependen no sólo de las variables de entradas actuales sino también de las anteriores. Todos los FSSM tienen un conjunto de estados, incluido el estado inicial, un alfabeto fuente y una función de transición que según la combinación de estado y variable de entrada le asigna un estado siguiente. Los estados de la máquina le dan unas capacidades de memoria limitadas. El sistema puede estar a la vez en varios estados con diferente valores de pertenencia en cada uno de ellos.

Como cualquier sistema difuso necesita una base de conocimiento definido por los expertos. La creación y mantenimiento de este sistema es complejo. Por lo que el aprendizaje se realiza de forma automática por medio de un Genetic Algorithm (GA) [6–8]. La combinación de los dos sistemas (GA y FFSM) se llama GFFSM y genera un modelo robusto y eficaz. El sistema GFFSM finalmente permite la adaptación en entornos reales no hospitalarios, y es adaptable a diferentes sujetos, al no estar sujeto a una base de conocimiento fija.

GFFSM realiza el aprendizaje automático de los individuos formados por las transiciones entre los estados de la máquina de estados difusos (RB), y de los parámetros de las funciones de pertenencia trapezoidales (DB) de los tres términos lingüísticos definidos; pequeño (S), mediano (M) y grande (B). La codificación cromosómica de los distintos individuos de la población está formada por RB y DB donde la codificación es binaria y decimal, respectivamente. El método de cruce y mutación realizado para la parte DB es *BLX-Alpha* y *bitwise mutation*, respectivamente. Mientras que los métodos de cruce y mutación para la parte RB son *two-point* y *uniform mutation*, respectivamente. El número de estados (K) coincide con el número de las actividades a reconocer: sentado, de pie y andando.



(a) Reglas para el cambio entre estados.



(b) Función de pertenencia trapezoidal.

Figura 4.8: Aprendizaje de GFFSM [59].

La función fitness del modelo GFFSM corresponde Error Absoluto Medio - Mean Absolute Error (MAE).

$$MAE = \frac{1}{K}\frac{1}{N}\sum_{i=1}^{K}\sum_{t=0}^{N} abs(s_i[t] - s_i^*[t]) \tag{4.3}$$

donde K es el número de estados posibles, N es el número de muestras del data set, $s_i[t]$ y $s_i^*[t]$ son el grado de activación obtenido y esperado respectivamente para cada uno de los estados q_i en cada instante de tiempo.

4.4.2. Adaptación máquinas de estado difuso con aprendizaje en estilo Michigan

Este estudio propone utilizar el modelo GFFSM con una segunda aproximación Michigan, pare ello utiliza la propuesta de boosting para inferencia *single winner* presentado en [54] (ver artículo [26]). En este caso, se define el número máximo de reglas y las variables de entrada al modelo Fuzzy -así como sus particiones-, dejando evolucionar los conjuntos implicados para cada una de las características. Los modelos obtenidos se evalúan con el MAE para comparar los resultados (ver Ecuación 4.3).

En esta aproximación de GFFSM cada regla esta formada por un estado inicial (S[t]), un conjunto de condiciones de entrada (C), un estado final (S[t+1]) y un peso (w). Las reglas tienen el siguiente formato **IF** ($S[t]$ *es estado*) **Y** C **Entonces** $S[t+1]$ *es estado*. El valor de inferencia de cada regla se calcula al aplicar minimum t-norm ($T_{min}(a,b) = min\,\{a,b\}$) en el operador AND y Lukasiewicz t-conorm($\perp_{Luk}= \; max\,\{a+b,1\}$) en el operador OR sobre C.

A diferencia del trabajo original [54], nuestro algoritmo por defecto se mantiene en el estado previo, al menos que alguna regla diga lo contrario. El algoritmo utilizado para calcular cual es la regla ganadora en cada instante t, solo tiene en cuenta aquellas reglas que tengan el estado inicial correspondiente al estado resultante de la muestra previa. Además el algoritmo sólo aprende reglas nuevas si estas mejorar el sistema de reglas existentes, en caso contrario se descartan.

4.5. Identificación de patrones de forma automática

Este estudio ha llegado a un punto en cual con las metodologías previamente desarrolladas somos capaces de identificar entre tres actividades bien diferenciadas (de pie, sentado y andando). El problema reside en identificar todas aquellas actividades que no se encuentran en el grupo de estudio. Es materialmente imposible obtener un patrón personalizado de cada posible actividad.

Por ello se propone la utilización de metodologías de TS para la identificación automática de patrones mas específicamente se utiliza SAX [34]. Uno de sus aspectos mas relevantes de esta técnica es el bajo coste computacional que permite embeberla fácilmente.

Se propone un algoritmo dividido en tres etapas (ver Figura 4.9). El primer paso es la recogida y preprocesado de los datos obtenidos por medio de los acelerómetros colocados en ambas muñecas, con el fin de obtener el valor de la característica sBA correspondiente al Bloque T5 de la Tabla 4.2. A continuación se implementa un sistema HAR de aprendizaje automático y por último se procede a la generación de alarmas si se esta sufriendo un episodio de ictus.

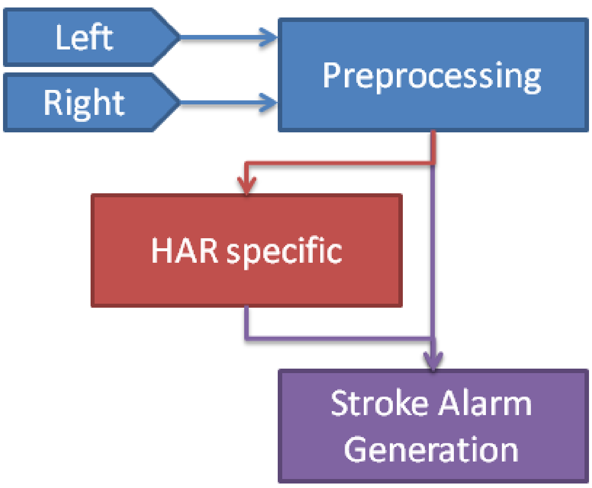


Figura 4.9: Diagrama de flujo del aprendizaje automático y de la generación de alarmas. Left y Right corresponden a los datos de los acelerómetros tri-axiales.

El algoritmo propuesto en este estudio para la identificación de las actividades de forma automática se puede ver en Algoritmo 1 y en [57]. Donde $mBA_{L,R}$ y $sBA_{L,R}$ son la media y la desviación estándar de los datos. El subíndice L y R representan las manos izquierda y derecha, respectivamente. Estos valores serán utilizados para la normalización de las ventanas TS. La similitud entre dos patrones se calcula con cualquier t-conorm, como Lukasiewicz t-conorm (ver apartado 4.4.2).

Data: X: TS de tamaño n, usando la normalización
Result: A Conjunto de actividades y su certidumbre
X'=SAX(X);
for *cada A* $\in$ *RegistroActividades* **do**
    for *cada Ymov* $\in$ *PatronesDeActividades(A)* **do**
        simXY=semejanza(X',Ymov);
        Actualizar certeza(A) de acuerdo con simXY;
    end
    $S = \{< A, certeza(A) > \forall A \mid certeza(A) > 0\}$;
    return S;
end

Algoritmo 1: SAX4HAR

El reconocimiento de los movimientos por si sólo no aporta información sobre si el sujeto esta sufriendo o no un episodio de ictus. Es necesario determinar si el movimiento es anómalo o no para generar la alarma de ictus. Por ello una vez identificados los distintos patrones se procederá a la detección de los *patrones anómalos*. El algoritmo propuesto con este fin es el siguiente (ver Algoritmo 2).

En este algoritmo se utilizan los valores de ambas manos, además el estado sentado ha de ser identificado previamente de manera independiente para cada mano. En el caso de estar en el estado sentado, el BA se normaliza mediante el $mRBA_h$ y $sRBA_h$, la media y la desviación estándar respectivamente.

Se han considerado tres niveles: bajo cuando con el sujeto debe llevar a cabo algunas tareas de baja actividad como la lectura, media durante la siesta y bajo cuando el individuo está durmiendo en este caso el nivel de actividad es muy reducido durante un período de tiempo muy largo.

Data: X_h: TS de tamaño n, usando la normalización $mRBA_{L,R}$ y $sRBA_{L,R}$ ESTADOS CERTEZAS del sujeto, niveles de la actividad reposo y contadores
Result: A Conjunto de posibles alarmas, niveles de la actividad reposo y contadores

```
if se cree en Reposo then
    Actualizar nivel de la actividad reposo;
end
X'=SAX(X);
for cada alarma del tipo AT do
    for cada Ymov ∈ PatronesDeActividades(AT) do
        simXY=semejanza(X',Ymov);
        if simXY es ALTO then
            Fijar alarma AT activa;
        end
    end
    Actualizar el ContadorDeTiempos para AT;
    if ContadorDeTiempos de AT es ALTO_AT then
        Generar alatma AT;
    end
end
```

Algoritmo 2: SAX4ALARMS

Por ejemplo, teniendo en cuenta el caso de una persona, cuando una mano no muestra actividad y la otra muestra cierto movimiento, entonces eso podría sugerir una parálisis parcial. Por el contrario, un nivel bajo de actividad en ambas manos podría caracterizar una parálisis total.

Una vez obtenidos los niveles de actividad se procede a generar las alarmas identificadoras de los movimientos anómalos, para ello se han utilizado tres umbrales diferentes. Los valores de los umbrales TH1, TH2 y TH3 se fijaron para el número correspondiente de muestras durante un período de 6 segundos, 6 segundos, y 14 segundos, respectivamente.

Los resultados obtenidos por medio del Algoritmo 1 y del Algoritmo 2 se discuten en el apartado 5.3.

Capítulo 5

Discusión de Resultados

En estos trabajos [21, 22, 57–59] realizamos un estudio completo sobre la utilización de la aceleración en la identificación de las distintas actividades humanas.

Mediante el estudio de los datos recopiladas a través de los acelerómetros (ver apartado 4.1), tratamos de responder a las siguientes preguntas:

- ¿Cuál es la actividad llevada a cabo por el sujeto en cada momento?
- ¿Cuales son las características representativas de andar, estar sentado y estar de pie?
- ¿Es la adaptación de GFFSM válida para el problema HAR con el dispositivo de adquisición de datos localizado en la muñeca?
- ¿Es posible reconocer patrones anómalos?

Cabe destacar que debido a la dificultad de recopilar datos de un paciente durante un episodio de ictus. Ha sido necesario crear una batería real de pruebas de sujetos sanos con simulación realística de episodios de ictus.

5.1. Selección de características

En los siguientes trabajos [21, 58, 59] realizamos la recopilación de las características y transformaciones existentes en el estado del arte representativas de los movimientos humanos y relacionadas con los acelerómetros como método de adquisición.

Nuestro objetivo era realizar un filtrado previo de las 126 características iniciales, para reducir el espacio de características y con ello facilitar y reducir el coste computacional del análisis posterior del conjunto de características restantes.

5.1.1. Selección de características por medio de filtros

En [58] y [21] se aplicaron las técnicas de ICC y MI (ver apartado 4.3.1) sobre el *Dataset 1*. Cabe destacar que se seleccionó ICC como técnica de filtrado en lugar de MI.

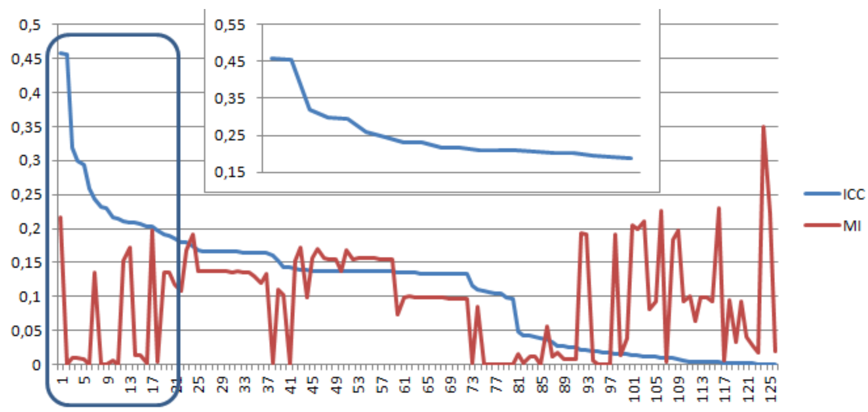


Figura 5.1: Valores de ICC y MI para las 20 características con mayor valor ICC.

Cabe destacar que en este punto del estudio se habrán obtenido los siguientes grupos de características: *Sub-Dataset 1*, *Sub-Dataset 2* y *Sub-Dataset 3*

5.1.2. Selección de características por medio de PCA-Vote

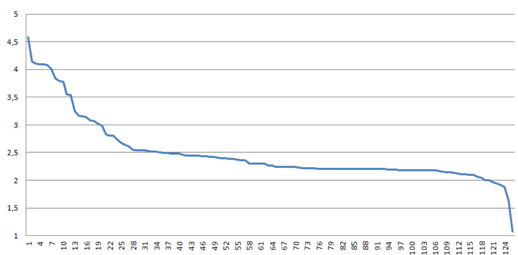
A partir de las conclusiones y resultados obtenidos en los trabajos [58] y [21] (ver apartado 5.1.1). Se plantea la utilización de PCA-Vote para la realización del filtrado basado en PCA (ver apartado 4.3.2).

Es importante destacar que la novedad de este trabajo, reside no en la utilización de PCA para realizar FS, sino en la utilización de un algoritmo de selección más complejo *PCA-Vote* (ver apartado 4.3.2 y [59]).

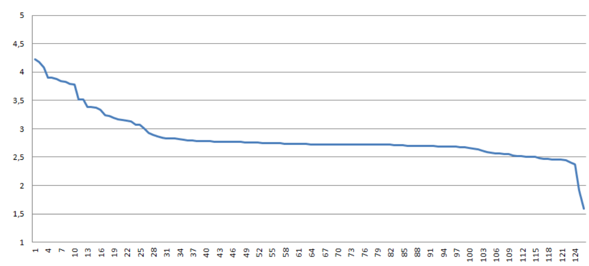
Los resultados al aplicar el método PCA-Vote son los siguientes. En la Figura 5.2 se observan todas las características del dataset, estas han sido ordenadas por el valor obtenido con el algoritmo PCA-Vote.

Mano Izquierda		Mano Derecha	
Característica	PCA-Vote	Característica	PCA-Vote
T1 Kurtosis A	4,585	T15(a^z,10)	4,225
T13(a^x,a^z)	4,145	T1 Kurtosis b^z	4,180
T3(a^x)	4,105	T1 Skewness b^x	4,075
g^x	4,095	T15(a^x,10)	3,900
T15(a^z,6)	4,090	T13(a^x, a^z)	3,900
a^x	4,085	T1 Kurtosis b^y	3,880
T15(a^x,7)	4,010	a^x	3,845
T1 Kurtosis by	3,835	T3(a^x)	3,830
T15(a^y,8)	3,790	g^x	3,795
T1 Skewness b^y	3,780	T1 Skewness b^z	3,775
T1 Kurtosis b^z	3,555	T15(a^z,6)	3,520
T13(a^x, a^y)	3,535	T1 Kurtosis b^x	3,515
T15(a^x,10)	3,255	T7(a^y,a^z)	3,385
T15(a^y,7)	3,170	T13(a^x,a^y)	3,385
T7(a^x, a^y)	3,155	T15(a^z,1)	3,375
T15(a^y,10)	3,145	T15(a^y,2)	3,330
T1 Skewness b^y	3,080	T13(a^y, a^z)	3,240
T15(a^x,1)	3,070	T1 Skewness b^y	3,225
T13(a^x,a^z)	3,020	g^y	3,190
T15(a^z,6)	2,985	a^y	3,165

Tabla 5.1: Las 20 características con mayor valor de PCA-Vote. Estos dos grupos de características se denominan *Sub-Dataset PCA Left* y *Sub-Dataset PCA Right*.



(a) Mano izquierda.



(b) Mano derecha.

Figura 5.2: Valor de PCA-Vote.

En la Tabla 5.1 se muestran las 20 características con mayor valor obtenido con el método de selección de características PCA-Vote. Estas características son usadas posteriormente por el método wrapper, para la selección del subconjunto de 3 características con mejor valor de fitness.

5.1.3. Selección de características por medio del Wrapper

Una vez conocida la validez del planteamiento de los modelos GFFSM para el reconocimiento de las actividades propuestas, se continuó con la validación del sistema wrapper-GFFSM propuesto en el apartado 4.3.3. Para ello se utilizan los tres grupos de características (*Sub-Dataset 1*, *Sub-Dataset 2* y *Sub-Dataset 3*) obtenidos en el apartado 5.1.1.

Selección de características partiendo del subconjunto ICC

Inicialmente para validar el modelo wrapper-GFFSM se entrenó el wrapper con el *Sub-Dataset 1*. El subconjunto de tres caracaterísticas seleccionadas por el wrapper fue a^x, g^y y T15(a^y,10) (ver Figura 5.3).

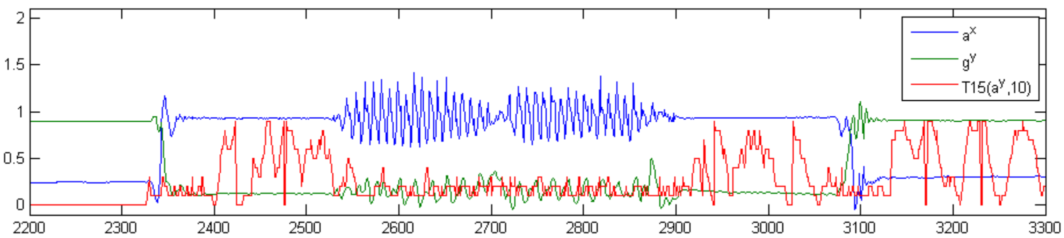


Figura 5.3: Representación del subconjunto de 3 características seleccionadas por el wrapper con *Sub-Dataset 1*.

Hay que destacar que en este punto del estudio se obtuvo un subconjunto de 3 características diferente al inicialmente propuesto. Por ello y con el fin de validar el modelo wrapper-GFFSM se realizó una comparativa (ver Tabla 5.2 Figura 5.4) entre el modelo GFFSM-a con las características iniciales (T4, T10 y T6) propuesto en [8] y el subconjunto de 3 características seleccionado por el wrapper WGFFSM(a^x, g^y y T15(a^y,10)).

Por medio de esta comparativa queda demostrada la capacidad del wrapper en la selección de un nuevo subconjunto con menor tasa de error y por tanto mejorar el modelo de reconocimiento de patrones.

Continuando con la validación del sistema wrapper-GFFSM, se propone la utilización de *Sub-Dataset 2* y *Sub-Dataset 3* para entrenar un modelo wrapper-GFFSM, con el fin de comparar los resultados del wrapper obtenidos con *Sub-Dataset 1* (ver artículo [21]). Las características seleccionadas por el wrapper son:*Sub-Dataset 2*(a^x,$T3a^y$,$T12$), *Sub-Dataset 3*(a^x,$T3a^x$,$T6$).

	GFFSM-a	WGFFSM
Fold 1	0,09	0,01
Fold 2	0,09	0,11
Fold 3	0,15	0,03
Fold 4	0,05	0,02
Fold 5	0,11	0,02
Fold 6	0,05	0,04
Fold 7	0,06	0,05
Fold 8	0,05	0,05
Fold 9	0,11	0,02
Fold 10	0,05	0,03
Average	0,08	0,04

Tabla 5.2: Valores MAE de los folder de la validación cruzada 10K-folder.

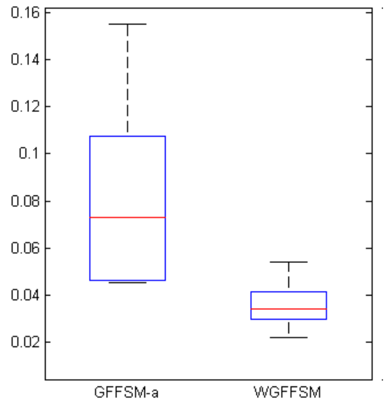


Figura 5.4: Comparativa de los GFFSM con dos subconjuntos diferentes de características.

En la Figura 5.5 se han representado las características seleccionadas como óptimas para cada conjunto de los 3 Sub-Dataset.

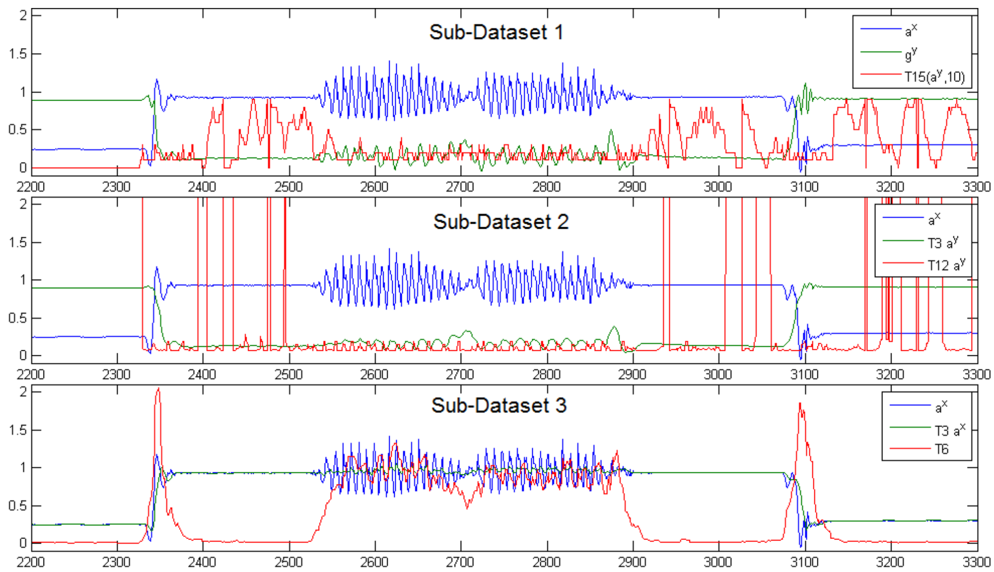


Figura 5.5: Representación de los subconjuntos seleccionados por el wrapper para *Sub-Dataset 1*, *Sub-Dataset 2*,*Sub-Dataset 3*, respectivamente.

Cada uno de los dataset son validados con dos validaciones cruzadas diferentes *5x2 K-folder* y *10 K-folder*. Hay que destacar que la tasa de error mas baja para ambas validaciones se ha obtenido con el *Sub-Dataset 3*. Concretamente con la validación *10 K-folder*, siendo 0.0199, 0.0208 y 0.0041, el promedio, la mediana y la desviación estándar, respectivamente.

Cabe reseñar que el valor promedio de los 10 *K-folder* de este nuevo subconjunto es de 0.0199 y mejora los valores obtenidos en el trabajo [58] donde el promedio era de 0.0365.

Selección de características partiendo del subconjunto PCA-Vote

Hay que destacar que, al utilizar bancos de pruebas reales la validación cruzada que mejor representa la adquisición de un conjunto de datos de entrenamiento proporcionalmente menor al número de muestras de testear, es la validación *5x2 K-folder*. Por ello en este estudio se utiliza esta validación con el fin de aproximarnos a una situación real.

Una vez obtenidos los grupos de características *Sub-Dataset PCA Left* y *Sub-Dataset PCA Right* por medio del método PCA-Vote (ver apartado 5.1.2), estos se utilizan para ejecutar un método wrapper-GFFSM estilo Pittsburgh.

El mejor subconjunto de 3 características seleccionado por el wrapper-GFFSM Pittsburgh a partir de *Sub-Dataset PCA Right* para la mano derecha es g^x, T15(a^x,1), T15(a^x,10) y para la mano izquierda con *Sub-Dataset PCA Left* es a^x, g^x, T15(a^z,10) (ver Figura 5.6).

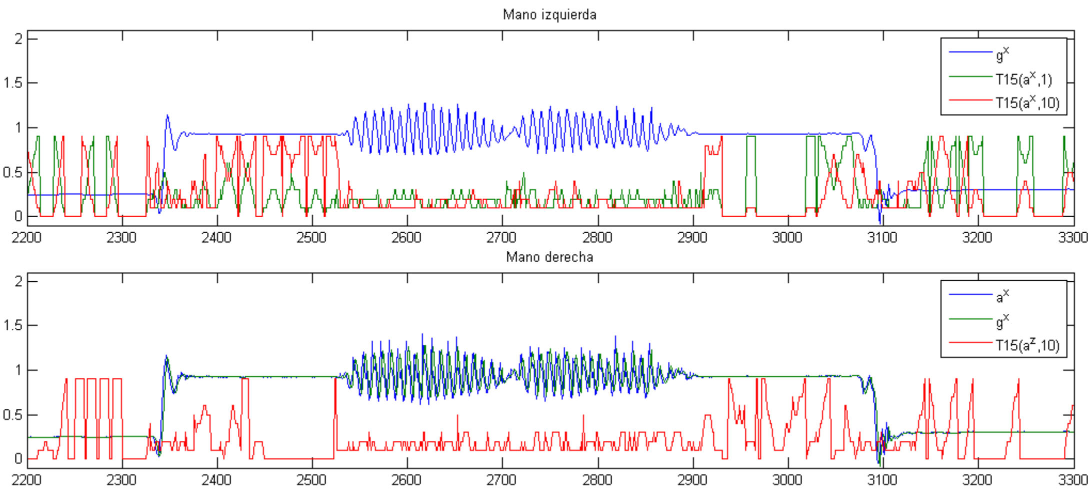


Figura 5.6: Subconjunto de características seleccionadas por el wrapper.

En este estudio se ha reducido la tasa de error del sistema GFFSM de forma significativa y progresiva, por medio de la combinación de FS por medio de dos filtros diferentes ICC y PCA-Vote y la utilización de un wrapper-GFFSM (ver Figura 5.7, en la Tabla 5.3 y [59]).

	Mano izquierda		Mano derecha	
	wGFFSM_ICC	wGFFSM_PCA	wGFFSM_ICC	wGFFSM_PCA
Fold 1	0,0020	0,0341	0,0321	0,0073
Fold 2	0,0016	0,0428	0,0196	0,0062
Fold 3	0,1250	0,0146	0,1158	0,0148
Fold 4	0,0350	0,0093	0,0397	0,0072
Fold 5	0,0015	0,0095	0,0175	0,0139
Fold 6	0,0394	0,0100	0,0088	0,0051
Fold 7	0,0834	0,0033	0,0194	0,0325
Fold 8	0,0666	0,0071	0,0041	0,0045
Fold 9	0,0072	0,0044	0,0139	0,0187
Fold 10	0,0011	0,0115	0,0156	0,0096
Average	0,0363	0,0147	0,0287	0,0120

Tabla 5.3: Media de los valores MAE de la validación 10K-folder.

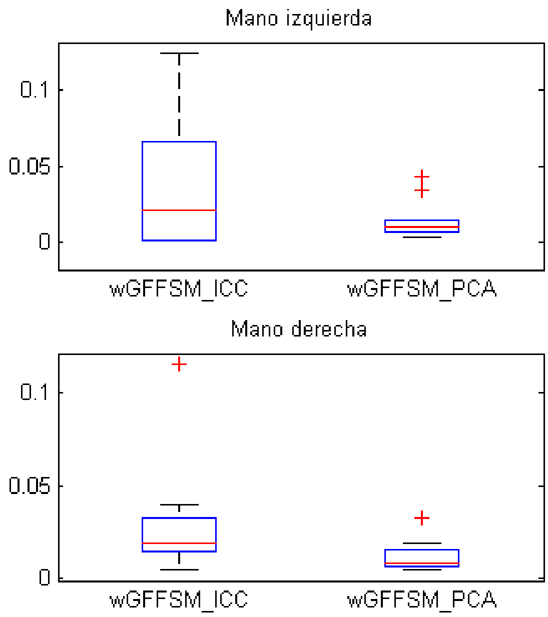


Figura 5.7: Tasa de error con una validación del tipo *5x2 K-folder*.

5.2. Reconocimiento de actividades

5.2.1. Máquinas de estado difuso con aprendizaje en estilo Pittsburgh

El objetivo principal era determinar la eficiencia del GFFSM en HAR (ver [22]). Para ello, basándonos en el trabajo de [8], se entrenó un modelo GFFSM de estilo Pittsburgh con el subconjunto de 3 características T4(SMA), T10(Δ), T6(AM) (ver Figura 5.8).

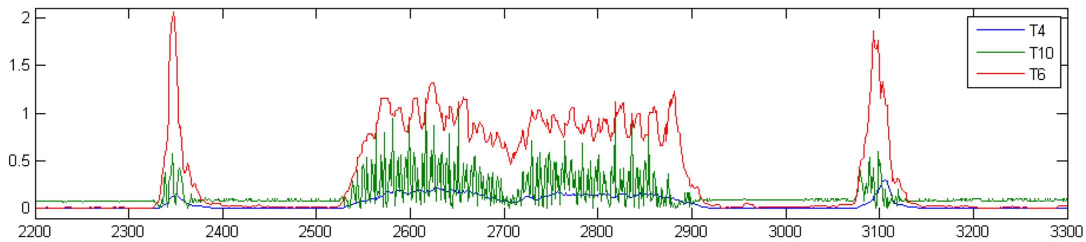


Figura 5.8: Representación de las características iniciales (T4(SMA), T10(Δ), T6(AM)) de una serie.

Cabe destacar que se determinó que 300 generaciones sería el valor a utilizar en los entrenamientos futuros de los modelos GFFSM, debido a la elevada tasa de error que implicaba la utilización de 200 generaciones. Para ello se realizó una comparativa con ambas parametrizaciones y las características T4, T10 y T6 (ver Tabla 5.4 y [58]).

Los resultados obtenidos muestran una alta tasa de éxito en el reconocimiento de las actividades propuestas. Por lo que queda demostrada la validez de los modelos GFFSM para el reconocimiento de las actividades.

5.2.2. Adaptación máquinas de estado difuso con aprendizaje en estilo Michigan

Este estudio ya ha determinado la validez de 2 subconjuntos de 3 características cada uno, y la validez de estos para mejorar el modelo GFFSM Pittsburgh. Por ello en [59] se propone la implementación y validación de un modelo GFFSM estilo Michigan. Para mas información sobre este sistema ver el apartado 4.4.

	GFFSM-a200		GFFSM-a300	
	Test	Time	Test	Time
Fold 1	0,09	3837,53 s	0,01	6300,82 s
Fold 2	0,09	4706,87 s	0,11	6561,90 s
Fold 3	0,15	3409,03 s	0,03	6462,27 s
Fold 4	0,05	4004,64 s	0,02	6149,53 s
Fold 5	0,11	5744,61 s	0,02	6082,63 s
Fold 6	0,05	4261,52 s	0,04	6390,64 s
Fold 7	0,06	4085,39 s	0,05	6478,03 s
Fold 8	0,05	4407,55 s	0,05	5914,35 s
Fold 9	0,11	4343,58 s	0,02	6223,38 s
Fold 10	0,05	4055,12 s	0,03	6262,34 s
Promedio	0,08	4285,58 s	0,04	6282,59 s

Tabla 5.4: Valores MAE de la validación 10K-folder.

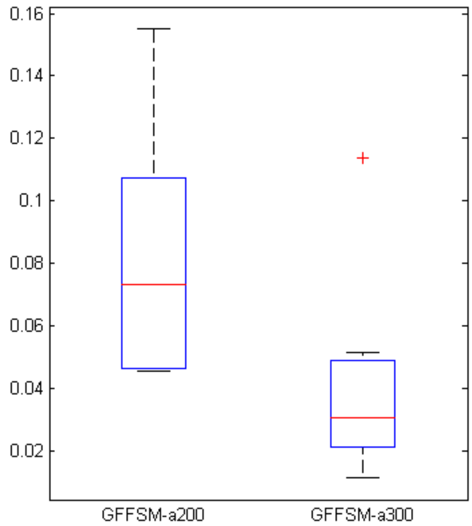


Figura 5.9: Comparativa de los GFFSM con dos subconjuntos de características diferentes.

Otra aportación que se realiza en este estudio es la comparación de las dos aproximaciones GFFSM (Pittsburg y Michigan) y de las dos técnicas de FS desarrolladas en este trabajo. Con ese fin se modela GFFSM Michigan para los subconjuntos seleccionados por ICC en [21] y PCA en [59], ver Figuras 5.10 y 5.11 y Tablas 5.5 y 5.6, respectivamente. En este caso wGFFSM, bGFFSM5r y bGFFSM6r corresponden a los sistemas GFFSM Pittsburgh y GFFSM Michigan de 5 y 6 reglas, respectivamente.

	Mano izquierda			Mano derecha		
	wGFFSm	bGFFSM5r	bGFFSM6r	wGFFSm	bGFFSM5r	bGFFSM6r
Fold 1	0,002	0,001	0,088	0,032	0,028	0,025
Fold 2	0,002	0,001	0,001	0,020	0,036	0,037
Fold 3	0,125	0,001	0,001	0,116	0,043	0,047
Fold 4	0,035	0,001	0,001	0,040	0,012	0,022
Fold 5	0,001	0,001	0,000	0,018	0,074	0,057
Fold 6	0,039	0,000	0,003	0,009	0,025	0,025
Fold 7	0,083	0,001	0,001	0,019	0,036	0,036
Fold 8	0,067	0,001	0,032	0,004	0,025	0,023
Fold 9	0,007	0,001	0,000	0,014	0,024	0,071
Fold 10	0,001	0,000	0,003	0,016	0,046	0,061
Mean	0,036	0,001	0,013	0,029	0,035	0,040

Tabla 5.5: Valores MAE de la validación 10K-folder.

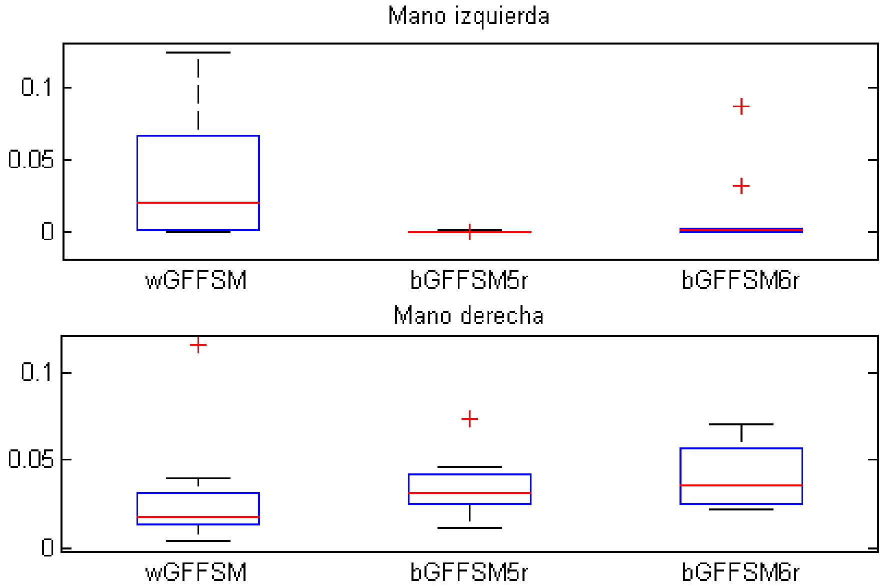


Figura 5.10: Tasa de error con una validación del tipo *5x2 K-folder*, para ambas manos.

Hay que destacar que aunque para la mano derecha se obtiene el mejor rendimiento para el GFFSM Pittsburgh (wGFFSM), este no es estadísticamente mejor que el GFFSM Michigan(bGFFSM). Mientras que para la mano izquierda el modelo bGFFSM supera claramente al resto de métodos. Incluso reduce el número de reglas necesarias a 5.

	Mano izquierda			Mano derecha		
	wGFFSm	bGFFSM5r	bGFFSM6r	wGFFSm	bGFFSM5r	bGFFSM6r
Fold 1	0,034	0,018	0,016	0,007	0,011	0,135
Fold 2	0,043	0,023	0,021	0,006	0,090	0,018
Fold 3	0,015	0,026	0,022	0,015	0,027	0,048
Fold 4	0,009	0,024	0,028	0,007	0,011	0,011
Fold 5	0,009	0,055	0,035	0,014	0,022	0,011
Fold 6	0,010	0,021	0,021	0,005	0,036	0,018
Fold 7	0,003	0,023	0,023	0,033	0,027	0,034
Fold 8	0,007	0,035	0,027	0,005	0,014	0,014
Fold 9	0,004	0,029	0,028	0,019	0,013	0,013
Fold 10	0,011	0,039	0,041	0,010	0,097	0,022
Mean	0,015	0,029	0,026	0,012	0,035	0,032

Tabla 5.6: Media de los valores MAE de la validación 10K-folder.

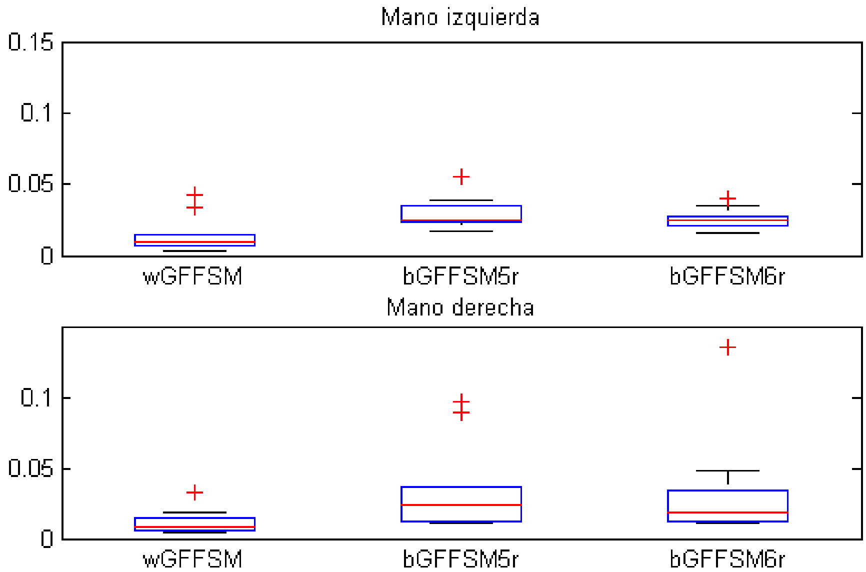


Figura 5.11: Tasa de error con una validación del tipo *5x2 K-folder*.

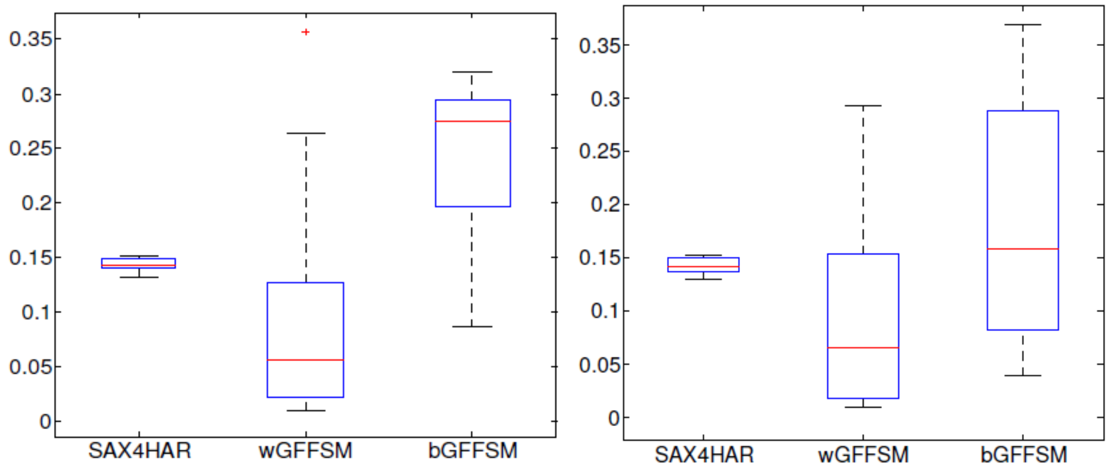
Por otro lado a partir del subconjunto de características seleccionadas por PCA-Vote, GFFSM estilo Michigan (bGFFSM) no mejora los resultados obtenidos con GFFSM Pittsburgh para ninguna de las manos.

Atendiendo a los resultados obtenidos, destacamos la siguiente conclusión, ambas aproximaciones del modelo GFFSM parecen ser buenas opciones, aunque Michigan aporta una reducción en el número de reglas, esta reducción hace su integración en sistema embebidos más fácil.

5.3. Identificación de patrones de forma automática

El objetivo principal de este trabajo [57] es el de solventar el problema de la identificación de los movimientos anómalos, para ello en este estudio se propuso un algoritmo automático (ver apartado 4.5) para la identificación de los patrones de las distintas actividades.

Como se ve en la Figura 5.12 el algoritmo no mejora sustancialmente ninguno de los métodos GFFSM.



(a) Mano izquierda. (b) Mano derecha.

Figura 5.12: Comparativa de los valores MAE para los algoritmos; SA4HAR, GFFSM estilo Pittsburgh y Michigan

Cabe destacar la eficiencia en la identificación de la actividad de sentado (ver Tabla 5.7), esto facilita la detección de episodios de ictus, al sufrir los sujetos en su mayoría un colapso, durante un episodio de ictus.

		Obtenido					
		Mano izquierda			Mano derecha		
		De pie	Sentado	Andando	De pie	Sentado	Andando
Real	De pie	672/33117	17108/3858	3091/1296	1261/ 26116	18106/1758	1369/3929
	Sentado	2316/1178	36617/18487	253/1066	2266/486	36186/20267	194/760
	Andando	430/2530	2805/1175	30830/23628	838/1	1973/1590	31011/24960

Tabla 5.7: Matriz de confusion. En azul los valores correspondientes al algoritmo 1 y en negro los valores correspondientes a wGFFSM.

5.3.1. Generación de alarmas

Una vez aplicado el Algoritmo 1, se procede a la generación de alarmas por medio del Algoritmo 2. Las alarmas son provocadas por la detección de movimientos anómalos o de caídas.

Con el fin de poder testear el Algoritmo 2, se recogen datos del hombre durante un periodo de 10 noches. Para ellos se analizaron dos períodos de 40 minutos de duración uno al principio de la noche (escenario 1) y otro en el medio de la noche (escenario 2). El algoritmo Algoritmo 2 se ejecuta dos veces: la primera con los umbrales normales y en la segunda con el conjunto de umbrales subestimados. Los resultados de la experimentación se muestran en la Figura 5.13 (escenario 1) y la Figura 5.14 (escenario 2).

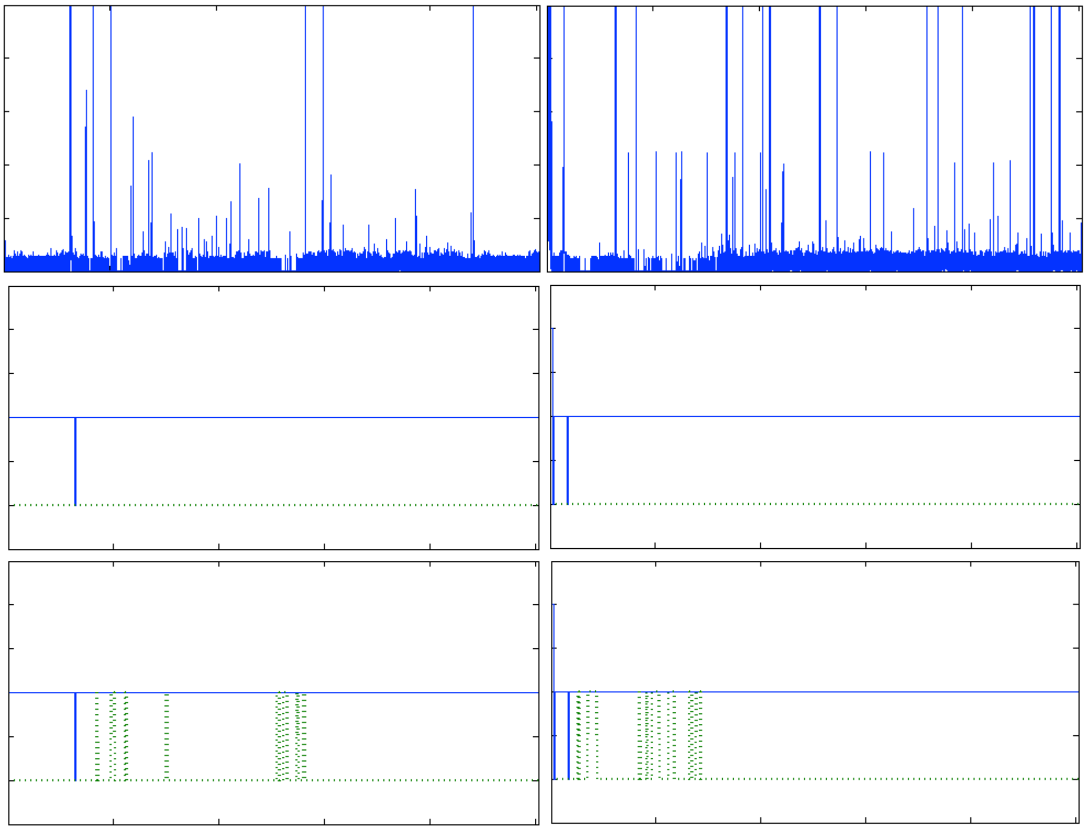


Figura 5.13: Resultados generados por el Algoritmo 2 de generación de alarma de ictus durante el escenario 1.

En las Figuras 5.13 y 5.14 se observan los resultados generados por el Algoritmo 2 de generación de alarma de ictus. La figura esta dividida en tres secciones (superior, central e inferior). La parte superior muestra los valores de sBA (Bloque T5 de la Tabla 4.2) para las manos izquierda y derecha (columna izquierda y columna derecha)- el rango del eje Y está comprendido entre 0 y 0.1 y muestra movimientos muy pequeños. La parte central muestra para cada lado (izquierdo y derecho respectivamente) el estado estimado, que casi siempre es EN REPOSO, y la la línea de puntos verdes representa la alarma de brazo paralizado, esta alarma no se ha disparado en ningún momento. La parte inferior muestra las mismas variables pero con umbrales de tiempo muy subestimados para que la alarma se dispare.

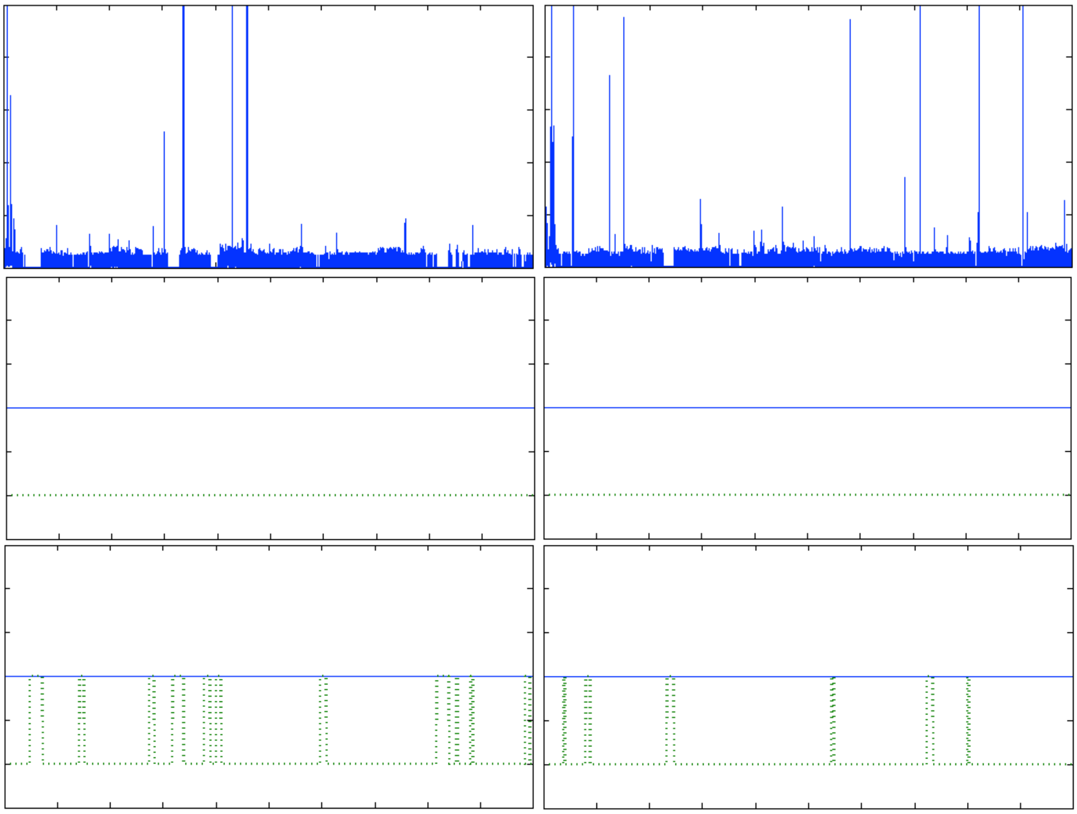


Figura 5.14: Resultados generados por el Algoritmo 2 de generación de alarma de ictus durante el escenario 2.

Capítulo 6

Conclusiones y trabajos futuros

En esta sección, se presentan las conclusiones obtenidas a partir de la investigación realizada a lo largo de los diferentes trabajos descritos en esta memoria.

La presente tesis tuvo como objetivo comprobar la eficacia de los *dispositivos wearable* y métodos HAR en el diagnostico precoz del ictus. Esto quiere decir que por primera vez se utilizó la combinación de ambas técnicas con este fin. Para ello se crearon dispositivos y aplicaciones que han permitido recopilar los datos utilizados en los estudios aquí presentados.

Para poder llevar a cabo este estudio, primero se realizó un estudio del estado del arte sobre las publicaciones existentes; para ello, hemos estudiado por un lado las características y por otro lado los métodos más interesantes. Se han analizado en profundidad los diferentes estudios y gracias a la ayuda prestada por los médicos se han identificado las ventajas y desventajas de cada uno de ellos. Finalmente se seleccionaron tres líneas de trabajo bien diferenciadas: FS, GFFSM, SAX.

Los objetivos de este trabajó eran el de identificar las características representativas del movimiento humano y el de desarrollar nuevas técnicas capaces de ser competitivas y embebidas e incluso mejorar a las metodologías publicadas anteriormente.

Para ello, hemos presentado varios métodos novedosos entre ellos un algoritmo de FS PCA-Vote para la reducción del espacio de características, otros dos métodos basados en GFFSM estilo Michigan y SAX para la implementación de técnicas HAR y por último un algoritmo para la generación de alarmas. En todos los casos, se ha demostrado su validez mediante los estudios experimentales necesarios y la comparativa con metodologías ya existentes.

A lo largo de la presente investigación logró demostrarse que la combinación de los acelerómetros con GFFSM y SAX son una herramienta valida a la hora de afrontar problemas del tipo HAR. Por otro lado, el gran espacio de características que se obtienen de los datos recopilados con los acelerómetros, dificulta el entrenamiento de las distintas metodologías. Además las metodologías propuestas son viables económicamente y embebibles en *dispositivos wearable* complejos.

A modo de resumen, mostramos a continuación las principales conclusiones extraídas durante el desarrollo de esta memoria:

- Los dispositivos wearable como los acelerómetros son una herramienta valida a la hora de afrontar problemas del tipo HAR. Sin embargo, el gran espacio de características que se obtienen de los datos originales, dificulta el entrenamiento de las distintas metodologías.

- El método GFFSM estilo Michigan permiten reducir significativamente el número de reglas necesarias para la resolución del problema HAR.

- Técnicas más simples, como SAX son muy potentes en el reconocimiento de ciertas actividades en comparación con otros algoritmos mas complejos como GFFSM.

- La utilización de un método de aprendizaje automático y personalizado reduce los costos de recogida de datos, al no ser necesario un amplio conjunto de sujetos de diversas edades, sexos, etnias, etc...

6.1. Futuras líneas de estudio

Para terminar con esta memoria, presentamos las líneas futuras de investigación que han surgido o sobre las que podemos trabajar a partir del trabajo realizado en esta memoria.

Si bien el presente trabajo abordó cómo identificar y diagnosticar episodios de ictus la innovación constante en los dispositivos eléctricos no se han tenido en cuenta. En futuras investigaciones un tema interesante a tratar sería el uso de otros dispositivos en solitario o combinados, sin aumentar el coste económico del sistema final. Esto implicará un estudio pormenorizado de las tecnologías existentes.

Este estudio se ha centrado en el reconocimiento de movimientos anómalos, por lo que sería interesante aplicarlo con otros fines médicos. Una posibilidad sería el estudio de patrones anómalos durante el sueño. Este tipo de anomalías podrían indicar si los pacientes sufren apneas, reduciendo tanto los costes económicos como el tiempo de diagnostico. Ya se han dado los primeros pasos en esta línea de trabajo como se puede ver en [23] [5].

A su vez sería necesario estudiar la viabilidad y la validez de los algoritmos propuestos en otros ámbitos. Debido a que en los últimos años han emergido nuevos campos de investigación como los *hogares inteligentes* y las empresas, entre otros. Por ello se propone realizar un estudio de la viabilidad de estas técnicas con el fin de mejorar y optimizar resultados en estos ámbitos.

Además es imprescindible analizar la viabilidad y la validez durante un episodio de ictus real de la metodología SAX propuesta.

Nos gustaría estudiar a su vez, la viabilidad y la validez de aplicar este modelo en varios sujetos de pruebas en un espacio no hospitalario, ni en un banco de pruebas. Además de estudiar los datos recogidos antes, durante y después de haber experimentado un episodio de ictus. Para ello se espera poder trabajar con sujetos con alta probabilidad de sufrir episodios de ictus.

Capítulo 7

Artículos

La presente tesis doctoral, de acuerdo con el informe correspondiente autorizado por los Directores de Tesis y el Órgano Responsable del Programa de Doctorado, se presenta como un compendio de tres trabajos previamente publicados. Las referencias completas de los artículos en revistas internacionales con revisión a pares e indexadas que constituyen el cuerpo de la tesis son los siguientes:

1. Improving human recognition and its application in early stroke diagnosis. (ver apartado 7.2.1)

2. Features and Models for Human Activity Recognition. (ver apartado 7.2.2)

3. A Hybrid Intelligent Recognition System for the Early Detection of Strokes. (ver apartado 7.2.3)

Así mismo, se considera oportuno incluir las siguientes conferencias internacionales con revisión a pares que han constituido parte de la base formativa del doctorando:

1. A Preliminary Study on Early Diagnosis of Illnesses Based on Activity Disturbances. (ver apartado 7.3.1)

2. Human Activity Recognition and feature selection for stroke early diagnosis. (ver apartado 7.3.2)

3. Early diagnosis of Stroke: bridging the gap through wearable sensors and computational models. (ver apartado 7.3.3)

7.1. Factor de Impacto

INFORME SOBRE EL FACTOR DE IMPACTO (FI) DE LAS PUBLICACIONES

Tesis doctoral presentada por D./Dª Silvia González González en la modalidad de "compendio de publicaciones".

Factor de impacto (FI) de las publicaciones según el Journal Citation Reports del año 2014

Revista	FI	Categoría	SCImago Journal Rank (SJR)
International Journal of Neural Systems	6.056	Computer Science, Artificial Intelligence	1,131
Neurocomputing	2.005	Computer Science, Artificial Intelligence	0,898
Integrated Computer-Aided Engineering	4.667	Computer Science, Artificial Intelligence	1,119

7.2. Artículos

7.2.1. Features and models for human activity recognition

González, S.; Sedano, J.; Villar, J. R.; Corchado, E.; Herrero, A. & Baruque, B. Features and models for human activity recognition Neurocomputing, 2015, 167, 52 - 60

Features and Models for Human Activity Recognition

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Abstract

Human Activity Recognition (HAR) is aimed at identifying current subject task performed by a person by analyzing data from wearable sensors. HAR is a very challenging task that has been applied in very different areas such as rehabilitation, localization, etc. During the past ten years, plenty of models, number of sensors and sensor placements, and feature transformations have been reported. From this bunch of previous ideas, what seems to be clear is that the very specific applications drive to the selection of the best choices for each case.

Present research is focused on early diagnosis of stroke, what involves reducing the feature space of gathered data and subsequent HAR, among other tasks. In this study, an Information Correlation Coefficient (ICC) analysis was carried out followed by a wrapper Feature Selection (FS) method on the reduced input space. Additionally, a novel HAR method is proposed for this specific problem of stroke early diagnosing, comprising an adaptation of the well-known Genetic Fuzzy Finite State Machine (GFFSM) method.

To the best of the authors knowledge, this is the very first analysis of the feature space concerning all the previously published feature transformations on raw acceleration data. The main contributions of this study are the optimization of the sample rate, selection of the best feature subset, and learning of a suitable HAR method based on GFFSM to be applied to the HAR problem.

Keywords: Human Activity Recognition, Genetic Fuzzy Finite State Machine, Feature Domain Reduction, Feature Selection, Information Correlation Coefficient

1. Introduction

This research aims at developing a solution for the early diagnosis of stroke and the rehabilitation of elder people after a disruptive event: an injure due to a falling, a seizure onset, etc. In this context, only a small subset of activities are to be identified among those that a human being can usually do and hence,the recognition of those activities is simplified. On the other hand, activity recognition devices help to improve the mobility of elder people during rehabilitation, so technology is enhancing quality of life for both elder and injured people.

Every human being performs different activities during the day and Human Activity Recognition (HAR) targets their identification. Though walking recognition is nowadays a clear-cut task [1], the recognition of other activities is not. It is difficult due to the fact that there are many different activities that a person may perform and some of them could even co-occur at the same time (talking to another person or eating a sandwich while walking, reading and being seated, etc.), a wide spread of feature transformations and HAR methods have been applied up to now [2, 3, 4]. Many techniques of data gathering, including video-images, are being used but tridimensional accelerometers are the data sources for most previous HAR studies.

The main problem to be solved in this research is the issue of HAR for early diagnosis of stroke onsets. During such episodes, the upper limbs are the parts of the body that best reflect the differences regarding normal behaviour. According to this idea, two triaxial accelerometers are usually placed on the subject's wrists. The hypothesis is that with these sensors we would be able to recognize an onset due to the differences in the movement patterns. However, these movement patterns will depend on the task the subject is carrying out. Therefore, early diagnosis of stroke also includes HAR. Interesting enough to mention, the activities to be identified also depends on the focused population: generally speaking, the older you are the lower the amount of activities you perform during everyday life. Additionally, the quality of the movement may be rather different depending on the age of people: the younger the faster. Thus, the target population define the different activities that may be excluded for recognition and the age reduces the amount of movement; movement for older people is lower than that for younger people while performing the same activities.

A light wearable device might be enough for the data gathering, preprocessing and analysing provided the number of activities to be recognize is kept small. Previous studies have analyzed the windows size for pre-processing the continuous data flow coming from data sources [5]. Once the data is properly pre-processed, they must be analyzed.

To do so, one of the most interesting HAR techniques that can be deployed in embedded devices is the Genetic Fuzzy Finite State Machine (GFFSM) [6], which also handles expert knowledge with high accuracy. To this end, this study is focused on enhancing the HAR using 3DACC sensors in wearable devices. The aim of this research is two-fold: on one hand, the selection of the 3DACC transformations is analyzed and a feature subset is chosen; on the other hand, the improvements on the GFFSM model obtained due to the reduced feature subset are explored. The study also makes use of this GFFSM model for HAR, but additionally tackles several issues identified as relevant in the HAR literature, such as those concerning the diversity of transformations from the acceleration raw data and how to reduce the dimensionality and the different methods for cross validation used so far.

The remainder of present paper is organized as follows. Next section deals with the challenging task of HAR, including an overview of the input feature domain, as well as an in-depth review of the HAR literature. Section 3 introduces the proposed method and its different stages: a two-step Feature Selection (FS) and a HAR modeling by means of the GFFSM. Subsequently, section 4 is devoted to evaluate and discuss the experimentation carried out. Finally the main conclusions from the obtained results as well as the future work are drawn in section 5.

2. A Review of Human Activity Recognition

After several years of study, a wide spectrum of features, calculated as transformations from raw acceleration data, have been proposed for HAR. A set of features is chosen for each one of the applied methods according to different criteria. This section describes the main features from those that have been proposed in the literature up to now; afterwards, the previous work on HAR is analyzed and compared.

2.1. From Acceleration Data to the Input Feature Space

Nowadays, the most common sensor applied in HAR is the tri-axial accelerometer. Data gathered from this type of sensor, known as raw data (RD, a_i^x, a_i^y and a_i^z; $a_{i,j\in\{x,y,z\}}$ for the sake of brevity), should be decomposed in the gravity acceleration (G) -that is due to each gravity, g_i^x, g_i^y and g_i^z or

$g_{i,j\in\{x,y,z\}}$- and the BA - which is due to the human movement, b_i^x, b_i^y and b_i^z or $b_{i,j\in\{x,y,z\}}$-. The ability of BA to discriminate among different human gestures is documented in [7]. Nevertheless, the literature includes the use of a wide variety of transformations (the most interesting described below), where w stands for the window size -if needed-, and sub-indexes $i \in \{1, \ldots N\}$ and $j \in \{x, y, z\}$ stand for the number of the sample and the axis, respectively. It is worth mentioning that all these features computed on each of the possible signals (RD, BA and G) would generate a feature space with more than 190 features, whose processing and analysis are very challenging tasks indeed.

The following features have been previously applied to HAR:

1. The *mean, deviation and higher momentum statistics* values for the RD [8] or for the BA [9, 7], and the RD *mean absolute deviation* $MAD_j = \frac{1}{w}\sum_{i=1}^{w}|a_{i,j} - m_j|$ [10, 8], where m_j is the mean value of $a_{i,j}$.
2. The *Root Mean Square* $RMS_j = \sqrt{\frac{1}{w}\sum_{i=1}^{w}|a_{i,j}^2|}$ [10].
3. The *sum of the absolute values* of the BA [11] $sBA_i = \frac{1}{w}\sum_{t=i}^{i+w}\sum_{j\in\{x,y,z\}}$ $|b_{t,j}|$, the *vibration of the sensor* (Δ) [9] $\Delta_i = \frac{1}{w}\sum_{t=i}^{i+w}\sum_{j\in\{x,y,z\}} a_{t,j}^2 - g_{t,j}^2$ and the *tilt of the body* ($tilt_i = \frac{1}{w}\sum_{t=i}^{i+w}|a_i^y| + |a_i^z|$ [6]. The two former transformations were designed to detect whether the sensor registers no movement at all, as fixed to an steady object, while the latter is used whenever the sensor axes match with the body axes.
4. The *Signal Magnitude Area* $SMA = \frac{1}{w}\cdot\sum_{i=1}^{w}(|b_i^x| + |b_i^y| + |b_i^z|)$ [9, 12, 7] discriminating between gravity acceleration and BA.
5. The *Amount of Movement* $AM_i = \sum_{v=\{x,y,z\}} \mid max_{t=i+1}^{i+w}(b_t^v) - min_{t=i+1}^{i+w}(b_t^v) \mid$ [6]: calculated as the maximum difference between the values of BA within the sliding window.
6. The Delta coefficients for estimating the first order time derivate of each of the G signal components [12]: $\Delta g_t^{\{x,y,z\}} = \sum_{d=-D}^{D} d \cdot g_{t+d}^{\{x,y,z\}} / \sum_{d=-D}^{D} d^2$, where the shift D is parameterized to the algorithms and $g_t^{\{x,y,z\}}$ stands for each of the three axis G components.
7. The Shifted Delta Coefficients (SDC) for estimating the first order time derivative of the BA signal components in the vicinity of the current timestamp [12]: $\Delta b_{t+i\cdot P}^{\{x,y,z\}} = \frac{\sum_{d=-D}^{D} d\cdot b_{t+i\cdot P+d}^{\{x,y,z\}}}{\sum_{d=-D}^{D} d^2}$, where $b_t^{\{x,y,z\}}$ stands for each one of the three axis BA components, N is the number of base

features from which they are calculated, D stands for the same as in the delta calculations, P is the distance between samples and K is the number of samples taken.

8. The Average Energy (AE) [13, 9, 7]: calculated as the sum of the squared discrete FFT component magnitudes of the signal in a window of a fixed size. This features allows to discriminate between static and dynamic activities. Although it is calculated for each axis, the aggregation or the average over the three axes is often used [7].
9. The correlation between axes [13]: calculated for each pair of axes as the ratio of the covariance and the product of the standard deviations. This feature is useful to discriminate one dimensional activities if the sensor is properly placed. As stated in [7], this feature allows the discrimination between walking and climbing stairs.
10. The Intensity of the Movement (InMo) [14], which is the mean first derivative of the raw acceleration data, $InMo_t^{v\in\{x,y,z\}} = \frac{1}{w}\sum_{i=0}^{w-1} \cdot |a_{t-i}^v - a_{t-i-1}^v|/\Delta x_t$. Δx_t represents the time between samples, which can be ignored if the sampling rate is kept constant. The window size is given by the value of w.
11. The Time Between Peaks (TBP) [8], time in milliseconds between peaks in the sinusoidal waves associated with the frequency response of most activities (for each axis).
12. The Binned Distribution [8, 7]: as stated by the authors, this measure is used with sliding windows of size w. For each window the range should be calculated as $maximum - minimium$; then, the range is divided into 10 equal size bins; finally, it is recorded what fraction of the w values falls within each of the bins. This approach is named as Relative Binned Distribution (RBD). In this study, it is proposed the Absolute Binned Distribution (ABD) that is calculated using the lower and upper acceleration values as the range to be divided in bins.

In many of the solutions sliding windows (with or without shifting) are proposed and the typical window size converges to the samples within a period of 2 seconds. Features are typically normalized to 0-mean 1-standard deviation and/or scaled to the interval [0, 1] before further preprocessing. Using frequency-derived features, employing FFT or similar ones, over long time-windows have been found more suitable for long duration and quasi-periodic signals like walking, cycling or teeth brushing. Otherwise, when classifying shorter duration and non-periodic activities, transitions or a short sequence of steps, then the time-domain representation has been found as a better solution [12].

2.2. Previous Work on HAR

The characterization of human movement, specially while walking, is well documented in the literature [1]. Nevertheless, disruptive events, such as injury falling, strongly modifies the way patients move [15]. Particularly the patient's gait is severly affected. Due to this reason, and also because walking is one of the most sensible activities in human dependence, the gait and the patient kinematics have been broadly studied in the literature so far [16, 15].

Most of the previous studies are based on the analysis of video-images of the patient gait or movements through well-known mechanical methods [17, 16, 18, 19]. These studies are mainly focused on the rehabilitation of the patient and aimed at developing new therapeutical training techniques, providing interesting conclusions, and determining the relevant variables for characterizing the gait pattern.

Since the appearance of low cost and high performance accelerometers in the market, the recognition of human activity got the focus. Plenty of studies have analyzed the performance of this type of devices for stroke rehabilitation evaluation [20] and activity level measuring [21]. Some of the studies reported the used of different sensors and techniques, like accelerometers and electromyography [22] or accelerometers and electrocardiograph sensors [3]. One of those studies presented the combination of accelerometers and pressure gauges within the shoes for discriminating between three activities (sitting, standing and walking) of stroke patients [23]. In this study, Support Vector Machines (SVM) were proposed for classification of the activity, and rates of 99% of recall and 76.9% of precision were achieved. Though the classification performance is relatively good, it is worth noting that this approach can only discriminate between normal and abnormal walking as the rest of the activities are mainly related to the upper limbs.

There are also several studies concerning the use of accelerometers as the only source of information for HAR. [24] was one of the very first studies in HAR using accelerometers, in which several feature extraction methods were applied before modeling the classifiers of the different activities. Three different classifiers were applied: for the raw accelerometer data from the two accelerometers -one on each hip-, for the subsets of Principal Component Analysys (PCA) and Independent Component Analysis. In each case, the most relevant feature subset were normalized to 0 mean and 1 standard deviation; an sliding window of 256 samples with 64 sample shift was used. Afterwards, wavelet transformations were carried out over the windowed data. A Multi-Layer Perceptron was trained with back propagation for the classification of four different activities: {Stop, Walking, Walking Upstairs, Walking Downstairs}. The classification error was used for evaluation each model, and the back propagation weight updated was based in the momentum.

A well known contribution to the field of HAR was proposed in [25]. In that study, the authors proposed the use of the divide and conquer strategy, detecting first static postures from dynamic activities. Then, specific decision trees were generated for each case, either static or dynamic. The framework was structured around a binary decision tree in which movements were divided into classes and subclasses at different hierarchical levels. General distinctions between movements were applied in the top levels, and successively more detailed subclassifications were made in the lower levels of the tree. This framework was used to develop a classifier to identify basic movements from the signals obtained from a single, waist-mounted triaxial accelerometer. Nevertheless, the main drawback of these methods is the computational complexity of the calculations that prevents them from being deployed in embedded devices.

An extension of the former study was presented in [26], where a sensor in the hip was used. The movements were first divided into activity (dynamic activities) and rest (static activities) using the SMA. Then, according to the postural orientation, it was proposed to decide the current activity and orientation. In spite of the obtained results from this approach and its low complexity, the main drawback of this study is that apart from falling, no other abnormal behavior can be detected using the sensor in the hip.

In [12] a rule and heuristic-based decision system is proposed for discrimination between the states of lying, standing, walking, as well as with the transitions between states. The transitions rules are learned through a gaussian mixture model. This work is very interesting in the sense that it keeps track of the current state, that is, the cHA. Nevertheless, as far as only one sensor in the hip is used, this is not valid for the problem faced in present study. Moreover, the tilt of the body as well as the orientation of the body are rather different for present study.

In [2], Hidden Markov Models are proposed for automatic segmentation and classification of HAR. The underlying idea is that determining the activity that the current TS belongs to is no longer needed; only the number of activities to be identified are needed. To show the results up to 5 sensors, 4 triaxial accelerometers and one gyroscope were distributed among the chest, upper arms, ankle and thigh, respectively. The promising results in auto segmentation lacks in requiring a relatively high number of sensors. Similarly, a genetic algorithm driving the learning of a Fuzzy Finite State Machine was proposed in [6], using a sensor placed in the central part of the body. This study, which was called GFFSM, was found very suitable and will be further explained in the next subsection.

A very interesting idea is shown in [4], where a sparse representation of the input feature domain is proposed. This representation uses TS windows as a set of relevant motifs for each activity, each motif is the input feature with the information from the TS window. Whenever a new TS window is to be classified, the most suitable set of motifs is determined and thus the corresponding activity is proposed. Though this approach is conceptually rather novel and interesting, the main drawback of this method is again the computational cost that makes this method unfeasible for being introduced in embedded devices.

The use of triaxial accelerometers on the wrist is documented in [10, 7]. In the former approach, up to 24 features were analyzed using dynamic Linear Discriminant Analysis; the best ranked features in each step drive the basis function classifier update to an iterative process that ends when a suitable error rate is obtained. Interestingly, this approach allows to evolve the activity set to detect, though the activity set applyed in the experimentation is not described. The study presented in [7] details the general procedure for obtaining the set of features and, in this case, the neural classifier. Interestingly, this study proposed the common PCA for choosing the best feature subset, though they proposed the feature extraction instead of FS.

Currently, there is a trend to introduce HAR as an add-on to smartphones as far as the deployment cost is highly reduced [14, 8, 27]. In [14], three sensors were placed in the dominant wrist, hip and ankle; up to six different activities were studied: resting, typing, gesticulating, walking, running, and cycling. To classify the activity, two well known methods were analyzed: a C4.5 tree and a Feed-forward Neural Network, although only the latter was found useful. Similarly, but with a different feature subset, [8] proposed the time between peaks and a discretization of the sliding window to feed a J48 decision tree. Finally, a discussion about the benefits of using the data from sensors included in smartphones is presented in [27].

Present study focuses on choosing the best feature subset for a specific HAR model. The FS is a two-step method, an initial filtering one followed by a wrapper FS algorithm. After that, the final HAR model is learned.

3. Proposed Soft Computing Method for HAR

This section introduces the lightweight HAR method proposed in this study to differentiate between a reduced set of activities. To do so, two small wearable sensors are placed on the wrists of the person under analysis, as previously described. Once these data are gathered, a two-stage method is applied, as depicted in Fig. 1.

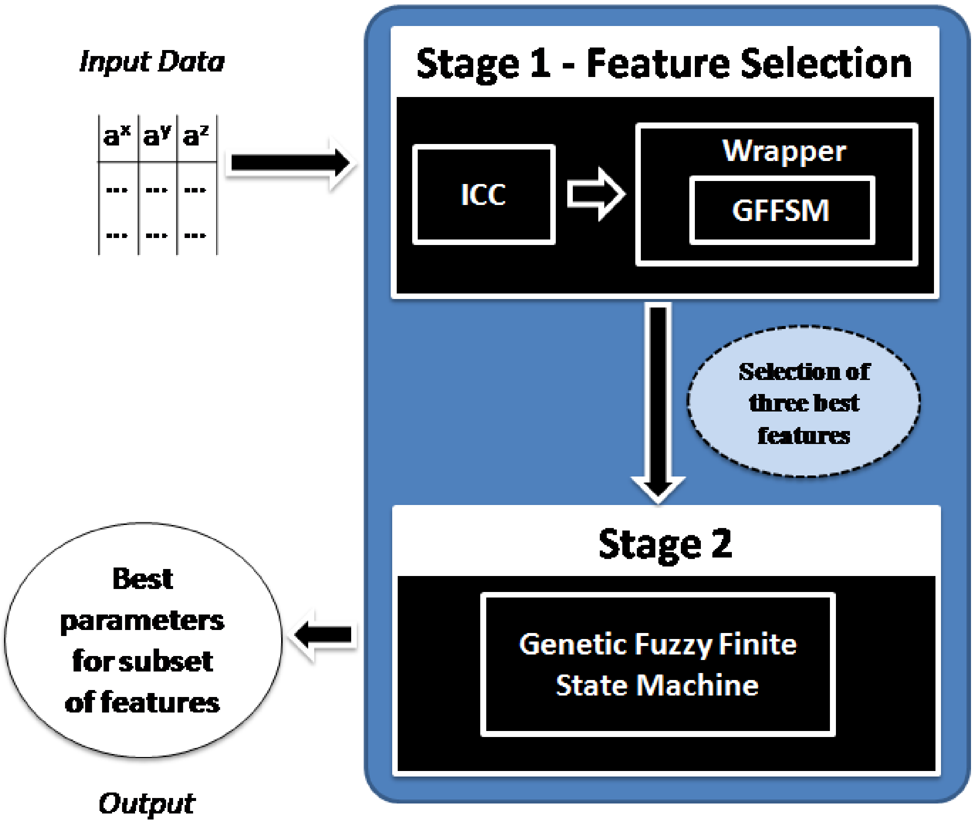


Figure 1: The two-step FS method. After data gathering and pre-processing, the input feature domain is calculated. The FS comprises an ICC step where the most representative features are determined and a GFFSM-based wrapper-like FS method. The final GFFSM model is obtained afterwards, using the best feature subset.

The well-known GFFSM HAR method is applied in present study due to its easy implementation in embedded devices. Nevertheless, this method must be adapted to work in unison with the sensors on the wrists because the original approach features does not reflects the current sensor placement. In addition, the problem of choosing the most suitable raw acceleration transformations is still present with the aforementioned adaptation. Consequently, using sensors located on the wrists introduces the problem of selecting which are the most suitable data transformations for the GFFSM performance. Therefore, the idea underneath is based on reducing the dimensionality of the input domain by means of a two-stage FS, a former filtering stage based on ICC and a latter stage using a wrapper FS algorithm.

As it is known, a wrapper FS method choses the feature subset with the best fitness value. To evaluate each feature subset, the FS method learns a certain classifier or model and the chosen error measure is assigned as the fitness value of the feature subset. Thus, when the learning is complete, a wrapper FS method produces the feature subset and the model itself. Nevertheless, in most cases, the learning of the model during the feature selection is relaxed to avoid high computational costs. Therefore, once finished and the best feature subset is chosen, then the process ends with a full learning of the model.

In this study it is adapted a well-known hybridized method: the Steady-state Genetic Algorithm (SSGA) [28]. In this method, a Genetic Algorithm (GA) evolves the feature subset while, for evaluating the feature subset, a GFFSM is learnt for the feature subset with a relaxed set of parameters. This GA is a steady-state approach with a percentage of elite individuals defined a-priori. After the FS, the GFFSM is learnt with the complete parameter set for the best feature subset found so far. The whole approach is presented in Figure 1.

Up to 150 features can be generated by the different transformations introduced in subsection 2.1. Due to this huge amount of features, using the wrapper FS previously detailed would lead to high computational costs. Therefore, a filtering FS is deployed to reduce the dimensionality to the 20 most promising features before the wrapper FS is applied. This former stage will evaluate each feature with the Information Correlation Coefficient (ICC), and the most interesting features will be selected for the wrapper FS stage.

In the following subsections the stages of the proposed method are comprehensively described. Firstly, the GFFSM stage is presented and its adaptation is detailed. Then, the filtering and wrapper FS stages are described.

3.1. Genetic Fuzzy Finite State Machine Stage

In this study, the solution proposed by [6] is applied; consequently, this subsection is devoted to briefly describing this approach. The main contribution presented in [6] is a GA driving a Pittsburg approach of the Fuzzy Finite State Machine for detecting human activity $GFFSM = \{Q, U, f, Y, g\}$, running the rules and learning the partitions. The rules to be tuned are extracted from a predefined Finite State Machine, which is depicted in Fig. 2, considering only a set of three states {Seated, Upright, Walking}.

This approach makes use of one triaxial accelerometer placed in the centre of the back, and three input variables are used: the dorso-ventral raw acceleration, the amount of movement and the tilt of the body. For each input variable, three linguistic labels ($n_i = 3, \forall i$) with Ruspini trapezoid membership functions are used, those $n_i + 1$ parameters are needed to be learnt for each input variable. A GA evolves the partitions and the rules in a Pittsburg style as 72 binary genes encode part for the rules; 12 real-coded genes for the membership function parameters. The BLX$-\alpha$ crossover operator was proposed as focused on only one antecedent of chosen rules.

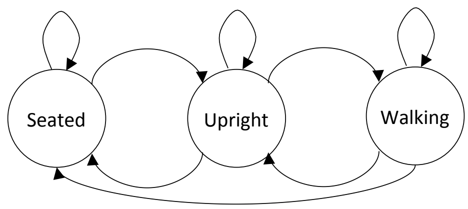


Figure 2: The Fuzzy Finite State Machine proposed for this study. The allowed transitions defined the structure and consequents of the fuzzy rules, while the final antecedents are tuned with the learning process.

The fitness function is the mean absolute error (MAE), calculated as $MAE = \frac{1}{N}\frac{1}{T}\sum_{i=1}^{N}\sum_{j=0}^{T} abs(s_i[j] - s_i^*[j])$, where T is the number of examples in the data set, $s_i[t]$ and $s_i^*[t]$ are the degree of activation and the expected degree of activation, respectively, of state q_i at time $t = j$. The GA is completely defined with a binary tournament, generational replacement with elitism, two-point crossover for the rule base and BLX-α crossover for the real-coded genes that is applied twice for obtaining two new pair of chromosomes and classical bitwise mutation for the rule base. Additionally, uniform mutation is applied for the real-coded part. Termination occurs whenever the first of the following conditions applies: MAE takes 0 value, the expected number of generations is reached or there are a number of generations without changes in MAE. The remainig genetic parameters are: 100 individuals and 300 generations.

Nevertheless, this approach can not be directly applied in the current study as far as the sensors are placed on the wrists; therefore, the amount of movement, the dorso-ventral acceleration, and the tilt of the body, though easy to compute, looses its meaning.

3.2. Filtering Feature Selection Stage

Filtering is usually employed when a big amount of features are available and there is a suitable measurement for ranking them. Nevertheless, when talking about HAR, rather few researches have been reported with this scope. A preliminary study of the most interesting features using the ICC measurement over the whole data set was carried out in [29]. However, in this study, an analysis using the ICC as the ranking measurement is defined but for different cross validation (CV) schemes.

Firstly, a standard experiment should be defined, and several runs of this experiment should be done; each run will provide us with a time series (TS) data set.

Secondly, three different feature datasets are generated with the available TS data sets: i) DATA1, a global one including all the data gathered, ii) DATA2, a 5x2 CV style grouping of TS, and iii) DATA3, a 10-fold CV style grouping of TS. Both DATA2 and DATA3 comprise up to 10 different data sets including data from different TS.

The main reason for these groupings is to evaluate how the ICC is biased due to the different schemes and thus, when high differences are found, it would mean that ICC is seriously biased and perhaps it might not be the best measurement for FS. In the case of DATA 1, the 20 best-ranked features are chosen for the wrapper FS. In the cases of DATA2 and DATA3, the 20 best-ranked features are selected from each fold and the union of all these folds generates the outcome for the next FS stage. Interestingly enough, the filtering stage will end up with three features subsets for further processing in the next FS stage.

3.3. Wrapper Feature Selection Stage

The well-known SSGA FS method [30] is adapted to drive the learning of the GFFSM and also the selection of the best feature subset [29]. Thus, a GA will evolve the population of individuals, each individual representing a subset of three features from the input space. The parameters for the GA devoted to FS are 30 generations with 26 individuals, using the one-point crossover operator with probability 0.8. The mutation operator is also flipping one of the three-selected features among the available candidates; the mutation probability is set to 0.02. The fitness of each of the individuals is calculated as the MAE of the GFFSM model learnt from the feature subset the individual chooses.

Learning the GFFSM within the wrapper is relaxed to bound the computational costs: in this case, the GA runs 50 generations with 76 individuals, the $\alpha-$crossover operator probability is set to 0.8 for an α value of 0.3. The mutation operator is the classical bitwise mutation for the rule base and the uniform mutation for the real-coded part; the mutation probability is set to 0.02.

The following GA early stop conditions are defined: i) the convergence measured as 25 generations without changes in the MAE of the best individual, and ii) reaching a MAE fitness lower than 0.02 at any generation.

Finally, the GFFSM is obtained for each of the three different feature subsets, one for each case: DATA1, DATA2, and DATA3. The value for the GFFSM parameter subset is that proposed in the original research: 100 individuals, 300 generations and the same crossover and mutation operators and probabilities. This final GFFSM model is referred for comparison purposes as WRAPPER. Figure 3 illustrates the whole feature selection stage and its outcome.

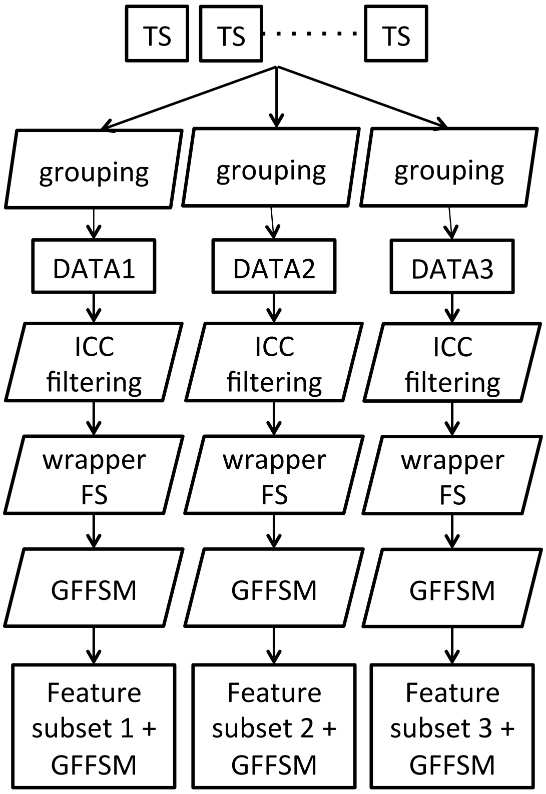
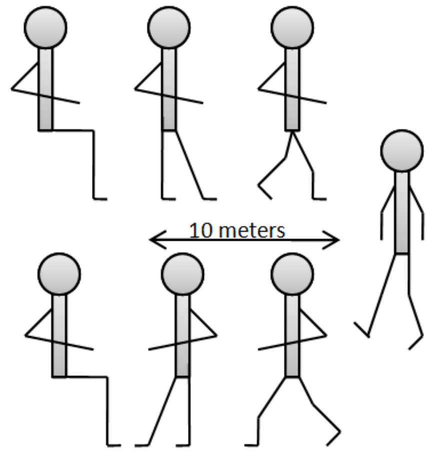


Figure 3: The proposed FS procedure: the overall outcome includes a feature subset and the corresponding GFFSM model.

4. Evaluation and Experimentation

As previously stated, this study focuses on early stroke diagnosing, thus the HAR analysis is always concerned with the typical activities of the focused population, namely WALKING, STANDING and RESTING. The experimental validation performed in this study is aimed at evaluating which one of the proposed alternatives is the best for the recognition of these three activities. To do so, three different datasets have been generated and analyzed. The obtained results are described in this section.

In order to gather the data, the subject under analysys is provided with two bracelets (figure 4(b)) each one of them with a tri-axial accelerometer - the ADXL345 sensor has been used in present study- with a sampling frequency of 16 Hz. Ten runs of a typical rehabilitation test (figure 4(a)) will



(a) Subject movements: being seated, standing up, walking, coming back, standing up, and being seated.

(b) The bracelets capacity allows the store of data from up to 45 minutes and the data can be consequently downloaded to a computer.

Figure 4: Figure(a) The rehabilitation test carried out with different subjects movements. Figure(b) The set of bracelets used in this experimentation, one for each wrist.

be carried out and all the data will be manually segmented and classified according to the activity the subject is owe to do. This segmentation is performed in a similar way to that stated in the original GFFSM study [6]: known states are assigned with total certainty, while transitions are asigned with imprecise observations, e.g. 0.7/SEATED+0.3/STANDING.

To obtain results from the bracelets the analysed subject stayed seated for a period of time $T1$, then stood up and stayed in that position for a period of time $T2$, then started walking following a 10-meter straight line on the floor and went back to the original standing up location, stayed stand up for $T2$ seconds and finally sitted down and stayed resting for $T1$.

The rehabilitation test carried out involved the following steps (see right side of Fig. 3): the subject should be seated during a time T1, then should stand up and stay on that position during T2. Afterwards, the subject will start walking following a straight line on the floor (10 meters) and go back. The subject shall stand up during T2 and, finally, keep seated during T1. T1 and T2 have been set to 60 seconds.

The experimentation, thus, will include i) the data gathering as explained before, ii) computing the transformations, iii) performing the FS: the former filtering step followed by the wrapper FS with the relaxed GFFSM, iv) learning the adapted GFFSM as explained in section 3.1, and v) learning the GFFSM with the best feature subset and with the complete GFFSM parameter set. A flowchart of the experimentation for each of the arrangements (DATA1, DATA2 and DATA3) is depicted in Fig 5.

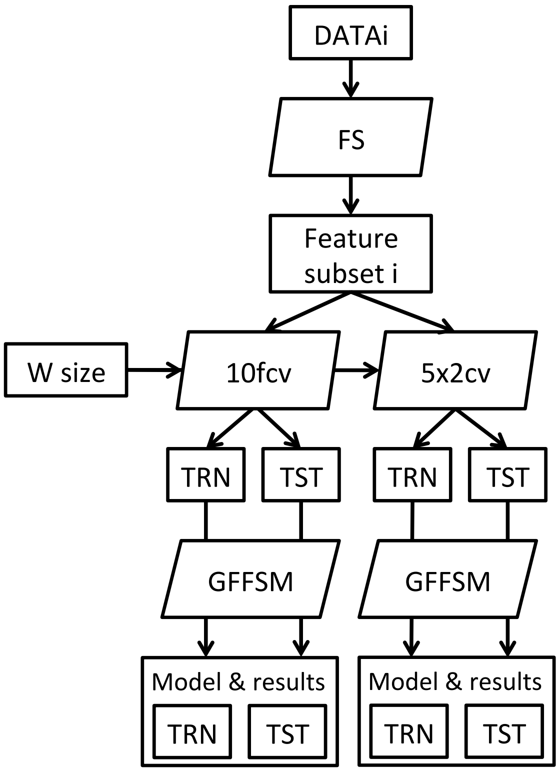


Figure 5: Flowchart of the experimentation for each DATA arrangement. Once prepared the DATAi, FS takes place outcoming with the feature subset. Consequently, the original data set for these features is prepared and two cross validation schemes are employed: 5x2 and 10f CV. For each fold, a GFFSM is learnt and results from training and testing are obtained. TRN and TST stands for the corresponding folds used in training and test; consequently, with the TRN/TST data sets the train/test results are obtained. These folds are generated according to the cross validation scheme.

Two cross validation schemes (5x2 and 10f) are used to study how the features help in each case for obtaining a suitable model. In case that for certain data arrangement the best model is found for both CV schemes, it can be said that that arrangement is clearly the best one. Next subsections deliver the results obtained from each one of the stages: FS and GFFSM learning.

4.1. Feature Selection Results

As stated above, the DATA1 processing generates a reduced space containing the 20 best-ranked features. For the remaining arrangements, it would depend of the features chosen from each fold. In this case, 22 and 31 features were finally chosen from DATA2 and DATA3, correspondingly.

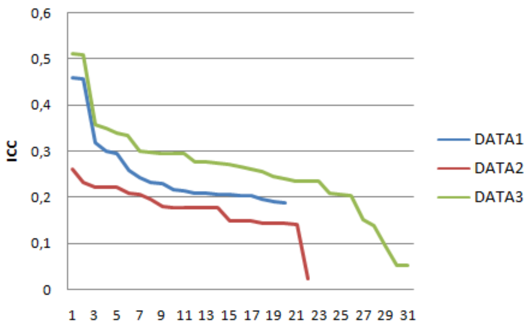


Figure 6: For DATA1 the results of the 20 ICC best features. For the DATA2 and DATA3 the average of the ICC results in the 10 folders.

The feature subset obtained for each arrangement after the filter and the wrapper FS steps are depicted in Table 1.

DATA1	DATA2	DATA3
a^x	a^x	a^x
g^y	RMS^y	RMS^x
$RBD^y; bin = 10$	TBP^y	AM

Table 1: Feature subsets for each arrangement after the two-step FS.

4.2. GFFSM Alternatives for HAR Modeling

Once the best feature subset for each arrangement has been found, its time for modelling. Interested reader should recall that for each feature subset obtained from FS on one of the data arrangements- a GFFSM model is to be obtained using a combination of window size and cross validation as shown in Figure 5.

Table 2 includes the results for all the possible combinations, while the boxplots with the MAE for the best individual obtained for each fold can be seen in Figure 7, for a window size of 10 samples.

The feature subset obtained from the arrangement DATA3 performs better in both 5x2 and 10f CV. Therefore, it can be concluded that this feature subset is the best candidate for the final application.

	Feature Subset 1		Feature Subset 2		Feature Subset 3	
	5x2	10K-Folder	5x2	10K-Folder	5x2	10K-Folder
Average	0.0509	0.0408	0.0490	0.0418	0.0332	0.0199
Median	0.0400	0.0391	0.0391	0.0369	0.0209	0.0208
Deviation	0.0298	0.0134	0.0276	0.0197	0.0306	0.0041

Table 2: Statistical test results for the MAE. Std stands for standard deviation.

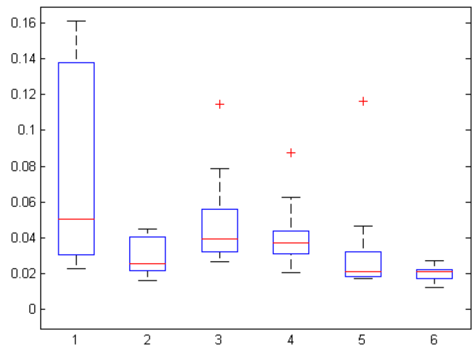


Figure 7: Features subset 1 for 5x2 and 10K-Folder CV, Features subset 2 for 5x2 and 10K-Folder CV and Features subset 3 for 5x2 and 10K-Folder CV are marked on the boxplot, respectively.

In Table 3, the statistical results for the three different GFFSM releases are depicted. The model obtained after the FS stage really outperforms the rest of candidates; consequently, the FS selection stage and the subsequence analysis is found valid. With these results we can conclude that the HAR recognition stage for an early stroke diagnosis tool is not conclude but satisfactory, thus its time to focus on alarm generation. Further HAR studies should be focused on learning the GFFSM rules as well as the partitions, which might reduce the number of rules and also the computational resources needed for integrating these models in embedded devices.

	GFFSM-a	GFFSM-w	WRAPPER
Average	0.0391	0.0365	0.0199
Median	0.0306	0.0343	0.0208
Deviation	0.0292	0.0098	0.0041

Table 3: MAE testing rates for the GFFSM-a [11] (with features SMA, Δ, and the AM), the GFFSM-w [29] (with features a^x, g^y, and $RBD^y; bin = 10$), and the Wrapper (with features a^x, RMS^x, and AM).

5. Conclusions

This study presents a Soft Computing method for modelling and validation in HAR, focusing on three different activities: being seated, standing up and walking. The main objective of this study is choosing the best combination of parameters to get the subset of features that best describes this HAR problem while the activity conditions are modelled at the same time. So, this study proposes a FS method to reduce the space dimensionality of features that differs from previous work.

In kkeping with this idea, a Hybrid Artificial Intelligent Method has been designed an applied. In a first stage, a filter FS is deployed to reduce the dimensionality by evaluating each feature with ICC. Then, the most important features are selected for the wrapper stage. Since the features are chosen, a wrapper FS method using GFFSM is the responsible of searching for the best feature subset associated with each data set and for modelling the human activity. Finally, different schemes are used for validation of the best parameters for features subset and the model from the best data set with different runs.

From the obtained results some conclusions are drawn. Firstly, the use of a cross validation scheme for feature selection might improve the overall outcome. Perhaps a voting scheme may also improve the performance of the feature filtering stage. Secondly, the window size has been found problem specific, thus the different studies in the literature should have made such analysis without reporting it. Finally, it has been found a proper feature subset and the corresponding GFFSM model for HAR, which is to be deployed in further research concerning early stroke diagnosis.

Future work envisages the implementation of more stages in the Finite State Machine, easing the experts reutilization of the presented approach. Further research would be done to include others styles to tackle the learning for the fuzzy rule base of the GFFSM instead of predefining it.

6. Acknowledgements

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7. References

[1] M. P. Murray, A. B. Drought, R. C. Kory, Walking patterns of normal men, Journal of Bone and Joint Surgery 46 (2) (1964) 335–360.

[2] F. Chamroukhi, S. Mohammed, D. Trabelsi, L. Oukhellou, Y. Amirat, Joint segmentation of multivariate time series with hidden process regression for human activity recognition, Neurocomputing http://dx.doi.org/10.1016/j.neucom.2013.04.003i.

[3] T. Fujimoto, H. Nakajima, N. Tsuchiya, H. Marukawa, K. Kuramoto, S. Kobashi, Y. Hata, Wearable human activity recognition by electrocardiograph and accelerometer, in: IEEE 43rd International Symposium on Multiple-Valued Logic, 2013.

[4] M. Zhang, A. A. Sawchuk, Human daily activity recognition with sparse representation using wearable sensors, IEEE Journal of Biomedical and Health Informatics 17 (3) (2013) 553–560.

[5] J. Sedano, S. González, B. Baruque, Á. Herrero, E. Corchado, Soft computing for the analysis of people movement classification, in: V. Snsel, A. Abraham, E. S. Corchado (Eds.), Soft Computing Models in Industrial and Environmental Applications, Vol. 188 of Advances in Intelligent Systems and Computing, Springer Berlin Heidelberg, 2013, pp. 241–248.

[6] A. Ávarez-Álvarez, G. Triviño, O. Cordón, Body posture recognition by means of a genetic fuzzy finite state machine, in: IEEE 5th International Workshop on Genetic and Evolutionary Fuzzy Systems (GEFS), 2011, pp. 60–65.

[7] J.-Y. Yang, J.-S. Wang, Y.-P. Chen, Using acceleration measurements for activity recognition: an effective learning algorithm for constructing neural networks, Patter Recognition Letters 29 (2008) 2213–2220.

[8] J. R. Kwapisz, G. M. Weiss, S. A. Moore, Activity recognition using cell phone accelerometers, ACM SIGKDD Explorations Newsletter 12 (2) (2010) 74–82.

[9] S. Wang, J. Yang, N. Chen, X. Chen, Q. Zhang, Human activity recognition with user-free accelerometers in the sensor networks, in: Proceedings of the International Conference on Neural Networks and Brain ICNN&B'05, Vol. 2, IEEE Conference Publications, 2005, pp. 1212–1217.

[10] Y.-P. Chen, J.-Y. Yang, S.-N. Liou, G.-Y. Lee, J.-S. Wang, Online classifier construction algorithm for human activity detection using a tri-axial accelerometer, Applied Mathematics and Computation 205 (2) (2008) 849–860.

[11] S. González, J. R. Villar, J. Sedano, C. Chira, A preliminary study on early diagnosis of illnesses based on activity disturbances, in: S. Omatu, J. Neves, J. M. C. Rodríguez, J. F. Paz Santana, S. R. Gonzalez (Eds.), Distributed Computing and Artificial Intelligence, Vol. 217 of Advances in Intelligent Systems and Computing, Springer International Publishing, 2013, pp. 521–527.

[12] F. R. Allen, E. Ambikairajah, N. H. Lovell, B. G. Celler, Classification of a known sequence of motions and postures from accelerometry data using adapted gaussian mixture models, Physiological Measurement 27 (2006) 935–951.

[13] L. Bao, S. S. Intille, Activity recognition from user-annotated acceleration data, in: A. Ferscha, F. Mattern (Eds.), Proceedings of the Second International Conference Pervasive Computing, PERVASIVE 2004, Vol. 3001 of Lecture Notes in Computer Science, Springer, 2004, pp. 1–17.

[14] N. Györbiro, Á. Fábián, G. Hományi, An activity recognition system for mobile phones, Mobile Networks and Applications 14 (2009) 82–91.

[15] M. Ahmed, S. Ahmed, Kinetics and kinematics of loading response in stroke patients (a review article), Annals of King Edward Medical University 14 (4) (2008) 143–147.

[16] I. de Quervain, S. Simon, S. Leurgans, W. Pease, D. McAllister, Gait pattern in the early recovery period after stroke., The Journal of Bone and Joint Surgery, American Volume 78 (10) (1996) 1506–1514.

[17] H. P. von Schroeder, R. D. Coutts, P. D. Lyden, E. B. Jr., V. L. . Nickel, Gait parameters following stroke : A practical assessment, Journal of Rehabilitation Research and Development 32 (1) (1995) 25–31.

[18] K. Hollands, Whole body coordination during turning while walking in stroke survivors. ph.d. thesis, school of health and population sciences, Ph.D. thesis, University of Birmingham (2010).

[19] S.-R. Ke, H. L. U. Thuc, Y.-J. Lee, J.-N. Hwang, J.-H. Yoo, K.-H. Choi, A review on video-based human activity recognition, Computers 2 (2013) 88–131.

[20] B. Knorr, R. Hughes, D. Sherrill, J. Stein, M. Akay, P. Bonato, Quantitative measures of functional upper limb movement in persons after stroke, in: Conference Proceedings of the 2nd International IEEE EMBS Conference on Neural Engineering, 2005, 2005, pp. 252– 255.

[21] D. Rand, J. J. Eng, P.-F. Tang, J.-S. Jeng, C. Hung, How active are people with stroke? : Use of accelerometers to assess physical activity, Stroke 40 (2009) 163–168.

[22] S. H. Roy, M. S. Cheng, S.-S. Chang, J. Moore, G. D. Luca, S. H. Nawab, C. J. D. Luca, A combined semg and accelerometer system for monitoring functional activity in stroke, IEEE Transactions on Neural System Rehabilitation Engineering 17 (6) (2009) 585–594.

[23] G. D. Fulk, E. Sazonov, Using sensors to measure activity in people with stroke, Top Stroke Rehabilitation 18 (6) (2011) 746–757.

[24] T. J.Mantyla, J.Himberg, Recognizinghumanmotion with multiple acceleration sensors, in: IEEE International Conference on Systems, Man and Cybernetics, Vol. 3494, 2001, pp. 747–752.

[25] M. Mathie, B. Celler, N. Lovell, A. Coster, Classification of basic daily movements using a triaxial accelerometer, Medical & Biological Engineering & Computing 42 (5) (2004) 679–687.

[26] D. M. Karantonis, M. R. Narayanan, M. Mathie, N. H. Lovell, B. G. Celler, Implementation of a real-time human movement classifier using a triaxial accelerometer for ambulatory monitoring, IEEE Transaction on Information Technology in Biomedicine 10 (1) (2006) 156–167.

[27] L. G. M. de la Vega, S. Raghuraman, A. Balasubramanian, B. Prabhakaran, Exploring unconstrained mobile sensor based human activity recognition, in: 3rd International Workshop on Mobile Sensing, 2013.

[28] J. Casillas, O. Cordón, M. del Jesus, F. Herrera, Genetic feature selection in a fuzzy rule-based classification system learning process, Information Sciences 136 (1-4) (2001) 135–157.

[29] J. R. Villar, S. González, J. Sedano, C. Chira, J. M. Trejo, Human activity recognition and feature selection for stroke early diagnosis, in: 8th International Conference on Hybrid Artificial Intelligence Systems HAIS, Vol. Lecture Notes in Artificial Intelligence, Springer, 2013.

[30] J. Casillas, O. Cordon, M. J. Del Jesus, F. Herrera, Genetic feature selection in a fuzzy rule-based classification system learning process for high-dimensional problems 136 (1-4) (2001) 135–157.

7.2.2. Improving human activity recognition and its application in early stroke diagnosis

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IMPROVING HUMAN ACTIVITY RECOGNITION AND ITS APPLICATION IN EARLY STROKE DIAGNOSIS

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The development of efficient stroke-detection methods is of significant importance in today's society due to the effects and impact of stroke on health and economy worldwide. This study focuses on Human Activity Recognition (HAR), which is a key component in developing an early stroke-diagnosis tool. An overview of the proposed global approach able to discriminate normal resting from stroke-related paralysis is detailed. The main contributions include an extension of the Genetic Fuzzy Finite State Machine method and a new hybrid feature selection algorithm involving Principal Component Analysis and a voting scheme putting the cross-validation results together. Experimental results show that the proposed approach is a well-performing HAR tool that can be successfully embedded in devices.

Keywords: Feature Selection, Genetic Fuzzy Finite State Machine, Genetic Fuzzy Systems, PCA, Stroke.

1 Introduction

Stroke represents a huge health and economic problem: it ranks second in fatal diseases worldwide[1] and first in disability-causing diseases, entailing a total cost of $240 billion in 2010 in the USA, which is expected to double between 2012 and 2030 because of the aging population.[2] Stroke consists of a sudden loss of some brain functions, usually including right or left limbs paralysis (also called hemiplegia) due to either a cerebral haemorrhage or a cerebral infarction, the latter being much more common (85% of strokes).

Cerebral infarction is caused by a thrombus that obstructs the blood flow in a cerebral artery and deprives brain cells of oxygen and glucose, which leads to cell death, and the subject will most likely suffer permanent sequelae unless the thrombus is timely dissolved by infusion of a specific drug.[3] If successful, cerebral tissue will recover and so will function, but that depends on how soon the treatment is given: in the first one and a half "golden hours", one out of three patients treated will completely recover. An estimate of 1.9 million neurons are lost[4] every minute the treatment is delayed, which means that four and a half hours after stroke onset there is no benefit left from receiving the treatment and it can even be harmful.[5]

Given these facts, the question is why only about 5% of people suffering a stroke receive this treatment. The answer is quite simple: they arrive too late at the hospital, even after informative public campaigns and

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in-hospital patient circuit optimization have been implemented in order to reduce the stroke onset-to-treatment interval as much as possible. All too often, the patient does not recognize the symptoms or, being asleep or alone, the paralysis does not allow him/her to seek help. The usefulness and supportive aid of a potential device able to raise an alarm in such situations is of clear and significant importance.

Hand paralysis is part of 2/3 of strokes at onset,[6] and unlike the leg, partial recovery of which frequently allows walking, hand function is not so often regained.[7] Detecting an abnormal absence of hand movement could identify 530,000 of the 795,000 strokes that happen each year in the USA.[6] In this study, we consider hand paralysis as a surrogate marker of hemiplegic strokes and thus develop a new movement detection device for stroke detection, integrating hand activity recognition and stroke onset discovery models. Unlike a simple Actigraph able to detect movement or its absence, the proposed device can discriminate normal resting from stroke-related paralysis. The new movement-detecting device consists of two modules, each mounted on one wrist of the subject, which can measure quantitative and time-related characteristics alongside the movement of each wrist, as well as the asymmetries between them. Both combined can differentiate normal hand rest from paralysis due to stroke. These two modular components should be easy to wear and cheap to produce and they have therefore been designed as small devices to be mounted in light bracelets.

The main normal hand movements and resting patterns for the different daily activities need to be included and labelled as normal in the proposed device. If unilateral absence of hand movement, significantly different from the normal pattern, is detected, an alert of a possible stroke is sent and immediate transportation to the nearest hospital for urgent treatment is implemented.

The underlying model for the development of the proposed stroke-detection device is depicted in Fig. 1.[8] The process is divided into two main steps as follows: a Human Activity Recognition (**HAR**) stage and a Stroke Onset Detection stage. The former is responsible for determining the current Human Activity (**cHA**) and detailing this topic represents the main aim of this study. The latter is devoted to evaluating the abnormality of the current movements once the cHA is known, and it is not analysed in this work. This study addresses the HAR stage needed and a valid solution is described which is technically sound and can be embedded in wearable devices in order to be deployed.

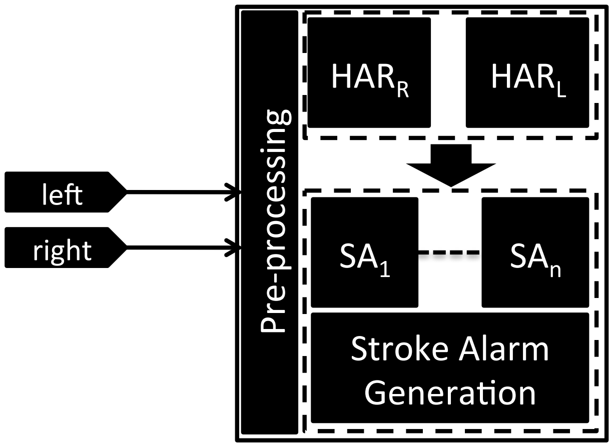

Fig. 1 The solution's block scheme. Two tri-axial accelerometers are placed, one on each wrist. The data gathered from the sensors is used for i) detecting the cHA, ii) perform a specific pattern analysis for the cHA, and iii) generation and submitting the corresponding alarms. Both ii) and iii) are part of the Stroke Onset Discovery step.

Analysing the current literature concerning HAR leads to the conclusion that the HAR methods are quite specific and that the required computational resources make the majority of proposals unfeasible. Furthermore, the high number of transformations from the raw acceleration values introduces a new complexity to the problem since the best subset should be found.

In this research, the well-known Genetic Fuzzy Finite State Machine (**GFFSM**) method[9,10] is engaged in the HAR stage due to its easy-to-embed quality. The GFFSM method is extended to further learn the whole rule set in addition to learning the fuzzy partitions and rule antecedents.[11-14] Furthermore, a complete method for choosing the best feature subset based on a voting scheme together with Principal Component Analysis (**PCA**)[15-17] is presented. The current experimentation can be considered preliminary because no exhaustive test with high-risk population has been done yet, but the remarkable results encourage us to continue with this line of research.

The organization of this study is as follows. Section 2 deals with the basic knowledge for HAR and in Sect. 3, the complete method for HAR is fully detailed. The experimentation and the discussion of the results are included in Sect. 4. A detailed discussion on the results is included in Sect. 5. Finally, the main conclusions of this research are drawn.

2 Human activity recognition review

Nowadays, the main research in HAR is concerned with the use of tri-axial accelerometers. After several years of study, a wide range of features calculated as transformations from the raw acceleration data have been proposed. Each HAR method chooses its own set of features according to different criteria.

Furthermore, each HAR method has its own characteristics, like the number of sensors, the transformations that are used and the recognition techniques. Consequently, one of the very first steps is to choose the best feature space among the available transformations and consider the technique to be used. Thus, this section starts by describing the main features in the literature and, afterwards, a review of the literature concerned with HAR methods is presented.

2.1 From the acceleration data to the input feature space

The measurements from tri-axial accelerometers, known as raw data (**RD**, a_i^x, a_i^y and a_i^z; or $a_{i,j\in\{x,y,z\}}$ for the sake of brevity), can be decomposed into gravity acceleration (**G**) -due to each gravity, g_i^x, g_i^y, g_i^z; $g_{i,j\in\{x,y,z\}}$- and body acceleration (**BA**) -which is due to the human movement, b_i^x, b_i^y, b_i^z; $b_{i,j\in\{x,y,z\}}$.

The capacity of the BA for discriminating among different human gestures is documented.[15] Nevertheless, the literature includes the use of a wide variety of transformations. Besides, all these features can potentially be computed on each of the possible signals (RD, BA, G and, in some cases, on their components), leading to a feature space with more than 190 features, which is a very challenging task indeed.

In many of the solutions, sliding windows with or without shifting are proposed; the typical window size converges to the samples within a period of 2 seconds. Features are typically normalized to 0-mean 1-standard deviation and/or scaled to the interval [0, 1] before further pre-processing.

In order to include as much information as possible for the interested reader, an exhaustive list of the most common transformations and their mathematical expressions are included in Table 1, where w stands for the sliding window size -when needed-, and subscripts $i\in\{1,\ldots,N\}$ and $j\in\{x,y,z\}$ stand for the number of the sample and the axis, respectively. Each feature will hereinafter be referred to with its name or with its corresponding transformation reference Tx.

Using frequency-derived features employing FFT or similar over long time-windows has been found to be more suitable for long duration, quasi-periodic signals like walking, cycling or brushing teeth. Otherwise, when classifying shorter duration and non-periodic activities, transitions or a short sequence of steps, the time-domain representation has been found to be better.[19]

It is interesting to mention the wide spread of transformations that have been used for specific HAR methods. Each specific case includes a number of sensors applied on different places on the body. However, there is no reason to disregard any of them because the concept they have introduced may be useful for the current HAR task. Therefore, a feature selection step must be used so that the most interesting features for the specific problem can be chosen.

2.2 A brief review of the HAR literature

The characterization of human movement, especially in walking, is well documented in the literature.[20] Nevertheless, stroke has a strong influence on the way patients move,[21] and particularly the patient's gait is affected. Due to this, and also because walking is one of the most sensitive parameters in human dependence, the gait and the patient's kinematics have been studied.[21,22]

Most of the studies are based on the analysis of video-images of the patient's gait or movements through well-known mechanical methods,[22-26] though there are also studies using the distributed home automation sensors.[27]

These studies are mainly focused on the rehabilitation of the patient and for developing new therapeutic training techniques, providing interesting conclusions and determining the relevant variables for characterizing the gait pattern.

Since the appearance of low cost and high performance accelerometers in the market, the recognition of human activity has gained focus. Plenty of studies have analysed the performance of this type of device for stroke rehabilitation evaluation[28] and activity level measurement.[29] Some of these studies reported the use of different sensors and techniques, like accelerometers and electromyography[30] or accelerometers and electrocardiograph sensors.[31]

Ref.	Transformation	Calculation	Ref.	Transformation	Calculation
T1	Mean, standard deviation and higher momentum statistics values for the RD[34] or for the BA[18,35]	Well known statistics	T2	Intensity of the movement[39]	$InMo_t^{j\in\{x,y,z\}} = \frac{1}{w}\sum_{i=0}^{w-1}\left\|a_{t-i}^v - a_{t-i-1}^v\right\| / \Delta x_t$
T3	Root Mean Square[36]	$RMS_j = \sqrt{\frac{1}{w}\sum_{i=1}^{w}\left\|a_{i,j}^2\right\|}$	T4	Signal magnitude area[19]	$SMA_t = \frac{1}{w}\sum_{i=1}^{w}\left(\left\|b_i^x\right\| + \left\|b_i^y\right\| + \left\|b_i^z\right\|\right)$
T5	Sum of the absolute values[37] for the BA	$sBA_i = \frac{1}{w}\sum_{t=i}^{i+w}\sum_{j\in\{x,y,z\}}\left\|b_{t,j}\right\|$	T6	Amount of movement [10]	$AM_i = \sum_{v=\{x,y,z\}}\left\| \max_{t=i+1}^{i+w}\left(b_t^v\right) - \min_{t=i+1}^{i+w}\left(b_t^v\right)\right\|$
T7	Correlation between axes[38] for each signal RW, G or BA	$corr(x,y) = \frac{\mathrm{cov}(x,y)}{(std(x) * std(y))}$	T8	Shifted Delta Coefficients for the BA[19]	$\Delta b_{t+i*P}^{x,y,z} = \sum_{d=-D}^{D} d \cdot b_{t+i*P+d}^{\{x,y,z\}} / \sum_{d=-D}^{D} d^2$
T9	Mean absolute deviation[34,36]	$MAD_j = \frac{1}{w}\sum_{i=1}^{w}\left\|a_{i,j} - m_j\right\|$	T10	Vibration of the sensor[35]	$\Delta_i = \frac{1}{w}\sum_{t=i}^{i+w}\sum_{j\in\{x,y,z\}} a_{t,j}^2 + g_{t,j}^2$
T11	Average energy[18,35,38]	$Energy = \frac{\sum_{i=1}^{\|w\|}\left\|F_i\right\|^2}{\|w\|}$	T12	Time between peaks[34]	Different algorithms in the literature, Ref. 34 is among them
T13	Tilt of the body[10]	$sBA_i = \frac{1}{w}\sum_{t=i}^{i+w}\left\|a_i^y\right\| + \left\|a_i^z\right\|$	T14	Delta coefficients for the G[19]	$\Delta g_t^{\{x,y,z\}} = \sum_{d=-D}^{D} d \cdot g_{t+d}^{\{x,y,z\}} / \sum_{d=-D}^{D} d^2$
T15	Binned distribution, relative binned distribution and absolute binned distribution[18,34]	Statistical count of TS values within each of the window range subintervals.			

Table 1 List of most common transformations of the acceleration data. **TS** stands for time series.

One of those studies presented a combination of accelerometers and pressure gauges within shoes for discriminating between sitting, standing and walking of stroke patients.[32] In this study, Support Vector Machines were proposed for classification of the activity, and results of 99% of recall and 76.9% of precision were achieved. Though the classification is relatively good, it is worth noting that this approach can only discriminate between normal and abnormal walking, as the rest of the activities are mainly perceived in the upper limbs.

There are also several studies concerning the use of accelerometers as the only source of information for HAR. One of the very first studies in HAR using accelerometers is available in Ref. 33, in which several feature extraction methods were applied before modelling the classifiers of the different activities. Three different classifiers were learned: for the raw accelerometer data from the two accelerometers -one on each hip-, for the PCA feature subset and for the Independent Component Analysis.

In each case, the most relevant feature subset was normalized to 0 mean and 1 standard deviation; a sliding window of 256 samples with a 64-sample shift was used. Afterwards, wavelet transformations were carried out over the windowed data. A Multi-Layered Perceptron with back propagation was learned for the classification task of 4 classes: *Stop, Walking, Walking Upstairs, Walking Downstairs*. The classification error was used for evaluating each model, and the back propagation weight updating was based on the momentum.

A well-known contribution in HAR was proposed in Ref. 40. In this study, the authors used the “divide and conquer” strategy, detecting first static postures from dynamic activities. Specific decision trees were generated for each case, either static or dynamic. The framework was structured around a binary decision tree in which movements were divided into classes and subclasses at different hierarchical levels: general distinctions between movements were applied in the top levels, and successively more detailed sub-classifications were made in the lower levels of the tree.

This framework was used to develop a classifier to identify basic movements from the signals obtained from a single, waist-mounted tri-axial accelerometer.

Still, the main drawback of these methods is the complexity of the calculations, which cannot be carried out in embedded devices.

An extension of the former study was presented in Ref. 41, where a sensor in the hip was used for HAR. The movements were first divided into activity (dynamic activities) and rest (static activities) using the T4 transformation. According to the postural orientation, the current activity and orientation were then decided. Despite the results obtained from this approach and the low complexity, the main drawback of this study is that, apart from falling, no other abnormal behaviour can be detected using the sensor in the hip.

In Ref. 21 a rule and heuristic based decision system is proposed for discrimination between the states of lying, standing and walking, as well as with the transitions between states. The transitions rules are learned through a Gaussian mixture model. This work is quite interesting in the sense that the system can keep track of the current state; that is, the cHA. Nevertheless, as long as the system uses only one sensor in the hip, this is not valid for the problem faced in this study. Also, the tilt of the body and its orientation are designed for user-centred sensors, which is not the scenario for the current study. Furthermore, the complexity of the solution makes it unfeasible to transfer this to embedded systems.

Hidden Markov Models have also been proposed for automatic segmentation and classification of HAR.[42] The underlying idea is to determine the conditions that, given the number of states and the segmented data sets, fire the set of finite state machines, making change from one state (activity) to another.

To show the benefits of this approach, the results were based on up to 5 sensors, 4 tri-axial accelerometers and one gyroscope, which were distributed among the chest, upper arms, ankle and thigh, respectively. However, this relatively high number of sensors is the main drawback of this approach.

The GFFSM method was proposed for HAR using a sensor placed in the central part of the body.[9,10] Briefly, the GFFSM is a fuzzy finite state machine that drives the classification of cHA. The fuzzy partitions and the memberships involved in each of the transition rules are learnt in a Pittsburg style for the current subject; this learning gives the method the generalization capability. This study was found to be extremely suitable and will be further explained in the next subsection. One of the main advantages of this solution is that it can easily be transferred to embedded devices; however, the drawbacks are that the solution must be modified to manage the sensors on the wrists and that a previous training stage is needed to adapt it to the current subject.

A very interesting idea is shown in Ref. 43, where a sparse representation of the input feature domain is proposed. Briefly, this representation makes use of TS windows as a set of relevant motifs for each activity; each motif is the input features with the information from the TS window.

Whenever a new TS window is to be classified, the most suitable set of motifs is determined and thus the corresponding activity is proposed. Although this approach is conceptually quite novel and interesting, its main drawback is the computational cost, which makes it unfeasible if it is to be introduced in embedded devices.

The use of tri-axial accelerometers on the wrist has been previously documented.[15,36] In Ref. 36, up to 24 features were analysed using dynamic linear discriminant analysis; the best ranked features in each step drive the function basis classifier update in an iterative process that ends when a suitable error value is obtained.

Interestingly, this approach allows the evolution of the activity set to be detected. The study presented in Ref. 15 details the general procedure for obtaining the set of features and, in this case, the neural classifier. Furthermore, this study proposed the Common PCA for choosing the best feature subset, although they proposed feature extraction instead of feature selection.

Currently, there is a trend to introduce HAR as an add-on to smartphones as long as the deployment cost is significantly reduced.[34,39,44] In Ref. 39 three sensors were placed in the dominant wrist, hip and ankle; up to six different activities were studied: resting, typing, gesticulating, walking, running, and cycling.

To classify the activity two well-known methods were analysed: C4.5 and feed-forward neural network, although only the latter was found to be useful. Similarly, but with a different feature subset,[34] the time between peaks and a discretization of the sliding window to feed the J48 decision tree was proposed. Finally, the benefits of using the data from sensors included in smartphones were discussed in Ref. 44.

3 A novel approach to HAR in embedded devices

As stated before, hand paralysis is part of 2/3 of strokes at onset;[6] therefore, for this study the sensors have been placed on the wrists. The idea is to learn the way the subject moves to determine the cHA.

This proposal is focused on generating a valid HAR solution that can be embedded in cheap electronic devices, which is a preliminary step before developing the whole solution described in the introduction section. Besides, it is known that the older the subject the smaller the arm characteristic movements, thus, further study will be needed in order to validate this approach with a group of subjects from the focus population.

To this end, the device placed on each wrist should be responsible for HAR. Clearly, the HAR method should be as light as possible if we consider current embedded devices' computational resources for reduced power consumption.

Additionally, taking into account the focus population, the activities to be identified are bound to a greatly reduced set. In this study we have considered only three activities -WALKING, RESTING and STANDING-, which represent the main set of activities carried out by the subjects with high stroke risk.

Considering these restrictions and constraints, we have chosen what seems to be the most promising technique. In this sense, one of the valid techniques, if we consider the computational limitations, is the GFFSM. This technique might not be valid for a medium-high size set of activities, but it has been found valid for the considered problem.[8] This approach has made use of only one sensor placed on the back of the subject, so adaptation of the method is required: this is the most interesting feature set for using the GFFSM when the sensors are placed on the wrists. Furthermore, the GFFSM requires a learning stage for adapting the model to the current subject.

In preliminary studies, the GFFSM technique was adapted to the problem.[37] Furthermore, a feature selection (**FS**) based on filtering according to the Information Correlation Coefficient measurement and then a wrapper method has allowed us to optimize the adapted GFFSM.[45] However, in this latter study it was concluded that further analysis was needed with methods like the PCA. Besides, it was also found that the learning method of the GFFSM would be enhanced with a Michigan approach.[46] Consequently, the current study is concerned with two main issues:

- A two-stage FS devoted to a) evaluating and filtering the set of features using a novel voting approach based on PCA, and b) using the wrapper FS presented in Refs. 45 and 47 with the best ranked features from step a).
- Developing a Michigan approach for the GFFSM that makes use of a boosting meta-heuristic in order to obtain the most suitable set of rules to drive the HAR.

The remaining contents of the section are organized as follows. In subsection 3.1 the FS method is explained and detailed, including the voting scheme proposed based on the PCA transformation. Subsection 3.2 is devoted to the description of the original GFFSM method, its adaptation and enhancements, together with the novel Michigan approach using boosting. It is interesting to highlight that the whole approach is a complex solution based on the memetic computing principles of design.[48]

3.1 A two-step Feature Selection method

The FS includes two stages: first filtering using a voting scheme based on PCA ranking and a second stage using a GFFSM wrapper FS with the most interesting feature subset found in the filtering FS.

The reason for this hybridization comes from the experience in the preliminary studies with the different runs of the experiments for the same subject. It was found that running the same experiment for the same subject and performing the same filtering strategy -including PCA- could lead to different feature subsets. And if all the data sets for the same subject are joined and PCA is performed, another different feature subset is also obtained.

The question that arises is which of the feature subsets is the best one. The answer to this question can be found by introducing a second wrapper type FS stage that considers the conjunction of all the feature subsets found.

Introducing this second stage is a good solution found in the literature so far. But the problem is that the conjunction of the feature subsets increases the dimensionality of the feature space for the second FS stage, which eventually decreases the performance of the FS and even introduces high computational costs.

Consequently, there is a need for a method that joins the results from all the PCA analysis over each of the folds and over the sequencing of all the data sets. The filtering stage that is proposed in the next subsection tackles this problem, while the wrapper FS stage is detailed in subsection 3.1.2.

3.1.1 The filtering FS stage

The underlying idea is to take advantage of carrying out several runs of the same rehabilitation test for a subject;[25] each test generates a TS of accelerations and its transformations that are segmented as stated in Ref. 10. This study proposes a feature filtering method as follows (see Fig. 2).

Two main ballots are managed: the first one considers each of the TS independently, performing a poll to obtain a feature subset and then merging the results from all the TS; the second one considers all the TS in a single TS. Finally, the results from both ballots are merged and the output feature subset is obtained.

The same *voting scheme* is performed for all the polls. This voting scheme will be used for transferring the PCA rankings to the original feature space. The voting scheme is defined by the following rules, introducing a weighted *Approval Voting* scheme: [49]

- The TS is normalized using the mean and standard deviation of the sample.
- PCA chooses the transformations to reach 95% of representation. Let ***M*** be the number of transformations at that representation level.
- The transformations are ranked in ascending percentage of representation, that is, the best ranked transformation is assigned with the rank ***M/M***, the second best with the ***(M-1)/M***, etc. All the values are in the interval (0, 1].
- Each transformation votes for as many features as are involved in its computation.
- Voting means assigning the rank to each of the candidate features.
- Features from the original space accumulate the ranked votes.
- The higher the sum of ranked votes, the higher the relevance of the feature.

As mentioned before, a ballot is carried out to poll for a feature subset from each TS. For each poll, the PCA ranking is transferred using the voting scheme described above. In order to accumulate the results from each poll, the mean rank of each feature is calculated; the voted features are sorted according to this mean value. This rank is the outcome of the first ballot.

The second ballot considers the samples from all the TS, joining them in one data set. After applying PCA to this data set, the ranking is transferred to the original feature space using the same voting scheme. The outcome of this second ballot is the rank of the features in the original space.

Finally, we merge the results from each ballot using a 50/50% weighted voting. Sorting the features in the original space according to the descending order of votes allows the input feature domain to be filtered.

The selection of the weight for the final rank (50/50%) has been chosen as a compromise since there is no certain knowledge of which of the approaches may be better. Perhaps further analysis is required, but as far as the research team envisages, the results will be rather problem-specific and no general proposal of weights will eventually be found.

3.1.2 The wrapper FS stage

A second FS stage is needed in order to choose the best three features for the GFFSM. In this study, the well-known Steady State Genetic Algorithm FS method[50], as

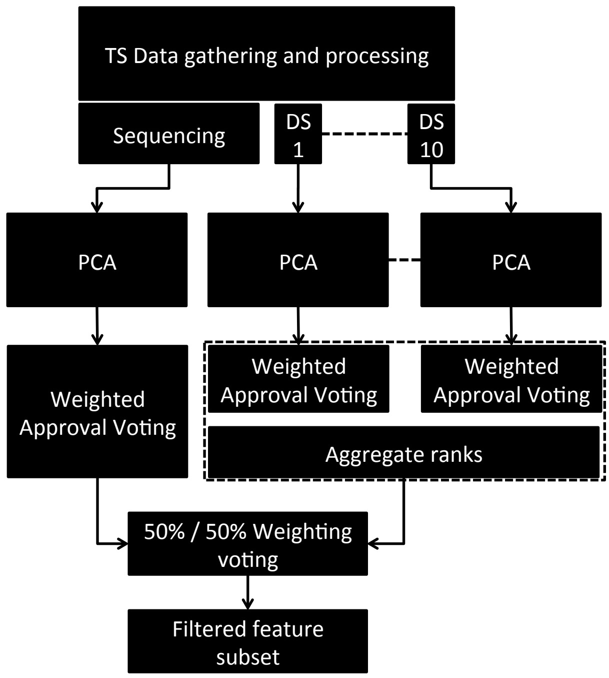

Fig. 2 Overview of the voting scheme. Two ballots are carried out, one for the set of TS and a second one for the sequence of TS. The weighted approval voting method is used for the aggregation of the translated PCA rankings. Both ballots have the same weight in the final results. DS stands for data set.

stated in Ref. 47, is adapted and applied to the problem as in Ref. 45.

In short, this wrapper FS selects a subset of features of a given certain dimension by means of a genetic algorithm (**GA**).[51] Each individual represents a subset of features from the input domain and includes a model. This model is learnt during the individual's fitness evaluation, and the error measurement obtained is assigned to optimize the individual fitness. Thus, this FS method not only selects the feature subset but also generates the desired model. Consequently, the computational cost of this method is relatively high.

For this approach, the feature subset is set to a size of 3. To evaluate an individual, a GFFSM model is learnt for the individual's feature subset and the classification error generated from the GFFSM's validation is set as the individual's fitness.

A 5x2 cross-validation scheme is used for training and testing the GFFSMs: from the collections of 10 TS gathered for the subject, a random half are used for training and the remainder is used for validation. A relaxed set of parameters must be used to decrease the computational cost of the GFFSMs training.

The outcome of this stage is the reduced feature subset of the most promising three features for the HAR method. However, as a relaxed set of parameters was used within the wrapper, the obtained GFFSM model can still be improved, so a complete learning stage should come after the FS.

3.2 The HAR method

This subsection is devoted to the thorough explanation of the GFFSM, from the original proposal to current developments. Thus, it will deal with the following aspects: i) the original GFFSM contribution, ii) the adaptation and enhancements found so far, iii) a brief on a boosting method for learning fuzzy rule sets, and iv) the novel boosting meta-heuristic to learn the Michigan approach GFFSM.

3.2.1 The original GFFSM

The GFFSM was detailed in Ref. 10: a GA evolves the Fuzzy Finite State Machine for HAR. The GFFSM is defined as the tuple *{Q,U,f,Y,g}*, where Q is the state of the system, U is the input vector, f is the transition function which calculates the state of the system, Y is the output vector and g is the output function which calculates the output vector.

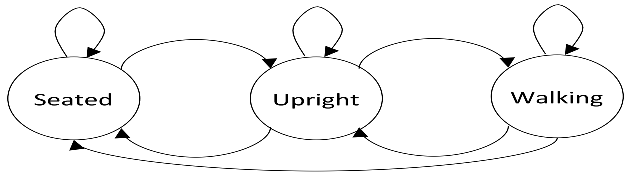

Fig. 3 The original GFFSM a priori defined states and transitions.

The state of the system is defined as a linguistic variable, with $\{q_1, \ldots, q_n\}$ as labels, and one label per state. For each time step the system has a state activation $S[t]=(s_1[t], \ldots, s_n[t])$, with $s_i[t]$ in [0, 1] and the sum of the activation levels is always 1. The transitions are the fuzzy rules that are allowed, which are defined a priori, as depicted in Fig. 3.

A change in the state is considered if any of the rules has a firing strength higher than 0. The output of the system is the set of new state activation levels, which induces the new state.

Three input variables are used: the dorsoventral acceleration a_i^z, the amount of movement (T6) and the tilt of the body (T13), each of them considered linguistic variables with 3 labels each. Ruspini trapezoid membership functions are used, so we need to learn up to 4 parameters for each input variable. A GA evolves the partitions and the rules in a Michigan style: up to 72 binary genes coding the rules and 12 real-coded genes for the membership function parameters.

The fitness function is the Mean Absolute Error (**MAE**), which is calculated using Eq. (1). In this equation, T is the number of examples in the data set, and $s_i[t]$ and $s_i^*[t]$ are the degree of activation and the expected degree of activation, respectively, of state q_i at time step $t=j$.

$$MAE = \frac{1}{N}\frac{1}{T}\sum_{i=1}^{N}\sum_{j=0}^{T}\left|s_i[t]-s_i^*[t]\right| \tag{1}$$

The GA is completely defined with a binary tournament, generational replacement with elitism, two-point crossover for the rule base and BLX-**α** crossover for the real-coded genes applied twice for obtaining two new pairs of chromosomes and a classical bitwise mutation for the rule base and uniform mutation for the real-coded part. Termination occurs whenever one of the following conditions applies: MAE reaches 0 value, or the expected number of generations is reached or there are a number of generations without MAE changes.

3.2.2 Previous works for adapting the GFFSM

As in this study the sensors are placed on the wrists, this approach cannot be directly applied: when the tilt of the body, though easy to compute, loses its meaning, the dorsoventral acceleration is no longer available.

In Ref. 37 a different set of variables was chosen as the most conceptually similar to the original ones: the signal-magnitude area (T4) and the sensor vibration (T10) have been used instead, while the amount of movement (T6) was retained. Furthermore, the genetic parameters were slightly modified to 100 individuals and 200 generations. This model will henceforward be denoted by ***aGFFSM***.[37]

Moreover, a higher resource consuming method was proposed and evaluated (hereinafter, ***gGFFSM***) with 300 generations, 100 individuals and considering the crossover operator as being able to combine genes from more than one rule antecedent.

The Information Correlation Coefficient measurement has been used for filtering the feature domain together with the wrapper FS stage detailed in the previous subsection;[38] the 20 most suitable features were chosen from the filtering stage; then the wrapper FS was carried out. The most representative features found were the a^x, g^y and T15(a^y,10) for the right hand and T13(a^x,a^z), T6 and T15(a^z,10) for the left hand. The GFFSM model trained using this feature subset is denoted by ***wGFFSM***, using the same parameter setting as gGFFSM.

Actually, gGFFSM and wGFFSM triggered similar results while both were found to outperform the adapted aGFFSM when using 10-fold cross-validation, and the two approaches were comparable (see Fig. 4). The wGFFSM performed with less deviation and a slightly higher median MAE value of the best individual found in each run during the cross-validation process.

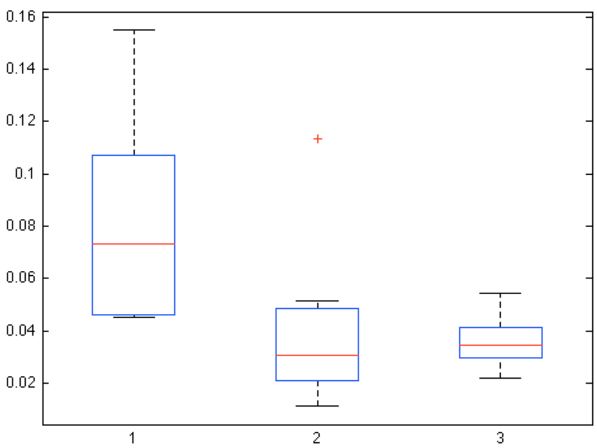

Fig. 4 Comparison of MAE classification errors of the aGFFSM (1), gGFFSM (2) and wGFFSM (3): the two latter are comparable and clearly outperform the former.

However, some repetitive errors have provided evidence that perhaps the current rule set could be optimized, so a change in the learning paradigm was required. The next two subsections deal with the new GFFSM proposal.

3.2.3 Learning fuzzy rules through boosting

Fuzzy classifiers can be learnt using boosting, that is, by learning an incremental rule set that best suits the training data. In this study we made use of the proposal for learning fuzzy classifiers through boosting by means of the single-winner inference.[52] Thus, the current subsection only gives an outline of the algorithm; readers interested in further details should refer to the original contribution.

Let p be the number of classes in the data set of size m samples, n the number of features and N the number of rules. A fuzzy rule set is represented as the relationship Ax{1,…,p}, with $A=\{Aj\}_{j=1,\dots,N}$ being the antecedent of a fuzzy rule. Typically, the antecedents are expressed as Cartesian products of fuzzy sets.

A fuzzy classifier is that model that infers a class k to an example x by means of $\textbf{arg max}_k \bigvee_j A^j(x) \wedge s_k^j$, with s_k^j being the membership degree of rule j to class k.

The single-winner boosting fuzzy rule learning algorithm provides a rule for each iteration based on the number of explained samples. The algorithm firstly finds a feasible rule antecedent A_j and then estimates the rule–class memberships.

The full algorithm is outlined in Fig. 6 and Fig. 5. The former includes a GA algorithm for finding valid fuzzy rule antecedents, while the latter deals with the evaluation of each individual within the population and the single winner inference.

3.2.4 A boosting extension to the GFFSM

It is proposed to use the Michigan style to tackle the learning of the fuzzy rule base of the GFFSM, instead of pre-defining it. Hereinafter, this model is referred to as boosting GFFSM (**bGFFSM**). The Michigan learning style represents each rule as an individual of the population, and the final fuzzy rule set is obtained as the set of the best individuals found up to that point in the evolution.

Procedure: Boosting Fuzzy Rules
Input:
a data set of size m; the number of rules to learn N
Output:
a rule base of size N
R=[]
for each rule r=1,…,N
run a GA
call *AddOneRule* for each individual
add the rule of minimum fitness value to R
for j=1,…,N
make all s_k^j=0 but the maximum one $s_{q(j)}^j$
return R

Fig. 6 The Boosting Fuzzy Rules learning algorithm with the single winner inference.

However, the method for learning the fuzzy rules plays an important role in the final model. In this study we have chosen to learn fuzzy rules using boosting and single-winner inference, as proposed in Ref. 51, although some adaptations were needed. For the sake of simplicity, this section only highlights the main idea of the chosen algorithm, referring interested readers to the original contribution for further details. The required adaptations will be detailed afterwards.

As explained in Ref. 52, each rule added to the rule base increases the number of explained examples in the data set (see the algorithm in Fig. 6). The point is that while Adaboost makes use of the max operator as t-conorm, boosting makes use of the sum operator: the candidate to be added to the rule set is the one that maximizes the updated number of explained samples. Thus, instead of having the capacity of a fuzzy state variable as in the original GFFSM contribution, using boosting ends up choosing one single label as a consequence, with its corresponding weight.

Moreover, the authors proposed an algorithm *AddOneRule* that makes use of a GA to find a rule that maximizes the number of explained examples (see algorithm depicted in Fig. 5). Consequently, the computational cost of this learning scheme is higher than that of the Pittsburg approach.

Some adaptations to the method are needed in order to learn GFFSM. Firstly, the rules should reflect the Fuzzy Finite State Machine with a single state as a consequence. This means that, although some other linguistic labels can be learned for each rule candidate, only the label that maximizes the number of explained samples receives the award: no feedback concerning the rest of the state labels is generated. It is therefore better to include more than one single label as the possible outcome of a rule.

Procedure: AddOneRule
Input:
a rule base of size N; a fuzzy rule antecedent A^{N+1}
Output:
a rule base of size N+1 and a numerical value of fitness
$S_{kj}=s_k^j$, $\forall$k=1,…,p j=1,…,N
Initialize S_{kN+1} randomly
do
I'=I
for j=1,…,N+1, i=1,…,m
Iij=1 if rule j wins in example x_i, 0 otherwise
$F_{ji}=A^i(x_i)\cdot I_{ij}$ $\forall$j=1,…,N+1 i=1,…,m
$Z_{ki}=4(y_k(x_i)-0.5)$ $\forall$k=1,…,p i=1,…,m
S'=S
$S=Z\cdot F^t\cdot(F\cdot F^t)^{-1}$
$S=\alpha\cdot S+(1-\alpha)\cdot S'$
while ||S-S'||<ε
return S and fitness=||Z-S·F||

Fig. 5 The *AddOneRule* algorithm for learning one new rule, including the single winner inference.

The linguistic labels are provided with three uniformly distributed trapezoidal membership functions; thus 4 real parameters should be learnt for each fuzzy variable and 12 real parameters should be learnt for the partitions. To do so, it is proposed to learn the partitions with the original GFFSM Pittsburg approach; once the partition is learnt, then the boosting learning takes place.

The antecedents of all the rules in the classifier have been defined according to the boosting method (see algorithms in Fig. 6 and Fig. 5):[52] $A=\{A_f^j\}$, with $f=1\ldots n$ referring to variables, $j=1\ldots M$ referring to rules, n is the number of input variables (in this case, n=3) and M is the number of rules to learn, which is given as a parameter. As with the original GFFSM contribution, the rules include any label combinations of the three antecedent linguistic variables (Low, Medium and High), so A_f^j can be any combination of these labels. The rule part of the antecedent is composed of one initial state label plus 9 linguistic terms (3 per input variable) for a total of 10 binary-coded genes.

T is the number of examples in the data set, and S_k^j is the matrix of sample explanations used to determine which of the samples are explained or not and which is the rule that best explains each sample. Each candidate's rule is given a rank according to the number of samples it explains: the state that best ranks a candidate rule is the one chosen as its consequence.

For computing the antecedent of the firing strength of a rule, the min and max operators are used as the t-norm and the t-conorm, respectively.

Finally, only rules that introduce a change between the initial and final states are learnt; otherwise, the boosting method can get stuck. To do so, the candidates with different initial and consequent states are awarded.

4 Experiments and discussion of the results

The different tests carried out aim to validate each of the hypotheses of this study, regarding i) the performance of the boosting-based GFFSM, ii) the feature selection step outcome endorsement, and iii) the final experimentation with the best results found so far. This section deals with each of these steps as follows: the next subsection gives details concerning data gathering; subsection 4.2 focuses on the pre-processing and the cross-validation, while the last subsections are devoted to testing and discussing the above-mentioned points.

It is important to point out that the experimentation to be included is not a medical study of patients from the focus population, but proof-of-concept experiments designed from the computer science perspective to obtain a valid tool that can henceforward be tested in a medical study: we do expect to carry out a medical study once the whole approach is finished. Consequently, readers should not expect to find here a detailed protocol or an exhaustive description of the subjects under study.

4.1 Materials and methods

For this study, a pair of data-logging bracelets with a sampling frequency 16 Hz, to be worn on the wrists, has been developed (see Fig. 7). Each bracelet, which is identified for the left or right hand, includes a tri-axial accelerometer with a predefined range up to 3G and a USB port. These bracelets are able to store data from several experiments lasting up to 40 minutes. The batteries last about 10 days, so there should not be any problems with their autonomy.

In order to systematically evaluate the proposal, a test should be defined. To do so, several test beds were analysed from the literature of rehabilitation studies.[53] The different studies establish patterns to be carried out by the subject, i.e., making the subject walk 10 meters discarding 2 meters at each end.[54] The question is which of the tests would allow us to validate the HAR proposal and the answer needs to consider the current problem with the set of activities to detect it.

After analysis of the different approaches, the stroke rehabilitation test[25] was finally selected as the test to be carried out by the subjects, though small variations were introduced. In the original test, the subject starts from sitting for T1 seconds, then stands up and stays still for T2 seconds. Afterwards, the subject has to walk a distance of 3 meters, turning 45º and walking a further 3 meters; then the subject retraces the path to the original position, and there stands still for T2 seconds. Finally, the subject sits and stays in that position for another T1 seconds.

Some small modifications were introduced. Firstly, the 45º turn, which was introduced to test the stroke patients' ability to change direction, was not included. The walking distance was extended to 10 meters in order to include enough walking cycles. Finally, the periods T1 and T2 were set at 10 and 5 seconds, respectively. This modified rehabilitation test is

Fig. 7 The developed bracelets, each one with the mark for the left (Izda.) and right (Dcha.) hands.

hereinafter referred to as SRTEST.

To test the approach proposed in this paper to determine its validity, one male and two female members of the research team were chosen as test subjects. All these subjects were in a good health condition, and a normal fit state. The age of the subjects varied from 28 to 46 years old, which is clearly outside the focus population. However, as long as the current problem is actually to evaluate if the proposal is suitable for HAR purposes, this is considered adequate for a proof-of-concept experiment.

For the purpose of this experiment, each subject carried out 12 runs of the SRTEST and the first two were discarded: they were done simply to get used to the test, and to avoid moving differently from usual when sitting, standing or walking. In addition, these repetitions of the test would allow us to obtain statistical data from the experiments.

4.2 Data pre-processing and cross-validation

All the data is manually segmented and classified according to the activity that the subject has to do, in the same way as proposed for the original GFFSM work.[10] For computing the features, a sliding window of 10 samples wide and one sample shift are used. In this way, known states are classified with complete certainty, while transitions between actions are assigned with imprecise data, e.g., 0.7/SEATED+0.3/STANDING. So up to 10 TS are gathered and segmented for one subject.

Finally, the segmented data for each run is considered a data set, which means that up to 10 different data sets are available for training and testing. Furthermore, one more data set has been generated containing the segmented data from all the runs.

Typically, HAR studies in the literature make use of 10-fold cross-validation. The cross-validation scheme used in this study is a kind of 5x2 cv in which 5 random TS data sets are chosen for training and the 5 remaining sets are kept for testing. This is not the usual way of working with TS, but by using this scheme a better resemblance of the real deployment of the device and models is obtained, as many completely unknown TS are given to the model. However, higher classification errors than those that can be obtained for the usual 10-fold cross-validation schemes in different related studies are also expected.

Table 2 Experiment parameters for each of the GFFSM approaches.

Parameter	**aGFFSM**	**gGFFSM wGFFSM**	**bGFFSM**
Generations	200	300	300+10/rule
Population size	100	100	50
Elite pop. Size	1	1	40
Subpop. size	-	-	10
Crossover prob.	0.8	0.8	1
Mutation prob.	0.02	0.02	0.1
Interchange prob.	-	-	0.01
Crossover BLXα	0.3	0.3	0.3
No. of rules	8	8	Up to 6
Generations w/o progress	50	50	100+10/rule
Logitboost α	-	-	0.75
Maximum number of iterations	-	-	4

4.3 Comparison of GFFSM HAR methods

Four different GFFSM approaches are to be compared within this subsection: the aGFFSM, gGFFSM and wGFFSM presented in subsection 3.2.1 and the

Table 3 Comparison of MAE classification errors results after the 5x2 cross-validation for the *right hand*. Mn, Md and Std stand for mean, median and standard deviation, respectively.

Fold	aGFFSM	gGFFSM	wGFFSM	bGFFSM 5 rules	bGFFSM 6 rules
1	0.0780	0.0757	0.0321	0.0283	0.0248
2	0.0552	0.1920	0.0196	0.0365	0.0370
3	0.1293	0.0645	0.1158	0.0426	0.0473
4	0.1489	0.0848	0.0397	0.0119	0.0218
5	0.0439	0.0216	0.0175	0.0753	0.0573
6	0.1362	0.0540	0.0088	0.0248	0.0248
7	0.2550	0.0525	0.0194	0.0355	0.0355
8	0.0680	0.0826	0.0041	0.0251	0.0235
9	0.0936	0.0341	0.0139	0.0244	0.0705
10	0.0208	0.0540	0.0156	0.0462	0.0611
Mn	0.1029	0.0716	0.0287	0.0349	0.0404
Md	0.0858	0.0593	0.0185	0.0319	0.0362
Std	0.0679	0.0468	0.0323	0.0169	0.0177

Table 4 Comparison of MAE classification errors results after the 5x2 cross-validation for the *left hand*. Mn, Md and Std stand for mean, median and standard deviation, respectively.

Fold	aGFFSM	gGFFSM	wGFFSM	bGFFSM 5 rules	bGFFSM 6 rules
1	0.0842	0.1474	0.0020	0.0008	0.0877
2	0.1971	0.1161	0.0016	0.0011	0.0012
3	0.1084	0.0642	0.1250	0.0008	0.0007
4	0.2401	0.0247	0.0350	0.0015	0.0015
5	0.1768	0.1848	0.0015	0.0008	0.0001
6	0.0683	0.1763	0.0394	0.0002	0.0029
7	0.3659	0.1406	0.0834	0.0012	0.0015
8	0.1310	0.0913	0.0666	0.0010	0.0322
9	0.2257	0.0566	0.0072	0.0008	0.0001
10	0.1135	0.0339	0.0011	0.0002	0.0029
Mn	0.1711	0.1036	0.0363	0.0009	0.0131
Md	0.1539	0.1037	0.0211	0.0008	0.0015
Std	0.0903	0.0580	0.0431	0.0004	0.0280

bGFFSM learned with the single winner inference described in subsection 3.2.4.

The parameters for learning each of the methods are shown in Table 2. Both the number of generations and the convergence stop condition for the bGFFSM vary according to the rules that have been added.

Results are shown in Table 3 and Table 4 for the right and left hand, respectively. The data shown comes from the best individual in each run with the cross-validation method. For the bGFFSM, two columns are reported. When learning the model with 6 rules with the Boosting approach, we need to learn the model with 5 rules first, so results with 5 and 6 rules are included.

As can be seen, there is a totally different scenario with regard to that presented in Ref. 45: the performance of the different methods is completely different as a consequence of the different cross-validation methods.

This study, with bigger validation data sets, benefits from the cross-validation method representing a more general solution. However, as these methods were learnt with smaller data sets, they perform with a slightly higher error measurement and the results could perhaps still be enhanced if more TS were available for training and testing.

Furthermore, the boxplots of the results for the results shown above are depicted in Fig. 8 and Fig. 9 for the right and the left hand, respectively. Both methods wGFFSM and bGFFSM are found to be the most suitable methods, although the gGFFSM's behaviour changes remarkably with the hand that is considered.

In addition, it is remarkable that the bGFFSM got worse with 6 rules than with 5 rules. This might be due to different factors; for instance, the reduced number of samples for learning the sixth rule may induce rules that introduce noise instead of enhancing the model. Besides, it might also be due to the different number of samples in the data sets for each class.

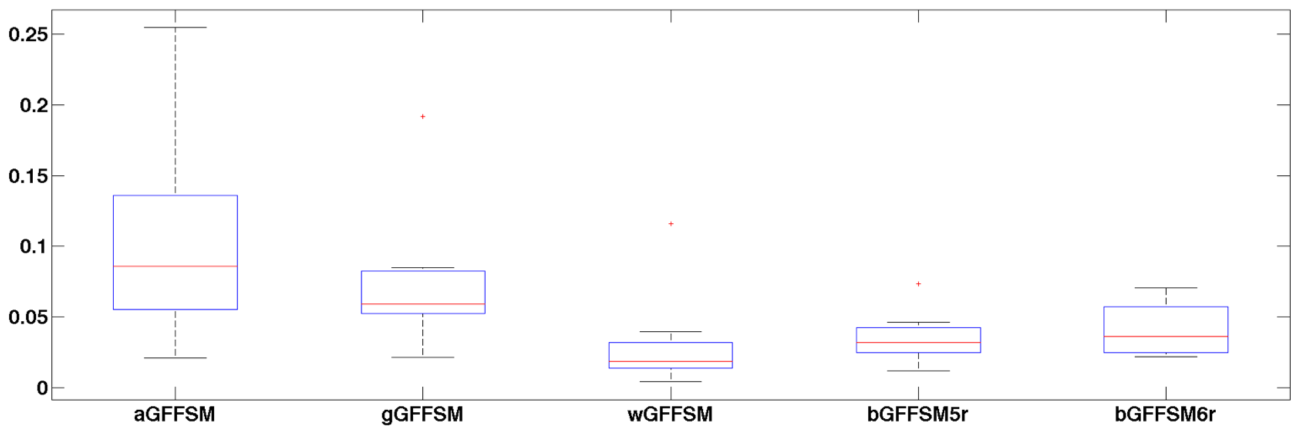

Fig. 8 MAE classification errors boxplot of the best individuals from the results of each run for the right hand. The best performance is obtained for the wGFFSM, but it is not statistically better than the bGFFSM.

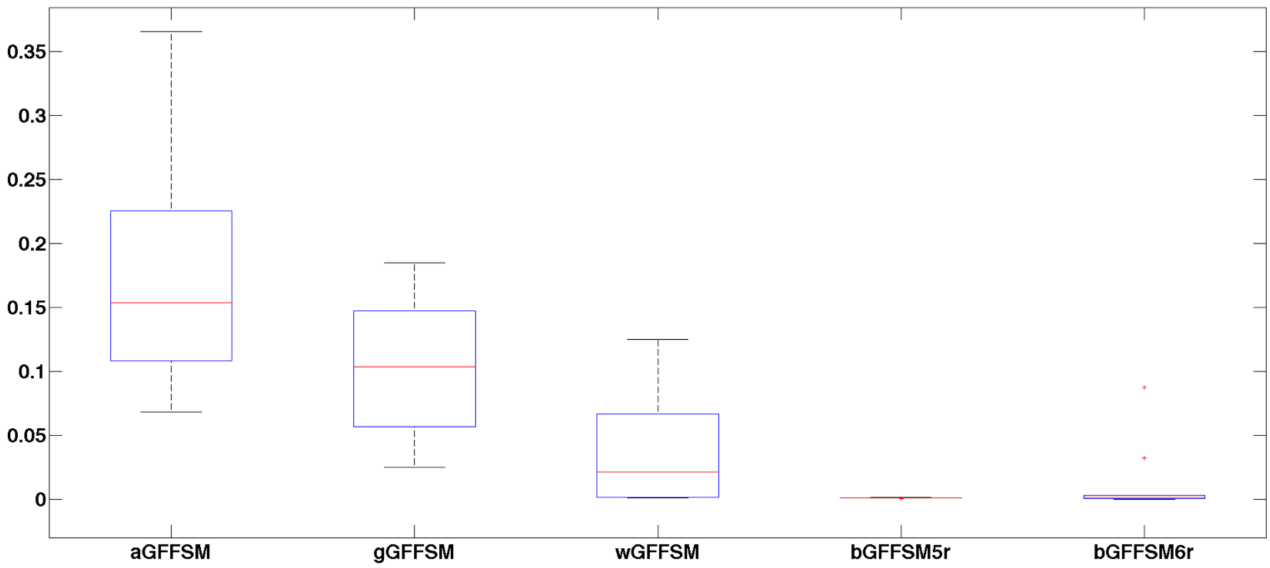

Fig. 9 MAE classification errors comparison boxplot for the best individual left hand for each run: the bGFFSM clearly beats all the other methods: using five rules is enough.

4.4 Evaluation of the FS method

In this stage, the results from the PCA sorting and filtering on the original feature space are presented. As stated in subsection 3.1.1, the most remarkable PCA transformations are used for the voting and ranking of the features.

Afterwards, the 20 features with the highest ranks will be chosen for a second FS stage, the wrapper FS. The exhaustive lists of the best features according to the PCA voting scheme for each hand are presented in Table 5.

The wrapper FS gathers these reduced feature subsets and learns wGFFSM models with the relaxed set of parameters. Two sets of parameters are needed: those related with the GA for evolving the feature subset and those related with the wGFFSM's learning GA.

The parameters for the GA devoted to FS are 30 generations with 26 individuals, using the one point crossover operator with a probability of 0.8. The mutation operator is also flipping one of the three-selected features among the available candidates; the mutation probability is set to 0.02. The fitness of each of the individuals is calculated as the MAE of the GFFSM model learnt from the feature subset the individual has chosen.

Learning the GFFSM within the wrapper is bound by the computational costs: in this case, the GA runs 50 generations with 76 individuals, and the α-crossover operator probability is set to 0.8 for an α value of 0.3. The mutation operator is the classical bitwise mutation for the rule base and the uniform mutation for the real coded part; the mutation probability is set to 0.02.

The following GA early stop conditions are defined by: i) the convergence measured as 25 generations without changes in the MAE of the best individual, and ii) reaching an MAE fitness lower than 0.02 at any generation.

Finally, the best subset of features found for each hand were $\{g^x, T15(a^x,1), T15(a^x,10)\}$ for the left hand and $\{a^x, g^x, T15(a^z,10)\}$ for the right hand. The most interesting issue from these feature subsets is that the chosen features are basic transformations or even the raw data.

Table 5 The 20 most relevant features after the PCA voting scheme. This reduced feature subset is the input space for the wrapper FS.

Left hand		**Right hand**	
Feature	***Votes***	***Feature***	***Votes***
T1 Kurtosis A	4,585	T15(a^z,10)	4,225
T13(a^x,a^z)	4,145	T1 Kurtosis b^z	4,180
T3(a^x)	4,105	T1 Skewness b^x	4,075
g^x	4,095	T15(a^x,10)	3,900
T15(a^z,6)	4,090	T13(a^x, a^z)	3,900
a^x	4,085	T1 Kurtosis b^y	3,880
T15(a^x,7)	4,010	a^x	3,845
T1 Kurtosis b^y	3,835	T3(a^x)	3,830
T15(a^y,8)	3,790	g^x	3,795
T1 Skewness b^y	3,780	T1 Skewness b^z	3,775
T1 Kurtosis b^z	3,555	T15(a^z,6)	3,520
T13(a^x, a^y)	3,535	T1 Kurtosis b^x	3,515
T15(a^x,10)	3,255	T7(a^y,a^z)	3,385
T15(a^y,7)	3,170	T13(a^x,a^y)	3,385
T7(a^x, a^y)	3,155	T15(a^z,1)	3,375
T15(a^y,10)	3,145	T15(a^y,2)	3,330
T1 Skewness b^y	3,080	T13(a^y, a^z)	3,240
T15(a^x,1)	3,070	T1 Skewness b^y	3,225
T13(a^x,a^z)	3,020	g^y	3,190
T15(a^z,6)	2,985	a^y	3,165

4.5 The final GFFSM modelling

Once the most relevant features have been chosen, we can evaluate the best models found so far with the complete set of parameters –those which were shown in Table 2: the wGFFSM and the bGFFSM. Table 6 and Table 7 include the results obtained from each hand.

It is worth noting that the wGFFSM has been really enhanced while the bGFFSM has not: this is totally the opposite of what was expected. The boxplots can potentially help us to understand what is happening in this process.

Fig. 10 and Fig. 11 depict the boxplots for the left and right hand, respectively. As mentioned before, the bGFFSM got worse for both cases of 5 and 6 rules. This fact can be easily explained if we observe the aggregated confusion matrix (see Table 8) for all the folds. In fact, the number of samples labelled with WALKING is significantly higher than the sum of the rest of the classes.

Consequently, PCA may have driven the feature selection to those features that better reflect the most common class. Therefore, the results for the class STANDING were worse, which in turn affects the overall results in a negative way. One of the main

Table 6 Right hand MAE classification error test results obtained from the best model of each fold using the best feature subset after the PCA voting FS.

Fold	wGFFSM	bGFFSM 5 rules	bGFFSM 6 rules
1	0.0073	0.0107	0.1355
2	0.0062	0.0896	0.0185
3	0.0148	0.0273	0.0476
4	0.0072	0.0109	0.0109
5	0.0139	0.0215	0.0114
6	0.0051	0.0359	0.0178
7	0.0325	0.0268	0.0337
8	0.0045	0.0135	0.0136
9	0.0187	0.0127	0.0127
10	0.0096	0.0965	0.0219
Mn	0.0120	0.0345	0.0323
Md	0.0085	0.0242	0.0181
Std	0.0086	0.0320	0.0380

Table 7 Left hand MAE classification error test results obtained from the best model of each fold using the best feature subset after the PCA voting FS.

Fold	wGFFSM	bGFFSM 5 rules	bGFFSM 6 rules
1	0.0341	0.0176	0.0156
2	0.0428	0.0233	0.0207
3	0.0146	0.0261	0.0220
4	0.0093	0.0242	0.0278
5	0.0095	0.0554	0.0355
6	0.0100	0.0213	0.0213
7	0.0033	0.0235	0.0231
8	0.0071	0.0352	0.0265
9	0.0044	0.0287	0.0278
10	0.0115	0.0388	0.0408
Mn	0.0147	0.0294	0.0261
Md	0.0097	0.0252	0.0248
Std	0.0131	0.0111	0.0074

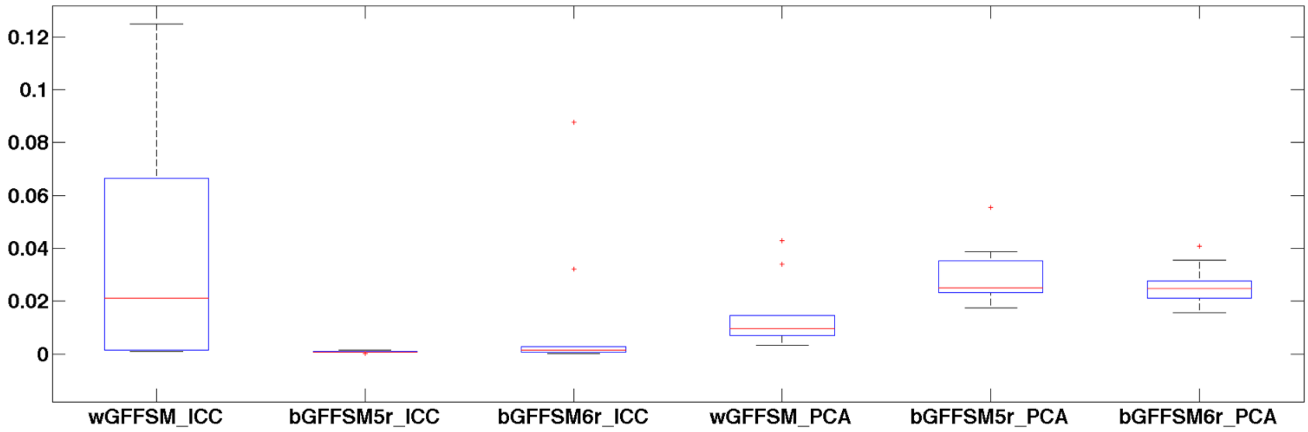

Fig. 10 Left hand comparison MAE classification error boxplot. The bGFFSM did not improve with the PCA FS. The ICC refers to the feature subset using the Information Correlation Coefficient obtained from the previous studies.

conclusions that is drawn from this experimentation is that the SRTEST should be more carefully designed, considering an increase of the times T1 and T2.

5 Discussion of the results

Some comments can be drawn from the experience detailed above. Firstly, the hybrid FS method including the PCA might represent a good compromise when dealing with TS. In general, the deviation of the results is greatly reduced, although in some cases the model performs worse than when carrying out the filtering FS with the Information Correlation Coefficient and the same wrapper FS. It is clear that the experiments should be very carefully designed, but there is no doubt either that the results obtained have improved. The latter leads to our second point: the SRTEST in its current formulation is not completely valid and the different scheduled states should last about the same time.

Besides, the GFFSM models perform satisfactorily and the results are reasonable. Moreover, this model can be easily deployed in embedded systems. Only the fuzzy characteristics concerning the membership functions and the table for looking up the rules need updating from one subject to other. The results for all the subjects were quite similar, so the models are robust among the testing population. However, the tests were run on a population that is different from the target users in the overall research.

This experimentation was aimed at finding suitable models to use and to test if their outcome was accurate or not. To validate this HAR model in stroke patients, a specific study in this population should be undertaken.

One interesting question is what would happen if it were found that more than the presented activities are required. This model was developed with the premise that only three states were required and that the GFFSM will perform well with them, but the performance will certainly decrease with the number of activities.

From this, two main possibilities arise. The first one is to expand this model to 5 activities or introduce the “divide and conquer” principle to group the activities, including a classifier for each group: this would eventually require more computation in the bracelet, which might increase its cost. The second one includes evaluating alternative solutions that might be easily transferred to embedded devices. In this case, for instance, totally different approaches will be analysed,

Table 8 Left hand aggregated confusion matrix for the gFFSM6r when using the ICC / PCA feature subset. The errors for the STANDING state have increased significantly.

	RESTING	STANDING	WALKING
RESTING	23655/23862	220/4	15/24
STANDING	675/10	11990/11545	45/1155
WALKING	84/118	21/765	16265/15487

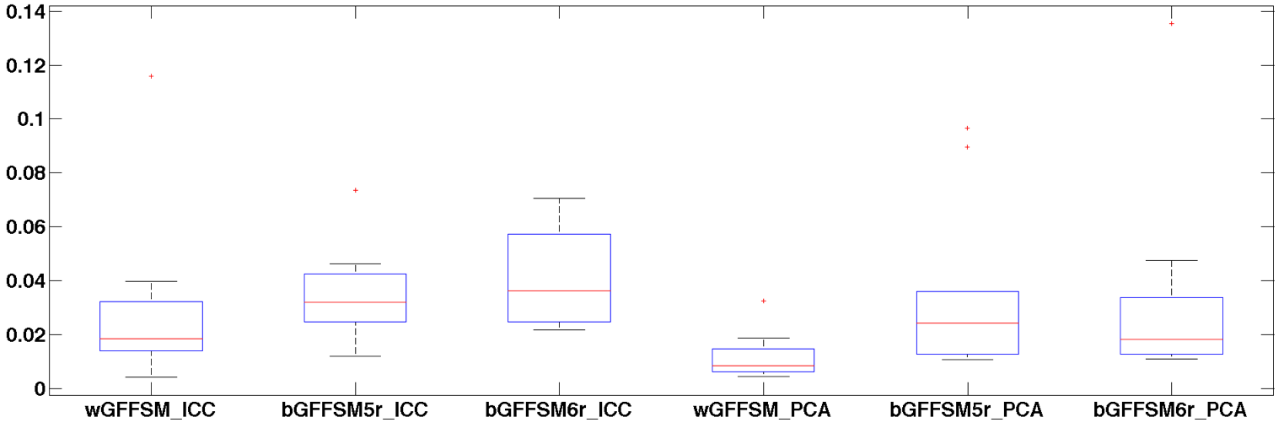

Fig. 11 Right hand comparison MAE classification error boxplot. The feature subset found after the PCA filtering FS slightly enhances the different methods, but does not clearly outperform the results found using the Information Correlation Coefficient.

because, as indicated in the state-of-the-art, most solutions are too complex to be embedded.

Furthermore, the same approach for HAR can be used for different topics, for instance, trying to detect the onset of epilepsy. This is also a very interesting topic in which the cHA is needed, and good discrimination between some types of activities and the onset characteristics that might resemble a similar response in the accelerometers is required.

6 Conclusions

This study is devoted to HAR in the context of stroke alarm generation. A proposal for stroke alarm generation is given and the HAR block has been fully analysed, while stroke onset detection is left as future work. In this scenario, the focus population must perform the activities considered: only three main activities were to be detected.

In order to develop an embedded solution, the GFFSM model has been adapted and extended with new algorithms, including the use of a boosting heuristic for learning the fuzzy system. Furthermore, a novel voting feature selection method based on rolling back the PCA rankings has enhanced the performance of the method.

The step for HAR included in our solution for developing a stroke onset alarm generation can be considered solved, as the MAE results are really impressive. Both the wGFFSM and the bGFFSM approach seem to be good options, although the latter is preferable due to the reduced number of rules required: this reduction makes its integration in embedded solutions easier.

However, the SRTEST test has been found to lack class balance so a better design would be needed. When testing the solution with subjects within the focus population, the balance of the classes within the data sets obtained from the SRTEST should be guaranteed.

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References

1. V. L. Feigin, M. H. Forouzanfar, R. Krishnamurthi, G. A. Mensah, M. Connor, D.A. Bennett et al., Global and regional burden of stroke during 1990-2010: findings from the Global Burden of Disease Study 2010, *Lancet* **383:9913** (2014) 245-254.
2. B. Ovbiagele, L. B. Goldstein, R. T. Higashida, V. J. Howard, S. C. Johnston, O. A. Khavjou et al., American Heart Association Advocacy Coordinating Committee and Stroke Council. Forecasting the future of stroke in the United States: a policy statement from the American Heart Association and American Stroke Association, *Stroke* **44**(8) (2013) 2361-75.
3. G. Adams, M .J. del Zoppo, D. L. Alberts, L. Bhatt, A. Brass, R. L. Furlan et al., Guidelines for the Early

Management of Adults With Ischemic Stroke, *Stroke* **38** (2007) 1655-1711.

4. J. L. Saver, Time Is Brain—Quantified, *Stroke* **37**(1) (2006) 263-266.
5. W. Hacke, M. Kaste, E. Bluhmki, M. Brozman, A. Dávalos, D. Guidetti et al., Thrombolysis with Alteplase 3 to 4.5 Hours after Acute Ischemic Stroke, *The New England Journal of Medicine* **359** (2008) 1317-290.
6. R. L. Sacco, S. E. Kasner, J. P. Broderick, L. R. Caplan, J. J. Connors, A. Culebras et al., An Updated Definition of Stroke for the 21st Century. A Statement for Healthcare Professionals from the American Heart Association, *Stroke* **44** (2013) 2064-2089.
7. T. S. Olsen, Arm and leg paresis as outcome predictors in stroke rehabilitation, *Stroke* **21** (1990) 247-251.
8. J. R. Villar, S. González, J. Sedano, C. Chira and J. M. Trejo, Early diagnosis of stroke: bridging the gap through wearable sensors and computational models, in *Proceedings of the 9th International Conference on Applied Mathematics ICAM9* (2013) 122-125.
9. A. Álvarez-Álvarez, G. Triviño and O. Cordón, Human gait modeling using a genetic fuzzy finite state machine, in *IEEE Transactions on Fuzzy Systems* **20**(2) (2012) 205-223.
10. A. Ávarez-Álvarez, G. Triviño, O. Cordón, Body posture recognition by means of a genetic fuzzy finite state machine, in *IEEE 5th International Workshop on Genetic and Evolutionary Fuzzy Systems (GEFS)* (2011) 60-65.
11. H. Adeli and S. L. Hung, *Machine Learning - Neural Networks, Genetic Algorithms, and Fuzzy Sets* (John Wiley and Sons, New York, 1995).
12. H. Adeli and K. Sarma, *Cost Optimization of Structures – Fuzzy Logic, Genetic Algorithms, and Parallel Computing* (John Wiley and Sons, West Sussex, United Kingdom, 2006).
13. N. Siddique and H. Adeli, *Computational Intelligence - Synergies of Fuzzy Logic, Neural Networks and Evolutionary Computing* (John Wiley, West Sussex, United Kingdom, 2013).
14. K. Sarma and H. Adeli, Fuzzy Genetic Algorithm for Optimization of Steel Structures, *Journal of Structural Engineering, ASCE* **126**(5) (2000) 596-604.
15. A. Weingessel and K. Hornik, A Robust Subspace Algorithm For Principal Component Analysis, *Int. J. Neur. Syst.* **13**(307) (2003), DOI: 10.1142/S0129065703001650.
16. A. Meraoumia, S. Chitroub and A. Bouridane, 2D and 3D Palmprint Information, PCA and HMM for an Improved Person Recognition Performance, *Integrated Computer-Aided Engineering* **20**(3) (2013) 303-319.
17. S. Ghosh-Dastidar, H. Adeli and N. Dadmehr, Principal Component Analysis-Enhanced Cosine Radial Basis Function Neural Network for Robust Epilepsy and Seizure Detection, *IEEE Transactions on Biomedical Engineering* **55**(2) (2008) 512-518.
18. J. Y. Yang, J. S. Wang and Y. P. Chen, Using acceleration measurements for activity recognition: an effective learning algorithm for constructing neural networks, *Pattern Recognition Letters* **29** (2008) 2213-2220.
19. F. R. Allen, E. Ambikairajah, N. H. Lovell, B. G. Celler, Classification of a known sequence of motions and postures from accelerometry data using adapted Gaussian mixture models, *Physiological Measurement* **27** (2006) 935-951.
20. M. P. Murray, A. B. Drought and R. C. Kory, Walking patterns of normal men, *Journal of Bone and Joint Surgery* **46**(2) (1964) 335–360.
21. M. Ahmed and S. Ahmed, Kinetics and kinematics of loading response in stroke patients (a review article), *Annals of King Edward Medical University* **14**(4) (2008) 143-147.
22. I. de Quervain, S. Simon, S. Leurgans, W. Pease and D. McAllister, Gait pattern in the early recovery period after stroke, *The Journal of Bone and Joint Surgery, American* **78**(10) (1996) 1506-1514.
23. K. Subramanian and S. Suresh, Human Action Recognition using Meta-Cognitive Neuro-Fuzzy Inference System, *International Journal of Neural Systems* **22**(6) (2012) 1250028-15.
24. H. P. von Schroeder, R. D. Coutts, P. D. Lyden, E. Billings Jr. and V.. Nickel, Gait parameters following stroke: A practical assessment, *Journal of Rehabilitation Research and Development* **32**(1) (1995) 25-31.
25. K. Hollands, *Whole body coordination during turning while walking in stroke survivors*. Ph.D. Thesis, School of Health and Population Sciences, University of Birmingham (2010).
26. S. R. Ke, H. L. U. Thuc, Y. J. Lee, J. N. Hwang, J.H. Yoo and K. H. Choi, A review on video-based human activity recognition, *Computers* **2** (2013) 88–131.
27. J. A. Iglesias, P. Angelov, A. Ledezma and A. Sanchis, Human Activity Recognition Based on Evolving Fuzzy Systems, *International Journal of Neural Systems*, **20**(5) (2010) 355-364.
28. B. Knorr, R. Hughes, D. Sherrill, J. Stein, M. Akay and P. Bonato, Quantitative measures of functional upper limb movement in persons after stroke, in *Proceedings of the 2nd International IEEE Conference on Neural Engineering EMBS* (2005) 252-255.
29. D. Rand, J. J. Eng, P. F. Tang, J. S. Jeng and C. Hung, How active are people with stroke? Use of accelerometers to assess physical activity, *Stroke* **40** (2009) 163-168.
30. S. H. Roy, M. S. Cheng, S. S. Chang, J. Moore, G. D. Luca, S. H. Nawab and C. J. D. Luca, A combined SEMG and accelerometer system for monitoring functional activity in stroke, *IEEE Transactions on Neural System Rehabilitation Engineering* **17**(6) (2009) 585-594.
31. T. Fujimoto, H. Nakajima, N. Tsuchiya, H. Marukawa, K. Kuramoto, S. Kobashi and Y. Hata, Wearable human activity recognition by electrocardiograph and

accelerometer, in *43rd International IEEE Symposium on Multiple-Valued Logic* (2013).
32. G. D. Fulk and E. Sazonov, Using sensors to measure activity in people with stroke, *Top Stroke Rehabilitation* **18**(6) (2011) 746-757.
33. J. Mantyla and T. Himberg, Recognizing human motion with multiple acceleration sensors, in *IEEE International Conference on Systems, Man and Cybernetics* **3494** (2001) 747-752.
34. J. R. Kwapisz, G. M. Weiss, and S. A. Moore, Activity recognition using cell phone accelerometers, *ACM SIGKDD Explorations Newsletter* **2** (2010) 74-82.
35. S. Wang, J. Yang, N. Chen, X. Chen and Q. Zhang, Human activity recognition with user-free accelerometers in the sensor networks, in *Proceedings of the International Conference on Neural Networks and Brain ICNN&B'05,* vol. **2** (IEEE Conference Publications 2005) 1212-1217.
36. Y. P. Chen, J. Y. Yang, S. N. Liou, G. Y. Lee and J. S. Wang, Online classifier construction algorithm for human activity detection using a tri-axial accelerometer, *Applied Mathematics and Computation* **205**(2) (2008) 849-860.
37. S. González, J. R. Villar, J. Sedano and C. Chira, A preliminary study on early diagnosis of illnesses based on activity disturbances, in *Proceedings of the 10th International Conference on Distributed Computing and Artificial Intelligence*, (2013).
38. L. Bao and S. S. Intille, Activity recognition from user-annotated acceleration data, in *Proceedings of the Second International Conference Pervasive Computing, PERVASIVE 2004*, LNCS 3001 (Springer Verlag 2004) 1-17.
39. N. Györbiro, A. Fábían and G. Hományi, An activity recognition system for mobile phones, *Mobile Networks and Applications* **14** (2009) 82-91.
40. M. Mathie, B. Celler, N. Lovell and A. Coster, Classification of basic daily movements using a triaxial accelerometer, *Medical & Biological Engineering & Computing* **42**(5) (2004) 679–687.
41. D. M. Karantonis, M. R. Narayanan, M. Mathie, N. H. Lovell and B. G. Celler, Implementation of a real-time human movement classifier using a triaxial accelerometer for ambulatory monitoring, *IEEE Transactions on Information Technology in Biomedicine* **10**(1) (2006) 156-167.
42. F. Chamroukhi, S. Mohammed, D. Trabelsi, L. Oukhellou and Y. Amirat, Joint segmentation of multivariate time series with hidden process regression for human activity recognition, *Neurocomputing* **120**(23) (2013) 633-644.
43. M. Zhang and A. A. Sawchuk, Human daily activity recognition with sparse representation using wearable sensors, *IEEE Journal of Biomedical and Health Informatics* **17**(3) (2013) 553-560.
44. L. G. Mojica, S. Raghuraman, A. Balasubramanian and B. Prabhakaran, Exploring unconstrained mobile sensor based human activity recognition, *3rd International Workshop on Mobile Sensing* (2013).
45. J. R. Villar, S. González, J. Sedano, C. Chira and J. M. Trejo, Human Activity Recognition and Feature Selection for Stroke Early Diagnosis, in *8th International Conference Hybrid Artificial Intelligent System HAIS 2013*, LNCS 8073 (Springer Verlag, 2013) 659-668.
46. F. Herrera, Genetic Fuzzy Systems: Taxonomy, Current Research Trends and Prospects, *Evolutionary Intelligence* **1** (2008) 27-46.
47. J. R. Villar, S. González, J. Sedano, E. Corchado, L. Puigpinós and J. de Ciurana, Meta-heuristic improvements applied for steel sheet incremental cold shaping, *Memetic Computing* **4**(4) (2012) 249-261.
48. F. Neri and C. Cotta, Memetic algorithms and memetic computing optimization: A literature review. *Swarm and Evolutionary Computation* **2** (2012) 1-14.
49. S. J. Brams and P. C. Fishburn, *Going from Theory to Practice: The Mixed Success of Approval Voting*, 2003 Handbook on Approval Voting Studies in Choice and Welfare (Springer Verlag, 2010) 19-37.
50. J. Casillas, O. Cordón, M. J. del Jesus and F. Herrera. Genetic Feature Selection in a Fuzzy Rule-Based Classification System Learning Process, *Information Sciences* **136**(1-4) (2001) 135-157.
51. T. Weise, *Global Optimization Algorithms – Theory and Application*, http://www.it-weise.de/projects/book.pdf.
52. L. Sánchez and J. Otero, Boosting fuzzy rules in classification problems under single-winner inference, *International Journal of Intelligent Systems* **22**(9) (2007) 1021-1035.
53. B. Langhammer, *Physical Therapy Tests in Stroke Rehabilitation*, International Encyclopedia of Rehabilitation (last visited, October 2014) http://cirrie.buffalo.edu/encyclopedia/en/article/116.
54. S. Ahmed, N. E. Mayo, J. Higgins, N. M. Salbach, L. Finch and S. L. Wood-Dauphinée, The Stroke Rehabilitation Assessment of Movement (STREAM): A Comparison With Other Measures Used to Evaluate Effects of Stroke and Rehabilitation, *Physical Therapy Journal* **87** (2003) 617-630.

7.2.3. A hybrid intelligent recognition system for the early detection of strokes

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A Hybrid Intelligent Recognition System for the Early Detection of Strokes

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Abstract. The increasing prevalence of wearable sensors and low-cost mobile devices have prompted the development of systems for automated diagnosis. Here we focus on models and algorithms for the early detection of strokes that are implanted in a wearable device that generates warning alarms and automatically connects to e-health services, ensuring timely interventions at the onset of a stroke. The proposed approach employs two wearable devices to monitor movement data that involve two main stages: Human Activity Recognition (HAR) and alarm generation. Two different HAR methods capable of classifying current human activity are developed and compared: one uses genetic fuzzy finite-state machines, and the other relies on Time Series (TS) analysis. Furthermore, an algorithm using Symbolic Aggregate approXimation (SAX) TS representation is proposed for alarm generation purposes, which is triggered by the detection of anomalous movements. The proposed methods are evaluated using realistic data gathered from healthy individuals. A discussion of topics related to the learning issues involved in these techniques is included. It is worth mentioning that the proposed algorithms can be easily transferred to embedded systems and can benefit from reduced learning costs.

Keywords: Early Stroke Detection, Human Activity Recognition, Ambient Assisted Living, Time Series Analysis, SAX

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1. Introduction

Over recent years, the focus of Artificial Intelligence applications in medicine has ranged from brain-computer interfaces for human assistance [24][35][44][40] and devices for diagnostic purposes [3][4][5][17][28], to specific utilities for information extraction [7][23] and efficient microarray analysis [11]. Even early mortality prediction is a research focus [21]. One of the most promising fields is computer-based diagnosis [34], particularly early stroke detection.

Stroke diagnosis is a very challenging problem that has only been partly addressed [19][32][37] Although diagnostic methods may vary with age [37], there are clear symptoms of a stroke episode, described by the FAST (*Face drooping, Arm paralysis, Speech difficulties, Time to act* [19]) informative campaign for early diagnosis [31][32]. By far the most remarkable symptom of a stroke is the loss of voluntary movement in one or more of the limbs.

In all cases, a patient suffering from the onset of a stroke needs a trained care assistant close by to recognize the symptoms; in many stroke situations, an isolated individual would be unable to request help alone. Interestingly, there are factors that increase the risks of stroke onsets, among them cholesterol [49], smoking, and the intake of a certain amount of alcohol [33]. A very up-to-date definition and review of strokes may be found in [38], while [43] contains an impressive account of a personal stroke episode by a doctor.

Cerebral infarction explains around 85% of all strokes [1]. There is no approved treatment for the remaining 15% of all cerebral hemorrhages, although thrombolytic drug treatment can counter cerebral infarction, by clearing the thrombus that may occlude the cerebral arteries. If successful, cerebral tissue and its function will recover, although the speed of treatment is crucial. In the first one-and-a-half hours (the so-called "golden hour"), one out of every three patients treated in this way will fully recover.

Frequently, there are several different signs and symptoms, although these are usually accompanied by paralysis, which is responsible for most temporary and permanent disabilities. Indeed, hemiplegia is the main sequel [12] of a stroke with grave consequences for the patient and indirectly for the carer. The hand is usually more severely affected than the leg. Arm paralysis is in fact so common in stroke patients that it appears in well-known scales, such as the Prehospital Cincinnati Stroke Scale. Even with a complex, drawn out rehabilitation process, recovery is not always completely achieved [13].

The movements of a person suffering a stroke episode are usually described as asymmetrical: one side moves while the other remains rather still [43]. The main symptom is collapse while standing still, walking, or even when seated. Hand paralysis is non-individual and may be monitored by a movement-detection device. These devices can learn the main patterns of normal behavior of each type of activity. Consequently, detecting either asymmetrical movements or deviations in these normal patterns would allow early detection of strokes.

Hybrid Artificial Intelligent Systems provide useful methods for the development of tools to diagnose human illnesses and human behavior [7][29][41][50]. A method based on Genetic Fuzzy Finite State Machines (**GFFSM**) was recently proposed for Human Activity Recognition (**HAR**)[6], and applied in the early stroke diagnosis [48].

In this paper, the response is taken one step further by presenting an alternative to the HAR module: early stroke diagnosis is addressed using wearable devices -3D accelerometers (**3DACC**)- equipped with alarms for stroke onset recognition. The aim is to develop a non-invasive and cheap device that can detect abnormal behavior in the individual; repetition of such movements should set off the alarm, alerting health workers and, whenever necessary, emergency health care services, [22] and dosing the thrombolytic drug within the golden hour.

The approach in this work is presented in two steps: a HAR stage and a Stroke Onset Detection stage. The former is responsible for classifying current Human Activity (**cHA**) and the latter for evaluating the abnormality of the current movements once the cHA classification is given. A bracelet that incorporates 3DACC was developed, through a complete analysis and evaluation of the proposed algorithm, and was then tested in the experimentation stage.

The organization of this paper is as follows. The next section summarizes the basic knowledge for early stroke diagnosis. Then, in Section 3, the proposed approach is detailed. The experimentation and discussion on the results are then included in Section 4. The main conclusions of the research appear at the end of the paper.

2. Design decisions related to wearable devices for early stroke diagnosis

We will focus on the stroke risk population, which includes adults above 56 years of age. Within this group, we will try to measure and to identify a selection of the most suitable activity subset covering, as far as possible, the relevant everyday activities that are valid for stroke diagnosis, including *Resting*, *Walking* and *Small Movements*.

Ambulation is a well studied topic [29] and there are enormous differences in movements depending on age: the older the individual, the smaller the degree of movement. Thus, the evaluation of frequency related patterns is not suitable as it varies with age and individuals.

While *Walking* is conceptually clear [16], the remaining activities need further explanation [27]. *Resting* refers to situations in which the individual is either seated or lying down and is totally inactive, for instance when sleeping, resting or having a nap. *Small Movements* refers to situations in which the individual is seated, lying down or standing up while performing any low-level activity. It is worth noting that the active individual can simultaneously perform several different tasks. For instance, an individual might be walking while snacking or repeating a pattern while speaking. In this study, the identification of gestures is not addressed.

Finally, it is worth mentioning the special case of falling. Whenever an elderly person suffers a fall, it may result in a fracture –typically- of the hip or pelvis. In this case, the individual might be conscious but cannot ask for help. Conversely, the fall might produce concussion, due perhaps to a stroke episode, requiring immediate assistance, which would therefore require the alarm to be set off. Furthermore, it would of interest to categorize relative wrist positions, so as to define relatively abnormal positions that would assist in the alarm generation process.

Apart from these movement-related issues, some restrictions need to be considered, so that the approach would not only be valid but also realistically useful. Firstly, the device should be wearable and conveniently fitted, without discomfort, in the daily life of the individual wearer. Secondly, it should be affordable. Thirdly, it should be user friendly and easy to configure: any learning and tuning processes for optimal adaption to individual needs, if required, should be easy to follow.

All these restrictions lead to several design decisions. The number of sensors should be kept as low as possible, to reduce both cost and the size of the device. In this study, only two tri-axial accelerometer sensors are proposed, each one in a bracelet worn on the wrist. This design is based on the idea that the upper limbs are more affected than the lower limbs in stroke situations and that the lack of movement is more generally observed in the hands for any human activity. Moreover, the available techniques and all the implemented models should be valid for deployment in micro-controlled devices. The premise "Keep It Simple" needs to underlie any decision and its implementation.

3. Proposed approach for stroke episode recognition and stroke onset early detection

This study proposes a two-block approach for early stroke diagnosis: a HAR method to determine the cHA, allowing us to discriminate between human activities, and an alarm generation stage where a pattern recognition method is used to classify movements (as normal or otherwise) from the cHA detected by the HAR device. The data from the 3DACC feeds directly into a pre-processing stage, which is needed as each block requires a different set of features and acceleration transformations. Figure 1 depicts the flowchart of the blocks; the remainder of the section is devoted to the presentation of all details behind the proposed approach.

The data from the 3DACC sensors (one on each wrist) are used for detecting the cHA as well as for detecting abnormal behavior of the individual. Consequently, the stroke alarm state is activated whenever there is a lack of movement or whenever the movements suggest that a fall might have occurred.

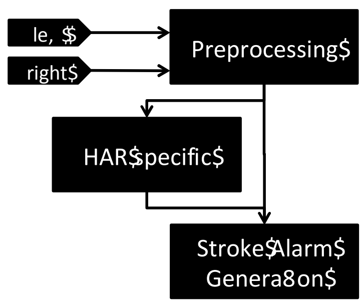

Figure 1 The block diagram for the whole approach. *Left* and *Right* represent the tri-axial accelerometer data from each wrist. After the pre-processing, the HAR takes place and then the alarm generation is updated.

Placement of the sensors on the wrist has previously been confirmed as a valid approach in this type of situation [36]. Even though some reports show that the wrists might be the worst location for obtaining good HAR results [52], the need to evaluate abnormal behavior means that this placement is more suitable, as opposed to the torso or the legs, for instance, as they barely reflect any change when the individual is engaged in low-motion activities such as reading.

We therefore need to estimate the current activity of the individual and then whether the lack of motion is due to paralysis or a fall. In a previous study, a HAR method making use of GFFSM [6] was adapted in [15] and enhanced [48]. However, there is a limit on the number of activities that can be considered, and finding valid alternatives might enhance the overall HAR and assist with the correct definition of the aforementioned limit.

This topic is one of the main goals of this research and is studied in depth in the next subsection. The current research goes one step further with a different HAR method and a proposal for the alarm generation stage. The goal is to keep these modules sufficiently simple to allow their implementation in micro-controlled devices. Moreover, the key data, such as the cHA for each wrist and the stroke alarm state should where necessary be sent to an e-Health system.

This section is divided into three subsections, each dealing with an overview of the previous approach, the novel HAR method and the alarm generation stage.

3.1. Human Activity Recognition using GFFSM

A two-stage HAR method has recently been proposed in [48]: on the one hand, a Feature Selection (**FS**) stage reduces the input domain dimensionality; on the other, GFFSM modeling generates the classifier. The cross validation considered the crossing of individuals rather than the crossing of data samples. Furthermore, the FS included two stages: a filtering FS stage followed by a wrapper FS phase. The final GFFSM modeling trained the Fuzzy Finite State Machine with different learning strategies [2][42]: several approaches were compared, ranging from Pittsburgh fixed-size rule set tuning to boosting Michigan learning.

The cross-validation shuffles the data from the individuals that will be used for training and for validation. In this way, all the Time Series (**TS**) from a single individual are considered either for training or for validation purposes, according to the cross-validation shuffling that is performed.

FS filtering is a very interesting voting algorithm for the fusion of the results of different Principal Component Analyses (**PCA**, [14],[29],[51]). Whenever PCA is applied, the rollback of the ***M*** most relevant transformations –up to 95% of representation- is performed. To do so, the transformations are sorted according to their percentage of representation. Let us consider that a transformation is located at position p. This transformation is assigned a rank (M-p+1)/M, and the features involved in its computation receive the vote of the rank times the percentage of representation times the corresponding coefficient. In this way, each feature is voted on the basis of the PCA results by aggregation of the marks from all the transformations in which the feature is involved.

Two main ballots were performed: one for the whole training data set and a second one fold by fold. In the former case, the whole training data set is aggregated for all the individuals, then PCA is performed, and the features are then voted. In the latter case, PCA is independently performed for each fold; so different voting results are obtained. Finally, the approval-voting scheme is applied [8] by aggregating the votes from each fold, using the mean of the votes. The voting scheme is also applied to the results from each ballot, using the same weight. As a result, each feature in the original space gets a vote from the different PCA transformations, which is used for ranking and filtering.

The second FS stage, as mentioned above, is a wrapper FS. In this case, the FS method is an adapted version [45],[46],[47] of the Steady State Genetic Algorithm FS [10]. The wrapper makes use of a genetic algorithm to learn a GFFSM; a relaxed set of parameters is used in this learning, in order to reduce the computational cost. Consequently, the output of this FS is a feature subset used for developing the GFFSM classifier with a suitable set of parameters to optimize the model; however, the GFFSM will need further training before its performance is acceptable.

The last stage of the proposal referred to in [48] deals with the learning of the final GFFSM models once the feature subset has been chosen. The original GFFSM –where the 3DACC were placed on the center of the individual's back- has been adapted to the current problem. Furthermore, different learning strategies, varying from Pittsburgh learning to the boosting of Michigan fuzzy rules, were all analyzed and compared. The most promising method found so far was GFFSM learned with Boosting with the Single Winner Inference algorithm [39].

This approach appeared to fit the HAR requirements perfectly, which is one of the steps in the current study for stroke recognition. Nevertheless, it could be said that the higher the number of activities the lower the performance of the HAR method. Consequently, the activity set should be limited to only those activities that may be interesting for the stroke recognition.

3.2. SAX-based Human Activity Recognition

The limitation regarding the number of activities led us to analyze different approaches that would eventually be implemented in embedded devices. Interestingly, the analysis of different TS representations [30] showed the simplicity and potential use of Symbolic Aggregate approXimation (SAX) [25] in this context.

Using 3DACC means that the measurements of raw data from the sensors should be decomposed into gravity acceleration (G) and body acceleration (**BA**), resulting from human movement. Using a lowpass and a highpass filter, respectively, we can obtain both accelerations with its three components per axis. The value of BA may be computed as $BA_i = \sqrt{\left(b_i^x\right)^2 + \left(b_i^y\right)^2 + \left(b_i^z\right)^2}$, with the following three components: $\left(b_i^x, b_i^y, b_i^z\right)$. The capacity of the BA to discriminate between different human gestures is documented in [51].

Let $mBA_{\{L,R\}}$ and $sBA_{\{L,R\}}$ be the mean and standard deviation of the movements during the daily living activities of the individual, both calculated by means of an initial test. The sub-index L and R stand for the left and the right hand, respectively. These values will be used for normalization of the TS windows.

The algorithm proposed for HAR is included in Figure 2; for the sake of brevity, it is shown rather schematically. This algorithm makes use of SAX, a well-known TS representation technique [25]. The main idea is that for each of the focused activities, a set of SAX patterns that are fairly usual when performing the activity should be identified. These patterns should be as general as possible, in the sense that if they are common to a wide variety of individuals the results are more generalized. However, it is enough to carry out these activities for a short period of time and then extract them using I-Nearest Neighbor or similar algorithms [26].

Once the parameters detailed above are set, the problem is solved as classifying the cHA based on activities with a similar associated pattern. The aggregation of similarities can be any t-conorm, such as the Lukasiewicz t-conorm –the bounded addition-.

Some issues need further study, for example learning the membership functions and their tuning to the focused individual, as well as the method for measuring similarities between TS representation. Interestingly enough, the computational cost and resources needed for implementing this algorithm are kept rather small, which is one of the main enhancements of this technique. The last part of the algorithm is related to the point at which the alarm is generated at the onset of a stroke or after a fall.

3.3. Alarm generation following stroke onset and falls

With regard to alarm generation, the study proposed in [47], where an algorithm for alarm generation based on the SAX TS representation is proposed, is worth mentioning. Besides, the approach presented in [9] was considered both for abnormal movement detection and for detecting falls.

The TS from both bracelets are used in this case, and the state of resting should be previously detected, on an independent basis for each hand. In the case of a resting state, the BA is normalized using the μ_{RBA_h} and σ_{RBA_h}, the mean and standard deviation of the signal of the BA when the individual is resting; the h sub-index is related with the -left or right- hand. These values should be calculated in an initial test.

The SAX4ALARMS algorithm shown in Figure 3 briefly outlines the proposed approach. In its current state, the algorithm is focused on alarm generation in

```
Procedure: SAX4HAR
Input:
    X: a TS of size n, normalized using mBA_L,R
    and sBA_L,R
Output:
    A set of possible activities and their certainties
X'=SAX(X)
for each A in RegisteredActivities do
    for each Ymov in PatternsOfActivity(A) do
        simXY=similarity(X',Ymov)
        Update certainty(A) according to simXY
S={<A, certainty(A)> ∀A | certainty(A)>0}
return S
```

Figure 2 Algorithm for HAR using the SAX TS representation.

the RESTING state, because this is the most common scenario at the onset of a stroke. However, the structure would be the same, even if the whole set of alarms were considered: just by introducing more alarms and their corresponding patterns and thresholds.

The algorithm works as follows. Firstly, the cHA is estimated –by means of a HAR method, the SAX4HAR for instance-; the time spent in each state is also updated. Whenever the individual is in a RESTING state, the current resting amount of movement level is determined.

Three different resting activity levels have been considered: when the individual has just begun a RESTING state (short rests, with the individual carrying out some low activity tasks like reading), when doing nothing –for instance, if the individual is having a nap, then the activity level is clearly low- and when the individual is sleeping –which means that the activity level is highly reduced over a longer period of time.

The similarity of the signal from each hand is compared with the typical sequences of inactivity for each case. The certainty of setting off the corresponding alarms for either partial or total paralysis, or for fall detection, increases with the patterns that are found. For instance, considering the case of the individual in a RESTING state, when one hand shows no activity and the other hand shows some, then that might suggest partial paralysis. Conversely, a rather low activity level in both hands might characterize total paralysis. Each alarm has a minimum waiting time in the same alarm state, with specific time periods for each alarm.

In this study, health experts have provided the following time thresholds. The first threshold (**TH1**) is calculated using the scenario in which an upper limb is considered to be affected by paralysis on the basis of the current activity of the individual. If the individual is found RESTING, on the basis of the movements of one hand, and is found not to be RESTING, on the basis of the other hand, for more than 6 minutes, then the partial paralysis alarm is set off. Thus TH1 is the number of samples according to the sampling rate for which the individual should remain in this state before activating the partial paralysis alarm.

The second threshold **TH2** is related with the RESTING state for both hands, so if one of the hands is performing active resting –i.e., it is moving slightly to try to reach an object– and the other does not perform any movement for more than 6 minutes, then the partial paralysis alarm is once again activated. Again, TH2 is the corresponding number of samples in this scenario for this alarm set up.

Procedure: SAX4ALARMS
Input:
  X_h: a TS of size n, normalized using $mRBA_{L,R}$ and $sRBA_{L,R}$
  STATES, CERTAINTIES of the subject
  resting activity level & counters
Output:
  A set of possible alarms & resting activity level & counters

```
if Resting State is believed then
  update the resting activity level
end if
X'=SAX(X)
for each alarm type AT do
  for each Ymov ∈ RegisteredSequences(AT) do
    simXY=similarity(X', Ymov)
    if simXY is HIGH then
      set the AT alarm as active
    end if
  end for
  Update time counter for AT
  if time counter of AT is HIGH_AT then
    Generate AT alarm
  end if
end for
```

Figure 3 Simplified alarm generation algorithm. This algorithm is the responsible of detecting any alarm condition and of generating the corresponding alarms when needed.

Finally, the third threshold, **TH3**, is concerned with RESTING for long periods, such as when having a nap or when asleep at night. In this case, if a hand does not perform any movement for periods of time longer than 14 minutes, then the alarm for partial paralysis is triggered. TH3 also includes the corresponding number of samples for this period.

When the partial paralysis alarms are set off for both hands, then the total paralysis alarm is also triggered. As stated in the case of HAR, the set of typical sequences or patterns for each alarm type and hand are learned in a previous training phase with the individual, as the patterns are rather specific to each person.

This proposal and the associated algorithms are still under design and evaluation; it is worth mentioning that the whole approach has a reduced computational cost that can easily be implemented in embedded solutions.

4. Experiments and results

Several tests have been carried out as follows: i) an evaluation and comparison of SAX-based HAR methods; and, ii) the evaluation of the SAX-based method for stroke alarm generation, in order to evaluate the approach presented in this study. This section deals with each of these steps: the first subsection describes the details of data collection and cross-validation; the second subsection reports the test results and discusses the above-mentioned points.

4.1. Materials and experimental methods

In this study, a pair of data logging wrist bracelets, with a sampling frequency of 16 Hz, was developed (see Figure 4). Each bracelet, which is identified for the left and the right hand, includes a tri-axial accelerometer and a USB port. Using these bracelets, an individual completes the different tests with the corresponding repetitions for statistical purposes; after which the data is segmented.

Two different tests were considered in this study: i) a HAR test for evaluating the SAX-based HAR method; and, ii) a test for validating the SAX algorithm for stroke alarm generation. Each of these tests needs specific data sets that were obtained using the above bracelets.

A well-known stroke rehabilitation test (for short, SRT [18]) was chosen for gathering the data sets concerning the HAR comparison. Two individuals carried out 10 runs of the SRT and a TS was obtained from each run. The individuals were of a different sex and age, both outside the focus population. The first individual was ambidextrous, while the second individual was right handed.

In the SRT, an individual remains seated for a period of time T1, then stands up in the same position for a period of time T2, and then walks along a line on the floor, coming back to the original standing position and remaining there for T2 seconds, and finally sits down and rests for T1. The line on the floor is a 10-meter straight line leading to another 10-meter straight line at an angle of 45 degrees from the former.

Figure 4 The tri-axial bracelets used in this study, one for each hand.

All the data were manually segmented and classified according to the individual activity, in the same way as was proposed in the GFFSM in the original work [2]. For computing the features, a sliding window 10 samples wide and one sample shift were used. In this way, known states were classified with complete certainty, while transitions between actions were assigned with imprecise data, e.g., 0.7/SEATED + 0.3/STANDING. This means that up to 10 TS were gathered and segmented for each individual. Finally, the segmented data for each run was considered a data set, so up to 10 different data sets were available for training and testing.

Typically, the HAR studies in the literature make use of a 10-fold cross-validation. If a 10-fold cross-validation on the data sets from of the 10 repetitions of the SRT test are carried out, 10 folds would be generated, each one containing 9 data sets for training purposes and one data set for the final validation. However, in our opinion, this cross-validation method is neither suitable for HAR method evaluation, nor for comparitive purposes: the generality of the model is not significantly well tested.

Besides, the SAX-based HAR method requires no parameter-based training; only the calculation of some statistical estimators taken from the data. In this study, we advance a more challenging cross-validation method: to do so, we propose a 10-fold cross validation where only one single data set of those from the 10 repetitions of the SRT test will be used for the calculation of the statistics, while the remaining data sets will be used for the validation of the results of the model.

In fact, the higher the ratio between the size of the test and the training data sets, the higher the expected error; however, this cross-validation scheme would eventually lead us to evaluate the generalization of the model. Using this scheme, a better resemblance of real deployment of the device and the models is obtained, as many completely unknown TS are given to the model. The lower the training parameters of a HAR method, the easier its deployment.

Moreover, data sets for evaluating the SAX-based stroke alarm generation algorithm have also been gathered. In this case, the individual was asked to sleep wearing the bracelets for ten nights; the bracelets were turned on once the individual was in the bed, and the data was gathered. In this scenario, no segmentation is needed because the individual is resting. The same cross-validation scheme detailed above was used: the TS from one run was used for learning the statistic parameters and the remaining TS were used for studying the evolution of the algorithm.

4.2. Evaluation of the HAR method

The Mean Absolute Error (**MAE**, see Eq. 1) was used for evaluating each individual when learning a GFFSM model. Thus, the MAE will also be used for evaluating the SAX4HAR method. For computing the MAE, T_i is the number of examples in the data set **i**, N is the number of available data sets, and $s_i[t]$ and $s_i^*[t]$ are the degree of generation state $q_i[t]$ and the expected degree of generation, respectively, both at time step t.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{T_i}\sum_{t=1}^{T_i} abs\left(s_i[t] - s_i^*[t]\right) \quad (1)$$

The results obtained for the SAX4HAR method are presented in Table 1 to Table 6. The results shown in Table 1 and Table 2 are concerned with the MAE from the cross-validation folds. The results yield errors of around 10%; however, these statistics give no clear idea of how the TS are classified.

From Table 3 to Table 6, the corresponding confusion matrices for each hand are included. From these results, in spite of the training based on data from a single data set, the SAX4HAR correctly classifies the majority of samples in the RESTING and the WALKING states. However, the results for the STANDING state were not so valid. This may be due to the SRT, which sets a long standing still position for the individual for a relatively long time, which is unusual in human behavior. Moreover, this period of standing still that is set by the SRT establishes that the individuals should keep calm, with almost no movement at all: hence the SAX4HAR classifies a high percentage of the samples incorrectly at this stage. Furthermore, the SRT test produces a relatively smaller percentage of samples in this state, so the set of SAX sequences is not properly extracted. Further research is needed in order to make the SAX4HAR algorithm more robust in this type of scenario.

In addition, the SAX4HAR approach has been compared with a well-known HAR method: the GFFSM proposed in [2], adapted in [15] and outperformed in [48]. The two versions of this latter work will be used in the comparison; namely the enhanced Pittsburgh GFFSM (**wGFFSM**) and the Michigan-style classifier using boosting and single winner inference (**bGFFSM**). All the methods were trained using data from one SRT run and tested with the remaining folds, in order to compare the current solution with these two approaches. It is worth noticing that training a GFFSM with this cross-validation scheme will penalize the outcome of the methods,

Table 1 MAE results for HAR using the SAX4HAR for the first subject.

	Left hand		**Right hand**	
Fold	**Train**	**Test**	**Train**	**Test**
1	0.1045	0.1374	0.1312	0.2018
2	0.0406	0.1597	0.1621	0.2271
3	0.1377	0.1849	0.1765	0.2274
4	0.0710	0.1184	0.0956	0.1558
5	0.2476	0.1216	0.2396	0.1474
6	0.0548	0.0625	0.0818	0.1104
7	0.0416	0.0713	0.0711	0.1268
8	0.0418	0.0602	0.0563	0.1038
9	0.0403	0.0636	0.0459	0.1086
10	0.0492	0.0591	0.3450	0.0708
Mean	0.0829	0.1039	0.1405	0.1480
Median	0.0520	0.0949	0.1134	0.1370
Std	0.0664	0.0467	0.0941	0.0546

Table 3 MAE results for HAR using the SAX4HAR for the second subject.

	Left hand		**Right hand**	
Fold	**Train**	**Test**	**Train**	**Test**
1	0.1026	0.1515	0.1095	0.1527
2	0.1874	0.1412	0.1897	0.1402
3	0.1742	0.1398	0.1678	0.1369
4	0.1738	0.1436	0.1812	0.1434
5	0.1697	0.1417	0.1694	0.1400
6	0.1453	0.1371	0.1564	0.1340
7	0.1106	0.1481	0.1161	0.1448
8	0.1210	0.1471	0.1167	0.1500
9	0.1257	0.1321	0.1110	0.1304
10	0.1027	0.1516	0.1094	0.1527
Mean	0.1413	0.1434	0.1427	0.1425
Median	0.1355	0.1426	0.1366	0.1418
Std	0.0328	0.0063	0.0330	0.0077

although this scheme would better resemble a real scenario –where the users can not be reasonably asked to perform long and cumbersome training tests-.

The parameters used for training the wGFFSM and the bGFFSM are given in Table 7. The second individual results for both methods are shown in Table 8 to 11, and Figure 5 and Figure 6 for comparison purposes. The results for the best GFFSM individual found so far are reported for both hands in Table 8 (wGFFSM) and Table 9 (bGFFSM). The interested reader can compare these results with those obtained for the SAX4HAR (see Table 1 and Table 2). Clearly, the wGFFSM results were slightly better than the SAX4HAR results; however, the variability in their performance is a compromise and can easily be seen in Figure 5 and Figure 6. The span of the results for SAX4HAR is really narrow, while the wGFFSM has a wider spread of results. This means that SAX4HAR is more robust with respect to the training data; while the performance of the wGFFSM is bound by the same upper limit as the SAX-based method. Furthermore, the bGFFSM has the worst performance of the two comparative methods.

The wGFFSM confusion matrices are shown in Table 10 and Table 11 for the left and right hands, respectively. These confusion matrices cannot be compared with those of the SAX4HAR, because the transitions are not classified by the GFFSM: the confusion matrixes seem to be better than those of the SAX4HAR, because these unclassified samples are

Table 2 Confusion matrix for the first subject's left hand.

		Obtained class		
Real Class		STANDING	RESTING	WALKING
	STANDING	560	2927	288
	RESTING	4901	30661	4758
	WALKING	8155	1268	32625

Table 4 Confusion matrix for the first subject's right hand.

		Obtained class		
Real Class		STANDING	RESTING	WALKING
	STANDING	616	3270	344
	RESTING	5261	33769	4944
	WALKING	8243	1381	27680

Table 5 Confusion matrix for the second subject's left hand.

		Obtained class		
Real Class		STANDING	RESTING	WALKING
	STANDING	672	17108	3091
	RESTING	2316	36617	253
	WALKING	430	2805	30830

Table 6 Confusion matrix for the second subject's right hand.

		Obtained class		
Real Class		STANDING	RESTING	WALKING
	STANDING	1261	18106	1369
	RESTING	2266	36186	194
	WALKING	838	1973	31011

not included. Nevertheless, if the percentage of corrected classified samples is computed, it can be seen that SAX4HAR is rather similar or even better than wGFFSM, except for the STANDING class.

This fact is quite interesting, as one of the main claims of this study is that the approach needs almost no training, only the mean and standard deviation of the different states. The reduced training feature comes from the fact that the smaller the number of actions for setting up a device, the better its acceptance by the consumer. Consequently, the experimentation results show SAX4HAR as a very promising solution.

To conclude, we can state that i) the SAX4HAR is a valid HAR recognition method with a reduced computational cost; ii) there is a need for improving the set of sequences for characterizing the different states, particularly the STANDING state; and iii) the number of states might be increased provided that

Table 7 Experiment parameters for each of the GFFSM approaches.

Parameter	wGFFSM	bGFFSM
Generations	300	300+10/rule
Population size	100	50
Elite pop. Size	1	40
Subpop. size	-	10
Crossover prob.	0.8	1
Mutation prob.	0.02	0.1
Interchange prob.	-	0.01
Crossover BLXα	0.3	0.3
No. of rules	8	Up to 6
Generations w/o progress	50	100+10/rule
Logitboost α	-	0.75
Maximum number of iterations	-	4

computation time and resources for the different TS comparison remain low.

4.3. Evaluating the alarm generation module

Once the HAR is considered solved, the focus shifts to the alarm generation patterns in response to the onset of a stroke. This section is devoted to the evaluation of the alarm generation algorithm.

To do so, data from the older individual while asleep over ten different nights was gathered. The SAX4HAR algorithm, together with the alarm generation module, was run using the same cross-validation scheme as for HAR. Thus, the whole approach has, in the first place, to classify the state as RESTING, and, in the second, to generate the alarms according to the given thresholds.

Two sets of thresholds will be given to test this alarm generation routine; one with approximate values established by experts, another with a set of extremely reduced threshold values, to simulate possible stroke onsets, testing the validity of the alarm generation rules. This decreased set of thresholds is simply to give a clear picture of alarm generation; the thresholds should be evaluated with individuals in realistic tests.

As stated above, the time thresholds TH1, TH2 and TH3 were fixed to the corresponding number of samples for a period of 6 minutes, 6 minutes, and 14 minutes, respectively. However, whenever the alarms were set off in order to test the alarm generation algorithm, the thresholds were computed using seconds instead of minutes.

Table 8 MAE results for the wGFFSM and the second subject.

	Left hand		Right hand	
Fold	**Train**	**Test**	**Train**	**Test**
1	0.0000	0.3561	0.0055	0.2929
2	0.0028	0.0511	0.0014	0.0935
3	0.0043	0.2636	0.0023	0.0095
4	0.0000	0.0214	0.0002	0.1722
5	0.0075	0.0190	0.0003	0.1530
6	0.0000	0.0608	0.0008	0.0181
7	0.0005	0.0233	0.0020	0.0967
8	0.0000	0.0099	0.0005	0.0369
9	0.0090	0.0979	0.0000	0.0159
10	0.0000	0.1273	0.0004	0.0349
Mean	0.0024	0.1041	0.0014	0.0921
Median	0.0002	0.0560	0.0007	0.0652
Std	0.0034	0.1175	0.0017	0.0906

Two periods of the night for an individual were presented, each 40 minutes long, in order to show the results: scenario 1 at the beginning of the night, and scenario 2 in the middle of the night. The SAX4ALARMS algorithm was run twice: with the normal set of thresholds and with the reduced set.

Results from the stroke alarm generation experimentation are shown in Figure 7 (scenario 1) and Figure 8 (scenario 2). In both figures, the upper part shows the BA when the individual is asleep at nighttime. The y-axis maximum values are 0.1 g, which means that there was no activity at all. The central and lower parts of these figures show the results of

Table 9 MAE results for the bGFFSM and the second subject.

	Left hand		Right hand	
Fold	**Train**	**Test**	**Train**	**Test**
1	0.1610	0.2839	0.0598	0.2881
2	0.0362	0.3127	0.0202	0.1764
3	0.3124	0.0947	0.2623	0.3686
4	0.3060	0.0860	0.3089	0.0827
5	0.3198	0.3191	0.4625	0.1404
6	0.3593	0.2443	0.2997	0.0388
7	0.0985	0.2650	0.3130	0.0508
8	0.3103	0.2924	0.2274	0.2841
9	0.0624	0.2951	0.2939	0.2929
10	0.3049	0.1967	0.3043	0.1078
Mean	0.2271	0.2390	0.2552	0.1832
Median	0.3055	0.2745	0.2968	0.1584
Std	0.1234	0.0860	0.1288	0.1173

Table 10 Confusion matrix for the second subject's left hand using the wGFFSM; 9011 samples are classified as Transitions.

Real Class	Obtained class		
	STANDING	RESTING	WALKING
STANDING	33117	3858	1296
RESTING	1178	18487	1066
WALKING	2530	1175	23628

Table 11 Confusion matrix for the second subject's right hand using the wGFFSM; 15479 samples are classified as Transitions.

Real Class	Obtained class		
	STANDING	RESTING	WALKING
STANDING	26116	1758	3929
RESTING	486	20267	760
WALKING	1	1590	24960

evaluating the SAX4ALARMS algorithm on the TS: the lower part corresponds to running the algorithms with highly reduced time thresholds, so that the alarms will be set off. The dotted line that is shown in these central and lower parts is the alarm generation state. In the central part, it can be seen that the alarm was never set off. Nevertheless, several alarms were set off in the lower part.

4.4. Discussion of results

Some differences in the fluctuation of the BA for the two scenarios were noted, as at the beginning of the night there is more activity than when the individual is deeper asleep. Nevertheless, the TS was classified as RESTING in both scenarios as the output during the test for the SAX4HAR algorithm. The SAX4HAR algorithm may be enough for specific activities, such as RESTING, which is of high relevance in this stroke episode onset recognition, because in the most serious cases the individual can collapse. Furthermore, the simplicity of this algorithm is one of the main advantages.

It is worth noticing that the movements of each hand are completely independent, so the need for studying the partial paralysis appears to be a good decision.

Besides, when the thresholds were reduced by a matter of seconds the alarms were clearly set off (see the lower parts of both Figure 7 and Figure 8). Although the algorithm for setting off the alarms is fairly simple, it seems to perfectly match the requirements for normal individuals. Nonetheless, it has to be tested on individuals from the target population.

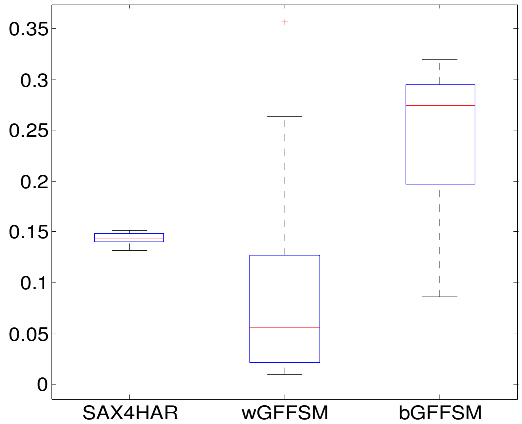

Figure 5 Boxplot of the MAE results for the left hand. The wGFFSM has better error values, although the errors are highly dependent on the data. The SAX4HAR is more robust against the data set variability.

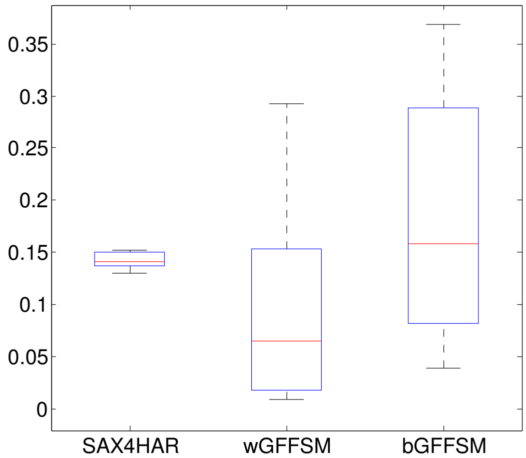

Figure 6 Boxplot of the MAE results for the right hand. The same conclusions as for the left hand (Figure 5) can be found in this boxplot, although in this case there is no clear best method.

Furthermore, the different thresholds need to be validated and, perhaps, new alarm rules might be proposed for different stroke types as well as heuristics. For instance, if a fall is detected and then no activity is detected except RESTING and the alarms are set off, then the individually almost certainly has a serious problem.

The time thresholds will limit the time response of the algorithm, that is, longer thresholds will induce bigger time gaps between the onset of the stroke and the alarm generation. Additionally, the algorithms proposed in this study can easily be transferred into embedded systems.

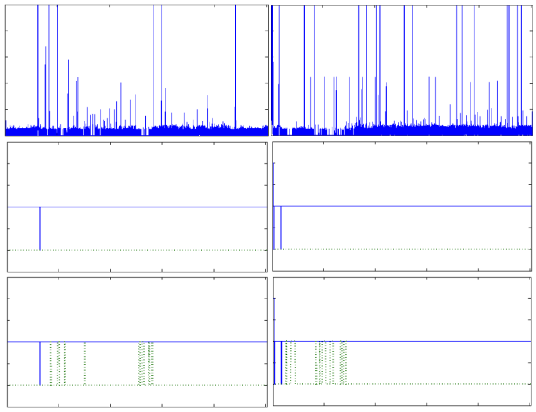

Figure 7: Results for stroke alarm generation: scenario 1, a nighttime period when the individual is asleep. The upper part shows the BA for the left and right hands on their corresponding sides –the y-axis range is 0 to 0.1, showing very small movements-. The central part depicts the estimated state -almost always fixed to RESTING- and the alarm for arm paralysis –the dotted line- which does not go off; on the left and on the right hand side, respectively. The lower part includes the same variables, but with highly underestimated time thresholds so that the alarms go off.

It can quite rightly be said that the SAX4ALARMS algorithm includes no intelligent models. The inclusion of thresholds and these types of rules is not a new proposal and has been validated in certain situations; for instance, one of the best known examples concerns the detection of falls [8]. Often, the simpler approach is better. Applying the simplicity principle as expressed in the form of Ockham's Razor is certainly an effective means of countering high computational models [20]. Nonetheless, it is clear that a compromise usually has to be struck between simplicity and highly complex methods.

It is important to stress the way in which this approach should be deployed. The impact of smartphones in society provides new opportunities for progress in biomedicine, mainly in cases of diagnosis and patient logging. In this case, the approach should be completed as follows. On the one hand, the individual should be given two bracelets, one for each hand. These bracelets should make use of low energy communications, such as Blue Tooth Low Energy. Preprocessing and communications should be analyzed to balance energy consumption. These devices should be connected to the individual's Smart watch, responsible for sending the information to the web services and for local signaling, to attract the attention of bystanders in a position to provide assistance. Web-based services should manage the assignment of medical services.

The solution presented in this study, once completed and validated, will potentially reduce the time gap between stroke episode onset and delivery of thrombolytic medication by means of ITC. Finally, it should be said that all issues concerned with the distribution of the decision-making process are beyond the scope of this study, despite the obvious interest in their discussion.

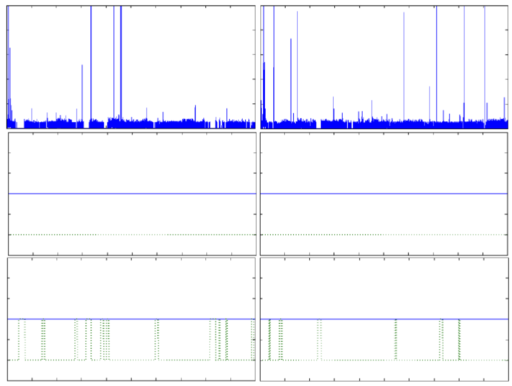

Figure 8 Results for the stroke alarm generation, in scenario 2. The upper part includes the BA values; the central and upper part shows the SAX4ALARMS algorithm results with the time thresholds fixed by the experts –central part- and the highly underestimated time thresholds –lower part-. As for scenario 1, the alarms went off in those periods where no activity was detected.

5. Conclusions

This study has concerned itself with ambient assisted living issues for the generation of alarms in cases of stroke onset, which could allow timely delivery of thrombolytic medication, to mitigate the long-term effects of these attacks.

A solution has been presented, based on wearing two bracelets that include 3D accelerometers that work with intelligent algorithms: i) for classifying human activity; and; ii) for setting off the alarms when the individual's behavior does not show a symmetrical amount of movement. A specific bracelet has been developed and a complete analysis of both algorithms has been carried out in the experimentation stage.

Some interesting results of this study are that, concerning HAR, a simple algorithm can outperform more complex models in terms of results and computational costs. The algorithms proposed in this study may easily be transferred into embedded systems. Moreover, the alarm generation module, although still in need of further experimentation with the target population, appears to be suitable for setting off alarms in case of an asymmetrical amount of movement.

Quite clearly, experimentation with the target population calls for special agreements with each individual and various national associations, among other reasons to protect data privacy; these types of agreements can de drawn out and would require suitable funding. Ongoing and future work focuses on these two directions to continue to enrich and to expand this research.

Acknowledgement

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References

[1] H. P. Adams, G. del Zoppo, M. J. Alberts, D. L. Bhatt, L. Brass, A. Furlan, R. L. Grubb, R. T. Higashida, E. C. Jauch, C. Kidwell, P. D. Lyden, L. B. Morgenstern, A. I. Qureshi, R. H. Rosenwasser, P. A. Scott and E. F.M. Wijdicks, Guidelines for the Early Management of Adults With Ischemic Stroke, Stroke 38 (2007), 1655-1711.

[2] H. Adeli, and S.L. Hung, Machine Learning - Neural Networks, Genetic Algorithms, and Fuzzy Sets, John Wiley and Sons, New York (1995).

[3] M. Ahmadlou, H. Adeli, and A. Adeli, Fractality and a Wavelet-Chaos-Neural Network Methodology for EEG-based Diagnosis of Autistic Spectrum Disorder, Journal of Clinical Neurophysiology 27:5 (2010), 328-333

[4] M. Ahmadlou, H. Adeli, and A. Adeli, Improved Visibility Graph Fractality with Application for Diagnosis of Autism Spectrum Disorder, Physica A: Statistical Mechanics and its Applications, 391:20 (2012), 4720-4726.

[5] M. Ahmadlou, H. Adeli, and A. Adeli, Fractality Analysis of Frontal Brain in Major Depressive Disorder, International Journal of Psychophysiology, 85 (2012), 206-211.

[6] A. Álvarez-Álvarez, G. Triviño and O. Cordón, Body posture recognition by means of a genetic fuzzy finite state machine, IEEE 5th International Workshop on Genetic and Evolutionary Fuzzy Systems GEFS (2011), 60-65.

[7] E.N. Arcoverdo Neto, R.M. Duarte, R.M. Barreto, J.P. Magalhaes, C.M. Bastos, T.I. Ren and G.D.C. Cavalcanti, Enhanced real-time head pose estimation system for mobile device, Integrated Computer-Aided Engineering 21:3 (2014), 281-293.

[8] S. J. Brams and P. C. Fishburn, Going from Theory to Practice: The Mixed Success of Approval Voting, 2003 Handbook on Approval Voting Studies in Choice and Welfare (Springer Verlag, 2010) pp. 19-37.

[9] T. R. Burchfield and S. Venkatesan, Accelerometer-based human abnormal movement detection in wireless sensor networks, in Proceedings of the 1st ACM SIGMOBILE international workshop on Systems and networking support for healthcare and assisted living environments HealthNet'07 (2007), 67-69.

[10] J. Casillas, O. Cordón, M.J. del Jesus and F. Herrera. Genetic Feature Selection in a Fuzzy Rule-Based Classification System Learning Process, Information Sciences 136(1-4) (2001) pp. 135-157.

[11] C. Chira, J. Sedano, M. Camara, C. Prieto, J.R. Villar and E. Corchado, A Cluster Merging Method for Time Series Microarray with Product Values, International Journal of Neural Systems 24:6 (2014), 1450018-1/18.

[12] A. D. Dromerick and S. A. Khader, Medical complications during stroke rehabilitation, Advances in Neurology 92 (2003), 409-413.

[13] E. Duarte, B. Alonso, M.J. Fernández, J.M. Fernández, M. Flórez, I. García-Montes, J. Gentil, L. Hernández, F.J. Juan, J. Palomino, J. Vidal, E. Viosca, J. J. Aguilar, M. Bernabeu, I. Bori, F. Carrión, A. Déniz, I. Díaz, E. Fernández, P. Forastero, V. Iñigo, J. Junyent, N. Lizarraga, L. López de Munaín, I. Máñez, X. Miguéns, I. Sánchez and A. Soler, Stroke rehabilitation: Care model, Rehabilitación 44:1 (2010), 60-68.

[14] S. Ghosh-Dastidar, H. Adeli, and N. Dadmehr, Principal Component Analysis-Enhanced Cosine Radial Basis Function Neural Network for Robust Epilepsy and Seizure Detection," IEEE Transactions on Biomedical Engineering, 55:2 (2008), 512-518.

[15] S. González, J. R. Villar, J. Sedano and C. Chira, A preliminary study on early diagnosis of illnesses based on activity disturbances, Proceedings of the 10th International Conference on Distributed Computing and Artificial Intelligence DCAI, Advances in Intelligent Systems and Computing 217 (2013), 521-527.

[16] H. Hemami, B. D. Clymer and M. Hemami, Simulation of control and synthesis of a constrained movement towards rehabilitation exercises, Integrated Computer-Aided Engineering 19:4 (2012), 351-364.

[17] L.J. Herrera, C.Fernandes, A.M. Mora, D. Migotina, R. Largo, A. Guillén and A.C. Rosa, Combination of Heterogeneous EEG Feature Extraction Methods and Stacked Sequential Learning for Sleep Stage Classification, International Journal of Neural Systems 23:3 (2013), 1350012-1/20.

[18] K. Hollands, Whole body coordination during turning while walking in stroke survivors. Ph.D. Thesis, School of Health and Population Sciences, University of Birmingham, 2010.

[19] C.S. Hogdson, To FAST or not to FAST, Stroke 38 (2007) 2631-2632.

[20] G. Iacca, F. Neri, E. Mininno, Y.-S. Ong, and M.-H. Lim, Ockham's Razor in memetic computing: Three stage optimal memetic exploration, Information Sciences 188:1 (2012), 17-43.

[21] A. Itrat, S. Alam, E. Walker and I. Katzan, Abstract TP180: Markedly Elevated High-sensitive C-reactive protein (hsCRP) Predicts Early Mortality Among Stroke Patients, Stroke 44 (2013), ATP180.

[22] R. Kassab, J.-C. Lapayre, J.-B. Aupet, F. Marzani and C. Pieralli, Scars collaborative telediagnosis platform using adaptive image flow, Integrated Computer-Aided Engineering 20:1 (2013), 3-14.

[23] D. Li, L. Xu, E. Goodman, Y. Xu and Y. Wu, Integrating a statistical background-foreground extraction algorithm and SVM classifier for pedestrian detection and tracking, Integrated Computer-Aided Engineering 20:3 (2013), 201-216.

[24] J. Li, J. Liang, Q. Zhao, K. Hong and L. Zhang, Design of Wheelchair Assistive System Directly Steered by Human Thoughts, International Journal of Neural Systems 23:3 (2013), 1350013-1/12.

[25] J. Lin, E. Keogh, S. Lonardi, and B. Chiu, A Symbolic Representation of Time Series, with Implications for Streaming Algorithms, In proceedings of the 8th ACM SIGMOD Workshop on Research Issues in Data Mining and Knowledge Discovery (2003).

[26] Jessica Lin, Sheri Williamson, Kirk Borne, and David DeBarr. 2012. Pattern recognition in time series. Advances in Machine

Learning and Data Mining for Astronomy. Eds. Kamal, A., Srivastava, A., Way, M., and Scargle, J. Chapman & Hall. To Appear.

[27] Y. Liu and C. Pomalaza-Ráez, On-chip body posture detection for medical care applications using low-cost CMOS cameras, Integrated Computer-Aided Engineering 17:1 (2010), 3-13.

[28] R.J. Martis, U.R. Acharya, J. H. Tan. A. Petznick, C.K. Chua and E.Y.K. Ng, Application of Intrinsic Time-scale Decomposition (ITD) to EEG Signals for Automated Seizure Prediction, International Journal of Neural Systems 23:5 (2013), 1350023-1/16.

[29] A. Meraoumia, S. Chitroub and A. Bouridane (2013), 2D and 3D Palmprint Information, PCA and HMM for an Improved Person Recognition Performance, Integrated Computer-Aided Engineering 20:3 (2013), 303-319.

[30] M. P. Murray, A. B. Drought and R. C. Kory, Walking Patterns of Normal Men, Journal of Bone and Joint Surgery 46:2 (1964), 335-360.

[31] NHS UK, Stroke – Act F.A.S.T, http://www.nhs.uk/actfast/Pages/stroke.aspx, Technical Report, National Health System, 2013.

[32] NSA, Warning Signs of Stroke, http://www.stroke.org/site/PageServer?pagename=SYMP, Technical Report, National Stroke Association, 2013.

[33] NSA, Reducing Risk and Recognizing Symptoms. Stroke is a brain attack!, http://www.stroke.org/site/DocServer/ReducingRisk_8-09.pdf?docID=3027, Technical report, National Stroke Association, 2013.

[34] I. Osorio, Automated Seizure Detection Using EKG, International Journal of Neural Systems 24:2 (2014), 1450001-1/10.

[35] G. Rodrıguez-Bermudeza, P.J. Garcıa-Laencina and J. Roca-Dorda, Efficient Automatic Selection and Combination of EEG features in Least Squares Classifiers for Motor-imagery Brain Computer Interfaces, International Journal of Neural Systems 23:4 (2013), 1350015-1/17.

[36] S. H. Roy, M. S. Cheng, S.-S. Chang, J. Moore, G. de Luca, S. H. Nawab and C. J. de Luca, A Combined sEMG and Accelerometer System for Monitoring Functional Activity in Stroke, IEEE Transactions on Neural System Rehabilitation Engineering, 17 (2009), 585-594.

[37] B. Sabayan, J. Gussekloo, W. de Ruijter, R. G. J. Westendorp and A. J. M. de Craen, Framingham Stroke Risk Score and Cognitive Impairment for Predicting First-Time Stroke in the Oldest Old, Stroke 44 (2013), 1866-1871.

[38] R. L. Sacco, S. E. Kasner, J. P. Broderick, L. R. Caplan, J. J. Connors, A. Culebras, M. S. V. Elkind, M. G. George, A. D. Hamdan, R. T. Higashida, B. L. Hoh, L. S. Janis, C. S. Kase, D. O. Kleindorfer, J.-M. Lee, M. E. Moseley, E. D. Peterson, T. N. Turan, A. L. Valderrama and H. V. Vinters, An Updated Definition of Stroke for the 21st Century. A Statement for Healthcare Professionals From the American Heart Association/American Stroke Association, Stroke 44 (2013), 2064-2089.

[39] L. Sánchez and J. Otero, Boosting fuzzy rules in classification problems under single-winner inference, International Journal of Intelligent Systems 22(9) (2007) pp. 1021-1035.

[40] Z. Sankari, H. Adeli, and A. Adeli, Wavelet Coherence Model for Diagnosis of Alzheimer's Disease, Clinical EEG and Neuroscience, 43:3 (2012), 268-278.

[41] Y. E. Shao, C.-D. Hou, C.-C. Chiu, Hybrid intelligent modeling schemes for heart disease classification, Applied Soft Computing 14:A (2014), 47-52.

[42] N. Siddique, and H. Adeli, Computational Intelligence - Synergies of Fuzzy Logic, Neural Networks and Evolutionary Computing, Wiley, West Sussex, United Kingdom (2012).

[43] J. B. Taylor, Jill Bolte Taylor's stroke of insight, http://www.ted.com/talks/jill_bolte_taylor_s_powerful_stroke_of_insight.html, TED.com, 2008.

[44] S. Tolu, M. Vanegas, J.A. Garrido, N.R. Luque, and E. Ros, Adaptive and Predictive Control of a Simulated Robot Arm, International Journal of Neural Systems 23:3 (2013), 1350010-1/15.

[45] J. R. Villar, S. González, J. Sedano, E. Corchado, L. Puigpinós and J. de Ciurana, Meta-heuristic improvements applied for steel sheet incremental cold shaping, Memetic Computing 4(4) (2012) pp. 249-261.

[46] J. R. Villar, S. González, J. Sedano, C. Chira and J. M. Trejo, Human Activity Recognition and Feature Selection for Stroke Early Diagnosis, in 8th International Conference Hybrid Artificial Intelligent System HAIS 2013, LNCS 8073 (Springer Verlag, 2013) pp. 659-668.

[47] J. R. Villar, S. González, J. Sedano, C. Chira and J. M. Trejo, Early diagnosis of Stroke: bridging the gap through wearable sensors and computational models, Proceedings of the International Conference of Applied Mathematics ICAM9 (Baia-Mare, Romania, 2013).

[48] J. R. Villar, C. Chira, S. González, J. Sedano and J. M. Trejo-Gabriel-Galán, Improving human activity recognition and its application in early stroke diagnosis, International Journal of Neural Systems, in press.

[49] X. Wang, Y. Dong, X. Qi, C. Huang and L. Hou, Cholesterol Levels and Risk of Hemorrhagic Stroke. A Systematic Review and Meta-Analysis, Stroke 44 (2013), 1833-1839.

[50] D. Wang, C. Quek, G. See Ng, Ovarian cancer diagnosis using a hybrid intelligent system with simple yet convincing rules, Applied Soft Computing 20 (2014), 25-39.

[51] A. Weingessel and K. Hornik, A Robust Subspace Algorithm For Principal Component Analysis, Int. J. Neur. Syst. 13(307) (2003), DOI: 10.1142/S0129065703001650.

[52] J.-Y. Yang, J.-S. Wang and Y.-P. Chen, Using acceleration measurements for activity recognition: an effective learning algorithm for constructing neural networks, Pattern Recognition Letters 29 (2008), 2213-2220.

[53] L. Zhang, T. Liu, S. Zhu and Z. Zhu, Human Activity Recognition based on Triaxial Accelerometer, 7th International Conference on Computing and Convergence Technology (ICCCT) (2012).

7.3. Conferencias

7.3.1. A preliminary study on early diagnosis of illnesses based on activity disturbances

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A preliminary study on early diagnosis of illnesses based on activity disturbances

Silvia González, José R. Villar, Javier Sedano, and Camelia Chira

Abstract Recently, the human stroke is gathering the focus as one of the diseases with higher mortality and social impact. In addition, it has a long-term treatment and high rehabilitation costs. Therefore, the early diagnosis of stroke can take advantage in avoiding the stroke itself or highly reducing its effects. Up to out knowledge, no previous study on stroke early diagnosis has been published in the literature. This study deals with the early detection of the stroke based on accelerometers and mobile devices. First, an discussion on the problem is presented and the design of the approach is outlined. In a first stage, it is necessary to determine what is the subject doing at any moment; thus, human activity recognition is performed. Afterwards, once the current activity is estimated, the detection of anomalous movements is proposed. Nevertheless, as there is no data available to learn the problem, a realistic proposal for simulating stroke episodes is presented, which lead us to draw the conclusions.

Key words: Ambient Assisted Living, Stroke Early Diagnosis, Genetic Algorithms, Fuzzy State Machines

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1 Introduction

Stroke is a cerebrovascular abnormal blood circulation upheaval that disrupts the normal function of a region in the brain. Stroke is considered one of the main causes for mortality and a leading cause of disability throughout the world [8, 9]. In case of disability, the rehabilitation is a long term process that does not guarantee reaching the patient normality.

Physical activity helps in the reduction of the stroke risks [6], but it is not enough. Current methods for diagnosing the stroke are based on the observation of the patient's behaviour when passing through a simple positional test in which the patient is told to keep his/her arms in parallel or to walk through a line [6, 8]. It has been found that the sooner the diagnosis the lower the stroke consequences [8]. Consequently, detecting the abnormality in the patient movements represents a challenge in the diagnosing of the stroke.

It is well known that human beings have very characteristic movements. Actually, the most well-known and characterized movement is walking, which has been completely defined [10]. The main part of the studies have been carried out in video based motion analysis system [7, 8]. Recently, the use of accelerometer-based methods are reaching the focus due to several reasons [12, 14]: the reduction of the diagnosing costs, the possibility of further data analysis and the ubiquity among others. The possibility for automatically detecting several human movements and its validity are pushing the balance towards the use of accelerometers as main sensors for human motion detection and classification [13].

This study is focus on using accelerometers for the early detection of the stroke, which would provide the method for reducing its effects in the society and in the individual: an early detection would reduce the patient recovery period. An analysis of the problem and the solution design lead towards a two stage method: the former stage includes the Human Activity Recognition (HAR), while the latter is the responsible of detecting abnormalities in the activities and the alarm generation. This is a preliminary study, so we adapt a HAR technique and then evaluates the data from the accelerometer and propose how the diagnosing of the stroke can be afforded for one of the analyzed activities.

The organization of the manuscript is as follows. Next section deals with the Stroke characterization and the design of the solution. In addition, this section will briefly introduce the hypothesis for stroke episode detection. Afterwards, the HAR method is outlined and its adaptation to the specific stroke problem is detailed. In Sect. 4, the full experimentation of the HAR is included, as well as a further discussion on detecting abnormal movement episodes when the subject is walking. Subsequently, the conclusions drawn and the future work are depicted.

2 Analysing the stroke early detection

The most common and well-known symptoms of stroke episode include mainly one side only numbness of the face, arm, hand or leg; dizziness and trouble walking; collapse; loss of balance and coordination; and speech disorders among others. As stated before, the first neurological exam test carried out is requesting the subject to carry on some specific movements that will clearly be far from normal.

The characterization of the human movement, specially when walking, has been well documented in the literature [10]. Figure 1 shows the schematic representation of a normal walk extracted from the previously referred study. As known, stroke highly influences the way patients move [1], particularly the patient's gait is clearly affected. Due to this reason, and also because walking is one of the most sensible parameters in human dependence, the study of the gait and the patient kinematics has been study so far in the literature [5, 1].

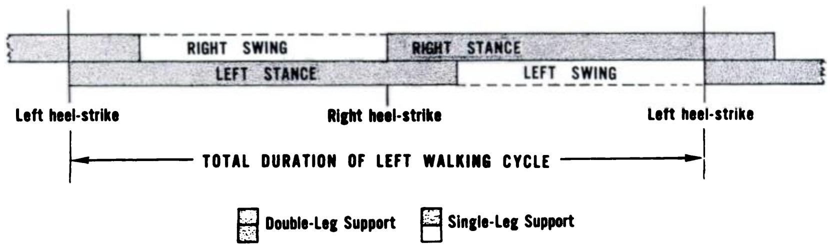


Fig. 1 Schematic representation of left walking cycle extracted from [10].

As stated in [5], there are several abnormalities in stroke patients, as the reduction of both the length of the stride and the cadence of the limbs, or the "abnormal movements of the upper extremity, the trunk, the pelvis, and the lower extremity on the unaffected side in an effort to compensate for the decreased velocity on the hemiplegic side." Moreover, in [8] found an evidence of disability in the gait when turning, and a difference in the pattern of the number of steps, time, gait velocity, step width and step and stride length has been observed.

Interesting readers should notice that there is no information about the very moment of an stroke episode. The only available information is, on the one hand, the experiences with stroke survivors and, on the other hand, the neurological exam test itself. Therefore, there are several hypothesis of how a patient behaves when an ictus episode occurs. The most relevant hypothesis are: i) the individual collapses and no movements are make for a relative extend, and ii) the individual behaves anomalously. The former hypothesis means that the subject keeps quite for far too long, while the second considers the findings from [5, 8].

In this study, the problem of detecting stroke episodes is faced, so both hypothesis should be analyzed. Consequently, one of the very first issues to obtain is to detect the current human activity the subject is doing. HAR needs the number of states to be defined before the learning phase starts. Thus, for the stroke early diagnosis we need establishing which are the most relevant states or activities to detect. As mention before, accelerometer-based HAR methods have been found successful, thus they will be used in this study.

Besides, the abnormalities expected to occur in stroke episodes are those mentioned before: i) there is an extended period of time without any movement, and ii) the dissimilarities of the movements with respect to those considered normal get increased. For identifying both kind of events a set of sensors is also need. Accelerometers are proposed for this aim because i) they are already deployed for HAR and ii) the lower the number of issues the subjects needs to wear the lower the costs and the better the subjects would accept to participate. In order to measure such differences, we propose placing a pair of sensors in both wrists. This configuration would help in detecting abnormalities in all of the possible states. Unfortunately, this design decision forces having HAR using those sensors instead of the most common solution of placing only one accelerometer on the hip or in the central part of the body.

3 Human activity recognition

In this study, we adopt the solution proposed by [3], where a Genetic Algorithm (GA) evolves the Fuzzy Finite State Machine for detecting human activity $GFFSM = \{Q, U, f, Y, g\}$, learning both the rules and the partitions. From a predefined Finite State Machine, which is depicted in Fig. 2, the set of states {Seated, Upright, Walking} and the initial set of rules are determined.

Three input variables -the dorso-ventral acceleration, the amount of movement and the tilt of the body- are used. For each input variable, three linguistic labels ($n_i = 3, \forall i$) with Ruspini trapezoid membership functions are used, thus $n_i + 1$ parameters are needed to be learnt for each input variable. A GA evolves the partitions and the rules in a Michigan style as 72 binary genes coding part for the rules; 12 real-coded genes for the membership function parameters.

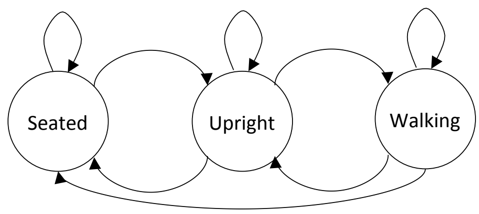


Fig. 2 The Fuzzy Finite State Machine proposed for this preliminary study.

The fitness function is the mean absolute error (MAE), calculated as $MAE = \frac{1}{N}\frac{1}{T}\sum_{i=1}^{N}\sum_{j=0}^{T} abs(s_i[j] - s_i^*[j])$, where T is the number of examples in the data set,

$s_i[t]$ and $s_i^*[t]$ are the degree of activation and the expected degree of activation, respectively, of state q_i at time $t = j$.

3.1 Adapting GFFSM approach to a different sensor placing

In this study, we consider the previous outlined method but with a different set of variables as far as we propose the use of accelerometers in both wrists instead of being in the hip. For the HAR, the dominant wrist acceleration data is used. Let a_i^x, a_i^y and a_i^z be the raw acceleration data, let g_i^x, g_i^y and g_i^z be the acceleration components due to the gravity G, extracted from the accelerometer raw data using low-pass filters [2]. Let b_i^x, b_i^y and b_i^z the body acceleration (BA) components, calculated as $a_i^{\{x,y,z\}} - g_i^{\{x,y,z\}}$ [2, 15, 16]. Then, this study proposes the use of a sliding window of size $w = 10$ samples and, for each one, the following input variables: i) *Signal Magnitude Area* (SMA), a well-known measure for discriminating between G and BA, which is calculated as $SMA_t = \frac{1}{w}\sum_{i=t+1}^{t+w}(|b_i^x| + |b_i^y| + |b_i^z|)$ [15, 16], ii) the sensor vibration $\Delta_t = \frac{1}{w}\sum_{i=t+1}^{t+w} \mid a_i^{x2} + b_i^{y2} + c_i^{z2} - g_i^2 \mid$ [15] and iii) the amount of movement, calculated as $\Delta_t = \sum_{v=\{x,y,z\}} \mid max_{i=t+1}^{t+w}(a_i^v) - min_{i=1}^{w}(a_i^v) \mid$ [3].

4 Experimentation in HAR

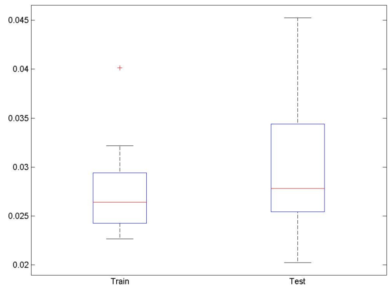
To test this prototype a well-known stroke patients rehabilitation test (for short, SRT) [7] will be carried out. Two bracelets will be given to a subject, each one with a tri-axial accelerometer with sampling frequency 16 Hz. Firstly, ten runs will be registered for a normal subject. All the data will be segmented and classified according to the activity the subject is owe to do. The data for these runs will be used for training and testing the HAR in a leave-one-folder-out manner, in order to obtain statistics results.

Table 1 shows the results obtained from this experimentation. The GA parameters employed in this study are those indicated in [3]: population size of 100 individuals in the population, crossover probability 0.8, the crossover α parameter is set to 0.3, the mutation probability 0.02, the maximum number of generations set to 200 and the maximum number with MAE unchanged fixed to 50.

From results it is shown that the current deployment of the GFSSM correctly classifies some of the activities while the walking activity recognition certainly performs worse. Comparing with the results presented in [3], we obtained remarkable similar MAE's results for walking. We have tested different GA parameters, but the obtained results are pretty close to those shown. Nevertheless, It is clear that the walking activity detection should be improved. Certainly, a PCA feature subset and different sliding window schema could help in this task.

Table 1 Obtained results for the HAR: mMAE and sMAE stand for mean and standard deviation of the MAE, respectively. On the right hand, the box plot of the right hand MAE over the leave-one-fold-out cross validation.

	Training		Testing	
Class	**mMAE**	**sMAE**	**mMAE**	**sMAE**
Seated	$1.8\ 10^{-4}$	$2.7\ 10^{-4}$	$2.3\ 10^{-4}$	$7.4\ 10^{-4}$
Upright	$3.6\ 10^{-3}$	$2.8\ 10^{-3}$	$3.6\ 10^{-3}$	$6.2\ 10^{-3}$
Walking	0.0098	0.0112	0.0117	0.0213
Overall	$3.5\ 10^{-3}$	0.0205	$3.4\ 10^{-3}$	$6.2\ 10^{-3}$



4.1 A discussion on the results and the stroke detection

As explained before, several hypothesis are addressed in analyzing what do occurs when an ictus episode arises. One of such hypothesis is that, in certain activities, the subject suffering the episode tends to make the corresponding movements asymmetrically. Let us focus in the activity of walking, where the subject has more difficulties making the movements of the affected part of the body (upper and lower limbs) than in the non-affected part and, thus, the signals from the sensors should be rather different. To evaluate the performance of ictus episode we develop an SRT in which the subject simulates an stroke episode by carrying a weight in one hand [7]. Four runs with the weight plus four runs without it were registered and all the data segmented and classified according to the activity the subject is owe to do.

Fig. 3 shows the evolutions of two variables with and without the weight. Thought the evolutions of the left side seem different from those to the right, simple approaches as that presented in [4] weren't able to discriminate between patterns. The same happens with well-known pattern matching techniques, such as the shape index factor [11]. Clearly, we can not state that the evolution of the measurements are so different to easily discriminate between the two health states, even though we a priori know the subject current activity is walking.

However, if the BA components from both hands are analyzed, we can conclude that something can be done and that using the energy measure -integration of the area under the curve- would eventually discriminate between the two stages (see Figure 4). This is why we claim that if we can determine the current human activity, then specific and simple techniques would allow us to generate suitable ictus episode alarms. Provided the methods are kept simple, the solutions found would eventually be deployed in mobile devices.

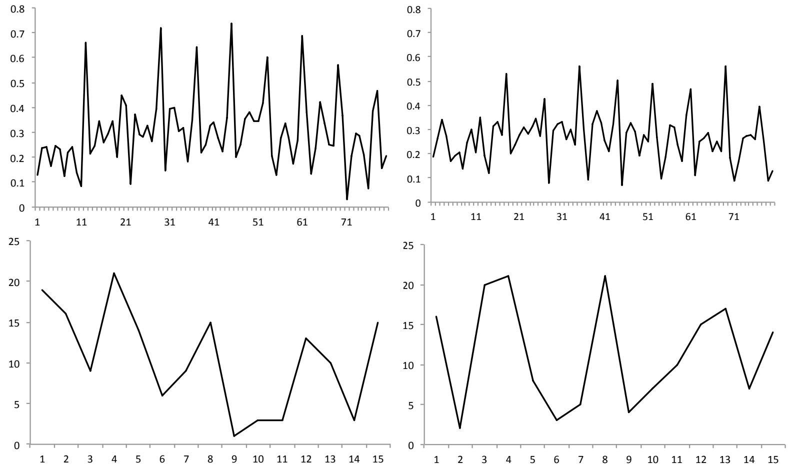


Fig. 3 Top: Evolution of the sum of the absolute values of the BA $|b_i^x| + |b_i^y| + |b_i^z|$ obtained from normal walking (left part) and walking with a weight (right part). Bottom: evolution of the SMA for normal behavior (left) and for an simulated ictus (right).

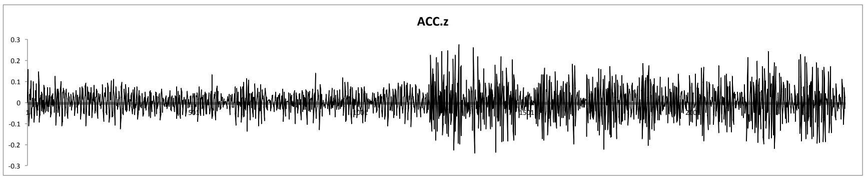


Fig. 4 SRT runs overall BA components: right hand b_i^z signal would eventually allow the discrimination of a stroke episode.

5 Conclusions and future work

This study faces the problem of early ictus diagnosis, which is a very challenging task. This study proposes a two step method that firstly estimates the human activity and then analyses the data for detecting anomalous movements. This hypothesis has been analyzed for the walking activity. Results show that although the approach should be highly improved in both stages, the high rate of success encourage to continue this research line. Consequently, future work includes developing several different techniques for human activity recognition and a rather sophisticated approach for the ictus diagnosis.

Acknowledgements This research has been partially supported through the projects of the Spanish Ministry of Science and Innovation PID 560300-2009-11 and TIN2011-24302, Junta de Castilla y Leon CCTT/10/BU/0002 and Agencia de Inversiones y Servicios de Castilla y Leon (record CCTT/10/LE/0001).

References

1. M. Ahmed and S. Ahmed. Kinetics and kinematics of loading response in stroke patients (a review article). *Annals of King Edward Medical University*, 14(4):143–147, 2008.
2. Felicity R Allen, Eliathamby Ambikairajah, Nigel H Lovell, and Branko G Celler. Classification of a known sequence of motions and postures from accelerometry data using adapted gaussian mixture models. *Physiological Measurement*, 27:935–951, 2006.
3. A. Ávarez-Álvarez, G. Triviño, and O. Cordón. Body posture recognition by means of a genetic fuzzy finite state machine. In *IEEE 5th International Workshop on Genetic and Evolutionary Fuzzy Systems (GEFS)*, pages 60–65, 2011.
4. T. Ryan Burchfield and S. Venkatesan. Accelerometer-based human abnormal movement detection in wireless sensor networks. In *Proceedings of the 1st ACM SIGMOBILE international workshop on Systems and networking support for healthcare and assisted living environments HealthNet '07*, pages 67–69, 2007.
5. I.A. de Quervain, S.R. Simon, S. Leurgans, W.S. Pease, and D. McAllister. Gait pattern in the early recovery period after stroke. *The Journal of Bone and Joint Surgery, American Volume*, 78(10):1506–1514, October 1996.
6. Siobhan Gallanagh, Terry J. Quinn, Jen Alexander, and Matthew R. Walters. Physical activity in the prevention and treatment of stroke. *ISRN Neurology*, doi:10.5402/2011/953818, 2011.
7. Kristen L. Hollands. *WHOLE BODY COORDINATION DURING TURNING WHILE WALKING IN STROKE SURVIVORS*. PhD thesis, School of Health and Population Sciences, University of Birmingham, 2010.
8. Haidzir Manaf, Maria Justine, Mazlifah Omar, Khairil Anuar Md Isa, and Zoolfaiz Salleh. Turning ability in stroke survivors: a review of literature. *ISRN Rehabilitation*, in press.
9. C. J. Murray and A.D. Lopez. Mortality by cause for eight regions of the world: Global burden of disease study. *Lancet*, 349(9061):1269–1276, 1997.
10. M. Pat. Murray, A. Bernard Drought, and Ross C. Kory. Walking patterns of normal men. *Journal of Bone and Joint Surgery*, 46(2):335–360, March 1964.
11. S. Phan, F. Famili, Z. Tang, Y. Pan, Z. Liu, J. Ouyang, A. Lenferink, and M. McCourt-O'Connor. A novel pattern based clustering methodology for time-series microarray data. *International Journal of Computer Mathematics*, 84(5):585–597, 2007.
12. Debbie Rand, Janice J. Eng, Pei-Fang Tang, Jiann-Shing Jeng, and Chihya Hung. How active are people with stroke? : Use of accelerometers to assess physical activity. *Stroke*, 40:163–168, 2009.
13. Megan P. Rothney, Emily V. Schaefer, Megan M. Neumann, Leena Choi, and Kong Y. Chen. Validity of physical activity intensity predictions by actigraph, actical, and rt3 accelerometers. *Obesity*, 16(8):1946–1952, August 2008.
14. Serge H. Roy, M. Samuel Cheng, Shey-Sheen Chang, John Moore, Gianluca De Luca, S. Hamid Nawab, and Carlo J. De Luca. A combined semg and accelerometer system for monitoring functional activity in stroke. *IEEE Transactions on Neural System Rehabilitiation Engineering*, 17(6):585–594, December 2009.
15. Shuangquan Wang, Jie Yang, Ningjiang Chen, Xin Chen, and Qinfeng Zhang. Human activity recognition with user-free accelerometers in the sensor networks. In *Proceedings of the International Conference on Neural Networks and Brain ICNN&B'05*, volume 2, pages 1212–1217. IEEE Conference Publications, 2005.
16. Jhun-Ying Yang, Jeen-Shing Wang, and Yen-Ping Chen. Using acceleration measurements for activity recognition: an efective learning algorithm for constructing neural networks. *Patter Recognition Letters*, 29:2213–2220, 2008.

7.3.2. Human Activity recognition and feature selection for stroke early diagnosis

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Human Activity Recognition and feature selection for stroke early diagnosis

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Abstract. Human Activity Recognition (HAR) refers to the techniques for detecting what a subject is currently doing. A wide variety of techniques have been designed and applied in ambient intelligence -related with comfort issues in home automation- and in Ambient Assisted Living (AAL) -related with the health care of elderly people. In this study, we focus on the diagnosing of an illness that requires estimating the activity of the subject. In a previous study, we adapted a well-known HAR technique to use accelerometers in the dominant wrist. This study goes one step further, firstly analyzing the different variables that have been reported in HAR, then evaluating those of higher relevance and finally performing a wrapper feature selection method. The main contribution of this study is the best adaptation of the chosen technique for estimating the current activity of the individual. The obtained results are expected to be included in a specific device for early stroke diagnosing.

Keywords: Ambient Assisted Living, Human Activity Recognition, Genetic Fuzzy Finite State Machine, Feature Selection, Genetic Algorithms

1 Introduction

Stroke is a cerebrovascular disease defined as a circulatory disorder that causes either a temporary or a permanent disorder of one or more areas of the brain. The most common symptom of stroke is loss of the ability to move voluntarily the limbs, either left, right or both. The hand is usually more severely affected compared to the leg [12, 8] . Even with a complex and long rehabilitation process, recovery is incomplete [9]. Cerebral infarction makes up to around 85% of all strokes [2, 1]. For the rest 15% of cerebral haemorrhages there is no approved treatment, but for the more prevalent cerebral infarction, there is one that can make a big difference: a thrombolytic drug that disrupts the thrombus occluding a cerebral artery. If successful, cerebral tissue will recover and so will function,

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but that depends on how fast the treatment is given. In the first one and a half "golden hour", one out of three patients treated will recover to his/her previous life. Unfortunately, reality is very different from what it could be expected: only a minority (5-15% of people suffering a stroke) arrive early enough to actually receive the treatment. Thus, a device that makes people with stroke arrive earlier can make a big difference in reducing death, disability and health costs in thousands of patients each year.

In this sense, determining the current activity of the subject is by no means a previous step before extracting rules that could eventually give advice or generate alarms for possible stroke attacks. Though walking is completely understood [15], activities like sitting or standing can include also eating, reading, etc. In this study we focus on the stroke risk population, which includes adults above 56 years old. Therefore, only the most remarkable activities are considered, as they represent the main part of the activities carried out in everyday life. Evidently, the older the subject is, the higher the probability the subject reduces his/her activities to {*walking*, *standing*, *resting*}, even though in each activity a wide variety of postures and gestures can be accomplished as well. As mentioned before, the partial or total paralysis detection would generate the corresponding emergency alarm. This research based such detection in the use of accelerometers placed in two bracelets to be wore in each wrist. Nevertheless, we do need to first estimate the current activity of the subject and then estimate whether the lack of motion is a paralysis or not. In a previous study [10], the Genetic Fuzzy Finite State Machine (GFFSM) method for Human Activity Recognition (HAR) [4] was implemented and adapted to the problem of stroke early diagnosing.

In this study, we analyze the different available transformations in the literature and evaluate which are the best suite candidates for being considered the inputs of the GFFSM. Moreover, with the chosen candidates we perform a wrapper feature selection (FS) based on the Steady State Genetic Algorithm (SSGA) FS method [6] but using the GFFSM instead of the KNN classifier. Finally, we evaluate and compare this method with the results from out first study. The main contribution of this paper includes the optimizing of the HAR method and the best feature subset for this task with the sensors placed on the dominant wrists. The remaining of this study is organized as follows. Next section includes the most updated and complete review of the raw acceleration data transformations in the literature, while Sect. 3 the transformation evaluation and the FS method with the GFFSM as classifier is detailed. Sect. 4 deals with the experimentation and the discussion on the results. The study finishes with the Conclusions.

2 Representation of the raw acceleration data

Using triaxial accelerometers induces that the measurement obtained from the sensors, known as raw data (RD, a_i^x, a_i^y and a_i^z; $a_{i,j\in\{x,y,z\}}$ for the sake of brevity), should be decomposed in the gravity acceleration (G) -that due to the each gravity, g_i^x, g_i^y and g_i^z or $g_{i,j\in\{x,y,z\}}$- and the body acceleration (BA) -which is due to the human movement, b_i^x, b_i^y and b_i^z or $b_{i,j\in\{x,y,z\}}$-. The capacity of the BA for discriminating among different human gestures is documented [19]. Nevertheless, the literature includes the use of a wide variety of transformations, the most interesting are related in the following, where w stands for the window size -if needed-, and subindexes $i \in \{1, \ldots N\}$ and $j \in \{x, y, z\}$ stand for the number of the sample and the axis, respectively.

1. The *mean, deviation and higher momentum statistics* values for the RD [14] or for the BA [18, 19] and the RD *mean absolute deviation* $MAD_j = \frac{1}{w}\sum_{i=1}^{w}|a_{i,j} - m_j|$ [7, 14] , where m_j is the mean value of $a_{i,j}$.
2. The *Root Mean Square* $RMS_j = \sqrt{\frac{1}{w}\sum_{i=1}^{w}|a_{i,j}^2|}$ [7].
3. The *sum of the absolute values* of the BA [10] ($sBA_i = \sum_{j\in\{x,y,z\}}|b_{i,j}|$) and the *vibration of the sensor* (Δ) [18] ($\Delta_i = \sum_{j\in\{x,y,z\}} a_{i,j}^2 - g_{i,j}^2 \sim \sum_{j\in\{x,y,z\}} b_{i,j}^2$) and the *tilt of the body* ($tilt_i = |a_i^y| + |a_i^z|$) [4]. The two former transformations were designed to detect whether the sensor register no movement at all, as fixed to an steady object, while the latter is assumed if the sensor axes correspond with the body axes.
4. The *Signal Magnitude Area* $SMA = \frac{1}{w}\cdot\sum_{i=1}^{w}(|b_i^x| + |b_i^y| + |b_i^z|)$ [18, 3, 19] discriminating between gravity acceleration and BA.
5. The *Amount of Movement* $AM_i = \sum_{v=\{x,y,z\}} \mid max_{t=i+1}^{i+w}(b_t^v) - min_{t=i+1}^{i+w}(b_t^v) \mid$ [4]: calculated as the maximum difference among the values of BA within the sliding window.
6. Delta coefficients for estimating the first order time derivate of each of the G signal components [3]: $\Delta g_t^{\{x,y,z\}} = \sum_{d=-D}^{D} d \cdot g_{t+d}^{\{x,y,z\}} / \sum_{d=-D}^{D} d^2$, where the shift D is parameterized to the algorithms and $g_t^{\{x,y,z\}}$ stands for each of the three axis G components.
7. Shifted Delta Coefficients (SDC) for estimating the first order time derivate of each of the BA signal components in the vicinity of the current time stamp [3]: $\Delta b_{t+i\cdot P}^{\{x,y,z\}} = \frac{\sum_{d=-D}^{D} d\cdot b_{t+i\cdot P+d}^{\{x,y,z\}}}{\sum_{d=-D}^{D} d^2}$, where $b_t^{\{x,y,z\}}$ stands for each of the three axis BA components, N is the number of base features from which they are calculated, D is the same D as in the delta calculations, P is the distance between samples and K is the number of samples taken.
8. Average Energy (AE) [5, 18, 19]: calculated as the sum of the squared discrete FFT component magnitudes of the signal in a window of a fixed size. This features allows to discriminate between static and dynamic activities.It is calculated for each axis; the aggregation or the average over the three axes is commonly used [19].
9. The correlation between axes [5]: calculated for each pair of axes as the ratio of the covariance and the product of the standard deviations. This feature is useful to discriminate one dimensional activities if your sensory is placed accordingly. As stated in [19], this feature can discriminate between walking and climbing stairs.
10. The Intensity of the movement (InMo) [11], which is the mean first derivative of the raw acceleration data, $InMo_t^{v\in\{x,y,z\}} = \frac{1}{w}\sum_{i=0}^{w-1} \cdot|a_{t-i}^v - a_{t-i-1}^v| / \Delta x_t$.

Δx_t represents the time between samples, which can be ignored if the sampling rate is kept constant. The window size is given by the value of w.

11. Time Between Peaks [14], time in milliseconds between peaks in the sinusoidal waves associated with the frequency response of most activities (for each axis).
12. Binned Distribution [14, 19]: as stated by the authors, this measure is used with sliding windows of size w. For each window the range should be calculated as $maximum - minimium$; then, the range is divided in 10 equal size bins; finally, record what fraction of the w values fell within each of the bins. This approach is called within this study Relative Binned Distribution (RBD). In this study, we also proposed the absolute binned distribution (ABD) that is calculated using the lower and upper acceleration values as the range to be divided in bins.

In many of the solutions sliding windows with or without shifting are proposed; the typical window size converges to the samples within the period of 2 seconds. Features are typically normalized to 0-mean 1-standard deviation and/or scaled to the interval [0, 1] before further preprocessing. Using frequency-derived features employing FFT or similar over long time-windows have been found more suitable for long duration, quasi-periodic signals like walking, cycling or brushing teeth. Otherwise, when classifying shorter duration and non-periodic activities, transitions or a short sequence of steps, then the time-domain representation has been found better [3]. The problem of finding the best set of features for HAR among the available transformations is the so called feature selection.

3 The wrapper feature selection and HAR method

In order to perform feature selection, this research studies a genetic algorithm driving a wrapper type FS method. The method is based on the SSGA [6], which was successfully adapted to a rather different problem [17]. Briefly, we will perform a wrapper FS method that makes use of a classifier for evaluating the individuals; each individual is a feature subset and the classifier is the GFFSM method for HAR. The method should find the feature subset that optimizes the GFFSM classifier.

3.1 GFFSM

As mentioned before, the well-known GFFSM is used [4]. This approach establishes the Finite State Machine (FSM) of the states and their transitions, the initial state machine proposed by the experts -in our case, the medical staff. Each state is considered a different label of a fuzzy variable STATE; the features are also considered fuzzy variables. A Ruspini partitioning scheme is initially proposed, and the transitions of the FSM represent the rules of the Fuzzy Rule Based System (FRBS). The GFFSM completes the learning scheme by means of a Genetic Algorithm that evolve both the fuzzy partitions and the rules in a Pittsburg style.

As explained before, the GFFSM approach was adapted for HAR using the accelerometers on the wrists instead of having only one sensor on the back [10]. The adaptation consisted in choosing a different subset of transformations (the SMA, Δ_i and AM features) instead of those proposed in the original paper (the dorso-ventral acceleration a_i^x, the AM and the tilt of the body). This adaptation was due to the different sensor placement that makes the axes trying their orientation with the time. This section gives a brief overview of the GFFSM and also outlines the wrapper FS method we used. The fitness function is the mean absolute error (MAE), calculated as $MAE = \frac{1}{N}\frac{1}{T}\sum_{i=1}^{N}\sum_{j=0}^{T} abs(s_i[j] - s_i^*[j])$, where T is the number of examples in the data set, $s_i[t]$ and $s_i^*[t]$ are the degree of activation and the expected degree of activation, respectively, of state q_i at time $t = j$.

3.2 The SSGA-based FS method

An adaptation of the well known Genetic Algorithm driven wrapper feature selection algorithm called SSGA [6] was reported in [17]. This algorithm evolves the feature subset choosing the features with the lower classification error when using the KNN algorithm. In this approach, the wrapper FS also learns the GFFSM and measures the fitness of each individual acceding to Algorithms 1 and 2. The feature subsets can not be reevaluated, and if generated during the evolution then the individuals are dropped without being considered as an intermediate population individual.

Algorithm 1 IND_EVALUATION: Evaluates a feature subset

Require: $< I, O >$ the input and output variables data sets
Require: ind the feature subset
Require: $maxFolds$ the number of cross validation runs
  for each fold $k = 1$ to $maxFolds$ **do**
    generate the train and test reduced feature data set
    Run a GFFSM $\rightarrow < FRBS_{best}^k, mse_{best}^k >$
    Keep the best $FRBS_{best}$ found
    Record the $mse_{best}^k, \forall k \rightarrow \{mse\}$
  end for
  Compute the average $mse_{best}^k, \forall k \rightarrow \widehat{mse}$
  return $[FRBS_{best}, \widehat{mse}, \{mse\}]$

4 Evaluation of the proposal

As a result, we have to design the experiments to validate if the above detailed method could eventually find the feature subset that optimizes the GFFSM, and

Algorithm 2 GA$^+$ Feature Selection

Require: $< I, O >$ the input and output variables data set
Require: N the feature subset size
Require: $maxFolds$ the number of cross validation runs
  Generate the initial population, Pop
  Evaluate each individual in the Pop
  $g \leftarrow 0$
  while $g < G$ **do**
    while $size(Pop') < (size(Pop) - |E|)$ **do**
      Generate new individuals through selection, crossover and mutation
      add valid individuals to Pop'
    end while
    extract the elite subpopulation $E \in Pop$
    for all individual ind in Pop' **do**
      $[ind.model, ind.\widehat{mse}, \{mse\}] = IND\_EVALUATION(I, O, ind, maxFolds)$
    end for
    $Pop = \{E \cup Pop'\}$
    sort Pop
    g++
  end while
  $FS \leftarrow Pop[0]$
  $[model, mse] \leftarrow$ corresponding model and MSE
  return $[FS, model, mse]$

the GFFSM should be not only the best model found so far by the wrapper FS method but should also enhance the previous studies. This section deals with the experimentation carried so far, that is, i) the data gathering, ii) the feature domain, iii) running the feature selection method and, finally, iv) comparing the obtained results and further discussion. Nevertheless, the FS approach could not be feasible in its original form and some adaptations were required. As far as the computation cost is extremely high so the time spent in each individual should be reduced. First of all, the GFFSM evolution was analyzed and it was found that the different runs within the cross validation similarly evolved and finally converged. This fact allows us to introduce some simplifications and reductions: on the one hand, the total number of individuals in a run was highly reduced for the FS evaluation. That is, during the FS evolution, the GFFSM genetic parameters were relaxed wrt those in the original paper [4]. Nevertheless, the best individual found after the FS would be trained in the same conditions in order to compare with previous studies. Moreover, the error stop condition was fixed to 0.02, allowing a certain amount of error as a compromise for reducing the computation costs. In addition, as there were no big differences between the cross validation folds, the cross validation scheme is reduced to a train-test data set. That is, five random folds were used for training and the remaining folds were kept for validation. All these simplifications would lead to obtain higher errors and perhaps the results would eventually be slightly biased; however, it is the simplest way to allow FS with a compromise between accuracy and completeness.

As mentioned before, the best individual found so far would be allowed to have the complete 10-fold cross validation with the same genetic parameters than in previous studies allowing us the comparisons.

4.1 Data gathering

To test this prototype a well-known stroke patients rehabilitation test (for short, SRT) [13] will be carried out. Two bracelets will be given to a subject, each one with a tri-axial accelerometer with sampling frequency 16 Hz. Firstly, ten runs will be registered for a normal subject. All the data will be segmented and classified according to the activity the subject is owe to do. The data for these runs will be used for training and testing the HAR in a leave-one-folder-out manner, in order to obtain statistics results. Only the data from the dominant wrist will be considered.

4.2 The initial feature subset

Using the whole set of the transformations presented in Sect. 2 leads to a rather high feature domain: each transformation induces three new variables due to the raw acceleration, but three more with the BA. Moreover, we can also calculate two more input features by means of aggregating the raw acceleration data or the BA for the three axis. Consequently, for each transformation we can calculate at most 8 new features. Instead of using the whole set of transformations, we performed first an analysis of the data and ranked the features using both the Mutual Information and the Information Correlation Coefficient [16]; previously, the features were scaled to the interval [0, 1]. In Fig. 1 the values of ICC for each feature in decreasing order is depicted, and the 20 features with higher ICC values were chosen.

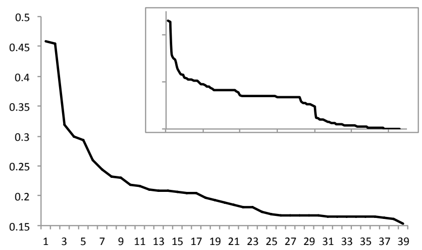

Fig. 1. Evolution of the ICC in decreasing order of the ICC value. The smaller image is the ICC for all the features.

4.3 Feature evaluation

The parameters used for the wrapper FS GA were 30 generations with 26 individuals in the population. The one point crossover operator executed with probability 0.8, while mutation's probability was 0.02. Moreover, the GA parameters employed for the GFFSM were a population size of 76 individuals in the population, crossover probability 0.8, the $\alpha-$crossover parameter is set to 0.3, the mutation probability 0.02, the maximum number of generations set to 50, stop error condition set to 0.02 and the stop criteria of the maximum number of generations with MAE unchanged fixed to 25. Finally, with the best performance feature subset the whole GFFSM method was carried out with the original parameters (100 individuals and 200 generations). This final model was used for comparison purposes and it is referred as WRAPPER.

In order to compare the obtained results, the GFFSM method adapted in [10] -which is called ORIG_ADAPT- and the method with several modifications for decreasing the restrictions in the crossover operators were carried out -which is called GA_MODIF-. The GA parameters in both cases were those detailed in the previous paragraph. In the second comparison method the crossover were carried out interchanging the rules at any available point instead of within each variable, thus it is expected that this method would eventually need more generations to converge. In this case, 300 generations were allowed.

4.4 Results and further discussion

The obtained results are depicted in Table 1 and in the box plot and MAE evolution from Fig. 2. Both models ORIG_ADAPT and WRAPPER converged, while the GA_MODIF was still evolving. Clearly, the FS method does not perform as well as expected due to the restrictions fixed on behalf of the computation cost reduction. Nevertheless, the model obtained from the chosen features undoubtedly outperforms the original method. Interesting enough, the spread of the individuals among the different cross-validation runs is kept rather small. On the other hand, the GA_MODIF results give us the clue that the learning method presented in [4] can still be optimized, perhaps by introducing learning in a Michigan style or by introducing fuzzy evaluations of the error. Finally, the selection of the best feature subset continues being a challenge that should be solved, and evaluation of other ranking and transforming measures can be introduced to choose the most suitable variables for HAR.

Method	Train				Test			
	Best	Mean	Median	Std	Best	Mean	Median	Std
ORIG_ADAPT	0.0299	0.0361	0.0368	0.0039	0.0453	0.0802	0.0730	0.0371
GA_MODIF	0.0213	0.0293	0.0311	0.0066	0.0114	0.0391	0.0306	0.0292
WRAPPER	0.0281	0.0331	0.0325	0.0029	0.0218	0.0365	0.0343	0.0098

Table 1. Results from the different configurations and feature subsets. See the text for acronyms' definition.

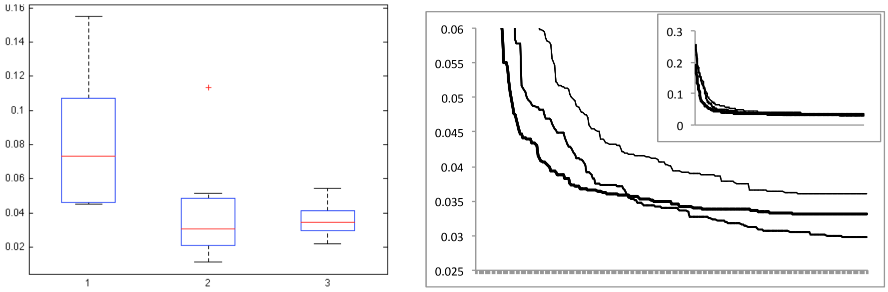

Fig. 2. Left part: Boxplot of the best individual found after the ten cross-validation runs. Rigth part: mean evolution of the MAE with the generations. ORIG_ADAPT, GA_MODIF and WRAPPER are marked with 1/thinner line, 2/mid-thick line and 3/thicker line on the boxplot/figure on the right, respectively. The methods with less than 300 generations appear with the best value constant filling the empty generations.

5 Conclusions and future work

In this study, the Genetic algorithm evolved Fuzzy Finite State Machine presented in [4] and adapted for using an accelerometer on the dominant wrist [10] is analyzed for searching the best feature subset. A wrapper FS method has been used but its performance is penalized due to the fixed computational restrictions. Nevertheless, it could be interesting to relax such restrictions as the spread obtained is the best in the comparison. Moreover, the relevance of the genetic operators and parameters is also outlined as a modified model with different crossover and higher number of generations also outperform the original method. Future work includes i) considering more computing resources to the wrapper FS method, ii) performing a more complex analysis of the genetic parameters and operators for improving the GFFSM, iii) including Michigan style solutions for learning the FSM and iv) analyzing the feature domain with more powerful methods to find out which features have more information concerning the current human activity. It is worth mentioning that this project is involved in the early stroke diagnosis using electronic intelligent devices.

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References

1. Adams, H.P., del Zoppo, G., Alberts, M.J., Bhatt, D.L., Brass, L., Furlan, A., Grubb, R.L., Higashida, R.T., Jauch, E.C., Kidwell, C., Lyden, P.D., Morgenstern, L.B., Qureshi, A.I., Rosenwasser, R.H., Scott, P.A., Wijdicks, E.F.: Guidelines for the early management of adults with ischemic stroke. Stroke 38, 1655–1711 (2007)
2. Adams, R.D.: Principles of Neurology. McGraw Hill, 6th edn. (1997)

3. Allen, F.R., Ambikairajah, E., Lovell, N.H., Celler, B.G.: Classification of a known sequence of motions and postures from accelerometry data using adapted gaussian mixture models. Physiological Measurement 27, 935–951 (2006)
4. Ávarez-Álvarez, A., Triviño, G., Cordón, O.: Body posture recognition by means of a genetic fuzzy finite state machine. In: IEEE 5th International Workshop on Genetic and Evolutionary Fuzzy Systems (GEFS). pp. 60–65 (2011)
5. Bao, L., Intille, S.S.: Activity recognition from user-annotated acceleration data. In: Ferscha, A., Mattern, F. (eds.) Proceedings of the Second International Conference Pervasive Computing, PERVASIVE 2004. Lecture Notes in Computer Science, vol. 3001, pp. 1–17. Springer (2004)
6. Casillas, J., Cordón, O., del Jesus, M., Herrera, F.: Genetic feature selection in a fuzzy rule-based classification system learning process. Information Sciences 136(1-4), 135–157 (2001)
7. Chen, Y.P., Yang, J.Y., Liou, S.N., Lee, G.Y., Wang, J.S.: Online classifier construction algorithm for human activity detection using a tri-axial accelerometer. Applied Mathematics and Computation 205(2), 849–860 (2008)
8. Dromerick, A., Khader, S.A.: Medical complications during stroke rehabilitation. Advances in Neurology 92, 409–413 (2003)
9. Duarte, E., Alonso, B., Fernández, M., Fernández, J., Flórez, M., García-Montes, I., Gentil, J., Hernández, L., Juan, F., Palomino, J., Vidal, J., Viosca, E., Aguilar, J., Bernabeu, M., Bori, I., Carrión, F., Déniz, A., Díaz, I., Fernández, E., Forastero, P., Iñigo, V., Junyent, J., Lizarraga, N., de Munaín, L.L., Máñez, I., Miguéns, X., Sánchez, I., Soler, A.: Stroke rehabilitation: Care model. Rehabilitación 44(1), 60 (68 2010)
10. González, S., Villar, J.R., Sedano, J., Chira, C.: A preliminary study on early diagnosis of illnesses based on activity disturbances. In: Omatu, S., Neves, J., Corchado, J.M., Paz, J.F.D., Rodríguez, S. (eds.) Distributed Computing and Artificial Intelligence, 10th International Conference. p. to be published (2013)
11. Győrbiro, N., Fábián, Á., Hományi, G.: An activity recognition system for mobile phones. Mobile Networks and Applications 14, 82–91 (2009)
12. Hogdson, C.: To fast or not to fast. Stroke 38, 2631–2632 (2007)
13. Hollands, K.: Whole body coordination during turning while walking in stroke survivors. Ph.D. thesis, School of Health and Population Sciences. Ph.D. thesis, University of Birmingham (2010)
14. Kwapisz, J.R., Weiss, G.M., Moore, S.A.: Activity recognition using cell phone accelerometers. ACM SIGKDD Explorations Newsletter 12(2), 74–82 (2010)
15. Murray, M.P., Drought, A.B., Kory, R.C.: Walking patterns of normal men. Journal of Bone and Joint Surgery 46(2), 335–360 (March 1964)
16. Peng, H., Long, F., Ding, C.: Feature selection based on mutual information: Criteria of max-dependency, max-relevance, and min-redundancy. IEEE Transactions on Pattern Analysis and Machine Learning 27(8), 1226–1238 (2005)
17. Villar, J.R., González, S., Sedano, J., Corchado, E., Puigpinós, L., de CIurana, J.: Meta-heuristic improvements applied for steel sheet incremental cold shaping. Memetic Computing 4(4), 249–261 (December 2012)
18. Wang, S., Yang, J., Chen, N., Chen, X., Zhang, Q.: Human activity recognition with user-free accelerometers in the sensor networks. In: Proceedings of the International Conference on Neural Networks and Brain ICNN&B'05. vol. 2, pp. 1212–1217. IEEE Conference Publications (2005)
19. Yang, J.Y., Wang, J.S., Chen, Y.P.: Using acceleration measurements for activity recognition: an effective learning algorithm for constructing neural networks. Patter Recognition Letters 29, 2213–2220 (2008)

7.3.3. Early diagnosis of Stroke: bridging the gap through wearable sensors and computational models

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EARLY DIAGNOSIS OF STROKE: BRIDGING THE GAP THROUGH WEARABLE SENSORS AND COMPUTATIONAL MODELS

Baia Mare
September 23-26, 2006

Contents

José R. Villar, Silvia González, Javier Sedano, Camelia Chira and José M. Trejo

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Early diagnosis of Stroke: bridging the gap through wearable sensors and computational models

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Stroke is a cerebrovascular disease defined as a circulatory disorder that causes either a temporary or a permanent disorder of one or more areas of the brain. The most common symptom of stroke is loss of the ability to move voluntarily the limbs, either left, right or both. The hand is usually more severely affected compared to the leg [**6, 9**]. For the more prevalent cerebral infarction (85% of the cases) there existsa thrombolytic drug that disrupts the thrombus occluding a cerebral artery. In the first one and a half "golden hour", one out of three patients treated will recover to his/her previous life.

Unfortunately, only a minority (5-15% of people suffering a stroke) arrive early enough to actually receive the treatment [**2, 7**]. Thus, a device that helps people notifying a rather possible stroke episode can make a big difference in reducing death, disability and health costs in thousands of patients each year. In addition, the algorithms to be implemented should be embedded in real hardware platforms so they can be introduce in wearable products. In spite of the increasing computing power and internal resources, the algorithms still have to be as light as possible and should constrain to scenarios of reduced power consumption and small memory capacity.

In this study, a new specific algorithm for Human Activity Recognition (HAR) is presented and compared with a well-known HAR technique [**3, 13**]. Moreover, a simple algorithm for generating alarms due to possible stroke cases is presented. Furthermore, evidence of more complex models are provided and left as future work. The obtained results are expected to be included in a specific device for early stroke diagnosing.

Acknowledgments. This research has been supported through the Spanish Ministry of Science and Innovation TIN2011-24302 project.

1. Introduction

As stated in [**5**], stroke is a cerebrovascular disease defined as a circulatory disorder that causes either a temporary or a permanent disorder of one or more areas of the brain. As the author stated, "Stroke is the second most common cause of death and major cause of disability worldwide. Because of the ageing population, the burden will increase greatly during the next 20 years, especially in developing countries." Paralysis is the most common symptom of stroke, specially the paralysis of the limbs. The paralysis could be either partial -one side of the body- or total -both sides-, and the upper limbs are usually more severely affected than the lower limbs [**6, 9**].

Cerebral infarction makes up to around 85% of all strokes [**1, 2**]. For the rest 15% of cerebral hemorrhages there is no approved treatment, but for the more prevalent cerebral infarction, there is one that can make a big difference: a thrombolytic drug that disrupts the thrombus occluding a cerebral artery. If successful, cerebral tissue will recover and so will function, but that depends on how fast the treatment is given. In the first one and a half "golden hour", one out of three patients treated will recover to his/her previous life.

In spite of this golden hour drug, only a minority (5-15% of people suffering a stroke) arrive early enough to actually receive the treatment [**2, 7**]: the main concern is related with the identification of the stroke episode by the relatives or because the episode occurs when the subject is alone. Thus, a device that helps people notifying a rather possible stroke episode can make a big difference in reducing death, disability and health costs in thousands of patients each year.

In this study a method for the early diagnosing of the stroke is introduced. Up to our knowledge, this is the very first study that propose low cost wearable sensors in the identification of this disease. For doing so, two wearable triaxial accelerometers -one in each wrist- would allow to identify the most remarkable stroke symptoms. The method includes a human activity recognition (HAR) method and, afterwards, a stroke paralysis alarm generator. As these algorithms should run in micro controllers the lowest the computational costs the better. The improvements found in this study include a novel light HAR method and the algorithm for early stroke diagnosing. Additionally, it is worth mentioning the proposed adaptation of well-known time series representation for the focused problem.

This study is organized as follows. Next section outlines the most remarkable behaviour of the subjects suffering a stroke episode. Then, the time series representation used in this paper are briefly described. Sect. 4 deals with the HAR method proposed in this study, while Sect. 5 presents the algorithm for alarm generation. These two latter sections also show experiment results and discussion. Finally, some conclusions and future work are included as a final section.

2. A brief description of Stroke's paralysis symptoms

The most common symptom of stroke is loss of the ability to move voluntarily the limbs, either left, right or both. The hand is usually more severely affected compared to the leg. In fact, arm paralysis is so common in stroke that it is used in scales by paramedics such as the Prehospital Cincinatti Stroke Scale. It has also been included in the FAST acronym, in public campaigns aimed at stroke early recognition (FAST stands for Face drooping, Arm paralysis, Speech difficulties, Time to act) [**9**]. Hand paralysis is also non-subjective so it can be monitored by a movement-detection device.

If we pay attention to these symptoms, they are usually described as an asymmetrical movements between both sides of the subject body: one part moves as usual as possible while the other is rather still. In addition, the main symptom is the collapse of the subject: this may occur after the subject had sat in a chair or fell in a bed, but also the subject might suffer a falling and then a collapse. Therefore, knowing the current human activity (cHA) could allow to differentiate between the collapse, falling or body asymmetries.

In addition, each combination of these possible remarkable states and the cHA would require its co-occurrence during a different amount of time. We must differentiate between the lack of movement in one part of the body when walking, reading or resting -whether it can be having a nap or sleeping or a collapse-; each of these combinations will take a different time to be consider worth alarming.

3. A light introduction to PAA and SAX

As detailed in [**4**], many techniques have been presented in the literature for time series (TS) representation and distance measuring, the Piecewise Aggregate Approximation (PAA) [**11**] and Symbolic Aggregate approXimation (SAX) [**12**] among others. These two latter have shown the best performance on aperiodic TS. As far as the available data from human activity is rather aperiodic, these two techniques are outlined.

Let X be a TS of length n previously normalized to zero mean and standard deviation of one. Let the desired representation domain dimension w. PAA finds the w size vector $\widehat{X}_i = [\widehat{x}_1, \ldots, \widehat{x}_w]$ calculated as $\widehat{x}_i = \frac{w}{n} \sum_{\frac{n}{w}(i-1)+1}^{\frac{n}{w}i} x_j$: the overall process consists in splitting the X in w intervals and each $\widehat{x}_i$ computed as the mean value within the corresponding interval.

Additionally, if the alphabet size is fixed to as, SAX divides the domain of the values of the X in as statistically equiprobable intervals taking advantage of the previous data normalization, each interval is assigned with one symbol. Whenever a PAA component falls within an interval the corresponding symbol is assigned in the SAX vector component. Furthermore, SAX also provides with a distance measure among SAX vectors.

4. A light human activity recognition method

Using triaxial accelerometers induces that the measurement obtained from the sensors should be decomposed in the gravity acceleration (G) and the body acceleration (BA) -which is due to the human movement, b_i^x, b_i^y and b_i^z-. Let $BA_i = \sqrt{{b_i^x}^2 + {b_i^y}^2 + {b_i^z}^2}$ measured for each sample of the TS.

In our approach, we make use of two wrist bracelets -each one with a triaxial accelerometer sampled at 16 Hz-. Let mBA and sBA be the mean and standard deviation of the movements during activities of daily living of the subject, both calculated by means of a initial test.

The algorithm proposed in this study for HAR is shown in Algorithm 1, though for the sake of brevity it is shown rather schematically; our real implemented algorithms are a bit more complex.

There are some issues that need further study, like the learning of the membership functions and its tuning to the focused subject as well as the method for measuring similarities between TS representation. Interestingly enough, the computational cost and resources needed for implementing this algorithm are kept rather small, which is one of the main enhancement of this technique. The last part of the algorithm is related with the stroke episode alarm generation.

Algorithm 1 Simplified SAX based HAR algorithm: $\{\mu_A/A, \forall A\}$

```
Require: X, a normalized TS of size n using mBA and sBA
Ensure: Computes the possible activities and their certainties
  Determine X̂ = SAX(X)
  for each A ∈ Registered Activities do
    for each Y_mov ∈ RegisteredActivityMovement(A) do
      Compute similarity between X̂ and Y_mov → simXY
      Update the certainty of X̂ of class A according to simXY
    end for
  end for
  if Resting State is believed then
    Determine the resting activity level HIGH, LOW, NONE
    Increment the corresponding counters
  end if
```

5. A simple algorithm for stroke diagnosing

Similarly to the previous algorithm, this study proposes the use of the SAX representation and some quite simple algorithms to detect anomalous human behaviors. The TS from both bracelets are used in this case, and the state of resting should be previously detected independently for each hand. In case of resting state, the BA is normalized using the $muRBA_h$ and $sRBA_h$, the mean and standard deviation of the signal of the BA when the subject is resting; the h subindex is related with the hand -left or right-. These values should be calculated in an initial test.

Algorithm 2 briefly outlines the propose approach; as in the former section, the algorithms are very roughly explained due to the space limitations. Firstly, some counters and the current resting level are determined in the previous algorithm. Afterwards, the similarity of the signal from each hand is compare with the typical sequences of inactivity. In case that the total inactivity keeps going on, the certainty of generating the corresponding alarm for the partial or total paralysis, and even for a falling detection alarm.

6. Experimentation and further discussion

Experiments carried out in this very preliminary study include two young subjects. Ten runs of the well-known stroke patients rehabilitation test (for short, SRT) [**10**]. Moreover, more tests were carried out with the subjects sleeping during a night. Neither tabular nor figures can be included in this extended abstract due to the length restrictions. We test to discriminate between resting and walking and the results were really impressive, with a perfect discrimination of the class, though this specific problem by itself is not very complex.

The algorithm for alarm generation seems to be coherent with the specifications given by the medical staff, though more work is needed to identify the sequences for identifying activity while resting. Furthermore, the results shows that the algorithms work as expected though the different threshold and the simplifications as well as the distance measure should be greatly improved.

7. Conclusions and future work

This study proposes two novel algorithms: a former one for human activity recognition, the latter for stroke early diagnosing. These algorithms require rather low both computational costs and resources. Obtained results are really promising, even with the simplifications of using only thresholds. Nevertheless, there are still plenty of research to carry out. Firstly, several intelligent algorithms

Algorithm 2 Simplified Alarm Generation Algorithm

Require: X_h, a normalized TS of size n with $mRBA_h$ and $sRBA_h$, $\forall h \in \{left, right\}$
Require: STATES and CERTAINTIES of the subject
Require: RESTING_LEVEL: $\{HIGH, LOW, NONE\}$
Ensure: Generates the suitable alarms
  Determine $\widehat{X_h} = SAX(X_h)$
  for each $Y_{mov} \in$ RegisteredAlarmSequences **do**
    Compute similarity between $\widehat{X_h}$ and $Y_{mov} \rightarrow simXY$
    if simXY is HIGH **then**
      Mark the detection of a {inactivity, falling}
    end if
  end for
  Update time of inactivity counters
  if time of inactivity is HIGH for the corresponding RESTING_LEVEL or a falling has been detected **then**
    Generate the corresponding alarm
  end if

should be designed for learning the different simplified parameters. Secondly, the algorithms should be refined. Thirdly, the experimentation should include the higher objective population as possible, as well as should include young people. We do expect to start the experiments by the final quarter of this year.

Bibliography

[1] R. D. Adams., *Principles of Neurology*, McGraw Hil, 1997

[2] H. P. Adams, G. del Zoppo, M. J. Alberts, D. L. Bhatt, L. Brass, A. Furlan, R. L. Grubb, R. T. Higashida, E. C. Jauch, C. Kidwell, P. D. Lyden, L. B. Morgenstern, A. I. Qureshi, R. H. Rosenwasser, P. A. Scott and E. F.M. Wijdicks. *Guidelines for the Early Management of Adults With Ischemic Stroke*, Stroke, 38(2007), 1655-1711

[3] A. Ávarez-Álvarez, G. Triviño, O. Cordón., *Body posture recognition by means of a genetic fuzzy finite state machine*, IEEE 5th International Workshop on Genetic and Evolutionary Fuzzy Systems (GEFS), IEEE Conference Publisher, Paris France, (2011), 409-413

[4] H. Ding, G. Trajcevski, P. Scheuermann, X. Wang and E. Keogh.*Querying and mining of time series data: experimental comparison of representations and distance measures*, Proc. VLDB Endow. 1:2 (2008), 1542–1552

[5] G. A Donnan, M. Fisher, M. Macleod and S. M. Davis- *Stroke*, The Lancet, 371:9624 (2008), 1612-1623

[6] A.D. Dromerick and S. A. Khader., *Medical complications during stroke rehabilitation*, Advances in Neurology, 92 (2003), 409-413

[7] E. Duarte, B. Alonso, M.J. Fernández, J.M. Fernández, M. Flórez, I. García-Montes, J. Gentil, L. Hernández, F.J. Juan, J. Palomino, J. Vidal, E. Viosca, J.J. Aguilar, M. Bernabeu, I. Bori, F. Carrión, A. Déniz, I. Díaz, E. Fernández, P. Forastero, V. Iñigo, J. Junyent, N. Lizarraga, L. López de Munaín, I. Máñez, X. Miguéns, I. Sánchez and A. Soler. *Stroke rehabilitation: Care model*, Rehabilitación, 44:1 (2010), 60-68

[8] F.J. Fernández-Gómez, F. Hernndez, L. Argandoa, M.F. Galindo, T. Segura and J. Jordn.*Pharmacology of neuroprotection in acute ischemic stroke*, Rev Neurol. 47:5 (2008), 253-60

[9] C.S. Hogdson. *To FAST or not to FAST*, Stroke, 38 (2007), 2631-2632

[10] K. Hollands*Whole body coordination during turning while walking in stroke survivors*, School of Health and Population Sciences. Ph.D. thesis, University of Birmingham (2010)

[11] E. Keogh, K. Chakrabarti, M. Pazzani and S. Mehrotra*Dimensionality Reduction for Fast Similarity Search in Large Time Series Databases* Journal of Knowledge and Information Systems 3 (2000), 263-286

[12] J. Lin, E. Keogh, L. Wei and S. Leonardi.*Experiencing SAX: a Novel Symbolic Representation of Time Series*, Data Mining and Knowledge Discovery 15:2 (2007), 107-144

[13] S. González, J. R. Villar, J. Sedano and C. Chira. *A preliminary study on early diagnosis of illnesses based on activity disturbances*, Distributed Computing and Artificial Intelligence, 10th International Conference, Berlin, 2013

Capítulo 8

Acrónimos

BA: Aceleración del Cuerpo - Body Aceleration.

CEM: Construction Engineering and Management.

ECG: Electrocardiograma - Electrocardiography.

FFSM: Máquinas de Estados Finitos Difusos - Finite Fuzzy State Machine.

FS: Selección de Características - Feature Selection.

G: Gravedad - Gravity.

GA: Algoritmos Genéticos - Genetic Algorithm.

GFFSM: Máquinas de Estados Finitos Difusos aprendidos mediante Algoritmos Genéticos - Genetic Finite Fuzzy State Machine.

HAR: Reconocimiento de la Actividad Humana - Human Activity Recognition.

HMM: Modelos Ocultos de Markov - Hidden Markov Models.

ICC: Coeficiente Correlación de la Información - Coefficient Correlation Information.

MAE: Error Absoluto Medio - Mean Absolute Error.

MI: Información Mutua - Mutual Information.

MLP: Perceptron Multicapa - Multi-Layer Perceptron.

OMS: Organización Mundial de la Salud.

PCA: Análisis de la Componente Principal - Principal Component Analysis.

RD: Aceleración - Raw Data.

RF: Random Forest.

SAX: Symbolic Aggregate approXimation.

SVM: Máquinas de Soporte Vectorial - Vector Machine Support.

TransRKELM: Transfer learning Reduced Kernel Extreme Learning Machine.

TS: Serie Temporal - Serial Time.

WISDM: Wireless Sensor Data Mining.

Bibliografía

[1] Zahraa Said Abdallah, Mohamed Medhat Gaber, Bala Srinivasan, y Shonali Krishnaswamy. Adaptive mobile activity recognition system with evolving data streams. *Neurocomputing*, 150, Part A:304 – 317, 2015. ISSN 0925-2312. doi:http://dx.doi.org/10.1016/j.neucom.2014.09.074.

[2] M. Ahmed y S. Ahmed. Kinetics and kinematics of loading response in stroke patients (a review article). *Annals of King Edward Medical University*, 14(4):143–147, 2008.

[3] Reza Akhavian y Amir H. Behzadan. Construction equipment activity recognition for simulation input modeling using mobile sensors and machine learning classifiers. *Advanced Engineering Informatics*, págs.–, 2015. ISSN 1474-0346. doi:http://dx.doi.org/10.1016/j.aei.2015.03.001.

[4] Felicity R Allen, Eliathamby Ambikairajah, Nigel H Lovell, y Branko G Celler. Classification of a known sequence of motions and postures from accelerometry data using adapted gaussian mixture models. *Physiological Measurement*, 27:935–951, 2006.

[5] María Luz Alonso Álvarez, Silvia González, Javier Sedano, Joaquín Terán, José Ramón Villar, EstrellaOrdax Carbajo, y María Jesús Coma Corral. Hybrid systems for analyzing the movements during a temporary breath inability episode. En Marios Polycarpou, André C.P.L.F. Carvalho, Jeng-Shyang Pan, Michał Woźniak, Héctor Quintian, y Emilio Corchado, eds., *Hybrid Artificial Intelligence Systems*, tomo 8480 de *Lecture Notes in Computer Science*, págs. 549–560. Springer International Publishing, 2014. ISBN 978-3-319-07616-4. doi:10.1007/978-3-319-07617-1_48.

[6] A. Alvarez-Alvarez, J.M. Alonso, G. Trivino, N. Hernandez, F. Herranz, A. Llamazares, y M. Ocana. Human activity recognition applying

computational intelligence techniques for fusing information related to wifi positioning and body posture. págs. 1–8, 2010. ISSN 1098-7584. doi: 10.1109/FUZZY.2010.5584187.

[7] A. Alvarez-Alvarez, G. Trivino, y O. Cordon. Human gait modeling using a genetic fuzzy finite state machine. *Fuzzy Systems, IEEE Transactions on*, 20(2):205–223, 2012. ISSN 1063-6706. doi:10.1109/TFUZZ.2011.2171973.

[8] A. Ávarez-Álvarez, G. Triviño, y O. Cordón. Body posture recognition by means of a genetic fuzzy finite state machine. En *IEEE 5th International Workshop on Genetic and Evolutionary Fuzzy Systems (GEFS)*, págs. 60–65. 2011.

[9] R. Venkatesh Babu, Badrinarayanan Rangarajan, Suresh Sundaram, y Manu Tom. Human action recognition in h.264/avc compressed domain using meta-cognitive radial basis function network. *Applied Soft Computing*, págs.–, 2015. ISSN 1568-4946. doi:http://dx.doi.org/10.1016/j.asoc.2015.06.054.

[10] Oresti Banos, Miguel Damas, Hector Pomares, Alberto Prieto, y Ignacio Rojas. Daily living activity recognition based on statistical feature quality group selection. *Expert Systems with Applications*, 39(9):8013 – 8021, 2012. ISSN 0957-4174. doi:http://dx.doi.org/10.1016/j.eswa.2012.01.164.

[11] Ling Bao y Stephen S. Intille. Activity recognition from user-annotated acceleration data. En Alois Ferscha y Friedemann Mattern, eds., *Proceedings of the Second International Conference Pervasive Computing, PERVASIVE 2004*, tomo 3001 de *Lecture Notes in Computer Science*, págs. 1–17. Springer, 2004.

[12] Akram Bayat, Marc Pomplun, y Duc A. Tran. A study on human activity recognition using accelerometer data from smartphones. *Procedia Computer Science*, 34:450 – 457, 2014. ISSN 1877-0509. doi:http://dx.doi.org/10.1016/j.procs.2014.07.009.

[13] Cagatay Catal, Selin Tufekci, Elif Pirmit, y Guner Kocabag. On the use of ensemble of classifiers for accelerometer-based activity recognition. *Applied Soft Computing*, págs.–, 2015. ISSN 1568-4946. doi:http://dx.doi.org/10.1016/j.asoc.2015.01.025.

[14] F. Chamroukhi, S. Mohammed, D. Trabelsi, L. Oukhellou, y Y. Amirat. Joint segmentation of multivariate time series with hidden process regression for human activity recognition. *Neurocomputing*, 120:633 – 644, 2013. ISSN 0925-2312. doi:http://dx.doi.org/10.1016/j.neucom.2013.04.003.

[15] Yen-Ping Chen, Jhun-Ying Yang, Shun-Nan Liou, Gwo-Yun Lee, y Jeen-Shing Wang. Online classifier construction algorithm for human activity detection using a tri-axial accelerometer. *Applied Mathematics and Computation*, 205(2):849–860, 2008.

[16] Saisakul Chernbumroong, Shuang Cang, y Hongnian Yu. A practical multi-sensor activity recognition system for home-based care. *Decision Support Systems*, 66:61 – 70, 2014. ISSN 0167-9236. doi:http://dx.doi.org/10.1016/j.dss.2014.06.005.

[17] Girija Chetty, Matthew White, y Farnaz Akther. Smart phone based data mining for human activity recognition. *Procedia Computer Science*, 46:1181 – 1187, 2015. ISSN 1877-0509. doi:http://dx.doi.org/10.1016/j.procs.2015.01.031. Proceedings of the International Conference on Information and Communication Technologies, {ICICT} 2014, 3-5 December 2014 at Bolgatty Palace & Island Resort, Kochi, India.

[18] I.A. de Quervain, S.R. Simon, S. Leurgans, W.S. Pease, y D. McAllister. Gait pattern in the early recovery period after stroke. *The Journal of Bone and Joint Surgery, American Volume*, 78(10):1506–1514, 1996.

[19] Wan-Yu Deng, Qing-Hua Zheng, y Zhong-Min Wang. Cross-person activity recognition using reduced kernel extreme learning machine. *Neural Networks*, 53:1 – 7, 2014. ISSN 0893-6080. doi:http://dx.doi.org/10.1016/j.neunet.2014.01.008.

[20] Siobhan Gallanagh, Terry J. Quinn, Jen Alexander, y Matthew R. Walters. Physical activity in the prevention and treatment of stroke. *ISRN Neurology*, doi:10.5402/2011/953818, 2011.

[21] Silvia González, Javier Sedano, José R. Villar, Emilio Corchado, Álvaro Herrero, y Bruno Baruque. Features and models for human activity recognition. *Neurocomputing*, 167:52 – 60, 2015. ISSN 0925-2312. doi:http://dx.doi.org/10.1016/j.neucom.2015.01.082.

[22] Silvia González, José R. Villar, Javier Sedano, y Camelia Chira. A preliminary study on early diagnosis of illnesses based on activity disturbances. En Sigeru Omatu, José Neves, Juan M. Corchado, Juan F. De Paz, y Sara Rodríguez, eds., *Distributed Computing and Artificial Intelligence, 10th International Conference*, pág. to be published. 2013.

[23] Silvia González, José Ramón Villar, Javier Sedano, Joaquín Terán, María Luz Alonso Álvarez, y Jerónimo González. Heuristics for apnea episodes recognition. En *International Conference on Soft Computing Models in Industrial and Environmental Applications, Burgos, Spain*. 2015.

[24] John J. Guiry, Pepijn van de Ven, John Nelson, Lisanne Warmerdam, y Heleen Riper. Activity recognition with smartphone support. *Medical Engineering & Physics*, 36(6):670 – 675, 2014. ISSN 1350-4533. doi: http://dx.doi.org/10.1016/j.medengphy.2014.02.009.

[25] Norbert Györbiro, Ákos Fábián, y Gergely Hományi. An activity recognition system for mobile phones. *Mobile Networks and Applications*, 14:82–91, 2009.

[26] Francisco Herrera. Genetic fuzzy systems: taxonomy, current research trends and prospects. *Evolutionary Intelligence*, 1(1):27–46, 2008.

[27] Kristen L. Hollands. *Whole body coordination during turning while walking in stroke survivors*. Tesis Doctoral, School of Health and Population Sciences, University of Birmingham, 2010.

[28] Dimitris Kastaniotis, Ilias Theodorakopoulos, Christos Theoharatos, George Economou, y Spiros Fotopoulos. A framework for gait-based recognition using kinect. *Pattern Recognition Letters*, págs.–, 2015. ISSN 0167-8655. doi:http://dx.doi.org/10.1016/j.patrec.2015.06.020.

[29] Bethany Knorr, Richard Hughes, Delsey Sherrill, Joel Stein, Metin Akay, y Paolo Bonato. Quantitative measures of functional upper limb movement in persons after stroke. En *Conference Proceedings of the 2nd International IEEE EMBS Conference on Neural Engineering, 2005*, págs. 252– 255. 2005.

[30] Aseem Kushwah, Sudhir Kumar, y Rajesh M. Hegde. Multi-sensor data fusion methods for indoor activity recognition using temporal evidence theory. *Pervasive and Mobile Computing*, 21:19 – 29, 2015. ISSN 1574-1192. doi:http://dx.doi.org/10.1016/j.pmcj.2014.10.009.

[31] Jennifer R. Kwapisz, Gary M. Weiss, y Samuel A. Moore. Activity recognition using cell phone accelerometers. *ACM SIGKDD Explorations Newsletter*, 12(2):74–82, 2010.

[32] Yongjin Kwon, Kyuchang Kang, y Changseok Bae. Unsupervised learning for human activity recognition using smartphone sensors. *Expert Systems with Applications*, 41(14):6067 – 6074, 2014. ISSN 0957-4174. doi:http://dx.doi.org/10.1016/j.eswa.2014.04.037.

[33] Steffen Leonhardt. Personal healthcare devices. En Satyen Mukherjee, RonaldM. Aarts, Raf Roovers, Frans Widdershoven, y Martin Ouwerkerk, eds., *AmIware Hardware Technology Drivers of Ambient Intelligence*, tomo 5 de *Philips Research*, págs. 349–370. Springer Netherlands, 2006. ISBN 978-1-4020-4197-6. doi:10.1007/1-4020-4198-5_17.

[34] Jessica Lin, Eamonn Keogh, Stefano Lonardi, y Bill Chiu. A symbolic representation of time series, with implications for streaming algorithms. En *Proceedings of the 8th ACM SIGMOD Workshop on Research Issues in Data Mining and Knowledge Discovery*, DMKD '03, págs. 2–11. ACM, New York, NY, USA, 2003. doi:10.1145/882082.882086.

[35] G.M. Lyons, K.M. Culhane, D. Hilton, P.A. Grace, y D. Lyons. A description of an accelerometer-based mobility monitoring technique. *Medical Engineering & Physics*, 27(6):497 – 504, 2005. ISSN 1350-4533. doi:10.1016/j.medengphy.2004.11.006.

[36] Inês P. Machado, A. Luísa Gomes, Hugo Gamboa, Vítor Paixão, y Rui M. Costa. Human activity data discovery from triaxial accelerometer sensor: Non-supervised learning sensitivity to feature extraction parametrization. *Information Processing & Management*, 51(2):204 – 214, 2015. ISSN 0306-4573. doi:http://dx.doi.org/10.1016/j.ipm.2014.07.008.

[37] Haidzir Manaf, Maria Justine, Mazlifah Omar, Khairil Anuar Md Isa, y Zoolfaiz Salleh. Turning ability in stroke survivors: a review of literature. *ISRN Rehabilitation*, in press.

[38] M.J. Mathie, B.G. Celler, N.H. Lovell, y A.C.F. Coster. Classification of basic daily movements using a triaxial accelerometer. *Med Biol Eng Comput*, 42(5):679–87, 2004.

[39] MathWorks. Elliptic filter design. 2014. URL http://es.mathworks.com/help/signal/ref/ellip.html.

[40] Ministerio de sanidad y política social. Estrategia en ictus del sistema nacional de salud. 2009. URL http://www.msssi.gob.es/organizacion/sns/planCalidadSNS/docs/EstrategiaIctusSNS.pdf.

[41] Shinki Miyamoto y Hitoshi Ogawa. Human activity recognition system including smartphone position. *Procedia Technology*, 18:42 – 46, 2014. ISSN 2212-0173. doi:http://dx.doi.org/10.1016/j.protcy.2014.11.010.

[42] F. Moayedi, Z. Azimifar, y R. Boostani. Structured sparse representation for human action recognition. *Neurocomputing*, 161:38 – 46, 2015. ISSN 0925-2312. doi:http://dx.doi.org/10.1016/j.neucom.2014.10.089.

[43] Mona M. Moussa, Elsayed Hamayed, Magda B. Fayek, y Heba A. El Nemr. An enhanced method for human action recognition. *Journal of Advanced Research*, 6(2):163 – 169, 2015. ISSN 2090-1232. doi:http://dx.doi.org/10.1016/j.jare.2013.11.007.

[44] C. J. Murray y A.D. Lopez. Mortality by cause for eight regions of the world: Global burden of disease study. *Lancet*, 349(9061):1269–1276, 1997.

[45] M. Pat. Murray, A. Bernard Drought, y Ross C. Kory. Walking patterns of normal men. *Journal of Bone and Joint Surgery*, 46(2):335–360, 1964.

[46] NHS. Stroke - act f.a.s.t. Inf. téc., National Health System, UK, 2013.

[47] Anne-Héléne Olivier, Richard Kulpa, Julien Pettré, y Armel Crétual. A velocity-curvature space approach for walking motions analysis. En A. Egges, R. Geraerts, y M. Overmars, eds., *Proceedings of the Motion in Games MIG 2009*, tomo 5884 de *Lecture Notes on Computer Science*, págs. 104–115. Springer Verlag, 2009.

[48] OM. Omsignal biometric smartwear. URL http://www.omsignal.com/.

[49] David R Paul, Matthew Kramer, Alanna J Moshfegh, David J Baer, y William V Rumpler. Comparison of two different physical activity monitors. *BMC Medical Research Methodology*, 7(26), 2007.

[50] Debbie Rand, Janice J. Eng, Pei-Fang Tang, Jiann-Shing Jeng, y Chihya Hung. How active are people with stroke? : Use of accelerometers to assess physical activity. *Stroke*, (40):163–168, 2009.

[51] Jorge-L. Reyes-Ortiz, Luca Oneto, Albert Samà, Xavier Parra, y Davide Anguita. Transition-aware human activity recognition using smartphones. *Neurocomputing*, págs.–, 2015. ISSN 0925-2312. doi:http://dx.doi.org/10.1016/j.neucom.2015.07.085.

[52] Megan P. Rothney, Emily V. Schaefer, Megan M. Neumann, Leena Choi, y Kong Y. Chen. Validity of physical activity intensity predictions by actigraph, actical, and rt3 accelerometers. *Obesity*, 16(8):1946–1952, 2008.

[53] Serge H. Roy, M. Samuel Cheng, Shey-Sheen Chang, John Moore, Gianluca De Luca, S. Hamid Nawab, y Carlo J. De Luca. A combined semg and accelerometer system for monitoring functional activity in stroke. *IEEE Transactions on Neural System Rehabilitiation Engineering*, 17(6):585–594, 2009.

[54] L. Sánchez y J. Otero. Boosting fuzzy rules in classification problems under single-winner inference. *International Journal of Intelligent Systems*, 22(9):1021–1034, 2007.

[55] Óscar D. Lara, Alfredo J. Pérez, Miguel A. Labrador, y José D. Posada. Centinela: A human activity recognition system based on acceleration and vital sign data. *Pervasive and Mobile Computing*, 8(5):717 – 729, 2012. ISSN 1574-1192. doi:http://dx.doi.org/10.1016/j.pmcj.2011.06.004.

[56] Weihua Sheng, Jianhao Du, Qi Cheng, Gang Li, Chun Zhu, Meiqin Liu, y Guoqing Xu. Robot semantic mapping through human activity recognition: A wearable sensing and computing approach. *Robotics and Autonomous Systems*, 68:47 – 58, 2015. ISSN 0921-8890. doi:http://dx.doi.org/10.1016/j.robot.2015.02.002.

[57] José R. Villar, Camelia Chira, Javier Sedano, Silvia González, y José M. Trejo. A hybrid intelligent recognition system for the early detection of strokes. *Integrated Computer-Aided Engineering*, 22(3):215–227, 2015. doi:10.3233/ICA-150488.

[58] José R. Villar, Silvia González, Javier Sedano, Camelia Chira, y José M. Trejo. Human activity recognition and feature selection for stroke early diagnosis. En *8th International Conference on Hybrid Artificial Intelligence Systems HAIS*, tomo Lecture Notes in Artificial Intelligence. Springer, 2013.

[59] José Ramón Villar, Silvia González, Javier Sedano, Camelia Chira, y José M. Trejo-Gabriel-Galan. Improving human activity recognition and its application in early stroke diagnosis. *Int. J. Neural Syst.*, 25(4), 2015. doi:10.1142/S0129065714500361.

[60] D.K. Vishwakarma y Rajiv Kapoor. Hybrid classifier based human activity recognition using the silhouette and cells. *Expert Systems with Applications*, 42(20):6957 – 6965, 2015. ISSN 0957-4174. doi:http://dx.doi.org/10.1016/j.eswa.2015.04.039.

[61] D.K. Vishwakarma, Prachi Rawat, y Rajiv Kapoor. Human activity recognition using gabor wavelet transform and ridgelet transform. *Procedia Computer Science*, 57:630 – 636, 2015. ISSN 1877-0509. doi:http://dx.doi.org/10.1016/j.procs.2015.07.425. 3rd International Conference on Recent Trends in Computing 2015 (ICRTC-2015).

[62] Herbert P. von Schroeder, Richard D. Coutts, Patrick D. Lyden, Edmund Billings Jr., y Vernon L . Nickel. Gait parameters following stroke : A practical assessment. *Journal of Rehabilitation Research and Development*, 32(1):25–31, 1995.

[63] Jin Wang, Ronghua Chen, Xiangping Sun, Mary F.H. She, y Yuchuan Wu. Recognizing human daily activities from accelerometer signal. *Procedia Engineering*, 15(0):1780 – 1786, 2011. ISSN 1877-7058. doi:10.1016/j.proeng.2011.08.331.

[64] Shuangquan Wang, Jie Yang, Ningjiang Chen, Xin Chen, y Qinfeng Zhang. Human activity recognition with user-free accelerometers in the sensor networks. En *Proceedings of the International Conference on Neural Networks and Brain ICNN&B'05*, tomo 2, págs. 1212–1217. IEEE Conference Publications, 2005.

[65] Shuangquan Wang y Gang Zhou. A review on radio based activity

recognition. *Digital Communications and Networks*, 1(1):20 – 29, 2015. ISSN 2352-8648. doi:http://dx.doi.org/10.1016/j.dcan.2015.02.006.

[66] K.D. Wise. Wireless integrated microsystems: Wearable and implantable devices for improved health care. págs. 1–8, 2009. doi:10.1109/SENSOR.2009.5285579.

[67] Jhun-Ying Yang, Jeen-Shing Wang, y Yen-Ping Chen. Using acceleration measurements for activity recognition: An effective learning algorithm for constructing neural classifiers. *Pattern Recognition Letters*, 29(16):2213 – 2220, 2008. ISSN 0167-8655. doi:http://dx.doi.org/10.1016/j.patrec.2008.08.002.

[68] Maryam Ziaeefard y Robert Bergevin. Semantic human activity recognition: A literature review. *Pattern Recognition*, 48(8):2329 – 2345, 2015. ISSN 0031-3203. doi:http://dx.doi.org/10.1016/j.patcog.2015.03.006.