# GIFT: Glove for Indoor Fitness Tracking System

Elder A. H. Akpa, Masashi Fujiwara, Yutaka Arakawa, Hirohiko Suwa, Keiichi Yasumoto
Graduate School of Information Science
Nara Institute of Science and Technology (NAIST)
Ikoma, Nara 630-0192, Japan
Email: http://ubi-lab.naist.jp/

***Abstract*—It has been intensively demonstrated that physical activity can enhance the mental and physical health of practitioners. In recent years, fitness activities became the most common way to engage in physical activities. In this paper, we propose a smart-glove based fitness activity tracking system that can detect athletes activities in any indoor fitness facility, with no need of attaching multiple sensors on the athlete's body. The system adopts force sensitive resistor (FSR) sensors to identify the type of exercise by analyzing the pressure distribution in the hand palm during fitness activities. To evaluate the performance of our proposed system, we ran a pilot study with 10 healthy participants over 10 common fitness activities. The experimental results showed an overall recognition accuracy rate of 87%. We believe the promising results would contribute to the works on personal assisted coaching systems and create enjoyable experiences when performing fitness activities.**

## I. Introduction

Myriad results of studies in the health domain have shown that regular practice of physical activity had beneficial effects on both mental and physical health [1] [2]. Among multiple means for regularly practicing physical activity, fitness activities are considered the most popular. Indeed, according to the 2017 Physical Activity Council report (PAC), in the U.S, 62.7% of 6+ years are engaged in fitness sport [3]. Europe was ranked first in terms of fitness club industry revenue, with around 35 billion U.S. dollars in 2014 [4].

In recent years, to engage, motivate and support people into the practice of physical activity, many pervasive systems and tools have been proposed by researchers and commercial industries. The general goals of these systems are to identify the activity (of one or many athletes), assess the physical performance, and support strategic decision-making to improve athletes' performance.

However, the majority of these systems require one or multiple on-body worn sensors (not always comfortable for the users)[5], ambient cameras [6], or sensors-embedded fitness equipment [7]. The use of such sensors, cameras, and smart materials tend to narrow down the scope of activities that can be monitored by a single system. For example, the system in [8] proposed the use of a smart-mat to recognize and count gym exercises. Although the system achieved good results (recognition rate of 82.5% and counting accuracy of 89.9%) for exercises performed on the mat (such as push-ups, crunches, and squats), it appears obvious that the system can not be used for gym exercises such as treadmill running, pull up or bench dip, which are not performed on a mat.

Our proposed system is motivated by the observation that fitness athletes (with no distinction of their gender, age, and goal) usually wear sports-gloves during their workout sessions. Indeed, they wear the sports-gloves for various reasons such as supporting grip pressure, protecting the hands from calluses and blisters, or increasing lift power [9]. For each fitness activity, there is one or multiple interactions between the glove and the athlete's body or between the glove and the workout materials. We thus propose to exploit these interactions for assessing workout performance, by designing a low-cost smart fitness-glove. This means we can monitor more activities than existing systems [10] [11], without the need to modify fitness environment or to attach multiple sensors to the athlete body.

In this work, we propose a fitness activity assessment system called GIFT, a Glove for Indoor Fitness activity Tracking. GIFT is a new smart-glove based system designed with 16 Force Sensitive Resistor (FSR) sensors, for tracking and recognizing activities performed in any fitness environment (Fig. 1). The system is designed to target the exercises of the 5 types of fitness training: a) flexibility training (e.g., standing calf stretch), b) dynamic strength training(e.g., squat), c) static strength training (e.g., plank), d) aerobic training (treadmill), e) circuit training (e.g., push up + bench dip + lunge).

Our final goal with GIFT is to provide with fitness athletes a real-time system that:

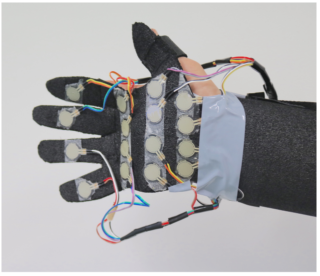
- Recognizes the activity being performed,
- Counts the number of repetitions (reps),
- Estimates the calorie burned out by each exercise,
- Recommends future exercises to achieve users' goal.

In this paper, we present the design of our smart-glove, as well as the activity recognition performance of GIFT. In an experimental trial ran over 10 frequently performed fitness exercises, with 10 participants, the system achieved an average of 87.0% recognition accuracy rate, using the Ensemble subspace KNN classifier algorithm.

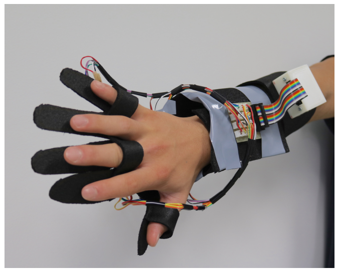
The remaining part of this paper is organized as follows. Section II reviews related works of sensorized gloves and other smart devices used for fitness activities. In Section III, we describe the overall design of the GIFT system. Then, the experimental setup and data collection are explained in Section IV. The activity recognition mechanism and results are detailed in Section V. Then, we discussed the obtained results in Section VI. Finally, the conclusion is presented in Section VII.



978-1-5386-3227-7/18/$31.00 ©2018 IEEE



(a) Inside view.



(b) Outside view.

Fig. 1: Prototype of the proposed Smart-glove.

## II. Related work

A wealth of related work exists on wearable sensors used for fitness activity recognition and performance evaluation. Systems such as Fitlinxx [12] and Fitbit [13] are already available in the market and used by thousands of people. Fitlinxx integrates multiple sensors on strength training machines to track the load of weight a user is moving, count the number of repetitions, and show training progress on a built-in display. Although the new version supports syncing users' smartphone or tablet, this system still requires the fitness manager to buy and install special training machines.

Fitbit is one of the most common wireless physical activity tracker. However, some studies [14] and discussions on the Fitbit Community website [15] revealed certain limitations of the Fitbit system. For example, non-step based activities (like push up) are not recognized, and Fitbit requires users to manually log strength training exercises (like dumbbell curl). Another well-known fitness tracking application, Google Fit, can record physical fitness activities including strength training and similar activity that involve counting reps [16]. However, it does not work on iPhone devices and the strength training feature is limited to a certain version of Android (available only on Android Wear 2.0).

In the category of research projects, Chang et al. [10] presented a system to track free-weight exercises, by incorporating a 3-axis accelerometer into a workout glove and another accelerometer on users' waist. They used a Naive Bayes Classifier and Hidden Markov Models to recognize the type of exercise. To count repetitions, they developed a peak counting algorithm and a method using the Viterbi algorithm. While their experimental results showed good results (recognition accuracy rate of $90\%$ and error count rate of around $5\%$ over $9$ different exercises), this system focused only on free-weight exercises such as bench press, biceps curl, and lateral raise.

Another work appears in [8], in which Sundholm et al. proposed a textile pressure sensor matrix, that can be integrated into exercise mats to recognize and count such exercises. Their experiment with 7 participants showed that the pressure sensor mat successfully distinguished 10 common gym exercises using a kNN-classifier. However, the system can not be used for gym exercises which are not performed on a mat such as treadmill running, bench press or chest fly. More works involving the use of pressure distribution were proposed to contribute to the research field of sports activity assessment, in general. Bo et al. [17] made a smart soccer shoe that uses textile pressure sensing matrices to detect and analyze the interaction between players foot and the ball. Instead of introducing add-ons to the shoe, they integrated the sensing element inside the shoe surface material in an unobtrusive fashion that can be manufactured together with the shoes. The sensor system consists of two $34$ and one $33$ pressure sensing matrices. Their experimental best performance reaches near $100\%$ accuracy for the 15 classes.

With respect to the aforementioned systems, we propose a low-cost smart fitness glove to track fitness exercises from stretching exercises to strength training exercises, without attaching multiple sensors on various body' areas of the users, and without the need to adjust existing layouts and environments of fitness centers.

## III. Design of the GIFT system

In this section, we detail the design of our proposed system. GIFT intends to record the pressure distribution applied to the user's palm during training sessions. Therefore, during the development of our prototype, we considered the following design aspects:

- Sensing zone: A smart-glove that well covers the palm surface will allow us to get the accurate location of pressure points, and the pressure distribution applied over all the palm surface.
- Low-cost: The proposed smart-glove should have a lower price cost than existing systems. The use of cheap off-the-shelf components helped us to quickly prototype a cheap smart-glove.
- Comfort level: Comfort is an important aspect when designing an IoT device. The glove should provide an acceptable or high comfort level to the user, without hindering users' movement.
- Portability: The device should work in any fitness center or fitness environment, and be lightweight.

The current prototype of the GIFT systems consists of 3 main components: 16 FSR sensors, a data sampling unit (DSU), and a computational and visualization terminal.

The $16$ pressure sensors are used to read the force applied to the palm when a user is performing a fitness exercise. FSR sensors are commonly used to detect physical pressure, squeezing and weight. They are easy to use and low-cost. In this work, we used the Interlink 402 Short Tail model, bought at $\$4.85$ each. Each sensor has an active sensing area of $12.70$ mm diameter, $0.46$ mm thickness, and can sense force up to $20$ N [18]. Each sensor outputs the voltage values corresponding to the pressure applied to it during the exercise.

The data sampling unit (DSU) reads the data from the force sensors and sends the data to a computer. It is composed of an Adafruit Feather 32u4 bluefruit, a $16$ channel multiplexer ($16chMUX$), and a resistor of $2k\Omega$. The Adafruit Feather has

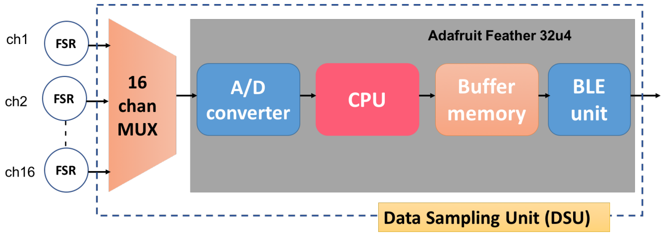



Fig. 2: System components of the smart-glove.

a resolution of AD converter of 10 bit and can read raw digital value from 0 to 1023. This unit samples and transfers sensing data via BLE (Bluetooth Low-Energy) at 5 Hz. The DSU and the 16 FSR sensors constitute the smart-glove that the athlete wears during his training session, and it is powered by a small 400mA/h Li-Po battery. Fig. 2 shows the components of the smart-glove system.

The computational terminal is used to read the data sent via Bluetooth from the data sampling unit. It provides, via a web-based user interface (UI), a real-time feedback of the activity's pressure distribution, with the option to save the data into a CSV file (Comma-Separated Values) for further processing. As for now, we use only one side of the glove pair. Fig. 3a shows an example of a user doing a knee-pull-in exercise while watching at the real-time visualization tool, and the corresponding pressure distribution applied on the palm during the exercise is shown in Fig. 3b.

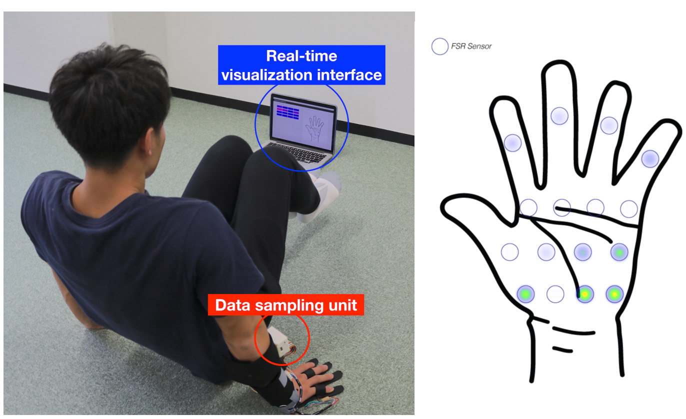
## IV. Experimental setup and Data collection

To evaluate the activity recognition performance of the system, we run a pilot study. We recruited 10 healthy participants aged between 22 and 30 years ($Mean = 25.9$, $SD = 3.21$), mostly male (1 female participant out of 10) to participate in the study. The weight of the participants ranges from 50 kg to 82.2 kg ($Mean = 67.2$, $SD = 10.07$), and height between 158 cm to 182 cm ($Mean = 173.4$, $SD = 6.32$). The participants were asked to perform 10 preselected fitness exercises while wearing the smart-glove. Each exercise is repeated 3 times, at the participant's natural speed and pace, to make the experiment more realistic. Each repetition lasts for 30 seconds, and the participants were allowed to take 1 minute-break between the repetitions. With participants' consent, the experiment was video recorded. The video will be used later as the ground truth, to evaluate our algorithm for counting exercise. The preselected fitness exercises are common exercises of the 5 types of fitness training group exercises, with each exercise targeting a particular muscle group of the body. Table I lists the 10 exercises along with their corresponding target muscle group. For the dumbbell curl activity, we provided participants with a 2 kg dumbbell.

TABLE I: Preselected fitness exercises with their target muscle group

| | *Exercises* | *Target muscle group* |
|---|---|---|
| 1 | Bench dips | triceps, shoulders |
| 2 | Climber | Hips, legs, quadriceps |
| 3 | Dumbbell curl | biceps |
| 4 | Knee-pull-in | Abdominals |
| 5 | Knee-twist-in | Abdominals |
| 6 | Plank leg raise | Lower back, glutes, triceps |
| 7 | Pilate dips (triceps) | triceps, biceps, shoulders, back |
| 8 | Push up | Chest |
| 9 | Side-to-side lunge | Glutes, quadriceps, butt |
| 10 | Wall push up | Arms, shoulder, chest |

Fig. 4 shows some of the performed exercises, with a corresponding pressure distribution and strength intensity applied on the glove for a participant during the training session. Table II provides an example of data collected for 1 second of push up performed by a participant. Each value represents the intensity of the strength (intensity range: between 0 and $1000V$) applied to each sensor when the user performs the movements of the exercise.




(a) (b)

Fig. 3: (a) A user performing a knee-pull-in exercise. The real-time visualization tool and the sample unit are indicated by the blue and red circles respectively. (b) The pressure distribution applied on the hand palm during the knee-pull-in exercise.

## V. Results

To identify the different fitness exercises during a fitness session, we extracted a set of features from the raw data captured by the smart-glove. Based on the observation of our dataset, we noted that all of the activities provoke different changes in the pressure distribution and the intensity, at different points on the palm surface, in the temporal domain. Thus, we computed time domain features (such as the mean value and the standard deviation), and frequency domain features like the power spectrum of FFT (Fast Fourier Transform). Each sensor represents a channel, and we called by "*weight*" the mean of the 16 channels' values in each sample. This means that for each row of the time series data, we compute the "*weight*" of the frame by using the following formula:

$$weight(t) = \frac{\sum_{1}^{16} channel_i}{16} \quad (1)$$

TABLE II: Example of data collected during a push up session

| *ch1* | *ch2* | *ch3* | *ch4* | *ch5* | *ch6* | *ch7* | *ch8* | *ch9* | *ch10* | *ch11* | *ch12* | *ch13* | *ch14* | *ch15* | *ch16* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 537 | 591 | 376 | 0 | 730 | 459 | 677 | 247 | 105 | 324 | 175 | 48 | 40 | 0 | 365 | 0 |
| 532 | 591 | 382 | 0 | 731 | 460 | 672 | 244 | 94 | 315 | 173 | 45 | 44 | 0 | 359 | 0 |
| 531 | 588 | 383 | 0 | 732 | 469 | 668 | 234 | 89 | 309 | 174 | 43 | 54 | 0 | 357 | 0 |
| 534 | 587 | 373 | 0 | 730 | 480 | 658 | 221 | 93 | 297 | 170 | 38 | 51 | 0 | 351 | 0 |
| 561 | 548 | 292 | 0 | 648 | 626 | 578 | 113 | 39 | 231 | 104 | 18 | 9 | 0 | 232 | 0 |

(a) Bench dips (b) Climbers (c) Dumbbell curl

(d) Knee twist in (e) Plank leg raise (f) Push up

Fig. 4: Exercises performed during the experiment, with their corresponding pressure distribution on the smart-glove.

TABLE III: Extracted features from the smart-glove raw data

| *Features set* | *Number of features* |
|---|---|
| Mean of each channel | 16 |
| Standard Deviation for each channel | 16 |
| Number of above mean crossing of the weight | 1 |
| Number of below mean crossing of the weight | 1 |
| Number of peaks of the weight | 1 |
| Skewness of the weight | 1 |
| Kurtosis of the weight | 1 |
| Band power of the weight | 1 |
| Mean frequency of the weight | 1 |
| Max power spectrum of the weight FFT | 1 |
| **Total** | **40** |

The *weight(t)* is represented as a column vector, which contains the mean of each row of the raw data obtained during the 30 seconds exercise time window.

Overall, 40 features were extracted and used to train the classification model. Table III describes the details of these features set, with the number of features extracted. Some of them have been intensively investigated in previous studies and proved to be effective for activity recognition [19] [20]. For example, the mean crossing feature has been heavily used in human speech recognition and handwriting recognition problems [19].

To develop our classifier, we tested various classification algorithms, particularly the Decision tree, Random Forest, SVM, k-NN and Ensemble methods. For the evaluation of the training data set, 10-fold cross-validation was conducted. We report the result for the classifier based on the Ensemble Subspace KNN method, which achieved the best recognition results. It is well-known that Ensemble methods can be used to better improve predictive performance that could be obtained from any of the constituent learning algorithms alone [21]. Fig. 5 shows the confusion matrix of the classification, along with the true positive and false negative rates of each exercise. The average classification accuracy is 87.0%. The highest classification rate (100%) is obtained with the wall push up exercise, while the climber exercise achieved the lowest classification rate of 67.0%.

In addition to the confusion matrix, we computed the area under the ROC curve (or Area-Under-curve: AUC) of the classifier for each exercise. A good rule of thumb states that any classifier with the area under the ROC curve less than 0.7 is poor, while any classifier with AUC greater than 0.9 is excellent [22] [23]. In our case, the classifier AUC for all the exercises is higher than 0.9. The bench dip, knee-pull-in, dumbbell curl, and wall push up achieved a UAC of 1.0, while the UAC of the climber, knee twist in and the plank leg are 0.94, 0.99, and 0.96 respectively. The three remaining exercises (side lunge, pilate dips, push up) have the same UAC of 0.97. Fig. 6 plots the ROC curves for classifying the climber and knee-twist-in fitness exercises.

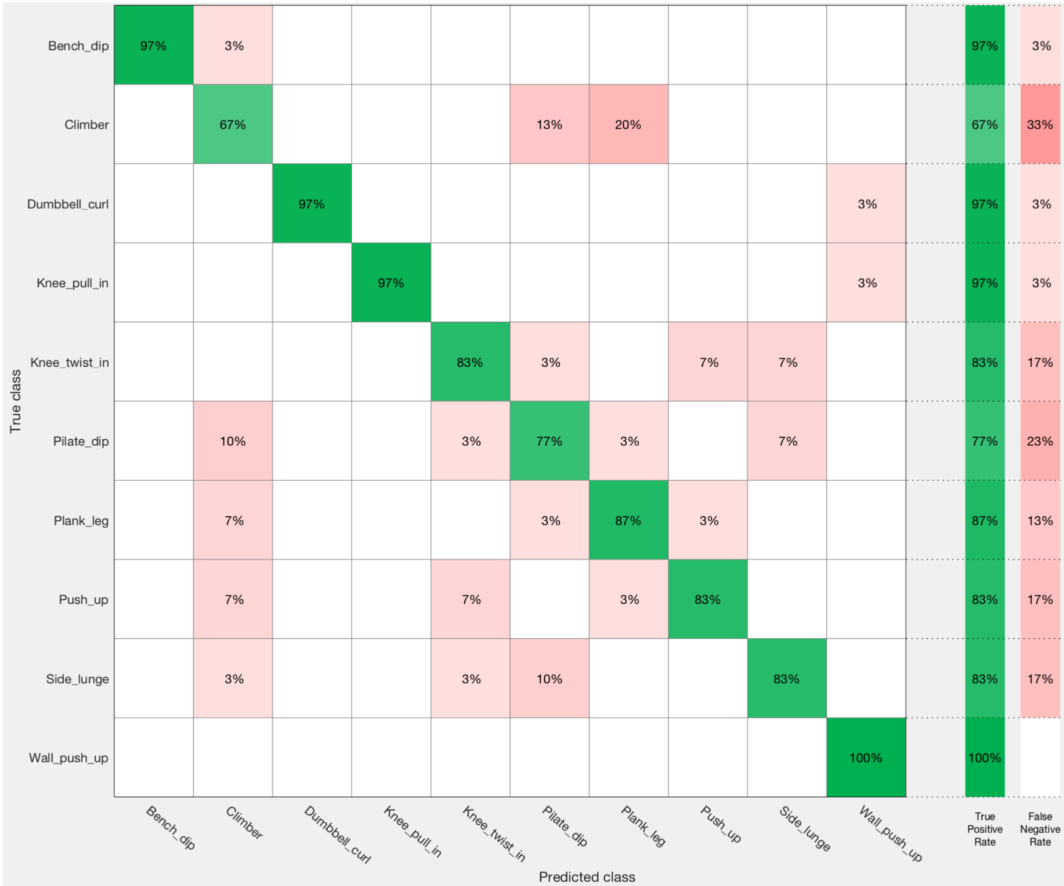



Fig. 5: Confusion matrix of the classifier.

## VI. Discussion

The overall classification result indicates a highly acceptable level of accuracy. Most of the misclassification happens among exercises such as climber and plank leg raise, where the athletes' hand are in direct contact with the ground. There is also an inaccurate prediction for exercise like pilate dips, where athletes keep the same posture till the end of the exercise. Yet, we think that extracting the features in a short time window (between the 5th and 20th seconds) can help reduce the observed misclassification rate because athlete movements are stable in this window range. Also, we intend to increase the classification accuracy, by adding to the current system, some position or orientation sensors (e.g. accelerometer, gyroscope). We consider the positive result of this exercise recognition phase as a great starting point to reach the final goal set for our GIFT system. An unavoidable challenge that we may face in future work will be to reduce the size of the smart-glove to make it more comfortable and easily adjustable to different hand size while keeping the high-resolution and low-cost aspect of the device.

## VII. Conclusion

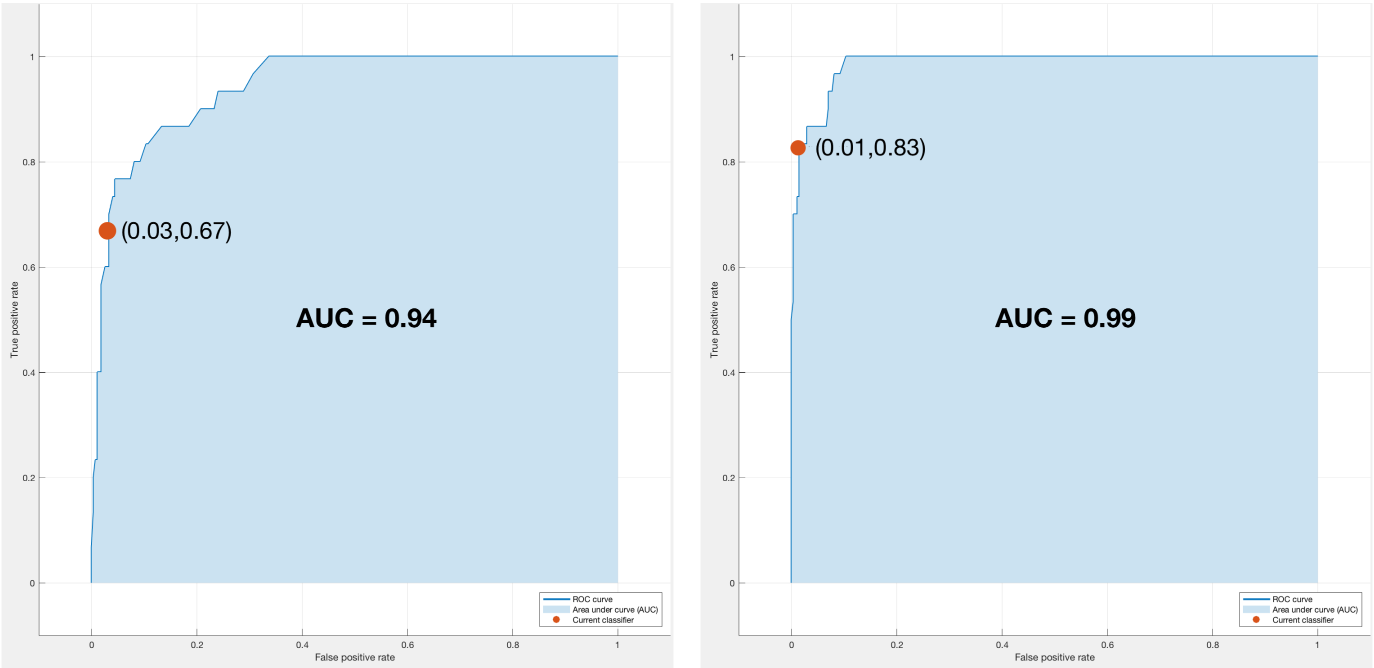
In this paper, we introduced GIFT, a smart-glove based system for indoor fitness activity tracking. The system relies on 16-FSR sensors to identify the type of exercise, by analyzing the pressure distribution applied on the hand palm during an exercise. We presented the design of the proposed smart-glove and the exercise recognition performance of the GIFT system. The classification accuracy was evaluated through an experiment over 10 common fitness exercises. Using the Ensemble subspace KNN method, the system achieved an average classification accuracy rate of 87%. We believe that this result is quite acceptable to allow us stepping forward the next goal of estimating the calorie burn out.
As future works, we intend to reduce the misclassification rate by incorporating sensors like accelerometer, to detect the athlete body orientation. Also, we plan to develop the algorithms to count the number of repetition and recommend the next exercise set for helping users to individually reach their fitness goal.

## Acknowledgment

This work was partly supported by JSPS KAKENHI Grant Number 26700007.

## References

[1] F. J. Penedo and J. R. Dahn, "Exercise and well-being: a review of mental and physical health benefits associated with physical activity," *Current opinion in psychiatry*, vol. 18, no. 2, pp. 189–193, 2005.




(a) Climber

(b) Knee twist in

Fig. 6: ROC curves for the climber and knee-twist-in exercises


[2] D. E. Warburton, C. W. Nicol, and S. S. Bredin, "Health benefits of physical activity: the evidence," *Canadian medical association journal*, vol. 174, no. 6, pp. 801–809, 2006.

[3] P. A. Council. (2017, Oct) 2017 participation report. current.pdf. [Online]. Available: http://www.physicalactivitycouncil.com/PDFs/current.pdf

[4] T. S. Portal. (2017, Oct) U.s. fitness center / health club industry revenue from 2000 to 2016. [Online]. Available: https://www.statista.com/statistics/236120/us-fitness-center-revenue/

[5] F. Mokaya, B. Nguyen, C. Kuo, Q. Jacobson, A. Rowe, and P. Zhang, "Mars: a muscle activity recognition system enabling self-configuring musculoskeletal sensor networks," in *Information Processing in Sensor Networks (IPSN), 2013 ACM/IEEE International Conference on*. IEEE, 2013, pp. 191–202.

[6] A. R. Doherty, P. Kelly, J. Kerr, S. Marshall, M. Oliver, H. Badland, A. Hamilton, and C. Foster, "Using wearable cameras to categorise type and context of accelerometer-identified episodes of physical activity," *International Journal of Behavioral Nutrition and Physical Activity*, vol. 10, no. 1, p. 22, 2013.

[7] G. Vernillo, A. Savoldelli, B. Pellegrini, and F. Schena, "Validity of the sensewear armband to assess energy expenditure in graded walking," *Journal of Physical Activity and Health*, vol. 12, no. 2, pp. 178–183, 2015.

[8] M. Sundholm, J. Cheng, B. Zhou, A. Sethi, and P. Lukowicz, "Smart-mat: Recognizing and counting gym exercises with low-cost resistive pressure sensing matrix," in *Proceedings of the 2014 ACM international joint conference on pervasive and ubiquitous computing*. ACM, 2014, pp. 373–382.

[9] LiveStrong. (2017, Oct) The benefits of wearing weight lifting gloves. [Online]. Available: https://www.livestrong.com/article/17819-benefits-wearing-weight-lifting-gloves/

[10] K.-H. Chang, M. Chen, and J. Canny, "Tracking free-weight exercises," *UbiComp 2007: Ubiquitous Computing*, pp. 19–37, 2007.

[11] I. Pernek, K. A. Hummel, and P. Kokol, "Exercise repetition detection for resistance training based on smartphones," *Personal and ubiquitous computing*, vol. 17, no. 4, pp. 771–782, 2013.

[12] ActiveLinxx. (2016, Dec) Power your fitlinxx system. [Online]. Available: https://www.activelinxx.com/services/

[13] Fitbit. (2017, Oct) Why fitbit? [Online]. Available: https://www.fitbit.com/whyfitbit

[14] J. E. Sasaki, A. Hickey, M. Mavilia, J. Tedesco, D. John, S. K. Keadle, and P. S. Freedson, "Validation of the fitbit wireless activity tracker for prediction of energy expenditure," *Journal of Physical Activity and Health*, vol. 12, no. 2, pp. 149–154, 2015.

[15] F. Community. (2017, Sep) Logging strength training. [Online]. Available: https://community.fitbit.com/t5/Alta/Logging-strength-training/td-p/1350809

[16] G. Fit. (2017, Oct) Step up your fitness. [Online]. Available: https://www.google.com/fit/

[17] B. Zhou, H. Koerger, M. Wirth, C. Zwick, C. Martindale, H. Cruz, B. Eskofier, and P. Lukowicz, "Smart soccer shoe: monitoring foot-ball interaction with shoe integrated textile pressure sensor matrix," in *Proceedings of the 2016 ACM International Symposium on Wearable Computers*. ACM, 2016, pp. 64–71.

[18] I. Electronics. (2017, Nov) Fsr 400 series data sheet. current.pdf. [Online]. Available: http://interlinkelectronics.com/datasheets/Datasheet_FSR.pdf

[19] T. Huynh and B. Schiele, "Analyzing features for activity recognition," in *Proceedings of the 2005 joint conference on Smart objects and ambient intelligence: innovative context-aware services: usages and technologies*. ACM, 2005, pp. 159–163.

[20] A. Bulling, U. Blanke, and B. Schiele, "A tutorial on human activity recognition using body-worn inertial sensors," *ACM Computing Surveys*, vol. 46, no. 3, pp. 1–33, 2014.

[21] L. Rokach, "Ensemble-based classifiers," *Artificial Intelligence Review*, vol. 33, no. 1, pp. 1–39, 2010.

[22] B. Logan, J. Healey, M. Philipose, E. M. Tapia, and S. Intille, "A long-term evaluation of sensing modalities for activity recognition," in *International conference on Ubiquitous computing*. Springer, 2007, pp. 483–500.

[23] D. L. Streiner and J. Cairney, "What's under the roc? an introduction to receiver operating characteristics curves," *The Canadian Journal of Psychiatry*, vol. 52, no. 2, pp. 121–128, 2007.