Journal of Advanced Sport Technology 4(2):29- 37 Received: July 14, 2020; Accepted: September 14, 2020

Original Research

A Framework to Identify and Count Popular Exercises Using Smartphone Sensors Based on Machine learning

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ABSTRACT

Smartphones have wide range of sensors such as gyroscopes or inertial sensors, which can be used for recognizing and tracking exercises. A framework, called TrainingPal, was proposed to automatically identify five types of cardio exercises and five types of resistance exercises. Included exercises were running, walking, rowing, using elliptical machine, and jumping jack. Sit-up, bench dip, push-up, squat, and lunge were included as popular resistance exercises. In addition to recognition of each exercises, the proposed framework was able to count number of repetitions of each exercise. To train and test the proposed framework, data was collected from Samsung Galaxy S7 edge, which was attached to the outer side of arm approximately 10 to 12 cm below the shoulder. To avoid overfitting, we used leave-one-subject-out cross validation. An overall accuracy of 91.71% was achieved in identifying different types of exercises. The accuracy ranged from 100% for push-ups to 60.33% for bench dips. The accuracy of the proposed framework in counting the exercises was 90%. The results suggested that the proposed framework can be used for identifying and tracking of the included exercises. The framework can be extended to other wearable devices.

Keywords: Exercise recognition, Exercise tracking, Inertial sensors, Smartphone.

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Introduction

In past decade, smartphones have surfaced as a tool with huge potentials for monitoring physical exercises and categorizing individual into different categories based on their physical activities. This will help us to tackle several health challenges arisen from physical inactivity. Being physically inactive is associated with an elevated risk of different chronic diseases such as type 2 diabetes and cardiovascular diseases (1-3). These chronic diseases are considered as the leading cause of death worldwide (4). Also, these chronic diseases cause major limitations in adults' daily lives (5,6) and are associated with huge costs for the healthcare systems and governments in both developing and developed countries (7).

In Iran, the leading death cause is cardiovascular diseases, which account for more than half of all annual deaths (6). With aging of population in prospective, the percentage of deaths because of cardiovascular diseases is expected to steadily rise over the next few years (6). Considering the role that using the wearable sensors can play in preventing cardiovascular, in recent years several studies has conducted to use the wearable sensors for monitoring the physical activities of their users (8, 9).

Moreover, by monitoring exercises, we can examine if a specific set of exercises are effective and we can continuously get feedbacks from users to improve their athletic performances. Monitoring the individual performances is more difficult in the high-intensity interval training, where a person does a series of exercises in a loop. Previous studies emphasized on the importance of performance tracking in the high-intensity interval training for achieving the desirable outcomes (10-12).

Recent advancements in sensor manufacturing led to possibility of mass production of small low power inertial sensors (13). These sensors showed huge potential for monitoring daily exercises and activities (14, 15) and monitoring patients with motor control problems such as patients with Parkinson's disease (16,17).

Modern smartphones have built-in 3D-accelerometer, magnetometer and gyroscope. Gyroscope and 3D-accelerometer data stream is essential for recording the angular velocity of the smartphone while magnetometers are used to estimate the orientation of the smartphone by recording direction and strength of the magnetic field (18). Different applications ranging from the automotive navigation (19) to mobile games (20) use these built-in sensors.

The smartphone sensors have been previously utilized to monitor physical activities. As an example, Guiry et al. (21) suggested a framework for recognition of cycling, walking, sitting, standing, running, stair/elevator descents/ ascents. The framework utilized data stream of sensors including gyroscope, magnetometer, accelerometer, light, GPS, and pressure. Shoaib et al. (22) relied on the data coming from gyroscope and accelerometer and built an algorithm to classify activities into walking, smoking, drinking coffee, eating, typing, writing, talking, jogging, walking upstairs, biking, walking downstairs, sitting, or standing.

Most of the existing frameworks aimed at recognition and counting of steps in running or walking and only a few previous studies focused on other types of exercises. while only a few ones included other types of exercises. As an example, in (23) a framework was proposed to categorize movements as crunches, shoulder lateral raises, bicep curls, push - ups, and jumping jacks using the data stream from wrist-worn smartphone. Here, we proposed TrainingPal, a framework for identifying and counting number of repetitions of five popular cardio and five strength exercises.

Material and Methods

Dataset

Considering the fact that data collection process involved negligible risk for the subjects, the study was exempted from the institutional ethics committee approval. We used the built-in magnetometer, 3D-accelerometer, and gyroscope of Samsung Galaxy S7 edge. The smartphone was attached by using an armband to the outer side of participants' arm (about 10 to 12 cm below the shoulder) .

Two female (aged 29 and 35) and two male (aged 31 and 25) participants were asked to perform five types of cardio exercises and five different strength exercises. Cardio exercises were Elliptical, Rowing, Walking on the treadmill, Running on the treadmill, and Jumping jack. Resistance exercises were Squat, Lunge, Sit-up, Push-up, and Bench dip. Speed for walking on the treadmill ranged from 4.8 to 7.7 km/h while running speed varied from 9.7 to 14.5 km/h.

We collected data from participants in multiple session and then divided each session into multiple sets of doing the exercises for the ease of participants. Prior to each session the armband was worn again by the user to ensure that the algorithm is robust to small changes in the places, where armbands are attached to the subjects .

We counted the repetitions, using the data stream from a video camera. The signal was separated manually based on the video. The video and the smartphone times had been synchronized before data collection .

Table 1 and 2 shows the description of the cardio and resistance exercises included in the dataset.

Table 1. Included cardio exercises and number of sets, sessions, and repetitions for each exercise.

Type	Total Duration (S)	No. of Sets	No. of Repetition	No. of Sessions
Walking*	2880	48	2659	8
Running*	2400	40	3586	8
Elliptical**	6000	10	7967	10
Rowing***	3600	24	3731	12
Jumping Jack	810	27	988	27

*collected using treadmill
**collected using elliptical machine
***collected using rowing machine

Table 2. Included resistance exercises and number of sets, sessions, and repetitions for each exercise.

Type	Total Duration (S)	No. of Sets	No. of Repetition	No. of Sessions
Squat	720	8	301	8
Lunge	720	8	782	8
Sit-Up	720	12	167	12
Push-Up	480	8	155	8
Bench Dip	600	10	276	10

Proposed Framework

The proposed framework comprised recognition and counting modules. The recognition module is a classifier to categorize the input signal recorded into ten different classes, corresponding to ten types of exercise included in this study .

The recognition module relies on a feature extraction and classifier sub-modules. Steps of the feature extraction module is illustrated in Figure 1. As indicated, a 12-dimensional feature vector including the accelerometer, gyroscope, and two sets of Euler angles in three directions was generated for each timestamp. To calculate the Euler angles, the TRIAD algorithm as suggested in (24) was utilized.

The feature vector was then fed into four different, namely support vector machine (SVM), bag of decision trees, K-nearest neighbor, discriminant analysis, were investigated to find the best classifier .

The counting module involves a Savitzky-Golay smoothing filter and a peak/valley detection unit followed by a peak/valley matching unit (25). Firstly, by using the Savitzky-Golay filter, the high frequency noise is eliminated from the signal recorded by accelerometer, gyroscope, and magnetometers. Then the dominant axis for the magnetometer (an axis with the highest range) was identified. For each type of exercise, among seven available signals (three from accelerometer, three from gyroscope, and the signal from the dominant axis of magnetometer), we selected three signals with the highest standard deviation were selected. The peaks and valleys were extracted from each one of the selected signals. If a peak or valley in particular timestamps was present in two (out of three) data streams, the timestamp was recorded as a full or half repetition of an exercise. Depending on the exercise type, each one or two local valleys/peaks could be equivalent of one repetition

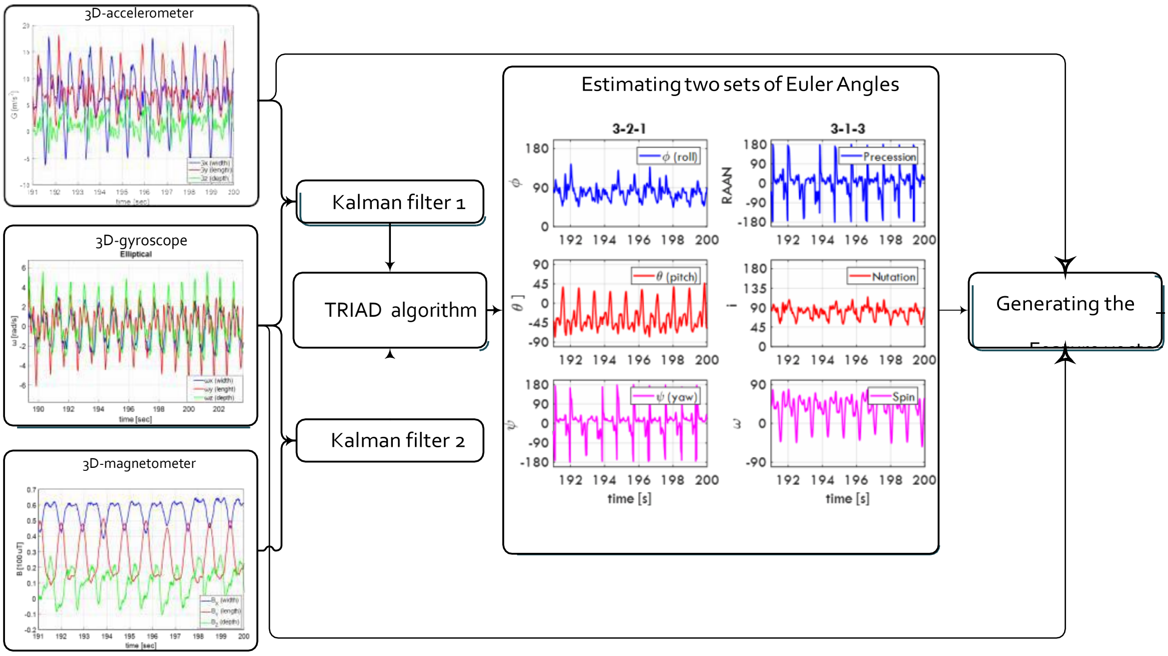

Figure 1. Steps of TrainingPal for recognition of different types of exercises

Evaluation

We evaluated the performance of the TrainingPal in two different cross-validation scenarios. In the first one, in each iteration of cross-validation, one of the sets was left out as the test data and the rest of the data was used as training set. We called this scenario leave-one-set-out cross validation. In the second scenario, each time all recording from a single subject left out as the test set and the classifiers were trained using the data from all subjects except for the test subject. By doing so, we ensured the classifiers were not over-fitted to the data. The reason for including the first scenario was possibility of personalizing the smartphone applications for their users. In another word, it would be possible for a user to train their smartphones' applications based on their own data (the algorithm would learn each individual's unique way of doing a movement) and later using the application. Therefore, there was point in doing both validation scenarios .

The algorithm was implemented and tested using MATLAB 2017b (Mathwork, MA, USA). The smartphone sensor data was collected using AndroSensor (developed by Fiv Asim and available for free on Google Play) and saved a csv file. The csv files were processed in MATLAB and data was fed into the machine learning model. To evaluate the accuracy of the model for various exercises and in each one of the scenarios, correct classification percentage was calculated (tables 3-6). The correct classification percentage represent percentage of correctly identified exercises divided by the total number of exercises in each one of the scenarios. We also explored how misclassified exercises were distributed across various types of exercises (Figure 2) .

We also investigated the accuracy of counting algorithm. To do so, we manually counted the exercises in each session and then divided the differences between actual number of repletion and the number of cycles segmented by the algorithm. By dividing this difference by the total number of exercises, the error rate was found. The accuracy is calculated by subtracting the error rate from 1.

Results

Accuracy of the framework in the recognition task

Table 3 and 4 shows the accuracy of different classifiers in recognizing various types of exercises in leave-one-set-out cross-validation scenario. Similarly, table 5 and 6 shows the accuracies of different classifiers in recognizing the cardio and resistance exercises in the leave-one-subject-out cross validation. In both scenarios, the recognition accuracy varied across different types of classifiers.

As indicated in table 3 and 5, all four classifiers performed well in identifying workout using elliptical machine and rowing. This is expected, as the sensory data from these two exercises differ considerably form the rest of the exercises.

Also, the error rate for cross validation was mostly lower than in leave-one-set-out cross-validation scenario compared to that of leave-one-subject-out cross-validation. The most probable reason for this could be the fact that in the leave-one-set-out cross-validation scenario, only one set was left out as the test set and other sets of the similar subjects was used to train model. Therefore, the classifier had learnt specific patterns of each subject from the training data. In the leave-one-subject-out cross-validation, such information was not available .
The results also showed that the k-nearest neighbor performed well in in the leave-one-set-out cross-validation scenario while did not reach a high level of accuracy in the leave-one-subject-out cross-validation for elliptical machine work-out, jumping jacks, squats, and lunges. This could be due to over-fitting of the classifier to the subjects .

Table 3. Performance of various classifiers in the identification of various types of cardio exercises in the leave-one-sequence -out cross-validation scenario

Type	SVM	Decision Tree Ensemble	K-nearest neighbor	Discriminant analysis
Treadmill -Running	79.72%	89.13%	89.86%	39.86%
Treadmill -Walking	96.38%	94.92%	94.92%	78.00%
Elliptical machine	99.32%	100.00%	100.00%	99.32%
Rowing machine	99.69%	100.00%	100.00%	99.69%
Jumping jack	98.52%	100.00%	100.00%	87.53%

Table 4. Performance of various classifiers in the identification of various types of resistance exercises in the leave-one-sequence -out cross-validation scenario

Type	SVM	Decision Tree Ensemble	K-nearest neighbor	Discriminant analysis
Squat	67.36%	100.00%	100.00%	62.50%
Lunge	100.00%	100.00%	100.00%	78.06%
Sit-up	75.28%	99.58%	99.58%	55.69%
Push-up	100.00%	100.00%	97.92%	30.42%
Bench dip	93.50%	98.00%	98.33%	78.17%

Table 5. Performance of various classifiers in the identification of various types of cardio exercises in the leave-one-subject -out cross-validation scenario

Type	SVM	Decision Tree Ensemble	K-nearest neighbor	Discriminant analysis
Treadmill -Running	96.01%	97.08%	90.17%	79.65%
Treadmill -Walking	92.13%	95.00%	91.13%	79.25%
Elliptical machine	96.40%	59.58%	11.82%	26.80%
Rowing machine	99.69%	98.75%	98.75%	44.06%
Jumping jack	83.33%	79.01%	38.52%	1.85%

Table 6. Performance of various classifiers in the identification of various types of resistance exercises in the leave-one-subject -out cross-validation scenario

Type	SVM	Decision Tree Ensemble	K-nearest neighbor	Discriminant analysis
Squat	71.67%	95.00%	77.78%	71.25%
Lunge	63.19%	37.50%	67.22%	73.19%
Sit-up	72.78%	100.00%	100.00%	56.53%
Push-up	100.00%	97.92%	100.00%	0.00%
Bench dip	60.33%	77.33%	100.00%	58.50%

The average acquired accuracy across all exercise types are also shown. Overall, the results suggest that the SVM achieved the best overall accuracy for the exercise recognition.
Figure 4 shows the SVM classifier performance in the leave-one-subject-out cross-validation. Each bar indicates one of the exercises and the labels from the SVM is shown as the segments of each bar. For example, SSVM correctly classified running in 92.13% and it mostly misclassified running as walking or elliptical. As expected, usually, the resistance exercises were not misclassified as cardio ones and vice versa. Therefore, the classifier performed well in recognizing the broader type of exercise (cardio or resistance).

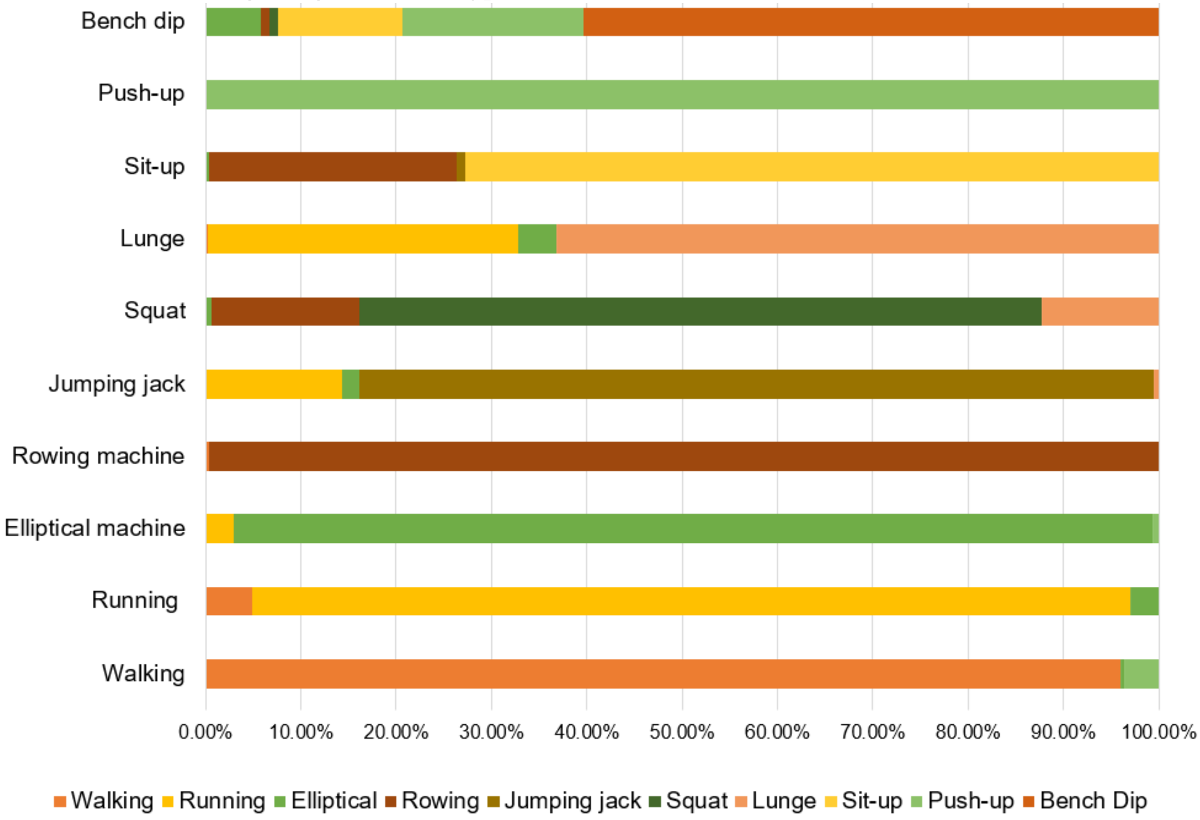

Figure 2- The performance of the SVM classifier in the leave-one-subject out scenario

Accuracy of the framework in counting task

Table 7 and 8 indicate the accuracy of the proposed framework for counting of cardio and resistance exercises, respectively. The lowest accuracies were obtained in counting bench dip and sit-ups while the framework achieved its highest accuracy for counting the elliptical machine workouts. The low accuracies could be due to the fact that the recorded durations of sit-ups and bench dip were relatively long for all participants and in most of cases they could not continue the exercise without resting in between phases of each attempt. As shown in the range columns of the table, in cardio exercises for all subjects the error rate was low, however larger variations in accuracies for different subjects were observed in counting repetitions of the strength exercises.

Discussion

In this study, a framework for identifying and counting ten different types of popular exercises were proposed. These exercises included cardio and resistance workouts. The included cardio exercises were running, rowing, walking, elliptical machine workout, and jumping jack while the resistance exercises were push-up, sit-up, squat, bench-dip, and lunge.

The results suggested that the performance of various classifiers differed. The best classifier was SVM, which achieved an accuracy of 91.71% for identifying different exercises in a scenario, where none of the participants' data was used during the training phase of SVM .

In counting different exercises, the proposed framework achieved a range of accuracy. The accuracy of the proposed framework was above 90% for all exercises. The promising results suggest that the proposed framework could be potentially extended to other types of wearable devices such as wrist-worn smart watches.

The current study has number of limitations. Although relatively large number of repetitions were available for each exercise, we only included four individuals. This is one the limitations of our study. This work was a proof-of-concept study to present feasibility of such system. Collecting a larger dataset and further validating the model could be a potential avenue for the future work. Such dataset for the future work should include subjects with different types of body shapes.

In spite of the above-mentioned limitation, it should be noted that despite limited number of individual, in leave-one-subject out scenario, in each iteration the model was trained in a way completely blinded to that test subject's data. High accuracy level in the leave-one-subject out evaluation scenario provides supporting evidences that the algorithm exhibit robustness against inter-subject differences in performing the exercises. Another limitation of the current study is collecting the data using single type of smartphone. As a potential future work, performance of various types of smartphones for data collection could be compared.

Conclusion

In this study, we proposed TrainingPal for identifying and counting number of common physical exercises. We showed that, when properly trained, the data for smartphone sensor can be used for identifying and counting both cardio and strength exercises. TrainingPal can provide feedbacks to the users about their speed in doing exercises. Specifically, in strength exercises tracking speed could help in avoiding training errors and overuse injuries. As an example, performing squats too fast could result in injuries to knee. A platform like TrainingPal, which tracks the squats, could give an estimate about user's speed and hence users can be warned if they are performing exercises in an improper speed. Such system can be integrated to web-based health documentation system of fitness centers (26) to automatically document user's progress over time.

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چکیده فارسی

شناسایی و شمارش حرکات رایج ورزشی بر اساس دادگان حسگر گوشی همراه به کمک یادگیری ماشین

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امروزه گوشی‌های هوشمند مدارای انواع مختلفی حسگر همانند ژیروسکوپ یا حسگرهای اینرشیال هستند. را در خود جای دادند این حسگرها می‌توانند برای شناسایی و شمارش حرکات ورزشی به کمک ما بیایند. در این مقاله، یک چارچوب برای شمارش و شناسایی حرکات ورزشی ارائه داده شده است که با کمک آن می‌توان پنج نوع حرکت کاردیو و پنج نوع حرکت قدرتی را شناسایی و شمارش کرد. به حرکات کاردیو در نظر گرفته شده دویدن، راه رفتن، پارو زدن، استفاده از ماشین الپتیکال و پروانه می باشد. حرکات قدرتی در نظر گرفته شده شامل دراز و نشست، شنا، اسکات، لانچ، بالا و دیپ نیمکت می باشد. علاوه بر شناسایی هر کدام از این حرکات ورزشی الگوریتم ارائه داده شده می تواند تعداد انجام هر یک از این حرکات را نیز بشمارد. برای آموزش و ارزیابی الگوریتم ارائه داده شده ابا استفاده از حسگرهای یک گوشی هوشمند گلکسی اس ۷اج سامسونگ داده جمع‌آوری شد. این گوشی همراه با استفاده از یک باند کشی ۱۰ تا ۱۲ سانتی متر پایین شانه بسته شد. برای ارزیابی هر بار داددگان یکی از سوژه‌ها به عنوان دادگان تست و دادگان سایر سوژه‌ها برای آموزش استفاده شد. چهارچوب ارائه داده شده، در کل، به صحت ۹۱٪ برای تشخیص انواع مختلف ورزش دست یافت. صحت این چهارچوب برای شمارش ورزش ها ۹۰٪ می‌باشد. نتایج حاصله نشان می‌دهد که چهارچوب ارائه داده شده می‌تواند برای شناسایی و شمارش ورزش‌های در نظر گرفته شده استفاده شود. این چهارچوب قابلیت تعمیم به دادگان ثبت شده از سایر ادوات پوشیدنی را دارد.

واژه‌های کلیدی: حسگرهای اینرشیال، گوشی هوشمند، شمارش حرکات ورزشی، شناسایی حرکات ورزشی.