Sensor array-based recognition of frequently appeared locations and activities

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Abstract: In recent years, the aging population of Japan is increasing fastly. In this society, smart environments especially smart home for senior care have attracted attention. One of the important issues in using smart homes is the resident's privacy. A smart home with a video camera or a microphone is too smart, and it may violate the resident's privacy. The purpose of this research is to establish the technology for building a smart home which preserves resident's privacy. In this paper, we use Sensor-Array consisting of 15 sensors to recognize frequently appeared user locations and activities in daily life. The experimental results show that the recognition rate is close to 100%.

Keywords: Senior care, Sensor Array, PIR Sensor, Artificial Intelligence

1. Introduction

This paper is organized as follows. The next section provides a brief outline of some fundamental knowledge related to this research. In Section 3, we show experimental results and how the sensor-array works.

2. Experimental Setting

2.1 Pyroelectric infrared sensor

The sensor we used is a pyroelectric infrared sensor (PIR sensor) commonly used for a human detector. The sensor output is binary. If it detects someone in the sensor coverage area, the sensor outputs "1". If nobody in the sensor coverage area, it outputs "0". The sensor outputs about 60 binary data per second.

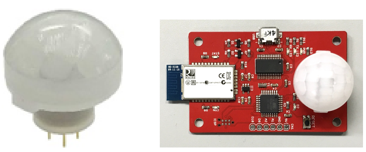

Fig. 1 Infrared sensor module

2.2 Sensor Array

In this research, we make a sensor-array consisting of 15 PIR sensors. The sensor operates asynchronously, and the output is sent to the host server. The room used for the experiment is roughly a rectangle. The size of the room is approximately 8.5mx4.0m, which is part of the system intelligence Laboratory at the University of Aizu. The sensor-array is installed on the ceiling as shown in Fig2.

3. Method

3.1 Moving Average

Binary data which sent from each sensor is not used directly as the input of training data. This is because Moving Average (MS) has more information than raw binary data, and this will be proved by the experimental results in this research. Binary data is converted to MA and input to MLP.

$$MA(n) = \frac{1}{W}\sum_{k=0}^{W-1} d(n-k) \tag{1}$$

$$W : \text{Size of sliding window}$$

$$n : W+0, W+1, W+2, \cdots$$

$$d(n) : \text{Sensor signal, 0 or 1}$$

The number of inputs of the MLP is equal to the number of sensors. The number of outputs of MLP is equal to the number of classes to be recognized. This research does not use any other information of moving average. In other words, we do not use sensor position information and information such as video camera and uses only information obtained from the sensors.

3.2 Machine Learning Model

Multilayer neural network is used for activity and location recognition. This type of neural network is called multilayer perceptron (MLP). The model used in this experiment consists of three layers, one input layer, one hidden layer, and one output layer. The MLPClassifier in all experiments is MLP Classifier-library contained in Python's scikit-learn. (see `http://scikit-learn.org/stable/modules/generated/sklearn.neural_network.MLPClassifier.html`) We used default values for most training parameters. One exception is the number of hidden units, which was set to 20 in our experiments.

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4. Experimental Results

Analyze the data sent from the sensor array and recognize the locations and activity strength.

4.1 Activity recognition

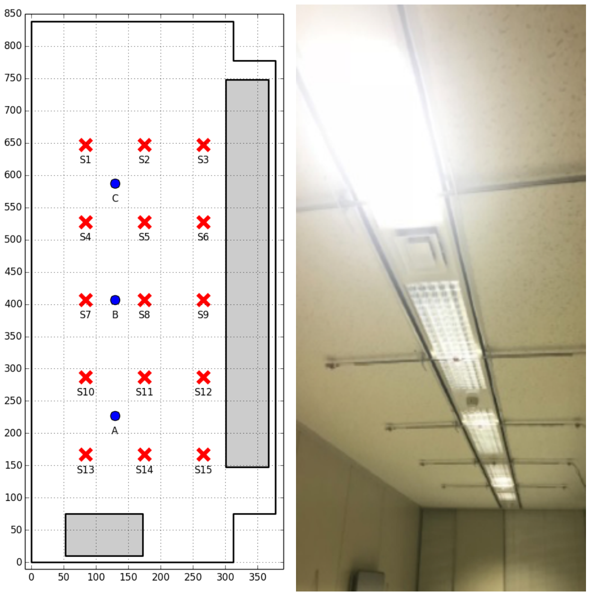

Fig. 2 The layout & location of Infrared Sensor-Array & Picture of Sensor-Array

Table 1 Activities to recognize

Level of activity strength	Group	BPM
1	Weak	20
2	Weak	30
3	Normal	50
4	Normal	60
5	Strong	80
6	Strong	90
7	Very strong	110
8	Very strong	120

First, we investigated whether recognize various activitiy using the proposed sensor array system. There are many kinds of activities seen in daily life. In this experiments, we divide daily life activity into 8 levels of activity strength. Then investigate whether training model can recognize the 8 levels. These 8 levels can be divided into four groups: Weak, Normal, Strong, Very strong. Each group has two levels(Table 1).

In the experiment, We used ”clapping” with different BPMs to emulate activities of different activity strength. The subject repeats ”clapping” according to the rhythm of the metronome, and the clapping speed (BPM) was divided into 8 levels of 20, 30, 50, 60, 80, 90, 110 (Table 1). Recognition of activity strength by the clapping speed may be far from the activity seen in real life. But it can be said that it is useful in analyzing whether the proposed system can recognize the difference in activity strength.

During the experiment, the subject entered the room alone, clapping 3 minutes at the specified place & BPM. This experiment was carried out at three locations as shown in (Fig.2). Therefore, we collected 24 types of data because there are 8 levels of activity strength and 3 locations A, B, and C, respectively.

For each position, activity intensity pair, about 10800 binary data were collected in 3 minutes. This is because the sensor transmits about 60 binary data per second.

(Table1) shows the results of activity recognition. The Accuracy means the average of results of 5-fold cross-validation.

Table 2 Results for activity recognition

Sliding window size	Accuracy (8 level)	Accuracy (4 level)
1	0.3670198327763662	0.537870056823996
10	0.4860297621963984	0.659569824464507
50	0.7242130501491816	0.841165182305762
100	0.8449042738348481	0.926949490225002
250	0.9451847517519759	0.984946492162393
500	0.9801224894596082	0.998387801817130
1000	0.9954421602665963	0.999995018754389

4.2 Location recognition

Next, using the same dataset, we conducted location recognition. There are 8 kinds of data pairs position, activity strength for each location. That is, for each location, it has about 86400 binary data because each location has 3 minutes x 8 = 24 minutes data.

Table 3 Results for location recognition

Sliding window size	Accuracy
1	0.997717250555113
10	0.999964367319487
50	1.000000000000000
100	1.000000000000000
250	1.000000000000000
500	1.000000000000000
1000	1.000000000000000

The results are shown in (Table 3). Location recognition requires less sliding window size to obtain the good results than activity recognition.

5. Conclusion

From experimental results, the sensor array can be useful for constructing privacy preserving smart home. For future work, we will estimate more complex locations and activities, and investigate how to recognize location and activity in real time.

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