Short Stick Exercise Tracking System for Elderly Rehabilitation using IMU Sensor

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***Abstract*—Stick exercises, which have been attracting attention for improving the health of the elderly, are usually performed in nursing homes under the guidance of nursing staff. However, in the current pandemic in which the elderly are advised to refrain from going out unnecessarily, it is desirable for each individual to be able to perform the stick exercises alone. In this study, we aim to develop a stick exercise support system that can automatically record the number of times an elderly person performs each type of stick exercise and provide feedback to improve the movement for each exercise. As a first step toward the realization of this stick exercise support system, we investigated a method for recognizing exercise movements using inertial measurement unit (IMU) sensors. In the evaluation experiment, 21 subjects performed 3 sets (10 times per set) of eight basic stick exercises. The exercise movements were classified based on the linear acceleration and quaternion data obtained from the IMU. As a result, 90 % of F-measure was achieved when using LightGBM as the learning algorithm.**

***Index Terms*—Activity recognition; Stick exercises; Health promotion; Machine Learning**

I. Introduction

Falls in the elderly often result in significant trauma, such as bone fractures, that require hospitalization and are not uncommonly followed by the victim becoming bedridden. Therefore, it is important to prevent such falls through daily moderate exercise. In recent years, stick exercises, which are easy to perform, have been attracting attention as a means to prevent falls and improve the health of the elderly [1]. Stick exercises are usually performed in nursing homes under the guidance of nursing staff. However, in the current pandemic situation in which it is advisable to refrain from going out unnecessarily, it is desirable for each individual to be able to perform the stick exercises by himself or herself. A system that can automatically record the number of times he or she has performed each stick exercise at home is therefore required.

Shen et al. developed MiLift, which can track workouts such as aerobic exercises and weightlifting with high accuracy using a smartwatch [2]. Takada et al. investigated the recognition accuracy of 10 different exercises for each wearable sensor position with a focus on body weight training without equipment [3]. 93.5% recognition accuracy was achieved when the sensors were placed at both the wrist and waist. In both of these studies, inertial measurement unit (IMU) sensors were attached to the body to realize highly accurate motion recognition, but the application of this method to stick exercises, which forms the focus of this study, has not yet been investigated.

In this study, we investigate an approach for identifying the stick exercises performed by a user in which an IMU sensor is attached to the stick used for the stick exercises. To evaluate the proposed method, we constructed a dataset consisting of sensor data collected from 21 experimental subjects performing three sets (10 times per set) of eight basic stick exercises (boutaisou). In the evaluation experiment, we evaluated the performance of the proposed method using the above dataset and confirmed that the proposed method can identify the stick exercise with approximately 90% accuracy in the leave-one-person-out scenario.

The remainder of this paper is organized as follows. In Sect. 2, we review the existing research related to the proposed system. In Sect. 3, we describe the proposed method for tracking stick exercises using an IMU sensor. In Sect. 4, we describe our evaluation experiments and the results. Finally, in Sect. 5, we conclude this paper and discuss future work.

II. RELATED RESEARCH

In this section, we describe the existing work on the related fields of health support for the elderly and exercise support.

A. Research on health support for the elderly

Dobre et al. developed a system that enhances the delivery of professional health care to the elderly through the provision of non-intrusive monitoring and support [4].

Richard et al. proposed a health management system that displays the temperature and heart rate data on a LCD and sends automatic notifications to caregivers and doctors [5]. Susnea et al. proposed a method to monitor the behavior of elderly people living alone and detect deviations from past behavior patterns [6]. However, these studies did not propose systems to encourage exercise in the elderly.

B. Research on exercise support

Voicu et al. proposed a human physical activity recognition system based on data collected from smartphone sensors [7]. Relevant features from the six activities of walking, running, sitting, standing, climbing, and descending are extracted by the system. An evaluation of the collected data shows that most of the activities could be recognized correctly, and an average accuracy of 93% was achieved in four of them. The challenge is to expand the scope of activities recognized to include other activities such as riding a bicycle.

Kurban et al. proposed a daily activity recognition system based on a 3-axis accelerometer that can be used in various body positions [8]. In this study, data were collected from the subjects as they performed walking, sitting, standing, jumping, and falling motions. The proposed method achieved an accuracy of up to 100% with an average accuracy of 96.54%.

Shen et al. developed MiLift, which can track workouts such as aerobic exercise and weightlifting with high accuracy using a smartwatch [2]. This system achieved more than 90% accuracy and repeatability in tracking both aerobic and weightlifting exercises.

Takada et al. investigated the recognition accuracy for 10 types of body weight training exercises without any equipment for each position of a wearable sensor [3].

Turmo et al. developed a system that supports the understanding, execution, and modification of a variety of exercises for a wide range of subjects [9]. The system uses BodyLights, which are 3D printed wearable optomechanical devices that can be placed at critical body parts and inside equipment. These devices project laser crosses based on the wearer's movements to help correct 18 targeted exercises.

Torigoe et al. focused on kendo, a representative martial arts in Japan, and proposed a method for detecting and recognizing striking motions through the use of IMUs to realize a support system for improving the user's kendo technique. To confirm the effectiveness of the proposed method, they collected inertial sensor data for the striking motions of subjects, who included both experienced and inexperienced kendoka, using four IMUs attached to the right wrist, waist, shinai tsuba, and shinai tip leather and detected five striking motions based on the dynamic time warping (DTW) distance obtained from the acceleration time series data. The hitting motion could be detected with 89.9% of F-measure [10]. The systems proposed in these studies can be used to recognize the activities and motor movements of elderly people. However, a system that evaluates and improves the stick exercise movements in the elderly by providing feedback has not yet been developed. Therefore, we decided to develop such a system.

III. STICK EXERCISE TRACKING SYSTEM

A. System overview

The goal of this study is to realize a stick exercise support system that can provide feedback to elderly users during exercises to improve their exercise movements using IMU sensors.

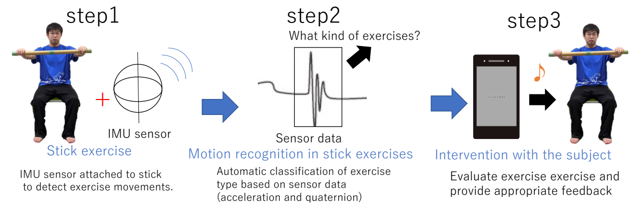

Fig. 1. System overview

Figure1 shows an overview of the proposed system. An IMU sensor is attached to a stick to detect the exercise movement. The system automatically classifies the type of exercise from the linear acceleration and quaternion sensor data, evaluates the exercise movements, and provides appropriate feedback. In this study, we aim to recognize the exercise events performed by the user as the first step toward the realization of the stick exercise support system.

B. Exercises for recognition

Eight basic exercises were chosen as recognition targets from the stick exercises introduced in [1] which are shown in Figure 2 and explained below.

Exercise A: Stick straddling exercise
: The exerciser holds the stick with both hands and straddles the stick without bending it. Next, the exerciser lifts his/ her hips off the chair and raises the stick to the back of the waist. Finally, the exerciser returns to his/her original position in reverse order. The effect of this exercise is to increase the flexibility of the legs and maintain the range of motion.

Exercise B: Stick lifting exercise
: The exerciser holds the stick with both hands and does the Banzai (holding up two hands) with a back straight. He/she breathes and raises his/her shoulder during the exercise. This exercise stretches the back and helps prevent falling to the side.

Exercise C: Body twisting exercise
: The exerciser stretches back and rotates the body to the left and right while holding the stick with both hands. Rotating the body helps improve the mobility of the spinal column and thorax. Body rotation is also a necessary element of getting back to one's feet after losing balance.

Exercise D: Sideways body tilting exercise
: The exerciser holds the stick with both hands, stretches back, and bends the body to the left and right. This exercise helps increase the flexibility of the rib cage.

Exercise E: Falling forward exercise
: The exerciser holds the stick with both hands, leans forward, and places the bar on the floor. By doing this exercise, the exerciser experiences weight loading on the sole of the foot and the forward leaning posture necessary for standing up.

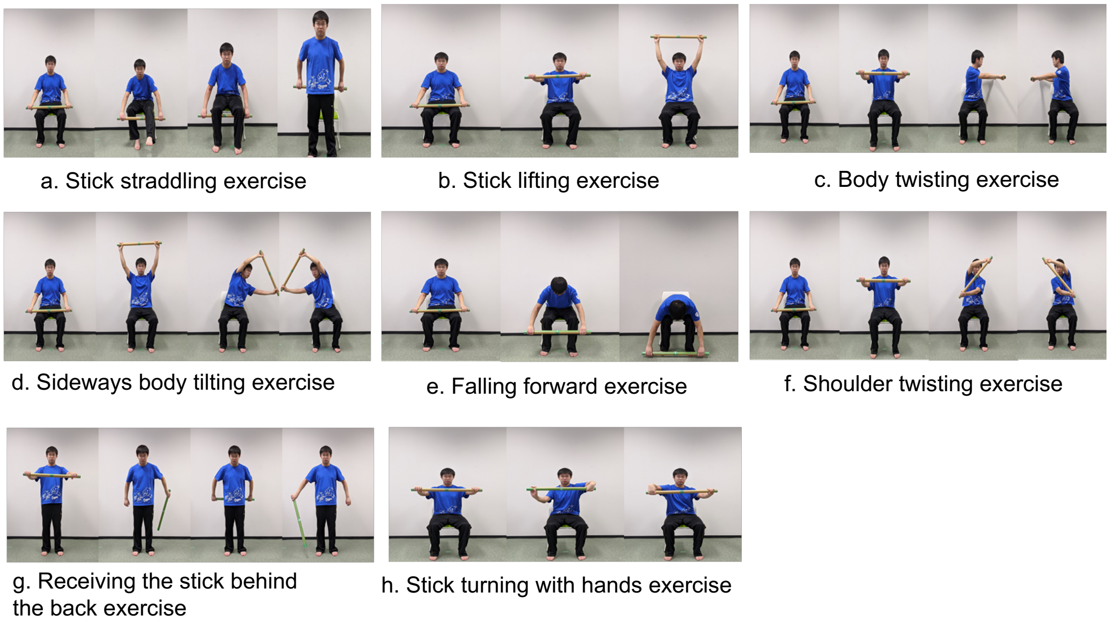

Fig. 2. 8 types of stick exercises

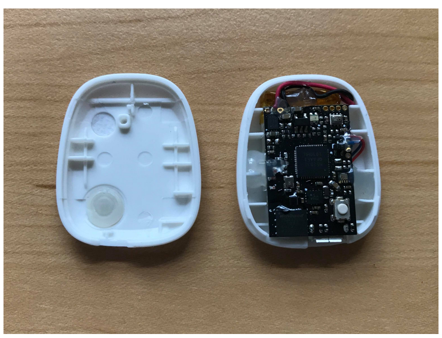

Fig. 3. IMU sensor used in the experiment

Exercise F: Shoulder twisting exercise

> The exerciser holds a stick with both hands and twist shoulders as if he/she were turning the stick in front of body. Twisting the shoulders can increase the mobility of the shoulders.

Exercise G: Receiving the stick behind the back exercise

> The exerciser passes the stick behind his/her back and receives it with the opposite hand. Manipulating the stick in an unseen location enhances body movement imagery and increases shoulder mobility.

Exercise H: Stick turning with hands exercise

> The exerciser holds the stick with both hands and rotates it by moving the wrists up and down alternately. This exercise can increase the mobility and flexibility of the wrists.

Fig. 4. Smart stick used in the experiment.

C. Sensor devices used and mounting position

In this study, we used the MetaMotionR[1] shown in Figure 3 as the IMU sensor device to classify the exercise movements. The IMU sensor can perform linear acceleration and quaternion measurements and has a recording rate of up to 100 Hz. It can also collect the linear acceleration and quaternion data wirelessly. The sensor is embedded in a hole in the center of the stick, as shown in Figure 4. The exerciser performs the exercise by holding both ends of the stick. Subjects performed the exercises by holding both ends of a stick. The way and angle of holding the sticks were adjusted so that all the subjects had the same angle.

IV. EXPERIMENT

A. Experiment summary

To evaluate the effectiveness of the proposed method, we conducted a data collection experiment with 21 male and female subjects in their 20s. The linear acceleration and quaternion measurement data from the IMU sensor were collected as the subjects performed three sets of each of the eight target

[1]https://mbientlab.com/metamotionr/

exercises (10 times per set) using the smart stick shown in Figure 4.

B. Sensor waveforms

The measurement results for a single run are shown in Figure 5. The figure shows the synthetic acceleration, which is the sum of the accelerations in the x, y, and z axes during each exercise, and the quaternion measurements. The horizontal axis shows the time, and the vertical axis shows the magnitude of the synthetic acceleration and quaternion measurements. From the results of this run, it can be seen that the synthetic acceleration of the straddling exercise (first column from the left, first row from the top in Figure 5) does not change significantly from the beginning to the end of the exercise because the straddling exercise does not involve any fast movements of the stick. The quaternion (second column from the left, first row from the top in Figure 5) also shows no significant changes in the w, x, y, and z components possibly because there are no large movements of the stick. The synthetic acceleration for the stick lifting exercise (third column from the left, first row from the top in Figure 5) has two periods of large acceleration, which we assume correspond to the raising and lowering of the arms. The magnitudes of the w and y components of the quaternion (fourth column from the left, first row from the top in Figure 5) decrease while the stick is being lifted. The synthetic acceleration during the body twisting exercise (first column from the left, second row from the top in Figure 5) shows a large overall change. We believe that the large change is due to the large and fast gymnastic movements involved in raising the stick to chest height, twisting the body to the left and right, and returning to the original position. The z component of the quaternion (second column from the left, second row from the top in Figure 5) is sometimes large and sometimes small because of the twisting to the left and right. The synthetic acceleration during the sideways body tilting exercise (third column from the left, second row from the top in Figure 5) does not change significantly in general. This is because although large movements are involved in this exercise, it is difficult to move the body quickly. In the quaternion (fourth column from the left, second row from the top in Figure 5), there are times at which the x component decreases when the z component increases and times at which the x component increases when the z component decreases. This is thought to be due to the larger changes in the z component when the body is tilted to the left or right. The synthetic acceleration during the falling forward exercise (first column from the left, third row from the top of Figure 5) is generally small. This is because this exerciser is only required to bring the stick from knee height to foot height in a sitting position, so the stick does not move very quickly. The y component in the quaternion (second column from the left, third row from the top in Figure 5) increases during the exercise after the arm is lowered and returns to its original value when the arm returns to its original position. The synthetic acceleration during the shoulder-twisting exercise (third column from the left, third row from the top in Figure 5) shows a large change from the beginning to the end of the exercise. This is because the exercise involves rapid movements in bringing the stick from knee height to chest height at the beginning, twisting to the left and right, and then returning the stick to the original knee height. In the quaternion (fourth column from the left, third row from the top in Figure 5), there are times at which the x component decreases when the z component increases and times at which the x component increases when the z component decreases. This is thought to be due to the fact that the change in the z component becomes larger when the shoulder is twisted to the left or right. The synthetic acceleration in the receiving the stick behind the back exercise (first column from the left, fourth row from the top in Figure 5) shows little overall change. This may be due to the fact that because the exerciser cannot see the stick, the exercise becomes difficult if the movements are too fast. The y component of the quaternion (second column from the left, fourth row from the top in Figure 5) rises at the beginning of the exercise and returns to its original value at the completion of the exercise because the stick is lowered with the left hand, received with the right hand, and then returned to its original position. The synthetic acceleration of the stick turning with hands exercise (third row from the left, fourth column from the top in Figure 5) has two sections with larger magnitudes because the stick is rotated in two separate movements. The y component in the quaternion (fourth column from the left in Figure 5, fourth row from the top) is larger at some times and smaller at others because it increases when the stick is first rolled in on the left hand and decreases when it is rolled in on the right hand.

C. Feature extraction

The feature values shown in Table 1 were calculated from the linear acceleration and quaternion data acquired at a sampling rate of 100 Hz from the IMU to build the machine learning model. These features are namely, the mean, standard deviation, median absolute deviation, maximum value, minimum value, sum of squares, entropy, quartile range, fourth-order Burg autoregression coefficient, range between minimum and maximum values, and the root mean square of the time-domain signal, and the skewness, kurtosis, maximum component, weighted average, spectral energy, frequency band power spectrum spectral energy, and power spectral density of the frequency-domain signals. These features were selected because they have been shown to be effective in previous studies on context estimation based mainly on inertial data [10]–[12].

D. Performance evaluation

The performance of nine typical machine learning algorithms, namely, the SVM artificial neural network (ANN), random forest (RF), decision tree (DT), LightGBM logistic regression (LR), k-nearest neighbor (KNN), naive Bayes (NB), and extra-trees (ET), was evaluated using leave-one-person-out cross-validation. Figure 6 shows a bar graph of the F-measure

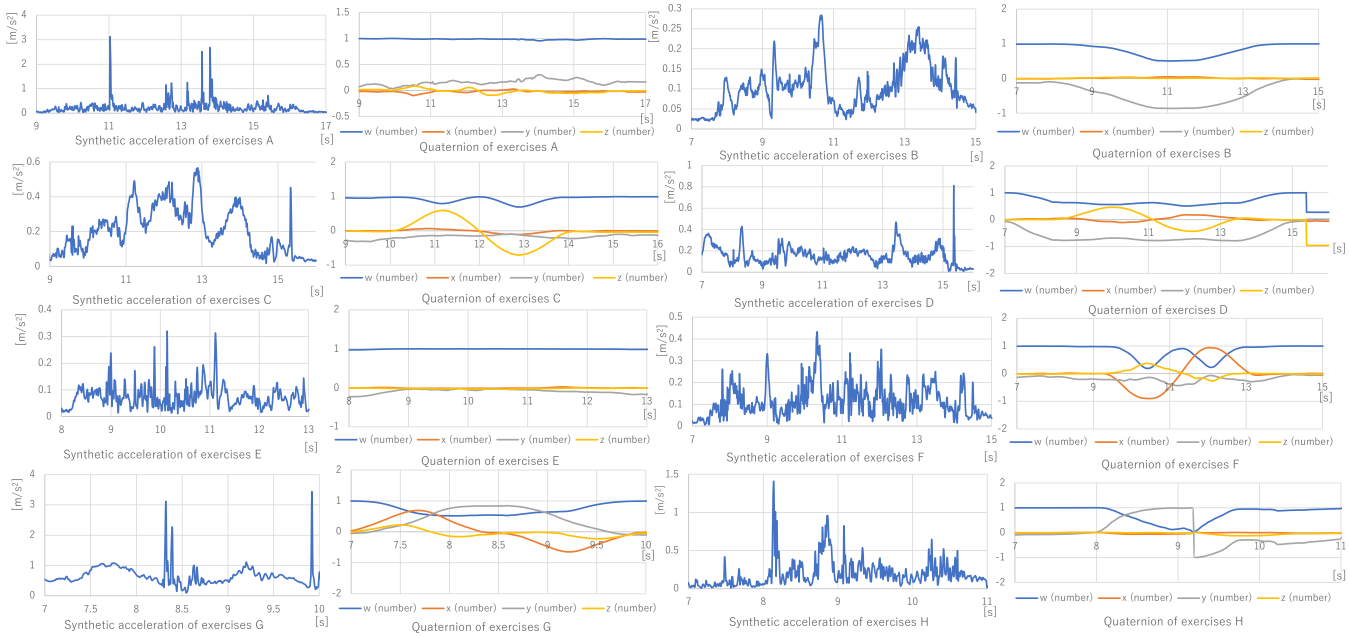

Fig. 5. Sensor waveform for each exercise

TABLE I
FEATURE LIST FOR SHORT STICK EXERCISE RECOGNITION

Function	Description	Formula	Type
means	Arithmetic mean	$\bar{s} = \frac{1}{N}\sum_{i=1}^{N} s_i$	TF
stds	Standard deviation	$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(s_i - \bar{s})^2}$	TF
mads	Median absolute deviation	$median_i(\mid s_i - median_j(s_j) \mid)$	TF
maxs	Largest values in array	$max_i(s_i)$	TF
mins	Smallest value in array	$min_i(s_i)$	TF
energys	Average sum of the squares	$\frac{1}{N}\sum_{i=1}^{N} s_i^2$	TF
entropys	Signal entropy	$\sum_{i=1}^{N}(c_i \log(c_i)), c_i = s_i / \sum_{j=1}^{N} s_j$	TF
iqrs	Interquartile range	$Q3(s) - Q1(s)$	TF
autorregresions	4th order Burg autoregression coefficients	$a = arburg(s, 4), a \in \mathbb{R}^4$	T
ranges	Range between smallest and Largest values	$max_i(s_i) - mix_i(s_i)$	T
rmss	Root square means	$\sqrt{\frac{1}{N}(s_1^2 + s_2^2 + \cdots + s_N^2)}$	T
skewnesss	Frequency signal skewness	$E[(\frac{s-\bar{s}}{\sigma})^3]$	F
kurtosiss	Frequency signal kurtosis	$E[(s-\bar{s})^4]/E[(s-\bar{s})^2]^2$	F
maxFreqInds	Largest frequency component	$argmax_i(s_i)$	F
meanFreqs	Frequency signal weighted average	$\sum_{i=1}^{N}(is_i)/\sum_{j=1}^{N} s_j$	F
energyBandsab	Spectral energy of a frequency band [a, b]	$\frac{1}{a-b+1}\sum_{i=a}^{b} s_i^2$	F
psds	Power spectral density	$\frac{1}{Freq}\sum_{i=1}^{N} s_i^2$	F

NSignal vector lengthQQuartileTTime domain features, FFrequency domain features.

achieved by the machine learning algorithms for each subject. Using LightGBM resulted in the highest F-measure of 90.0%. In comparison, Using NB resulted in the lowest F-measure of 52.4%. LightGBM achieved the highest F-measure because it combines the decision tree algorithm with gradient boosting. We can therefore conclude that LightGBM is an effective machine learning algorithm for the proposed method. Figure 7 shows the confusion matrix obtained from the evaluation of LightGBM, which achieved the highest F-measure. As can be seen from the figure, the F-measure is, in general, high. The F-measure of the stick straddling, stick lifting, body twisting, sideways body tilting, and receiving the stick behind the back exercises are about 90%, while those of the falling forward and stick turning with hands exercises are about 80%, which is a little lower than those of the other exercises. It can therefore be concluded that the stick exercises performed by the subject were recognized accurately most of the time. However, there were a few cases in which the exercise was not identified correctly, which may have resulted from the individual differences between the exercise movements of the

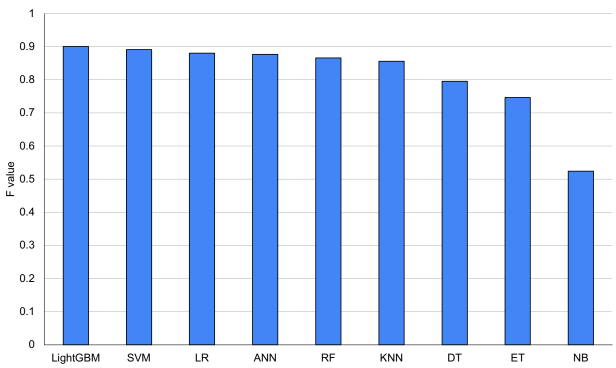

Fig. 6. F-value results for each machine learning algorithm

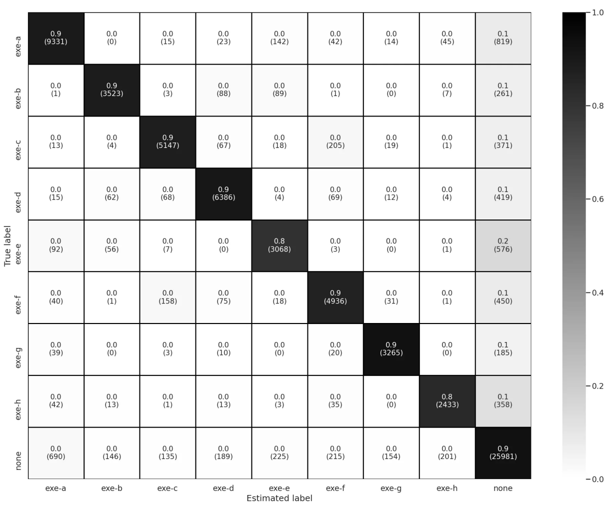

Fig. 7. Performance evaluation of LightGBM

21 subjects asked to perform the stick exercises. We would like to improve the proposed method in the future so that the exercise movements can be recognized more accurately.

V. CONCLUSION

In this paper, we investigated a method for recognizing exercise movements in the elderly and focused on stick exercises, which have attracted attention for fall prevention and health promotion in the elderly. To demonstrate the effectiveness of the proposed method, we asked 21 subjects to perform three sets of eight stick exercises (10 times per set). We classified the exercise movements using linear acceleration and quaternion data measured using an IMU sensor attached to the center of the stick. The target exercise movements are eight basic stick exercises comprising the stick straddling, stick lifting, body twisting, sideways body tilting, falling forward, shoulder twisting, receiving the stick behind the back, and stick turning with hands exercises. The measurement data obtained from the subjects were compared with laboratory data. The F-measure of nine typical machine learning algorithms in classifying the exercises based on the measurement data obtained from the subjects was evaluated. We found that LightGBM can recognize the eight stick exercises with an F-value that exceeds 90%. In the future, we will improve the proposed method by increasing the number of subjects. In addition, we plan to design feedback mechanisms to motivate habitual exercises and improve their exercise skills based on the IoT data-driven nudging concept [13].

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