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Recognizing the intensity of strength training exercises with wearable sensors

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A B S T R A C T

In this paper we propose a system based on a network of wearable accelerometers and an off-the-shelf smartphone to recognize the intensity of stationary activities, such as strength training exercises. The system uses a hierarchical algorithm, consisting of two layers of Support Vector Machines (SVMs), to first recognize the type of exercise being performed, followed by recognition of exercise intensity. The first layer uses a single SVM to recognize the type of the performed exercise. Based on the recognized type a corresponding intensity prediction SVM is selected on the second layer, specializing in intensity prediction for the recognized type of exercise. We evaluate the system for a set of upper-body exercises using different weight loads. Additionally, we compare the most important features for exercise and intensity recognition tasks and investigate how different sliding window combinations, sensor configurations and number of training subjects impact the algorithm performance. We perform all of the experiments for two different types of features to evaluate the feasibility of implementation on resource constrained hardware. The results show the algorithm is able to recognize exercise types with approximately 85% accuracy and 6% intensity prediction error. Furthermore, due to similar performance using different types of features, the algorithm offers potential for implementation on resource constrained hardware.

1. Introduction

Physical activity is an important component of a healthy life style. Evidence suggests that regular exercise participation results in improvements in the function of the cardiovascular system and the skeletal muscles [1] and significantly reduces the risk of developing different chronic diseases, such as hypertension, obesity, depression, and cardiovascular diseases [2–5].

Most health guidelines prescribe the recommended physical activity intake in terms of exercise duration and intensity [2]. While exercise duration can simply be measured with a stopwatch, exercise intensity is not as straightforward to capture. This is particularly true for stationary indoor exercises such as weightlifting and similar strength training activities that are unable to leverage the capabilities of the Global Positioning System (GPS) sensor. Speed and position, derived from the GPS data, can accurately represent the intensity of cardio training activities such as running or cycling, but are not suitable for activities performed in place such as upper body exercises. Capturing the intensity of such exercises is equally important, as studies have shown strength training is an important component of a balanced exercise regimen [6]. Additionally, exercise intensity awareness is important as undertraining fails to deliver optimal training benefits [7], while overtraining results in excessive exhaustion and consequently loss of exercise motivation [8]. Furthermore, appropriate exercise intensity is not only important for leisure activities. Studies have shown that in the medical rehabilitation environment, inappropriate exercise intensity could lead to injuries or even death in specific cases [9].

In this work, we introduce a hierarchical algorithm for detecting self-perceived intensity of strength training exercises. We define intensity as a derivative of Borg's rating of perceived exertion [10]. The algorithm uses two layers of supervised learning classifiers to first recognize the type of the exercise being performed and to detect the intensity of the exercise once its type has been recognized. The following allows us to perform intensity recognition more accurately and makes the algorithm easily extendible,

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as new exercises can be included with minimal interference with the existing classifiers.

We evaluate the algorithm for different upper body exercises using a set of wearable accelerometers mounted on the upper body of participating subjects. However, due to the modular hierarchical approach, the algorithm could easily be extended to support arbitrary exercises. We choose to relay solely on accelerometers, as they are small and cheap and have already been validated for measuring activity intensity [11]. We investigate whether the sensors provide sufficient information to derive exercise intensity information for two distinct types of acceleration features, namely single-sensor (SS) and multi-sensor (MS) features. We define SS features as features calculated from a single sensor in real-time. Consequently, raw data does not need to be communicated between sensors, which improves the sensor autonomy. In contrast, we define MS features as those based on acceleration data from at least two distinct sensors, thus requiring raw data to be transferred either between sensor nodes or to a common gateway, such as a smartphone. The paper provides the following contributions:

- A hierarchical algorithm for intensity recognition of strength training exercises.
- Evaluation of the algorithm in terms of exercise type recognition accuracy and intensity prediction error for a set of upper body exercises.
- Comparison of the algorithm performance for two distinct groups of features.
- A study of using the algorithm with different sliding window configurations, sensor setups, and number of training subjects.

The rest of the paper is organized as follows. In Section 2 we briefly describe the related work. Section 3 contains a short overview of the system proposed. Section 4 outlines the algorithm and explains individual processing steps. We describe the evaluation protocol in Section 5 and provide results in Section 6. A short discussion of limitations of the proposed approach is presented in Section 7 before we conclude the paper in Section 8.

2. Related work

There have been several industrial and academic attempts investigating quantitative observations of stationary activities, such as strength training and rehabilitation exercises. Most of the existing approaches are based on video [12,13], garment [14,15], or wearable sensors. Since our approach uses wearable sensor, the rest of this chapter outlines some of the relevant work using wearable technology.

In [16] authors propose a Wireless Body Area Network of accelerometers to monitor biometric parameters while exercising. The sensors are positioned on the body of the person exercising and are able to capture the correctness of exercise repetitions. The authors define exercise correctness based on the body posture and execution speed during exercise. However, the proposed approach is very exercise specific and does not provide any evaluation for a broader set of exercises.

Chang et al. [17] propose a system for monitoring free weight exercises. The proposed solution, comprised of a smartphone and two wearable sensors, is able to recognize different exercises along with the number of repetitions performed. However, the system does not report any information on the quality and correctness of exercises being performed.

Similarly, myHealthAssistant [18] captures exercise repetition count using a smart phone and a set of wearable sensors. The authors leverage the modern smart phone processing capabilities to deploy an algorithm based on a trainable classifier. The algorithm is able to recognize exercise repetitions in real time with minimal impact on overall system's resources, but does not offer any guidance on exercise correctness.

In [19] the authors propose an algorithm for spotting upper body exercises and predicting the number of repetitions performed. The algorithm is able to perform user independent exercise recognition from a continuous stream of data provided by an off-the-shelf smartphone placed in a commercial arm holster. However, similarly as in [17,18] the proposed algorithm is not able to provide any information on exercise correctness.

In our previous work [20] we have proposed an approach that was able to advance the solutions described by performing not only exercise repetition counting, but also capturing exercise correctness for a range of different exercises. Exercise correctness recognition was performed by detecting individual repetition's start- and end-points and consequently recognizing the exercising tempo. Similar work has also been proposed by Spina et al. [21]. They have proposed a smartphone based motion rehabilitation system for individual exercising of chronic patients. The system is able to process motion sensor data online on the phone and provide real-time acoustic feedback regarding the exercise performance and quality. However, both approaches use a single sensor device and are thus constrained to simple exercises only. Additionally, only basic exercise correctness metrics, such as exercising tempo, were considered.

We advance the related work by using a network of wearable accelerometers with different groups of acceleration features and by predicting another exercise correctness metric, namely exercise intensity.

3. System overview

The prototype system consists of an off-the-shelf smartphone and five wearable sensors connected over bluetooth into a piconet local area network. In such setting, the smartphone serves as a hub responsible for receiving data from up to seven interconnected sensors and doing all the heavy processing. Additionally, such setting makes it possible to easily transfer data and processed results from the smartphone to remote locations and thus enables real-time supervision of the training by rehabilitation specialists or personal trainers.

Five wearable 3-axis accelerometers were body-mounted on different body locations of the participants. The sensors were sampling acceleration data with a sampling frequency of 30 Hz, which has turned out to be adequate for recognition of activities with similar motion dynamics [20,22]. Due to the most discriminative type of motion, the following sensor mounting locations were selected (as depicted on the left in Fig. 1):

- chest,
- left and right wrist, and
- left and right upper arm.

All the sensors were mounted using standard sports equipment, such as cotton wrist and elbow bands and a textile chest strap. Such installation of the sensors is low-cost and does not require any specific or hard to acquire equipment. Furthermore and most importantly, the placement of the sensors is not obstructing the exercise execution in any way.

4. Hierarchical algorithm

This section describes the hierarchical algorithm for predicting exercise intensity. The idea of the algorithm is to break the intensity recognition problem into two sequential tasks and solve each