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# The RPM3D project: 3D Kinematics for Remote Patient Monitoring*

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**Abstract.** This project explores the feasibility of remote patient monitoring based on the analysis of 3D movements captured with smartwatches. We base our analysis on the Kinematic Theory of Rapid Human Movement. We have validated our research in a real case scenario for stroke rehabilitation at the Guttmann Institute[5] (neurorehabilitation hospital), showing promising results. Our work could have a great impact in remote healthcare applications, improving the medical efficiency and reducing the healthcare costs. Future steps include more clinical validation, developing multi-modal analysis architectures (analysing data from sensors, images, audio, etc.), and exploring the application of our technology to monitor other neurodegenerative diseases.

**Keywords:** Healthcare applications · Kinematic Theory of Rapid Human Movements · Human activity recognition · Stroke rehabilitation · 3D kinematics.

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[5] https://www.guttmann.com/en/

## 1 Introduction

Stroke, defined as the lack of blood flow or bleeding in the brain [1], is the second leading cause of death in Europe. Moreover, experts estimate that strokes will rise dramatically in the next 20 years due to an ageing population [6]. Moreover, 60% of the survivors have different degrees of disability, with a socio-economic impact of the first magnitude for the patient [2] [3], their environment, the health system and the society in general [4] [5]. Therefore, in addition to stroke prevention, it is crucial to find personalized and suitable treatments during stroke rehabilitation, the most important phase of stroke survivors.

The Kinematic Theory of Rapid Human Movement [6, 7, 8] provides a mathematical description of the movements made by individuals, reflecting the behaviour of their neuromuscular system. It has demonstrated a great potential for analysing fingers, hand, eye, head, trunk and arm movements as well as speech. According to the lognormal principle, the motor learning process and its deterioration with aging can be followed, allowing to monitor neuromuscular diseases in terms of the alteration of the ideal parameters. O'Reilly et al.[9] showed that brain stroke risk factors can be associated with the deterioration of many cognitive and psychomotor characteristics. The psychomotor tests demonstrated that the features extracted from the kinematic motion analysis of handwriting were successfully correlated with risk factors (e.g. obesity, diabetes, hypertension, etc.).

However, the use of the Kinematic Theory in monitoring rehabilitation processes is a challenge: it requires to collect and to analyse the movement data using robust, efficient and task oriented lognormal parameter extraction algorithms. These constraints must be removed to develop a universal tool for brain stroke treatments and rehabilitation. Stroke patients, especially in early stages of the recovery treatment, cannot write using a stylus on a tablet device, so most of the analysis of their motor skills improvement is based on simple hands or arms movements.

Recently, inertial and magnetic sensors, including accelerometers, gyroscopes and magnetometers, have been incorporated into wearables, such as smartbands, to assess, among others, the biomechanics of sports performance. These devices are increasingly popular, which make us propose the hand/arm movements as a source to extract the lognormal patterns. Moreover, these devices are not intrusive, so they could be used for continuous remote patient monitoring (RPM) in the rehabilitation stages and during the routine daily life of patients, improving the medical efficiency and reducing the healthcare costs.

For the above mentioned reasons, we aim to explore the use of the Kinematic Theory of Rapid Human Movements for analysing continuous 3D movements captured with smartwatches (a worldwide affordable and non-intrusive technology), and thus, to provide an objective estimator of the improvement of the patients' motor abilities in stroke rehabilitation.

[6] The Burden of Stroke in Europe: http://www.strokeeurope.eu/

This paper describes the RPM3D project [7] [10], which aims to make a step forward towards the removal of such constraints to develop a universal tool for monitoring rehabilitation processes. Indeed, such a tool can have a great impact in remote health care tasks in general. The integration of an analytic tool in a consumer and affordable technology such as smartwatches (instead of high-end clinical devices) could be used for continuous remote patient monitoring in the rehabilitation stages of different neuromuscular diseases, improving the medical efficiency and reducing the healthcare costs.

The overview of our approach is shown in Figure 1. The main project results are the following:

- We have developed a smartwatch application to record data from the inertial sensors of smartwatches (concretely, the Apple Watch).
- We have proposed a model to segment and classify the relevant gestures in continuous 3D movements for their posterior analysis.
- We have adapted the parameter extraction algorithms of the kinematic model to these relevant 3D movements captured with the smartwatch.
- We have defined the experimental protocol and validated our research in a real case scenario for stroke rehabilitation at the Guttmann Institute (neurorehabilitation hospital).

The innovation potential of this project is the provision of a new tool to obtain significant measures of the human movement of patients of brain strokes in the rehabilitation phase using wearable devices such as smartwatches. Conveniently calibrated, this tool can be seen as a *thermometer* of the human neuromotor system, and with the appropriate interpretation (according to the correlation with the clinical indicators), medical doctors will be able to make decisions on the rehabilitation prescription and treatment of patients.

The rest of the paper is organized as follows. In Section 2, we overview the state of the art. Next, in Section 3, we describe the application protocol and the capturing of data from the smartwatches. Section 4 is devoted to the recognition of movements, whereas Section 5 describes the kinematic analysis performed. Section 6 is devoted to the conclusions and future work.

## 2 State of the Art

Assessing the physical condition in rehabilitation scenarios is challenging because it involves Human Activity Recognition (HAR) [11] and kinematic analysis.

HAR methods must deal with intraclass variability and interclass similarities [12] [13]. Also, the detection of target (relevant) movements is difficult due to the diversity of non-target movements. In continuous time series data, the challenge is to detect and segment those subsequences (target movements) so that they can be properly analysed by the kinematic model. This is especially difficult when the movements are non-repetitive and that is why a major part of

[7] http://dag.cvc.uab.es/patientmonitoring/

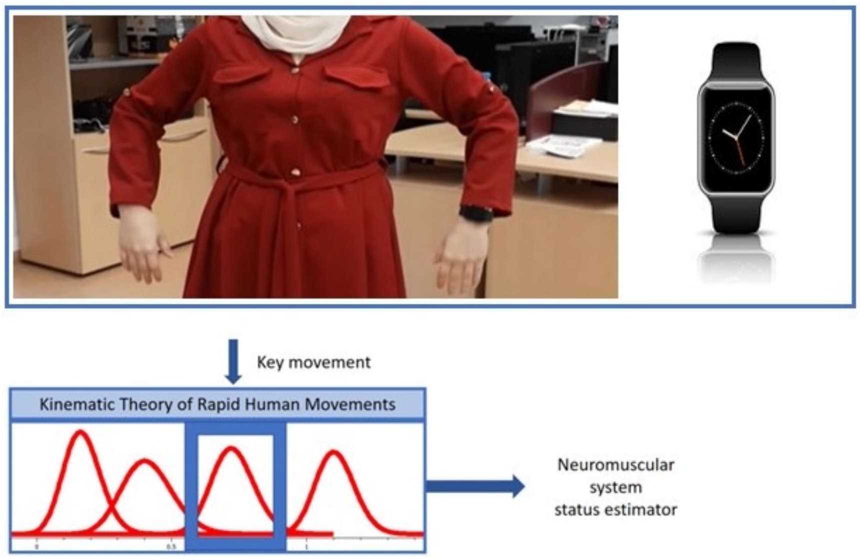


**Fig. 1: Overview of the pipeline.**

activity recognition works deal only with repetitive(periodic) movements such as: walking[14], stair ascent or descent [15], running, sport exercises [16]...

HAR is about seeking high-level knowledge that describes human activities, ergo HAR benefited broadly from deep learning since this latter one can provide automatic feature extraction [17] [18] [19].

At the same time, traditional machine learning like Support Vector Machines (SVMs) [20] [21], K-Nearest-Neighbours (KNNs) [22] [23] still provide an efficient accurate solution for HAR tasks due to the fact that they perform better in few data problems which is the case of most HAR tasks that suffer from data scarce.

As mentioned in the introduction, the Kinematic Theory of Rapid Human Movement [24] has demonstrated a great potential for monitoring neuromuscular diseases, but it requires robust algorithms to estimate the model parameters with an excellent precision for a meaningful neuromuscular analysis. So far, most algorithms (Idelog [25] and Robust XZERO [26, 27]) have mainly focused on 1D and 2D movements in a controlled scenario, e.g. pen movements on a tablet computer . This constraint makes the approach unrealistic for stroke rehabilitation. Stroke patients have severe mobility limitations, especially in early stages, so the analysis of their motor skills improvement is based on simple hands or arms movements. Thus, the recently proposed 3D algorithm [28] must be adapted to continuous movements in unconstrained scenarios (closer to real use cases). Finally, the hardware is an extra difficulty, because the smartwatch could be less accurate than clinical devices.

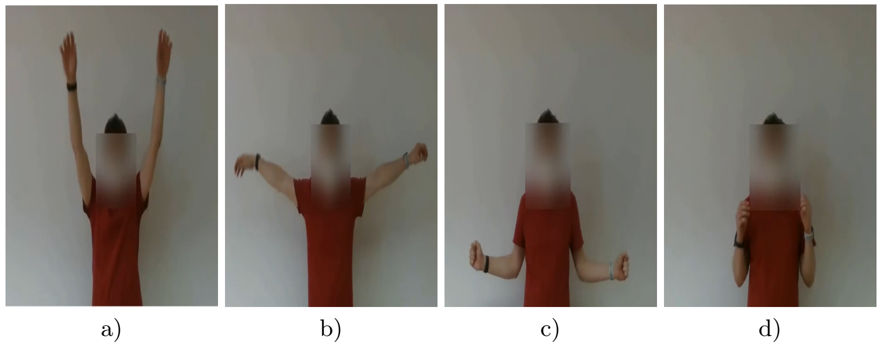


**Fig. 2: Target movements. a) Movement 1; b) Movement 2; c) Movement 3; d) Movement 4.**

In summary, the challenges are the following:

- The use of sensors from consumer devices instead of clinical devices, which can decrease the quality of the data for the application of the kinematic model.
- The extraction of the model parameters from the continuous 3D movement sequences for their posterior analysis.
- The accurate detection, segmentation and analysis of the target movements in uncontrolled scenarios.

## 3 Application Protocol and Data Capturing

Next, we describe the application protocol and the recorded movements.

### 3.1 Application Protocol

We have designed an upper-limb assessment pipeline inspired by the Fugl-Meyer Assessment scale, an index to assess the sensorimotor impairment in stroke patients. Concretely, we have defined four target (non-repetitive) movements (see Figure 2), based on the following joint movements:

1. Shoulder extension/flexion
2. Shoulder adduction/abduction
3. External/internal shoulder rotation
4. Elbow flexion/extension

We have recorded these movements in two scenarios:

- L1 is a constrained scenario which consists in performing the same target movement in a sequence, but alternating the arm (left, right or both).

- L2 is an unconstrained scenario, where target movements appear inside longer sequences that include non-target movements (e.g. common daily life activities like eating, pouring water into a glass, brushing your teeth, scratching the ear, etc.).

As a proof of concept, we have recorded data from 25 healthy individuals and 4 patients from Guttmann Institute. Out of the 25 healthy individuals, 48% are women and 52% are men. While for the patient population, there is one woman and 3 men. Healthy and patient individuals' age range between 20 and 60 years.

The users wear two watches, one in each wrist. Patients data was recorded along four sessions with an interval of one to two weeks, while healthy individuals' data was recorded in one session.

### 3.2 Data Capturing

We have developed an application for the Apple Watch 4 to record the sequences of movements, as shown in Fig1. The user-generated acceleration (without gravity) for all three axes of the device, unbiased gyroscope (rotation rate), magnetometer, altitude (Euler angles) and temporal information data have been recorded in the watch's internal memory at 100Hz sampling rate.

The two watches are synchronised thanks to an audio signal. Afterwards, the data is transmitted to the mobile phone and the cloud service. Finally, the signal is **preprocessed** to minimize the sensor drift, which often leads to inaccurate measures and larger accumulated error.

## 4 Human Activity Recognition

We have used the Euler angles and the linear acceleration. To detect the target movements in the unconstrained scenario L2, we explored two segmentation options:

1. Segmenting the complete sequence using non-overlapping sliding windows (namely action recognition).
2. Picking the positive peaks in the signal as candidates to be relevant movements (namely gesture spotting).

We have also explored two classification methods. First, SVMs, a machine learning approach typically used in HAR, together with the following feature vector set: the mean, the minimum, the maximum and the standard variation of the window. Second, Convolutional Neural Networks (CNN), a deep learning model in which the input is the linear acceleration signal instead of a feature vector set. More details can be found at [29].

As shown in Table 1, action recognition is preferable. In healthy individuals, the SVM classifier obtains better results (84% in L1 and 61% in L2) than the CNN one (65% in L1 and 59% in L2) because the CNN is a data hungry method. Concerning gesture classification, the results by the two classifiers are similar.

**Table 1: HAR classification and spotting results**

| | **Healthy Individuals** | | | | **Patients** | |
|---|---|---|---|---|---|---|
| | **Action Recognition** | | **Gesture Spotting** | | **Action Recognition** | **Gesture Spotting** |
| **Scenario** | **SVM** | **CNN** | **SVM** | **CNN** | **SVM** | **SVM** |
| ***L1*** | **84%** | **65%** | **55%** | **60%** | **56%** | **41%** |
| ***L2*** | **61%** | **59%** | **51%** | **53%** | **41%** | **35%** |

In patients, the accuracy in the unhealthy body part decreases (56% in L1 and 41% in L2) in comparison with their healthy side (84,5% in L1 and 61% in L2), because these movements are less accurate due to their loss of motor function.

## 5 Kinematic Analysis

The Kinematic Theory of Rapid Human Movements describes the resulting speed of a neuromuscular system action as a lognormal function [6, 7, 8]. To analyse the 3D movements captured by smartwatches, we utilize a recently proposed 3D extension of the Sigma-Lognormal model [28] to decompose observed 3D movements into sequences of elementary movements with lognormal speed. There are several model parameters that can be analysed with a view to the patients' motor abilities.

Here, we focus on the signal-to-noise-ratio (SNR) between the observed trajectory of the smartwatch and the reconstructed trajectory using the analytical model. A high SNR indicates a high model quality, i.e. a good representation of the 3D movement. Furthermore, healthy subjects tend to achieve a higher SNR than patients with motor control problems [24].

**Table 2: Kinematic analysis mean standard deviation**

| | Healthy Individuals | Patients |
|---|---|---|
| Samples | 649 | 126 |
| Duration [s] | $4.1 \pm 1.0$ | $4.9 \pm 0.8$ |
| Number of Lognormals | $17.3 \pm 4.7$ | $17.6 \pm 4.5$ |
| SNR [dB] | $22.2 \pm 2.8$ | $21.3 \pm 2.1$ |

Table 2 and Fig 3 present the first results of our kinematic analysis, comparing 649 movements from 25 healthy individuals with 126 movements from 4 patients. In both cases an excellent SNR is achieved, indicating that the 3D Sigma-Lognormal model is suitable for analysing the smartwatch movements. Furthermore, we observe that the patients needed more time to execute the

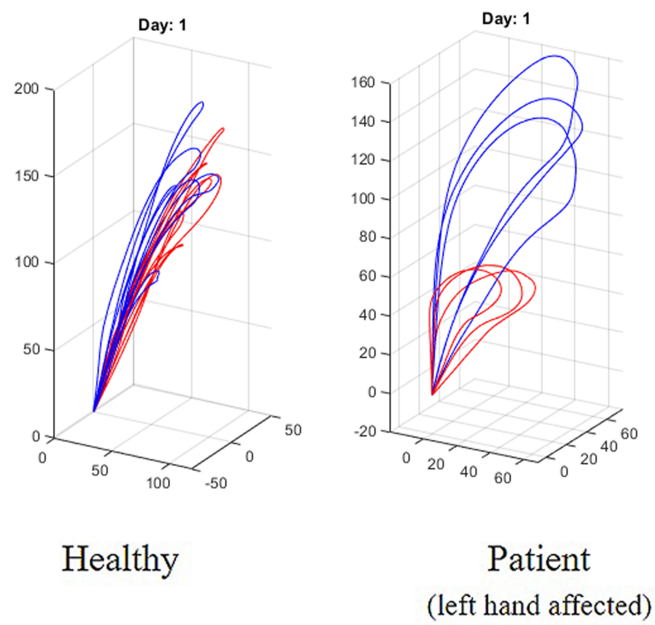


**Fig. 3: Kinematic analysis results.**

movements, more lognormals were needed to model the patients' movements, and a lower SNR was achieved. The difference in SNR is statistically significant (Mann-Whitney U test, $p < 0.0001$). These observations are consistent with the lognormality principle [28] and encourage a more detailed kinematic analysis of the patients' motor abilities based on the Kinematic Theory.

## 6 Conclusion and Future Steps

In this paper, we have presented the RPM3D project, which aims to ease the monitoring of patients during the neurorehabilitation stages.

In the future, we plan to focus on the continuous and remote monitoring of the patients' neuromotor status. Concretely:

- We will to perform more clinical validation through an exhaustive analysis of the correspondence between the kinematic analysis and the clinicians' estimations. We will also continue the comparative analysis between healthy users and patients.
- We will explore the use of other lower-cost wearables (e.g. smarbands) and also, the possibility to combine the sensor data with video images or speech.

Also, we would like to recognize functional (purposeful) movements to determine the degree of integration of the affected side of the body in the patients' daily life actions.
– We will explore the adaptation of our approach for monitoring patients suffering from Multiple Sclerosis or Parkinson diseases, the ageing effects in elderly people, the effects of medication in clinical trials, etc.

## 7 Acknowledgement

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