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Machine learning-based fall detection system using smart passive UHF sensor tag on the shoes

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Abstract: Along with increasing the number of elderly people, the demand for healthcare services has been growing. It is crucial to detect the elderly's falling-down rapidly for reducing the risk of their hospitalization since they might be unable to get up by themselves. To cope with this issue, various sensor based monitoring systems have been widely developed. This paper proposes a fall detection system using passive Radio Frequency Identification (RFID) sensor tags which can measure not only Received Signal Strength Indicator (RSSI), but also pressure with changes in impedance. In our method, the passive sensor tags are attached to indoor footwear to identify basic daily activities using RSSI fluctuations and pressure data in shoe sole. Our battery free sensor brings advantage to make users walk comfortably and vanquish the fear of damaging sensors. The results of behavior analysis performed by four examinees have validated the effectiveness of person-independent strategies.

Keywords: Fall Detection, Passive RFID Tag, Machine Learning

1. Introduction

1.1 super-aging society

In the super-aging society of Japan, an annual report on the aging society published in 2018 reported that the aging rate will reach about 38.4 percent by 2065 because of increasing life expectancy with advancement in medical technology [1]. Accordingly, in order to assist the elderly in their daily life, the demand for health care services in a nursing home has been growing. For example, Figure 1 shows that elderly people live in a personal room in the nursing home [2]. Health care services need to be able to immediately respond to emergencies of the elderly user such as falls and injuries. Although, the caring staff cannot keep an eye on the elderly day and night because of a shortage of caregivers. Elderly people living in a care facility tend to experience an accidental fall more often than those who live in their own houses. In fact, the accidental fall is accounted for approximately 60 percent of personal injuries in nursing homes [3]. The elderly might not be able to recover by themselves or ask for help immediately in case of the fall. Therefore, earlier fall detection and notification is crucial to reduce the risk of hospitalization or fatal situation. Yet, over 80 percent of all the accidental falls occur at nursing homes when busy caregivers cannot keep an eye on the elderly. In order to implement an early fall detection and notification, a health monitoring system based on Internet of Things has been developed. Many previous researches on activity recognition or fall detection of the elderly have already been proposed effective technologies such as vision-based detection or sensor-based detection.

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Fig. 1 The personal room of a resident in a nursing home

1.2 sensor-based solutions

Fall detection or activity recognition systems can be generally divided into four major categories, which are cameras, wearable, and sensors deployed in the indoor environment or attached to daily use objects. The camera monitoring system, which can usually provide better performance, has been widely used. This system allows the caring staff to be surely notified and immediately deal with accidents. Such a vision-based system, however, is apt to raise privacy concerns. Moreover, the camera depends largely on illumination or may not work properly in a dark environment, for example at night.

The wearable approach can collect health data and body posture data. The user can contact the medical center about their health conditions when an emergency happens. However, such a method has several shortcomings. Some users feel uncomfortable in wearing devices or may forget to wear them. In addition, such devices typically need replacement of batteries or recharging. To deal with these issues, many sensors are embedded inside the environment. The main advantage is that users do not have to carry any devices or sensors and maintain them regularly. But, there are some challenges of a sensor-based system that need to install a lot of sensors on the wall or house. Signal disturbance from the environment might be also frequently associated with harmful consequences.

In the on-object sensor-based approach, sensors are attached to objects of daily use. Generally, the sensors attached to the body or wearing objects easily reflect the subject movement more than the sensors is installed in the environment. Therefore, this approaches have been attracted attention in recent years. This method is similar to the wearable approach, but users are not required to wear extra devices.

This research aims to develop a fall detection system based on sensor technology for elderly people at nursing home.

2. Related work

2.1 passive RFID tag

The passive RFID technology is playing an important role in the field of fall detection or activity recognition systems. It is because the passive RFID tag is battery-free, cheap and easily attached to any object. Figure 2 shows that this sensor is composed of an integrated circuit chip and an antenna typically on top of a substrate. The operating frequency range is 916.7 to 920.9 MHz at UHF RFID Japan band. An RFID reader transmits radio waves to tags through an antenna and captures these backscattered signals, which are tag ID and Received Signal Strength Indication (RSSI). RSSI values indicate the signal strength, which depends on the distance between the antenna and tag, the orientation of the tag, and the body blockage. The RSSI's accuracy is extremely low in a complex environment due to signal interference or signal collision.

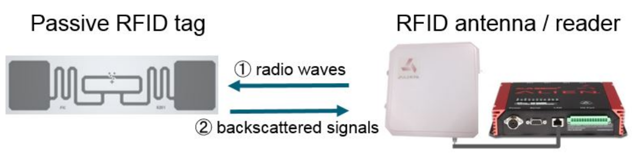


Fig. 2 Passive RFID tag

2.2 fall detection system

In recent years, many fall detection systems have been conducted using passive RFID tags. RFID antennas and passive tags can be easily deployed at the nursing home for elderly care, and caregivers can obtain information immediately in case of emergency.

Yao et al. [4] presented activity recognition based on device-free RFID technology with machine learning. The system uses passive RFID tags deployed in arrays on the wall for capturing activity information using the RSSI signal. The system can classify the activities or detail motions using signal fluctuations induced by the subject' s movements. Although, predicting activities using only fluctuation patterns is not easy, so it becomes sometimes sensitive. A limitation of this work is accuracy under person-independent validation. The recognition accuracy decreases significantly for the person-independent cases. This means that different subjects with heights or body shapes affect signals fluctuation in different ways even performing the same activity. Moreover, the system needs to install many sensors on the wall.

Yakushiji et al. [5] presented state detection using passive RFID tags embedded in the user's clothes. This system detects the state of the wearer in the personal room from reading results of passive tags. One of the limitations of this method is that it needs to remove and replace sensors in the clothing. Therefore, this method might increase the burden of caregivers. Moreover, the results show that the limitation is unstable for detecting walking.

3. System requirements

The following system requirements have been defined:

1). to reduce the cost and the burden of the install of the sensor system,
2). to reduce uncomfortability wearing the sensor,
3). to apply machine learning techniques,
4). to reduce the subject and environment dependency.

The reasons and contributions of our research are the following.

1). Easy install allows caregivers without any knowledge of technology to install the system. Low-cost sensors are essential since a nursing home may not afford to purchase an expensive solution.
2). A lightweight and battery-free sensor are attached to objects of daily use to reduce discomfort in wearing the sensor. Our approaches can avoid privacy violations and battery explosion.
3). Machine learning techniques allow for automatic classification, which can make a task more accurate and efficient than a human decision.
4). If a good system is independent of the subjects or the environment, the trained model need not to be re-trained. If machine-learning training models are person-dependent, it is difficult to classify the activity using the dataset of new subjects.

4. Methodology

4.1 passive RFID sensor tag

In Figure 3, passive RFID sensor tag is composed of RFMicron's Magnus S chip [6]. This chip can measure moisture or pressure by measuring changes in impedance, and then tag translates this into a Sensor Code (range 0 - 31). When a stimulus loop comes into close proximity to a metallic, Sensor Code changes.

The proposed system uses passive sensor tags as a pressure sensor by sandwiching a cushion in between a tag and a layer of the metal sheet. Figure 4 shows that when the metal sheet is pressed, the impedance changes and Sensor Code exceed the threshold (value is 16) as detecting pressure.

4.2 indoor footwear

The risk of injury from falls increases by up to 10 times in elderly people who are barefoot or wearing socks compared with those walking wearing indoor footwear [7]. Moreover, elderly

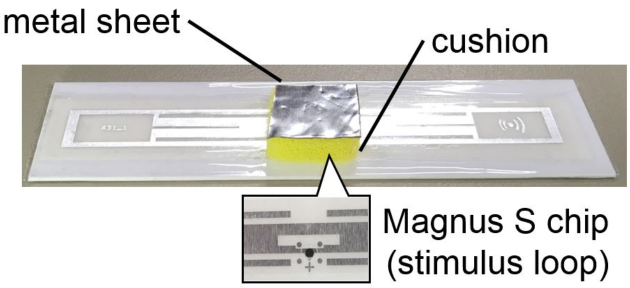


Fig. 3 Passive RFID sensor tag

Fig. 4 Transition of Sensor Code in pressure monitoring

people should avoid walking without shoes because the risk of foot trauma could increase. Therefore, in Figure 5, elderly people routinely wear appropriate indoor shoes on a daily basis to reduce the risk of slipping or foot trauma [2] [8]. Indoor footwear for elderly people is usually made of soft material and has a moderate grip.

For this reason, some fall detection or activity recognition system have attempted to integrate different sensors in indoor footwear. Footwear-based systems typically consist of pressure sensors or inertial sensors with battery embedded into the bottom sole. However, these system may lead to being potentially hazardous incidents such as battery explosion. Therefore, Footwear-based systems should be comfortable and safe for wearing.

In the proposed method, passive sensor tags with pressure sensing capability attached to indoor footwear. The advantage is that the user can wear comfortably without fear of damaging the sensors. Accordingly, this approach can satisfy the system requirements (1) and (2).

Fig. 5 Indoor footwear

4.3 tag placement

Weak signals or signal interference occur when passive tags are attached too close to each other or RFID reader is trying to obtain too many passive tags at the same time. Therefore, tag placement is critical for classifying activities.

The basic idea of identifying activities is simple. Considering features of RSSI value by comparing with static activity, the RSSI significantly fluctuate during walking when the user moves legs.

In Figure 6 shows the first step that the passive tags attached to each front shoe (instep, inside, outside, heel, toe) to read some tags even though elderly people face any direction. In the second step, three passive sensor tags attached to each sole shoe for plantar pressure measurement. If the user lifts the foot off the floor, Sensor Code does not exceed the threshold. On the other hand, passive sensor tags measure pressure when the sole shoe touches the floor.

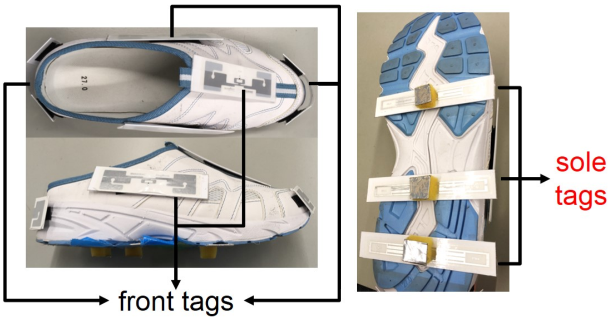


Fig. 6 Tag placement

4.4 system overview

Machine learning techniques allow automatic creation of classifiers. A supervised machine-learning model was trained to recognize activities using RSSI values and Sensor Code obtained from passive sensor tags. In Figure 7, system overview of our proposed method, when the trained model classifies the accidents using feature data from raw data, it sends an alert notification to caregivers. One of the limitations of the proposed system is unable to monitor the upper body activities. Therefore, all activities or motion in daily life are not considered. The proposed system monitors basic daily life activities including walking, standing, and falling.

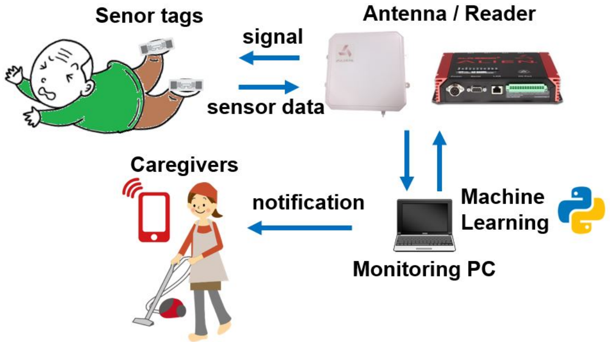


Fig. 7 System overview

5. Experimetns

5.1 objective of experiments

In order to achieve the system requirements, the objective of experiments is the evaluation of the subject-independent strategy. The stable performance of the subject-independent is useful for real-world applications since the model no need to be re-trained for different subjects. Moreover, in our objective, two different models with and without using Sensor code features were trained and evaluated performance to evaluate the effectiveness of passive sensor tags.

Figure 8 shows that this experiment consists of several stages such as data collection, sliding window, feature extraction and classification. In our experiment, 3 male and 1 female undergraduate and graduate students voluntarily (aged from 21 to 24) participated as subjects and performed each activity in a natural way. Feature extraction from the raw data is essential to characterize activities with a sliding window method. The leave-one-subject-out method is implemented to evaluate the subject-independent strategy. The main goal of the research is to develop a real-time fall detection system. Before the real-time system starts to be utilized, in this paper, the performance of the proposed method is evaluated through our experiments.

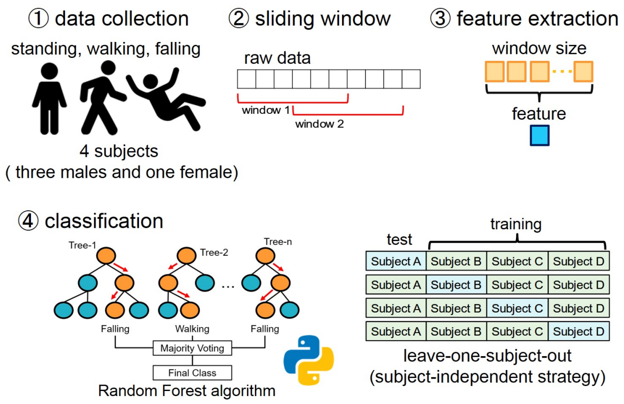
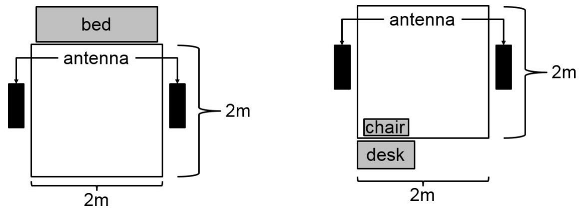


Fig. 8 Experimental workflow

5.2 experimental setting

In the experimental setting, the RFID hardware is deployed in the room, eg, Alien ALR-9900+ Enterprise RFID Reader, circularly polarized antennas [9]. There is no universal experimental setup for evaluating. In our experiments, to evaluate the environment dependencies, different experiments are conducted in two scenarios. Figure 9 (a) shows that one male and one female performed at the room with a bed (2 m × 2 m). On the other hand, Figure 9 (b) shows that two males performed at the room with a desk and chair (2 m × 2 m). In both scenarios, the two circularly polarized antennas are placed 0.2 meters above the floor facing each other. Table 1 summarizes comparison with experimental setting of related work.



(a) Room with bed (b) Room with desk and chair

Fig. 9 Experimental environment

Table 1 Comparison with experimental setting

	Proposed	**Yao [4]**	**Yakushiji [5]**
attachment	shoes	wall	cloth
sensor data	signal strength pressure data	signal strength	reading results
subject	three males one female	five males one female	one male
environment	two rooms	real environment	one room

5.3 data collection

RSSI values and Sensor Code are obtained at a sampling rate of 10Hz. Each passive sensor tag record consists of a tag ID, a time-stamp, an antenna ID, RSSI value, Sensor Code.

A false-negative reading indicates the failure of detecting the tag. For example, signals can be lost when a signal collision happens or passive tags might be hidden underneath the object. In this study, if the antenna cannot read data from the sensor tags, the RSSI value is set to 0.

All subjects repeated each activity ten times, 40 seconds each by changing the orientation and place without imposing a precise position. Therefore, data of each activity are collected 400 seconds per one subject. In this experiment, the most common types of falls were performed which are a forward direction, a backward direction and a lateral fall.

5.4 raw data

Figure 10 shows the raw time-series data plot for each activity. In Figure 10 (a), three activities sequentially performed by subject to analyze raw data collected from passive tags. The subject performed including standing, walking and falling, and then remaining on the ground. Figure 10 (b) and (c) show that rhythmic variances in RSS values can be observed when walking activity with leg movements. This information is useful in classifying walking activity from other activities. On the other hand, in Figure 10 (d), Sensor Code does not exceed the threshold during falling activity because the sole shoe does not touch the floor.

Figure 11 shows the pressure monitoring rate of sole shoe passive sensor tags for each activity. During standing activity for each subject, the radio signal from RFID antenna often does not reach passive sensor tags attached shoe sole because the signal strength is reduced for hiding underneath the sole. During the falling activity, the data of subject B indicates the detecting pressure, which means passive sensor tags detect the pressure. This is because he performed to keep the feet flat on the floor by bending the knees only once in the experiments.

Identifying activities is not easy on the basis of only raw data since their approach is not intuitive. Therefore, several features are extracted from raw data of each tag with a sliding window.

(a) performing each activity

(b) RSSI of right front tags

(c) RSSI of left front tags

(d) Sensor Code of each sole tags

Fig. 10 Raw data for each activity

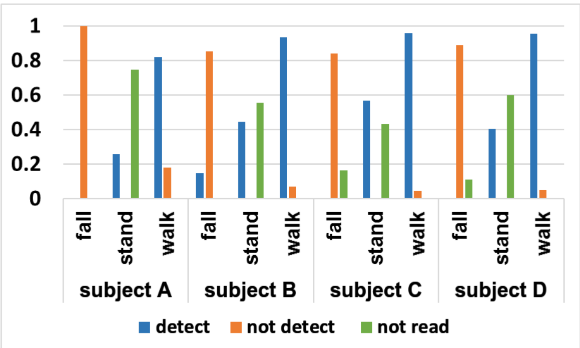


Fig. 11 Pressure monitoring rate of sole shoe sensor tags

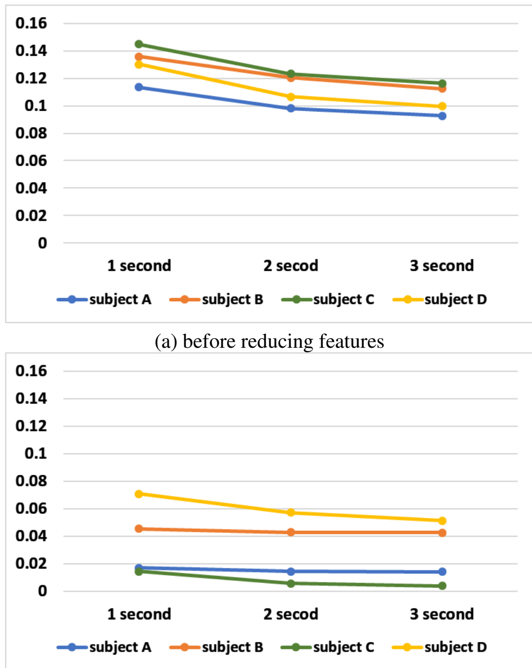
5.5 feature extraction

An overlapping sliding-window approach is applied, and each window series is labeled with one activity. The selection of the window length is essential. If the small window size is selected, the window possibly contains insufficient information for making the decision. The false-negative reading rate is reduced as the window length is increased. However, if the window length is too wide, the latency increases.

The standard deviation of the RSSI (except 0) is extracted to differentiate between walking activity and static activities (standing, falling). Similar feature sets might have no advantage in recognition accuracy and "zero" feature data can make data classification's performance decreased. As shown in the Figure 12 (a), the rate of "zero" feature data that caused by false-negative is high. Therefore, in order to reduce the number of features, the proposed system uses max standard deviation RSSI of each front and sole shoe. As a result, the Figure 12 (b) shows that the rate of "zero" feature data has decreased. Moreover, as a result of comparison with window size, all features are extracted using a 3-second sliding window with 2-second overlapping. Figure 13 shows that feature data plot extracted from raw data in Figure 10. In Figure 13 (a), the standard deviation of the RSSI indicates high value during walking.

The difference between the max and minimum Sensor Code, which indicates the high value during walking in Figure13 (b), is also extracted. In standing and falling, no significant changes in RSSI values. Therefore, static activities are classified based on Sensor Code values. The one-hot encoding on categorical data means creating vectors of one and zero.

Figure 13 (c) shows that this feature consists of three vectors, (1) detecting pressure, (2) not detecting pressure, (3) not reading tags. For example, the vector of "detect pressure" set as 1 when one of the Sensor Code is exceeded the threshold at window size and other vectors set as 0. On the other hand, the vector of "not reading tags" set as 1 when all sole tags are not read caused by false-negative reading.



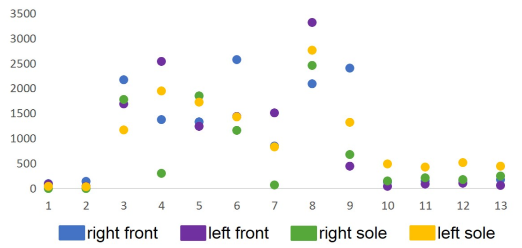
(a) before reducing features

(b) after reducing features

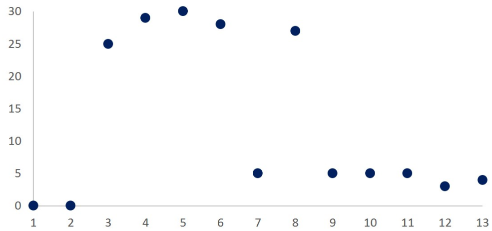
Fig. 12 Comparison with the window size and the number of features

5.6 machine learning

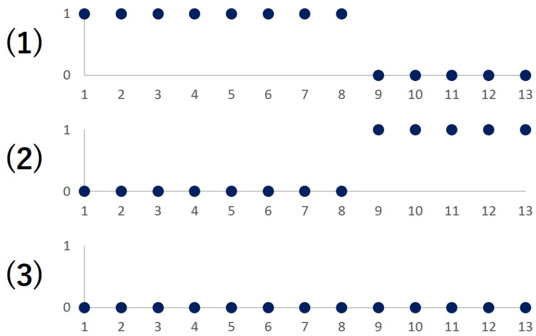
In order to evaluate the effectiveness of passive sensor tags, two different models with and without using Sensor Code feature sets were developed and evaluated. Moreover, to evaluate the effect of subject variations, the leave-one-subject-out method is applied. Base on the leave-one-subject-out method, three subjects data are used for training and the remaining one subject is



(a) max standard deviation RSSI



(b) difference between the max-min Sensor Code



(c) one hot encoding on categorical data

Fig. 13 Feature extraction

used for test.

Different types of supervised machine learning algorithms have been generally used in fall detection systems to build a model from training data in the fall detection system. Random Forest algorithm based on ensemble learning is one of the most popular classification methods [10]. This algorithm builds multiple decision trees trained with a bagging mechanism and takes a majority vote to get a stable prediction. The advantage of the random forest is known to be robust to noise and refrains from overfitting. In our experiment, the random forest algorithm is adopted for recognizing activities. For parameter tuning, the number of trees is 50, the maximum height of trees is set to 10.

6. Result

In the experimental results, performance scores are compared with two different models. In addition, leave-one-subject-out training is evaluated and averaged the results of all subjects.

To evaluate our methods, the specificity is the number of correct detection divided by the number of detections, while the sensitivity is the number of correct detections divided by the number of true activity. F-measure is the harmonic mean of specificity and sensitivity.

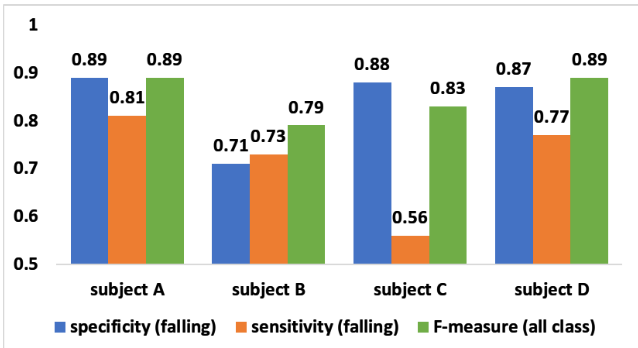
$$\text{specificity} = \frac{\text{number of correct detection}}{\text{number of detections}}$$

$$\text{sensitivity} = \frac{\text{number of correct detection}}{\text{number of true activity}}$$

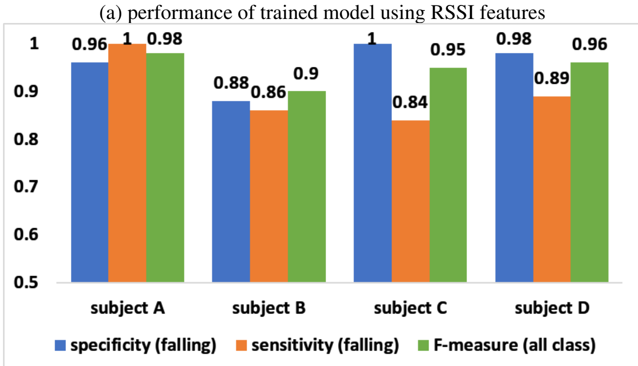
$$\text{F-measure} = 2 \times \frac{\text{specificity} \times \text{sensitivity}}{\text{specificity} + \text{sensitivity}}$$

The fall detection system turned out no alarm even though the users had a fall accident. This situation may cause serious problems. On the contrary, the false alarm means no fall happens. Therefore, sensitivity for fall detection is more important than non-fall activity. Compare the performance of the different model and obtain the leave-one-subject-out test results, Figure 14 shows the specificity and the sensitivity of fall activity, and the averaged F-measure of all activities. In Figure 14 (a) shows that a sensitivity of subject C is quite low since the falling activity is confused with the standing activity. Each standard deviation of the standard deviation RSSI values is a similar pattern. On the other hand, in Figure 14 (b), trained model using RSSI and Sensor Code features, the sensitivity for fall detection reached to 100%, 86%, 84% and 89% of subject A, subject B, subject C and subject D, respectively. Therefore, the trained model with Sensor Code features can divide the static activities and reduce to be sensitive to training subjects' physical characteristics such as heights or body shapes. Moreover, our approach can reduce the effect caused by different rooms.

Table 2 gives comparison with the system requirements. Advantages of the proposed method are easy-install and comfort to the user. The proposed method achieved higher accuracy than related work on subject-independent validation.



(a) performance of trained model using RSSI features



(b) performance of trained model using RSSI and Sensor Code features

Fig. 14 Comparison with the different trained models

Table 2 Comparison with system requirements

	Proposed	**Yao [4]**	**Yakushiji [5]**
system install	easy	complicated	easy
cost	low	low	low
comfortability	good	excellent	good
machine learning	Random Forest	dictionary-based approach	C4.5 and SVM
subject dependency	good	average	n/a

7. Conclusion

Fall detection system was proposed using using passive RFID sensor tags with pressure sensing capability and machine learning techniques. In this paper, our system requirements were focused on the following tasks: (1) to require a low-cost sensor and easy install, (2) to reduce uncomfortable wearing the sensor, and (3) to reduce the subject and environment dependency.

The proposed method is provided an easy-to-use solution by using low-cost sensor and attaching to the indoor footwear. Moreover, the user can wear comfortably without any restriction on activity or fear of damaging the sensors because of using battery-free sensor. In the experiments, in order to validate the dependency on on subjects and environments, four subjects participated as subjects and performed each activity at different rooms in a natural way, and then the leave-one-subject-out method is applied. Moreover, to evaluate the effectiveness of sensor tags, two different models with and without using Sensor Code feature sets of passive sensor tags were developed and evaluated. As a result, the sensitivity of the trained model with Sensor Code features is higher than the trained model without them. Therefore, our approach can reduce the effect caused by different bodies and rooms by using passive RFID sensor tags.

As a remaining problem, a real-time system will be developed and conducted in a real environment which is the nursing home.

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