Classifying Weight Training Workouts with Deep Convolutional Neural Networks: A Precedent Study

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Abstract
In recent years, deep learning algorithms have been widely used in both academic research and practical applications. This study uses a deep convolutional neural network to analyze and predict physical movements. We evaluated the effectiveness of our proposed network by recruiting a professional fitness trainer and let the trainer wear a smart watch equipped with an accelerometer capable of assessing physical movement. The results confirmed the ability of the network to correctly predict the bench press, dips, squat, deadlift, and military press with an accuracy rate of 92.8%. This preliminary study has several limitations such as a low sample size and the lack of a specified network layer. In subsequent studies we plan to address these limitations by extending our investigation to include the analysis of diverse movements.

Author Keywords
Smart watch; Weight training; Movement analysis; Deep learning

ACM Classification Keywords
H.4.m. Information systems applications (e.g., HCI): Miscellaneous

Introduction

Deep learning algorithms have been widely used and have become more popular than machine learning algorithms such as support vector machine (SVM) [2]. In fact, methods based on deep learning have become the norm in the fields of computer vision, speech synthesis and recognition, and text mining [7,9,10], and this is bound to happen in the field of human-computer interaction (HCI) [5].

Although human activities have previously been widely studied by employing machine-learning algorithms [1,3,6,8], the use of deep learning algorithms seems feasible in this regard. First, the massive amount of raw data generated by body movements can be suitably analyzed with neural networks. Second, a demand for the ability to categorize activities such as walking, running, and stepping up and down exists.

This study aims to classify representative workouts using a deep convolutional neural network, as a precedent study for confirming the reliability and validity of these algorithms to classify physical movements. A total of five types of weight-training exercises (i.e., bench press, dips, squat, deadlift, and military press) were selected with the intention of using a deep learning method to distinguish among them. We collected data by using the accelerometer of a smart watch. We plan to use the results of this study in further research on human activity recognition.

Methods

One professional weight lifting trainer was recruited for this study, assuming that a professional trainer would perform the different types of workouts properly, which would facilitate classification. Admittedly, this approach has its limitations in that the sample is restricted. However, it should be kept in mind that this study is a precedent study for classifying weight lifting workouts. The assessment of massive amounts of big data from the nonprofessional population forms part of our plans for future study.

A Motorola Moto 360 wearable fitness device was used for the experiment. The Android Wear operation system, on which the device is based, provides a software development kit (SDK) to allow developers to access and use sensor data such as those generated by the accelerometer. However, the device, inasmuch as it is a common general device and not a specialized accelerometer, is unstable at times in terms of assessing acceleration data. The average sampling rates of the device, which were initially set to 20 Hz, were found to range from 15 to 30 Hz due to instability of the experimental apparatus. The time required to carry out each type of workout was measured with a stopwatch to crosscheck the task information.

The professional trainer was asked to perform five representative types of workouts including the bench press, dips, squat, deadlift, and military press. The trainer repeated each workout ten times for one set and performed ten sets of each workout in total. The trainer was required to obtain sufficient rest between sets in order to minimize muscular fatigue. The bench press, squat, and deadlift were performed with a total weight of 20 kg, which was not inclusive of the weight of the bar, whereas the dips and military press were carried out without weights. Proper form was regarded as more important than the use of heavy weights in this study.

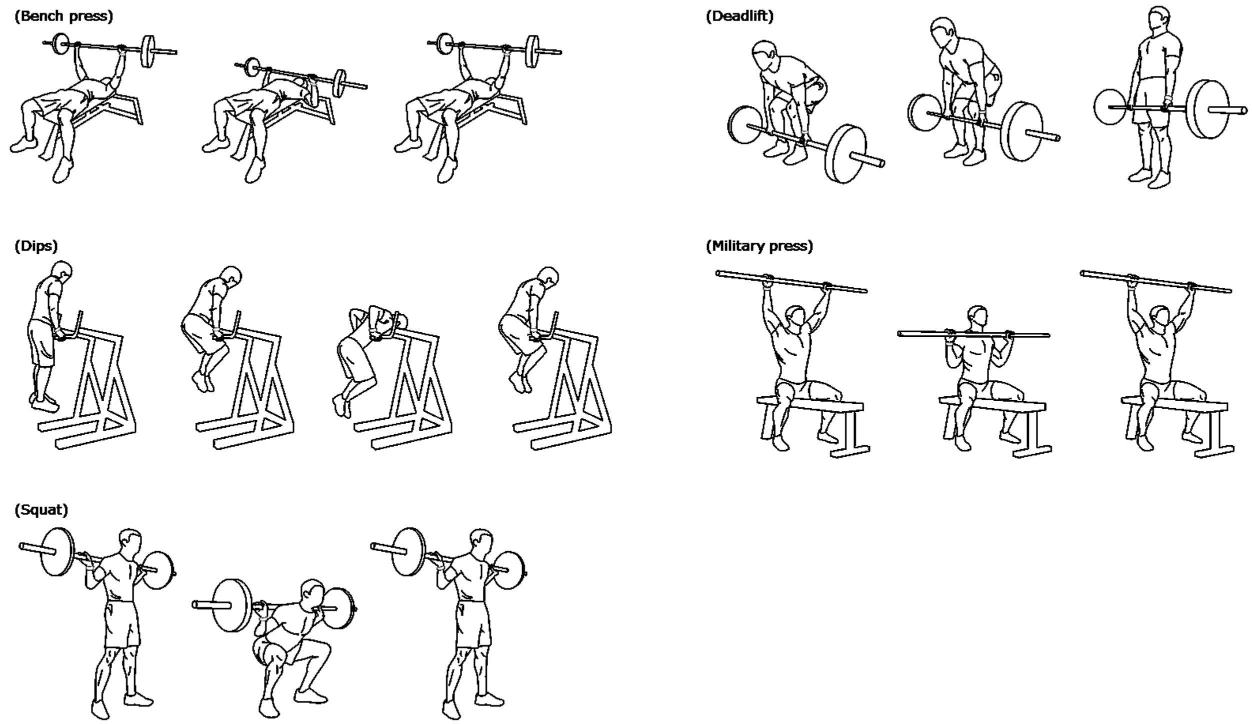

Figure 1: Five representative types of workouts by a professional trainer wearing a smart watch

Results

Data was preprocessed to be changed into a suitable form. Above all, a time window, which would be approximately equivalent to one cycle of a workout, was defined as the minimum unit of analysis. Then, features, including the average time and standard deviation for the acceleration data along each axis, were calculated. A total of six input data were formed because three-axis accelerometers were adopted in typical inertial measurement unit (IMU) sensors.

The deep convolutional neural network was applied using the Microsoft Computational Network Toolkit (CNTK) platform. This study referred to previous studies [4,11] for the layer setting. Stochastic gradient descent with a fixed momentum of 0.9 was used, whereas the learning rate was set as 0.1 for the whole dataset. Note that the amount of data used in this study was not massive; therefore, it was not necessary to perform computing accelerated by a graphical processing unit (GPU).

As a result, the accuracy rate in the prediction of the five major types of workout (i.e., bench press, dips, squat, deadlift, and military press) was determined to be 92.8%. The accuracy rate was reduced to 82.6% when the analysis targeted only the three workouts (i.e., bench press, dips, and squat) regarded as the most important workouts. However, the classification performance drastically increased to 100% in terms of the accuracy rate, for two of the representative workouts (i.e., bench press and squat).

Discussion

The results would depend on the methods selected to assess and preprocess the data. Considering that the stability (e.g., normalization of data) of data produced by smart watch devices has recently been increasing, this would also increase the overall accuracy rate for predicting and classifying physical movement. Nevertheless, the current level of device stability seems to be sufficient to enable training and testing algorithms to be applied. Of course, multiple sensors, which are located on arm, abdomen, waist, leg, as well as wrist, would improve predictive performance.

The deep convolutional neural network is expected to bring in a new era in the field of human activity analysis, as it affects computing domains such as computer vision and speech. Note that some researchers criticize deep learning for the lack of theoretical background. In this study we used various layers such as convolutional and maxpooling layers that were previously used in studies in other research domains. In future work, our intention is to apply networks specialized in activity tracking and compare it to other algorithms. One of limitations of this study was that the result was not compared to other classifiers.

Moreover, subsequent studies involving more subjects who are both professional and nonprofessional trainers would be expected to improve the performance of the results in terms of reliability and validity. In addition, various motions other than bench press, dips, squat, deadlift, and military press would need to be analyzed. Movements with heavy weights would be also compared to those with light weights. In future, the extent of the workout would be checked with the aim of making predictions.

Conclusion

This study aimed to classify weight-training workouts using data acquired via the accelerometer of a professional weight trainer's smart watch. Target workouts, regarded as representative forms, included bench press, dips, squat, deadlift, and military press. The results of our classification experiments showed an accuracy rate of 92.8%, indicating the high performance of our algorithm.

A detailed explanation of the results is not provided due to the fact that only one participant was recruited and the layers for the deep convolutional neural network were not parametrically optimized. However, as a precedent study, the possibility for the analysis of physical activity with deep learning algorithms was confirmed.

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