UNIVERSIDAD DE OVIEDO

MASTER IN SOFT COMPUTING
AND INTELLIGENT DATA ANALYSIS

PROYECTO FIN DE MÁSTER
MASTER PROJECT

PERIODICAL REPORT ABOUT PERSONAL PHYSICAL ACTIVITIES

DANIEL SÁNCHEZ VALDÉS
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TUTOR/ADVISOR:
GRACIÁN TRIVIÑO BARROS
JUAN CARLOS ÁLVAREZ

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Abstract

New technologies allow human beings to acquire huge amounts of information about their physical environment. Currently, the challenge consists of automatically interpreting this information by providing each specific user with descriptions remarking the relevant and hiding the irrelevant according with his/her specific goals. To convert data into knowledge is necessary to interpret and represent the data in a understable way, giving in each type of situation their relationship with data context and, in general, with information related with each specific phenomenon.

During the last few years, the availability of new sensors and microprocessors has made possible to develop devices aimed to recognize the human body postures using accelerometers. The application of these devices is arising in fields so diverse as activity recognition, medicine or video console games.

This research project is located in the field of Human Activity Recognition. Its main goal consists of using sensors included in mobile phones to acquire data about the physical activity of a person.

Here, by using triaxial accelerometers embedded in current mobile phones, it is possible to generate a periodic (daily, weekly and so on) linguistic report, including relevant information such as activities carried out, intensities, trends, etc. The report focuses on those aspects that are important when the user (patient) is following a therapy or wants to extract some conclusions about his/her physical behaviour (routine activities, habits...).

As a result of the research on Computational Theory of Perceptions, this project describes a computational application able to generate linguistic descriptions of personal physical activities.

It is included a practical application where it is described how to build a Granular Linguistic Model of a Phenomenon to model these physical activities. A complete analysis of results has been done showing the advantages of this linguistic descriptor.

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Chapter 1

Introduction

1.1 Purpose

The present Master's Project report is written in order to get the Master's Degree in Soft Computing and Intelligent Data Analysis from the University of Oviedo.

This project will develop the skills and techniques learned during the Master showing how a real world problem which consists of modeling the accelerations produced during the human gait can be solved using the knowledge acquired during the course. Therefore, this document is not only a research project, but it is also a demonstration of the academic results achieved during the development of the Master courses.

The main goal of this research project is to design and model a computational application, based on our reseach in the field of Computational Theory of Perceptions, able to generate linguistic descriptions about personal physical activities in a period of time. In previous works in the *Computing with Perceptions Research Unit*, we have generated linguistic descriptions of different types of phenomena. For example, we generated financial reports from data taken from the Spanish Securities Market Commission (CNMV) [16] and linguistic descriptions about relevant features of the Mars' Surface [1]. In the field of Intelligent Transportation Systems (ITS) we generated linguistic reports about the traffic on roundabouts [25], about the traffic evolution in roads [2] and we generated assesing reports in truck driving simulators [9, 10].

In this research line, this project develops a Granular Linguistic Model of a Phenomenon which tries to summarize and highlight the relevant aspects of the data obtained from mobile phones accelerometers, providing a useful tool for therapists and helping the user to better understand his/her lifestyle and daily habits.

1.2 Scope

The project scope was defined as a combination of an academic project and a research project. It tries to avoid technical detail while still giving an accurate description of concepts and techniques used that were learned during the Master.

The main tools and techniques presented belong to our contribution to the Computational Theory of Perceptions and some definitions and concepts are presented. Although the most relevant information is described in detail, we address the reader to the bibliography if more explanation is required.

In addition, a practical application, that not only can be seen as a demonstration of the goodness of our proposal but it must also be seen as an example in order to build similar applications in more easy or complex environments, is presented.

1.3 Contents

This project is divided into six chapters, including the Introduction.

In chapter 2 the main concepts of our approach to linguistic description of complex phenomena are introduced. First, several basic concepts of our contribution to the Computational Theory of Perceptions aimed to develop computational systems able to generate linguistic descriptions, are presented. Then, the main components of the architecture are explained in detail.

Chapter 3 explains the software development kit developed to implement the Granular Linguistic Model of a Phenomenon following a structure procedure. The idea is to establish a set of functions that make the implementation easier and application independent, so the mechanism followed and the tools used are the same for all the researchers of *Computing with Perceptions* unit.

Chapter 4 especifies how to use the concepts introduced in Chapter 2 to linguistic description of physical activities. In this chapter, is shown the Granular Linguistic Model of a Phenomenon developed for this application, explaning in detail each Computational Perception and Perception Mapping used to solve this task. We define principal physical activities of human life and which features are of interest to extract. The goal is to make relevant reports which depend of the final treatment or therapist support.

Chapter 5 presents the experimentation carried out. In this chapter, is explained how to acquire data and which elements are needed to develop this application.

Chapter 6 presents some products of consolidated success and significant market impact, analyzing what are the differences and similarities they share with our system.

Finally, chapter 7 draws the conclusions about this framework, summarizing the contributions and academic results achieved during the development of this project. Additionally, it presents future open problems that this framework can tackle.

Chapter 2

Computational Theory of Perceptions

2.1 Introduction

Traditionally, engineers use differential equations to model the behavior of systems in our environment. However, when the system grows in complexity, the number of variables and equations becomes intractable. The models based on fuzzy logic (FL) are an alternative to deal with those systems where obtaining the appropriate differential equations is difficult or impossible.

FL is widely recognized for its ability for linguistic concept modeling and its use in system identification. On the one hand, semantic expressiveness, using linguistic variables [29] and rules [15], is quite close to natural language which reduces the effort of expert knowledge extraction. On the other hand, being universal approximators [5] fuzzy inference systems are able to perform nonlinear mappings between inputs and outputs and are able to model dynamical systems in a comprehensible way [19].

Computational Theory of Perceptions (CTP) was introduced in Zadeh's seminal paper "From computing with numbers to computing with words - from manipulation of measurements to manipulation of perceptions" [27] and further developed in subsequent papers, e.g., [28]. It grounds on the fact that human cognition is based on the role of perceptions, and the remarkable capability to granulate information in order to perform physical and mental tasks without any traditional measurements and computations. Natural language (NL) is a suitable powerful tool to describe our perceptions.

According with the dictionary [26] *to perceive* is "to interpret our physical sensation in the light of experience". We could say that, generating linguistic descriptions consists of interpreting the available input data by instantiating a generic linguistic model of the monitored phenomenon.

Fig. 2.1 shows our approach to the architecture of a computational system for generating linguistic description of data indicating processes with ovals and data structures with rectangles. After analyzing the user requirements, software engineers, collect a corpus of NL expressions that are typically used in the application domain to describe the relevant features of analyzed phenomenon. During a preliminary off-line stage, the designer analyzes the particular meaning of each linguistic expression in specific situation types to build *Granular Linguistic Model of Phenomena* (GLMP) and *Report templates*. Later on, the *Report* is obtained from *input data* as result of instantiation processes of these two generic data structures.

In the following sections these components will be thoroughly explained.

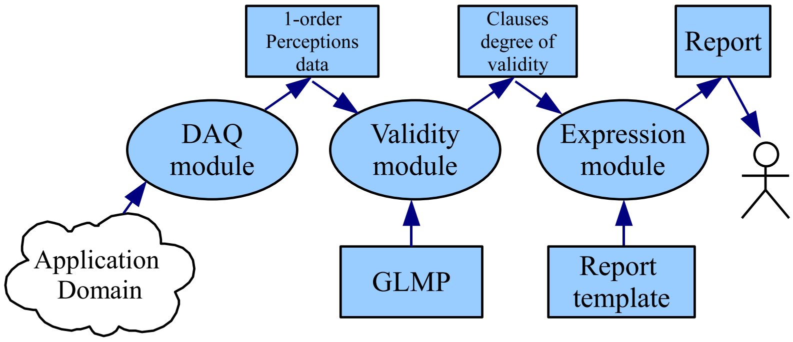


Figure 2.1: Architecture of a computational system for generating linguistic description of data

2.2 Granular Linguistic Model of Phenomena

In the research line of CTP, we have developed GLMP as a useful paradigm for developing computational systems able to generate linguistic descriptions of data. The components of GLMP are described in the following subsections.

2.2.1 Computational Perception (CP)

The concept of CP is based on the concept of *linguistic variable* [29]. CPs are computational models of units of information (granules) acquired by the designer about the phenomenon to be modeled, i.e., CPs correspond with specific parts of the phenomenon at certain degree of granularity. A CP is a couple (A, W) described as follows:

$A = (a_1, a_2, \ldots, a_n)$ is a vector of linguistic expressions (words or sentences in NL) that represents the whole linguistic domain of CP. In the application context, each a_i describes the value of the CP in each situation of the phenomenon with specific degree of granularity. These sentences can be either simple, e.g., $a_i =$"*You have spent short time walking*" or more complex, e.g., $a_i =$"*Usually, on weekends you spend more time sitting*". During the preliminary off-line stage, these values are assigned by the designer extracting the most suitable sentences from the linguistic corpus of the application domain.

$W = (w_1, w_2, \ldots, w_n)$ is a vector of validity degrees $w_i \in [0, 1]$ assigned to each a_i in the specific context. The value of validity depends on the application, i.e., it is a function of the precision of each sentence to describe specific input data. During the on-line stage, this validity values are assigned (and updated) in function of the phenomenon current state. Typically, A is a strong fuzzy partition of the domain of existence of CP and therefore $\sum w_i = 1$

For example, provided input data, a $CP_1 = (A_1, W_1)$ that models the perception of the amount of time the user has been standing could be instantiated as:

a_1="You have spent very short time standing", $w_1 = 0$

a_2="You have spent short time standing", $w_2 = 0.6$

a_3="You have spent a normal amount of time standing", $w_3 = 0.4$

a_4="You have spent quite time standing", $w_4 = 0$

a_5="You have spent too much time standing", $w_5 = 0$

2.2.2 Perception Mapping (PM)

We use PMs to create and aggregate CPs. There are many types of PMs and this paper explores two of them. A PM is a tuple (U, y, g, T) where:

U is a vector of input CPs, $U = (u_1, u_2, \ldots, u_n)$. We call first order perception mappings (*1-PMs*) when U are not CPs but values $z \in \mathbb{R}$ being provided either by sensors or obtained from a database.

y is the output CP, $y = (A_y, W_y)$.

$g()$ is an aggregation function employed to calculate the vector of fuzzy degrees of validity assigned to each element in y, $W_y = (w_1, w_2, ..., w_{n_y})$. It is a fuzzy aggregation of the input vectors $W_y = g(W_{u_1}, W_{u_2}, ..., W_{u_n})$, where W_{u_i} are the degrees of validity of the input perceptions. In Fuzzy Logic many different types of aggregation functions have been developed. For example g could be implemented using a set of fuzzy rules. In the case of *1-PMs*, g is built using a set of membership functions as follows:

$$W_y = (\mu_{a_1}(z), \mu_{a_2}(z), \ldots, \mu_{a_{n_y}}(z)) = (w_1, w_2, \ldots, w_{n_y})$$

where W_y is the vector of degrees of validity assigned to each a_y, and z is the input data.

T is a text generation algorithm that allows generating the sentences in A_y. In simple cases, T is a linguistic template, e.g., *"The user is walking at {low/normal/high} speed"*.

It is worth noting that, at the current development stage of our technology for linguistic descriptions of data, A_y is assigned by the designer during the off-line stage but this could be not the case in the future. We foresee to provide the designer with some capabilities for automatically processing this type of information.

2.2.3 Granular Linguistic Model of Phenomena

The GLMP consists of a network of PMs. Each PM receives a set of input CPs and transmits upwards a CP. We say that each output CP is *explained* by the PM using a set of input CPs. In the network, each CP covers specific aspects of the phenomenon with certain degree of granularity.

As mentioned above, we call *first order perception mappings* (*1-PM*) to those which are input to the GLMP. We call first order computational perceptions (*1-CP*) to the output of *1-PM*. PMs which input are CPs are called *2-PM* and their outputs are *2-CP*. This classification is inspired on the definition of the three worlds by Popper, namely, world-1 of physical objects (*phenomena*), world-2 of the perceived objects (*1-CP*) and world-3 of the mental objects built by using the objects in the world-2 (*2-CP*) [20].

Using different aggregation functions and different linguistic expressions, the paradigm GLMP allows the designer to model computationally his/her perceptions. Note that, after being instantiated with a set of input data, the GLMP provides a structure of valid sentences that in medium size applications could include hundreds of sentences.

2.2.4 Validity Module

Once a sample of input data is available, the Validity Module uses the aggregation functions in the GLMP to calculate the validity degree of each CP. Therefore, this module provides as output a collection of linguistic clauses together with their associated degrees of validity.

2.2.5 Expression Module

Provided a set of valid linguistic clauses, the goal is to combine this information to build a linguistic report. This module deals with generating the most relevant linguistic report by choosing and connecting the adequate linguistic clauses based on a **Report Template** data structure.

Chapter 3

Software development for the GLMP

As part of this work, I thought that the creation of a suitable software is essential to generalize the procedure followed in every GLMP implementation. This software development was created in *R environment*.

R is an open source programming language and software environment for statistical computing and graphics. The R language is widely used among statisticians for developing statistical software and data analysis. The source code for the R software environment is written primarily in C, Fortran, and R. R is freely available under the GNU General Public License, and pre-compiled binary versions are provided for various operating systems. R uses a command line interface; however, several graphical user interfaces are available for use with R.

R provides a wide variety of statistical and graphical techniques, including linear and nonlinear modeling, classical statistical tests, time-series analysis, classification, clustering, among others. R is easily extensible through functions and extensions, and the R community is noted for its active contributions in terms of packages. There are some important differences, but much code written for R runs unaltered. Many of R's standard functions are written in R itself, which makes it easy for users to follow the algorithmic choices made. For computationally intensive tasks, C, C++, and Fortran code can be linked and called at run time.

R is an interpreted language typically used through a command line interpreter. Like many other languages, R supports matrix arithmetic. R's data structures include scalars, vectors, matrices, data frames (similar to tables in a relational database) and lists. The R object system is extensible and includes objects for, among others, regression models, time-series and geospatial coordinates. R supports procedural programming, object-oriented programming with generic functions. A generic function acts differently depending on the type of arguments it is passed. In other words the generic function dispatches the function (method) specific to that type of object.

This software development kit is composed by three main functions, namely, *g_mf*, *integral* and *g_rules*. These functions are explained below:

g_mf: This R function calculates the validity degree of each linguistic label which define a CP. This function has two input arguments. The fist argument corresponds to the input vector data and the second one establishes the knowledge base. The knowledge base specifies those parameters needed to build the set of trapezoidal membership functions which define the CP. Every trapezoidal membership function is a curve defined as:

$$f(x;a,b,c,d) = max(min(\frac{x-a}{b-a},1,\frac{d-x}{d-c}),0) \tag{3.1}$$

The parameters a and d locate the "feet" of the trapezoid and the parameters b and c locate the "shoulders", as it is shown in Fig. 3.1.

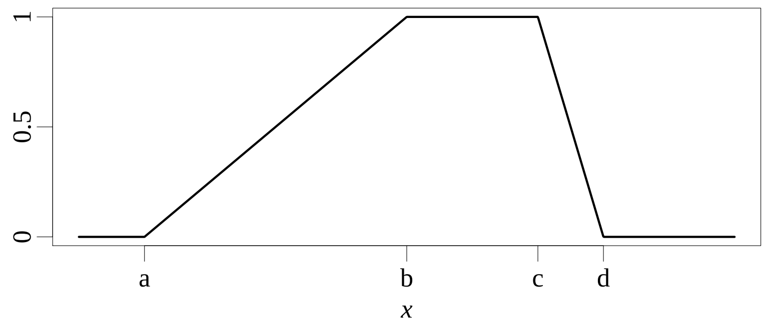


Figure 3.1: Design parameters of a trapezoidal membership function.

The user has two options when he/she creates the knowledge base of each CP:

- The knowledge base can be implemented in a .txt file where each line defines the parameters *a,b,c,d* of each linguistic label. R code reads this file and works with it.
- Another interesting option consists in specifying the number of labels (c) and the initial (a) and final(b) domain limits, when the CP is defined by a set of c uniform partitions. For example, if we have a CP defined by 5 uniform linguistic labels in the domain [0,15], the process consists in introducing these three parameters (0,15,5), obtaining the result shown in Fig. 3.2.

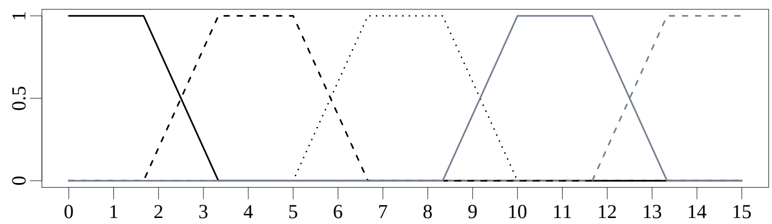


Figure 3.2: CP definition using *g_mf* function.

integral: This R function receives as inputs the output of a CP and the knowledge base (KB) which defines the trapezoidal membership functions of the new CP linguistic labels. It returns the membership degree of each input with respect to each linguistic label defined in the KB.

g_rules: This R function was created to work with *if-then* rules. It is a really useful tool when we want to implement a Finite Fuzzy State Machine. The set of possible rules, generated by expert knowledge, has to be codified in a .txt file as follows: the first row of the file indicates de number of linguistic terms in the consequent and its singleton values; the second row of the file indicates the number of antecedents and the indexes which represents the number of elements of each antecedent; the rest of rows represents the set of binary-coded rules in disyuntive normal form (DNF).

3.1 Application Example

An example of a GLMP which explains the efficiency of energy consumption during weekends can be seen in Fig. 3.3. There are first-order computational perceptions (1-CP_{n_1}) and second-order computational perceptions (2-CP_{n_2}), being n_1 and n_2 the first-order and second-order computational perceptions identifiers, respectively.

Based on the structure of the GLMP, it can be easily seen that there must be different functions corresponding to analyze the first-order computational perceptions and the second-order computational perceptions respectively based on the different types of KB. In the following subsections, it is explained how each computational perception is calculated.

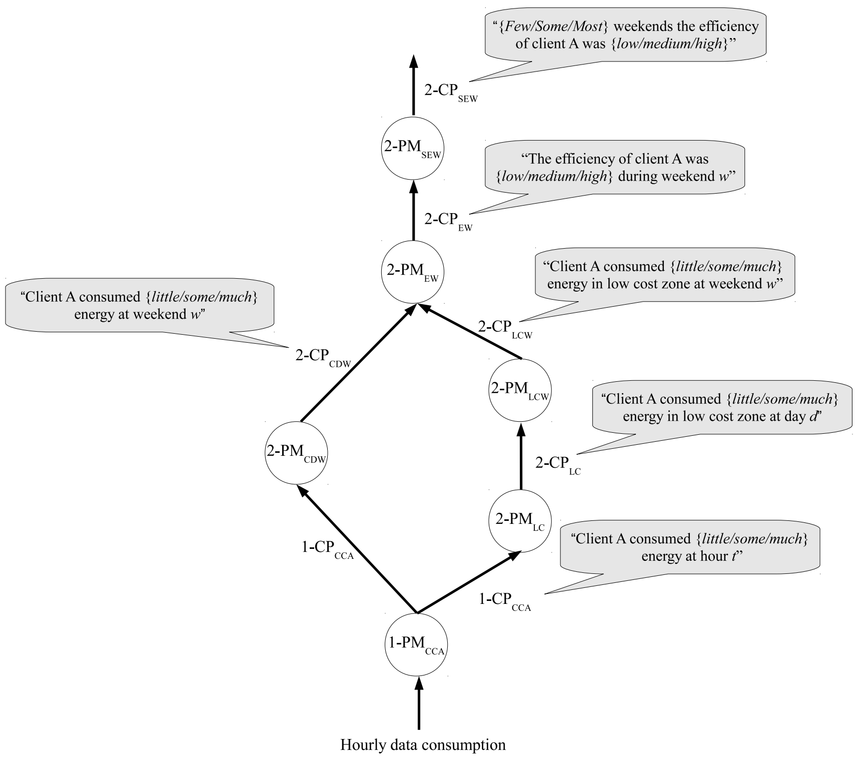


Figure 3.3: GLMP which explains the efficiency of energy consumption during weekends.

3.1.1 1-CP_{CCA}: Consumption of client A

This first-order perception mapping has as input a file which contains a time series with the hourly consumption of client A ("clientA.txt"). To produce the validity degree for the sentences: "The client A consumes {little/some/much} energy at hour t", we have to call the function `g_mf.R`, which has as first argument the input (`'clientA.txt'`) and as second argument the knowledge base. This KB can be introduced by the user or providing the a .txt file with the information.

This function returns the validity degree corresponding to each of the trapezoidal membership functions (MFs) included in the KB. The file containing the KB has as much rows as the number of linguistic labels (in the case of little, some and much it has 3 rows with four elements in each row coding the modal points of each MF).

The set of sentences of 1-CP_{CCA} is structured as follows:
$a_{CCA_1} \rightarrow$ "Client A consumed little energy at hour t"
$a_{CCA_2} \rightarrow$ "Client A consumed some energy at hour t"
$a_{CCA_3} \rightarrow$ "Client A consumed much energy at hour t"

3.1.2 2-CP_{CDW}: Consumption of client A during weekends

To produce the validity degree for the sentences: "Client A consumed {little/some/much} energy at weekend w", we have to do quantification by means of an integral function.

This integral is calculated with the function `integral.R`, which has as input arguments the first-order computational perception 1-CP_{CCA} and the KB of weekend which comprises the window size of the integral and the membership function of weekend.

The set of sentences of 2-CP_{CDW} is structured as follows:
$a_{CDW_1} \rightarrow$ "Client A consumed little energy at weekend w"
$a_{CDW_2} \rightarrow$ "Client A consumed some energy at weekend w"
$a_{CDW_3} \rightarrow$ "Client A consumed much energy at weekend w"

3.1.3 2-CP_{LC}: Consumption of client A in low cost zone

This second-order perception mapping has as input the output of the first-order perception 1-CP_{CCA}. To produce the validity degree for the sentences: "Client A consumed {little/some/much} energy in low cost zone at day d", we have to do quantification by means of the integral function.

This integral is calculated with the function `integral.R`, which has as input arguments this first-order perception 1-CP_{CCA} and the KB of the low cost zone which comprises the window size of the integral and the membership function of the low cost zone.

The set of sentences of 2-CP_{LC} is structured as follows:
$a_{LC_1} \rightarrow$ "Client A consumed little energy in low cost zone at day d"
$a_{LC_2} \rightarrow$ "Client A consumed some energy in low cost zone at day d"
$a_{LC_3} \rightarrow$ "Client A consumed much energy in low cost zone at day d"

3.1.4 2-CP_{LCW}: Consumption of client A in low cost zone during weekends

This second-order perception mapping has as input the output of the previous second-order perception 2-CP_{LC}. To produce the validity degree for the sentences: "Client A consumed {little/some/much} energy in low cost zone at weekend w", we have to do quantification by means of an integral function.

This integral is calculated with the function `integral.R`, which has as input arguments the second-order perception 2-CP_{LC} and the KB of weekend which comprises the window size of the integral and the membership function of weekend (the size of this linguistic label has to be the same as the defined one in subsection 3.1.2).

The set of sentences of 2-CP_{LCW} is structured as follows:
a_{LCW_1} → "Client A consumed little energy in low cost zone at weekend w"
a_{LCW_2} → "Client A consumed some energy in low cost zone at weekend w"
a_{LCW_3} → "Client A consumed much energy in low cost zone at weekend w"

3.1.5 2-CP_{EW}: Efficiency of client A during weekends

This second-order perception mapping is calculated by means of fuzzy if-then rules of the form:

IF "Client A consumed little energy at weekend w" AND "Client A consumed little energy in low cost zone at weekend w" THEN "Efficiency of weekend w was medium"

IF "Client A consumed little energy at weekend w" AND "Client A consumed some energy in low cost zone at weekend w" THEN "Efficiency of weekend w was high"

...

IF "Client A consumed much energy at weekend w" AND "Client A consumed much energy in low cost zone at weekend w" THEN "Efficiency of weekend w was medium"

In this practical example there are 9 (3 x 3 possible combinations) rules which are codified in its correspondient .txt file. The first row is codified as *3,0,5,10*, which means that the number of linguistic terms in the consequent is 3 and the singleton values are 0, 5, and 10. The second row is codified as *2,1,3,4,6*, which means that the number of antecedents is 2, the colums 1 to 3 correspond to the first antecedent and the colums 4 to 6 correspond to the second antecedent. Once we have defined the KB, we obtain the output of the rule by means of the function `g_rules.R`.
The set of sentences of 2-CP_{EW} is structured as follows:
a_{EW_1} → "The efficiency of client A was low during weekend w"
a_{EW_2} → "The efficiency of client A was medium during weekend w"
a_{EW_3} → "The efficiency of client A was high during weekend w"

3.1.6 2-CP_{SEW}: Summary of efficiency of client A during weekends

This second-order perception mapping has as input the output of the previous second-order perception (2-CP_{EW}). To produce the validity degree for the sentences: "{Few/Some/Most} weekends the efficiency of client A was {low/medium/high}" we have to calculate the cardinality of efficiency attending to labels {low/medium/high} by means of the average.

Now we have to calculate the validity of the subset of sentences. To make this possible we use the function `g_mf.R`, which has as arguments the input the efficiency of each linguistic label {low/medium/high} and the knowledge base.

The set of sentences of 2-CP_{SEW} is structured as follows:
$a_{SEW_{11}} \rightarrow$ "Few weekends the efficiency of client A was low"
$a_{SEW_{12}} \rightarrow$ "Some weekends the efficiency of client A was low"
$a_{SEW_{13}} \rightarrow$ "Most weekends the efficiency of client A was low"
$a_{SEW_{21}} \rightarrow$ "Few weekends the efficiency of client A was medium"
$a_{SEW_{22}} \rightarrow$ "Some weekends the efficiency of client A was medium"
$a_{SEW_{23}} \rightarrow$ "Most weekends the efficiency of client A was medium"
$a_{SEW_{31}} \rightarrow$ "Few weekends the efficiency of client A was high"
$a_{SEW_{32}} \rightarrow$ "Some weekends the efficiency of client A was high"
$a_{SEW_{33}} \rightarrow$ "Most weekends the efficiency of client A was high"

In this practical example we receive from an electrical company the hourly consumption of "client A" and we want to extract relevant features about his/her energy consumption on weekends. Apart from obtaining useful linguistic reports about his/her consume with different types of granularities (hour t, day d, weekends w), we show some relevant information offered by the system developed:

"The efficiency of client A during weekend *1* was medium. That weekend, client A had a little energy consumption but he/she also had a little energy consumption in low cost zone."

...

"The efficiency of client A during weekend *7* was low. That weekend, client A had a high energy consumption and he/she had a little energy consumption in low cost zone."

...

"Some weekends the efficiency of client A was low or medium, and few weekends it was high."

Chapter 4

CTP for Personal Physical Activities Identification

4.1 Introduction

This chapter describes how to apply our approach for linguistic description of complex phenomena to the daily physical activities identification of a person. The relevant modules needed to produce the linguistic description of the physical activities identificated are explained.

To explore the possibility of estimating the body posture and activity of a person analyzing the three orthogonal accelerations that are produced when wearing a three axial accelerometer, is a well-known and widely studied in recent years problem. Monitoring the body posture and the human activity of a person can be useful, by itself or combined with other techniques, for many applications, e.g., personal navigation or medical assistance, personal security, etc. In [6], accelerometers were used in a clinical environment to develop a long-term mobility monitoring of older adults to check how healthy was their lifestyle and to prevent chronic diseases. In [7], authors use accelerometers in gait and balance evaluation to assess falls risk and mobility monitoring. In this work, dealing with the imprecision and variability of the signal, the analysis has been done by means of Fuzzy Logic.

A really interesting application of this project research is the measurement of a patient's health outside a doctor's office. This is something currently limited to questionnaires which are hindered by deficiencies in memory and subjectivity of the patient. This project investigates the health properties which can be inferred from a patient's gait using widely available, commonly carried smart phones. In this line, new technology is beginning to provide information which was previously impossible to attain. For example, continuous monitoring of a patient's health could be used to gauge the progress during rehabilitation. Medicines and physical treatments could be adjusted related to the condition of the patient from continuous health monitoring data. Diagnosis could be improved using continuous information by providing a clearer picture of the patient's health. Devices need to be designed in order to take the measurements while maintaining enough accuracy to be useful while still allowing the device to be affordable. Furthermore, the measurements must be taken in a comfortable way to the patient and foolproof to use. The idea of continuously taking data from a patient in an inexpensive way is new and offers many alternatives of study.

Using mobility measured by gait analysis in order to infer health information is a new area of study in continuous monitoring [23]. The analysis of personal physical activities would be used to assess the overall healthiness of a subject, taking into account that walking gives a good indication of the energy expenditure of an individual.

The subject of analyzing a person's gait in order to infer health information is not new, however, most of the research has been focused on diagnosing serious medical conditions by analyzing the walking patterns. As a contribution of our Research Unit, in [4], a practical application is presented where it is described how to build Fuzzy Finite State Machines (FFSM) to model the human gait of a set of people by using Genetic Algorithms and expert knowledge, and, in [3] the human gait is used as an interesting example of complex phenomenon evolving in time that is modeled by a GLMP, including a FFSM to represent the behaviour of this type of phenomena in a human friendly way.

In this project research, we analyze the physical activities performed by the user along a period of time (typically one day) only by taking acceleration data from his/her mobile phone situated in the front pocket of his/her trousers (non-intrusively method). What is also interesting is that the user can leave the mobile phone at any time, identifying that the device is not with him/her. That is, the user develops normal activities of daily living, without any restriction of taking strange devices in specific places or being movements restricted. The only thing he/she needs is to carry out his/her smartphone in the trousers (any position and orientation are allowed).

It is really interesting to know that a good number of studies have focused in the analysis of the effects of depression by means of analysing the patient's gait. In this case, studies employed sophisticated sensors and precise motion capture techniques, which is limited to a lab setting making and being unrealizable in continuous health monitoring. In the same way, this research would be interesting in the monitoring of people with different health problems: weight, heart, physical rehabilitations and so on. Specially important is the possibility of monitoring elderly people or people with some mental disorder, trying to identify falls or abnormalities in the course of daily activity. In this direction some studies have been done [12, 17, 13] investigating the effect of speed dependency on lateral gait parameters of elderly people, the balance and gait features in children with dyslexia [18], or the analysis of the utility of accelerometers to measure physical activity in children attending an obesity treatment intervention [21].

This project research correctly identifies activities as important as walking, standing, sitting, climbing and down stairs... In addition, it calculates, in a approximate way, the number of burned calories, the time spent in each activity and providing relevant reports which linguistically describe the evolution and summary of each day activity. The procedure followed to develop this complex task is thoroughly described in the next sections.

4.2 DAQ Module

4.2.1 Introduction

Mobile devices, such as mobile phones, music players, and portable computers have recently begun to incorporate diverse and powerful sensors. These devices include different types of sensors, such as GPS, audio (microphones), image (cameras), light, temperature, direction (compasses) and acceleration. Because of the small size of these "smart" mobile devices, their substancial computing power, their ability to send and receive data, and their nearly ubiquitous use in our society, these devices open up exciting new areas for data mining research and applications.

To develop an experimental application, we have chosen *Android-based* mobile phones as plataform because the Android operating system is free, open-source, easy to program, and is expected to quickly become a dominant entry in the mobile phones marketplace. Most of Android phones contain triaxial accelerometers that measure acceleration in three spatial dimensions (x, y and z accelerations). This characteristic is exploited in this research project to analyze the accelerations produced in person's daily routine activities, such as walking, sitting, climbing stairs, etc., while keeping the mobile phone in the pocket. This idea has been proposed in some research like a way of biometric identificatoin [14] or owner identification.

Data collection was acquired and stored by an Android application that we created to run on mobile phones. Through this application we can control what data is collected as well as how frequently it is done. This topic is widely explained in subsection 4.2.3.

The reason why we decided to use this type of devices is that smart phones are not specialized sensors but are widely available commercial devices that are routinely carried by millions of users. Furthermore, we relied only on the device being carried in the user's pocket, a natural location to carry such a device, while other works typically involved the user being monitored with multiple sensors, often placed in awkward body locations.

4.2.2 Android World

Android is a Linux-based operating system for mobile devices such as smartphones and tablet computers. It is developed by the Open Handset Alliance, led by Google, and other companies.

Google purchased the initial developer of the software, Android Inc., in 2005. The unveiling of the Android distribution in 2007 was announced with the founding of the Open Handset Alliance, a consortium of 86 hardware, software, and telecommunication companies devoted to advancing open standards for mobile devices. Google releases the Android code as open-source, under the Apache License. The Android Open Source Project (AOSP) is tasked with the maintenance and further development of Android.

Android has a large community of developers writing applications ("apps") that extend the functionality of the devices. Developers write primarily in a customized version of Java. Apps can be downloaded from third-party sites or through online stores such as Google Play (formerly Android Market), the app store run by Google. In October 2011, there were more than

500.000 apps available for Android, and the estimated number of applications downloaded from the Android Market as of December 2011 exceeded 10 billion.

Android was listed as the best-selling smartphone platform worldwide in Q4 2010 by Canalys with over 300 million Android devices in use by February 2012. According to Google's Andy Rubin, as of December 2011, there were over 700,000 Android devices activated every day. Android has been updated frequently since the original release of "Astro", with each fixing bugs and adding new features. Each version is named in alphabetical order, with 1.5 "Cupcake" being the first named after a dessert and every update since following this naming convention.

Figure 4.1: Android logo.

4.2.3 Experimental Android Application: *SensAcq*

Android applications are usually developed in the Java language using the Android Software Development Kit, but other development tools are available, including a Native Development Kit for applications or extensions in C or C++, Google App Inventor, a visual environment for novice programmers and various cross platform mobile web applications frameworks.

Applications can be acquired by end-users either through a store such as Google Play or the Amazon Appstore, or by downloading and installing the application's APK file from a third-party site.

Google Play is an online software store developed by Google for Android devices. An application program called *Play Store* is preinstalled on most Android devices and allows users to browse and download apps published by third-party developers, hosted on Google Play. As of October 2011, there were more than 500,000 apps available for Android, and the estimated number of applications downloaded from the Play Store as of December 2011 exceeded 10 billion. The operating system itself is installed on 130 million total devices.

Only devices that comply with Google's compatibility requirements are allowed to preinstall and access the Play Store. The application program filters the list of available applications to those that are compatible with the user's device, and developers may restrict their applications to particular carriers or countries for business reasons.

The developed application, called *SensAcq*, captures and stores the accelerations produced by the user who carries the mobile phone in his/her pocket. This simple application was designed to establish a useful interface which the user acts with. The application logo is shown in Fig. 4.2.

Figure 4.2: SensAcq logo.

When we start the application, we can see several visualization and interaction options:

- *Triaxial acceleration measure*. Acceleration values are constantly actualized and displayed on the screen. It is not necessary that the application be storing data to show the x, y and z accelerations.
- *"Storing Data"* button: pressing this button the application starts to store captured data. Once this button is pressed, it is disabled until we press the button "Stop". The accelerations acquisition period is configurable by software but in this application it is fixed to 15 miliseconds.
- *"Stop"* button: this button is only enabled from when the "Storing Data" button is pressed. "Stop" button and "Storing Data" button are never simultaneously enabled. When we press the "Stop" button the application automatically generates a *Comma-Separated Values* (.csv) file and it is returned to the initial interface.
- *Edit text bar*. To introduce the measure name, the application includes an edit field text where the user can assign the name he/she wants. When the .csv file is generated the date of the measure is automatically added to the name, to facilitate subsequent identification of each measurement file.

Figure 4.3: *SensAcq* waiting interface.

Figure 4.4: *SensAcq* running interface.

Fig. 4.3 and 4.4 show the SensAcq interfaces when the application is waiting and capturing data. The flowchart that the application follows is shown in Fig. 4.5.

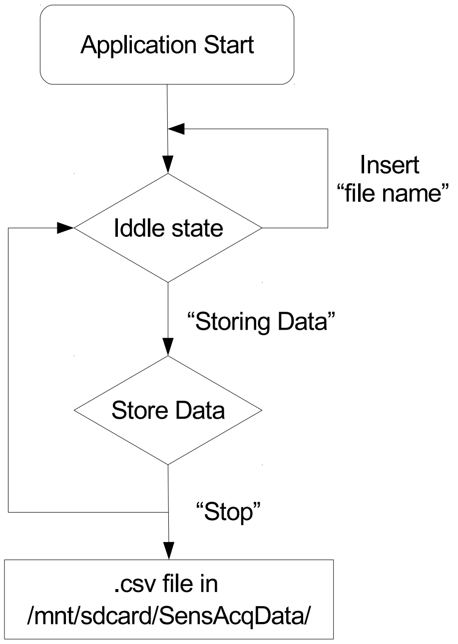


Figure 4.5: *SensAcq* flowchart.

The class and functions application diagram is depicted in Fig. 4.6. SensAcqActivity is the main application class and it is its start point. AccDataFile is a class which defines objects to write measurement data into a specific .csv file.

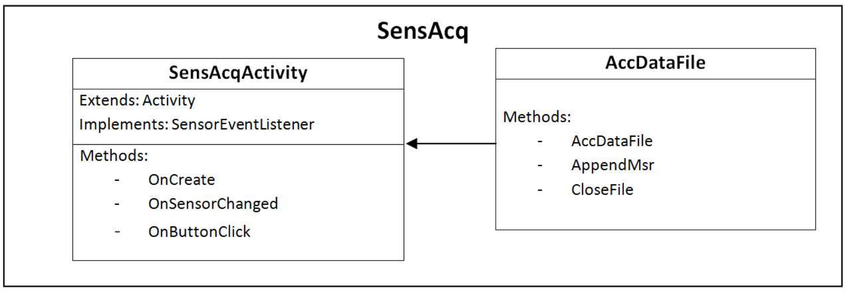


Figure 4.6: Class and functions application diagram.

SensAcqActivity.OnCreate

It is the method which is executed when the application is started. This is a method inherited from *Activity*, and it is needed to be overwritten in all applications. In this particular case, it represents the application layout, inicializates all variables related to text fields and buttons, acquires the service to management the system power and records the service class to attend the acceleration sensor variations. The application is prepared to acquire data as fast as possible but Android does not assure that sample frequency be constant. This fastest sample rate depends of the mobile phone model but is typical that this value be equal to 15 miliseconds.

SensAcqActivity.OnSensorChanged
Every time the accelerometer produces a new measure (event), the systems automatically executes this method with the new available data. What is done by the application is displaying this data and, if it is storing data, the application store the information with a timestamp coded in a string with the following format:

$$i,x,y,z,t,$$

where i is the measures counter till the instant t; x, y and z are the acceleration values in m/s^2; and t is the timestamp relative to start time. Sometimes, Android system produces repeated measures over time (problem detected in some mobile phones models). To avoid this duplicity, these values with a difference in their timestamp lower than 5 miliseconds are filtered.

SensAcqActivity.OnButtonClick
When the user presses any button on the GUI, Android launches the execution of this method. This allow to distinguish which button was pressed and it acts according to the flowchart shown in Fig. 4.5.

When the *"Storing Data"* button is pressed, a new AccDataFile object is instantiated. Also, by means of the management power system, is established that the CPU can not enter in suspension mode while the application is acquiring and storing data.

When the *"Stop"* button is pressed to finish the recording, the file where the application was storing data is closed, and the management power systems return to normal state.

AccDataFile.AccDataFile
This is the class constructor which receives the file name and concatenates it with a string that represents the date and time at that moment. The final string, which is also the name of the .csv file, has the following format:

$$'filenameDD\_MM\_HHhMMm.csv'$$

Then the application checks that there is a storage system (sdcard) and it creates the file in /SensAcqData/. From that moment, the file is ready to receive acquiring data.

AccDataFile.AppendMsr
This method is called every time the accelerometer produces a new measure. It receives the format string explained before, and writes it in the file.

AccDataFile.CloseFile
This method is called when the measurement is finished. It closes the file where the application is writing data.

4.3 Validity Module

Fig. 4.7 shows the GLMP designed which summarizes and highlights the relevant aspects of the physical activities identification. As it can be seen, it is composed by first and second order computational perceptions as well as perception mappings that combine and aggregate these CPs.

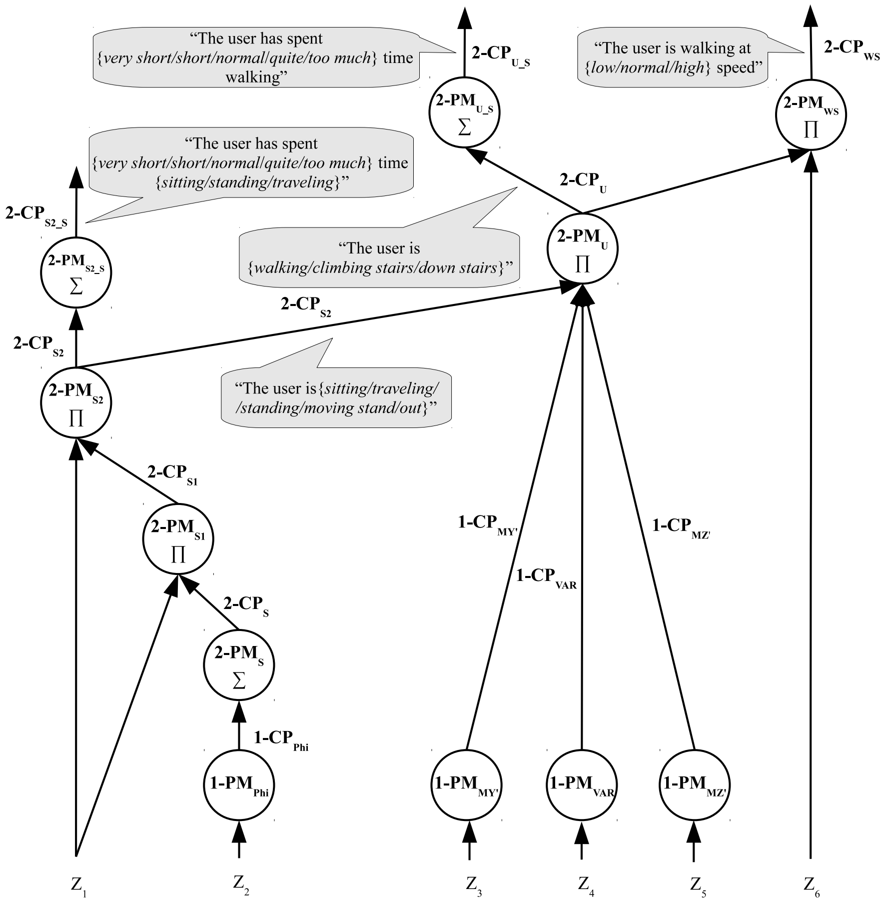


Figure 4.7: GLMP for the linguistic description of the physical activities identification.

Here, we used x, y and z accelerations provided by triaxial accelerometers embedded in actual mobile phones (thanks to the developed application *SensAcq*, presented in 4.2). At first, some mathematical operations are performed to calculate some relevant magnitudes needed as GLMP inputs. These inputs are represented as Z_1, Z_2, Z_3, Z_4, Z_5 and Z_6:

Accelarations Module (*AM*) (Z_6) and its Variance (Z_1) along the time. A vector sum is calculated for each sequence using the Pythagorean summing of values from the three sensing axes: $AM = \sqrt{x^2 + y^2 + z^2}$. To measure how far the set of accelerations is spread out the AM variance is calculated. Fig. 4.9 shows a graphical example of the transformation of triaxial accelerations into the vector sum of each sequence.

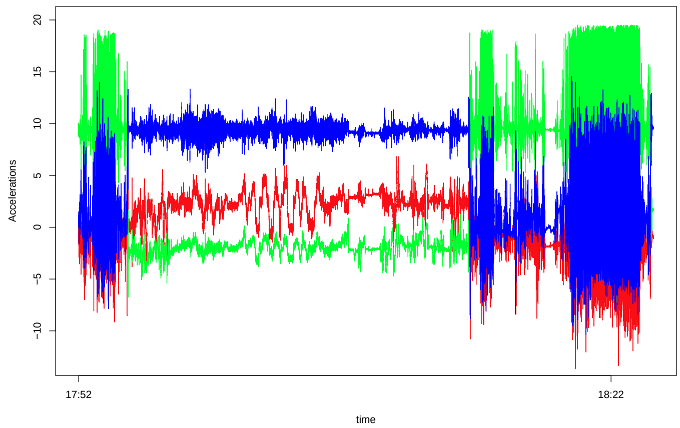


Figure 4.8: x, y and z accelerations.

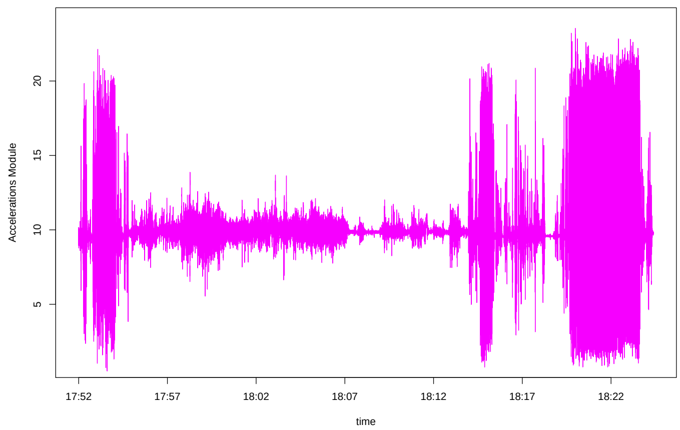


Figure 4.9: Accelerations Module.

Moving Azimuth Variance (Z_2). From experiments we have concluded that the analysis of polar coordinates and, specially the azimuth variance processing, is a very good measure to identify relevant changes in mobile position. We will see how aggregating this information and the AM variance of each sequence we really know when the user is sitting or standing. Fig. 4.11 shows graphically the azimuth oscillation during a recording period. We can visually see the existing value breaks along the sequence, which indicates important changes in mobile position.

Accelerations y (Z_3, Z_4) and z (Z_5) of the user axes(*y' and z' accelerations*). Once we can distinguish between the two well-defined states (standing or sitting), analyzing the values of the three axes accelerations in each state we can define the position in which the mobile was inside the trousers pocket. These axes are relative to the mobile phone and they need not coincide with the user axes so, it is important to identify in which position the mobile was introduced

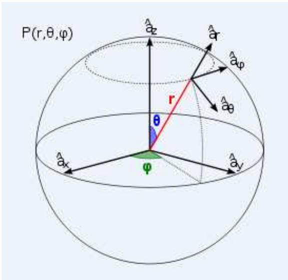


Figure 4.10: Polar coordinates.

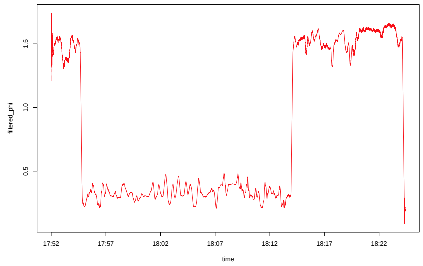


Figure 4.11: Azimuth of an experiment.

into the trousers pocket. This operation is available since the data processing is offline, that is, whole data is analyzed and some relevant features can be extracted to determine the mobile position. User can leave mobile phone whenever he/she wants but is required that he/she returns it to the pocket always in the same position and orientation (whatever he/she chose at first moment). Mobile phones axes orientations are specified in Fig. 4.12.

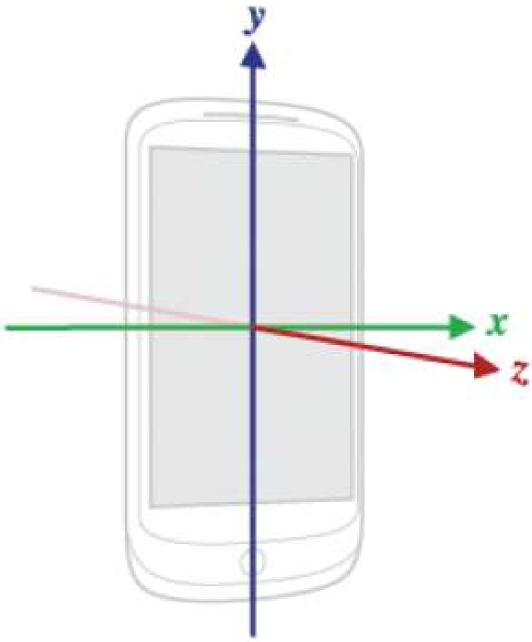


Figure 4.12: x, y and z axis orientation.

It is easy to see that, when user is sitting, the mobile phone is flat so, almost all gravity force falls on its z axis (positive or negative depending of the orientation). On the other hand, when user is standing, gravity force is distributed between the x and y mobile phone axes (again the sign depends of the mobile orientation inside the pocket). Fig. 4.13 shows a graphical representation of two basic discriminating postures: standing and sitting. The arrows indicate the direction of the active accelerometer axes and the acceleration values correspond to the accelerometer output at each orientation in units of g.

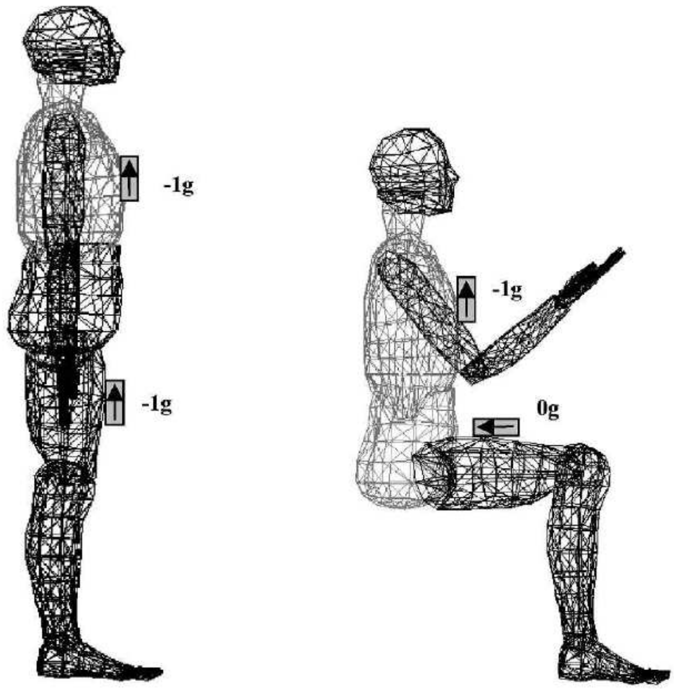


Figure 4.13: Standing and sitting postures.

Once we know the mobile phone orientation we can transform its axes into our global coordinate axes, which corresponds to the user ones (user axes are the same as mobile phone ones in upright position and the display facing forward, Fig. 4.14). We assume that the mobile phone approximately adopts one of the eight positions shown in Table 4.1, inside the pocket.

Figure 4.14: Reference position.

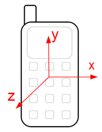
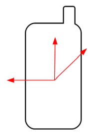
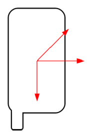
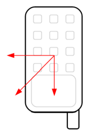
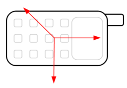
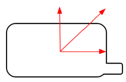
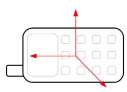
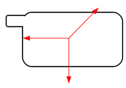
Possible positions	**Axes transformation**
	$x' = x$ $y' = y$ $z' = z$
	$x' = -x$ $y' = y$ $z' = -z$
	$x' = x$ $y' = -y$ $z' = -z$
	$x' = -x$ $y' = -y$ $z' = z$
	$x' = -y$ $y' = x$ $z' = z$
	$x' = y$ $y' = x$ $z' = -z$
	$x' = y$ $y' = -x$ $z' = z$
	$x' = -y$ $y' = -x$ $z' = -z$

Table 4.1: Mobile phone positions into the pocket and their axes transformations

4.3.1 First order perceptions

As has been explained above, we use several numeric measures as input data. A set of corresponding 1-CPs are defined in this subsection. For all the CPs described in the following subsections, the validity degrees are obtained by means of a set of uniformly distributed trapezoidal membership functions (MFs) forming a strong fuzzy partition (SFP) [22].

Azimuth angle variance (1-CP_{Phi})

U = Z_2, that represents the numerical values of the *Moving Azimuth Variance* in each period of time.

A The set of possible sentences is the following:
a_{Phi_1} → *"The azimuth angle variance has been small"*
a_{Phi_2} → *"The azimuth angle variance has been big"*

g(Phi**)** These two linguistic labels are represented with trapezoidal membership functions defined by their vertices as follows: *small* (-inf,-inf,0.65,0.75), *big* (0.65,0.75,inf,inf)

Mean y′ (1-$CP_{MY'}$)

The output $y_{MY'}$ corresponds to moving averages of windows of size 5 seconds. This allow us to know in a more detailed way how is the evolution of the y' acceleration average along the time.

U = Z_3, that represents the numerical values of the acceleration corresponding to the user y-axis, called y'.

A The set of possible sentences is the following:
$a_{MY'_1}$ → *"The moving average of y' is low"*
$a_{MY'_2}$ → *"The moving average of y' is high"*

g(MY'**)** These two linguistic labels are represented with trapezoidal membership functions defined by their vertices as follows: *low* (-inf,-inf,8.9,9.1), *high* (8.9,9.1,inf,inf)

Variance y′ (1-CP_{Var})

U = Z_4, that represents the numerical values of y' and models the moving variance of windows of size 5 seconds.

A The set of possible sentences is the following:
a_{Var_1} → *"The moving variance of y' is low"*
a_{Var_2} → *"The moving variance of y' is medium"*
a_{Var_3} → *"The moving variance of y' is high"*

g(Var**)** These three linguistic labels are represented with trapezoidal membership functions defined by their vertices as follows: *low* (-inf,-inf,11.5,12.5), *medium* (11.5,12.5,14.5,15.5), *high* (14.5,15.5,inf,inf)

Mean z′ (1-$CP_{MZ'}$)

This 1-CP is calculated in the same manner as the previous one. In this case, the input corresponds to the The output $y_{MZ'}$ responds to the moving averages of windows of size 5 seconds.

U = Z_5, that represents the numerical values of the acceleration corresponding to the user z-axis, called z'.

A The set of possible sentences is the following:
$a_{MZ'_1} \rightarrow$ *"The moving average of z′ is low"*
$a_{MZ'_2} \rightarrow$ *"The moving average of z′ is high"*

g(MZ') These two linguistic labels are represented with trapezoidal membership functions defined by their vertices as follows: *low* (-inf,-inf,0.9,1.1), *high* (0.9,1.1,inf,inf).

4.3.2 Second order perceptions

The second order perceptions are calculated based on subordinate CPs. For this application, we defined seven 2-CPs which describe the physical activities at different levels of detail. In this GLMP, we can distinguish between two types of 2-CPs: there are 2-CPs that aggregate (Σ) the information from the same subordinate CP (2-CP_S, 2-CP_{S2_S} and 2-CP_{U_S}) and 2-CPs which combine (Π) information from different subordinate CPs (2-CP_{S1}, 2-CP_{S2}, 2-CP_U and 2-CP_{WS}).

Initial State (2-CP_S)

This 2-CP distinguishes between two different states, standing and sitting, but it does not know which state corresponds to each one. These two initial states are called *state 1* and *state 2*, and they are recognized by big changes in the azimuth angle variance along the time.

U = 1-CP_{Phi}

A The set of possible sentences is the following:
$a_{S_1} \rightarrow$ *"The mobile is in state 1"*
$a_{S_2} \rightarrow$ *"The mobile is in state 2"*

g(S) It is a 2-CP that aggregates the output of 1-CP_{Phi} by means of a *Fuzzy Finite State Machine*. The 1-CP_{Phi} specifies when the azimuth angle variance has been small or big, producing a state change in this latter situation. If the mobile phone is in *state 1* and a big azimuth angle variance is produced, the mobile phone changes to *state 2*. If the mobile phone is in *state 2* and another big azimuth angle variance is produced, the mobile phone returns to *state 1*. 2-CP_{S1} will assign which of these two states corresponds to sitting or standing states.

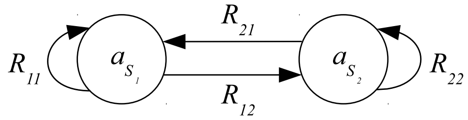


Figure 4.15: State diagram of the FFSM for 2-CP_S modeling.

Fig. 4.15 shows the FFSM diagram. We can see two different states and 4 fuzzy rules: 2 rules (R_{ii}) to remain in each state and other 2 rules (R_{ij}) to change between them. These rules are listed as follows:

R_{11}: IF a_{S_1} AND a_{Phi_1} THEN a_{S_1}
R_{22}: IF a_{S_2} AND a_{Phi_1} THEN a_{S_2}
R_{12}: IF a_{S_1} AND a_{Phi_2} THEN a_{S_2}
R_{21}: IF a_{S_2} AND a_{Phi_2} THEN a_{S_1}

Where, the first term in the antecedent computes the previous validity degree of the sentence a_{S_i}, i.e., w_{S_i}; the second term describes the condition imposed on the 1-CP_{Phi}; finally, the consequent rule defines the next *state*. To calculate the validity degrees of the senteces associated with each *state j* (w_{S_j}), a weighted average using the firing degree of each rule R_{ij} (ϕ_{ij}) is computed as defined in Eq. 4.1:

$$w_{S_j} = \frac{\sum\limits_{i=1}^{2} \phi_{ij}}{\sum\limits_{i=1}^{2} \sum\limits_{j=1}^{2} \phi_{ij}} \tag{4.1}$$

where ϕ_{ij} is calculated using the minimum for the AND operator.

State 1 (2-CP_{S1})

Looking at accelerations module variance in each initial state (state 1 or state 2) we will know which state corresponds to sitting and which one to standing. The global acceleration module variance of *standing* state would be bigger than acceleration module variance of *sitting* state.

U = {2-CP_S and Z_1, that represents numerical values of the *Accelerations Module Variance*}

A The set of possible sentences is the following:
a_{S1_1} → *"The user is sitting"*
a_{S1_2} → *"The user is standing"*

g($S1$) is implemented using an expert fuzzy rule of type:
If (state 1 acceleration module variance) is bigger than (state 2 acceleration module variance) then (state 1 is standing and state 2 is sitting),
else, (state 1 is sitting and state 2 is standing).
When we know which state corresponds to standing and which one corresponds to sitting, these new CPs inherit the membership degrees of *state 1* and *state 2* CPs.

State 2 (2-CP_{S2})

This CP distinguishes among five different states attending to the accelerations module variance of *sitting* or *standing* state. When the output of 2-CP_{S1} is sitting, the output of 2-CP_{S2} would be *sitting*, *traveling by car* or *out*. "Out" state represents the time when the mobile phone is not in the trousers pocket, being on a table or somewhere with no movement at all. When user is traveling by car, the accelerations module variance is much bigger than when the user is sitting, and when the mobile phone is on the table, the accelerations module variance is similar to zero. On the other hand, when the output of 2-CP_{S1} is standing, the output of 2-CP_{S2} would be *standing*, *moving stand* or *out*. "Out" state represents the same idea than previous case. When user is standing the accelerations module variance is much smaller than when he/she is moving.

U = {2-CP_{S1} and Z_1, that represents numerical input corresponding to the *Accelerations Module Variance*}

A The set of possible sentences is the following:
a_{S2_1} → *"The user is sitting"*
a_{S2_2} → *"The user is traveling"*
a_{S2_3} → *"The user is standing"*
a_{S2_4} → *"The user is moving stand"*
a_{S2_5} → *"The mobile phone is not with the user"*

g($S2$) Attending to the output *sitting* of the 2-CP_{S1}, the linguistic labels which represents the 2-CP_{S2} are defined with trapezoidal membership functions as follows: *sitting* (0.001,0.005,0.07,0.09), *traveling* (0.07,0.09,inf,inf), *out* (-inf,-inf,0.001,0.005).
Attending to the output *standing* of the 2-CP_{S1}, the linguistic labels which represents the 2-CP_{S2} are defined with trapezoidal membership functions as follows: *standing* (0.001,0.005,0.9,1.1), *movingstand* (0.9,1.1,inf,inf), *out* (-inf,-inf,0.001,0.005).

State 2 Summary (2-CP_{S2_S})

U = 2-CP_{S2}

A The set of possible sentences is the following:
$a_{S2_{S1}}$ → *"The user has spent very short time sitting"*
$a_{S2_{S2}}$ → *"The user has spent short time sitting"*
$a_{S2_{S3}}$ → *"The user has spent a normal amount of time sitting"*
$a_{S2_{S4}}$ → *"The user has spent quite time sitting"*
$a_{S2_{S5}}$ → *"The user has spent too much time sitting"*
$a_{S2_{S6}}$ → *"The user has spent very short time standing"*
$a_{S2_{S7}}$ → *"The user has spent short time standing"*
$a_{S2_{S8}}$ → *"The user has spent a normal amount of time standing"*
$a_{S2_{S9}}$ → *"The user has spent quite time standing"*
$a_{S2_{S10}}$ → *"The user has spent too much time standing"*
$a_{S2_{S11}}$ → *"The user has spent very short time traveling"*
$a_{S2_{S12}}$ → *"The user has spent short time traveling"*
$a_{S2_{S13}}$ → *"The user has spent a normal amount of time traveling"*
$a_{S2_{S14}}$ → *"The user has spent quite time traveling"*
$a_{S2_{S15}}$ → *"The user has spent too much time traveling"*

g($S2_S$) The validity degrees are obtained by means of the aggregation function g_{S2_S}, which is based on the $\alpha-$cuts method proposed by [8].
For example, using the validity degree w_{S2_1} of *"The user is sitting"*, we calculate the percentage of time the user is sitting contained at each $\alpha-$level (N_α) by means of Eq. 4.2, with $\alpha \in \mathrm{A} = \{0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9\}$.

$$N_\alpha = \frac{1}{n}\sum_{i=1}^{n} F_\alpha(w_{S2_1}) \tag{4.2}$$

where:

$$F_\alpha(w_{S2_1}) = \begin{cases} 1 & \text{if} \quad w_{S2_1} > \alpha \\ 0 & \text{if} \quad w_{S2_1} \leq \alpha \end{cases} \tag{4.3}$$

Then, we calculate the membership degree of each N_α to each element of the set of linguistic quantifiers: $\{Q_0, \ldots, Q_5\} = \{Very\ short, Short, Normal, Quite, Too\ Much,\}$, e.g., $\mu_{Q_4}(N^j_\alpha) = Quite(N^j_\alpha)$. Fig. 4.16, 4.17, 4.18 shows the linguistic labels defined on the domain of the amount of time for each state (*sitting*, *standing* or *traveling*), being n a empirically calculated maximum which varies depending of the recording length. This linguistic labels distribution has to be done by an expert according to a medical treatment or a final goal, that is, the amount of time a user spends sitting can be labeled as *normal* for some users and *too much* for other ones with different needs.

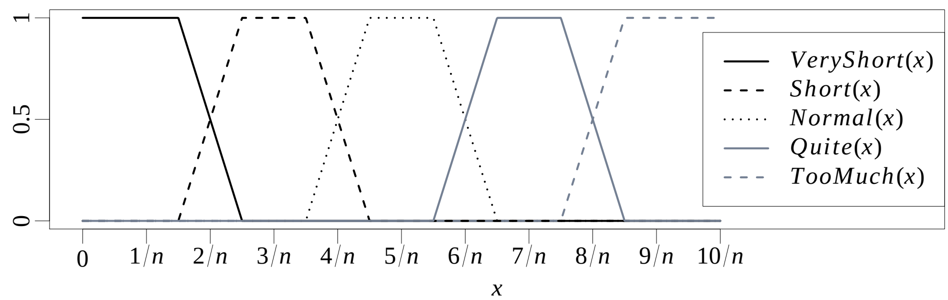


Figure 4.16: Linguistic labels that represent the linguistic quantifiers for time spent sitting.

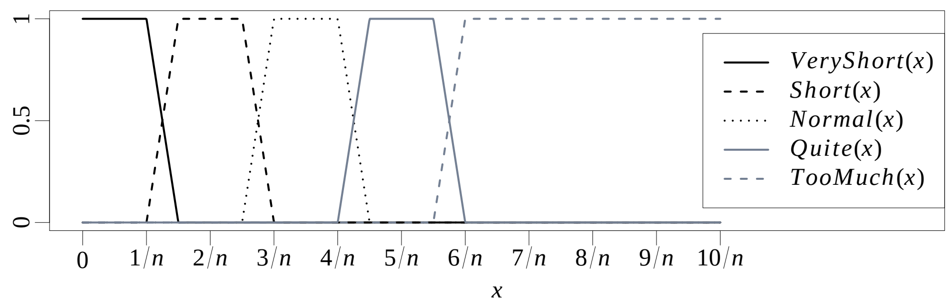


Figure 4.17: Linguistic labels that represent the linguistic quantifiers for time spent standing.

The last step consists in calculating the average value of the membership degrees obtained for each $\alpha-$level using Eq. 4.4. The number of elements in the set A is the level of resolution, i.e., $|A| = 10$ in this particular case.

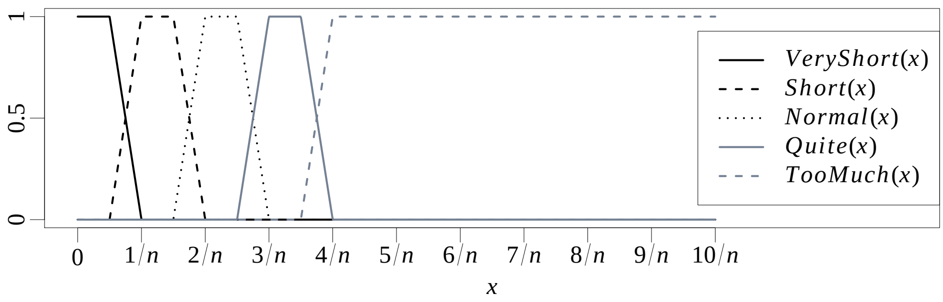


Figure 4.18: Linguistic labels that represent the linguistic quantifiers for time spent traveling.

$$w_{S2_{Si}} = \frac{1}{|\mathrm{A}|} \sum_{\forall \alpha \in \mathrm{A}} \mu_{Q_i}(N_\alpha) \tag{4.4}$$

This final value contains the relevant information about the amount of time spent sitting, standing or traveling, e.g., the validity degree of the sentence "The user has spent quite time sitting" ($w_{S2_{S4}}$) will be determined by Eq. 4.5:

$$w_{S2_{S4}} = \frac{1}{|\mathrm{A}|} \sum_{\forall \alpha \in \mathrm{A}} Quite(N_\alpha) \tag{4.5}$$

Up state (2-CP_U)

All the input information is combined to extend the concept of *moving standing*, developed in the 2-CP_{S2}.

U = {1-$CP_{MY'}$, 1-$CP_{MZ'}$, 1-CP_{Var} and 2-CP_{S2}}

A The set of possible sentences is the following:
a_{U_1} → *"The user is walking"*
a_{U_2} → *"The user is climbing stairs"*
a_{U_3} → *"The user is down stairs"*
a_{U_4} → *"The mobile phone is not with the user"*

g(U) This CP works with the output *moving stand* of the 2-CP_{S2}. To distinguish when the user is walking, climbing stairs or down stairs, this function g is implemented using the following set of expert fuzzy rules:

- IF (the moving average of z′ is low) AND (the moving variance of y′ is low or medium) THEN (the user is climbing stairs)
- IF (the moving average of z′ is high) AND (the moving variance of y′ is medium or high) THEN (the user is down stairs)
- IF (any of the previous fuzzy rules is true) OR (the sum of previous fuzzy rules is lower than *moving stand* membership degree) THEN (the user is walking).

Up state Summary (2-CP_{U_S})

U = 2-CP_U

A The set of possible sentences is the following:
$a_{U_{S1}} \rightarrow$ *"The user has spent very short time walking"*
$a_{U_{S2}} \rightarrow$ *"The user has spent short time walking"*
$a_{U_{S3}} \rightarrow$ *"The user has spent a normal amount of time walking"*
$a_{U_{S4}} \rightarrow$ *"The user has spent quite time walking"*
$a_{U_{S5}} \rightarrow$ *"The user has spent too much time walking"*

g(U_S) The validity degrees are obtained by means of the aggregation function **g(U_S)** as the same manner as **g($S2_S$)** calculated the validity degrees of 2-CP_{S2_S}, that is, by using the $\alpha-$cuts method proposed by [8]. The set of linguistic labels is defined as shown in Fig. 4.19. In this case is also important to remind that this linguistic labels distribution has to be done by an expert according to a medical treatment or a final goal.

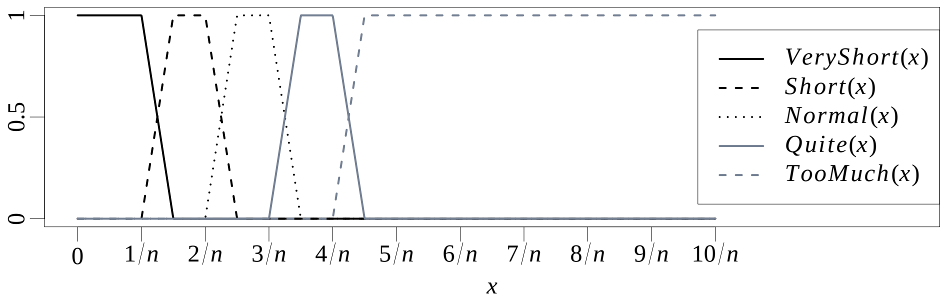


Figure 4.19: Linguistic labels that represent the linguistic quantifiers for time spent walking.

Walking Speed (2-CP_{WS})

U = {2-CP_U and Z_6, that represents numerical *Accelerations Modules*}

A The set of possible sentences is the following:
$a_{WS_1} \rightarrow$ *"The user is walking at low speed"*
$a_{WS_2} \rightarrow$ *"The user is walking at normal speed"*
$a_{WS_3} \rightarrow$ *"The user is walking at high speed"*

g(WS) This 2-CP extends the concept of *walking*, specifying the walking speed at each period of time. The way of procedure is analysing moving windows of size 10 seconds to obtain the walking speed evolution along the time.
The three linguistic labels which define the walking speed are represented with trapezoidal membership functions as follows: *low* (-inf,-inf,1,1.5), *medium* (1,1.5,2,2.5), *high* (2,2.5,inf,inf).
To estimate the walking speed we analyze the *Accelerations Module* for each moving

window of 10 seconds. A quadratic curve fits this accelerations modules at standardised walking speeds [13]. To obtain this fitting curve we have made some experiments which are explained in Chapter 5.

4.4 Expression Module

Apart from the goal of obtaining suitable text to be showed to users, the linguistic reports can be used by therapysts with the aim of understanding physical changes, rehabilitation evolutions, patients' habits of life and so on. Using the set of available CPs in the GLMP which informs about the physical activities of a person, the developed application provides two different types of linguistic description reports: a daily report which describes linguistically and graphically the physical activities, their duration and intensity throughout the day, and a periodical report that summarizes physical activity trends throughout a specific period of time (typically one week). In both cases it has been applied basic report templates; see in [1] an example of template that change the structure of the report depending on the validity degrees of the sentences. In [24] the developed application provides two different types of linguistic reports: an specific report and a periodical report, in a similar way as we do.

Final reports have to be designed with the help of experts who are following the medical treatment evolution of a patient and are interested in extract some relevant information of the physical activities he/she carries out. Thanks to the enormous potential of the GLMP developed, experts can handle a large amount of information.

Therefore, final report consists in the generation of a *.pdf* document which summarizes through linguistic descriptions the relevant aspects the expert need to know. This linguistic report can be accompanied of those graphics that could help to better understanding of conclusions. The main difference between this technology and the rest is that expert receives information in a friendly way, that is, he/she only needs to read a few text lines to know which lifestyle presents the patient, without having to understand lots of graphics or data difficult to analyze and long-time consumers.

The *Expression Module* has the goal of answering the main questions an expert want to know when he/she is going to design and elaborate a treatment program or giving medical assessment. Some of the frequently asked questions may include the following:

q_1 How much time has the user spent walking/sitting/standing/traveling?

q_2 How much time has the user left the mobile phone?

q_3 When the user walks, at what speed does it?

q_4 How much energy has the user consumed during this week/month?

q_5 Is there any day or days in which the user has any special trend?

The GLMP has to be capable to provide to the *Expression Module* the tools it needs to answer the previous questions. The set of possible sentences the *Expression Module* handles is very extensive and we present some of them:

Daily Report

"Today, the user has spent {very short/short/a normal amount of/quite/too much} time {sitting/standing/walking/traveling}".

"His/her average walking speed has been {low/normal/high}".

"There have been some moments in which the user has walked at high speed".

"There has been t hours/minutes in which he/she has not taken over the mobile phone. During this period of time we consider that he/she was sitting to estimate the energy consumption.".

"The user has burned {few/enough/many} calories, most of them {sitting/standing/walking}".

...

Periodical Report

Weekly Report

"This week the user has consumed {less/the same/more} energy than it was provided".

"This week the user has walked {less/the same/more} time than it was provided".

"This week the user has been {sitting/standing} most of time".

"Day_x and Day_y the user has spent much {less/more} time {walking/sitting/standing/traveling} than other days".

"Day_z the user has spent much {less/more} energy that the rest of weekdays".

"Energy consumption has been very similar every days of the week".

...

Monthly Report

"Usually, on weekends the user walks much more time than the rest of weekdays".

"Generally, Day_x and Day_y of the week the user spent to much time {sitting/standing/traveling}".

...

Chapter 5

Experimentation: Activity Recognition through Mobile device

This research project has had a high experimentation component during its development phase. The process of obtaining the walking speed fitting curve estimation is explained in subsection 5.1. This curve allows us to know, in an approximate way, the speed at which the user walks at any moment [13].

To ensure the reliability and accuracy of the developed system we believed advisable to perform a series of tests in which a set of activities were carried out, contrasting the real sequence of activities with the output sequence the application gives. The way to procedure constists of making two different types of experimentation. On the one hand, 10 tests last approximately one hour were developed. In each test the activities carried out and their initial and final times were targeted for next checking. On the other hand, to simulate a real experimentation, we obtained the accelerations generated for a whole day over a full week. Each daily recording period consisted of 10 hours of continuous recording, monitoring the whole day. The main goal of this "real" experimentation resides in demonstrating that significant conclusions can be drawn from the observation of a long periods of time by comparing results, trends an so on. This experiment also allowed us to understand the behavior of the application during recording periods of several hours, and the characteristics of the data volume obtained. Both experiments are explained in subsections 5.2 and 5.3, respectively.

5.1 Walking speed fitting curve estimation

A quadratic curve estimate fits the root mean square of each x, y and z sequence of accelerations and allows us to estimate the walking speed of a person. It is really important to work with the acceleration module because it makes the system independent of mobile position and orientation.

To obtain the walking speed fitting curve we have practised several experiments which consist in acquiring acceleration data from 15 people of diverse characteristics (weight, height...) walking at different speeds, to cover all range of speed possibilities. These people carried a mobile phone with the developed application in a pocket of their trousers.

Fig. 5.1, 5.2, 5.3 and 5.4 show an example of the experiments realized by 4 users, walking at different speeds. We can see how the x, y and z accelerations RMS, and their module, vary depending on the walking speed.

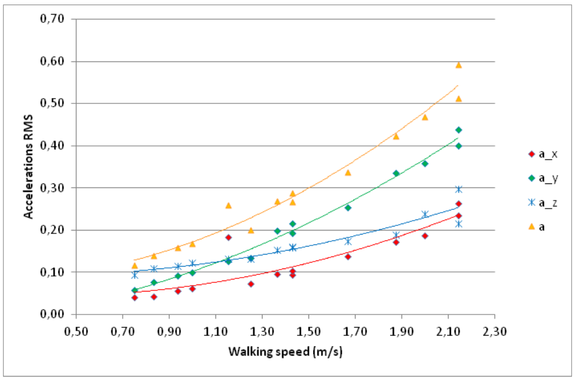


Figure 5.1: User 1 accelerations trend.

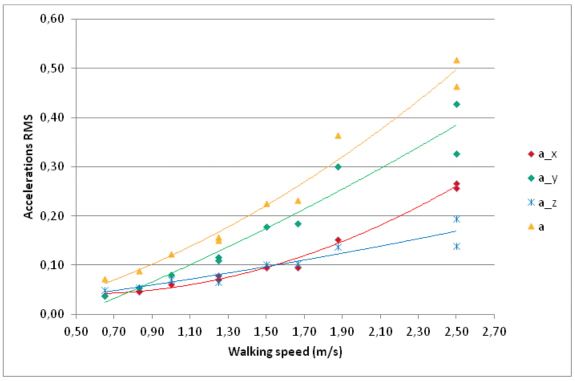


Figure 5.2: User 2 accelerations trend.

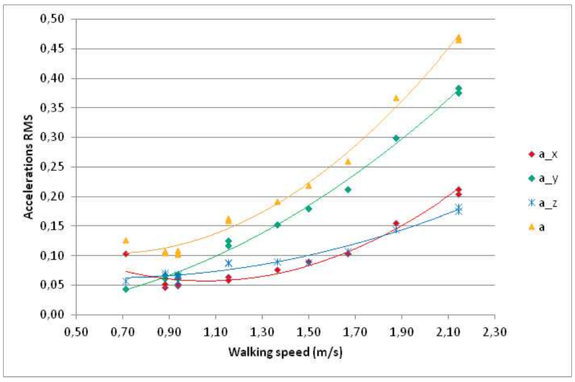


Figure 5.3: User 3 accelerations trend.

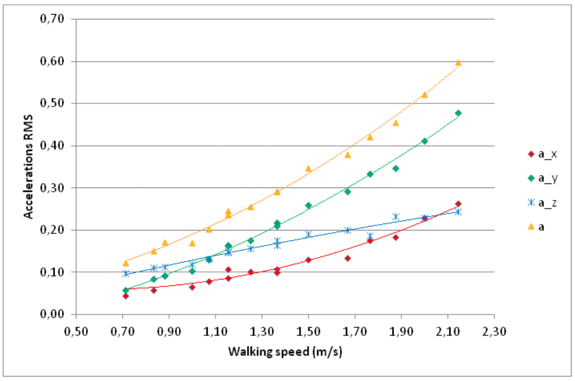


Figure 5.4: User 4 accelerations trend.

We can observe that the fitting curve that approximates the acceleration module (RMS) generated at each walking speed is really similiar among individuals, regardless of their physical characteristics. Due to this fact, combining the 15 acceleration module fitting curves, we obtained a quadratic curve that allows us to estimate pretty well the walking speed of a person at any time. Fig. 5.5 shows graphically the walking speed fitting curve obtained, which corresponds to the following equation with $R^2 = 0.9318$:

$$y = -1.546x^2 + 4.2064x + 0.3605, \tag{5.1}$$

Note that abscissa and ordinate axes of Fig. 5.5 are switched with respect of axes presented in Fig. 5.1, 5.2, 5.3 and 5.4. The reason is that, with the obtained fitting curve, we introduce the acceleration module RMS at each time and the graphic returns the user walking speed.

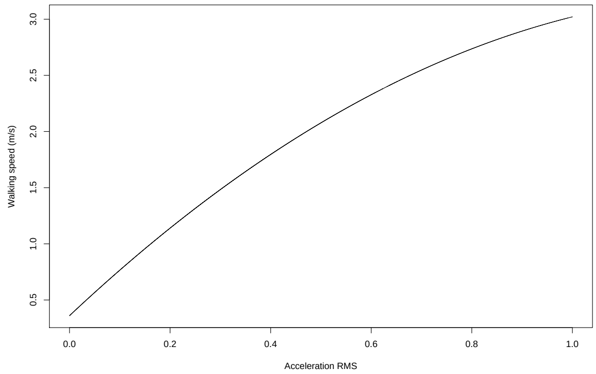


Figure 5.5: Plot of walking speed fitting curve estimation.

5.2 Short-Time Experiments

Along the whole research process, lots of short-time experiments were done to adjust and correct the application program which analyzes input data. In this subsection there are only specified ten of these short-time experiments, used to check the accuracy. Table 5.1 indicates in the first column the name and duration in minutes of each test; in the second column the set of temporally ordered activities developed is shown (these activities could be repeated along the time); in the third one are specified the total number of correctly classified activities; in the forth column are specified the total number of misclassified activities, with their corresponding duration; and finally, the last column shows the percentage of time the activity identification was correct, with respect to the total time shown in first column.

Test names and duration	**Number of activities**	**Number of correctly classified activities**	**Number of misclassified activities**	**% of time correctly classified**
Test 1 (58′)	10	10	1 (1′)	98.28
Test 2 (96′)	9	9	0	100
Test 3 (45′)	7	7	1 (1′)	97.77
Test 4 (65′)	8	8	0	100
Test 5 (58′)	11	10	1 (1′)	98.28
Test 6 (40′)	11	11	0	100
Test 7 (63′)	8	8	0	100
Test 8 (48′)	5	5	0	100
Test 9 (38′)	7	7	0	100
Test 10 (63′)	9	8	1 (1′)	98.41

Table 5.1: Some short-time experimental results

This way to calculate the percentage of error was thought to penalize not only the fact of misclassifying an activity but to penalize the amount of time this classification is wrong. For example, imagine one recording hour with a list of 10 secuencial activities, and the application correctly classifies all of them but, in a precise moment, the application detects an strange acceleration and misclassified it, adding another activity to the list with a very short period of time. With this error measure this misclassification is much less penalized than with other methods, for example, taking only into account the number of correctly/incorrectly classifications. If we compute the average of the ten obtained percentages, we obtain that the **99.27%** of the time the activities are correctly classified, which means that our application has a very high success rate. Analyzing the incorrectly classified activities we could check that these errors typically corresponds to minor mistakes which are not relevant when producing a linguistic report of conclusions, making that the system works pretty well.

All of these experiments were developed with the mobile phone into one of the front trousers pockets. Then, an example of one of these short-time experiments is shown. It corresponds to the test number *6* of the previous Table 5.1. The list of activities carried out is the following:

1.- "The application is started with mobile phone on a table"

2.- "We introduced the mobile phone into the pocket and we *stood* a few minutes"

3.- "We *walked* some minutes at home"

4.- "We *down stairs* to the garage"

5.- "We *walked* to the car"

6.- "We *stood* beside the car keeping some things"

7.- "We got in the car and gave a *drive*"

8.- "When we arrived to the destination, we left car and we *walked* some minutes"

9.- "We walked *upstairs* several floors"

10.- "We *stood* some minutes"

11.- "Finally, we *sat* and some minutes later we stopped the application"

The list of activities we obtain from the application output is the following. Remember that the state *"Out"* corresponds to the state when the mobile phone is not with the user. With the symbol (✓) we indicate that the activity was correctly identified; with the symbol (✗), by contrast, we indicate that the activity is confused by other or it has not been produced.

"19:00 - 19:18 Out (✓)"

"19:18 - 19:19 Standing (✓)"

"19:19 - 19:21 Walking (✓)"

"19:21 - 19:21 Down stairs (✓)"

"19:21 - 19:22 Walking (✓)"

"19:22 - 19:23 Standing (✓)"

"19:23 - 19:38 Traveling (✓)"

"19:38 - 19:41 Walking (✓)"

"19:41 - 19:42 Climbing stairs (✓)"

"19:43 - 19:43 Standing (✓)"

"19:43 - 19:49 Sitting (✓)"

Each experiment provides the previous *"activities diary"*, a linguistic report specifying relevant characteristics of the recording and a illustrative graphic that shows in an intuitive manner the activities identification performed by the application. The graphic obtained in test number *6* is shown in Fig. 5.7, where we can see each activity recognized drowed in its particular color (see legend).

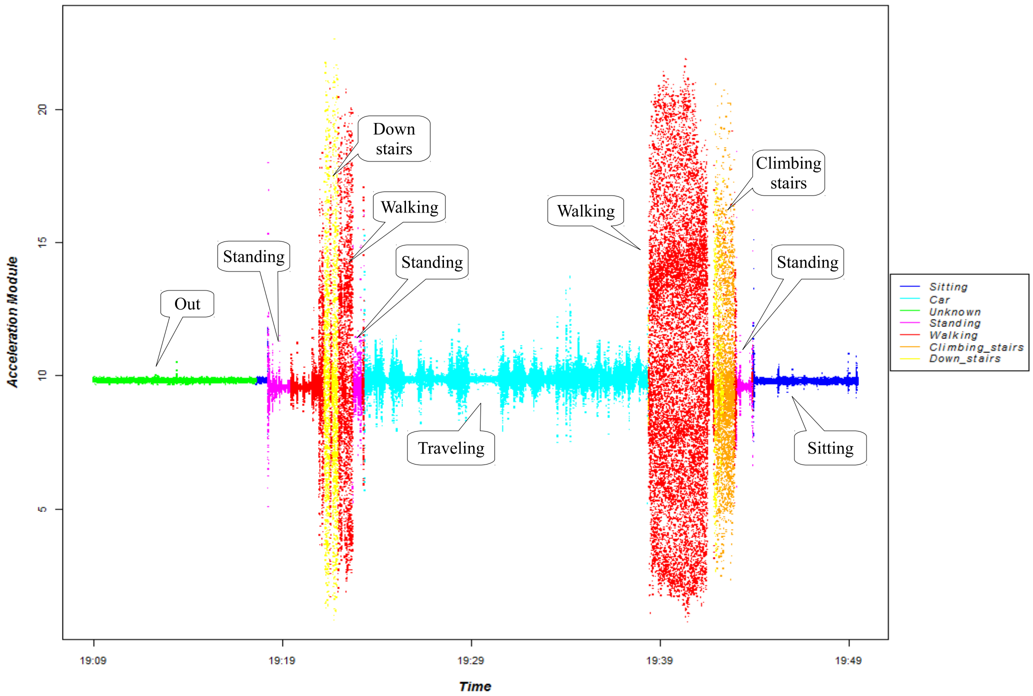


Figure 5.6: Output graphic of short-test number 6.

In addition, this research project highlights by the linguistic ability of generating relevant reports for the user, just as an expert would do. In this short-time experiment, we introduce a set of specifications relative to the amount of time the user should, hypothetically, walk, be sitting, as well as the quantity of energy he/she must spend. This configuration set has to be done by an expert attending to the patient features or pursued objectives. With the established configuration the application generated a linguistic report as following one:

"During these 40 minutes you have spent short time walking. Your average walking speed has been normal."

"In addition, you have spent quite time sitting. You should move more to achieve the objectives!"

"There has been 8 minutes in which you have not taken over the mobile phone. During this period of time we consider that you were sitting to estimate the energy consumption."

"You have burned very few calories, most of them sitting. You should do a little more exercise."

Daily energy consumption, which of course determines the caloric needs, is composed by three important components, *physical activities*, *thermogenic action of food* and *basal metabolism*.

Last factor is the most important in modifying the energy consumption, depending of duration and intensity of the physical activity.

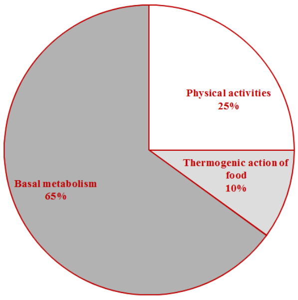


Figure 5.7: Energy consumption components.

Total energy consumption is calculated multiplying the basal metabolic rate (BMR) by the physical activities coeficients, according to the type of the developed activity. In this project, we are only interested in calculating the energy consumption derived from physical activity, excluding the rest of components. Energy consumption is approximately calculated multiplying the energy *consumption factor of each activity* by the *time spent* in this activity and the patient *corporal weight*. Each activity factor and how to calculate the approximate energy consumption has been extracted from [11], a report of a Joint *Food and Agriculture Organization* (FAO)/ *World Health Organization* (WHO)/ *United Nations University* (UNU) Expert Consultation. Table 5.2 shows the set of activity factors used in this application.

$$\textit{Energy consumption for each physical activity} = \textit{Activity factor}\ \left(\frac{kcal}{kg*min}\right)\ \textit{x Time spent (min) x User weight (kg)}$$

Activity	**Activity Factor** $\left(\frac{kcal}{kg*min}\right)$
Sitting	0.028
Standing	0.029
Down stairs	0.097
Climbing stairs	0.254
Slow walking	0.038
Normal walking	0.063
Fast walking	0.106

Table 5.2: Activity factors.

Together with previous information, some interesting graphics are offered to constrast information and extending the knowledge that the linguistic report gives us. Thereby, Fig. 5.8 extends the information giving in the linguistic report about the user walking speed, displaying its trend (in *m/s*) along the time. Fig. 5.9 graphically shows, by means of bar plots, the distribution of energy consumption by activity (in *kcal*), with respect to the total (last bar).

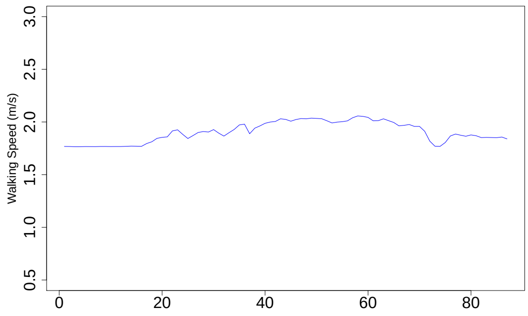


Figure 5.8: User walking speed trend.

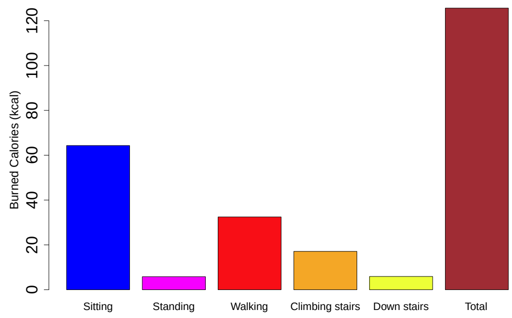


Figure 5.9: Energy consumption by activity.

5.3 Full Day Experiments

Apart from doing short-time experiments we wanted to check our application reliability when the acquisition time corresponds to a long time period, typically 10 hours. The idea is to simulate a real user monitoring, acquiring and storing all the accelerations derived from whole day activities. In addition, to prove that relevant and really interesting conclusions can be extracted from several days oberservation trends, we monitored the user during 7 days.

Expression Module takes information of GLMP, combining each daily output and extracting relevant conclusions from a period of time (some days of special interest for user, a week, half a month, a month or whatever the user/therapist wants/needs). The 7 days experiment produced the following linguistic report:

"During this week the user has consumed less energy than it was provided. In order to meet his/her objectives, he/she should increase his/her activity level."

"Energy consumption has been very similar every days of the week."

"The day of the week that the user has walked less time was on Thursday, however, on Sunday he/she has gone far longer than the other days."

"Tuesday and Saturday the user has spent much more time standing than other days. This time falls within the limits of normality, not worring."

"The user spends too much time sitting. He/she should reduced as much as possible the time spent sitting."

In addition, if the user or the therapist want to ascertain the information provided by the linguistic report, the application offers the opportunity of checking the bar graphics where the comsumption rate for each day of the week, according to the total of each activity, is displayed (Fig. 5.10, 5.11, 5.12, 5.13 and 5.14). All of this information can be combined with some numerical information which specifies the approximate energy consumption (in *kcal*) calculated for each activity. For example, the total energy consumed during the experimental week was approximately equal to 11.000 kcal.

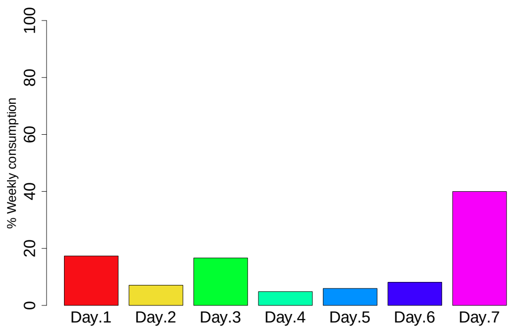


Figure 5.10: Time spent walking.

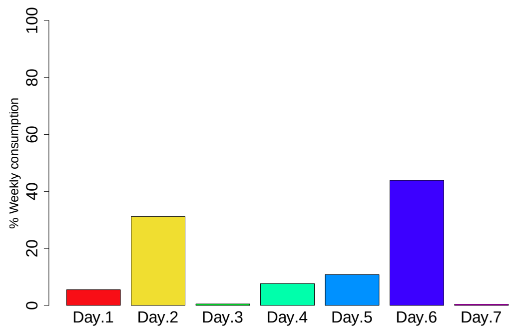


Figure 5.11: Time spent standing.

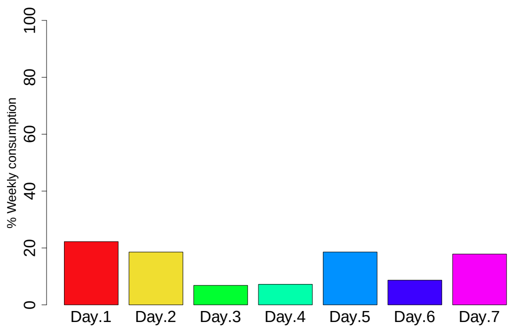


Figure 5.12: Time spent sitting.

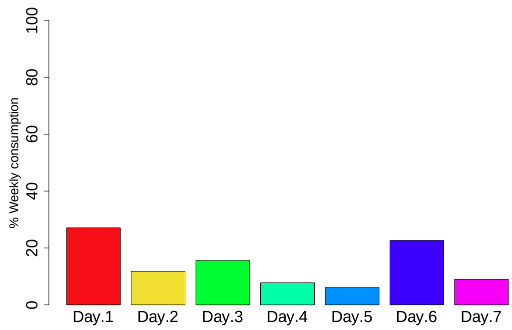


Figure 5.13: Time spent traveling.

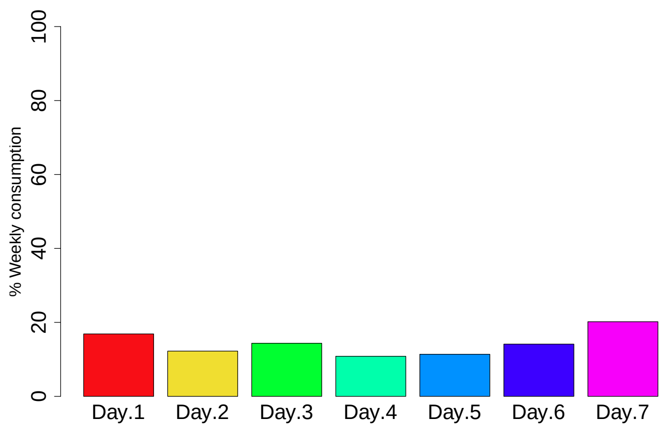


Figure 5.14: Energy consumption respect to the total.

Chapter 6

Current Market Products

People every day is more concerned about their health and appearance. This fact makes that nowadays lots of applications and products are designed to follow the daily physical activity level, energy consumption, etc. This section presents some of these products which are actually in the market, some of them as mobile phone applications and other as specific products.

6.1 Mobile phone applications

Mobile phone applications is a growing field of using your mobile as a free personal trainer and fitness partner. Some applications are developed in this reasearch line, such as *runtastic*, *Android Trainer* or *Strava*, but the most famous one is *Endomondo Sports Tracker* (fig. 6.1).

Figure 6.1: Endomondo Sports Tracker interface.

This application has two different versions: paid and free versions. Paid version reaches between 100.000 and 500.000 downloads; these figures increase to 1.000.000 - 5.000.000 downloads in the free version.

All of these mobile phone applications has something in common, that is, all of them use the GPS sensor to knowing your position and, by this manner, know how much distance you have traveled. Since our Android application was thought to be installed in actual mobile phones, this functionality can be added, but this project research does not include such study because it is something widely studied, preferring to focus in the physical activity identification and linguistic report.

The main difference between out project and all of these developed applications lies in the physical activities identification. We automatically recongnize the activity the user is carrying out. However, other applications needs to know what you are doing, asking to the user to introduce the activity he/she is going to carry out. Most of these applications does not distinguish among different intensities, giving a little accurate information about energy consumption. Their information is mainly limited to combining how much time has the user spent in traveling some distance (time counter and GPS sensor).

In addition, our application also differs to other ones in providing relevant linguistic reports about the patient physical activities, its trends, usual and unusual behaviours or specific information about the evolution inside a medical treatment. This linguistic information can be accompanied by summarizing graphics. Other applications only offers statistical information, based on distance and time consumed, with more or less sofisticated interfaces (music, personal trainer voice, possibility of sharing results on social networks like Facebook...). These commercial applications are directed to a sport people, rather than to an audience that needs to know its daily life routine.

6.2 Fitbit Ultra

The Fitbit Ultra uses a three-dimensional accelerometer, similar to that in the Wii Remote, to sense user movement. The Tracker measures steps taken, distance walked, calories burned, floors climbed, and activity duration and intensity. It uses an OLED display to display this and other information such as the battery level. It also measures sleep quality: how long it takes the wearer to fall asleep, how often they wake up over the course of the night, and how long they are actually asleep.

A wireless base station is included to receive data from the Tracker and also charge its battery. When connected to a computer the base station will upload data to the Fitbit. From the website, a number of features are possible: seeing an overview of physical activity, setting and tracking goals, keeping food and activity logs, and interacting with friends. Use of the website is free.

As our application, Fitbit Ultra needs to be fixed in a trousers pocket or belt. To know the number of steps taken, the device uses a podometer information, which is a very approximate measure since the device is worn the whole day and the most of the time the podometer is going to register wrong measures. To know the number of floors climbed the system includes an altimeter that measures elevation gain in terms of floors, with one floor roughly equivalent to ten feet. This idea does not taken into account if the user up by elevator or stairs and, logically, the energy consumption is not the same. To know how often the user wakes up over the

Figure 6.2: Fitbit Ultra.

course of the night and how long he/she are actually asleep, user needs to slip the Fitbit into a wrist band, and worn on his/her non-dominant hand. As *Endomondo Sports Tracker*, Fitbit Ultra allows to find and add friends, create groups, and share goals with other community members Fitbit.

The main difference between this system and our own application is that, once more, this product does not make linguistic reports about daily physical activities (it only offers the number of steps taken, the number of floors climbed, the number of miles traveled, the number of calories burned and how active the user is). All of this information is extracted from accelerations generated during the whole day, without distinguishing one activity from each other. If we attend to [11], where it is explained that the energy consumption depends not only of the time you spend doing an activity but the own activity and the intensity you carry it out, this way of estimating the energy consumption seems somewhat unreliable.

6.3 Nike+ FuelBand

The Nike+ FuelBand is an accelerometer worn on the wrist, translating the wearer's daily movements into proprietary "Nike Fuel" in order to track their activity and energy expenditures.

Figure 6.3: Nike+ FuelBand

The Nike+ FuelBand has bluetooth equipment and can be connected and sync with a computer or mobile phone. The app will show a diagram of user's daily exercise and encourage people to keep fit by acheiving the goal that established by the Nike+ FuelBand application. User sets his/her daily goal and Nike+ FuelBand tracks his/her progress, lighting up from red to green throughout the day.

As Fitbit does, this device only see the degree of user activity, indicating when the activity degree goal has been reached. This is basically done taking into account the variations in the wristband accelerometer, and this may be affected by many types of situations. The application does not identify whether the user is walking, climbing stairs or sitting in his/her desk moving his/her arms.

Again, our automatic linguistic report generation represents an advantage over the way to present data of Nike+ FuelBand. In this case the number of calories, steps, distance traveled and activity degree are presented. It does not espefify which activities the user carries out, nor the time spent in each one. As in previous cases, Nike + FuelBand offers much less information and less accurate than our system, being a system specially designed for sports people.

Figure 6.4: Nike+ FuelBand interface examples

Chapter 7

Concluding Remarks

7.1 Conclusions

In this Master's Project has been successfully achieved the main goal presented in the *Introduction*, which consisted of modeling a computational application based on our research in the field of the CTP. We have shown how a GLMP allows generating relevant linguistic descriptions of complex phenomena. We have developed the skills and techniques learned during this Master, giving a demonstration of the academic results achieved during the development of this work.

We have focused our efforts in the **development of a GLMP which describes the most common physical activities of a person** during a day. Information that feeds the first order computational perceptions comes from the accelerations produced by the user in his/her daily life developing, acquired by triaxial accelerometers. This information is aggregated and combined, generating a set of sentences which are collected by the *Validity* and *Expresion* modules to give them a validity degree and generating relevant linguistic reports, respectively. Periodical reports can be obtained aggregating the output generated by the GLMP of each recording period. Thereby, useful weekly/monthly linguistic reports can be provided, allowing the extraction of conclusions derived from long time periods observations (trends, habits, manners...).

Practical application lies in the use of current mobile phones, which have embedded large number of sensors, **to acquire and store user accelerations**. Monitoring the body posture and the physical activity of a person can be useful for applications such as medical assistance, trying to identify abnormalities in the course of daily activity. Using mobile phones' accelerometers allow the health monitoring of a patient during a rehabilitation or treatment, acquiring data in an inexpensive and non-intrusive way.

We have used Android based mobile phones as platform for developing a simple application which acquires and stores data in a simple and intuitive way. In order to validate the accuracy of the activity recognition system performed **we have practised two different types of experiments**. On the one hand, we analyzed 10 short tests. For each test, the user recorded the accelerations and took note of the activities performed during the sessions, obtaining an average of correct classification rates equal to 99.27%. On the other hand, we wanted to check the application reliability under full day recordings, acquiring 10 hours of data every day. The goal of this second experiment was to probe the possibility of aggregating these full day recordings to extract relevant conclusions from long time treatments periods, typically weeks or months. Both experiments allow us to demonstrate the viability of our approach to create real commercial applications.

7.2 Future Work

This research project is a subject constantly growing and it has a great potential to be improved. We think that actual market products, like shown in Section 6, represents a business oportunity through joint collaboration. Every device capable of acquiring data from sensors (accelerometers or any other) are susceptible of making a relevant linguistic report which summarizes the collected information. Anyway, next list includes future works needed to improve actual project, allowing it to compete in the market. Some of these works are already underway, expanding the application supply and its growth.

- One of the first things we want to add to the actual application is the possibility of **detecting falls**. This new activity identification would be very useful in physical rehabilitation treatments or older people tracking.

- Accordance with the above idea, it could be interesting to combine the accelerometer information with the **GPS** measurements. This improvement allows to know the path followed in a walk and the total distance traveled by the user.

- A good way of communication between the user and the therapist who is following him/her, may be the creation of a **Web Server** where data could be uploaded and stored every day. Both user and therapist could access to the information through the application web page, serving as system to exchange opinions, advices, treatment changes, etc.

- When a whole day is monitored, the amount of data acquired and stored is really huge. Since the data analysis treatment is off-line, this amount of data had to be sent to the Central Web Server, being a problem to send so much information. To solve this trouble, we believe essential to develop a codification type to send the information. One type of codification could be storing only accelerations changes, removing those repeated accelerations in time. Another interesting data reduction could consist of increasing the sample period, which is actually fixed to 15 miliseconds.

- In recent years, **social networks** are having a great impact on society and a great amount of information is shared through them. An interesting proposal, that applications such as shown in Section 6 practice, would be the possibility that users who use our application will share their linguistic summaries reports in their favorite social networks. This improvement would be translated in a big advertising campaign for promote the application among the millions of users with a social network account.

- If based Android application is going well, to develop an application for **new operating systems**, like iPhone OS or Symbian OS, would be interesting.

Appendix A

Short-Time Experiments Results

Performed Activities	**Linguistic Report Activities**
"Mobile on table"	*"17:47 - 18:13 Out (✓)"*
"*Walking* at home"	*"18:13 - 18:14 Walking (✓)"*
"*Down stairs* to the garage"	*"18:14 - 18:14 Down stairs (✓)"*
	"18:14 - 18:14 Walking (✓)"
	"18:14 - 18:15 Down stairs (✓)"
"*Walking* to the car"	*"18:15 - 18:15 Walking (✓)"*
"*Standing* beside the car keeping some things"	*"18:15 - 18:16 Standing (✓)"*
"*Traveling* by car"	*"18:16 - 18:31 Traveling (✓)"*
"*Walking*"	*"18:31 - 18:33 Walking (✓)"*
"*Climbing stairs* to home"	*"18:33 - 18:33 Down stairs (✗)"*
	"18:33 - 18:34 Climbing stairs (✓)"
"*Walking* and *standing* at home"	*"18:34 - 18:35 Standing (✓)"*
	"18:35 - 18:35 Walking (✓)"
	"18:35 - 18:35 Standing (✓)"
	"18:35 - 18:35 Walking (✓)"
	"18:35 - 18:36 Standing (✓)"
"Mobile on table"	*"18:36 - 18:45 Out (✓)"*

Table A.1: Short-time experiment 1

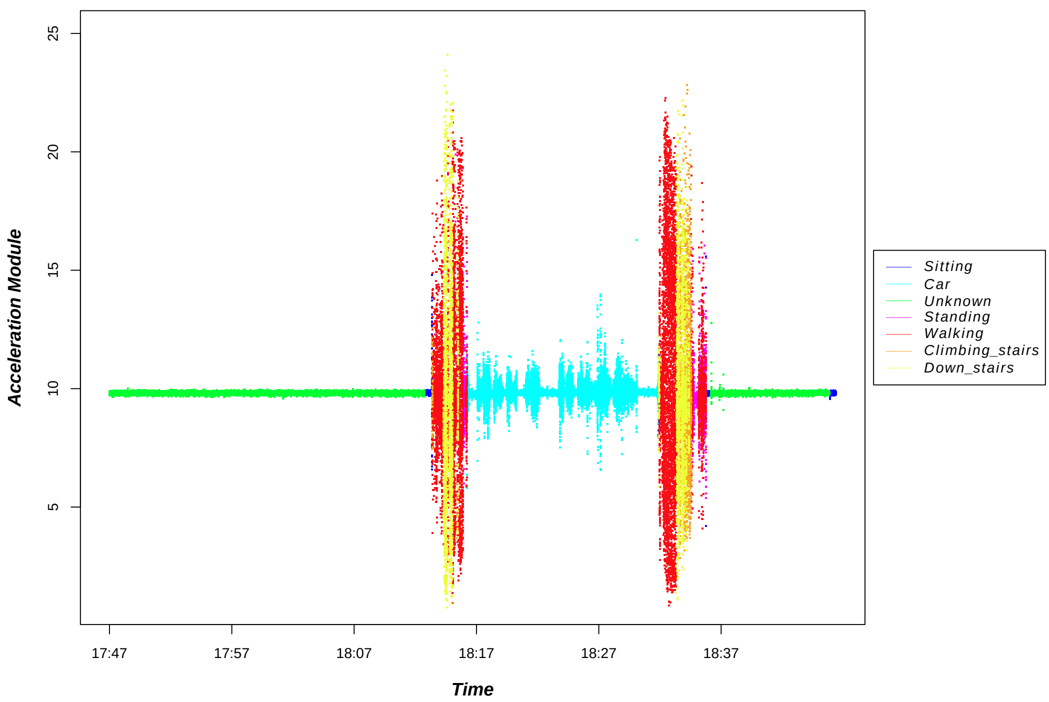


Figure A.1: Short-time experiment 1

Performed Activities	Linguistic Report Activities
"Mobile on table"	"*20:22 - 20:35 Out* (✓)"
"*Walking* and *standing* at home"	"*20:35 - 20:36 Standing* (✓)" "*20:36 - 20:38 Walking* (✓)"
"*Down stairs* to the street"	"*20:38 - 20:38 Down stairs* (✓)"
"*Walking* at the street"	"*20:39 - 21:05 Walking* (✓)"
"*Climbing stairs* to home"	"*21:05 - 21:06 Climbing stairs* (✓)"
"*Standing* and *walking* at home"	"*21:06 - 21:07 Standing* (✓)" "*21:07 - 21:07 Walking* (✓)" "*21:07 - 21:08 Standing* (✓)"
"Mobile on table"	"*18:36 - 18:45 Out* (✓)"

Table A.2: Short-time experiment 2

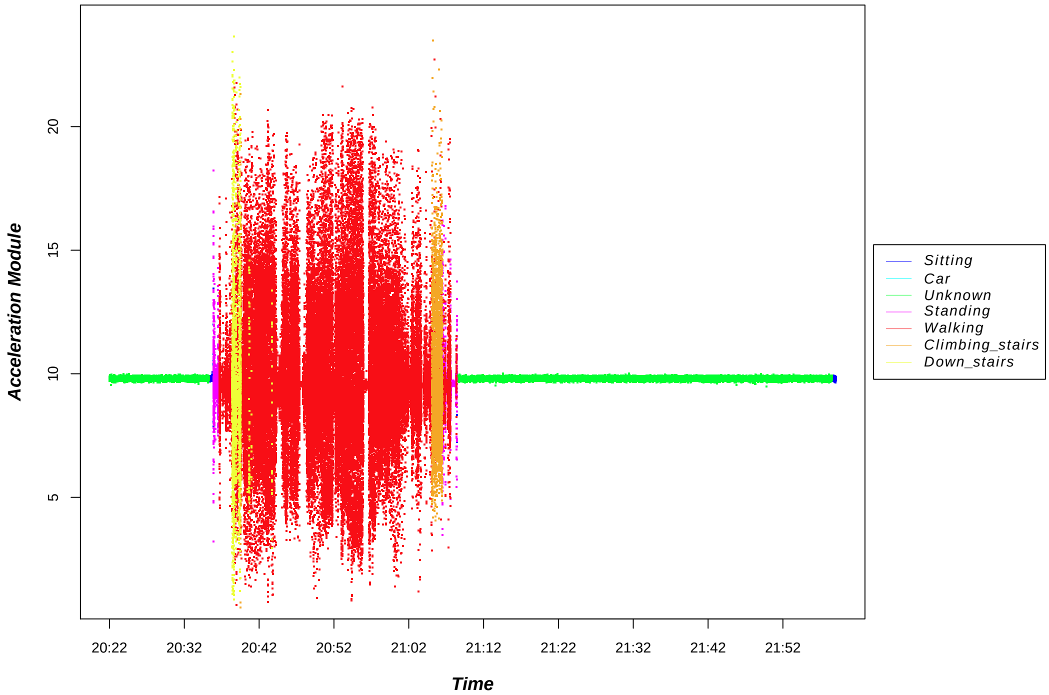


Figure A.2: Short-time experiment 2

Performed Activities	**Linguistic Report Activities**
"Mobile on table"	"*22:08 - 22:16 Out* (✓)"
"*Walking* to the car"	"*22:16 - 22:21 Walking* (✓)"
"*Traveling* by car"	"*22:21 - 22:21 Climbing stairs* (✗)" "*22:21 - 22:35 Traveling* (✓)"
"*Walking* and *standing* in the street"	"*22:35 - 22:40 Walking* (✓)" "*22:40 - 22:41 Standing* (✓)" "*22:41 - 22:45 Walking* (✓)"
"Climbing stairs"	"*22:45 - 22:45 Climbing stairs* (✓)"
"*Walking* and *standing* in the cinema"	"*22:45 - 22:46 Standing* (✓)" "*22:46 - 22:46 Walking* (✓)"
"*Sitting* in the cinema"	"*22:46 - 22:53 Sitting* (✓)"

Table A.3: Short-time experiment 3

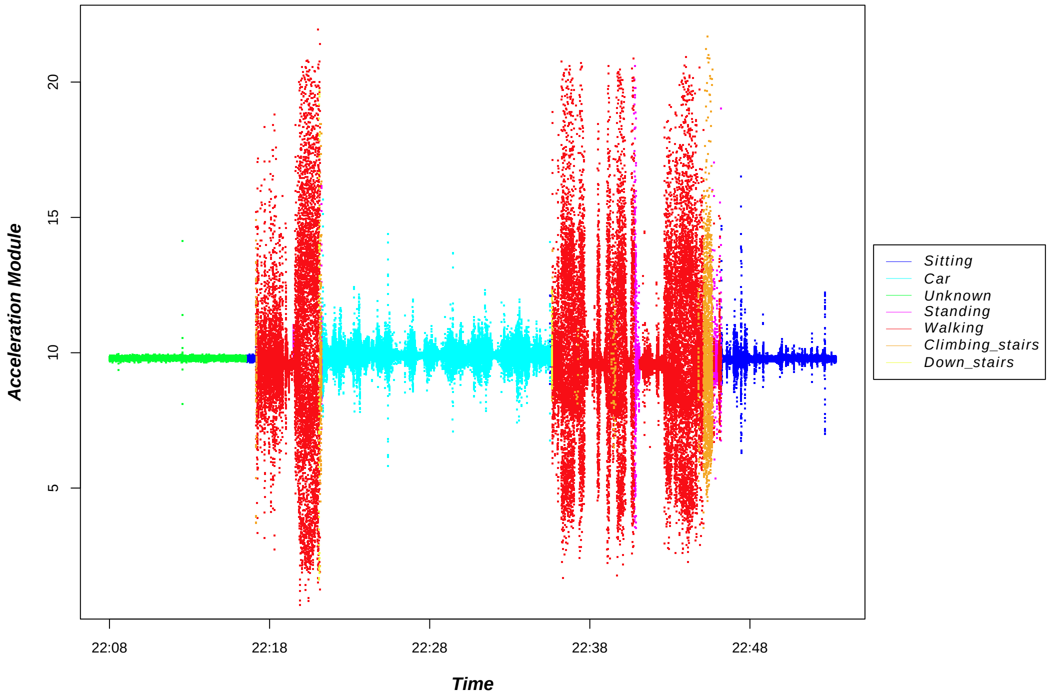


Figure A.3: Short-time experiment 3

Performed Activities	Linguistic Report Activities
"*Sitting* in the cinema"	"*00:42 - 00:53 Sitting* (✓)"
	"*00:53 - 01:00 Walking* (✓)"
"*Walking* and *standing* to the car"	"*01:00 - 01:00 Standing* (✓)" "*01:00 - 01:06 Walking* (✓)"
"*Traveling* by car"	"*01:07 - 01:20 Traveling* (✓)"
"*Walking* to home"	"*01:20 - 01:21 Walking* (✓)"
"*Down some stairs* at street"	"*01:21 - 01:21 Down stairs* (✓)"
	"*01:21 - 01:22 Walking* (✓)"
"*Walking* and *standing* in the street" "*Walking* and *standing* in the cinema"	"*22:45 - 22:46 Standing* (✓)" "*01:22 - 01:26 Standing* (✓)" "*01:26 - 01:26 Walking* (✓)"
"*Standing* at home"	"*01:26 - 01:27 Standing* (✓)"
"Mobile on table"	"*18:36 - 18:45 Out* (✓)"

Table A.4: Short-time experiment 4

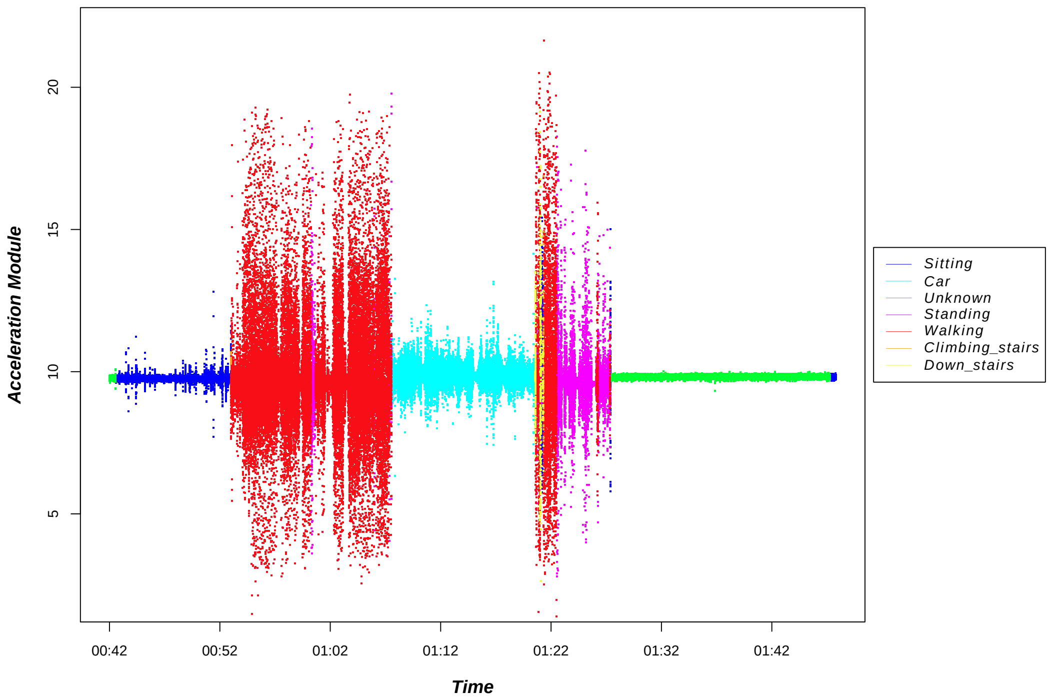


Figure A.4: Short-time experiment 4

Performed Activities	Linguistic Report Activities
"*Standing* at home"	"*09:40 - 09:41 Standing* (✓)"
"*Walking* at the street"	"*09:41 - 09:43 Walking* (✓)"
	"*09:43 - 09:43 Down stairs* (✓)"
"*Down stairs* to the street"	"*09:43 - 09:44 Walking* (✓)" "*09:44 - 09:44 Down stairs* (✓)" "*09:44 - 09:44 Walking* (✓)" "*09:44 - 09:44 Down stairs* (✓)"
"*Walking* to the car and *standing* beside"	"*09:44 - 09:45 Walking* (✓)" "*09:45 - 09:46 Standing* (✓)"
"*Traveling* by car"	"*09:46 - 09:57 Traveling* (✓)"
"*Walking* and *standing* in the garage"	"*09:57 - 10:00 Walking* (✓)" "*10:00 - 10:01 Standing* (✓)" "*10:01 - 10:16 Walking* (✓)"
"*Climbing stairs* to home"	"*10:16 - 10:16 Climbing stairs* (✓)"
"*Walking* to home"	"*10:16 - 10:17 Walking* (✓)"
"*Walking* and *standing* at home"	"*10:17 - 10:24 Walking* (✓)" "*10:24 - 10:24 Down stairs* (✗)" "*10:24 - 10:25 Walking* (✓)" "*10:25 - 10:25 Standing* (✓)" "*10:25 - 10:26 Walking* (✓)" "*10:26 - 10:26 Standing* (✓)" "*10:26 - 10:26 Walking* (✓)" "*10:26 - 10:26 Standing* (✓)" "*10:26 - 10:27 Walking* (✓)"
"*Sitting*"	"*10:27 - 10:41 Sitting* (✓)"

Table A.5: Short-time experiment 5

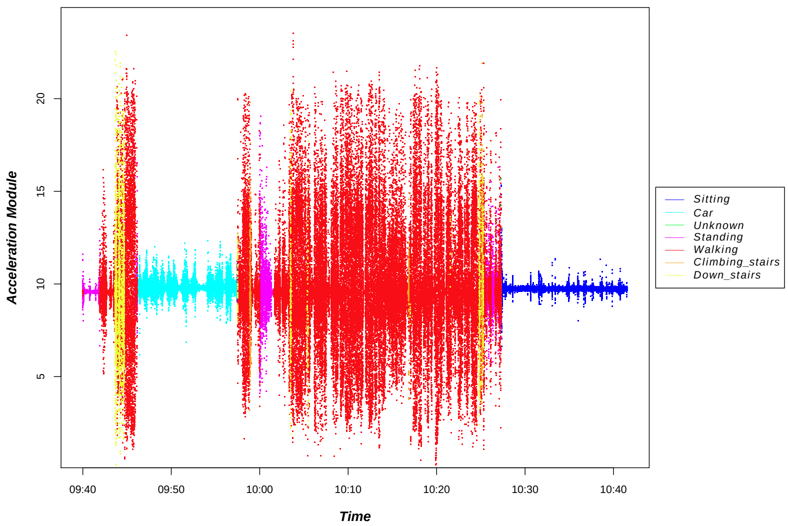


Figure A.5: Short-time experiment 5

Performed Activities	**Linguistic Report Activities**
"Mobile on table"	*"19:09 - 19:17 Out (✓)"*
"*Standing* at home"	*"19:18 - 19:19 Standing (✓)"*
"*Walking* to the garage"	*"19:19 - 19:21 Walking (✓)"*
"*Down stairs* to the garage"	*"19:21 - 19:21 Down stairs (✓)"*
"*Walking* to the car and *standing* beside"	*"19:21 - 19:22 Walking (✓)"* *"19:22 - 19:23 Standing (✓)"*
"*Traveling* by car"	*"19:23 - 19:38 Traveling (✓)"*
"*Walking* at the street'	*"19:38 - 19:41 Walking (✓)"*
"*Climbing stairs* to home"	*"19:42 - 19:42 Climbing stairs (✓)"*
"*Walking* and *standing* at home"	*"19:42 - 19:43 Walking (✓)"* *"19:43 - 19:43 Standing (✓)"*
"*Sitting*"	*"19:43 - 19:49 Sitting (✓)"*

Table A.6: Short-time experiment 6

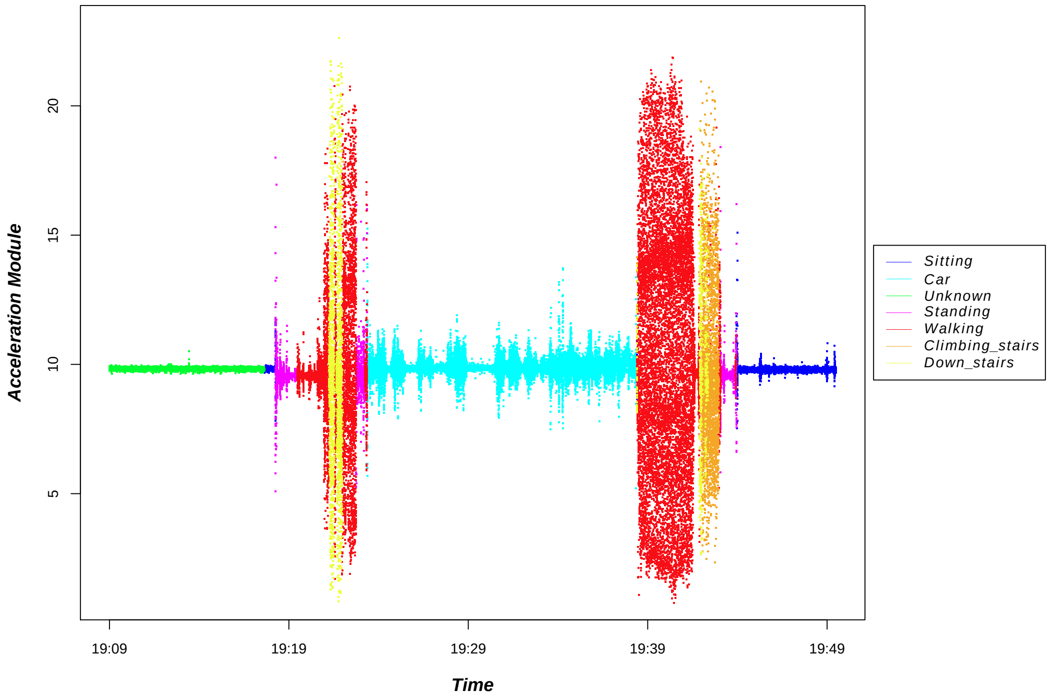


Figure A.6: Short-time experiment 6

Performed Activities	**Linguistic Report Activities**
"*Down stairs* to the street"	"*19:51 - 19:51 Down stairs* (✓)"
"*Walking* to the car"	"*19:51 - 19:56 Walking* (✓)"
"*Traveling* by car"	"*19:56 - 19:59 Traveling* (✓)"
"*Sitting* in the car"	"*19:59 - 20:03 Sitting* (✓)"
"*Traveling* by car"	"*20:03 - 20:16 Traveling* (✓)"
"*Walking* and *standing* in the street"	"*20:16 - 20:20 Walking* (✓)" "*20:20 - 20:23 Standing* (✓)" "*20:23 - 20:24 Walking* (✓)"
"*Sitting*"	"*20:24 - 20:54 Sitting* (✓)"

Table A.7: Short-time experiment 7

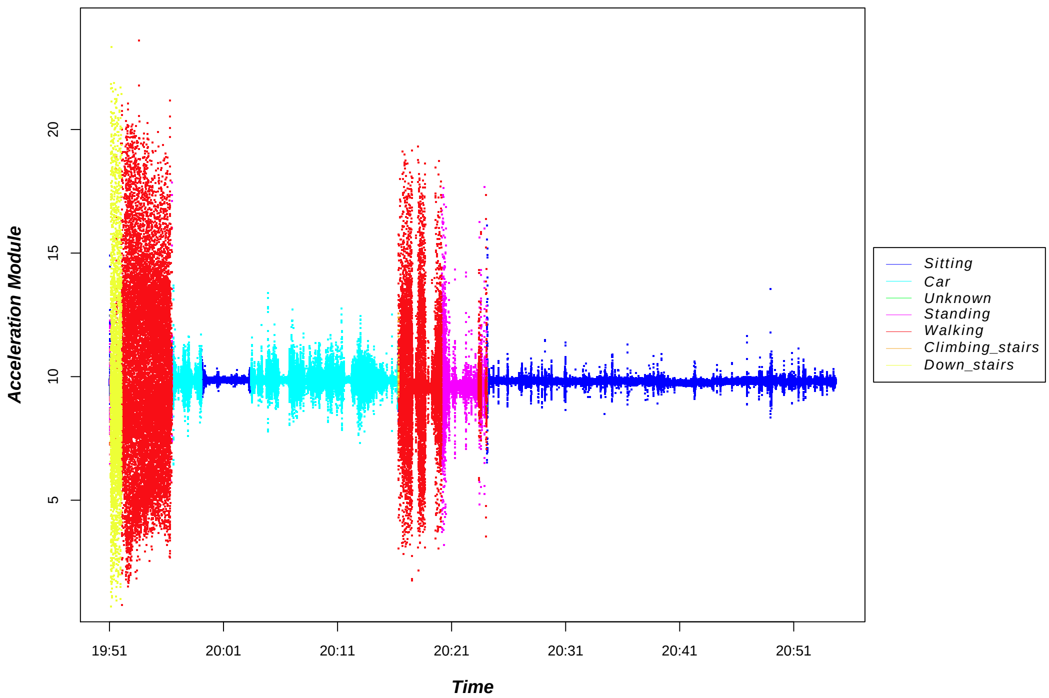


Figure A.7: Short-time experiment 7

Performed Activities	**Linguistic Report Activities**
"*Walking* at the street"	"*20:55 - 20:55 Walking* (✓)"
"*Climbing some stairs*"	"*20:55 - 20:56 Climbing stairs* (✓)"
"*Walking* and *standing* in the street"	"*20:56 - 20:58 Walking* (✓)" "*20:58 - 21:01 Standing* (✓)" "*21:01 - 21:05 Walking* (✓)" "*21:05 - 21:05 Standing* (✓)" "*21:05 - 21:18 Walking* (✓)" "*21:18 - 21:18 Standing* (✓)" "*21:18 - 21:21 Walking* (✓)" "*21:21 - 21:21 Standing* (✓)" "*21:21 - 21:24 Walking* (✓)" "*21:24 - 21:24 Standing* (✓)" "*21:24 - 21:26 Walking* (✓)" "*21:26 - 21:26 Standing* (✓)" "*21:26 - 21:27 Walking* (✓)" "*21:27 - 21:27 Standing* (✓)"
"*Traveling* by car"	"*21:27 - 21:40 Traveling* (✓)"
"*Sitting*"	"*21:40 - 21:43 Sitting* (✓)"

Table A.8: Short-time experiment 8

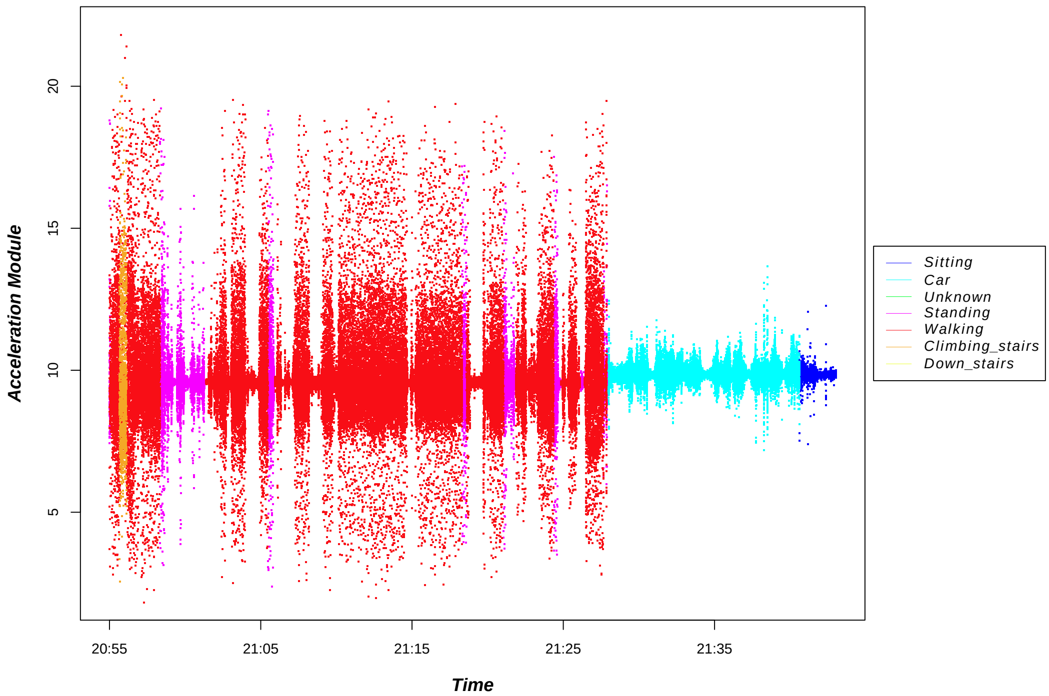


Figure A.8: Short-time experiment 8

Performed Activities	Linguistic Report Activities
"Mobile on table"	*"09:52 - 10:12 Out (✓)"*
"*Walking* at home"	*"10:13 - 10:13 Walking (✓)"*
"*Down stairs* to the garage"	*"10:13 - 10:14 Down stairs (✓)"* *"10:14 - 10:14 Walking (✓)"* *"10:14 - 10:14 Down stairs (✓)"*
"*Walking* to the car and *standing* beside"	*"10:14 - 10:15 Walking (✓)"* *"10:15 - 10:15 Standing (✓)"*
"*Traveling* by car"	*"10:15 - 10:27 Traveling (✓)"*
"*Sitting*"	*"10:27 - 10:30 Sitting (✓)"*

Table A.9: Short-time experiment 9

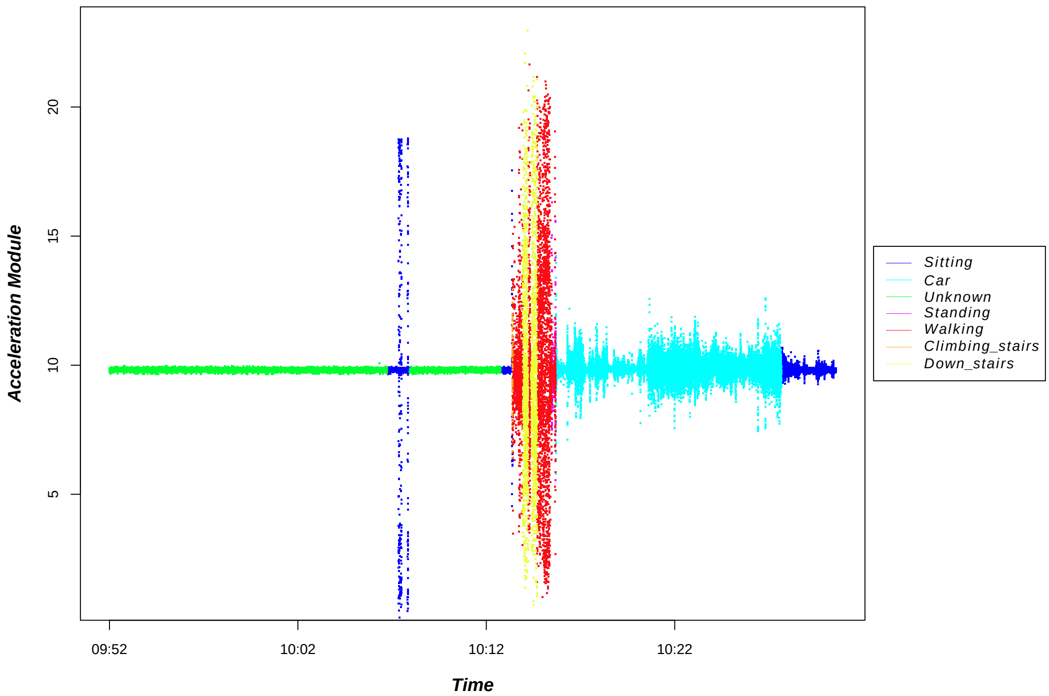


Figure A.9: Short-time experiment 9

Performed Activities	Linguistic Report Activities
"*Traveling* by car"	"*10:44 - 10:54 Traveling* (✓)"
"*Walking* at the street"	"*10:54 - 10:56 Walking* (✓)"
"*Climbing stairs* to home"	(✗)
"*Walking* and *standing* at home"	"*10:57 - 10:57 Walking* (✓)" "*10:57 - 10:57 Standing* (✓)" "*10:57 - 10:58 Walking* (✓)" "*10:58 - 10:58 Standing* (✓)" "*10:58 - 10:58 Walking* (✓)" "*10:58 - 10:58 Standing* (✓)" "*10:58 - 10:59 Walking* (✓)" "*10:59 - 10:59 Standing* (✓)"
"*Sitting*"	"*10:59 - 11:01 Sitting* (✓)"
"*Standing* and *walking* at home"	"*11:01 - 11:04 Standing* (✓)" "*11:04 - 11:04 Walking* (✓)" "*11:04 - 11:05 Standing* (✓)"
"*Sitting*"	"*11:05 - 11:20 Sitting* (✓)"
"*Standing* and *walking* at home"	"*11:20 - 11:20 Standing* (✓)" "*11:20 - 11:20 Walking* (✓)"
"*Sitting*"	"*11:20 - 11:47 Sitting* (✓)"

Table A.10: Short-time experiment 10

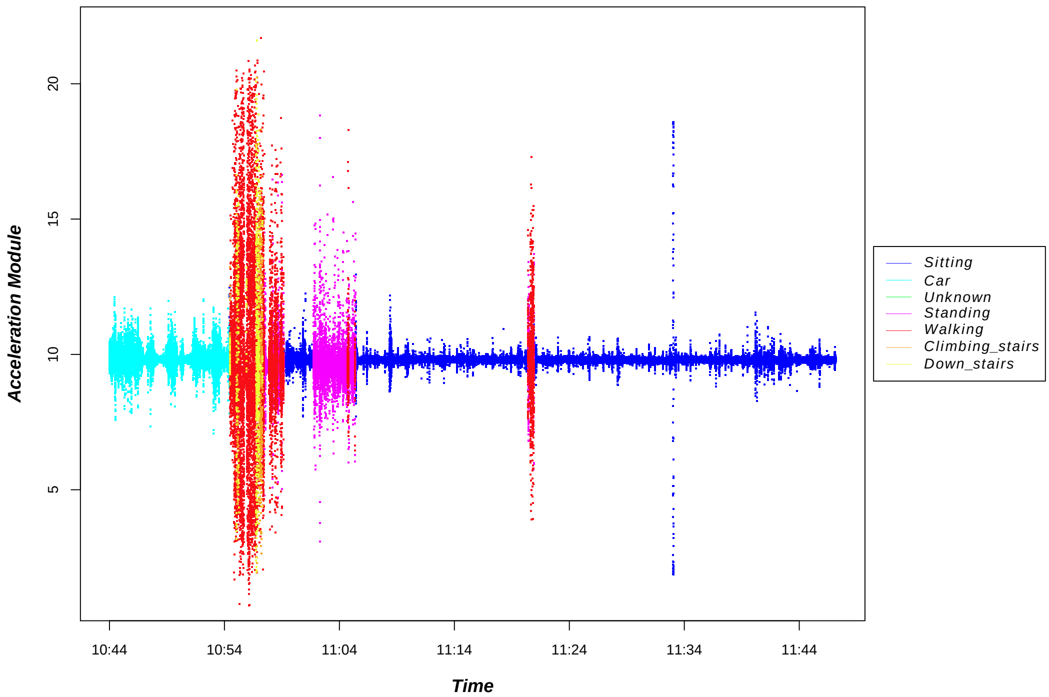


Figure A.10: Short-time experiment 10

Appendix B

Full Day Experiments Results

Report of Day 1

"Today, you have spent a normal amount of time walking. Your average walking speed has been normal."

"In addition, you have spent quite time sitting. You should move more to achieve the objectives!"

"There has been 3 hours and 14 minutes in which you have not taken over the mobile phone. During this period of time we consider that you were sitting to estimate the energy consumption."

"You have burned enough calories, most of them sitting and walking."

Report of Day 2

"Today, you have spent short time walking. Your average walking speed has been normal."

"In addition, you have spent quite time sitting."

"It is worth noting that you have spent quite time standing."

"There has been 2 hours and 52 minutes in which you have not taken over the mobile phone. During this period of time we consider that you were sitting to estimate the energy consumption."

"You have burned few calories, most of them sitting and standing. You should do a little more exercise."

Report of Day 3

"Today, you have a normal amount of time walking. Your average walking speed has been normal."

"In addition, you have spent a normal amount of time sitting and very short time standing."

"There has been 5 hours and 24 minutes in which you have not taken over the mobile phone. During this period of time we consider that you were sitting to estimate the energy consumption. You should carry the mobile phone with you!"

"You have burned enough calories, most of them walking."

Report of Day 4

"Today, you have spent very short time walking. Your average walking speed has been low."

"In addition, you have spent a normal amount of time sitting."

"There has been 4 hours and 43 minutes in which you have not taken over the mobile phone. During this period of time we consider that you were sitting to estimate the energy consumption. You should carry the mobile phone with you!"

"You have burned few calories, most of them sitting. You should do a little more exercise."

Report of Day 5

"Today, you have spent short time walking. Your average walking speed has been normal."

"In addition, you have spent quite time sitting. You should move more to achieve the objectives!"

"There has been 4 hours and 59 minutes in which you have not taken over the mobile phone. During this period of time we consider that you were sitting to estimate the energy consumption. You should carry the mobile phone with you!"

"You have burned few calories, most of them sitting. You should do a little more exercise."

Report of Day 6

"Today, you have spent short time walking. Your average walking speed has been normal and sometimes high."

"In addition, you have spent a normal amount of time sitting. You have spent quite time traveling."

"It is worth noting that you have spent too much time standing."

"There has been 2 hours and 29 minutes in which you have not taken over the mobile phone. During this period of time we consider that you were sitting to estimate the energy consumption."

"You have burned few calories, most of them sitting and standing. You should do a little more exercise."

Report of Day 7

"Today, you have spent too much time walking. Your average walking speed has been normal and sometimes high."

"In addition, you have spent quite time sitting and very short time standing."

"There has been 4 hours and 27 minutes in which you have not taken over the mobile phone. During this period of time we consider that you were sitting to estimate the energy consumption."

"You have burned many calories, most of them walking. Well done!"

Weekly Report

"During this week the user has consumed less energy than it was provided. In order to meet his/her objectives, he/she should increase his/her activity level."

"Energy consumption has been very similar every days of the week."

"The day of the week that the user has walked less time was on Thursday, however, on Sunday he/she has gone far longer than the other days."

"Tuesday and Saturday the user has spent much more time standing than other days. This time falls within the limits of normality, not worring."

"The user spends too much time sitting. He/she should reduced as much as possible the time spent sitting."

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