Data Analytics for Athlete Safety in Training

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Abstract Data Analytics for Athlete Safety in Training (DFAST) is a system designed to improve performance and safety in athlete training. Wearable devices on the athlete send real-time data on movement, accelerations, rotations, heartrate, etc., to the system during workout. The system uses machine learning to analyze the data and send back real-time alerts to the athlete via the wearable device so that the athlete can correct posture and technique, thereby increasing safety.

Keywords Athlete training · Safety · Wearable devices · Machine learning

Physical fitness training is an important aspect of an athlete's overall performance. Athletic trainers (AT) engage with their clients and educate them on proper techniques to avoid or lessen the risk of injuries while training. The trainers also serve as medical responders to offer rehabilitation from injuries. The American Medical Association in fact recognizes athletic trainers as healthcare professionals who assist in the prevention, diagnosis, assessment, treatment, and rehabilitation of muscle and bone injuries and illnesses. Shanley et al. [10] describe AT as one who "is uniquely positioned to positively affect the overall health care of this population." Pike et al. [7] state that the presence of ATs is crucial in training athletes in secondary schools, given the levels of adolescents' participation in athletics and associated injuries. However, it is found that there is a major shortage of ATs, or they are just not being hired, which effects the quality of treatment and training received by the athletes.

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Post et al. [8] suggest that more than 53% of schools in CA did not employ ATs. Shanley et al. [10] report that athletic injuries among young adolescents account for almost 500,000 physician visits and over 50% of these injuries are preventable with proper athletic training. It is in this context that we present initial results of Data Analytics for Athlete Safety in Training (DFAST), a work in progress on a system which monitors athlete training to supplement or substitute ATs when they are not available and to provide feedback or training instructions.

1 Role of Wearables

Wearables are used by many to help track fitness progress with Q2 2021 showing a 34.4% increase in sales over the same quarter in 2020 [1]. In addition, ankle and waist wearables have been shown to be effective at monitoring the form while working out [2, 5, 6, 9]. Fuller et al. [3] showed that although wearables can be accurate in measuring steps and heart rate, the constant upgrading and redesigning to new models suggests the need for more current reviews and research.

The goal of DFAST is to use current technologies to provide a seamless interface for athletes to obtain feedback from their wearable devices on their training in real time. We use Internet of things (IoT) to establish the confluence between the wearable devices, sensors, and the cloud to collect data, analyze it, and provide meaningful feedback on their training and performance, so athletes can improve their performance and reduce the chances of injury. Hooren et al. [4] discuss the capabilities of existing current technologies, specifically wearables, in providing real-time feedback to assist in training athletes. Current wearables are equipped with sophisticated sensors that can be used to monitor several variables from the most basic vitals, such as heart rate, blood pressure, steps, speed, and quality of sleep, to more advanced data related to kinematics and mechanics of each task performed by an athlete. This kind of rich information obtained by the sensors impacts the quality of feedback that can be provided by the wearable device to the athlete in training. Hooren et al. [4] also suggest that it is this holistic feedback, which includes both physiological and psychological aspects such as motivation and personalization that will positively influence an athlete to improve performance and reduce injury.

In this paper, we describe our initial attempts to quantify data from specific workouts (Bicep Curls and Squats), so that an athlete may get real-time feedback from the system, if the performance deviates from a "baseline". The baseline itself will be derived, for each type of workout, by aggregating and processing data from several athletes, performing under the supervision of a coach or instructor. Presented in the rest of the paper is a description of the system architecture for DFAST, data collection, data cleaning, and initial experimental results for our attempts to quantify the quality of the workout.

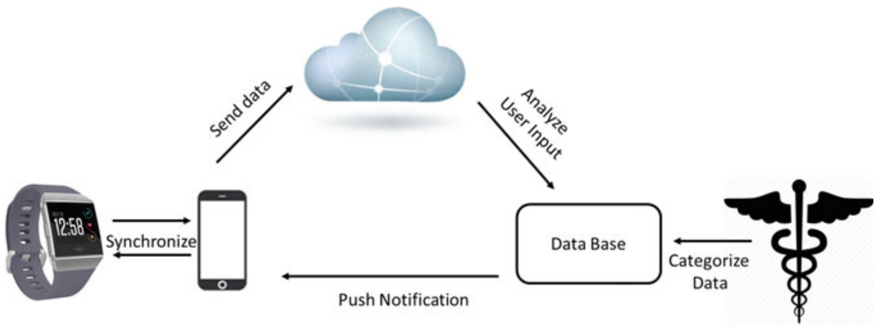

Fig. 1 Internet of things system architecture for DFAST

2 System Architecture

Figure 1 describes the architecture of DFAST. IoT is the underlying technology that connects several pieces of the application. Each individual athlete will use a mobile phone that is connected to a wearable device. The mobile phone + the wearable device, in this case a Fitbit, is used to allow the athlete to personalize his information and settings and collect data for individual activities. The data is transferred via IoT to the cloud for processing. Machine learning is used to check for the accuracy of each activity such as bicep curl, squats, etc., and provide real-time feedback to the athlete on the accuracy of the posture while training. The athlete can access this feedback on their wearable device and make appropriate changes per the feedback obtained improve performance and reduce the chances of injury.

3 Bicep Curls

Baseline exercise data was collected from six athletes and four non-athletes. Videos of each exercise were analyzed by a professional, and the data was categorized into correct or incorrect with subcategories for the type of error. Utilizing Fitbit watches, an application was designed to measure acceleration, rotation, orientation, and heart rate. With the measurements, the data is delivered from the watch to a centralized database stored in the cloud.

4 Feature Engineering and Data Cleaning

The athlete data is cast into a time series using a custom script that isolates each workout session. The new session is added to previous five. If there are no previous recorded sessions at the start of the first workout, blank regions are filled with zeroes.

Fig. 2 Bicep curl at full extension. The form on the left is defined as good, and the one on the right as bad

Initially, the entire workout is randomly assigned the target label of good or bad, even if only segments of the workout are bad. One of the issues denoted in the bicep curls was the rotation of the wrist at full extension (Fig. 2). To save time, data points above horizontal were relabeled as good.

5 Methodology

The trained data consists mostly of good workouts with only a few bad workouts. A cosine similarity metric is used to determine how well a data point matches the good baseline workout data, and from this comparison, a performance rating is provided to the user. Records are matched with a label when the similarity score is greater than a threshold. The threshold ensures that irrelevant data does not influence the measurement. Matches are assigned a score based on the target label. If the record does not match any label, then it is assumed that the data point is bad and is assigned a value of zero. The scores are then averaged for the entire workout to get an overall rating for the workout session or averaged for each record to get a rating over time throughout the workout session.

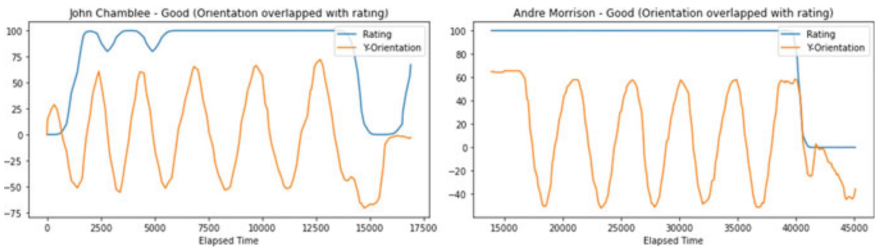

Fig. 3 Ratings for good bicep curls from the test set overlapped with the watch orientation

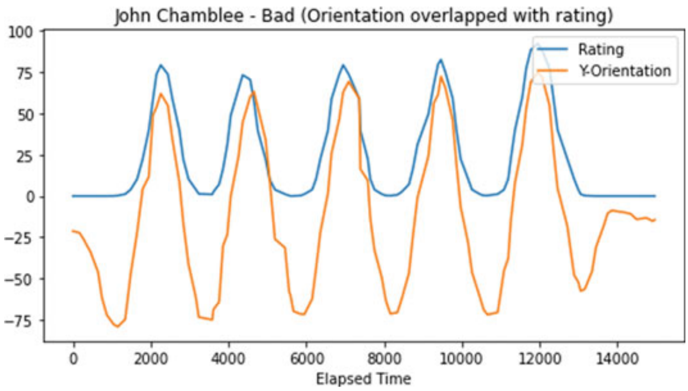

Fig. 4 Ratings for bad bicep curls from the test set overlapped with the watch orientation

6 Results

Figures 3 and 4 detail the rating over time of bicep curls with the wrist rotated at extension, as seen in Fig. 2. Because the wrist is not rotated at the peak of the bicep curls, it is rated higher at those points.

7 Squats

In the case of squats, data was collected for two separate workouts, one with "good form" and one in which the athlete was leaning too far forward. Fitbit data for both workouts show interesting features, which can be used to generate feedback to the athlete.

Figure 5 shows plots of acceleration (x, y, and z) readings for leaning forward too much (left) compared to keeping good form (right). We note that

1. Good form has majority of oscillations in z-direction. Learning forward shows oscillations in x-direction.

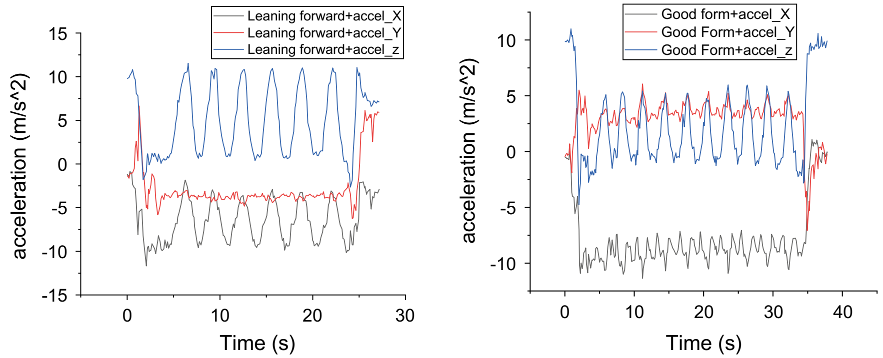

Fig. 5 *x*-, *y*-, and *z*- acceleration squat data (left) leaning forward, (right) good form

2. We can use the amplitude of the acceleration in the *x*-direction as an indicator that the person is leaning forward too much and provide feedback to adjust form.

Figure 6 shows a similar trend in the Euler orientations. The good form data has only small amplitude oscillations of the y-orientation compared to the leaning forward data.

As a test, we also performed FFT analysis of the rotation_*y* for both cases, for which the time series data is shown in Fig. 7.

FFT results of rotation about *y*-axis show that for the good form data, the y rotations show a narrow peak with small amplitude, but a much larger amplitude for the forward leaning case (Fig. 8).

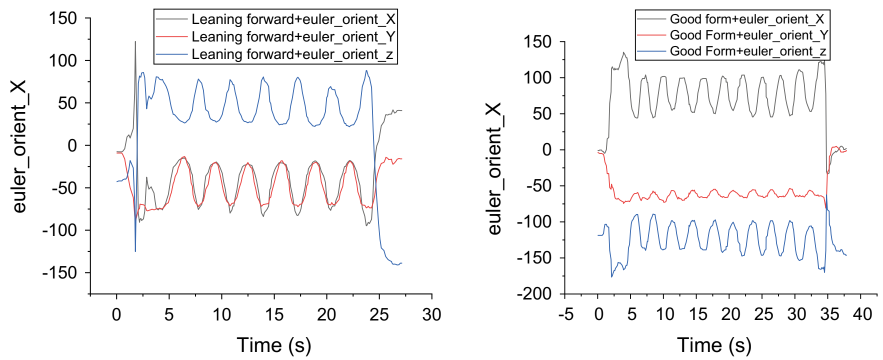

Fig. 6 Euler orientations (-*x*, -*y,* and -*z*) (left: leaning forward, right: good form)

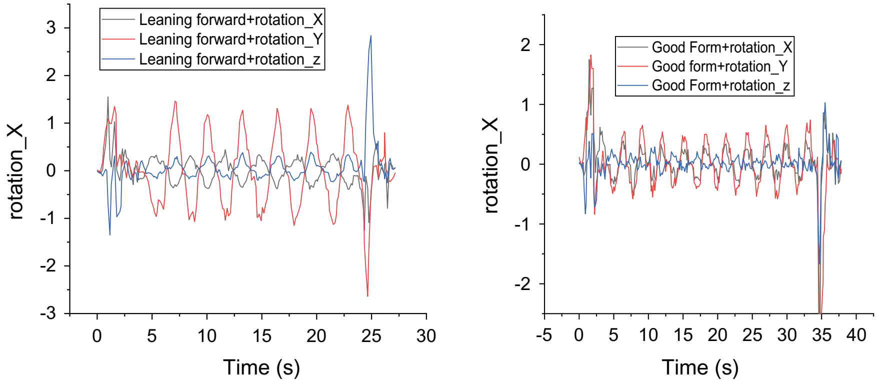

Fig. 7 Rotations (_x, _y, and _z) leaning forward (left) and good form (right)

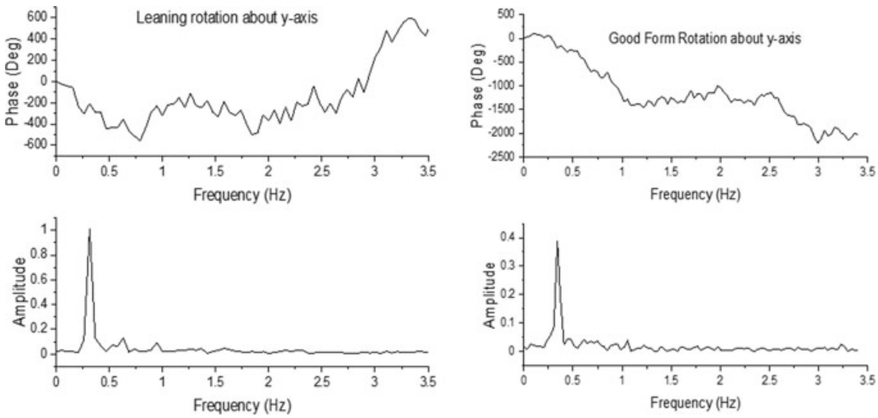

Fig. 8 FFT results of the y-axis data for squats: (left) leaning forward, and (right) good form

8 Conclusions and Further Development

Analytics of wearables data from workouts yields reliable indicators of "good form" workouts and deviations from the baseline. We continue to analyze all the data using cosine similarity, FFT, and other standard techniques of analyzing time series data, to produce quantitative, real-time feedback to athletes during workouts.

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