A Fall Detection System Using Low Resolution Infrared Array Sensor

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***Abstract*—Nowadays, aging society is a big problem and demand for monitoring systems is becoming higher. Under this circumstance, a fall is a main factor of accidents at home. From this point of view, we need to detect falls expeditiously and correctly. However, usual methods like using a video camera or a wearable device have some issues in privacy and convenience. In this paper, we propose a system of fall detection using a low resolution infrared array sensor. The proposed system uses this sensor with advantages of privacy protection (low resolution), low cost (cheap sensor), and convenience (small device). We propose four features and based on them, classify activities as either a fall or a non-fall using k-nearest neighbor (k-NN) algorithm. We show a proof-of-concept of our proposed system using a commercial-off-the-shelf (COTS) hardware. Results of experiments show the detection rate of higher than 94 % irrespective of training data contains object's data or not.**

I. INTRODUCTION

Currently, elderly people account for 23.3 % of the total population in Japan [1]. Japan also has problems that the number of elderly people who live alone increases and that of employees engaging in care work decreases. From the viewpoint of reducing the burden on the working generation, the demand for monitoring system is becoming higher. According to the reference [1], 70 % of elderly people want to live in their own home when their physical function is reduced. Under these circumstances, 63 % of accidents of elderly people occur at home. Main accident locations are a living room (25.8 %) and stairs (13.1 %). The action that has been taken at the time of the accident at home is most often walking (29.0 %), including climbing stairs. In light of current state of domestic accidents of elderly people, an accident likely to happen the most is a fall at home. It can be said that detecting a fall expeditiously and correctly is important in the monitoring system.

The elderly monitoring systems can be divided into a wearable system and a non-wearable system. The wearable systems require users to wear some sensors. They use sensors, such as RFID (Radio Frequency IDentification) [2] or the acceleration sensor [3]. These systems can estimate object's behavior with high accuracy, however, wearing some sensors is onerous or can be a load. On the other hand, the non-wearable systems can estimate object's behavior without wearing senor. Therefore, they are user-friendly and suitable for elderly monitoring. However, the non-wearable systems such as a video camera [4, 5, 6] have some issues about privacy and accuracy in darkness. As a method for solving these issues, systems such as fusion sensors [7], ultrasonic sensors [8], and infrared sensors arranged in an array [9] have been proposed. However, the fusion sensor-based system [7] supposes a fall at a very narrow area like a sill of a door, hence this system is not suitable for monitoring an entire living room. The ultrasonic sensor-based system [8] and the infrared sensor-based system [9] detect a fall based on posture, hence these systems may judge as a fall when the object just lies down. Moreover, the system [9] needs a lot of infrared sensors.

To solve aforementioned issues, we propose a novel fall detection system using a low resolution infrared array sensor, referred to as the infrared array sensor. This sensor has infrared sensors inside and we can get a temperature distribution. Thus, things that could not be satisfied by the usual pyroelectric sensors are made possible: still human body detection, moving direction detection, and the temperature distribution detection. The infrared array sensor has advantages of a low privacy invasion (the number of pixels is much smaller than that of usual camera), available in darkness, small and cheap (about US$25 per piece). We enable to detect a fall by using four new features and classify as a fall and a non-fall. We show a proof-of-concept of our proposed system using a commercial-off-the-shelf (COTS) hardware. Results of experiments show the detection rate of higher than 94 % irrespective of training data contains object data or not.

The reminder of this paper is as follows. Section II describes proposal. Section III explains four features proposed for classification. In section IV, experiments are detailed. Finally, a conclusion is drawn in section V.

II. SYSTEM MODEL

In this paper, we use the infrared array sensor mounted on a ceiling to detect a fall, as shown in Fig. 1. We assume the sensor has $m \times n$ pixels (the number of infrared sensors inside) and the detection environment is a living room of ordinary homes. Fall detection algorithm of the proposed system is shown in Fig. 2. First, the infrared array sensor

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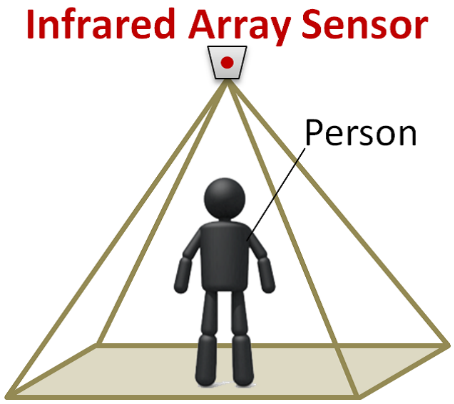

Fig. 1. Position of the sensor.

sends a temperature distribution of interest to the computers. Second, the computer extracts features from the temperature distribution sent from the sensor. Finally, features (input data) are compared with training data in database (DB) and the temperature distribution is classified as a fall or a non-fall. To classify, we propose four features explained in the next section and use k-nearest neighbor (k-NN) algorithm as a classifier for simplification. In this algorithm, input data consists of the k closest training data in the feature space. After Euclidean distance between the input data and the training data is calculated, majority vote is performed by k nearest training data. k-NN requires a small amount of calculation when the scale of training data DB is small and has a small feature.

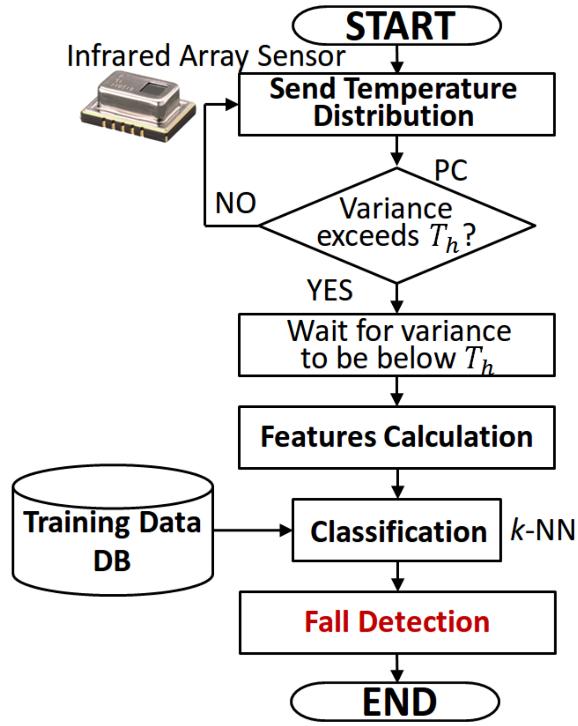

Fig. 2. Fall detection algorithm of the proposed system. Threshold T_h and features are mentioned in section III.

III. Features

In this paper, we use the following four features to classify fall or non-fall using k-NN.

- N_f : The number of consecutive frames where motion is detected
- P_{max} : Maximum number of pixels that variance of temperature changed during N_f
- T_{max} : Maximum variance of temperature during N_f
- D_m : Distance of a maximum temperature pixel before and after an activity

Features, N_f, P_{max}, and T_{max} use variance calculated from a temperature distribution as shown in Fig. 3. For each temperature of $m \times n$ pixels obtained from the infrared array sensor, variance of temperature is calculated during a time window. If small values of N_f and P_{max} are obtained, our system judges as a non-fall on the basis of a certain threshold before classification of k-NN.

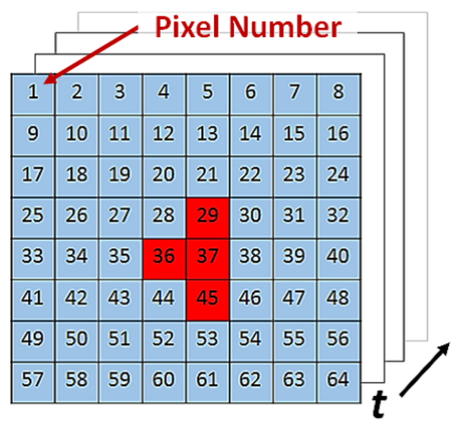

Fig. 3. Temperature variance of each pixel is calculated. Time window width is determined according to a primary experiment. We used the time window width of 20 frames in all the experiments in this paper. (The sensor of Fig. 3 has 8×8 pixels)

A. N_f : The number of consecutive frames where motion is detected

The number of pixels is counted when variance of temperature calculated during time window exceeds a certain threshold T_h. The threshold is determined so that the system dose not react when there is no one in detection area (we used the threshold T_h of 1 °C^2 in this paper). The time window width is determined according to a primary experiment. We used the time window width of 20 frames in all the experiments in this paper. The feature N_f is the number of frames that exceed the threshold in succession as shown in Fig. 4. This feature depends on the time that an action takes (e.g. This feature of a fall tends to be small and that of non-fall like sitting tends to be large).

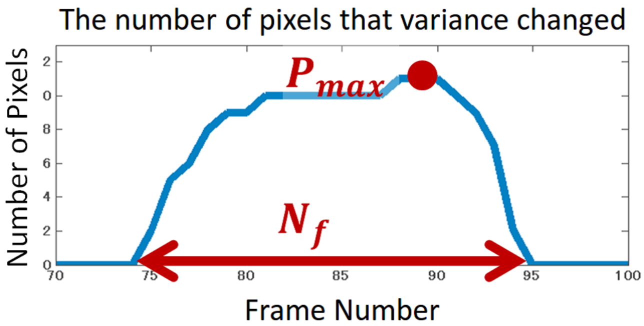

Fig. 4. Features N_f and P_{max}.

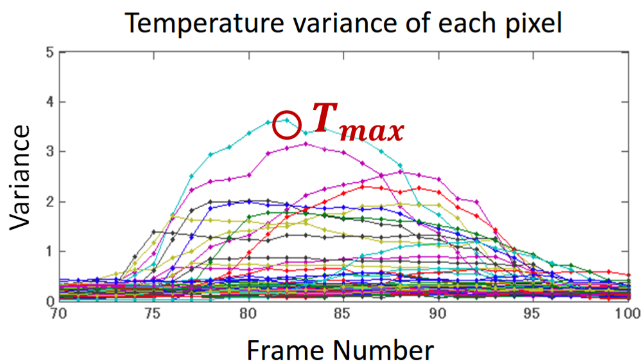

Fig. 5. Feature T_{max}.

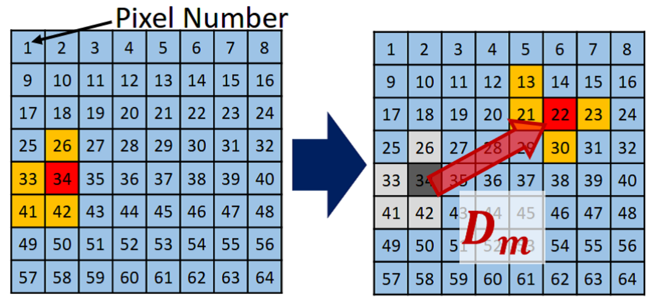

Fig. 6. Feature D_m.

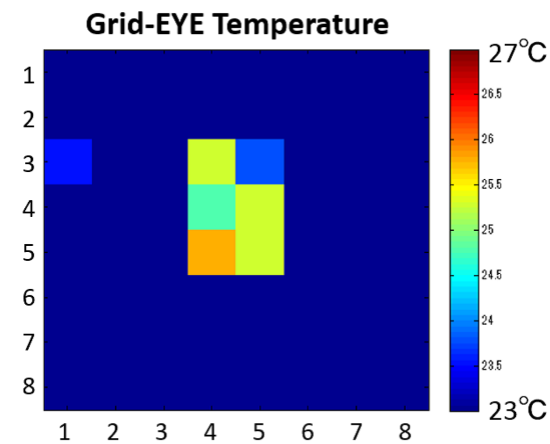

Fig. 7. Temperature distribution when Grid-EYE detects a human sitting below the sensor. Indexes of x-axis and y-axis indicate the position of infrared sensors inside Grid-EYE.

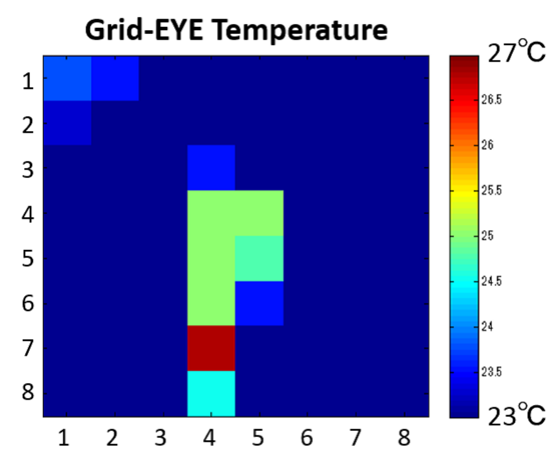

Fig. 8. Temperature distribution when Grid-EYE detects a human falling below the sensor. The number of high temperature pixels is larger than when sitting.

B. P_{max} : *Maximum number of pixels that variance of temperature changed*

The feature P_{max} is the maximum number of pixels counted in the interval of N_f as shown in Fig. 4. When a fall occurs, this feature tends to be large, because body surface area measured by the sensor tends to be large.

C. T_{max} : *Maximum variance of temperature*

The feature T_{max} is the maximum variance of temperature in all pixels in the interval of N_f as shown in Fig. 5. When a fall occurs, this feature tends to be large, because temperature of the pixel largely changes.

D. D_m : *Distance of maximum temperature pixel before and after an activity*

The feature D_m is the Euclidean distance between the positions of the pixel where maximum temperature is observed in 10 frames after the end of N_f and 10 frames before the start of N_f as shown in Fig. 6. The number of frames is decided from preliminary experiments and may change according to sensor's frame rate. In this paper, the position of the pixel where temperature is the largest in all pixels is regarded as the object's position, because the sensor usually detects the maximum temperature at a neck in our experimental environments. This feature tends to be large when a big body motion like a fall occurs.

IV. Experiments

A. Device

In this paper, we use an infrared array sensor called Grid-EYE [10] which is typically used for high performance home appliance, energy savings in office, and automatic door and

TABLE I
SPECIFICATIONS OF THE SENSOR

Model number	Grid-EYE (AMG8831)
The number of pixels	8×8 (64 pixels)
Temperature range	0∼80 °C
Temperature accuracy	±2.5 °C
Detection distance	Max. 5 m
Frame rate	10 fps
Temperature output resolution	0.25 °C

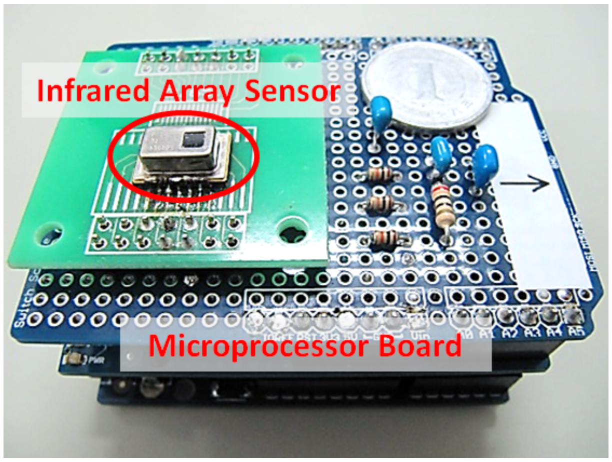

Fig. 9. The device used in experiments is composed of the infrared array sensor and the microprocessor board.

elevator. The sensor has 64 infrared detectors (8×8 pixels) and when the sensor is attached to the ceiling, it is possible to collect values from each pixel as the indoor temperature distribution. This sensor is suitable for detecting body temperature when installed on the ceiling, because temperature range of measuring object is 0 °C to 80 °C (temperature output resolution : 0.25 °C) and maximum detection distance is 5 m. We detect fall by extracting four features from the temperature distribution sent from the sensor and classifying fall or non-fall using k-NN algorithm.

We used Arduino Uno R3 [11] as a microprocessor board to control the sensor and send the temperature distribution to a computer. The received temperature distribution is analyzed and classified to detect fall by a computer with MATLAB R2013a.

B. Results

We conducted experiments to evaluate our system. Experimental specification is listed in TABLE II. In this paper, we use $k = 5$ because results were almost the same when we applied odd numbers from 5 to 13 as a value of k. Six subjects participated in the experiments and they performed falling down ten times, sitting down five times, and walking five times per person (Sitting down and walking are categorized as a non-fall). However, the number of times of walking varies from person to person, because this activity is recognized as one

TABLE II
EXPERIMENTAL SPECIFICATION

Room	A
Ceiling hight	2.57 m
Detection area	3.5 m×3.5 m
Room temperature	23 °C
Floor material	Mattress
Subjects	6 (Male 5, Female 1)
Activity (times)	Fall (60), Non-fall (82)
Classifier	k-nearest neighbor algorithm

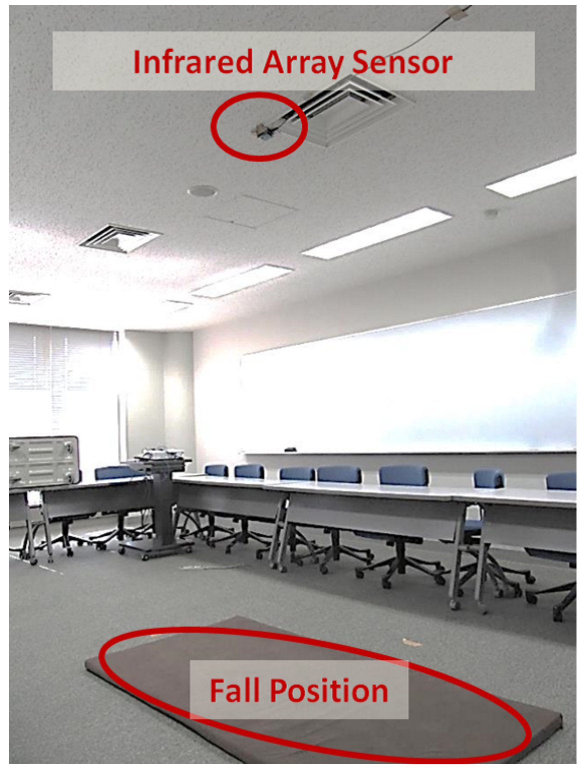

Fig. 10. Experimental environment (Room A)

action each time a subject goes in and out the detection area. We prepare two types of training data. One is training data that contains data of subject for the classification (Case 1). The other is training data that does not contain data of subject for the classification (Case 2). Percentage of correct answer is calculated as

$$\text{Accuracy} = \frac{\text{The number of correct classifications}}{\text{The number of all activities}} \tag{1}$$

Training data used in Case 1 was created based on the evaluation experiment explained above. Training data used in Case 2 was created based on the preliminary experiment conducted in four different days. Each room has a different temperature distribution and ceiling height. Experimental specification of training data is shown in TABLE III.

TABLE III
EXPERIMENTAL SPECIFICATION OF TRAINING DATA

Room	B	C	D	C
Ceiling height	2.61 m	2.66 m	2.59 m	2.66 m
Detection area	3.5 m	3.1 m	3.0 m	3.1 m
Room temperature	27 °C	19 °C	18 °C	16 °C
Floor material	Mattress			
Subjects	2	1	1	1
Activity (times)	Fall (30), Non-fall (172)			

TABLE IV
RESULT OF CASE 1

		Classified Class	
		Fall	Non-fall
Actual Class	Fall	98.3 %	1.7 %
	Non-fall	6.1 %	93.9 %

1) Case 1 : Training data contains subject's data: TABLE IV shows the result of Case 1. Training data was created based on data obtained from this experiment. However, each classification is performed excluding training data based on each input data. Accuracy of Case 1 is 95.8 %.

2) Case 2 : Training data does not contain subject's data: The result of Case 2 is shown in TABLE V and experimental specification of training data is shown in TABLE III. Training data was created in four different days. Classification is conducted using a leave-one-out cross-validation method. Accuracy of Case 2 is 94.3 %.

TABLE VI shows accuracy of two experiments. The amount of training data affects the results. We can validate that our system can detect a fall at detection rate of higher than 94% irrespective of training data contains object's data or not. In addition, there is no significant variation by the subject. Comparable results were obtained when we used SVM (Support Vector Machine) [12] as a classifier. It is known from preliminary experiments that accuracy decreases when objects are dressed warmly or difference between room temperature and body temperature is small. In this paper, we used one infrared array sensor which has 8×8 pixels inside. However, If you want to use an infrared array sensor that has more pixels or more sensors to expand the detection area, proposed scheme can be applied.

V. CONCLUSION

In this paper, we propose a system to detect a fall using a low resolution infrared array sensor. We mount the sensor on the ceiling and classify as a fall or a non-fall by k-nearest neighbor (k-NN) algorithm. Four features, the number of consecutive frames where motion is detected (N_f), maximum number of pixels that variance of temperature changed during N_f (P_{max}), maximum variance of temperature during N_f (T_{max}), and distance of a maximum temperature pixel before and after an activity (D_m) are introduced. Experiments show that our proposed system can classify as a fall or a non-fall, and achieve detection rate of higher than 94 % irrespective of training data contains object's data or not.

TABLE V
RESULT OF CASE 2

		Classified Class	
		Fall	Non-fall
Actual Class	Fall	92.5 %	7.5 %
	Non-fall	3.6 %	96.4 %

TABLE VI
ACCURACY OF TWO EXPERIMENTS

	Accuracy
Case 1	95.8 %
Case 2	94.3 %

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