Fall detection scheme based on temperature distribution with IR array sensor

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***Abstract*—In recent years, the rate of older people has been increasing with the aging of population. In such a situation, many older people are injured by falls every year. As a countermeasure, several studies have been proposed to inform others of a fall as a quick post-fall treatment. Therefore, fall detection methods using various sensors have been proposed. Assuming fall detection at places such as home or hospital room, a fall detection method without invasion of privacy and wearing anything is required. In this paper, we propose a fall detection method using IR array sensors. The method allows for fall detection that is inexpensive and capable of privacy protection in a non-wearable form. Also, we analyze temperature distributions using machine learning to enable quicker and more accurate fall detection. We evaluate multiple algorithms of machine learning to select best algorithm. Then, classifiers are created based on these algorithms. We calculate and compare the accuracy of these classifiers. One of the learning data is a series of temperature distribution data for 2 seconds. One temperature distribution is acquired every 0.1 seconds by IR array sensors installed on a ceiling. We prepare 1600 learning data (400 series of learning data each with 4 actions: fall, walking, lying, and none). Based on these data, classifiers are performed using multiple algorithms to determine accuracy. The most accurate algorithm is Voting classifier with 97.75% accuracy. Therefore, the evaluation result showed that the proposed method is possible to classify with high accuracy using IR array sensors based on these prepared learning data.**

***Index Terms*—fall, fall detection, IR array sensor, temperature distribution, machine learning**

I. Introduction

In recent years, aging is progressing with the advancement of technology in the medical field, etc. In 2015, the elderly (people aged 65 years) accounted for around 10% of the global population [1]. Rate of elderly in Japan is 26.6%, which is quite high compared to the United States (14.6%). In addition, rate of elderly in Japan is expected to be about 40% in 2060.

In such a situation, according to the World Health Organization (WHO), about 30% of elderly are injured by falls each year [2]. The frequency of falls increases with age and decline of health. Furthermore, in the medical field, falls are considered a serious problem. 5% of people injured by a fall have injuries that require hospitalization. In addition, 10$\sim$15% of causes of patient visits in the emergency department are falls. The elderly are more likely to die after being hospitalized by a fall. Even if the elderly do not die, they may have sequelae and affect their daily lives. When we consider aging in the future, falls among the elderly are expected to become more serious.

One way to prevent falls is to create a barrier-free environment. Barrier-free means mainly removing physical obstacles such as steps. It can reduce the frequency of falls. However, some elderly people might find it, they are hard to raise their feet due to muscles weakened, and fall where there is nothing. Therefore, it is difficult to entirely eliminate falls.

Accordingly, there are researches to eliminate the injury when falling [3]. Those studies have proposed methods to detect a fall at an early stage of a fall and reduce the impact of falls using an airbag. On the other hand, it is difficult to introduce in daily life because the airbag is high costly and requires the installation.

Furthermore, as a fall countermeasure, there is also the method of notifying others of the fall in order to perform the post-fall treatment after the fall more quickly. To notify others of fall, it is first necessary to detect a fall. Therefore, various studies have been conducted on fall detection. These detection methods are mainly divided into two types: a wearable type with a sensor and a non-wearable type with sensors mounted on a wall or a ceiling.

The wearable type fall detection methods, there is a method using a motion sensor [4], [5]. Motion sensor can detect acceleration, gravity acceleration, and acceleration direction, etc. Motion sensors detect falls based on those values. The motion sensors are located in a belt-like wearable device. In addition, there are fall detection methods using an acceleration sensor or a voice function of a smartphone instead of a motion sensor [6], [7].

One of the actual products for fall detection is the Apple Watch provided by Apple Inc. Apple Watches detect falls by analyzing wrist trajectory and impact acceleration using built-in accelerometers and gyroscopes. If there is no movement within 60 seconds after the fall is detected, the emergency call service can be automatically contacted. However, wearable detection methods require the device to be worn and are difficult to always wear at home or in a hospital room. Thus, this paper proposes a non-wearable type fall detection method.

As a non-wearable type fall detection method, some de-

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tection methods use a camera established on the wall of a room [8], [9]. These methods detect a fall based on the image acquired from the camera. The fall detection method using a camera enables fall detection in a comfortable life where you do not wear anything at home or in a hospital room. However, using camera images in daily life might violate privacy.

To avoid invasion of privacy, a depth sensor can be used for a non-wearable type fall detection method [10], [11]. The depth sensor emits infrared ray and obtains the distance based on the time until reflection and return. It recognizes shapes by applying infrared rays to various positions. This method detects a fall based on these data. However, this method will not catch on because the depth sensor is expensive. Thus, more inexpensive sensors should be used for the detection method as an efficient system.

Among inexpensive sensors, ultrasonic array sensors and IR array sensors are good candidates. Fall detection using the ultrasonic array sensor entails using a specific frequency instead of the infrared ray of the depth sensor [12], [13]. However, the detection range of the ultrasonic array sensor is narrow compared to the IR array sensor. Hence, this paper proposes a fall detection method using IR array sensors.

In this paper, we propose a fall detection method using IR array sensors. The IR array sensor acquires temperature distribution and enables fall detection based on temperature change. The IR array sensor makes it possible to introduce a fall detection method that does not violate non-wearable type privacy at a low cost. Therefore, the proposed fall detection method is considered to be an efficient system. In addition, we use machine learning to enable quicker and more accurate processing. The evaluation results show that the proposed method is possible to classify with high accuracy using IR array sensors based on these prepared learning data.

II. Proposed Fall Detection System

In this paper, we propose a fall detection method using IR Array sensors. It realizes an inexpensive fall detection method by non-wearable type that can protect privacy. The proposed system model is shown in Fig.1. In advance, the proposed system prepares learning data, performs machine learning, and creates a classifier. The fall detection method acquires a plurality of temperature distributions and detects a fall using the created classifier.

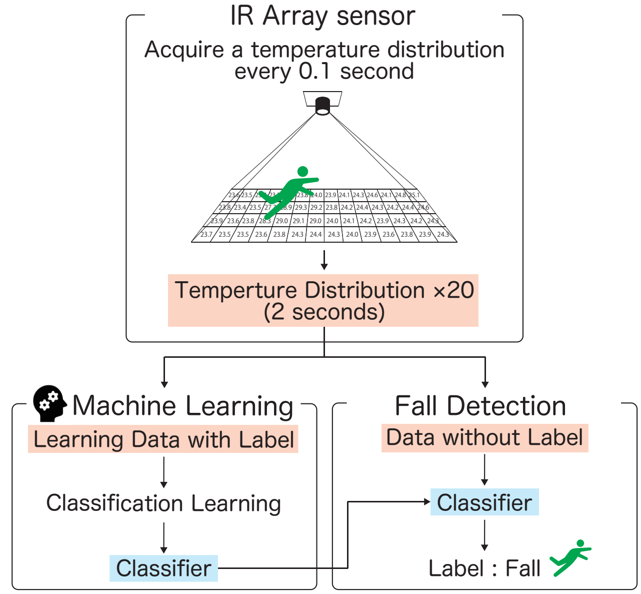
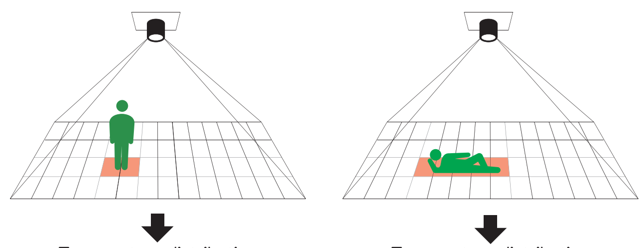


Fig. 1. Systemmodel



Temperature distribution in human standing state(°C)

25.6	23.18	25.52	23.33
26.77	24.12	22.81	21.66
24.56	24.89	24.08	23.34
24.33	23.4	23.41	22.12
24.02	23.26	22.32	22.84
24.53	29.59	24.39	22.97
24.08	29.56	23.55	21.74
23.89	23.29	21.89	23.27
23.05	23.28	22.07	23.37
23.54	22.96	23.11	21.94
22.51	22.89	22.58	21.58
22.96	24.07	23.01	23.13
23.28	22.88	23.55	22.11
24.64	26.05	24.16	22.8
27.26	25.13	24.07	24.56
25.19	25.02	24.84	25.43

Temperature distribution in human lying state(°C)

26.54	23.81	23.91	22.68
25.43	23.8	21.42	21.36
24.91	22.39	22.86	21.36
23.26	22.58	22.02	22.01
24.15	23.08	22.08	22.83
25.07	27.15	23.1	22.84
25.77	28.89	24.28	22.47
25.71	30.54	24.76	22.58
26.01	30.74	26.26	24.29
24.5	28.13	24.7	22.69
23.92	24.36	23.35	21.35
23.88	23.98	23.71	23.06
22.87	23	23.2	22.51
23.38	24.36	23.27	22.62
26.22	25.56	23.48	24.51
26.55	24.68	24.86	27.04

■ …Human area

Fig. 2. Person area in standing and lying

A. Decision of fall from a plurality of temperature distributions

This section explains decision to fall from a plurality of temperature distributions. Inside a room, the body temperature of a person is usually higher than temperatures of surrounding objects, walls, and floors. Based on this, it is possible to recognize an area of the temperature distribution having a temperature higher than the surrounding area as a person.

We suggest IR array sensors be installed on ceiling to acquire temperature distribution from overhead. The temperature distributions in a standing state and lying state, obtained from the IR array sensor installed on a ceiling are shown in Fig.2. In the temperature distribution in the standing state, the human area is two squares. On the other hand, in the temperature distribution in the lying state, the human area is five squares. It can be seen that human areas increase with changing from standing to lying. Thus, it is possible to detect a fall in the change of areas occupied by a human.

To acquire change of area occupied by a person, it is necessary to compare a plurality of temperature distributions.

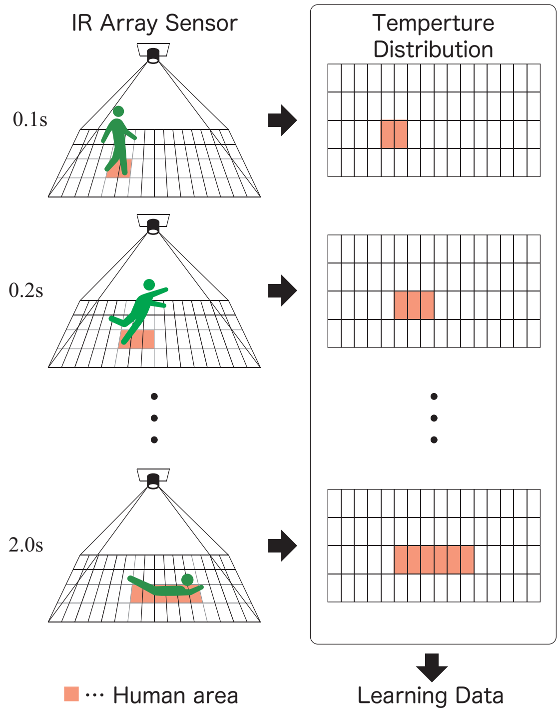


Fig. 3. Actions and temperature distributions in 2 seconds

The plurality of temperature distributions needs to be acquired at regular intervals. For this reason, the proposed method acquires a temperature distribution every 0.1 seconds and detects a fall by changes in the plurality of temperature distributions obtained in 2 seconds. An image of multiple temperature distributions and behaviors in 2 seconds is shown in Fig.3. Also, moving speed and acceleration can be determined from the plurality of temperature distributions acquired at regular intervals. It is possible to decide more detailed actions by these values.

In this paper, we use machine learning to analyze characteristics of changes of a plurality of temperature distributions. Thereby, a fall detection method using IR array sensors is realized.

B. Preparing learning data

For machine learning, it is necessary to prepare a large amount of learning data. Each piece of learning data consists of 2 seconds of temperature distribution acquired every 0.1 seconds and a label indicating the content of the action. As a label, we prepare four types of action patterns, the main activities in daily life: fall, walking, lying, and none. Falls are treated as a series of movements from the beginning of the fall to the complete lying on the ground.

C. Machine Learning

In this paper, machine learning is used for analysis of feature quantities in plurality of temperature distributions. Machine learning performs supervised learning and classifies actions. Supervised learning creates a classifier based on a large amount of prepared labeled learning data. The classifier performs labeling based on the features analyzed from the learning data set when receiving data with unknown label.

In addition, there are many algorithms for supervised learning. In this paper, machine learning creates some classifiers based on learning data using a plurality of algorithms. Then, verification data are classified using each classifier to determine the accuracy. The best accurate method of these classifiers is used for fall detection. As a method of determining the accuracy of learning data, a 5-division verification method is performed. As a method of determining the accuracy of learning data, 5-fold cross-validation is performed. 5-fold cross validation method classifies a large amount of learning data into five groups, uses four as learning data, and uses the remaining one as verification data. The data divided into each five is used as verification data to get each accuracy, and the average is obtained for accuracy. In section 2, we described a proposed system for fall detection that offers privacy protection in an inexpensive, non-wearable form.

III. Implementation

Implementation model of this paper is shown in Fig.4. In this paper, temperature distribution is acquired by Raspberry Pi 3 Model B using MLX90621 of Melexis as IR array sensor. After that, temperature distribution data is transferred to MacBook Pro for processing and machine learning.

A. IR Array sensor

IR array sensor "MLX90621" acquires a temperature distribution of 4×16 pixels. MLX90621 is shown in Fig.5. MLX90621 is possible to obtaine –20°C∼300°C, and the field of view is $120°\times25°$. The installation situation of MLX90621 is shown in Fig.6. In this paper, it is installed on a ceiling of 2.8 m in height, and the detection range is about 1m×7m. Therefore, one area per pixel is about 0.25m×0.45m. In addition, when detecting a fall at home or in a hospital room, the whole room cannot be viewed within the detection range of one IR array sensor. In this paper, temperature distribution is acquired using two IR array sensors to show extensibility.

B. Acquisition and processing of data

Raspberry Pi 3 Model B is used to acquire temperature distribution from MLX90621. The communication between Raspberry Pi and MLX90621 is performed by I2C communication. In I2C communication, roles are divided into master and slave, and the master side communicates with slaves using slave addresses. In this paper, Raspberry Pi is the master, and MLX90621 is the slave because MLX90621 has only one slave address, and it is necessary to prepare two Raspberry Pis as well as MLX90621.

After acquiring the temperature distribution, Raspberry Pi transfers data, including one temperature distribution data, the device number and acquiring time to MacBook Pro via a socket communication. MacBook Pro stores the acquired temperature distribution based on the device number, combines the temperature distributions having the same time, and creates

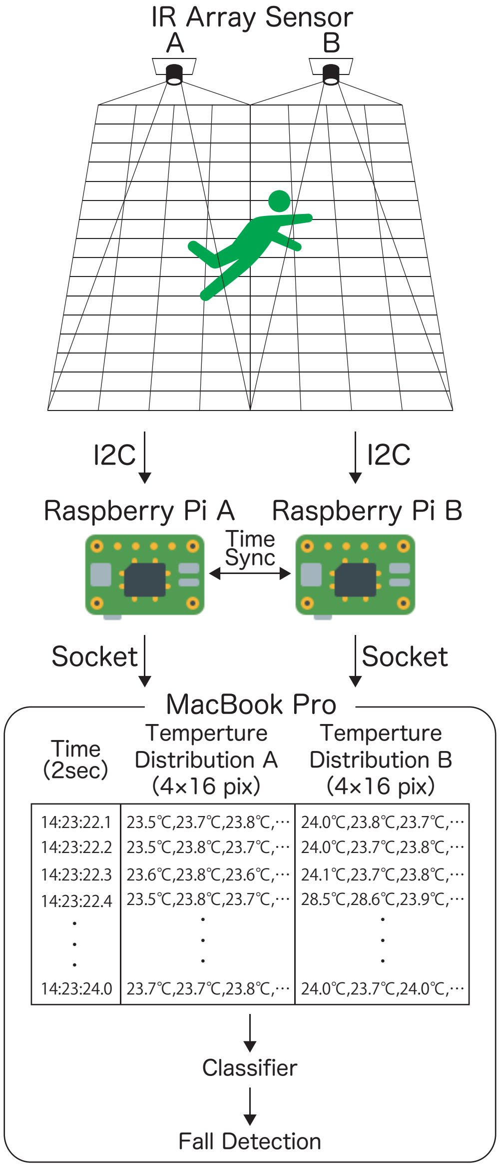


Fig. 4. Implemention Model

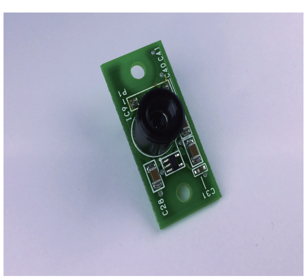


Fig. 5. MLX90621

one temperature distribution. Therefore, it is necessary to perform time synchronization between two Raspberry Pis, and use a socket communication to transmit the time of one Raspberry Pi to the other. We prepare each piece of learning data is combined 20 temperature distributions for 2 seconds.

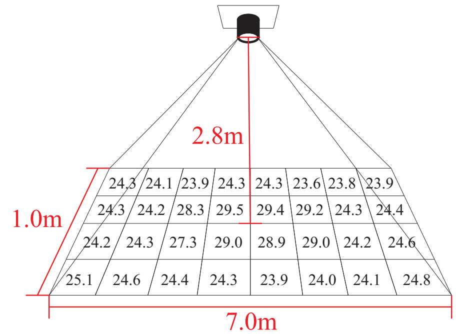


Fig. 6. Detection area of MLX90621

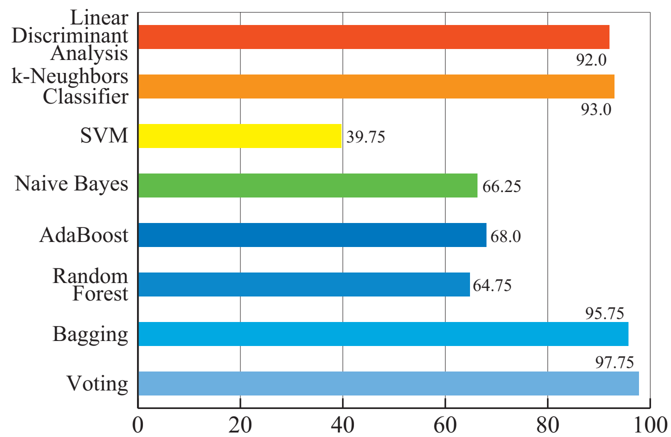


Fig. 7. Result of accuracies

C. Machine learning

Learning data are prepared 500 series by each of four behavior patterns of fall, walking, lying and none which are the daily action. Also, learning data are acquired by 10 people of different heights. Learning data of each action is acquired at place randomly to detect fall anywhere within the detection range."Walking" indicates walking for 2 seconds within the detection range. "Lying" indicates lying for 2 seconds in any state. "Fall" indicates the state from standing to falling. "Fall" was conducted on a 15 cm high airbed for safety. "None" indicates a state without human.

Machine learning is performed using scikit-learn, which is a Python open source machine learning library. Since there are plural classification algorithms for supervised learning, the most accurate algorithm among them is used for fall detection.

IV. Evaluation

Classification accuracies of each algorithm are shown in Fig.7. In this paper, we classified test data using multiple algorithms and obtained accuracy to select an algorithm of machine learning for fall detection. As multiple algorithms, Linear discriminant analysis, k-neighbors classifier, support vector machine(SVM), Naive Bayes, AdaBoost, RandomForest, Voting, and Bagging were used. Voting is a learning algorithm that classifies by majority rule based on the results of multiple learning algorithms. Therefore, Voting uses three of the multiple algorithms with high accuracy. Bagging is a learning algorithm that splits learning data and trains and combines and then classifies it. Bagging also uses one of the multiple algorithms with high accuracy.

We performed 5-fold cross validation method as a method to determine each algorithm accuracy. The number of learning data is 1600(4 actions $\times$ 400), and the number of verification data is 400(4actions $\times$ 100).

The results were as follows: the accuracy was 92.0% for linear discrimination, 93.0% for the k-neighbors classifier, 39.75% for support vector machines, 66.35% for Naive Bays, 68.0% for AdaBoost, and 64.57% for random forests. Bagging was 95.75% with the k-neighbor classifier better than the highly accurate linear discrimination. Voting was 97.75% using highly accurate linear discrimination, k-neighbor classifier, and bagging.

The highest accuracy algorithm was Voting classified with an accuracy of 97.75%. Hence, the accuracy of 97.75% is considered to be sufficient as a classifier for fall detection.

V. Conclusion

In this paper, we have proposed a fall detection method using an IR Array sensor, and realize a fall detection method that can protect privacy in an inexpensive, non-wearable form. This method uses machine learning for quicker and more accurate fall detection.

We performed machine learning of several algorithms based on multiple temperature distributions and evaluated each classifier. The most accurate algorithm is Voting with 97.75% classification. Therefore, it is considered sufficient to use machine learning for the proposed fall detection method. Action pattern of the learning data was limited to four types, but in the future, it is necessary to classify more action patterns such as changing state from standing to lying.

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