

The Gesture Recognition Technology based on IMU Sensor for Personal Active Spinning

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Abstract— Recently, as the desire for sustaining good health, has increased, spinning exercise to increase the exercise effect in a short time is getting the spotlight. In this paper, we developed a gesture recognition technology which enables busy persons to enjoy spinning exercise at any time and at any place they want using easy to carry wearable device. The proposed scheme provides a training system which collects real time data from an IMU (Inertial Measurement Unit) sensor attached to wrist and head of sports participants and analyzes the accuracy of spinning exercise using the decision tree-based classification scheme. For the validation of the spinning gesture recognition technology, we analyzed the performance of the proposal algorithm by applying it to the interactive gaming content platform. The results shows that the proposed the proposed technology can help users to enjoy correct spinning exercise program.

Keywords— gesture recognition, spinning program, IMU sensor

I. INTRODUCTION

As the life expectancy is close to age of a hundred and the desire for health care increases, more and more people expect to manage their health through exercise. Also many people want to save the exercise time as well as increase their health status during busy daily life. As the demand for a fitness program producing a high exercise effect in a short time has been increased, spinning exercise gain in popularity which results in large calorie consumption, body fat reduction, improvement in cardiorespiratory endurance and muscle endurance during the exercise [1], [2].

Spinning is a kind of G.X (Group Exercise) in which a group of persons rides on the bike while dancing along to exciting music. Spinning uses a spin bike to move the upper body to upper, lower, left, right, and wave according to the exciting music by changing their posture while sitting on a bicycle saddle or standing up during their riding. It is an aerobic exercise that shows intensive exercise effect

on whole body such as arm, leg, abdomen and waist. In order to achieve intensive exercise results, however, proper posture is required for the movement of upper and lower body as well as fast and violent pedalling on a bicycle.

There is a spinning program that allows spinning exercisers to follow the actual trainer's actions provided by live video streaming via a touch-screen tablet like Peloton's Spin-Bike training system [3]. In order to analyze the exercise effect, however, it does not provide proper measurement method whether the participants are following correct motion. If there is a method to measure the movement of the spinning exercise, it would be more helpful to increase the effectiveness of spinning exercise. Moreover, in order to enjoy the spinning exercise in a personal space, it is useful to adopt software games providing interactive exercise guidance in which exercise participants watch and follow the motion according to the contents.

In this paper, we propose a gesture recognition technology using the IMU sensor with built-in 3-axis acceleration sensor, 3-axis gyro sensor and 3-axis geomagnetic sensor. For the purpose of evaluating the gesture recognition performance, we adopted a gaming platform to measure the spinning motions, in which produces an interactive game containing the proposed algorithm.

The rest of the paper is organized as follows. In Section II, we describe related works which suggest gesture recognition systems using sensors for fitness and a customized fitness system related to spinning. In Section III, we illustrate the proposed gesture recognition technology based on IMU sensor in detail. In Section IV, we represent the

experiment to evaluate the proposed algorithm using a gaming content for spinning gesture recognition. Finally, we draw conclusions in Section V.

II. RELATED WORKS

The demands for the sports IoT (Internet of Things) are increased by using wearable sensors to measure human motions. In particular, many researchers suggest wearable systems which function to collect, transmit, and process biometric and physical information of users without restriction of time and space by using wearable sensor technologies.

[4] analyzed the human body state using a set of bio-signal gesture sensors, pulse wave sensors, and BCI devices. It provides an appropriate level of the spinning program using the detected spinning gesture agreement rate and work-rate by recognizing skeleton gesture in real time. [5] analyzed the user's real-time movements using an image sensor and a 3-axis acceleration sensor such as walking turning, running, and going down the stairs. To analyze the data obtained from the multi-sensor, it proposed a grid-based optical flow method and use SVM (Support Vector Machine) classification method. [6] developed a technology that automatically recognizes the rider's driving situation on a bicycle using a three-axis acceleration sensor and verified the performance by applying it to actual road driving data. [7] implemented a multi-sensor hardware platform to recognize human behavior by attaching various sensors to the body. [8] recognized the behavior of lying, walking, running, stepping down, and climbing stairs using a decision tree based classification. Those existing researches used camera and gesture sensor to recognize and analyze human motions.

In this paper, we recognize the spinning gestures using only small IMU sensors so that the user can enjoy spinning exercise anytime and anywhere. We analyze the spinning gestures in real time using the decision tree based classification technique based on the data of the IMU sensor, and we propose a recognition technique the spinning gestures using the analyzed result.

III. THE GESTURE RECOGNITION TECHNOLOGY

In this section, we introduce the proposed technology for recognizing gesture of spinning exercise. We designed and implemented an algorithm to recognize the spinning gestures using the IMU sensors and evaluated its performance.

A. Configuration of the gesture recognition technology

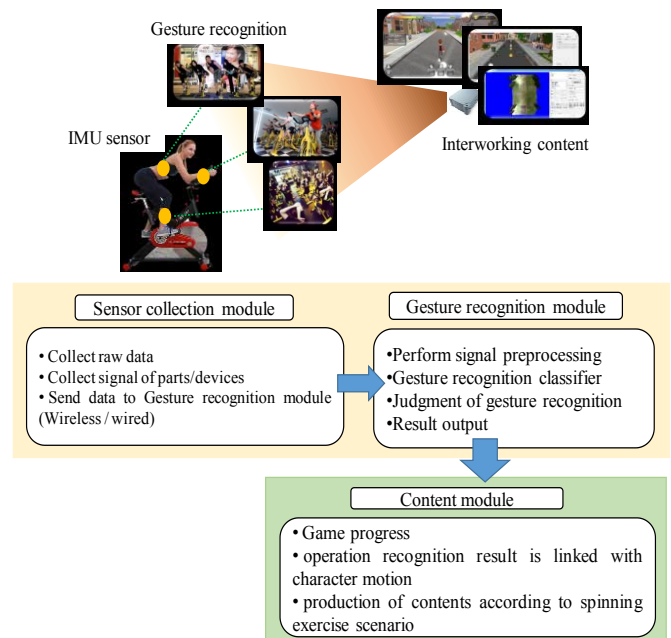


Figure 1. Module Architecture of the gesture recognition technology

The spinning gesture recognition technology consists of three parts as shown in Figure 1. First, the sensor collection module collects data from the IMU sensor attached to the user's wrist and head and transmits it to the gesture recognition module. After performing pre-processing of the acquired signals, the gesture recognition module recognizes and classifies the spinning gestures. Finally, the content module provides an API for interworking with spinning content [9] to verify whether spinning gesture recognition is properly measured.



Figure 2. Sensor attached appearance.

B. Collection and processing of IMU sensor signal of the sensor collection module

The sensor collection module processes the data collected by the IMU sensors to recognize the spinning gesture and transmits them to the gesture recognition module in real time. Although many researchers suggest gesture recognition technology using motion sensor and IMU sensor simultaneously, only IMU sensors are used in this paper so that it can enjoy spinning motion with small portable sensors only attached to human body.

We used commercial IMU sensor named MyAHRs (by Withrobot, Korea) including 3-axis acceleration sensor, 3-axis gyro sensor and 3-axis geomagnetic sensor. This sensor has a function to calculate the three dimensional angles (roll, pitch, and yaw) of the sensor. For the learning parameters, we used x, y, z axis values of acceleration sensor, x, y, z axis values of gyro sensor and roll, pitch, and yaw angles converted from the output of the IMU sensor.

The position of the IMU sensor is attached to the head and both wrists, where the dominant movements are detected during spinning as shown in Figure 2. All three sensors were connected to the PC by serial communication, and data were collected at the 100HZ sampling frequency. Sensor noise from each device was removed by applying Kalman filter and then transmitted to the gesture recognition module.

C. Gesture classifier of the gesture recognition module

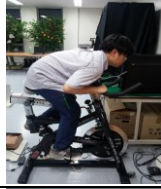
The gesture recognition module classifies the spinning gestures using the gesture classifier and determines whether the classified spinning gesture is properly executed.

Table 1 shows the nine spinning gestures classified by the gesture classifier. Several gestures are defined for the beginners easily to follow spinning exercise according to the guideline of a spinning specialist. It consists of nine basic gestures by simply moving body or arms without waving motion for high level exercise. The first one is stop gesture in which users turn pedals similar to the normal posture of riding a bicycle. The second and third gestures are up and down movements of upper body returning to its original position (stop gesture). The fourth gesture is to tilt the body to the left, and

the fifth to the right. The sixth and seventh are the lifting-up and lowering-down gestures of the left arm. Similarly the eighth and ninth gestures are lifting-up and lowering-down gestures of the right arm. Users start from the first gesture in the begging, and return to the first gesture again after finishing appropriate gesture.

In order to select the best method to classify the spinning gestures, one of the three methods among statistical technique, SVM classifier and decision tree classifier are selected by comparing the performances. In order to compare the three techniques, we performed experiments by attaching

TABLE 1. THE SPINNING GESTURES

	Gesture	photo
1	Stop	
2	Body up	
3	Body down	
4	Body left	
5	Body right	
6	Left arm up	
7	Left arm down	
8	Right arm up	
9	Right arm down	

one sensor to the wrist and recognizing the three arm gestures such as up, down, and stop. The input dimensions were 9 degrees from the data collected with 3 - axis acceleration, 3 - axis gyro and roll, pitch and yaw.

First, the statistical technique divides the gesture using the average distribution of the collected nine data. As shown in figure 3, the average value of 90~100 samples per gesture is calculated, and the frequency count of each signal is represented by a histogram. As a result of the nine data analysis, it was found that the gyro value is most suitable for the classification of the three arm gestures. In particular, we confirm that the gyro Z value is better compared to the gyro X and Y axis as shown in Figure 4. We set the threshold range for the three gestures using the average value of gyro Z and measured the performance.

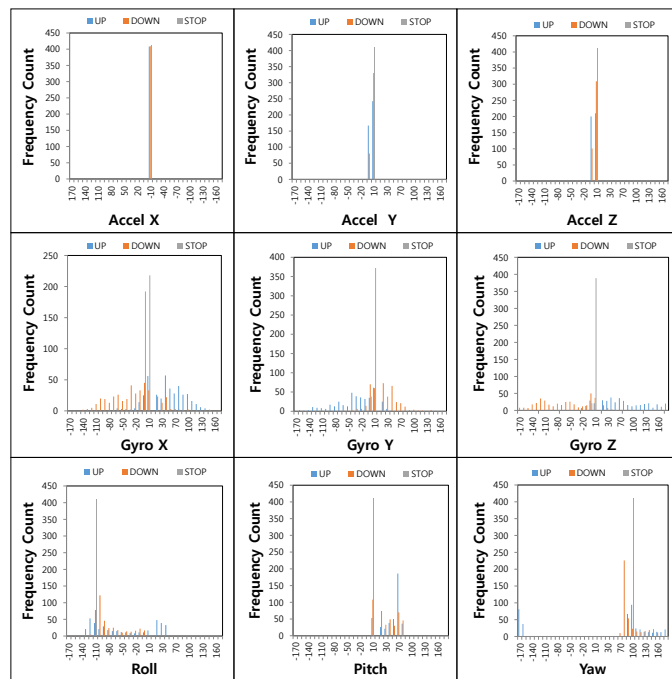


Figure 3. The average histogram of each sensor signal

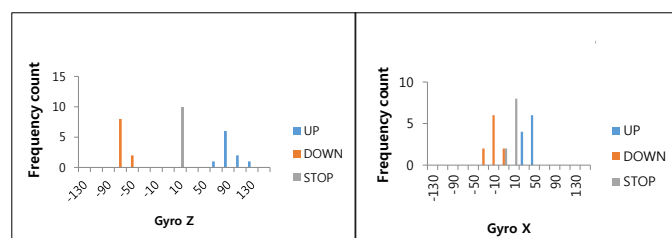


Figure 4. The average histogram of Gyro X, Z

Secondly, the SVM classifier collects 90 ~ 100 samples per gesture as one set, and collects n sets of such data to conduct SVM learning. We classified gestures based on the support vector obtained as a result of SVM learning and measured the performance.

Finally, the decision tree classifier used the same data as the SVM classifier, but the gestures were classified using the decision tree obtained from the learning result.

TABLE 2. TABLE OF COMPARISON OF THE THREE GESTURE RECOGNITION BY CLASSIFIER

Classifier	Recognition rate (%)
Statistical technique	94.1
SVM	95.8
Decision tree	97.3

As a result of classifying the gestures using three methods, the decision tree classifier showed the highest gesture recognition rate as shown in Table 2. Based on the experimental results, we developed a gesture recognition system using the decision tree classifier for nine spinning motions. Three IMU sensors were attached to both wrists and head to learn data for 27 input dimensions using the decision tree. We also used the bootstrapping method to improve the accuracy of the decision tree method. Four test data sets with different data were learned sequentially, and the wrong data was included in the test data set and then learned. The accuracy of the decision tree method was improved by repeating this process. One test data set contains a total of 180 sets. It consists of 27 input dimensions collected 90 to 100 samples per set from 3 sensors and 20 sets of data for one of nine gestures. We completed the final test data set by learning five times and learned it again to extract the decision tree.

As shown in Table 3, the bootstrapping method showed a higher gesture recognition rate than without using it. The table shows that as the number of test data sets increases, the recognition rate of the gesture using the decision tree increases.

TABLE 3. TABLE OF COMPARISON OF THE THREE GESTURE RECOGNITION BY CLASSIFIER

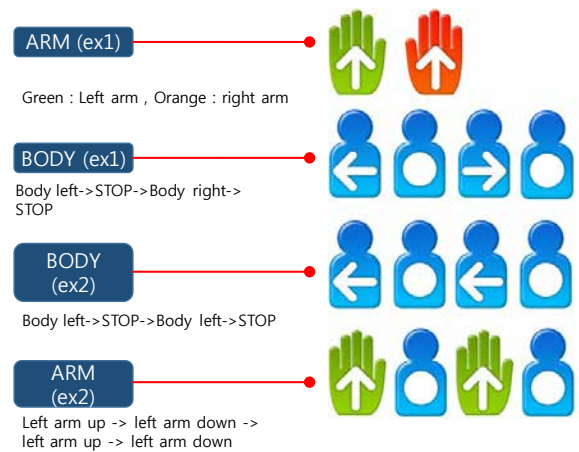
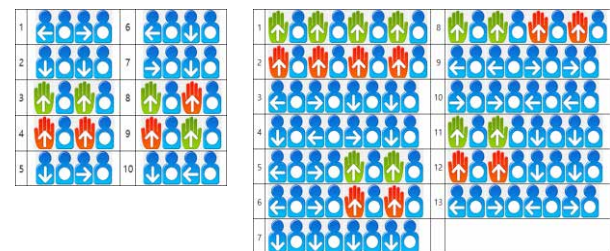
Classifier	Recognition rate (%)			
	Test data1	Test data2	Test data3	Test data4
Decision tree	85.50	86.78	84.38	85.65
Decision tree (with bootstrapping)	85.50	87.88	90.08	94.80

D. Interworking with the content module

In order to evaluate the spinning gesture recognition technology, we constructed the experimental environment by connecting the spinning contents with the API developed by us. Finally, nine spinning gestures were recognized using the decision tree with bootstrapping method. The experimental environment consists of a spinning bike, three wearable devices, a monitor and a PC with the spinning gesture recognition system and the spinning game content.

IV. EXPERIMENTS

As shown in Figure 5, nine spinning gestures were recognized using the action icon of the content. The left arm and right arm were separated into green and red, and the body was expressed as left, right, up, and down. An icon with a circle means return to the stop gesture. For example, after the body left gesture, the user maintains the stop gesture, then the body right gesture, and then the stop gesture. After raising your left arm or right arm, users hold the bike handle again. In other words, after all the gestures are done, you have to hold the stop gesture and then execute the next gesture. Each gesture was performed according to the beat of the music which was selected by the instructor during the actual spinning exercise. Music is played for 3 to 5 minutes per song, and the order of gestures is different for each music. As shown in Figure 6, there are random mixes of four-beat gestures and eight-beat gestures. As shown in Figure 7, the user can perform the spinning exercise by looking at the icon as if the actual instructor teaches the action. The content also provides a spinning motion picture for the beginners. And user can perform spinning exercises while viewing the screen whether correctly

**Figure 5.** Icon type of spinning gestures**Figure 6.** motion type of the spinning content**Figure 7.** Content launch screen

following the motions. When one song is finished, the accuracy of motion-followings in the spinning content is displayed at the screen as shown in Figure 8. The higher the recognition rate, the higher the accuracy of the motion.

In this experiment, 10 subjects who had no experience of spinning exercise were tested. Spinning music speed is played at 1x speed. The goal of the gesture recognition technology is to achieve the accuracy of motion detection using gaming contents more than 80.00%. All the subjects were experimented with the same music, and the results of the motion accuracy are shown in Table 4. As shown in the table, since the exercise performance of each individual is different, the results shows that different motion accuracies. If the

gesture is performed according to the icon and time signature, the motion accuracy is high. Conversely, if users missed the beat and failed to suggested gesture, the motion accuracy was low. The average of the total motion accuracy was 88.01%, which reached our target value. In order to accurately analyze the gesture recognition technology, it is necessary to do more experiments according to their individual exercise performance and accurately measure their motions.

TABLE 4. MOTION ACCURACY OF SUBJECTS

Subject	Motion accuracy (%)
1	88.9
2	88.3
3	85.2
4	83.4
5	87.5
6	90.2
7	89.4
8	91.2
9	89.5
10	86.5
Overall average	88.01

V. CONCLUSIONS

This paper presents a technology to recognize nine spinning gestures using IMU sensors to enable people to enjoy spinning exercise at the desired time and place. We classify the spinning gestures using the decision tree method with bootstrapping. In order to verify the performance of the spinning gesture recognition technology, we experimented with existing spinning contents. As a result, the average motion accuracy showed 88.01%, exceeding our target of 80%.

For the further works, it is necessary to measure and evaluate the performance for the wave gestures except nine suggested gestures. We expect that the proposed motion recognition technology will be applied to other sports activities.

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