Towards Qualitative Assessment of Weight Lifting Exercises Using Body-Worn Sensors

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ABSTRACT
Sports exercises are beneficial for general health and fitness. Some exercises such as weight lifting are particularly error-prone and using incorrect techniques can result in serious injuries. The current work aims to develop a weight lifting assistant that relies on motion sensors mounted on the body and integrated into gym equipment that provides qualitative feedback on the user's performance. We believe that by comparing motion data recorded from different parts of the body with a mathematical model of the correct technique, we will be able to qualitatively assess the user's performance, and provide a score and suggestions for improvement.

Author Keywords qualitative activity recognition, weight lifting, inertial measurement units, mobile phone

ACM Classification Keywords I.5.0 [Pattern Recognition]: General

General Terms Algorithms, Experimentation

INTRODUCTION
It is well-known that physical activity and sports exercises lead to a better and longer life. A recent consensus statement from the British Association of Sport and Exercise Sciences states that there is plenty of evidence showing that physical activity is associated with reduced risk of coronary heart disease, obesity, type 2 diabetes and other chronic diseases and conditions [1].

In particular, activities such as weight lifting need to be performed with a proper technique. Incorrect technique has been listed as the number one cause of training injury [2]. Moreover, free weights exercises account for most of the weight training-related injuries (90.4%) in the U.S., according to a recent study. The same study states that people using free weights are also more susceptible to fractures and dislocations than people using machines [3].

As an example, consider a user performing a biceps curl. In this exercise the athlete is supposed to raise a dumbbell with a curling motion through an arc, using the strength of the biceps, while keeping his elbows still and close to his body and his spine neutral. Common mistakes for this exercise include leaning back to use the body's momentum to move the weight and moving the elbows to use the shoulders muscles to help. However, there are no available systems that can detect such mistakes.

In this paper we report on our ongoing work on a sensor-based weight lifting system that provides qualitative feedback. Using several interconnected sensors, the system will be able to analyze users' movements during weight lifting and provide feedback on the quality of the performance to help them improve their technique and prevent from injuries.

RELATED WORK
Several types of sports have been investigated in UbiComp research. There has been work on model-based game analysis for football [4], wearable sensors and video for skiing [5], an enhanced table practice table for table tennis [6], and sensor-based motion analysis for rowing [7] and swimming [8, 9].

Very few projects have addressed the problem of providing computational support for weights training exercises. Chang et al. used sensors in the user's glove and waist to recognize different exercises and count repetitions, but they didn't use the gathered information to provide feedback to the user [10]. Moreover, even though activity recognition has been widely explored on different domains, very few works address qualitative aspects [7].

PROPOSED WEIGHT LIFTING ASSISTANT
Our main objective at the current stage is to develop a system that allows us to record a dataset rich enough to extract qualitative information on body movements. The system currently comprises sensors attached to the user's wrists, elbows, waist, and knees and on the dumbbells. With sensors on the waist, we hope to detect spine stability, while with sensors on arms, legs and dumbbells, we hope to analyse speed, range of motion and stability. Therefore, we could spot common mistakes like the ones in the example.

We are currently using two different types of IMUs: the Razor 9DOF and the XSens MT9. Both IMUs contain a three-axis accelerometer, gyroscope and magnetometer. The data from the Razor IMUs is streamed via Bluetooth to a Linux machine running the Context Recognition Network Toolkit (CRNT) [11]. The data from the XSens MT9 is streamed to the CRNT through an XBus Master controlling device. We opted for the CRNT because of its real-time data synchronization capabilities and its off-the-shelf drivers. To monitor the sensors, the CRNT sends metadata to a monitoring software running on a laptop (see Figure 1).

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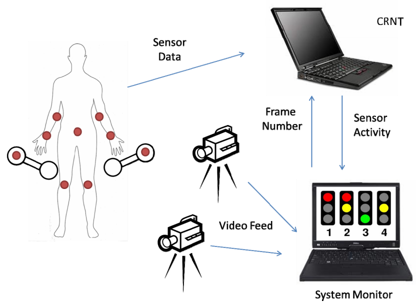

Figure 1. Experimental setup overview.

We plan to use the data in combination with domain knowledge to build a mathematical model describing the behaviour of each joint of the user's body. This model will serve as a template describing the correct technique. Later on we then plan to compare motion data to the model in real-time to assess the performance and provide suggestions to users on how to improve their technique. Ideally, the final system would run on a mobile phone running the CRNT with all the sensors streaming data to it.

The system will be evaluated by having professional trainers analyse our video recordings and by comparing their evaluation with the system's output.

DISCUSSION

Qualitative activity recognition is yet to be a mature area of research. Therefore, there isn't a unified approach to solve its problems and overcome its challenges.

Most previous works on activity recognition have taken the classification approach. This approach would require samples of all possible mistakes which would prove unfeasible to obtain within the scope of this project. We decided to use a template comparison instead. A template comparison algorithm not only allows us to detect common mistakes, but also to quantify the problem by calculating deviations from the optimal model.

Still considering the biceps curl example, a mathematical model for the position of the elbows would be something close to a horizontal line or a signal with low amplitude, since the elbows are supposed to remain stationary and close to the body. An improper technique might result in pulses in the position curve, indicating that the user is moving his elbows (see Figure 2). Hence, we could use the comparison of the signals as a possible quantitative metric for the quality of the exercise.

CONCLUSION

In this paper we have outlined ongoing work on developing a wearable assistant for qualitative assessment of weight lifting exercises. Even though our system is directed at weight lifting activities, we hope to develop a general approach to assess the quality of activities given a model of the correct way of doing it. Therefore, other applications of our approach might include assembly-line activities, dancing and other sports.

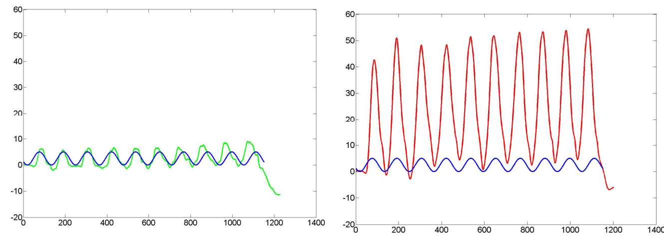

Figure 2. Data plots for a correct technique (green), an incorrect technique with the user lifting his elbows (red) and a model for a correct technique (blue).

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