Investigating the effect of sensor position for training type recognition in a body weight training support system

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Abstract
A body weight training (BWT) means the training which utilizes the self-weight instead of the weight machine. The feedback of form and proper training menu recommendation is important for maximizing the effect of BWT. The objective of this study is to realize a novel support system which allows beginners to perform effective BWT alone, under wearable computing environment. To make an effective feedback, it is necessary to recognize BWT type with high accuracy. However, since the accuracy is greatly affected by the position of wearable sensors, we need to know the sensor position which achieves the high accuracy in recognizing the BWT type. We investigated 10 types BWT recognition accuracy for each sensor position. We found that waist is the best position when only 1 sensor is used. When 2 sensors are used, we found that the best combination is of waist and wrist. We conducted an evaluation experiment to show the effectiveness of sensor position. As a result of leave-one-person-out cross-validation from 13 subjects to confirm validity, we calculated the F-measure of 93.5% when sensors are placed on both wrist and waist.

Author Keywords
Activity Recognition; Wearable computing; Fitness support.

ACM Classification Keywords
H.1.2 [Information Systems]: User/Machine Systems

Introduction

World Health Organization (WHO) has reported that about 31% of adults over 15 years of age over the world do not exercise enough and every year almost 3.2 million people die due to lack of physical activity[1]. Therefore, we focus on body weight training (BWT) which only uses body weight load to solve chronic lack of exercise. BWT is recognized as an exercise that can be easily practiced using the load of own body weight only, and is a practical and simple training method that can train muscles of the whole body around the core of body muscle. The feedback of form and proper training menu recommendation is important for maximizing the effect of BWT. However, unlike a body weight training under the guidance of a personal trainer, it is difficult to achieve the above mentioned effects when exercising alone, especially for amateurs and beginners. Many training applications (such as Freeletics Bodyweight [2]) have been provided due to the spread of mobile devices in recent years. However, these applications cannot recognize the BWT type or provide monitoring during BWT or qualitative evaluation. The objective of this study is to realize a novel support system which allows beginners to perform effective BWT alone, with wearable devices. To make an effective feedback, it is necessary to recognize the type of BWT with high accuracy. However, the accuracy is affected by the position of wearable sensors. Thereby, we need to know the sensor position which achieves high recognition accuracy. In this study, we clarify proper sensor position. Specifically, we clarify the relationship between 10 types of BWT (see Figure 1) that are our recognition targets and 9 positions that are our target positions of wearable sensors. Then, according to the training chosen by the user, the position which achieves high recognition accuracy is shown to the user.

Related Work

Along with the development of wearable computing in recent years, there are many researches which aim to make exercising effective by the use of wearable sensors. Chenguang et al. [3] developed MiLift, a training tracking system for performing automatic workout recognition and automatic segmentation by using a smartwatch. Zhou et al. [4] focused on the leg machine training and recognized leg workout type and, evaluated it. The pressure cloth sensor was worn on the thigh with a sports band and activity of the quadriceps muscle during workout was monitored using the change in surface pressure between the skin and the sports band. The studies [3, 4] are only workout type recognition by a single device and only evaluate using a special dedicated wearable sensor. Our idea is different from related researches because we present sensor position of the wearable sensor which achieves high accuracy recognition and constructs a system for evaluation with only commonly used sensors(e.g., accelerometer, gyroscope).

Sensors and Data Collection

In this study, we used SenStick [5] (Figure 2) developed in our laboratory as a sensor device for recognizing BWT. SenStick is equipped with 8 kinds of Micro Electro Mechanical Systems (accelerometer, gyroscope, magnetic, temperature, humidity, pressure, light, UV), and can record data with up to 100 Hz, and can send data to other device via Bluetooth Low Energy. We tried to recognize BWT type using only the acceleration and gyro sensors installed in the SenStick.

As shown in Figure 3, we attached SenStick in a total of 9 positions((1) Head: H, (2) Chest: C, (3) Left Wrist: LW, (4) Right Wrist: RW, (5) Waist: W, (6) Front Pocket: FP, (7) Back Pocket: BP, (8) Left Ankle: LA, (9) Right Ankle: RA). Our final goal is recognition and evaluation of BWT. For ex-

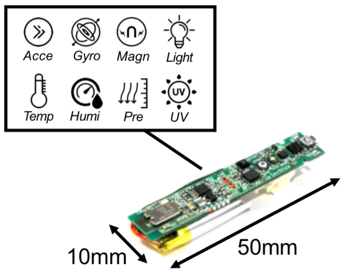

Figure 2: SenStick

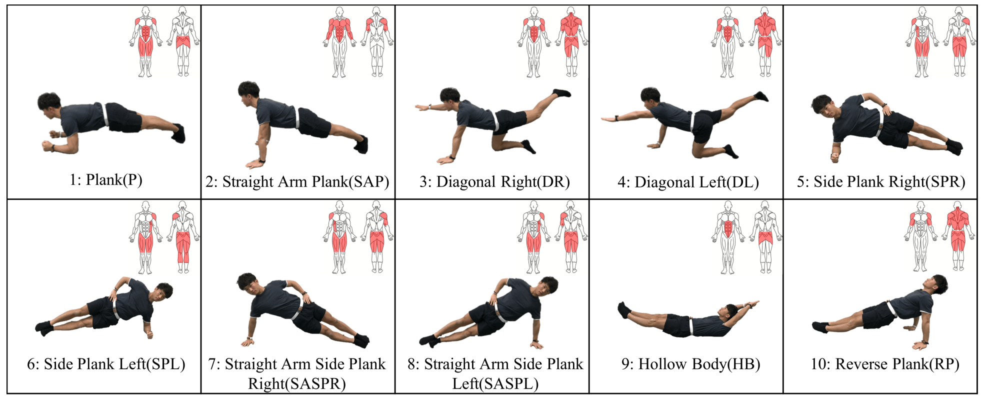

Figure 1: A body weight training as recognition targets(showing loading parts to muscles corresponding to each type)

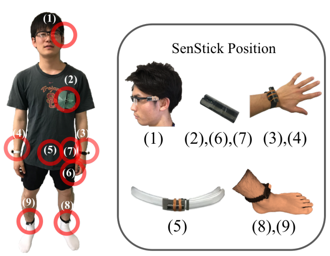

Figure 3: SenStick position

ample, sensing the shiver of the body during static BWT can quantify the person's core muscle. We set the sampling rate to 50 Hz for both acceleration and gyro in order to accurately measure detailed movements during BWT.

Machine Learning

Acceleration and gyro data were acquired respectively at sampling frequency of 50 Hz from SenStick in 1 second time window from which we extracted features. Data separated by the 1 second time window include enough samples to represent the characteristics of each motion as mentioned by previous studies [3, 6] on human motion recognition and is also appropriate for real-time attitude feedback. Therefore, we set the time window to 1 second. We calculated 7 features (average, maximum, minimum, median, difference between maximum and minimum, sum, variance) from acceleration and gyro data separated in each of 1 second time window samples. We used these features because previous research on context-aware systems using inertial data validated the effectiveness of these features [7, 8]. We evaluate the accuracy of BWT classifier which recognizes BWT type from extracted 7 features. The Random Forest (RF) is selected as the machine learning algorithm of a BWT classifier. BWT classifier is implemented by using Scikit-learn package [9] in python.

Classification Results

We describe 1) BWT recognition result for each sensor position by using the machine learning based on acceleration and gyro data collected from 9 SenSticks, and 2) validate the results from (1) by using recognition results for multiple subjects. In (1), 1 subject (23 years old, male, 174cm, 66kg) performed 3 sets of training, each of the 10 types of BWT for 20 seconds (as shown in Figure 1). Between the individual sets, there was enough break. Besides tracking the subject sensor data all BWT were also captured on video and segmented based on the video by hand. We created a classifier for BWT from the collected training data set of the subject (600 seconds). Then, we recognized BWT from the collected test data set (200 seconds)

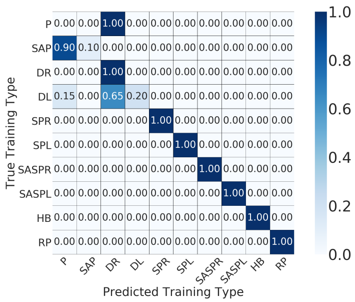

Figure 4: 1 Sensor(W)

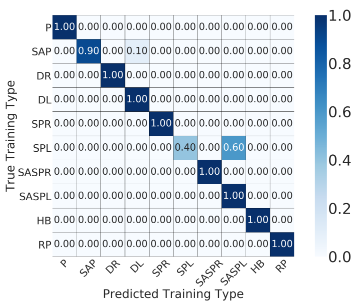

Figure 5: 2 Sensors(RW+B)

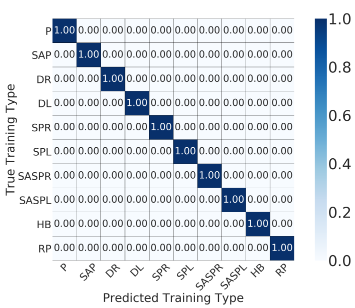

Figure 6: 3 Sensors(LW+RW+LA)

Table 1: BTW type recognition result by F-measure for each SenStick position

Ranking \ Number of Sensor	1 Sensor	2 Sensor	3 Sensor
1st.	W(73.0%)	RW+W(93.0%)	LW+RW+LA(100.0%)
2nd.	RA(72.0%)	RW+RA(91.5%)	LW+RW+W(99.0%)
3rd.	LA(70.5%)	W+LA(90.0%)	LW+W+LA(96.0%)
Ave.	71.8%	91.5%	98.3%

of another subject (25 years old, male, 174cm, 62kg). Table 1 shows BTW type recognition result by F value for each SenStick position. When there is only 1 sensor, SenStick position with the highest recognition accuracy is waist (W) and recognition accuracy is 73.0% (F-measure). Figure 4 shows the confusion matrix of waist (W) as sensor position. When there are 2 sensors, SenStick position with the highest recognition accuracy is right wrist (RW) and waist (W) and recognition accuracy is 93.0% (F-measure). Figure 5 shows confusion matrix of right wrist (RW) and waist (W) as sensor position. When there are 3 sensors, it can be recognized with high accuracy of 98.3% (F-measure) on average of the top 3. Figure 6 shows confusion matrix of left wrist (LW) and right wrist (RW) and waist (W) as sensor position.

Next, in (2), 13 other subjects (23 to 25 years old, 160cm to 183cm, 55kg to 85kg, male only) performed the same BWT each of the 3 sets of the 10 types for 15 seconds. with SenStick on the wrist and waist to investigate the validity of the result in (1). Then, we evaluated the recognition accuracy (F-measure) of BWT type using leave-one-person-out cross-validation using the collected sensor data (5,850 seconds). As a result, we found out that even with two sensors attached to both wrist and waist, we could recognize BWT with accuracy of 93.5% (F-measure).

Discussion

Waist is a position close to the body axis and is stable compared to positions on the side or limbs (e.g., wrist, ankle) [10]. These show more movement during BTW, i.e. recognition accuracy is highest when sensor is used only in the waist. Also, we found that high recognition accuracy is possible by attaching the sensor to both wrist and waist. Thus, if we attach smart-phone and smart-watch, which is a common device, on waist and wrist, we can recognize10 types BWT with high accuracy. Further, when 3 sensors were used, we could recognize with almost 100% accuracy. Hence, in the wearable computing environment, it can be suggested that it is possible to realize effective BWT without personal trainer.

As part of future work, we will also classify not only BWT but also activities of daily living because detecting BWT in daily living can assist both users and physicians in achieving better health care[11]. Also, we segmented by hand in this paper, but automatic segmentation between sessions is future work. Further, we aim to increase subjects to improve the generalizing capability of the model and implement visualization of BWT evaluation by information related to pose and shiver of the body. We also intent to create a qualitative BWT support system.

Conclusion

In this paper, we investigated 10 types BWT recognition accuracy for each wearable sensor position and clarified the position which achieves high recognition accuracy. As a result, we could recognize BWT with an accuracy of 73.0% (F-measure) with one sensor attached to the waist. Further, we confirmed that recognition accuracy could be improved to up to 93.0% (F-measure) by adding another sensor attached to the right wrist. As a result of leave-one-person-out cross-validation for 13 subjects to confirm validity, we achieved 93.5% accuracy when sensors are placed on both wrist and waist.

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