Human Sport Activities Recognition and Registration from Portable Device

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***Abstract*—The drop in costs of hardware prices have led to significant changes in the size of various processors and sensors in smartphones. These devices come with a big range of new, precise measurement taking tools and multi-location sensors (distance sensor, accelerometer, gyroscope, magnetometer, camera and lighting sensors). This has opened the door for new smart device apps that can use data mining applications relying on sensor data. One of the main uses is the recognition of human movements. In this study, we propose a recognition and tracking method in sports activities such as push-ups, sit-ups and squats using only smartphone sensors and a machine learning algorithm. The key location for the smartphone is the upper part of the user's left arm. To collect the data and produce features for classifying sports activities, the motion data from accelerometer and gyroscope sensors is used. The features are made of two sliding windows and additional data processing which renders our classifier even more versatile. Fast response time, light-weight and accurate sport recognition can be used in mobile applications like our Home Workout Fitness Tracker which can process all the data in real time and create a real time sports activities tracking system.**

Keywords*—human activity recognition, machine learning, sensors, Android application, accelerometer, gyroscope, push-ups, squats, sit-ups.

I. Introduction

Currently, more and more people are filling their lives with sports activities. For this purpose, smartphones are used to assist in capturing achievements of sport activities. Lower costs in making hardware have led to significant changes in the size, capabilities and functionality of various processors and sensors in smartphones. These devices come with a wide range of new, precise measurement taking tools and multi-location sensors like cellular radio, Wi-Fi radio, Bluetooth radio, microphone, cameras, GPS, accelerometer, gyroscope, compass, light and proximity sensors [2, 13]. This has opened the door to new smartphone apps that use different sensor data. One of the main uses is the recognition of human movements. The growing presence of sport activity recognition and data capturing gadgets still has a low market share. A common problem for people who are interested in their health and staying in shape is how to log and track sport activities during the workout. Therefore we came up with an idea of a smartphone application – a sport activity tracker, which uses tri-axial accelerometer and gyroscope data for recognition.

Smartphone sensor-based activity recognition topic is not new. Our work is slightly different from most previous works because we use already built commercial mass-marketed device rather than a research-only device. Instead of five or more devices placed on different parts of the human body we are using only one, at specific location. Our work goal is to recognize specific sport activities and count their repetitions, while performing and storing all recognitions and calculations to a single device. The classifier was built using only one person's sport activity data, but after processing and extracting features we created a universal classifier model, which is independent from the user; the key factor is location and position of the smartphone.

Our work has several features. Since we tested our classifier model in a real world environment with real people we can start collecting more data and improve our model for more sports activities, as a solution we can see improvement in pull-ups recognition and offer our app to a larger audience of users. In this way, our classifier would be able to recognize push-ups, squats, sit-ups and pull-ups. For such an application, there are almost no limits in functionality growth like joining heart rate monitor, GPS workouts and voice couching program, etc. Secondly, we can offer the classifier model and dataset that we developed for further future researches as a solid foundation to start with.

In the following paragraphs, we discuss the related work (paragraph 2), describe our dataset collection, and describe our classifier model and an approach which we use to recognize activity from sensor data (paragraph 3). As a result of the research, we will show our experiment data and the capabilities of our application (paragraph 4-5).

II. Related Work

Human activity recognition is a wide field for science, researches and data mining. Human activity recognition can be divided in two main groups of video sensor based activity recognition (VSAR) and physical sensor based activity recognition (PSAR) [1]. According to the review (PSAR) can be split in to two smaller groups of wearable sensors and object usage based activity recognition (WSAR and OUAR). Our research will uses wearable sensors embedded on the smartphone itself. In the other article of Activity Recognition on Mobile Phones [2] the author made a review about available sensors on the mobile phones. This review also provides main scope of activity recognition, methods of solving activity recognition problems, extracting features and basic algorithms for applying data mining. We can specify that our research in the category of using wearable sensors (in our case sensors on the smartphone) for human activity recognition.

Activity recognition using smartphones has a growing potential in the research of data mining since smartphones become equipped with a wide variety of sensors. The most effective sensors for activity recognition and data mining is accelerometer and little less used in the field are gyroscope and magnetometer. Each of those sensors producing three dimensional motion data. There are many studies done using these smartphone sensors for specific uses or applications, our project is not an exception. One of them is very similar [5], where two students were solving almost the same problem. They were making push-ups and non-push-ups recognition classifier using Support Vector Machine and Multilayer Perceptron. For feature extraction they used sliding window method with 1s, 2s, 4s and 8s length windows. They were solving not only push-up recognition problem but also introduced classifier of squats and sit-ups as a non-push-ups class. They achieved 98% classification rate for push-ups.

Other researchers [3-4, 6, 8] were solving walking, slow walking, jogging, going up stairs, going down stairs, sitting and standing recognition problems. In all these papers authors were using Weka (Waikato Environment for Knowledge Analysis) toolkit [9] and analyzed existing machine learning algorithms. Mostly in all researches the best recognition rate of over 90% was produced by the Multilayer Perceptron algorithm. Data were collected using smartphone accelerometer and gyroscope tri-axial sensors. Features for training set were produced using sliding window methods together examining and extracting values of mean, standard deviation, mean absolute deviation, time between peaks and the resultant magnitude.

Similar work but using different machine learning algorithm was done in a study [7] where authors were solving the problem of walking, jogging, running, going upstairs and going downstairs activity recognition. Recognition rate of 94% was achieved using DTW (Dynamic Time Warping) [10] algorithm simply by matching templates of the accelerometer sensor signal data. The strength of this method is, that it does not depend on the length of the signal. In this case specific accelerometer signal can be shorter or longer than its template. In this work as an additional feature was introduced context filtering, which was done by measuring user's heart rate and barometer readings when he was performing the activity.

III. Methodology

In this section we describe our main task of sport activity recognition and all the processes from start to finish of performing this task. In the section Overview we explain the algorithm of our sport activity recognition application.

A. Overview

To begin with at first we would like to introduce our algorithm structure which is shown in the Fig. 1. In this figure we can see User motion (human arm movement during sport activity) which is captured using smartphone sensors (accelerometer, gyroscope and magnetometer) and logged into smartphone's memory, then collected sensor data is send to Processing where main features are extracted. The next step leads to Machine Learning Algorithm where extracted features are classified and prediction is made for estimating sport activity. Having the same prediction which continuous for certain amount of time the Activity Repetition Counter counts and triggers about new counted sport activity repetition and all the results are send to GUI where user is able to see his progress. The main steps are explained in details below: Sensor – Section *C*; Preprocessing – Section *D*; Machine Learning Algorithm – Section *E*; Activity Repetition Counter – Section *F*.

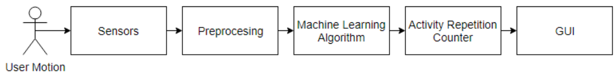

Fig. 1. Structure of the sports activity recognition system

B. System Environment

We have chosen Android-based smartphones as the platform for our project. The Android operating system is free, open-source, easy to program, and dominant in the smartphones market. For the project we will use 5.0 and higher versions of Android operating system, which gives us more features to work with and much bigger computing power. Furthermore, smartphones with higher OS versions have more precise sensors. Because of big computing power and built-in sensors, smartphones are an ideal platform for our application; we also require no internet access or additional machine for calculations. The collected data can be stored directly in the smartphone's memory, because the Android OS provides a built-in SQLite [12] database and big storage capacity.

C. Data Collecting

To begin with, first we need to decide which part of the human body is the best for locating the smart phone. We are collecting sport activities data such as push-ups, sit-ups, and squats workout, we need to locate smartphone [14] on human body so we can measure all of the listed activities. After some experimenting we found out that the most sensitive place for taking measurements with smartphone on human body is left upper arm next to the shoulder (left arm was chosen because of better smartphone GUI control with the right hand) with the screen facing outwards. We mounted the smartphone using duct tape instead of an armband for a better grip. For data collecting smartphone accelerometer, gyroscope and magnetometer sensor's data is captured with the Android application designed to access to Android sensor event services where we read sensor data. Because we are reading three tri-axial sensors, in total we have nine different arm motion signals (magnetometer x, y, z axis, gyroscope x, y, z axis and magnetometer x, y, z axis). Data reading frequency is 10Hz: every 100ms a new reading is made. Since we have limited resources of processing power in smartphone, we decided to use lower frequency of sensor data readings. Each sensor reading is added to the array list with an included timestamp. At the end of sport activity data logging we stop our application and save all collected data into a .csv format file located in smartphone's external data storage with a specified file name of sport activity, to easily access it with the computer.

D. Features Extraction

In previous step we collected our sensor data and now we need to extract some features to be able to make a training dataset and to train a classifier. During examination of our collected data, we noticed that some of the sensor's signals are unreliable. This is happening because sport activity repetition have a specific pattern, which can be seen in some of the sensors signals, but this pattern is not visible in all of the sensors signals. Some other signals have no pattern at all, for example all of the magnetometer signals were not matching the pattern and were unusable. Some of the signals were duplicated like accelerometer y and z axis. And some of the signals were reliable for one sport activity but not for another. We needed to select only those sensor (magnetometer x, y, z axis, gyroscope x, y, z axis and magnetometer x, y, z axis) signals which were useful for all sport activities, matched pattern and were most promising, also we need not to overload the smartphone processor. After time consuming and frustrating experimentation with the different combinations of signals we found out that the most appropriate signals are accelerometer x, z axis and gyroscope z axis. The problem was that we have different sport activities and at some point not all sensor's axis were used so the signal readings were almost strait line. Some of the measurements taken in the process are shown in the Fig. 2-4, where we can see different sport activities and three chosen signals (accelerometer x and z axis and gyroscope z axis) for later data processing.

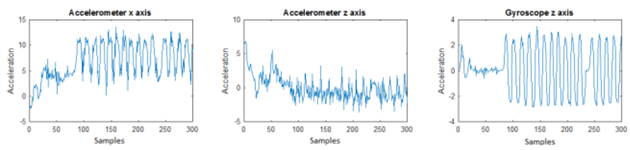

Fig. 2. Example of push-ups signals.

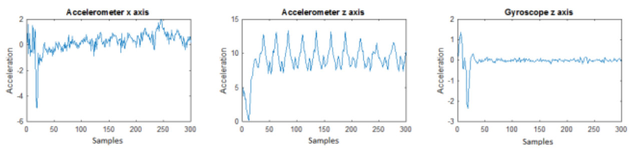

Fig. 3. Example of squats signals

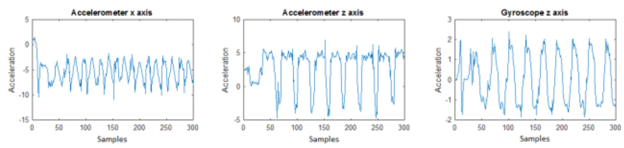

Fig. 4. Example of sit-ups signals

Since we have unlabeled data of accelerometer x, z axis and gyroscope z axis, we need to label class for each activity. We have three activities and lots of false data in between repetitions. From previous experimentations we learned, that in order to make accurate classifier we need to label only those signal parts which contain repetition and other must be labeled as false data. To do so we created simple program with MATLAB [15] for filtering and labeling signal data. The algorithm is very simple, using specific parameters of signal height, median, and signal length, we label those signal parts where it meets all parameter values. An example of the signal labeling is shown in the Fig. 5. Green vertical line is start of the filtered signal, red vertical line is middle of the filtered signal and blue vertical line is end of the filtered signal. During lots and lots of experimentations by filtering repetitions and making classifiers we came up with the solution of using two fixed signal lengths one of 13 samples and one of 25 samples for repetition filtration. That way we also need two classifiers instead of one, because two classifiers are more versatile for short and long signal sample ranges. We separate all collected data files into two groups of short and long repetitions and applied labeling algorithm for each of them.

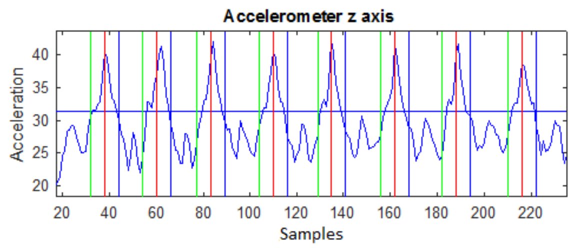

Fig. 5. Labeled signal example after filtration

The next question that we faced is how to train the classifier with the signal data. We cannot use the whole signal and also we cannot use only one signal sample for training the classifier. The idea is to split signal into small parts of 10 samples for 1 second signal classifier and 20 samples for 2 second signal classifier which came from the dataset analysis where we spotted that most of the sport activities' repetitions are in the interval of 0.5 to 3 seconds. The best way to split signal data is by using a Sliding Window (SW) method. Our SW consists of 10 samples in length, for each iteration we will select 10 rows at a time and transform it to 30 columns (30 columns because we have three different signals for each row) and after each iteration we will move one row lower. The same step we will repeat for 20 sample length SW, but instead 10 rows we will select 20.

E. Machine Learning Algorithms Comparison

Three sport activities were studied as listed above. We extracted features and labeled them to the classes of separate different sport activities, in total we have two training datasets for our machine learning classification problem. One dataset for short sport activities repetitions in average of 1 second time duration and one for longer sport activities repetitions in average of 2 second time duration. We performed and evaluated the performance of the following classifiers available in the Weka (Waikato Environment for Knowledge Analysis) toolkit [9], which are: Multilayer Perceptron, Random Forest, Simple Logistic and Logit Boost. Classifiers were trained and tested using a 10-fold cross validation method on the training datasets using default options. The summary of the trained and tested classifier with both datasets recognition rate for sport activities is shown in the TABLE I. The most promising are Multilayer Perceptron and Random Forest. Random Forest have advantage in training time and recognition rate for both 1 and 2 second classifier. In the other hand Multilayer Perceptron is losing in recognition rate for both classifiers and also in training time which is significant longer. Other two classifier methods Simple Logistic and Logit Boost are slightly lower in recognition rate, but still take less time to train than Multilayer Perceptron.

TABLE I. TABLE OF MACHINE LEARNING CLASSIFIERS TEST RESULTS

Machine Learning Classifier	Recognition rate, %	
	1 second	2 seconds
Multilayer Perceptron	97.144	96.7
Simple Logistic	97.06	95.837
Logit Boost	96.56	94.885
Random Forest	97.582	97.252

F. Sport Activity Repetition Counter

Looking at the result the best candidate would be Random Forest, but we decided to use Multilayer Perceptron. It seems to be, that even if perceptron is not so accurate in overall recognition rate, but in real world test it shown exact prediction for the current class comparing with Random Forest. Test was performed using 2 second signal classifier to classify 1 second test dataset. A Multilayer Perceptron and Random Forest recognition accuracy test on labeled dataset is shown in the Fig. 6. We can see that Multilayer Perceptron gives us almost the same prediction like one labeled in the training dataset. However Random Forest gives us only spikes that are far away from the required prediction. We must keep in mind that our goal is not just to recognize sport activities, but it is also to calculate repetitions and the closer we are to the labeled dataset pattern the better it is. Having spikes or one sample predictions per repetition like Random Forest have, we can't programmatically correct it or filter out some of the features, but with Multilayer Perceptron it is possible. For example, to count one repetition we must have at least 3 continuous predictions in a row without noise. Even if classifier is failing at same point, we still can rely on the average of continuous activity's predictions and improve repetition counter.

The additional repetition counter filtration is called as a safety feature. Furthermore, we have two classifiers instead of one universal and it provides us more chances to correctly recognize sport activities.

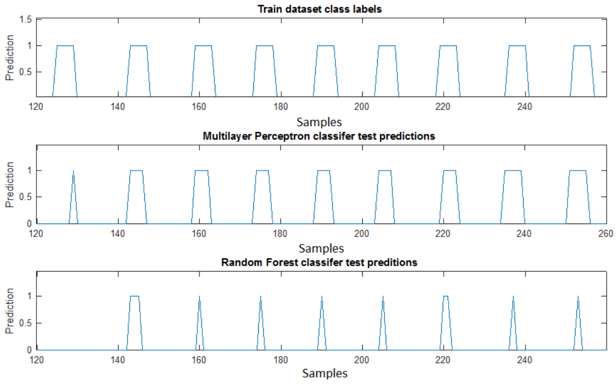

Fig. 6. Random Forest and Multilayer Perceptron prediction comparison

IV. RESULTS

The summary of results for our activity recognition experiments are presented in the TABLE II. This table specifies the experiment made in real world environment with real humans. Experiment consists of 9 subjects who were asked to perform specific workouts (push-ups, squats and sit-ups) and for each of the workout subject needed to do 10 repetitions of fast (from 0.5s to 1s), normal (from 1s to 2s) and slow (from 2s to 3s) repetition speeds. Before performing sport activities recognition test we provide short tutorial to the participants of how to perform each workout correctly. Then we mounted smartphone with the installed application (the application screen shots of main menu, history window and main sport activity tracker window are represented in the Fig. 7) on the subject's left upper arm. To calibrate smartphone's exact location on the arm we asked to stretch out participant's hands in horizontal position with the palms facing down. All the participants were men of different heights and weights.

TABLE II. TABLE OF SPORT ACTIVITY RECOGNITION TEST WITH REAL SUBJECTS

Participants	Push-ups			Squats			Sit-ups		
	Fast	Normal	Slow	Fast	Normal	Slow	Fast	Normal	Slow
1.	10	10	10	10	10	10	9	10	10
2.	8	10	10	8	10	10	7	9	10
3.	9	10	10	8	10	10	7	10	10
4.	10	10	9	10	10	10	8	10	10
5.	10	10	10	10	10	10	9	10	10
6.	10	9	8	10	9	9	10	10	10
7.	10	10	10	10	10	9	10	10	9
8.	10	10	9	10	10	8	10	10	9
9.	8	10	10	9	10	10	8	10	10
Recognition rate, %	94.444	98.889	95.556	94.444	98.889	96.667	86.667	98.889	97.778

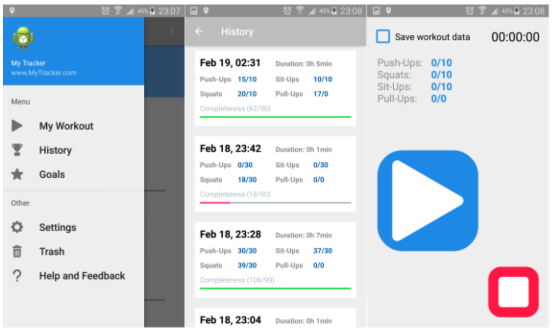

Fig. 7. Sport activity recognition application print screens

V. CONCLUSION

In this study, human sport activity recognition accuracy of up to 95% on sport activities such as push-ups, squats and sit-ups using a tri-axial accelerometer and gyroscope was obtained. The sensors' data was collected from one subject by performing listed sport activities workouts using a smartphone as a sensor which was located on the subject's upper left arm. Collected data was separated into two groups of short and long activity's repetition performing speeds, labeled, and features were extracted. The training datasets were made and two classifiers were trained for each of collected data group. Combining two classifiers, smartphone's sensors and additional filtering for repetition counting the Android application was created. To measure sport activity recognition accuracy the test of nine male subjects was performed and achieved the average of 95.8% sport activity recognition rate. The main benefits of the project are that sport activity recognition is done in smartphone by itself, using its own computing power and no additional devices, or servers, or internet access are require. All the collected data is processed in real time and have only 2 seconds time delay at displaying data in GUI, which is limited of 2 second classifier (longest time for getting 20 samples of data). The extracted features are little different from the previous works in other papers. The difference occurs that our method uses raw sensor's signal data instead of calculating additional features. During the recognition testing we have noticed that bad or misshape workout repetitions weren't counted, which leads us to make conclusion that application also promotes subject to perform right movements for the sport activity. Existing project can be easily improved with additional testing with more subjects especially women and new classifier can be made with the bigger training dataset made of more than one subject's data. Furthermore, according to the plan current application needs to be improved to be capable of recognizing pull-ups and etc., which was mentioned in the application specification. Then it would have more sports activities on the list and make application even more advance. Other feature is to set up additional module for voice coaching to make sport activity recognition application more user friendly by using phrases to describe how much repetitions left, when the goal is achieved and push user to exercise harder. The existing sport activity recognition algorithm has perfect core for adding more features by its flexibility and light framework. During the testing smartphone showed no visual lagging or overstress in performing the recognitions, it can be also used in a background mode when user can use other applications at the same time.

[19]

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