# Stroke Rehabilitation: detection of finger movements*

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**Abstract.** For several stroke cases, rehabilitation focuses on the pincer movements and grasps with the index and thumb fingers. The improvements in the coordination between these fingers guides the recovery of the subject. Obtaining a good measurement of these opening and closing movements is still unsolved, with robotic based high cost solutions. This research includes a preliminary study that analyses the use of tri-axial accelerometers to measure these movements and to evaluate the performance of the subjects. Under certain constraints, the solution has been found valid to detect the finger opening-closing pincer movements.

**Keywords:** Stroke Rehabilitation · Pincer movements · Hybrid Artificial Intelligent Systems.

## 1 Introduction

Stroke rehabilitation includes many different aspects according to the development of the onset itself and its consequences on the patient [12]. Indeed, the impact of the new technologies and developments has promoted a wide variety of methods and techniques using portable and relatively low-cost equipment that allows the patients to perform the rehabilitation in their own homes [6, 7, 17]. However, the main part of the rehabilitation is still carried out on health care centers, with or without specialized equipment. For instance, a robotic equipment was employed to perform and evaluate the rehabilitation of upper limbs (including the wrists and hands) [20]. Similarly, robotic systems were proposed for rehabilitation in [21]. In [2, 8], the authors proposed the combination of virtual reality with robot-assisted therapy to improve the adaptive control.

The rehabilitation includes exercises such as cone stacking [5], as well as many other types of exercises according to the part of the body that needs to be tackled. On this study, we focus on the rehabilitation of the hand fingers with patients that had suffered from a stroke [11, 19]. This type of exercises has

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been analyzed in depth for Parkinson Disease patients [9, 16]. In this context, there have been published some studies proposing robotic-based rehabilitation. In some cases, the authors focused on acute paralyzed patients [15] using a robotic glove that assists the patient in moving the fingers. A similar study analyzes how to develop a robotic-assisted globe to help in the rehabilitation of the hand fingers [14].

The solution of exoskeletons are mainly expensive and difficult to deploy; therefore, low complexity exoskeleton alternatives have also been proposed [3]. A completely different option is to assist the physiotherapist in measuring the performance of the rehabilitation patients. As an example, the authors proposed using rope-embedded strain sensors to measure the performance of the patients when closing or extending the index and thumb fingers, comparing the measurements with video recording [10].

In this study, we focus on assisting the physiotherapists in the rehabilitation of the patients when producing the pincer movement with the index and thumb fingers. To do so, we propose a simple sensing device to measure the improvements in the coordination between the index and thumb fingers. The sensing device includes a tri-axial accelerometer (3DACC) to register the changes in the acceleration of the index finger in order to decide whether the movement is being correct or not. This approach has been found valid with a specific configuration of the hand and fingers, tracking the movements of the user. For a specific participant, the use of thresholds were found valid, although not general.

This study is organized as follows. The next Section deals with the description of the device and the basis of the calculations, the data gathering and the experimental set up is also detailed. Section 3 copes with the results and the discussion on these results. Finally, the main conclusions and future work are detailed.

## 2 Material and Method

This section copes with the description of the device that is proposed in this study to determine the finger movements and the initial experimentation performed to validate the idea. The next Subsection describes the device, then the simple algorithm to detect the finger movements is detailed and finally the experimental set-up is explained.

### 2.1 A 3DACC device to measure the finger movements

This research proposes the use of 3DACC to detect the angular movement of the index and thumb fingers when performing the activity of pincer grasping, that is, closing and opening the arc between those fingers. 3DACC based wearable devices have been profusely employed in the detection or diagnosing of illnesses as well as human activities of daily living [13, 4, 1, 18]. Basically, they are cheap, do not require much effort in deploying and the measurement is reliable.

The developed prototype is shown in the left part of Fig. 1, where a 3DACC is placed on each finger end. The right part of Fig. 1 depicts the orientation of the 3DACC axes when properly placed on a participant. Each of the two external elements consists of a MEMS (microelectromechanical system) 3DACC sensor, configured with a full scale of $\pm 2g$ and a sampling frequency of 16 Hz.

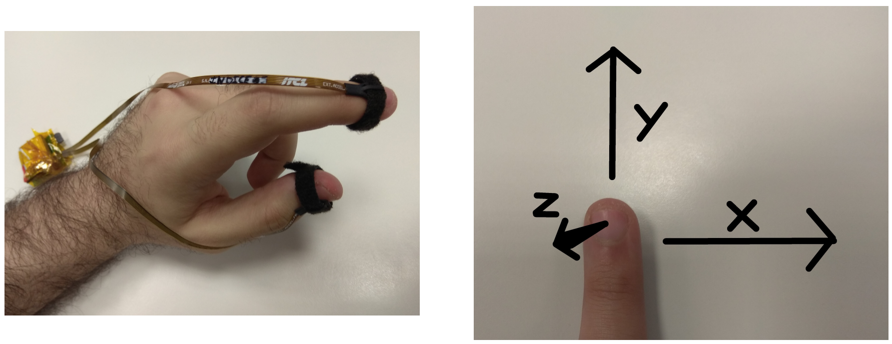


Fig. 1: Left part: The prototype sensing unit, with two 3DACC located on each finger end. Right part: 3DACC axes orientation relative to its finger. The z-axis is perpendicular to the finger, positive to the outside of the hand.

There are restrictions when using this first release of the prototype. Firstly, only opening and closing finger movements are allowed, with the hand steadily immobilized. The fingers must point to the positive $y$-axis, while the $x$-axis should be kept parallel to the rotation axis. Finally, the planes containing the angular movements of each finger should not form an angle higher than 60 degrees with the vertical direction (i.e., a rotation plane that is almost orthogonal to the gravity direction should be avoided); this can be achieved with the hand initially pointing upwards or downwards.

### 2.2 Detection of the movements

The angle function will be defined to have nice properties: it will increase when fingers move in the opening direction and decrease for movements in the closing direction. Its values will only depend on the current orientation of the rotation axis, so that its calculation will produce no error propagation; also this dependence will be continuous and stable. Having no error propagation is a very desirable property which implies that we do not need additional information (from other sensors or additional restrictions) to compensate the propagating errors. Error propagation usually arises from integration methods, which is why we have used a different approach.

In order to construct our model, we will deal first with the information coming from one 3DACC. Under the assumptions explained before, the acceleration measured by a 3DACC is given in Eq. (1), where $\mathbf{g}$, $\mathbf{a}_f$ and $\mathbf{n}$ denote the gravity, the acceleration of the finger during the angular movement, and some noise, respectively. The noise $\mathbf{n}$ will be assumed to be negligible, and for simplicity we will consider that $\mathbf{n} = 0$. For our purposes, a good enough estimation of $\mathbf{g}$ at a time instant $t_i$ can be obtained via the simple moving average filter of the last three samples.

$$\mathbf{a} = (a_x, a_y, a_z) = \mathbf{g} + \mathbf{a}_f + \mathbf{n} \tag{1}$$

For simplicity during our theoretical construction of the angle function, we will neglect the error of $\mathbf{g}$ with respect to the real gravity and assume that these coincide. Since $g := ||\mathbf{g}|| = \sqrt{g_x^2 + g_y^2 + g_z^2}$ is constant, we can identify the possible values of $\mathbf{g}$ with the 2-dimensional sphere surface $S^2(g)$ of radius $1g$. Note that a significant part of the orientation of the accelerometer during the movement is perfectly determined by $\mathbf{g}$, except for a possible rotation around the axis of direction $\mathbf{g}$ (which will not be the case under our assumptions), and when the accelerometer is not moving we have $\mathbf{a} = \mathbf{g}$, so that the partial orientation is known with good precision.

Our assumptions force the $x$-axis to coincide with the rotation axis, and $g_x$ to be constant. Therefore, Eq. (2) keeps constant, and the point $(g_y, g_z)$ lies on the circumference $S^1(r)$ of radius $r$ and axes $(y, z)$. We define the *angle function* $\theta(t)$ at the time instant $t$ as the corresponding angle of the point $(g_y, g_z)$ in $S^1(r)$ (Eq. (3)). Note that, with the corresponding identification via the inclusion $S^1(r) \subseteq S^2(r)$, the angle $\theta = 0$ corresponds to the direction given by the projection of $\mathbf{g}$ on the rotation plane.

$$r := \sqrt{g^2 - g_x^2} = \sqrt{g_y^2 + g_z^2} \tag{2}$$

$$\theta(t) := \mathrm{arctan2}\big(g_z(t), g_y(t)\big) \tag{3}$$

An important detail is that, in order to preserve the continuity of $\theta(t)$, we need to choose its value at the corresponding turn, just by adding or subtracting $2\pi$ as many times as necessary. Note that when we modify $\theta(t_i)$ in that way, we have a new function that not only depends on $t_i$ but also on the previous value $\theta(t_{i-1})$; but by abuse of notation we will still denote it as $\theta(t)$.

We can sum the contributions of the two angle functions, $\theta_I$ and $\theta_T$, of the index finger and thumb, which gives an angle function with intensified slopes (Eq. (4)), which can be used to detect the opening-closing movements.

$$\theta_S(t) := \theta_I(t) + \theta_T(t) \tag{4}$$

Note that if $r = 0$, the direction of $\mathbf{g}$ does not have enough information to determine the orientation and $\theta$ is not well-defined. In the case that the angle between the rotation axis and the direction of the gravity is *too small*, or equivalently, if $r$ becomes *too small*, then $\theta$ becomes unstable because of the nearby discontinuity, and therefore this model would not work properly. In practice, we smoothen $\theta_S$

with a simple moving average filter of 5 terms, and then use it to detect the movements in later steps of our algorithm.

The real-time algorithm proposed in this study aims to detect significant peaks on the angle function. Since significant peak detection is a very studied problem in the literature, we claim no innovation about our peak detection algorithm, although it was obtained as a result of this work. Significant peaks, also called real peaks, are usually a subjective concept whose parameters depend on the context and the measurement unit, so that we are not concerned with giving a formal definition.

At each instant $t_i$, the algorithm first checks if there is a local peak, and then decides to classify it, or not, as a significant peak. After a consecutive sequence minimum-maximum-minimum of significant peaks is found, if the differences between their instants $t_i$ and values $\theta_S(t_i)$ satisfy certain upper and lower threshold bounds, the algorithm notifies that a movement was detected in that interval and then some values (like the duration of the movement) can be calculated and returned as output. Some of the threshold values used are dynamic and updated in real time. Algorithm 1 outlines the developed algorithm.

**Algorithm 1:** An outline of the algorithm to detect movements.

```
Input: Receives a Time Series (TS)
Result: A list with the detected movements
Set sequence as an empty list;
Set movements as an empty list;
for each sample s at time t in TS do
    if s is a relative peak then
        Add ¡peak(s,t)¿ to sequence;
    else
        if s is a relative valley then
            Add ¡valley(s,t)¿ to sequence;
            if last 3 elements in sequence are valley, peak and valley then
                if the time and value constraints are accomplished then
                    Add ¡movement(t2,t)¿ to movements;
                end
            end
        end
    end
end
Return the movements list;
```

### 2.3 Data gathering and experimentation set up

All the samples were gathered by a stroke rehabilitation specialist who simulated the movements of the patients. The duration of each sample corresponds to 1 minute. The hand was not completely immobilized, which may have worsen the results. The 9 samples used in our statistics correspond to a downwards position of the hand, where only one type of movement is performed on each case, and for all possible cases including movement durations of 1s, 2s and 5s, and opening distances of 1cm, 3cm and 5cm.

Other samples where the hand orientation was invalid were gathered too, but these have not been included in the statistical calculations since our initial assumptions were not satisfied. The invalid samples that simulated strong tremblings gave always bad results (only noise was observed in the angle functions). For the invalid samples without trembling simulation, both good and bad results were obtained, depending on the duration and opening angle of each case.

In most part of the samples, for both valid and invalid cases, the thumb rotation movement was performed in wrong direction (laterally or even in opposite direction); due to these movements in wrong direction, the error of the angle function $\theta_S$ has been found greater than it was expected.

## 3 Results and Discussion

The obtained results are shown in Figures 2 to 4 and Tables 1 and 2. The figures correspond with 2 of the 9 instances used. Each figure shows the angle functions for both fingers, index and thumb, and the sum of both angle functions (i.e. $\theta_S$) where the movements are detected. In general and contrary to our assumptions, the hand was not immobilized and was allowed to slightly move during the experiment, and the thumb sometimes moved laterally or even backwards. As can be seen in the Figures, the movements were clearly identified even though the ratio signal/noise is about 0.5 radians, that is, the angle is even of smaller order of magnitude than the noise.

We can see the good results in the cases of fast pincer movements with duration of 1 and 2 seconds, while the performance were poorer when using 5 seconds although still acceptable. In this case, the detected movements were shorter than actually they were, probably because of some noise due to movements of the hand. Apart from the main 9 instances used in this study, other samples with non-valid orientations were studied as well but were not found useful: wrong finger orientations (with unsteady response) and strong tremblings cases, where the angle functions consisted primarily of noise and no peaks to be detected, were unacceptable.

In Tables 1 and 2, we compare the parameters calculated by the algorithm with the real data for the 9 instances with valid orientation.

## 4 Conclusions

This study is a preliminary research to measure the finger movements in the stroke rehabilitation. To do so, a device with two 3DACC sensors are placed on the tip outer face of the index and thumb fingers. With a sequence of transformations and angle measurements, we show that we can classify sequences of movements as valid or not. This research represents a proof of concept and a very

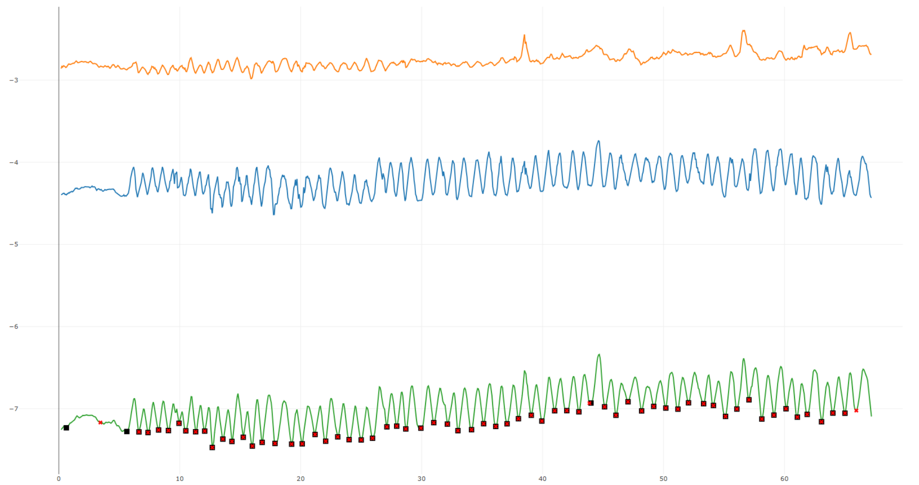

Fig. 2: Angle obtained for the movements in case of 1s, 3cm. The orange line is the angle in the thumb, the blue line is the angle in the index finger, the green line is the smoothed final angle, the black square dot is the starting point of a movement while the red cross is its ending point. The x-axis measures time, while the y-axis shows the angle.

simple decision mechanism based on thresholds is proposed. The experimentation with data gathered from a specialist in stroke rehabilitation mimicking the real movements the normal patients have shows this solution as very promising.

However, there is space for improvements. Firstly, current thresholds may not be suitable for any participant and more intelligent modelling techniques could be applied and developed to enhance the classification of the movements. We think that Deep Learning might be a good starting point, but we do not discard the use of Hidden Markov Models as well. Moreover, to reduce the number of constraints in the use of this solution we propose the use of more sensory elements, such as a magnetometer, so better experimental set up can be automatically detected; this approach would allow to construct a complete reference system for the orientation of the fingers relative to the hand, giving better detection of movements, and angles for pincer movements may be calculated with good precision even if the hand is moving and changing its orientation.

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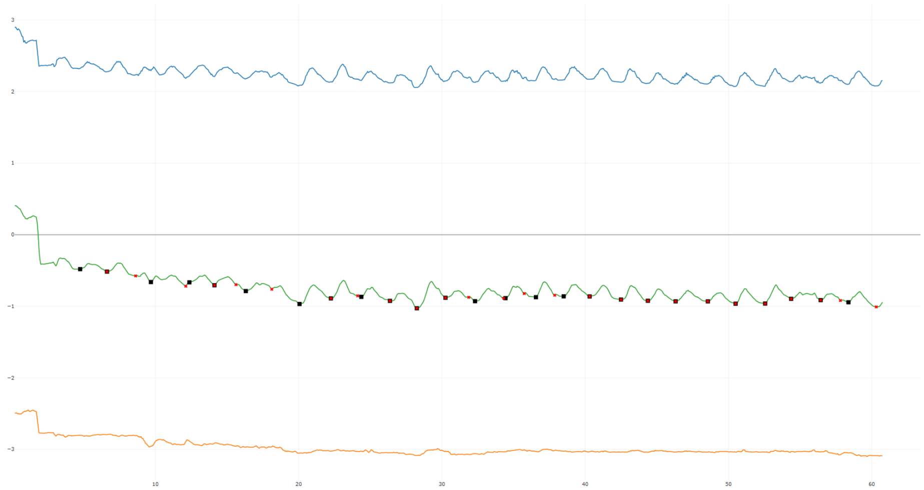


Fig. 3: Angle obtained for movements in case of 2s, 1cm. The orange line is the angle in the thumb, the blue line is the angle in the index finger, the green line is the smoothed final angle, the black square dot is the starting point of a movement while the red cross is its ending point. The x-axis measures time, while the y-axis shows the angle.

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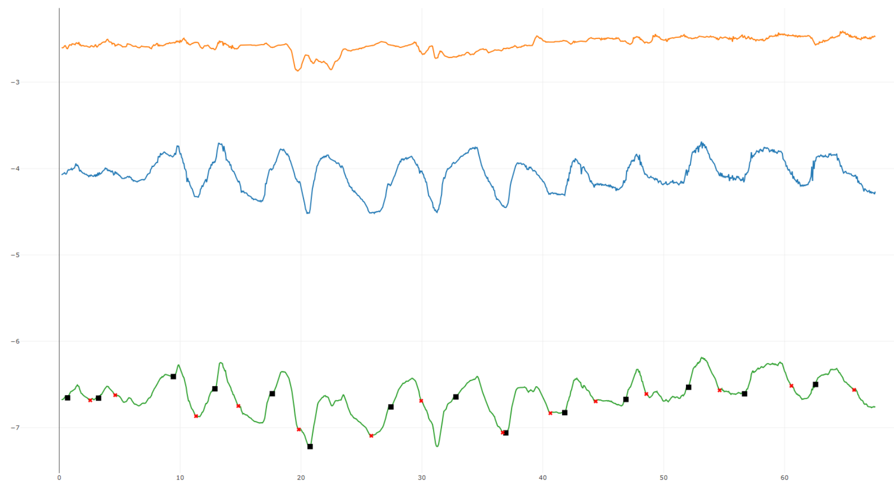

Fig. 4: Angle obtained for movements in case of 5s, 5cm. The orange line is the angle in the thumb, the blue line is the angle in the index finger, the green line is the smoothed final angle, the black square dot is the starting point of a movement while the red cross is its ending point. The x-axis measures time, while the y-axis shows the angle.


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Table 1: Algorithm performance for each case.

| Distance(cm) | Real Average Length (s) | Estimated Average Length(s) | Average Length Error (s) |
|---|---|---|---|
| 1 | 1 | 0.95 | -0.05 |
| 3 | 1 | 0.98 | -0.02 |
| 5 | 1 | 1.01 | 0.01 |
| 1 | 2 | 1.88 | -0.12 |
| 3 | 2 | 1.76 | -0.24 |
| 5 | 2 | 1.97 | -0.03 |
| 1 | 5 | 2.38 | -2.62 |
| 3 | 5 | 2.04 | -2.96 |
| 5 | 5 | 2.73 | -2.27 |

Table 2: Algorithm performance in terms of the number of detected movements. NoM stands for Number of Movements, while AMA stands for averaged maximum acceleration.

| Actual NoM | Estimated NoM | Error in NoM | AMA |
|---|---|---|---|
| 64 | 56 | -8 | 475 |
| 64 | 64 | 0 | 760 |
| 60 | 57 | -3 | 1021 |
| 30 | 26 | -4 | 371 |
| 32 | 31 | -1 | 602 |
| 32 | 31 | -1 | 658 |
| 14 | 11 | -3 | 1189 |
| 14 | 17 | 3 | 981 |
| 13 | 14 | 1 | 530 |

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