Automatic Gym Workout Recognition using Wearable Devices

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***Abstract*—It is well known among people that sports practice leads to a better quality of life and prevent diseases. Furthermore, according to some sources, the use of smartwatches is spreading worldwide, reaching almost 20% of U.S. population nowadays. Aiming at helping people at gym, we proposed a work that employs smartwatches to recognize and classify activities executed by the users, allowing users to exercise properly and easily. This way, the users will be able to control their exercise series more precisely, for instance. We develop a new open source application capable of capturing and providing data easily. We use all sensors available (e.g., accelerometer, gyroscope, magnetometer, barometer and linear acceleration) to capture as much data as possible to perform exercise classification after performing feature extraction.**

I. Introduction

There is a common sense that obesity and unhealthy habits are spreading worldwide. For example, Agha [1] showed that the percentage of obese young and elders will be over 25% and 60% in 2050, respectively. This problem can lead to significant long-term health consequences, such as diabetes, coronary heart diseases, osteoarthritis and risk of developing certain types of cancer.

To surpass that problem, studies verified that physical activity can result in a better quality of life, and reducing chances of heart diseases and cancer [2], [3]. According to the US Centers for Disease Control and Prevention (CDC), despite increasing awareness of these benefits, maintaining or expanding a regular exercise regimen is a challenge and therefore most people do not maintain adequate levels of physical activity [4]. In the last years, research studies has shown that automatic exercise tracking can motivate physical activities. For example, in the work Chan et al. [5] showed that the use of pedometer increased physical activity in a sedentary population.

Recently, the electronic industry started the development of equipments to track, evaluate and classify physical activities of different types performed by common users to facilitate and stimulate the practice of daily workout activities. We can cite pedometers and GPS devices to monitor running/walking exercises, while more advanced gadgets (e.g., stationary bicycles and treadmills) can share exercise summary.

Other examples of devices being used in activity tracking are smartwatches and smartbands[1], reaching almost 140 million of users [6]. They have several sensors and a system capable to process the captured data, without the help of external devices. Due to the practicality and efficiency, they are becoming widespread and useful in the users daily routine. However, these devices fails in two main categories: calisthenics[2] and weightlifting.

For some individuals, the weightlifting exercises may be more sustainable than walking or jogging, for lifestyle or preference reasons. The muscle strengthening activities is recommend, at least twice a week for adults, to help in the weight loss and to increase the general health [7].

Finally, due to the demand of tracking calisthenics and weightlifting exercises, our work intends to capture, recognize and classify physical activities performed by the users, wearing a smartwatch, at the gym, and automating the task that today can be done only by qualified professionals. This ongoing work focuses on proving the viability of the recognition and classification.

II. Related Work

Since smartwatches and smartbands are increasingly present in the day-to-day of millions of individuals, research enforcement developed about activity recognition using them is motivated toward recognize daily activities such as walking, running, sitting and climbing stair [8]. However, few works were published about gym exercises, more specifically, weightlifting.

Works focused on weightlifting achieved significant results, but they use a wide range of sensors spread throughout the body, avoiding the methods applications in daily routine of users. Below we will discuss some of these works.

Pernek et. al [9] used five body sensors that captured the accelerometer data. The pipeline was divided in two stages. The first recognizes the exercises being executed and the second evaluates the intensity of execution. This work extracted simple features from captured data, such as *minimum*, *maximum*, *mean*, *standard deviation* and *correlation*, and applied this features to a Support Vector Machine (SVM) classifier model, which is also capable of recognizing when there are no activities being performed. The proposed method achieved 96.6% accuracy, but did not perform repetition counts

[1]Smartbands are devices similar to smartwatches but have fewer sensors and act only on fitness and healthy environments.

[2]Calisthenics is defined as a type of functional exercise, in which the practitioner uses his own body weight to exercise, without using gym equipment or weights.

and the exercises were practiced separately. In addition, only six different types of exercises were used to train, being this amount far from the number of existing activities.

Velloso et. al [10] focused on creating models to qualify the execution of activities being performed using predetermined exercises. Due to this, they used sensors on gloves, belt, biceps and even on dumbbells to capture the largest amount of postural information. This work proposed methods to recognize mistakes and give feedback about the execution. To recognize mistakes, for each exercise, the method specified six different classes, each one of them representing common mistakes. Then, they trained a model using Random Forests to classify which mistake the user was making when exercising. As a result, they obtained between 74% and 86% accuracy using cross validation. However, only a small sample of users and exercises was used in order to validate the method.

Instead of sensors in the body, Zhou et. al [11] used a canvas made of conductive polymer fiber sheet that is capable of generating a heat map for each movement performed by the user. He used simple features such as mean, standard deviation, maximum, minimum and applied to a k-Nearest Neighbor (kNN) model, reaching an accuracy of up to 100%for each individual and counting the repetitions that each person performed in each set of exercises. Despite this, all the results achieved were in segmented exercises and there is no practical usage of a canvas in daily activities.

Although previous works had good results, they become unfeasible to be used in the day to day due to the price of gadgets, lack of practicality and difficulty of use.

III. Progress so far

Since the goal of our work is to recognize exercises performed by users, we initially wanted to capture user's data from smartwatches. However, due to the lack of apps available for this purpose, we propose to develop a new open source application capable of capturing and providing data easily. We used all sensors available (e.g. accelerometer, gyroscope, magnetometer, barometer and linear acceleration) to capture as much data as possible. All users performed the same exercises, having, at the end, plenty of data of multiple exercises repetitions. Then, we preprocessed this data using two protocols: Leave One Subject Out (LOSO) and Leave One Out (LOO), and computed multiple features (e.g. minimum, maximum, correlation) to improve the model's accuracy.

A. Data Capture

As aforementioned, there is no usable apps available for capturing and providing data easily. Therefore, our app is able to perform such capture and is available on google play, called [*Hidden due to the double-blind review process*][3]. The capture tool can be used from smartphones and smartwatchs. Here are some features provided:

[3]The capture application is available for download in the following link: https://play.google.com/store/apps/details?id=br.ufmg.dcc.ssig.sensorcap.

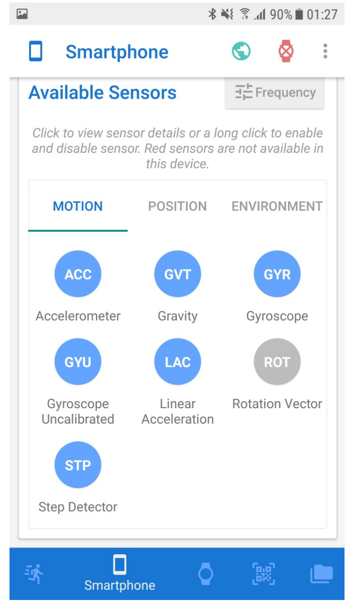

Fig. 1. Screen with available sensors.

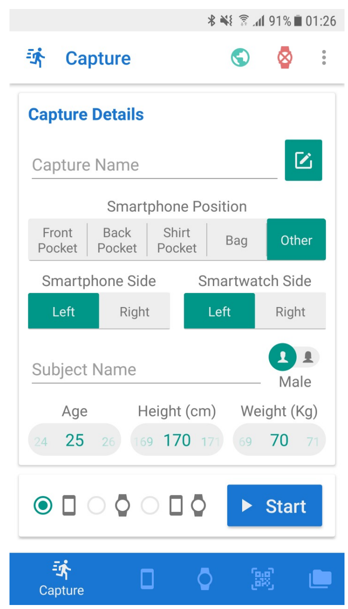

Fig. 2. User info screen.

- Choice of sensors: we let the user choose which sensors to use, from the sensors available on each gadget, as illustrated in Figure 1.
- User Metadata: in Human Activity Recognition (HAR), user's metadata (e.g. Age, Weight, Height, Gender) might be useful. We then let the user specify this data, as illustrated in Figure 2.

On the gym environment, there are plenty of exercise types, each of them focusing on different body muscles (e.g. Biceps Curl, Bench Press, Leg Press, Triceps Pressdown, Hammer Curl). Due to this variety, we defined which exercises we

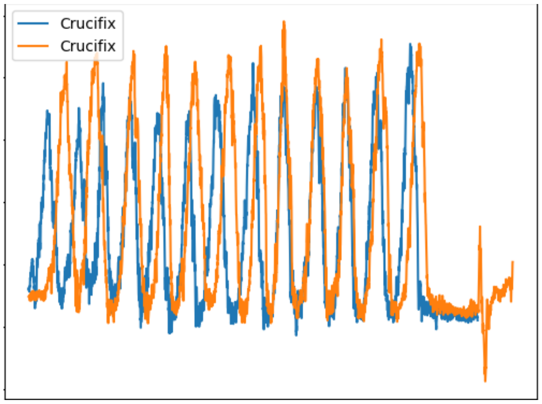

Fig. 3. Accelerometer data of different executions of crucifix by the same user.

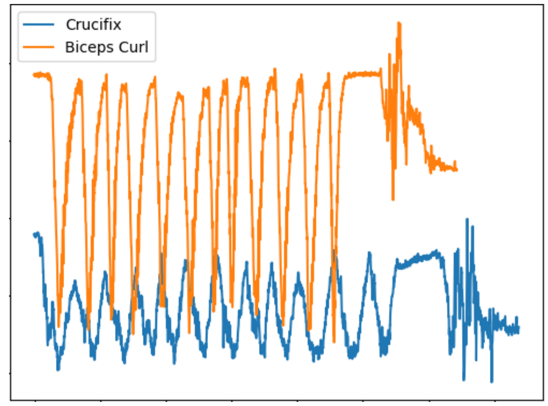

Fig. 4. Accelerometer data for Crucifix and Bicep Curl executed by the same user.

would capture, to obtain a better accuracy. Since smartwatches have the limitation of being used on wrist, exercises that aim to improve the leg muscles were discarded at first.

We also used different watch sensors (e.g. accelerometer, gyroscope, magnetometer, barometer and linear acceleration) and persons with different characteristics (e.g. weight, age, years of gym practice) in order to create a more discriminative model as the machine learning models are data sensitive, that is, every different type of data is useful and important.

B. Data preprocessing

With the data captured, we could fit the model with these data and classify the activities performed by the users. However, to obtain a better accuracy, we preprocessed the data.

Each sensor captures three different axis (x,y,z). So, for each axis, we performed a feature extraction step. Features aim at extracting relevant information from every exercise. Thus, enabling the model to recognize which exercise is being executed. Our sensor features used were: minimum, maximum, mean, standard deviation, variance, correlation and quantile to compose a feature vector. Where minimum, Maximum, Mean and Standard Deviation extract these values for all sensor axes. The variance computes the squared deviations from the mean for all axis. The correlation computes the similarities between two axis. Finally, the quantile cuts points dividing the range of a probability distribution into contiguous intervals with equal probabilities.

These features was chosen empirically, although some papers use them for HAR [12], [13]. As exercises have particular patterns, as shown if Figure 3 and Figure 4, this features can extract this patterns and make easier the learning step. As a result, for every person, we had a feature vector. And this feature vector was composed of seven features, each of them extracting three values for every sensor's axis, forming a feature vector with seven features, five sensors and three values per sensor (except Barometer that only has one axis and don't compute correlation) or 90 values in total.

C. Data Recognition

With the data captured, it is possible to recognize which exercises were performed by users. This recognition was performed through two machine learning models: Random Forest and SVM. Such models receive feature vectors as input, created in the previous step, from which a classification model is built. Note that if more data is available, we could use deep learning models instead, since they are better to recognize patterns.

D. Protocols

Protocol is the set of information, decisions and rules defined of an official act, such as an audience, conference or negotiation.

In the case of classification models, the protocol is a defined to validate the data. Then, it is divided between training and test according to different metrics and then the result generated is compared with the expected output. We used two existing protocols widely used so far: Leave one subject out (LOSO) and Leave one out (LOO).

The purpose of using LOO is to verify whether it would be possible to spatially separate the exercises performed by each user, that is, to verify if, for each user, the sensor data extracted from each exercise made the exercises spatially different from the others, in order to the model be capable of recognizing them. Otherwise, the LOSO protocol was used to verify if different users have different spatial representation, therefore it would be able to distinguish them and their activities using the proposed models.

IV. Tests and Results

To validate the hypothesis that it is possible to distinguish physical exercises, we performed preliminary tests. These tests consisted in recording certain previously established exercises with the same amount of repetition among users. The exercises chosen were: Crucifix, Triceps Pressdown, Biceps Curl, Hammer Curl and Supine, Figure 5. They were chosen because, although they are different, they have some similarities as Biceps Curl and Hammer Curl, in which the difference between

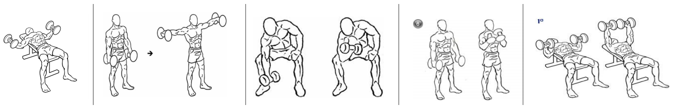

Fig. 5. Crucifix, Triceps Pressdown, Biceps Curl, Hammer Curl and Supine, from left to right.

them is the wrist rotation. Therefore, we were able to test our model and check if sensors could be discriminant to evaluate and recognize the correct exercise even if they were similar.

The sensors used by the smartwatch in the capture were accelerometer, linear acceleration, gyroscope, magnetometer and barometer.

Three different users were chosen to capture the data. Each one of them had different levels of experience with physical activities. For each of the individuals, five sets of exercises, executed five times each, were performed. That is, for each user there were twenty five captured files of each sensor, in which each file had twelve repetitions of a given exercise, totaling, in our case, three hundred sensor data files.

After the preprocessing stage, two machine learning models were used in order to test the classification accuracy, and validate our hypothesis. They were SVM and Random Forests using default parameters without fine-tunning.

For each model, we applied the proposed protocols. Using LOO, we split the captured data of users. And, for each user, we used one exercise for test and the other for training, testing with all exercises. We obtained 100% accuracy of every exercise executed using both SVM and Random Forests models. This showed us that every exercise has its own spatial representation, and could be distinguished from the others. On the other hand, using LOSO, we tested with two users and trained with the remaining one, testing with all users. The confusion matrix is presented in Figure 6. We observed that the SVM model had problems recognizing the exericises, while Random Forests had a great accuracy at the end.

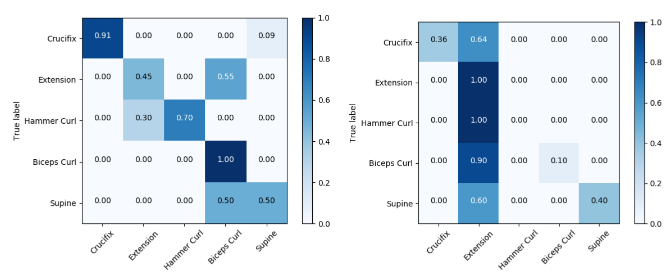

Fig. 6. Random Forest at left. SVM at right.

Although using SVM did not produce significant results, the model using Random Forest achieved this goal. Therefore, we could observe that, despite the small dataset, it was possible to discriminate and classify exercises of different people, validating our initial hypothesis.

V. CONCLUSIONS

This work demonstrates that smartwatches are a powerful gadget capable of recognizing different types of exercises on the gym environment using machine learning models with simple features, discarding the need of sensors all over the body and complex recognition models. Overall, the results of this paper suggest that using the smartwatch sensors makes possible the task of discriminating every exercises from the others, even if the exercises seem similar as 'Biceps Curl' and 'Hammer Curl'.

Although we reached good accuracy, we need to record more data from more users to create a more assertive model using, for instance, deep learning. In addition, as we have seen in [14], uninterrupted recognition, instead of segmented, is extremely important in order to be a useful tool, as users do not want to manage the watch while exercising. Finally, since gym users are demanding, we would like to provide some more feature as repetition counter and feedback provider.

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