3D Kinematics for Remote Patient Monitoring (RPM3D)

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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 have validated our research in a real case scenario for stroke rehabilitation at the Guttmann Institute (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; Stroke rehabilitation; Kinematic Theory of Rapid Human Movements; Human activity recognition.

1. INTRODUCTION

Stroke (lack of blood flow or bleeding in the brain) is the second leading cause of death in Europe, and experts estimate that strokes will rise dramatically in the next 20 years due to an ageing population [1]. Moreover, 60% of the survivors have different degrees of disability, with a socio-economic impact of the first magnitude for the patient, their environment, the health system and the society in general. 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. This project aims to explore the use of the Kinematic Theory of Rapid Human Movements [2] 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. However, the use of this kinematic model for 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.

This project makes 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 main project results are the following:

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

5. STATE OF THE ART

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

HAR methods must deal with intraclass variability and interclass similarities. 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.

The Kinematic Theory of Rapid Human Movement [2] provides a mathematical description of the movements made by individuals, reflecting the behaviour of their neuromuscular system. It 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 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 [3] 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.

In summary, the challenges are the following:

1) 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.
2) The extraction of the model parameters from the continuous 3D movement sequences for their posterior analysis.
3) The accurate detection, segmentation and analysis of the target movements in uncontrolled scenarios.

6. BREAKTHROUGH CHARACTER OF THE PROJECT

From a technological point of view, the breakthrough character of this project is the adaptation of the parameter extraction for the kinematic model to a sequence of continuous 3D movements in an unconstrained scenario using affordable devices (smartwatches). The parameter estimation is challenging in this scenario because the movements are unconstrained and recorded continuously. We state that the kinematic analysis can recover similar biomedical information about a patient without the constraints of a highly parameterized test.

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.

In the near future, the explosion in digital health technology and the pervasive use of IoT devices will allow people of all ages to be in an easier and better control of their health. Indeed, healthcare professionals will be able to collect data in real-time thanks to connected wearable devices incorporated in the daily routines and cloud-based systems and apps for the analysis of the health data.

This project can improve health care provision, enhancing the quality of care, improving the medical efficiency and reducing the healthcare costs. Also, the resulting technology can pave the way for applications not only in health and biomedicine, but also in biometrics, robotics, simulations, video games, human-machine interfaces, etc.

7. PROJECT RESULTS

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, 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. The users wear two watches, one in each wrist.

Data Capturing

We have developed an application for the Apple Watch 4 to record the sequences of movements, as shown in Fig.1.

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. 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.

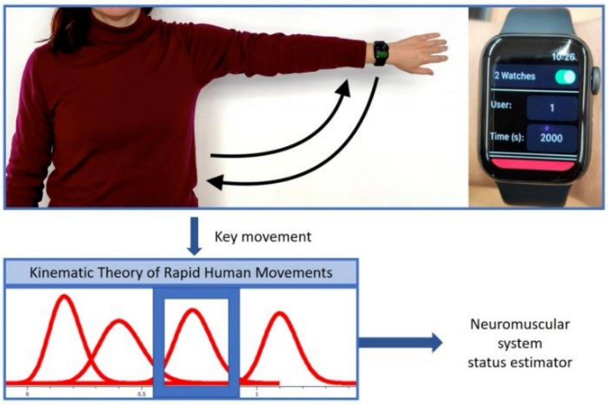

Fig. 1. Overview of our approach.

Tab. 1. HAR classification and spotting results.

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

HAR

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, Support Vector Machines (SVM), 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.

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. 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.

Kinematic analysis

The Kinematic Theory of Rapid Human Movements describes the resulting speed of a neuromuscular system action as a lognormal function [2]. To analyse the 3D movements captured by smartwatches, we utilize a recently proposed 3D extension of the Sigma-Lognormal model [3] 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 [3].

Table 2 and Fig. 2 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 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 [3] and encourage a more detailed kinematic analysis of the patients' motor abilities based on the Kinematic Theory.

Tab. 2. Kinematic Analysis (mean ± standard deviation).

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

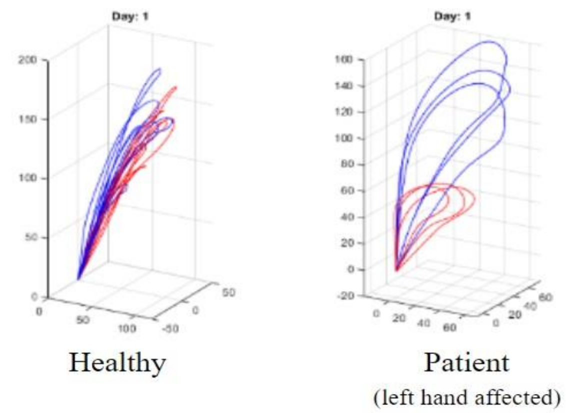

Fig. 2. Trajectory obtained from the accelerometer signal (right hand in blue and left hand in red color).

8. FUTURE PROJECT VISION

8.1. Technology Scaling

In the ATTRACT phase 2, we plan to make progress from our current TRL 3 up to TRL 6, demonstrating our technology in hospitals and rehabilitation centres.

We will scale up our technology through:

1. More clinical validation for the Minimum Viable Product with 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.

2. Incorporate other technological improvements, from the hardware and software point of view. First, we will explore other lower-cost wearables (e.g. smarbands) and combine the sensor data with video images or speech. Second, we will recognize functional (purposeful) movements to determine the degree of integration of the affected side of the body in the patients' daily life actions.

3. Iterate and pivot to improve product-market fit. Define the business models exploring different applications: stroke rehabilitation, monitoring neurodegenerative diseases, etc. We will participate in accelerator programmes on valorisation and commercialisation of digital health technologies (e.g. BStartupHealth, Open Innovation Forum, PRAXIS, etc.).

8.2. Project Synergies and Outreach

We will reinforce our consortium partnering with:

- Wearable sensors companies or manufacturers to offer a more low-cost wearable device (e.g. wristband, ankle bracelet, glove).

- Clinicians, hospitals, patients' associations and health public institutions to define other future applications (i.e. early detection, diagnosis or monitoring of other neuromuscular diseases) and ensure real market need.

- Researchers on signal processing, speech recognition and healthcare for developing joint software architectures for efficient multi-modal analysis (e.g. sensors, image, video, voice, etc.).

Our potential partners are the consortiums of the following ATTRACT projects (tentative list): DEBARE, MERIT-VA, BREEDING, DBGA, ECHOBRAIN, HERALD, iDMS, PEBI, PIZZICATO, SP-LADOS.

Concerning dissemination, we have considered to reach three target audiences: clinical community, commercial companies and public at large. We will regularly update our project website, create social media accounts, news in press, record promotional videos, publish scientific papers and make presentations and life demos of our prototypes in scientific conferences and trade shows (e.g. MWC, Medica Fair, CPhI Worldwide) to promote the transferability of our technology.

8.3. Technology application and demonstration cases

Our project outcomes and demonstration cases will benefit the areas of Scientific Research, Industry and Societal Challenges, concretely in health, demographic change and wellbeing.

Firstly, our tool will allow a continuous and remote monitoring of the patients' neuromotor rehabilitation after a stroke. We envision two main application scenarios:

- Monitoring the rehabilitation at hospitals. Our technology will not only complement the clinician's estimations, but it will also provide continuous (24/7) data concerning the patient's movements. For example, the percentage of usage of each arm can help to estimate the progressive incorporation of the affected side of the body in daily life activities.

- Remote monitoring of individuals undergoing rehabilitation at home, improving homecare health and well-being. In fact, monitoring the rehabilitation exercises that the patient does at home can offer an alternative/complement to costly rehabilitation sessions.

Secondly, we will explore the monitorization of patients suffering from Multiple Sclerosis or Parkinson diseases, the ageing effects in elderly people or the effects of medication in clinical trials.

8.4. Technology commercialization

We plan to study the patentability of our technology. As a first step, the consortium will sign a Joint Ownership Agreement to define the intellectual property and exploitation rights.

Target customers.

We will validate our technology via a B2B2C strategy: a B2B model focused on therapists acting as prescribers of technology to large telerehabilitation centres/companies; and a B2C model more focused on reaching the end-user (the patient).

Distribution channels.

We envisage the commercialization of our technology through two channels:

- Integration of the technology into existing online healthcare ecosystems, so that the therapists can better integrate all data and monitor the patients' evolution. Examples include the *Guttmann NeuroPersonalTrainer* [4] (online platform for cognitive telerehabilitation) and *HocoNet* [5] (online platform connecting all health data, including the existing hospital information system).
- Distribution through *Apple Store* for remote (and real-time) data capturing of patients, gaining visibility and enabling distance/remote data collection (compatible with *covid19* lock down).

Revenue streams.

As a tentative monetization strategy, license fees are planned, based in the number of users (patients) being monitored.

8.5. Envisioned risks

The main core risks and their corresponding mitigation actions are the following:

1) We cannot perform enough and exhaustive clinical trials with patients for a conclusive analysis. In this case, the action will be to contact other hospitals and patients' associations to incorporate more users.

2) We cannot break the market entry barrier convincing that there is a clear correlation between our data analysis and the clinical estimators. We plan to mitigate this risk with more diffusion campaigns and reaching key-opinion leaders in hospitals and rehabilitation centres to foster a general adoption of our technology.

3) We cannot attract innovators, entrepreneurs and investors to get the required funding for scaling up our technology. In such a case, we will increase our participation in different accelerator programmes and apply to national/international competitive calls.

8.6. Liaison with Student Teams and Socio-Economic Study

During the ATTRACT Phase 1, we have already liaised with Msc. students from ESADE, UPC and IED (in Barcelona). Concretely, we had three teams studying possible innovative applications and business models. The first team was focused on Strokes, the second in Parkinson and the third one in Multiple sclerosis.

The actions that we have taken during Phase 1 and we plan to continue during the Phase 2 are the following: Regular interviews and meetings (face-to-face and online) with researchers and therapists in our consortium to explain in detail our technology, perform live demos of our prototypes, provide with the scientific papers in which our technology is based.

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7. REFERENCES

[1] The Burden of Stroke in Europe: http://www.strokeeurope.eu/
[2] Plamondon, R., & O'Reilly, C. & Rémi, C. & Duval, T. 2013, The lognormal handwriter: learning, performing, and declining, Frontiers in psychology, 4(945): pp.1-14.
[3] Schindler, R. , Bouillon, M. , Plamondon, R. & Fischer, A., 2018, Extending the sigma-Lognormal model of the kinematic theory to three dimensions, 2018 International Conference on Pattern Recognition and Artificial Intelligence (ICPRAI), Montreal, Canada, 2018.
[4] Guttmann NeuroPersonalTrainer: https://gnpt.es/
[5] Hoconet: https://www.hocoma.com/solutions/hoconet/