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Using Inertial Sensors to Evaluate Exercise Correctness in Electromyography-based Home Rehabilitation Systems

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***Abstract*—Home-based rehabilitation systems can speed up recovery by enabling patients to exercise at home between rehabilitation sessions. However, home-based rehabilitation systems need to monitor and feedback exercises appropriately, as incorrect or imperfect exercises negatively impact the recovery of the patient. This paper describes a methodology for assessing the quality of rehabilitation exercises using inertial sensors, for a system that tracks exercises using surface electromyography sensors. This duality extends the information provided by the electromyography system since it provides a more comprehensive evaluation of posture and movement correctness. The methodology was evaluated with 17 physiotherapy patients, obtaining an average accuracy of 96% in detecting issues in the exercises monitored. The insights of this work are a first step to complement an electromyography-based home system to detect issues in movement and inform patients in real time about the correctness of their exercises.**

***Index Terms*—home-based rehabilitation, physical rehabilitation, electromyography, inertial sensors, muscular activation, posture, biofeedback**

I. Introduction

The ageing process observed in Western Countries challenges healthcare systems and physiotherapists. Older adults are more likely to fall, have a stroke, and develop cardiac diseases, which means that more people require physical rehabilitation than ever before [3]. In a context with many patients for roughly the same professionals, it is important that patients recover as soon as possible, so that professionals are free to attend other patients pressing needs.

To increase the effectiveness of rehabilitation programs, prescribed exercises should be executed correctly and within regular intervals [4]. Quite often though, the patient only performs the prescribed exercises during sessions at the clinic [5]. Moreover, when patients are motivated to perform exercises at home they are likely to face difficulties and deviate from the correct execution of exercises, resulting in the unconscious introduction of compensatory movements or postures, insufficient range of movements, improper timing of muscular activation, or even biomechanical misalignment [5], [6].

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Home rehabilitation systems hold the promise to support patients at home, by monitoring exercises and offering feedback on execution. However, to have an impact, home rehabilitation systems need to be able to accurately detect when exercises are not appropriately performed, to guide patients and avoid negative impacts of rehabilitation. In this context, the advances in the capabilities and the availability of wearable sensors present an opportunity to objectively measure movements and recognize human activities.

Assessing the quality of the performed exercises can be hard. For example, in (surface) electromyography-based platforms, it is only possible to detect the muscle's contraction or relaxation. To assess the quality of the performed exercises in terms of movement and posture, other sensors need to be added. For this reason, we used inertial sensors to characterize human motion, as these sensors are able to retrieve motion characteristics such as acceleration, rotation, angular velocity and posture information, and thus complement a home-based rehabilitation system based on electromyography.

The contribution of this paper is two-fold. First we present a methodology which complements the information provided by Surface electromyographic sensors (sEMG) rehabilitation systems that uses inertial data to characterize posture and movement correctness in ambulatory settings; the second contribution is a feasibility study of the algorithm's performance on a clinical context. The motivation for this work lies in the challenges arising from home-based physiotherapy programs.

This paper is organized in 7 sections. In Section II we describe previous work with applications for home-based rehabilitation. In Section III we present the architecture of the home-based rehabilitation system highlighting the main actors and interactions. The methods used for exercise evaluation are described in Section IV. Section V and VI present the results and discussion, respectively, of a feasibility study with physiotherapy patients. Section VII concludes this manuscript, highlighting some areas of future work.

II. Background

A. *Using electromyography for home-based rehabilitation*

In the context of home-based rehabilitation, the patient performs exercises without clinical oversight or feedback. Therefore, it is important to design a system that monitors

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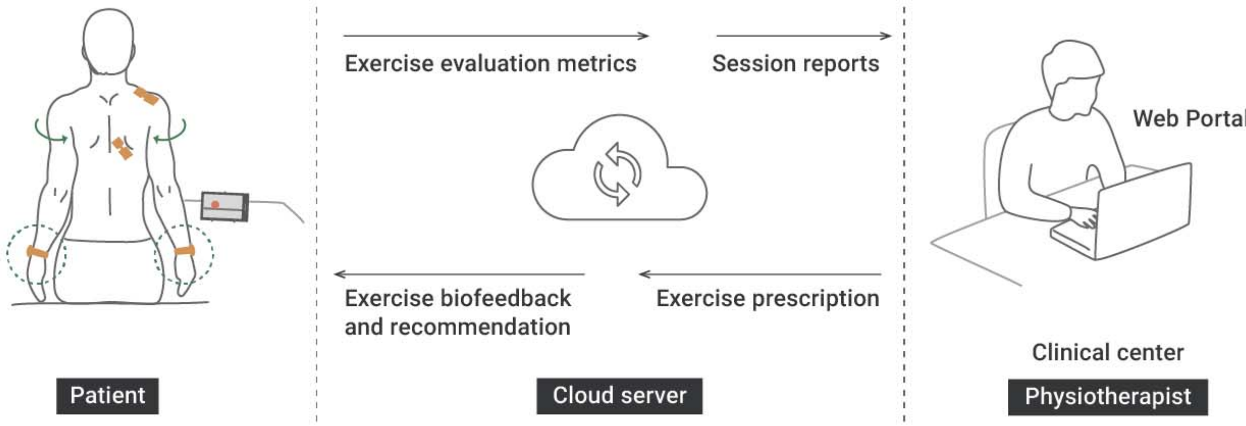

Fig. 1. System overview of the proposed home-based rehabilitation system. The patient wears the MuscleBANs, provided by the Physio@Home system [1], to monitor muscular activation during exercises (see scapula). As a complement to the system, inertial sensors were added to assess the posture of patients during exercise execution, highlighted in figure (see wrists). Both devices send raw data to a smartphone application that analyses it and displays a serious game animated according to the exercise (see [2]). The results of the exercise evaluation are also sent to a centralized server. Physiotherapists can later access processed data through a web portal, allowing them to monitor the patient's progress and issue recommendations.

the quality of the movements being executed. Given that a large part of rehabilitation programs involve the promotion of muscle activation over injured segments, the sEMG sensor emerged as a prime resource for biofeedback systems [7], [8]. The amplitude of the sEMG signal is related to muscle torque and activation, which provides information related to the muscular activity required for a given exercise as the optimal positioning to accomplish its execution [9], [10]. In the literature, sEMG was used to monitor daily living in functional assessment of stroke patients [11], upper limb rehabilitation [12], [13] and neck and shoulder disorders [14].

Despite being a valuable method for muscular assessment, the sEMG sensor fails to provide information regarding movement characteristics or the overall posture of the patient. This can be problematic because in rehabilitation it is important to ensure that the patient is performing the prescribed muscular loads under the correct posture and not introducing compensatory movements to the prescribed exercise. Therefore, it is important to introduce new information sources that can provide information regarding human motion.

B. Approaches to monitor exercise quality

Prior work has explored the use of computer vision algorithms and inertial sensors to assess the quality of exercises in home rehabilitation solutions. Microsoft Kinect has been a popular approach to retrieve the measurement of range of motion of human movement [15]–[18], despite not being developed with the intention of clinical use. The feedback on the exercise was often visual, with games or activities advancing when the exercise was performed appropriately.

Another common alternative was to track limb trajectories and posture with inertial sensors. These sensors are small, inexpensive and easy to setup, qualities which facilitate their adoption for ambulatory settings. The data from inertial sensors is often processed using machine learning techniques and classification models that categorize exercise with a binary classification (i.e. correctly vs. incorrectly executed) or multi-label classification (i.e. characterizing the type of error executed) [19]–[24]. The feedback provided to patients was often visual, drawing on serious games such as the Riablo system [25]. There were also systems providing auditory feedback on the execution of exercises, such as COPDTrainer [26], which emits a different sound when exercises are accurately or inappropriately performed [26].

The literature review showed the potential benefits of using sEMG and possible approaches to evaluate exercise quality. However, the number of solutions which combine sEMG and inertial sensors to evaluate the quality of rehabilitation exercises is limited. The closest studies [27], [28] have employed inertial sensors and sEMG alternately to monitor exercise execution, but not the quality of the exercises. In our work, we devise a solution which combines sEMG and inertial sensors in the context of the prescribed clinical exercises by the physiotherapist. To this end, we complement a sEMG home-based rehabilitation system, which detects periods of muscular activation, with inertial sensors, which allow a more comprehensive evaluation in terms of posture and movement during those periods.

III. Building a system to assess quality of exercises performed using Physio@Home

The Physio@Home [1] project aims to improve the efficiency of rehabilitation by supporting physiotherapy sessions at the clinic and at home with a biofeedback technological platform. The solution draws on wearable sensors used to track the execution of the movements and give biofeedback to the user[1]. The performance metrics collected during the exercise execution are stored and made available to the physiotherapist

[1]The biofeedback platform is described in [2].

through a web portal. The performed exercises are monitored by sEMG sensors, which analyse the contraction and relaxation of specific muscles. Nevertheless, while this sensor is a valuable asset to assess muscular activation, it fails to offer relevant information regarding the patient's posture.

The Physio@Home system has two main users: the physiotherapist and the patient, as depicted in Figure 1. Physiotherapists access a web interface to prescribe rehabilitation plans, monitor the patient's progress, evaluate the adherence to the scheduled plan, and view detailed reports containing the qualitative evaluation of exercises. Patients access the prescriptions through a mobile application which summarizes the rehabilitation plan and controls the wearable sensors.

With this work, we suggest adding inertial sensors to the existing solution to be able to improve the quality of the assessment of the performed exercises. The updated version of the system would be composed of two types of devices: two MuscleBANs[2] equipped with a sEMG sensor and a tri-axial accelerometer, and two inertial sensors [29] equipped with a tri-axial accelerometer, gyroscope and magnetometer. These devices communicate with a smartphone application using Bluetooth Low Energy and sample raw data at 50 Hz.

In this setup, the MuscleBANs would be attached using electrodes to the muscles, as in previous versions of the system, and the inertial sensors embedded in a bracelet, would be easily attached to different body locations according to requirements of the prescribed exercise. The proposed setup was designed to be applied in different rehabilitation exercises since all wearables can be efficiently attached to different body locations according to the requirements of each exercise.

Fig. 2. Exercises: (a) Isometric scapular retraction strengthening (Exercise 1), and (b) forward lunge (Exercise 2).

IV. Materials and Methods

In order to develop a methodology to assess the quality of exercises using inertial sensors, we performed data collections with patients currently taking part in physical rehabilitation programs. For that purpose, a dataset was collected at Centro de Reabilitação Professional de Gaia, a public rehabilitation center and clinic from Portugal. The methods used for data analysis comprise an automatic identification of the time intervals in which the patient was performing the exercise repetitions and a machine learning pipeline to recognize whether a repetition was correctly or incorrectly performed.

A. Participants

A total of 17 patients were selected for this study. The recruitment was performed by physiotherapists taking into account the clinical background and rehabilitation prescription of each patient. The patients, 10 males and 7 females with ages between 24 and 58 (average 42 $\pm$ 13 years), had different professional backgrounds, levels of education and clinical conditions (paralysis, hemiparesis, muscular strength and balance problems, among others). All participants were briefed on the motivation, primary objective and procedures of the research, along with the possibility to clear any doubts the participants could have. Following this explanation and dialogue all participants provided written informed consent.

[2]http://www.biosignalsplux.com/en/muscleban

B. Protocol

The data collection protocol was defined by the physiotherapists so that exercises were relevant in clinical context. Two different exercises were selected: exercise 1 was composed by an isometric scapular retraction strengthening, a static exercise depicted in Figure 2 (a); and exercise 2 was composed by a forward lunge, dynamic and functional exercise, depicted in Figure 2 (b). These exercises are frequently prescribed in physiotherapy programs and their selection intends to promote variability since they differ from each other in terms of movement required to perform the exercise and posture. Two MuscleBANs were attached to the upper and lower trapezium and two inertial sensors were placed on both wrists for monitoring exercise 1. Two MuscleBANs were attached to the quadriceps and upper trapezium muscles and two inertial sensors were placed on the thigh and on the ankle for monitoring exercise 2.

Data collection was performed at a rehabilitation clinic. The physiotherapists placed the wearables sensors according to the exercise to be performed and instructed patients to execute the exercises. The physiotherapists guided patients while they performed the exercises. Patients performed a variable number

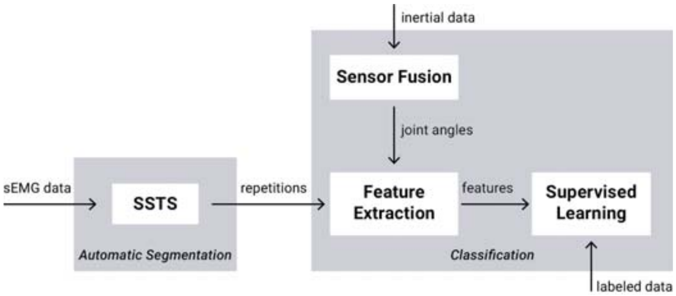

Fig. 3. Data analysis framework.

of repetitions (between five and ten) of each exercise. All sessions were video-recorded and the instants corresponding to the beginning and end of each repetition were manually annotated using a button press in a dedicated mobile data logger application.

C. Data Analysis

The video recordings from data collection protocol were analyzed and each repetition of the exercises was annotated in terms of correct and incorrect execution. Physiotherapists observed and commented on the exercise execution of patients while they were performing the exercises, reporting if the repetition was correctly executed or if there were any deviations and/or compensations. These comments were used as groundtruth in this study. Yet, it is important to mention that patients were not aware of physiotherapist's comments during the data collection process.

The data obtained from the four wearable devices was processed using a machine learning pipeline that ressembles [24]. As illustrated in the scheme of Figure 3, the pipeline was divided into two main stages: (1) automatic segmentation of repetitions based on sEMG; and (2) a supervised machine learning approach to classify repetitions into correct and incorrect executions and characterize the incorrect movement into a limited range of deviations. In contrast to previous work, we labeled exercises as correct and incorrect and not into different types of deviations[3].

For the rest of this subsection, we elaborate over the description of the data analysis pipeline. The segmentation of sEMG comprises the task of identifying the temporal intervals at which muscular activation is present, quite often achieved by analyzing the sEMG envelope. Since each subject executed several repetitions of the exercise during the protocol, it is expected that the resultant signal is composed of several intervals of activation. We used a recent tool called Syntactic Search for Time Series (SSTS) [30], which facilitates the process of defining and querying patterns on time series. The proposed methodology delivers a more interactive and expressive method of matching the desired patterns in time series. SSTS converts time series from the numeric into the symbolic domain using a set of connotation rules defined by the user. The search for patterns is defined in the symbolic domain using regular expressions.

[3] In the previous work, common deviations of the exercises were identified by physiotherapists. However, the physiotherapy patients performed many types of deviations, some of which could not be easily distinguished, which made the task of classifying deviations into types as impracticable.

TABLE I
TOTAL NUMBER OF TIME WINDOWS FOR FOR EACH CLASS.

Class	Exercise 1	Exercise 2
Correct	90	53
Incorrect	46	47

After the segmentation process, the inertial signals were subjected to a process of feature extraction. The signals were composed by raw accelerometer signals and also orientation signals calculated combining accelerometer and gyroscope data using a complementary filter to calculate absolute and relative angles of body segments [31]. A set of features were extracted from the windows resulted from the segmentation process. The set was composed by statistical features - skewness, kurtosis and histogram - and temporal features - mean, median, maximum, minimum, variance, temporal centroid, standard deviation, root mean square and auto correlation.

After feature extraction it was possible to observe that some of the features were correlated and it should be possible to remove correlated features without compromising overall data availability, therefore, the forward feature selection method was applied. The samples were classified using *scikit-learn* v0.19.1, a Python Machine Learning library, on Python 2.7.13, with three different: K-Nearest-Neighbours (KNN), Support Vector Machines (SVM), and Random Forest (RF). For validation purposes, leave-one-user-out cross validation was applied to ensure independence of the subject.

V. RESULTS OF EXERCISES EVALUATION

The Table I summarizes the class distribution for both exercises. For exercise 1 there is a class imbalance since the number of repetition performed correctly is higher than the number of incorrect repetitions. For exercise 2, the number of instances for each class is similar.

Results of the validation for the assessment of the classification performance are presented in Table II. Here, the amount of samples collected for exercise 1 was balanced to obtain equal number of class samples for each one of the classifiers, using the Synthetic Minority Over-Sampling Technique (SMOTE), implemented in *imbalanced-learn* v0.4.3. The classifiers trained separately, manual and automatic segmented time windows. Manual windows correspond to the annotations of the exercises repetitions during data collection, and automatic segmented windows result from the application of the automatic approach based on SSTS. Performance metrics such as accuracy, recall, and precision were computed. While accuracy measures the overall effectiveness of a classifier, recall measures the effectiveness of a classifier at identifying a desired label, and precision measures the classifiers ability to detect negative labels.

TABLE II

CLASSIFICATION RESULTS OBTAINED FOR KNN, SVM AND RF CLASSIFIERS FOR EACH EXERCISE AND FOR AUTOMATIC AND MANUAL SEGMENTATION.

		Accuracy (%)		Precision (%)		Recall (%)	
Exercise	Classifier	Manual	Automatic	Manual	Automatic	Manual	Automatic
1	KNN	96	98	86	98	81	60
	SVM	96	95	88	98	73	30
	RF	97	100	85	100	78	60
2	KNN	96	95	82	75	80	92
	SVM	95	95	86	70	79	70
	RF	98	95	87	70	78	95

The methodology achieved relatively high accuracy scores for all classifiers for both manual and automatic segmentation. Precision and recall were also high in general, however, for the automatic segmentation, in exercise 1, all classifiers demonstrated low levels of recall, and in exercise 2, precision in all classifiers was also lower compared with the manual segmentation.

VI. DISCUSSION

The results of the evaluation of the quality of the selected exercises performed in ambulatory settings detailed in Table II demonstrated that it is possible to correctly classify different rehabilitation exercises executions using inertial units with satisfactory levels of accuracy, when compared to the ones obtained in the literature [20]–[23], which evaluated exercises using information only from inertial sensors. However, the dataset of this study is significantly smaller than the ones from the aforementioned studies. A careful interpretation of the results is needed considering the dataset size of Table I.

For manually annotated repetitions, recall and precision maintained relatively high values, however, for the automatic segmentation repetitions, recall and precision were slightly lower for exercises 1 and 2, respectively, demonstrating more confusion in distinguishing correct from incorrect exercise execution. Results showed that KNN classifier achieved an average recognition accuracy of 96%, which is superior the other classifiers under test. For the automatic segmentation, the number of repetitions obtained were smaller compared to the ground-truth of the manual segmentation. In a real case scenario, and considering physical limitations of our dataset (paralysis, hemiparesis, muscular strength and balance problem, among others), it was difficult to have clear patterns of muscle activation, which influenced the performance of the SSTS tool. This also affected the performance of the classifiers when considering the automatic segmentation, which lead to value differences between automatic and manual segmentation. Performance metrics are, in general, significantly smaller for the automatic segmentation. Nevertheless, this limitation was only noticed since the methodology developed in [24] was tested in a real case scenario, which needs to be considered in future work.

Our study details a methodology that is still in development, and there are a few studies with a similar approach that we can directly compare to our work. As reported in Section II, some studies already combined accelerometers with electromyography sensors: Gamecho et al. [27] used a device with these two sensors to evaluate the performance of upper limb exercises for post-stroke or post-operative recovery cases, extracting muscle activity and limb tilt angles to be used as inputs in a mobile robot; and Liu et al. [28] extracted motion features including angles and muscle activity information also to be used as inputs in a upper limb rehabilitation training system. Both studies were concerned with biofeedback and their systems relied on direct comparison of muscle activation and limb tilt angles to pre-defined desired thresholds, in order to trigger a command in a robot and in a game, respectively. None of these studies combined sEMG and inertial data at the same time to ensure a more complete of evaluation the exercise execution.

This study demonstrated the viability of using inertial sensors to complement sEMG data. Firstly, sEMG data was used to segment all the repetitions. Secondly, inertial sensors were used to assess posture and movement correctness, which would be impracticable if the methodology was only dependent on sEMG. This duality of sensors allows evaluating the quality of rehabilitation exercises by ensuring correct postures are maintained during the moments of muscular activation. Additionally, our methodology can be modular and adaptable to other exercises since the bracelets with embed inertial sensors used in this study could easily be relocated to different anatomical segments if other exercises were selected.

VII. CONCLUDING REMARKS

This paper presented a methodology to use inertial sensors for evaluating exercises correctness in sEMG-based home rehabilitation systems. For that purpose, the feasibility of previous algorithms developed by the authors was validated in a clinical context.

The data was collected with patients currently taking part in physical rehabilitation programs where our approach achieved an average accuracy of 96% in distinguishing correct from incorrect exercise execution, recognizing the contribution of inertial sensors in extracting information regarding posture and movement to already existing sEMG-based systems.

As part of our ongoing research, the methodology presented in this study will be implemented in the Physio@Home system. This will support the biofeedback system with information regarding the posture of the patient and it will contribute to a more accurate guidance and correction of the exercises performed by patients at home.

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