

ExerSense: Real-time Exercise Segmentation, Classification, and Counting using IMU

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1. Introduction

While regular exercises provide us numerous benefits including healthier life and emotional well-being [1], maintaining the regular exercise is challenging [2, 3]. Fortunately, research studies have demonstrated that automatically tracking exercise can motivate physical activity [4]. However, almost all of current products target only walking/running or only indoor specific exercises separately while most of exercises and sports that have positive effects on health are combinations of running and other workouts.

The goal of this research is to develop an algorithm that provides a very accurate real-time segmentation, classification, and counting of physical exercises, including both indoor and outdoor, using only one sensor data collected from the general usage wearable devices.

2. Related Work

Dan et al. introduced RecoFit, a machine learning-based system for automatically tracking repetitive indoor exercises via an arm-based inertial sensor [5]. They achieved precision and recall greater than 95% in identifying exercise periods and counting that is accurate to ± 1 repetition 93% of the time while it needs 5 seconds to recognize exercises.

Prakash et al. introduced STEAR, a correlation-based system for step counting using an Inertial Measurement Unit (IMU) attached to an ear[6]. They addressed the advantages of the earbud IMU

and achieved 95% step-count accuracy.

Most of the related works achieved around 95% recognition for each defined exercise under the condition of only indoor workouts or only outdoor exercises like walking and running. Also, in the case of exercise recognition, it is too difficult to collect enough data to train the model for machine learning while only few samples are necessary for a correlation approach. So, this research aims to recognize both indoor and outdoor exercises while keeping with around 95% accuracy using a correlation-based method.

3. Proposed Method

The proposed method to segment, classify, and count exercise in real-time is separated into two phases: pre-processing and runtime. In the pre-processing phase, some data of targeted exercise are collected, and one single motion is saved as the template 3-Dimensional (3-D) acceleration for the exercise. The runtime phase starts with the segmentation of the streamed acceleration signal into single motion by finding the peaks in the synthetic signal. In order to find the peaks, the proposed method calculates the norm of 3-D acceleration, smoothens it, and applies a sliding window of 0.25s length. Then, every segmented 3-D acceleration signal is classified by comparison with each exercise template using a correlation-based algorithm shown in Figure 1, and count of exercise is incremented.

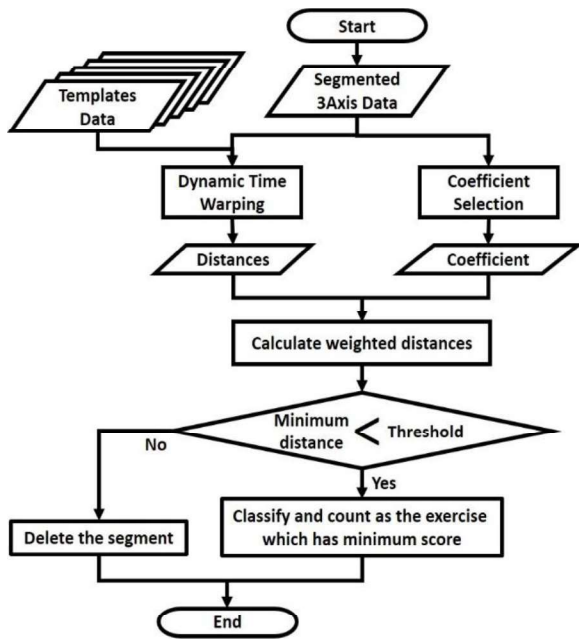


Figure 1. Classification flow of the proposed method

4. Experiment of the Proposed Method

In order to validate the proposed method, experiments have been conducted for five exercises: running, walking, jumping, push-ups, and sit-ups. Fifteen participants who self-assessed as performing exercise at least once a week performed randomly the five exercises while putting an IMU on their chest. Additionally, they attached a smartwatch, a smartphone, and the eSense earbud in the prevision of future works. Due to the missing values for six participants, we validated the proposed method using valid data of nine participants.

Table 1 shows the results of the segmentation algorithm and classification method. The proposed method achieved approximately 95% classification accuracy despite it includes segmentation error.

Table 1. The results of the proposed method

Phase	Precision	Recall	F1-score
Segmentation	97.9%	93.9%	95.9%
Classification	96.9%	93.0%	94.9%

Some overlooked segments are observed because of their low similarity with the templates, while some mistook exercises are observed because of the high similarity between transition movements and the template exercises.

5. Conclusion and Future Work

This work aimed to develop a segmentation algorithm and classification method to count some exercises, including indoor and outdoor, in real-time from an IMU signal. The proposed correlation-based method achieved approximately 95% classification accuracy, including segmentation error. The accuracy is similar or better than previous works that handled only indoor workouts and those use a vision-based approach. Also, while machine learning approaches need much data to create the classification model, our correlation-based method needs one sample of motion data of each target exercises.

A prototype of a shooting game using the same method and a virtual reality head-mounted display has been developed to demonstrate the possibility of the technology. For the next step, a more exciting game combining running and some workouts will be developed, and a user study will be performed to evaluate the effect on the motivations for exercises compare with other platforms.

References

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