Poster Abstract: Adaptive Gym Exercise Counting for myHealthAssistant

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ABSTRACT

This paper presents an adaptive counting approach that captures weightlifting exercise repetitions despite fluctuations in the speed of performing. By having a hybrid counting approach that utilizes both state counting based on mean acceleration information and a sensor-based peak detection, reliable gym exercise counting with low transmission rates is achieved. Both approaches are running in parallel and enable the system to adapt to changes in the exercise speed in real-time and without losing counting information sent in the past.

1. INTRODUCTION

The World Health Organization describes a paradigm shift towards integrated, preventive health care as well as equipping users with information, motivation, and skills in prevention and self-management as essential elements for solving the problem of an increasing number of chronic diseases [5]. As body sensor network (BSN) systems are capable of continuously monitoring a person's physiological and physical state, they form a promising tool that equips users with the required information and motivation. We presented a BSN-based preventive health care application [3] that captures daily activities as well as all aspects of a gym workout. The captured information is then used for motivating the person, could be shared with friends via social platforms or sent to a workout database which, in return, calculates a new workout plan based on completed workouts.

Previous work [1, 2] has identified the counting of repetitions for weightlifting exercises as an important feature in a gym workout diary. The authors of [1] present a comparison between two approaches for (detecting and) counting weightlifting exercises. They implemented a peak counting algorithm and the Viterbi algorithm with a Hidden Markov Model which were calculated off-line. An outcome of this work is that the counting algorithm has to be adapted to different exercise speeds in order to improve its accuracy.

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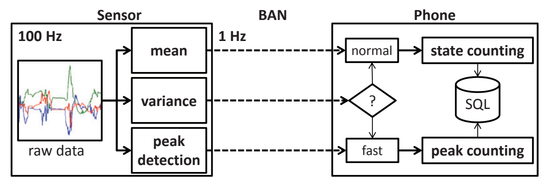

Figure 1: Data flow from raw data on the accelerometer to counting exercise repetitions on the phone.

We propose an adaptive counting algorithm running on a smartphone that adapts to different exercise speeds in real-time. For slow and normal workout speeds a state counting approach is performed. If the user increases the workout speed, the counting algorithm switches to a peak counting approach and vice versa.

This paper is structured as follows: First, a short system overview is presented. Afterwards, we describe the two counting approaches implemented in our system, a state counting approach and a sensor-based peak detection. Section 4 presents how the system decides for a counting approach after which conclusions are made.

2. SYSTEM OVERVIEW

The adaptive counting for weightlifting exercises is part of *myHealthAssistant* [3], an application which focuses on automated activity recognition and is built upon an event-based middleware we developed for BSNs [4]. The applications works on different granularities: For monitoring a person's daily activity, a coarse-grained activity recognition that detects only a few fitness-relevant activities is sufficient and does only require a small sensor network. For detecting all aspects of a gym workout, more precise activity recognition is necessary and additional information like the repetitions of weightlifting exercises is desired. Details on the system setup and the Gaussian model-based classifier for exercise recognition are given in [3]. For exercise counting, the application relies on information from an accelerometer embedded in a weightlifting glove that provides the mean and variance as well as peak information for each acceleration axis per second.

3. TWO-LAYER COUNTING

For the counting of gym exercises, a two-layer approach was followed, depending on the subject's speed of perform-

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ing the exercises. This is a necessity since the 1Hz communication between inertial sensors and the smartphone might become too slow to count repetitions of faster exercises (such as those performed with lighter weights). We cope with this by detecting the workout speed, and switch to peak detection on the inertial sensor boards for counting the exercise repetitions. For normal workouts, however, the mean values that the inertial sensors are sending by default can be re-used for the counting. The following describes how both counting approaches as well as the switching among both are implemented.

3.1 Exercise Counting on Phone

Visual inspection of the wrist's mean values sent every second by the sensors indicates that straightforward autocorrelation on the variance-dominant axis is sufficient for calculating the number of repetitions for those workouts that were done slowly. For this, an exercise state counting module on the smartphone calculates the dominant axis, and measures through autocorrelation and variance on the axis with the most dominant variance the number of repeating states as soon as a new exercise has started, in real time. Please refer [3] for more details.

Some exercises, however, can be executed in a higher tempo, which inadvertently leads to missed counts. This has led to an implementation of a similar peak detection algorithm on the inertial sensors themselves, as explained in the next section.

3.2 On-Sensor Peak Detection

To remedy missed counts of fast exercises, the inertial wireless sensor module is extended to preprocess not only the mean and variance per second, but also a basic peak detection, as depicted on the left side of Figure 1 and related to the technique presented in [1]. An alternative solution would be to increase the frequency at which the inertial sensors report mean and variance to the smartphone, but this would influence the power consumption as discussed in [3].

The sensor-based peak detection is done per axis and works as follows: A low pass filter of size five is applied on the last one hundred acceleration samples (which equals the one second time window) in order to filter out small variations that would cause tiny peaks to be reported. Then, peak detection is done on this filtered data by finding local maxima and minima over the last second. The two most pronounced peaks found per axis are then piggybacked on the packet carrying the mean and variance values of the wrist sensor. Thus, instead of being able to detect a repetition lasting at least 2 seconds by using the mean value, this process allows to detect recurring patterns over at least 1 second, using solely the most prominent peaks.

On the smartphone side, a peak counting module has to first decide whether one of these six values (two per axis) was significant for a finished repetition. For this, two parameters are important: 1) the dominant peak axis, and 2) a peak threshold characterizing a significant peak. In order to find these training parameters at runtime, a routine was designed that works completely unsupervised. A description of this routine is given in [3].

4. ADAPTIVE COUNTING

The evaluation of the sensor-based peak detection was done in MATLAB, using the accelerometer sensors with embedded peak detection during a speed-up workout set from the same subject on another day. The result of this unsupervised algorithm is a miscount rate of 12.12%. We believe that this is still sufficient since a proper workout should be done more slowly. Using the normal workout speed counting algorithm for a second training set resulted in four miscounts on the whole set of exercises and an overall miscount rate of 2.42%. The second training set was done by the same subject but on another day.

The decision on which counting approach should be used for a given exercise is done in real-time based on the variances for each incoming reading. This approach is sufficient if the user performs an exercise in constant speed. As soon as the user starts to vary the exercise speed, a permanent switching of the used counting approach leads to an increasing number of miscounts. The main reason is that state counting needs at least three seconds of readings in order to detect a repetition. For peak counting, it can be that repetitions are detected at the beginning of a movement, but the user increases speed until past the beginning. In this case, a repetition might be missed. Therefore, we propose an adaptive counting approach that performs both counting approaches in parallel and decides for an counting approach based on a sliding window of variance values. A variance threshold still decides for which approach should contribute to the total amount of repetitions, but with the benefit of enabling the counting approaches to look into the past and by avoiding a permanent switching between the approaches.

5. CONCLUSIONS AND FUTURE WORK

We presented a hybrid counting approach that consists of state counting based on mean acceleration values and an on-sensor peak detection. Both counting approaches showed good performance. Nevertheless, having an user changing the exercise speed leads to fluctuations in the selection of the counting approach and resulting miscounts. In order to avoid fluctuations and to allow the system to rely on past readings, a sliding window of variance values is used to decide which of the in parallel running counting approach should be used.

For future work, we will continue evaluating the gym exercise counting for extended use by expert users in order to measure the benefits of an adaptive counting approach and to decide on a optimal sliding window size.

6. REFERENCES

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