Physiotherapy Exercises Evaluation using a Combined Approach based on sEMG and Wearable Inertial Sensors

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Abstract: The efficacy of home-based physiotherapy depends on the correct and systematic execution of prescribed exercises. Biofeedback systems enable to accurately track exercise execution and prevent patients from unconsciously introduce incorrect postures or improper muscular loads on the prescribed exercises. This is often achieved using inertial and surface electromyography (sEMG) sensors, as they can be used to monitor human motion variables and muscular activation. In this work, we propose to use machine learning techniques to automatically assess if a given exercise was properly executed. We present two major contributions: (1) a novel sEMG segmentation algorithm based on a syntactic approach and (2) a feature extraction and classification pipeline. The proposed methodology was applied to a controlled laboratory trial, for a set of 3 different exercises often prescribe by physiotherapists. The findings of this study support it is possible to automatically segment and classify exercise repetitions according to a given set of common deviations.

1 INTRODUCTION

Over the last years, the world's ageing population and prevalence of chronic diseases has lead to an increasing demand of efficient healthcare systems (Stankovic et al., 2005). In general, physiotherapy is applied not only to functional repair, but also in the prevention of motor complications. In order to optimize the prescribed treatment program, the exercises must be executed repeatedly and in the correct manner.

Home-based exercise physiotherapy allows stimulating muscular activity more often, by enabling the patient to execute the prescribed exercises at home. However, home-based physiotherapy comes at the cost of an additional effort to properly educate the patients for its benefits, allowing to maintain a continued adherence to the program (Bassett, 2003). The exercises should be correctly and rigorously executed, however, patients often demonstrate uncertainty with regards to proper exercise technique and not remembering the complete training program as presented on the clinic (Smith et al., 2005). In these circumstances, several deviations may occur from the ideal movement: the unconscious introduction of compensation movements or postures, insufficient range of movements, improper timing of muscular activation or even biomechanical misalignment.

In order to overcome such challenges, biofeedback systems may be used. Biofeedback usually involves measurement of a target biomedical variable and relaying it to the user (Giggins et al., 2013). Providing patients with biofeedback during physiotherapy can have potential therapeutic effects, as it ensures movements and loads are being executed according to prescription and simultaneously engaging patients in their physiotherapy programs (Ferreira et al., 2014).

Biofeedback rely on different sensors to quantify motion. Inertial sensors play an important role in characterizing human motions, as they are able to retrieve motion characteristics such as acceleration, rotation, angular velocity and posture information. On the other hand, Surface electromyographic sensors (sEMG) can be used to evaluate muscular activation and contraction.

This work presents a feasibility study aiming to combine inertial and sEMG information. The main motivation lies on the challenges arising from real home-based physiotherapy programs. During such sessions, which may exhibit variability across subjects and environments, sEMG might be used to precisely identify the intervals of muscular activation. Inertial information is then used to characterize the posture and movement correctness, allowing a more accurate temporal resolution of classification.

The rest of this paper is organized as follows: Section 2 describes previous work on biofeedback systems and methodologies using inertial and sEMG

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senors applied to motion quantification. Section 3 describes the methods used for evaluating physiotherapy exercises, while Section 4 and 5 present the results and its discussion, respectively. Section 6 concludes this paper, highlighting some areas of future work.

2 RELATED WORK

In order to ensure the proper efficacy of physical physiotherapy programs, there is a need for continuous and systematic evaluation of the execution of prescribed exercises. Recent research has been trying to explore the opportunities arising from technological advances to provide enhancements in monitoring physiotherapy exercises in home environment. Outside the clinical environment, biofeedback systems rely on retrieving motion data, properly quantify and characterize such data and issue recommendations to the patient. Methods to achieve biomechanical analysis consist of force and balance platforms, vision-based motion capture systems and systems based on inertial sensors. (Barandas et al., 2015) used Microsoft Kinect to retrieve Range of Motion to provide real-time biofeedback. (Pereira et al., 2017) used multiple Inertial Measurement Unit (IMU) to estimate joint angles with a strong correlation between the proposed approach and the groundtruth, which was based on a video system.

For an unobtrusive evaluation of exercise quality, studies investigated the feasibility of inertial sensors to provide accurate classification of exercise performance in patients executing lower limb exercises for rehabilitation monitoring. (Giggins et al., 2014) used a logistic regression to classify between correctly and incorrectly labelled variations of 7 types of exercises, achieving an accuracy of 81-83% on binary exercise classification and 61-63% on multi-label classification (i.e. characterizing the type of error executed). (Huang et al., 2016) combine accelerometer and gyroscope data from 3 inertial sensors located on tight, shin and the foot, and through logistic regression, Decision Tree, Multilayer Perception Neural Network, Support Vector Machines, Random Forest, and Adaboost classifiers, achieved accuracies between 78-97% when classifying normal vs. error, and 92-97% when classifying the type of error occurred. More recently, (Bevilacqua et al., 2018) applied similar approaches to knee rehabilitation exercises on both clinical and healthy subjects. Using a single inertial sensor located on the shin, a binary classification using Random Forest and Decision Trees were applied to 4 different knee rehabilitation exercises, achieving overall accuracies of 88-97%.

Whilst inertial sensors proved to be valuable sources of information to characterize exercise execution, they still face some inherent limitations on distinguishing active vs. passive performance of a movement or ensuring information is being extracted from muscular loaded or unloaded performance of a given activity. sEMG can be used to overcome such limitations as the amplitude of sEMG signal is related to muscle torque and activation (De Luca, 1997). With this reasoning, (Roy et al., 2009) studied the feasibility of introducing sEMG data while monitoring activities of daily living in functional assessment of stroke patients. (Liu et al., 2017) proposed the development of an upper limb rehabilitation training system designed to be used by children with cerebral palsy. (Ghasemzadeh et al., 2010) studied the application of sEMG to assess human balance, where fiducial features based on the sEMG were used, with high accuracy, to provide significance of each quantitative parameter applied to balance assessment.

Another specific application of wearable technology in physiotherapy is the development of smart gloves to be integrated into serious games. The combination of IMUs to estimate orientation and piezoresistive force sensors to estimate fingers' compression and flexion can be used in hand movement physiotherapy systems for stroke patients. (Sun et al., 2017) implemented a linear discriminant analysis classifier to distinguish between a basic set of hand gestures and key press events. (Alexandre and Postolache, 2018) proposed a virtual reality game to stimulate patients performing interactive exercises while simultaneously recording motion parameters.

The related work allowed to highlight evidence of the notable properties of the IMU and sEMG sensors in the evaluation of Human motion, more precisely in physiotherapy contexts. Exercise execution in home environments, in which there is no direct supervision of a physiotherapist, must be accurately monitored. Patients may inadvertently perform additional deviations from prescribed exercises by performing compensation movements. Therefore, it is important to evaluate whether compensation exists when the muscular activation is being employed. This can be achieved by means of the sEMG, which in long-term home sessions might be used to accurately identify the intervals of muscular activation. Over those intervals, an accurate posture and exercises correctness evaluation can be performed.

3 MATERIALS AND METHODS

A cross-sectional analytic study was conducted to examine two research questions: 1) whether sEMG sensors can be used to automatically segment physiotherapy exercises repetitions, and 2) whether physiotherapy exercise classification performance can be improved using information regarding the posture of the patient during the exercise.

For that purpose, 7 subjects were recruited to perform three different physiotherapy exercises. Two Body Network Area (BAN)s[1] (depicted on Figure 1 a) and two inertial units (Fraunhofer AICOS, 2016) (depicted on Figure 1 b) were placed on the subject's body in locations defined to maximize the retrieval of relevant information for each exercise. During the acquisition, annotations were performed in real-time regarding instants that correspond to transitions between repetitions. Sensor data was then segmented manually (i.e. using the annotations) and automatically using the methodology that will be thoroughly presented in Section 3.3. A machine learning pipeline was then applied for classifying the exercises into correct and incorrect executions.

(a) (b)

Figure 1: Wearables used in this study: (a) two Body Network Areas placed on the lower and upper trapezium, and (b) two inertial units placed on the upper arm and forearm.

3.1 Data Collection

Participants
Seven healthy subjects, with an average age of 27 $\pm$ 1 years old, 4 men, 3 women, participated in this study. All participants had an active lifestyle and did not previously executed the prescribed exercises in physiotherapy contexts. Subjects requiring physical physiotherapy were not included in this first stage of the study since only the feasibility of the listed research questions was being explored at this stage. All participants provided informed consent before starting data collection.

Sensors
Two types of wearables were used for data collection: two inertial sensor units (equipped with a triaxial accelerometer, gyroscope and magnetometer), and two BAN's equipped with an electromyography sensor and an accelerometer. Inertial units were attached to the body through bracelets and BANs were attached to specific body locations using electrodes. These devices communicated wirelessly with a smartphone via Bluetooth Low Energy. The inertial data from both wearables was collected at 50 Hz. The raw sEMG was acquired at 1000 Hz, the sEMG envelope was calculated locally on the device and the resulting sEMG envelope was streamed at 50 Hz. The devices were placed on different locations of the body according to the exercise: inertial units were placed on specific body segments for the assessment of posture on upper and lower limbs and the BAN's wearables were placed on body locations which enabled to measure muscular activity.

Protocol
The data collection protocol was defined by a physiotherapist to ensure the exercises are relevant in clinical practice. Three physiotherapy exercises were selected from the *Physiotec*[2] exercise database. *Physiotec* divides physiotherapy exercises into three phases: phase 1 consists of static exercises, phase 2 is composed of dynamic and analytic exercises, and phase 3 includes dynamic and functional exercises. In order to promote variability, one exercise of each phase was selected. For each exercise, the physiotherapist defined two possible deviations which represented incorrect human postures often occurring during exercises execution. The selected exercises, respective deviations and wearables' location are listed in Table 1.

All data collection was performed in laboratory settings, where wearables were placed on each participant by the physiotherapist. Participants performed a variable number of repetitions (between five to ten) of each of the three studied exercises. The exercises were executed correctly and intentionally incorrectly, according to the deviations defined in Table 1. All the exercises and deviations were described to each participant prior to the start of data collection. The instants corresponding to the beginning and end of each repetition were manually annotated by a researcher during the protocol, consisting of groundtruth for the segmentation algorithm.

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

[2] https://www.physiotec.ca/index.php

Table 1: Exercises, wearables location, and deviations studied for each exercise (I refers to the inertial units, B to the BANs, and D represents the different deviations).

Exercise	Wearables Location	Deviations
1 - Isometric scapular retraction strengthening (Phase 1)	I - wrist and arm B - lower and upper trapezium	D1 - Forearm deviated from horizontal position (right forearm up) D2 - Forearm deviated from horizontal position (left forearm up)
2 - Prone scapular retraction (Phase 2)	I - wrist and arm B - serratus and upper trapezium	D1 - Compensatory projection of trunk (arms deviated from vertical) D2 - Incorrect arm position (shoulder displaced backwards)
3 - Forward lunge (Phase 3)	I - wrist and thigh B - knee and upper trapezium	D1 - Leg not perpendicular with the ground D2 - Compensatory leg deviation from vertical position

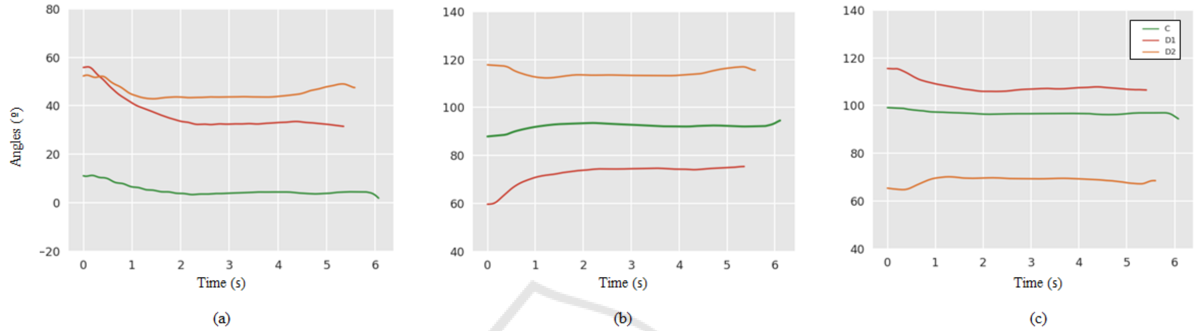

Figure 2: Angles (in degrees) computed from orientation during one repetition (x-axis) for correct (C) execution and with deviations 1 (D1) and 2 (D2). (a) Angle between the arm and forearm (elbow flexion/extension angle) during exercise 2, (b) angle with vertical of the forearm during exercise 1; (c) angle with vertical of the upper arm during exercise 2.

3.2 Signal Processing

The data obtained from the four wearable devices was preprocessed in order to reduce undesired noise using a low-pass filter. In order to characterize posture, the tilt angles (roll and pitch) were obtained from the accelerometer data of the BANs wearables. Additionally, to have more information regarding human posture, data from the accelerometer and gyroscope of these devices was fused using a second order complementary filter, bringing together the relevant information of each sensor to compute the orientation of the device. Applying the methodology developed in (Pereira et al., 2017), the orientation obtained enabled to compute the angle between the two inertial units in exercises 1 and 2, that is the angle between the arm and the forearm, which corresponds to the elbow flexion/extension angle (example illustrated in Figure 2 a for exercise 2), and also the angle of each inertial unit with the vertical (example illustrated in Figure 2 b and c for exercise 1). Angular information of anatomical segments allows discriminating between correct execution and the prescribed deviations. Proper assessment of exercise execution should not only ensure the patient is performing adequate muscular contractions, but also ensure the contractions are being performed with the correct posture and without the intentional introduction of compensatory movements.

3.3 Segmentation

As previously discussed in Section 2, the sEMG signal is related with muscular activation. The segmentation of sEMG comprises the task of identifying the temporal intervals in which activation is present, quite often by analyzing the sEMG envelope. In this study, we propose and validate a new method based on a syntactic approach. We used a recent tool called SSTS (Rodrigues et al., 2019), which is capable of exploring time series data for pattern and query search tasks.

Human reasoning has an inherent capability for recognizing patterns and complex structures. We can take advantage of this characteristic to ease the process of finding patterns in several time series applications. SSTS aims to facilitate the interaction between data scientists and the challenges arising from data manipulation and knowledge extraction. By proposing a symbolic method for pattern search, which is tightly related to the reasoning and visual analysis of time series data, it allows improving the pattern and query search task productivity, which was properly demonstrated on the aforementioned work. In this work, we also validate that assumption motivated by delivering a new automatic segmentation for sEMG data with minimum design effort taking the advantages of the SSTS capabilities. SSTS converts

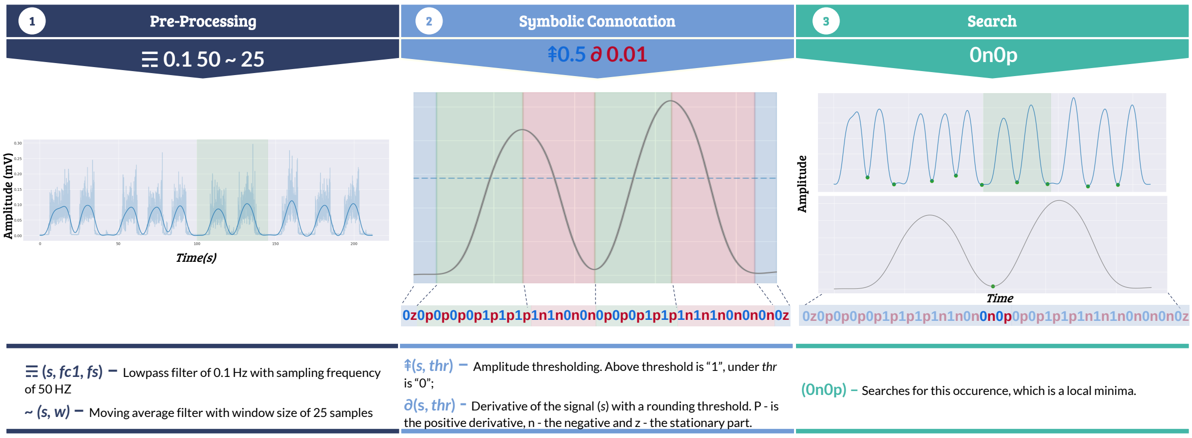

Figure 3: Initial sEMG segmentation. The sEMG signal is divided into cycles, which give an initial estimation of the activation period. Cycles are calculated by finding local minima using Syntactic Search for Time Series (SSTS).

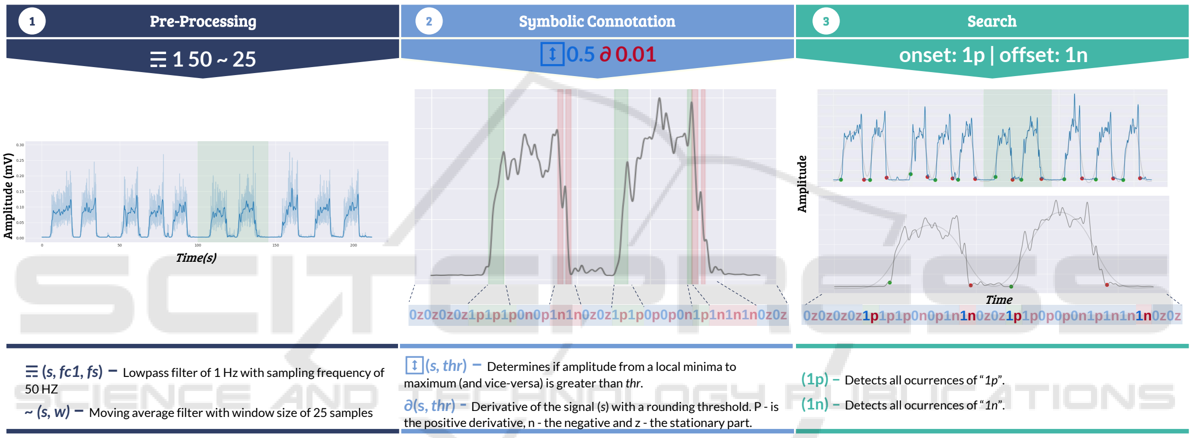

Figure 4: Accurate sEMG onset and offset detection. For each cycle previously detected the onsets are found by using SSTS to query for "*a pronounced amplitude rise*" and offsets by querying "*a pronounced amplitude decrease.*" False positives are eliminated by only considering the first occurrence of the onset search regex string and last occurrence of the offset search string.

time series data from numeric to string domain with the resource of 3 symbolic steps: (1) preprocessing; (2) symbolic connotation and (3) search. In the string domain, characterized by a symbolic representation defined by the user, queries are performed using string query methods. Whilst on the rest of this subsection we provide guidance to follow the methods used by SSTS to segment the sEMG, it is recommended that for a comprehensive understanding the reader may refer to the original publication.

Overview

The proposed sEMG segmentation is composed by two stages. Firstly, the sEMG activation periods are initially divided into cycles. This is accomplished by analyzing the lower frequency components of the signal as depicted on Figure 3. Whilst this procedure may at an initial glance be sufficient, it does not allow an accurate temporal resolution of the onset and offset events. Secondly, after the initial cycle segmentation there is a more accurate onset and offset detection within the time intervals corresponding to each detected cycle as depicted on Figure 4. This combined approach also reduces the occurrence of false positives.

Preprocessing

During this step, symbolic tokens are attributed to common methods for preprocessing. A string containing the set of tokens and their corresponding arguments are passed as input, thus, corresponding to the preprocessing methods and parameters. The sEMG envelope was filtered using lowpass filtering and moving average as described in Step 1 of Figure 3.

Connotation
The symbolic connotation step generates a sequence of symbols based on connotation methods defined by the user. Ideally, the method should be related to specific attributes of the time series that are considered relevant for the target search procedure. Each sample is represented by a number of tokens that correspond to the number of connotation methods that were used. In the current approach, two connotations methods were applied in the initial stage - amplitude thresholding and first derivative: "*0p*" represents a sample with value below a given threshold with positive derivative; "*0n*" represents a sample with value below a given threshold with negative derivative; "*1z*" would represent a sample with amplitude above the given threshold with zero derivative. The same reasoning applies to other connotation methods. The sEMG activation is characterized in the sEMG envelope by a significant rise in amplitude in comparison with the baseline (onset), followed by a plateau during muscular activation and terminating in a significant decrease in amplitude to baseline (offset). A well established method that is frequently used, takes into account this property. (Hodges and Bui, 1996) required that the mean of the points in a sliding window exceed a given threshold (the value usually is a multiple of the standard deviation). The applied connotation methods were inspired by that approach and are described in Step 2 of Figure 4.

Search
After the connotation step, the signal is translated from the numeric to the symbolic domain. A search string is used in the form of a regular expression (*regex*). The *regex* used in both stages is depicted in Step 3 of Figure 3 and 4. In the initial stage, in which the objective is to find the occurrences of local minima, the search consists of finding all the occurrences of: "*a negative first derivative, followed by a positive first derivative, below a given amplitude threshold*", which is expressed as *"0n0p*". The accurate onset detection is performed by querying for a *"pronounced amplitude rise"*, which holds true by the connotation method - "*1p*". Offset detection is achieved by querying for a *"pronounced amplitude decrease"* - "*1n*". It is worth to mention that muscular activity does vary during contraction periods and thus, the EMG envelope may in some circumstances have associated variability and noise. This fact leads to the appearance of false positives. However, since a rough estimation of EMG segmentation was achieved on the initial stage, we can remove the false positives by only considering the first positive match of "*1p*" for onset and the last positive match of "*1n*" for the offsets.

3.4 Machine Learning Pipeline

After segmentation, temporal and statistical domain features were extracted for each time window (Figueira et al., 2016). Statistical features such as skewness, kurtosis and histogram, and temporal such as mean, median, maximum, minimum, variance, temporal centroid, standard deviation, root mean square, and auto correlation, were extracted using Python *numpy* v1.11.3. After feature extraction, it was possible to conclude that many of the features were correlated and could be removed without loosing information, therefore, forward feature selection was applied.

Supervised learning methods were used to discriminate between a correct execution and a execution with a deviation, specifying the type of the deviation occurred. Therefore, each time window was classified into correct (C), deviation 1 (D1) and deviation 2 (D2). Using *scikit-learn* v0.19.1, a Python Machine Learning library, on Python 2.7.13, four classifiers were tested to addressed this problem: Decision Trees (DT), K-Nearest-Neighbours (KNN), Support Vector Machines (SVM), and Random Forest (RF). The classifiers trained separately manual and automatic segmented time windows (repetitions) and also two different set of features: features extracted only from the BANs and then features from all wearables, namely the two inertial units and the two BANs.

For validation purposes, leave-one-user-out-cross validation was employed in order to ensure independence of the subject. To evaluate the performance of each classifier, accuracy, sensitivity, and specificity were computed. While accuracy measures the overall effectiveness of a classifier, sensitivity measures the effectiveness of a classifier at identifying a desired label, and specificity measures the classifiers ability to detect negative labels.

Table 2: Total number of time windows for all three classes based on the method of segmentation.

Class	Exercise 1	Exercise 2	Exercise 3
Manual Segmentation			
C	63	71	57
D1	54	56	28
D2	53	55	27
Automatic Segmentation			
C	55	67	55
D1	51	56	27
D2	46	41	27

Table 3: Multi-label classification results obtained for DT, KNN, RF and SVM classifiers for each exercise and for each set of features (features extracted only from BAN and from BAN and Inertial Units). Mean and standard deviation of the specificity and sensitivity are reported in %.

			DT			KNN			RF			SVM		
Exer.	Set	Meas.	C	D1	D2	C	D1	D2	C	D1	D2	C	D1	D2
1	BAN	Sens	73 ± 32	98 ± 2	88± 18	78 ± 9	92 ± 5	90 ± 12	67 ± 30	87 ± 20	82 ± 17	80 ± 21	86 ± 17	97 ± 5
		Spec	82 ± 28	66 ± 36	73 ± 35	73 ± 25	78 ± 17	70 ± 15	61 ± 43	52 ± 44	57 ± 41	86 ± 18	80 ± 29	63 ± 29
	BAN + Inertial	Sens	100 ± 0	100 ± 0	99 ± 1	100 ± 0	100 ± 0	99 ± 26	100 ± 0	96 ± 5	99 ± 1	100 ± 0	100 ± 0	100 ± 0
		Spec	100 ± 0	98 ± 3	100 ± 0	100 ± 0	100 ± 0	100 ± 0	100 ± 0	98 ± 3	93 ± 11	100 ± 0	100 ± 0	100 ± 0
2	BAN	Sens	76 ± 13	90 ± 14	90 ± 8	86 ± 13	87 ± 7	91 ± 9	61 ± 23	85 ± 15	88 ± 18	54± 37	85 ± 20	96 ± 5
		Spec	80 ± 20	61 ± 29	75 ± 25	74 ± 17	82 ± 23	75 ± 19	74 ± 28	36 ± 22	60 ± 33	78 ± 21	53 ± 40	41 ± 40
	BAN + Inertial	Sens	96 ± 10	97 ± 7	97 ± 4	99 ± 1	100 ± 0	99 ± 2	95 ± 7	100 ± 0	94 ± 9	98 ± 5	98 ± 3	99 ± 1
		Spec	92 ± 14	95 ± 12	91 ± 22	98 ± 3	98 ± 3	100 ± 0	92 ± 14	89 ± 15	98 ± 3	100 ± 0	97 ± 4	95 ± 12
3	BAN	Sens	71 ± 21	91 ± 13	89 ± 12	48 ± 20	94 ± 5	98 ± 2	55 ± 15	79 ± 13	91 ± 13	40 ± 14	98 ± 3	98 ± 2
		Spec	95 ± 7	50 ± 30	71± 34	96 ± 4	53 ± 33	27 ± 20	77 ± 16	51 ± 27	22 ± 23	98 ± 3	66 ± 41	10 ± 15
	BAN + Inertial	Sens	100 ± 0	97 ± 4	100 ± 0	91 ± 16	97 ± 5	100 ± 0	95 ± 5	95 ± 6	90 ± 15	84 ± 13	100 ± 0	100 ± 0
		Spec	96 ± 7	100 ± 0	100 ± 0	96 ± 7	96 ± 7	86 ± 29	91 ± 9	71 ± 28	93 ± 14	100 ± 0	100 ± 0	70 ± 25

4 RESULTS

In this study, 7 participants performed three exercises which were labelled with 3 classes: correctly, and with deviations 1 and 2. Table 2 details the dataset collected applying manual and automatic segmentation, resultant from the annotations performed during data collection, and from the automatic segmentation approach described in Section 3.3, respectively. As it can be seen, the number of detected time windows (repetitions) applying automatic segmentation is lower than the ones that were manually annotated.

Results of the leave-one-user-out-cross validation for the assessment of the classification performance are presented in Table 3 and Table 4. It is presented the performance scores obtained for each exercise with the four classifiers considering the two sets of features: features extracted from the BAN data and features extracted from both the BAN and the inertial units. Relatively high average accuracy scores were achieved considering features from both wearable for all three exercises, being the DT and the KNN classifiers the ones that achieved higher accuracies. Additionally, sensitivity and specificity were also high in general, however, for exercise 3, KNN, RF, and SVM demonstrated a few confusion in distinguish classes D1 and D2, which compromise the value of the specificity for these two classes. Nonetheless, when using only features from the BANs wearables, accuracy considerably decreased, as well as specificity and sensitivity, for all four classifiers and exercises. For this case, the standard deviation values of the metrics presented are high, which means that the values obtained during validation were actually different depending on the test user.

Table 5 compares the overall accuracy of the classification performance for the manual and automatic segmentation, which was obtained when using features from all wearables. As it can be seen, the values presented are approximately identical, except in exercise 2 for RF and SVM classifiers.

Table 4: Mean accuracy and standard deviation (%) for DT, KNN, RF and SVM classifiers for each exercise and for each set of features (features extracted only from BAN and from BAN and Inertial Units). Mean and standard deviation are reported in %.

Exer	Set	DT	KNN	RF	SVM
1	BAN	76 ± 15	74 ± 8	60 ± 7	78 ± 13
	BAN + Inertial	99 ± 1	100 ± 0	97 ± 3	100 ± 0
2	BAN	72 ± 12	77 ± 10	60 ± 13	63 ± 11
	BAN + Inertial	94 ± 9	98 ± 2	93 ± 3	97 ± 5
3	BAN	71 ± 3	86 ± 7	57 ± 13	63 ± 6
	BAN + Inertial	98 ± 4	98 ± 2	97 ± 3	92 ± 6

Table 5: Overall accuracy (%) for DT, KNN, RF and SVM classifiers for each exercise and for manual and automatic segmentation.

Exer	Segmentation	DT	KNN	RF	SVM
1	Manual	99 ± 1	100 ± 0	97 ± 3	100 ± 0
	Automatic	100 ± 0	100 ± 0	97 ± 5	99 ± 1
2	Manual	94 ± 9	98 ± 2	97 ± 3	97 ± 5
	Automatic	97 ± 4	96 ± 7	89 ± 16	85 ± 11
3	Manual	98 ± 4	98 ± 2	97 ± 3	92 ± 6
	Automatic	93 ± 6	99 ± 6	96 ± 6	89 ± 6

5 DISCUSSION

This research study has explored whether sEMG sensors can be used to automatically detect exercises repetitions and whether additional inertial units placed on strategic segments of the body can contribute to distinguish correct exercise performance from deviations based on the human posture.

The use of sEMG sensor for automatic segmentation was achieved using the capabilities of SSTS. In order to ensure that the windows provided to classification stage were adequate and, consequently, the classifier was learning from representative data, a validation stage was performed. The automatically detected muscular activation periods (provided by the onset/offset pairs) that were shorter or longer than the expected duration according to the protocol weighted with a given tolerance were discarded. The number of discarded samples was higher for Exercises 1 and 2. In fact, later visual analysis of sEMG signals and automatic segmentation results allow to conclude that in those exercises noise and artifacts were more prominent, lowering the difference between the amplitude in muscular activation and baseline, hampering an adequate calculation of threshold.

The results presented on Table 3 and 4 revealed that is possible to correctly classify physiotherapy exercises performance from different phases using inertial units with satisfactory levels of accuracy. The use of inertial units showed a significant improvement (an increase of 27%, in average) on the accuracy of all classifiers in each exercise. Since the exercises deviations were defined based on incorrect postures, the attachment of inertial units which measure inclination of body segments, enabled to identify more accurately incorrect executions, which may be undetectable if only the tilt angles of BANs were used. Machine learning classification techniques were used to quantify wearable data acquired during the three exercises studied. Multi-label classifiers (which determine which deviation in a set of deviations) were employed and the efficacy of these classifiers was quantified using three efficacy scores; accuracy, sensitivity, and specificity. Results showed that KNN classifier achieved a recognition accuracy of $\geq$98%, which is greater than the other classifiers tested. However long training and testing times are required for KNN. The DT classifier achieved the second highest recognition accuracy in this study, and its training and testing times were lower than the KNN. Thus, the DT classifier proved to be an efficient classifier for detecting deviations from correct execution of physiotherapy exercises.

After identifying the improvement of the classification results through the use of inertial units in body segments, DT, KNN, RF, and SVM classifiers were also validated in the automatically segmented windows. The results of Table 5 demonstrated no significant changes in the accuracy values of all classifiers for each exercise, which proves the feasibility of the syntactic sEMG onset detection of exercise repetition, ensuring that muscular activation is being employed. For the automatic segmented windows, DT and KNN also achieved the best performances.

The results obtained allow a preliminary comparison to previous work that evaluated the use of inertial units and machine learning to assess exercises performance. The methodology presented in our study achieved higher results than (Giggins et al., 2014), and similar results to the (Huang et al., 2016) and (Bevilacqua et al., 2018) studies. Additionally, (Huang et al., 2016) and (Bevilacqua et al., 2018) also used automatic segmentation based on a template matching algorithm. However, it is worth to mention that the dataset of this study is significantly smaller than the datasets of the aforementioned studies. The size of the datasets was 58, 69 and 54 participants, respectively for (Giggins et al., 2014), (Huang et al., 2016) and (Bevilacqua et al., 2018). Therefore, the developed methodology needs to be tested and validated against a larger dataset for a more representative comparison with previous work. It is expected that accuracy might decrease with an increase of dataset size (Schnack and Kahn, 2016). However, we believe the process of combining inertial and sEMG data, by assuring classification is performed in the moment of muscular activation, provides more relevant information to the exercise performance and the physiotherapist.

Besides the size of the dataset collected, there are other limitations of this study that need to be considered. Firstly, the data collected was gathered in laboratory settings, where the exercises were performed under controlled conditions. These conditions may differ from what may occur at home. Furthermore, only two deviations were defined per exercise. In a home-based physiotherapy context, other deviations in performance may occur that were not considered when training the classifiers. Another limitation of this study is that the sample selected was a group of healthy subjects, so it was not possible to validate whether the classifiers performed differently for different populations.

Nevertheless, the results obtained in this study are important as they provide further evidence to suggest that sEMG signal could be used to detect exercise repetitions, and that features based on human posture could support the assessment of exercises performance. Moreover, the exercises selected in this study were from a worldwide database developed by physiotherapists, and were not specific for a single limb as the studies found in the literature. The exercises selected were one from each of the three phases of the physiotherapy process, which proves that the approach developed could be adapted for a wide range of exercises.

6 CONCLUDING REMARKS

This paper presents the development of a combined approach based on sEMG and inertial sensors for the evaluation of physiotherapy exercises. The applicability of our approach lies in the implementation on biofeedback systems to optimize home-based exercise execution. sEMG signal was used to identify temporal intervals in which muscular activation was present. This way, exercise repetitions were segmented into time windows where features related with human posture were extracted. Then, these features were fed to DT, KNN, RF, and SVM classifiers, which were able to distinguish between correct execution and deviations with an accuracy $\geq$92%. As part of our ongoing research, we will validate the proposed system on more extensive datasets. The sEMG segmentation will be assessed in a more controlled environment, using simulated data, to permit the evaluation of the temporal misalignment between the detected onset/offsets and groundtruth. The models proposed will be tested on a more extended dataset, comprising variability in terms of age and clinical history.

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