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Physical Training Gesture Recognition Using Wristwatch Wearable Devices

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Abstract

Lately, many companies have launched smart watch products with their own strong points, drawing consumers' attention. A smart watch has changed our life and made it more convenient, offering some different experiences compared to existing smart phones. More importantly, health care using this device has increasingly been the subject of people's attention and studies. Most of the existing studies have explored mobile devices and multiple sensors recognizing activities related to the routine such as walking, running, and going up and down the stairs. This study has focused on the use in physical training. We made a wearable device with some features of a smart watch, and studied how to make it recognize the activity the user is performing with the built-in accelometer and gyroscope. It is expected to be helpful for the individuals to manage their own exercise systematically and be practical in the health care industry.

Keywords: *Wearable device, accelometer, motion recognition, machine learning*

1. Introduction

Following the development and popularization of smart phone technology, wearable devices have recently been highlighted as a next-generation mobile computing technology. Wearable computing technology has been engraved as the starting point of ubiquitous computing technology since 1966, long before the smart phone technology. Not just major global companies, but many sport product companies have also launched innovative products and services in different areas such as U-health care, wellness, fitness, medical, and entertainment. Meanwhile, it is known that consumers have interests in wearable devices because they want to record their routines, improve general fitness, and experience the newest technology [1]. It means most of the consumers want to use wearable devices for health care.This result shows the contradiction in modern times that the scientific technology and financial power advance, but many different diseases increase as well — due to the lack of exercise.

Meanwhile, a smart phone is closely related to the habits and behaviors of its user as it is carried at all times. That's why a smart phone is frequently used to recognize behaviors and postures, and the most commonly used way is analyzing the acceleration vector extracted from the accelometer. An accelometer consumes less energy than other sensors and less influenced by the environment such as lighting and noise so that it may sense the user's movement constantly. In some cases, however, it is difficult to fully depend on the smart phone only since it is not fixed to a certain part of the body. The recognized result may be different depending on the location of the device, and the user does not have it in his or her hands while doing certain activities.

This study made a wearable device in the form of a watch with a built-in accelometer and a gyroscope, and suggested a method to utilize it for physical training by recognizing the exercise with the machine learning. The paper consists of the following: Chapter 2

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describes preceding research about motion recognition and posture recognition and difference between them and this study. Chapter 3 describes the proposed method for exercise motion recognition using wearable devices in detail, and Chapter 4 describes the process and the result of the test, and concludes the study.

2. Related Works

Due to the development of sensor technology in the past, several HCI (Human Computer Interaction) technology which humans could not have imagined in the past has emerged. For a long time, research has been made on behavior and posture recognition to capture users' motions due to physical activities in core fields of computer engineering such as machine learning, data mining, image processing, and artificial intelligence. More importantly, epoch-making development of mobile computing technology such as smart phones and wearable devices in which highly efficient sensors are integrated has been followed by active behavior and posture recognition studies for such mobile platforms.

A common way to recognize behavior or posture is to collect and analyze data from sensors such as acceleration sensors, gyroscope, or GPS of portable mobile devices to capture features and patterns which change along with the movement of users' bodies. Preceding researchers found optimum methods to recognize and capture more physical movements with higher performance by attaching fixed sensors all around the body [2]. They also tried to capture vibration patterns according to body movement using non-fixed sensors such as a smart phone [3]. Recently, they even studied to mix these two methods [4]. Like this, standardized methodologies are defined for sensor data-based behavior and posture recognition studies.

Recognizing physical activity patterns of users is classified into collecting data and extracting features, modeling and learning, and recognition. This study proposes a way to make a wearable device in the form of a watch — a common form found in daily lives — and classifying various exercise motions by focusing on the features of a wrist type device, not by using mobile devices or attaching the device to certain body parts.

3. Proposal

3.1. System Configuration

The following figure (Figure 1) displays the overall procedure of this study. First of all, it collects data with the wearable device and extracts features for the divider to learn the data. Extracted feature values are divided into two data groups (learning and test). It extracts features from two groups to use for the classification, then the divider learns the data with the learning dataset. Use the test data set to evaluate the accuracy of the classification.

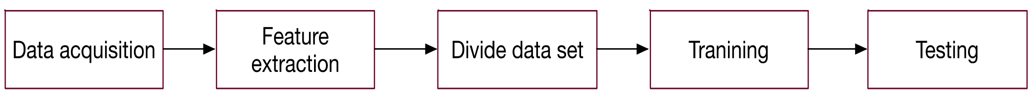


Figure 1. Procedure of Classifying Data

3.2. Device Manaufacture

We made a wearable device with 3-axis acceleration and gyro sensors to collect data. The device was designed to be wrapped around the wrist like a smart watch and to measure the different values. 3-axis acceleration sensor refers to the element detecting acceleration, the change of speed of three axes (x, y, and z) in the space per unit time. A gyro sensor measures the speed of each axis (rotating angle/time). For the test, I made a wearable device as shown in Figure 2. The device is connected to the host computer through a Bluetooth wireless interface. The sampling cycle is 10Hz, and it provides six sensor values (three axes of accelometer and three axes of the gyroscope). Table 4 illustrates the hardware specifications.

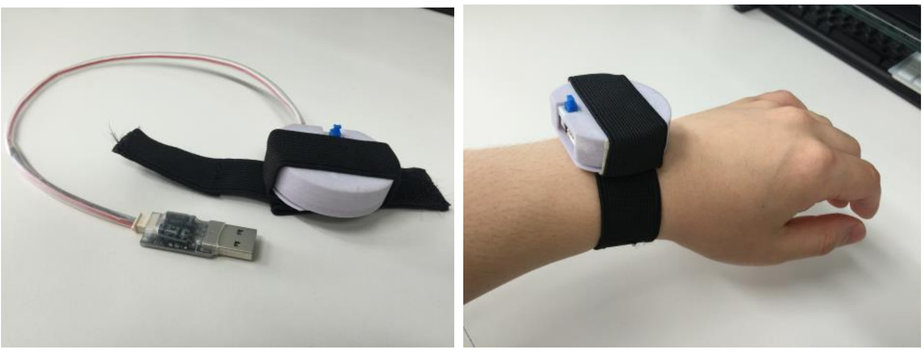


Figure 2. Appearance of Wearable Device

Table 1. Device Specification

Processor	ARM Cortext M3
Clock speed	16MHz
Communication	Bluetooth
Sensing period	0.1s

3.3. Movement Selection

Actual fitness centers have a lot of sporting equipment with different devices. As it is difficult for a device in the form of a smart watch to recognize and define motions not related to the limbs, we selected five equipments and exercises that are related to hands motions and common in fitness centers. Table 1 lists the selected exercise motions.

Table 2. List of Exercise Type

Exercise Type	Abbreviations
Long-pull	LP
High-pull	HP
Shoulder-press	SP
We3Chest-press	CP
Bench-press	BP

3.4. Data Collecting Method

Five volunteers (26 - 33 years old) wore the device and executed each exercise motion for three sets (ten times/a set) to collect data.

We applied the threshold technique to classify each exercise motion because exercises in fitness centers are to regularly repeat moving and pausing. Threshold technique is to assume a time of exercise (motion) is started when the amount of change of the sensor data is above a certain threshold. Based on the point that crossed the threshold, data for three seconds (1.5 seconds before and 1.5 seconds after the threshold) is a data set for a time of exercise motion. It is used in terms of a learning data that is to be used later. That is, the whole graph is not used as a learning data unit. Only the part that was cut off as above is learned, but the rest is discarded.

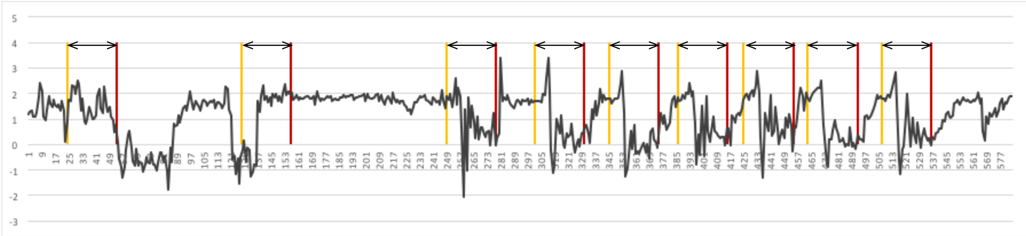


Figure 3. The Graph of the Whole Exercise Record Showing the Threshold-Applied Sections

Figure 3 illustrates the example of this process. This graph is the whole record of a user's one set of exercise. Data is collected at every point, but only the sections indicated by two-way arrows are actually used. Although the forms of the graph in cutoffs may look different from each other, it displays a similar form for the sections that the actual exercise can be assumed to be taken place. It is going to be further described, but this study does not assume the exercise activity with the forms in the graph. It simply makes it possible to exclude the unnecessary data, having repetitive movement from the start of the recording, by not actual exercise activities but other prepared actions.

3.5. Feature Extraction

For the divider to learn how to recognize and divide exercise motions, source data needs to be processed. Processing such source data and converting it to data useful for the divider is called feature extraction. In this study, six features (minimum value, maximum value, maximum-minimum deviation, average, standard deviation, and RMS) for each axis (x, y, and z) are extracted from the collected acceleration and gyro sensor data. Table 3 lists the extracted feature.

Table 3. List of the Extracted Features

Feature	Meaning
Min	minimum
Max	maximum
Minmax	max-min
Mean	mean
Std	standard deviation
Rms	root-mean-squre

3.6. Classification

The data set that was classified by one time exercise motion and feature extracted is classified into two sets; the training set and the test set. The training data set is first learned by a classification algorithm. The test set is used to evaluate the classification accuracy based on the data that was learned afterward. We evaluated the performance of five classifiers that can be used in the Weka toolkit — Multilayer Perception, Random Forest, LMT, SVM, Simple Logistic, and LogitBoost. Each classifier was learned and tested, using the 10-fold cross validation method in the extracted feature set. Multilayer Perception: A neural network in which more than one middle layer exists between the input layer and output layer. The middle layer between the two layers is called a hidden layer. The network is connected to the direction of the input layer, the hidden layer, and the output layer. It is a Feedforward network, having no connection in each layer or direct connection from the output layer to the input layer.

RandomForest: This is an algorithm originally proposed by Ho, *et al*. [11] It artificially selects a subset of features to train the divider. The ensemble divider consists of several decision trees. It is fast, working efficiently for big data sets. It has demonstrated higher accuracy than other multi-class dividers.

LMT: A logistic model tree basically consists of a standard decision tree structure with logistic regression functions at the leaves, much like a model tree is a regression tree with regression functions at the leaves. [12]

SVM: In machine learning, support vector machines (SVMs, also support vector networks) are supervised learning models with associated learning algorithms that analyze data and recognize patterns, used for classification and regression analysis. Given a set of training examples, each marked for belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples into one category or the other, making it a non-probabilistic binary linear classifier. [13]

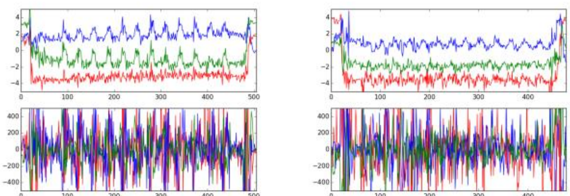
Simple Logistic: Simple logistic regression is analogous to linear regression, except that the dependent variable is nominal, not a measurement. One goal is to see whether the probability of getting a particular value of the nominal variable is associated with the measurement variable; the other goal is to predict the probability of getting a particular value of the nominal variable, given the measurement variable. [14]

LogitBoost: In machine learning and computational learning theory, LogitBoost is a boosting algorithm formulated by Jerome Friedman, Trevor Hastie, and Robert Tibshirani. The original paper casts the AdaBoost algorithm into a statistical framework. Specifically, if one considers AdaBoost as a generalized additive model and then applies the cost functional of logistic regression, one can derive the LogitBoost algorithm.[15]

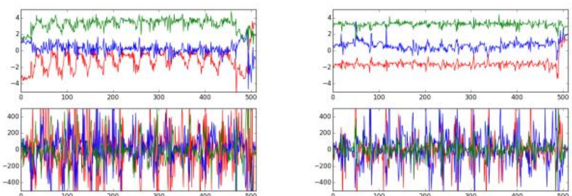
4. Test and Results

4.1. Exercise Data

Figure 3 shows the graph of the sensor data measured per each exercise motion. It is divided into two graph groups; the upper one shows the accelerometer data and the lower one shows the gyrosensor data. It is able to confirm that the graph looks different at each exercise motion.



Long-pull(LP) High-pull (HP) Sholder-press(SP)



Chest-press(CP) Bench-press(BP)

Figure 4. Result of Measured Sensor Data

4.2. Classification Result

Table 3 illustrates the classification accuracy per each classifier. In total, Multilayer Perception shows the best performance as 95.14%. 93.20% of Random Forsest is the nest, and the least is 86.84% by Logit Boost. Figure 4 shows the F-measure value per each classifier.

Table 3. Classification Accuracy of Different Classifiers

Classifier	Accuracy
Multilayer Perception	95.14%
SVM	90.29%
Random Forest	93.20%
LMT	92.23%
Simple Logistic	92.23%
Logit Boost	86.84%

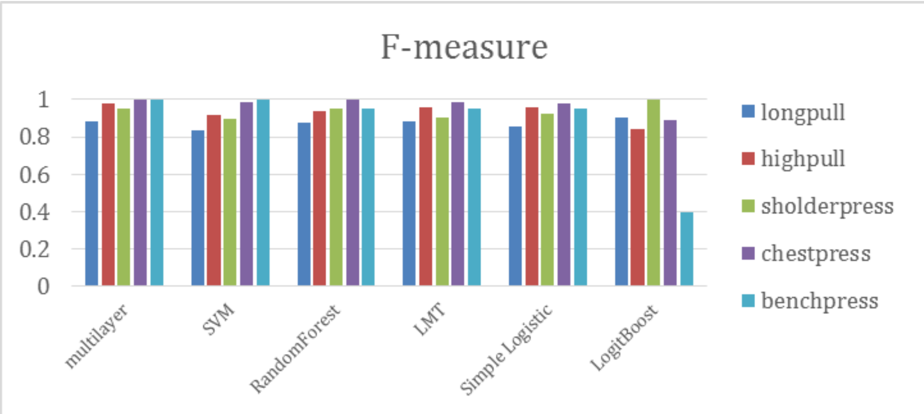


Figure 5. F-Measure for each Activity Using Five Classifiers

5. Conclusion

This study made a watch-formed wearable device, and suggested a physical training motion recognition system using the physical accelometer and the gyrosensor. It measured five exercise motions, applying a threshold method to assume the actual exercising section. The sensor data in the assumed section were analyzed to extract 30 features. The test confirmed that Multilayer Perception produces the best classification result (95.14%). This study is expected to be useful for the healthcare system using physical training.

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