

Sleep-pose Recognition Based On Pyroelectric Infrared Sensing Technology

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Abstract— In this paper, an innovative method based on Pyroelectric Infrared sensing is proposed for sleep-monitoring. First, a pyroelectric infrared sensor is used to receive the infrared radiation emitted from a human body. Then we extract the motion information by analyzing the features of analog signal, which is outputted from the pyroelectric infrared sensor. At last, the nearest neighbor algorithm based on modified Hausdorff-distance is employed to achieve the sleep position recognition. The experimental results show that the biggest correct classification rate of this method reaches 83.55%. This new method provides a nonintrusive way of sleep position recognition for sleep-monitoring.

Keywords—pyroelectric infrared sensor, modified Hausdorff distance matching, sleep position recognition

I. INTRODUCTION

Sleep is a necessary life activity for human, which occupies about one-third of their lifetime. In fact, the physical fitness is greatly affected by sleeping, while good sleep quality is the guarantee to regain strength and keep fit. Therefore, in the actual life, the monitoring and analysis of sleep is great meanings to promote health condition.

At present, the detection on respiration and heartbeat are the mainly ways to realize sleep-monitoring [1]. In clinical, this kind of sleep monitoring equipment is widely applied, which is goal-oriented, accurate and repeatable. However it has several drawbacks, such as the complexity, cumbersome operation, poor portability and expensiveness. Moreover, in order to gather the signal, it needs multiple electrodes to contact the body, which will bring great inconvenience and distress to patients.

Pyroelectric Infrared (PIR) sensor can detect the change of infrared radiation in a non-contact way, which is highly sensitive to the body movement. The sensor has following advantages such as wide range of application, concealment and ambient light interference resistance. The early application and research of the PIR sensor mainly concentrates on the body localization and tracking. Reference [2] detects the quantity, localization and motion of the body in the indoor environments by applying 8-unit PIR sensor array. Reference [3] detect the indoor location of body through an array, which consists of 5 pyroelectric sensors, and the correct recognition rate of the region is over 95%. Domestic researches in this area start relatively late, and the initial stage of research focus on object monitoring and applied extension. In fact, the specific information of the PIR output signal has not been fully utilized until the details attract the researchers' attention in recent years. Reference [4] applies the theory of compressive sensing (CS)

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to the mask design. Classify body motions with combination to the Gaussian Hidden Markov model, and the overall average recognition rate is higher than 90%.

Based on what have been mentioned above, this paper puts forward the application of PIR sensing technology to sleep-pose recognition. The results can be further used for sleep monitoring, routine activities monitoring and sleep quality assessment. All of which has broad application prospects in the home-pension field.

II. THEORY AND MODEL

The human body usually has a steady thermal radiation, and continues to have a heat exchange with the external environment[5]. The motion of the human body will creat a change of thermal radiation, and the PIR sensors can effectively detect it so as to implement an effective awareness of the motion.

A. Acquisition of sleep position signals

Fig. 1 shows a human body perception system model of the sleep-pose recognition based on PIR sensing.

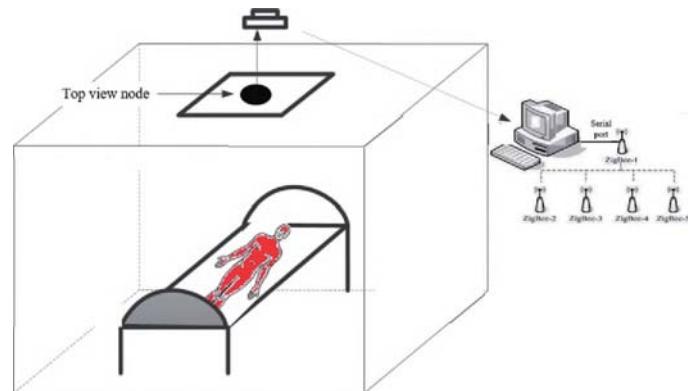


Figure 1. PIR sensing model bases on the top view.

The PIR node installed on the ceiling could carry out an infrared-sensing on the human body.

The device shown in Fig.2 is a sensor module used in this paper. It includes a PIR sensor and a hemispherical Fresnel lens in 8005 type, which could effectively enlarge the sensing area to a 100° cone area. In addition, the module also includes some hardware modules for signal processing.

And the PIR sensor will transform the motion information into a sequential temporal sequence. Then the information could be transferred to the computer for subsequent processing through the wireless transmitter module on the node.

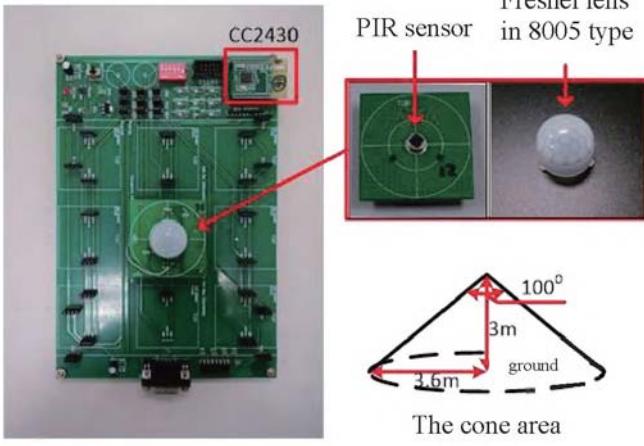


Figure 2. The top view node perception module.

Reference [6] establishes an action database, which defines 10 types of sleeping posture, as shown in table 1.

TABLE I. ACTION DATABASE

Action name	Action Specification
Waving left hand(M1)	Swing the left hand from the outside to the shulder
Waving right hand(M2)	Swing the rigth hand from the outside to the shulder
Waving hands (M3)	Swing the hands from the outside to the shulder
raising left hand(M4)	Swing the left hand from the outside to the chest
Raising right hand(M5)	Swing the rigth hand from the outside to the chest
Raising hands(M6)	Swing the hands from the outside to the chest
Raising left leg(M7)	Raising the left leg and getting it straight
Raising right leg(M8)	Raising the right leg and getting it straight
Rolling over to left(M9)	Rolling over to left and restoring
Rolling over to right(M10)	Rolling over to right and restoring

All movements need to be completed within the confined space, and keep the other parts of the body stationary. The 10 kinds of actions mentioned above have different dimensions of representativeness, and involve the alternating motion of sleep position through the whole body.

B. Sleep position recognition algorithm

Hausdorff distance is a lightweight tool measuring the similarity of different sequential sequences. It can overcome the time length variation and sequential skew among different sequences, and implicitly contain the constraints on the temporal relationships. Therefore, the hausdorff has been widely used in matching recognition of sequential sequences [7, 8].

This paper adopts the nearest neighbor identification method based on modified Hausdorff distance to determine the action category of the test sequence, where the discriminant process has been shown in Fig. 3.

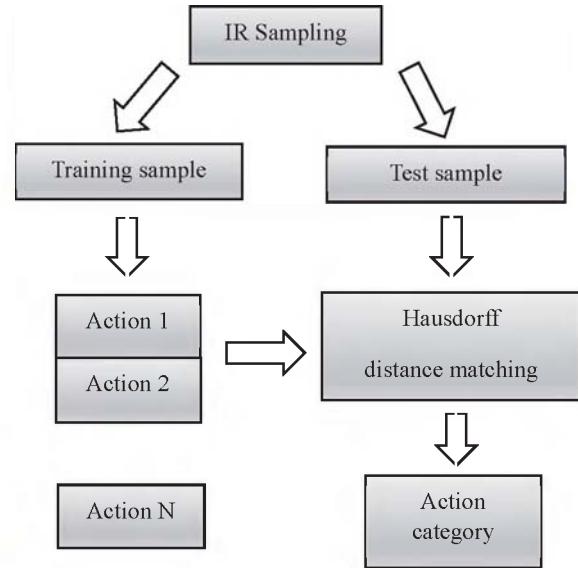


Figure 3. Decision process of action category based on Hausdorff distance matching.

Supposing that the training samples are indicated by set $A=\{a_1, \dots, a_{N_a}\}$, the test samples are indicated by set $B=\{b_1, \dots, b_{N_b}\}$. The distance between point a and point b is defined as Euclidean distance $d(a, b)=\|a - b\|$. The distance between sample point a and set $B=\{b_1, \dots, b_{N_b}\}$ is:

$$d(a, B)=\min_{b \in B} \|a - b\| \quad (1)$$

The distance between sample point b and set $A=\{a_1, \dots, a_{N_a}\}$ is:

$$d(b, A)=\min_{a \in A} \|a - b\| \quad (2)$$

The average directed Hausdorff distance between the two sample sets is:

$$d(A, B)=\frac{1}{N} \sum_{a \in A} (a, B) \quad (3)$$

$$\text{Similarly: } d(B, A)=\frac{1}{N} \sum_{b \in B} (b, A) \quad (4)$$

Taking the maximum value of the both distance, we can obtain the formula for calculating the corrected undirected Hausdorff distance:

$$hd(A, B)=\max(d(A, B), d(B, A)) \quad (5)$$

The pre-processed training samples of different action categories were treated as the reference templates and stored in the action database. We simply need to compare the elements of test sample set with the referential templates of action database. Then adopt the nearest neighbor criterion to judge the action categories, and the nearest decision criteria are shown as follows:

$$M=\operatorname{argmin} hd(A_n, B), 1 \leq n \leq N \quad (6)$$

Where M is the recognition result of the action category, and N is the total number of action categories.

III. EXPERIMENTAL AND DATA ANALYSIS

A. Collection of experimental samples

The experiment system of sleep position recognition has been shown in Fig. 1, where four pyroelectric infrared sensors

are installed on the top view node. Then fix the sensor nodes on the ceiling, opposite the experimental bed. The ceiling is 3 meters from the ground, and the sensor is about 2 meters from the human body.

In the actual experiment, the sampling frequency of the system is set to 10Hz. Generally speaking, each action process lasts about 5 seconds at the normal action rate. Therefore, there will roughly be about 50 valid signal sampling points of each action. In addition, we fix four PIR sensors on the sensor nodes and acquire the action information.

During the data acquisition phase, we invite 10 volunteers differing from genders, height and weight to participate in the experiment. The height of volunteers who participated in the experiment is roughly between 165cm and 185cm, and the weight is roughly between 45kg and 75kg. The 10 volunteers will repeat each action 10 times at a normal rate, so that 100 samples of each action could be obtained for training and testing.

The original output voltage signal of the sensing system, which is based on the PIR sensor, is a sequential sequence. In the experiment, the first volunteer repeated waving his hands 11 times, and we collect the original output voltage signal of the PIR detector. The wave figure of output voltage signal has been shown in the Fig. 4.

According to analyse the wave figure shown in Fig. 4, it can be concluded that: as for a kind of experimental action of an experimental volunteer, when the same kind of experimental action has been repeated 11 times, the wave figure obtained by the same PIR sensor in each sections are similar. However, the waveform features exist difference owing to the different PIR output signals.

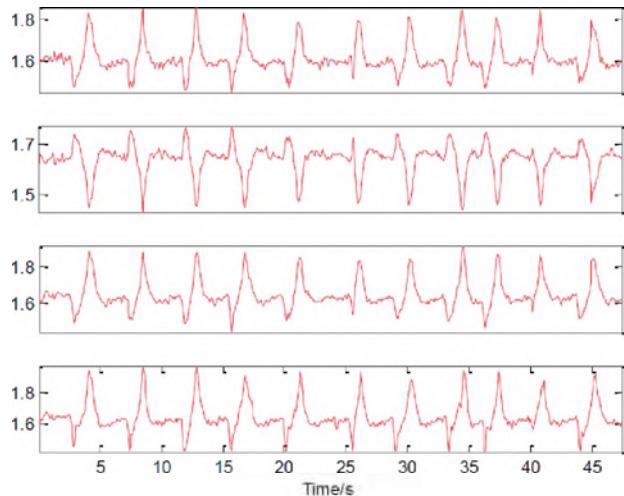


Figure 4: PIR sensor original output waveform corresponding to the action "waving hands".

Fig. 5 shows the wave figure of PIR detector output voltage, which is obtained by the first volunteer making 10 kinds of movement. By analyzing the signal wave shown in the following figure, it can be concluded that: as for the different kinds of action of an experimental volunteers, the voltage output signal wave figure comes from one PIR sensor are different.

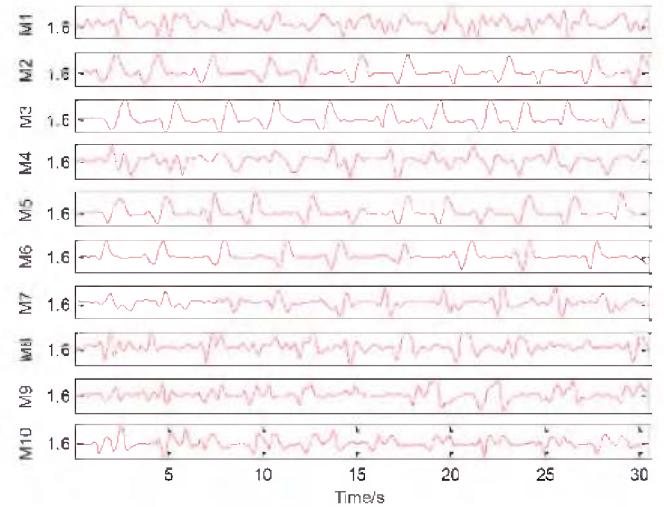


Figure 5: PIR sensor output voltage signal oscilloscope for action M1-M10.

Above all, it's agreed that the original output voltage sequence of the sensing system based on PIR sensor can be used as the action feature for sleep position recognition.

B. Data analysis

In order to realize the sleeping position detection, the first step is to randomly extract half of the samples in each action. Then using the samples for training to construct the sleep position database. Besides, the other half samples will be used for test. We obtain the statistical analysis result after 50-times cross matching.

According to the results of the experiment, we can obtain the average modified Hausdorff distance between each test action sample and other training action samples as shown in Fig. 6. From the graph, it is intuitive to show the difference of the average modified Hausdorff distance between each action and the other actions. The minimum value of average modified Hausdorff distance can be obtained only when we compare the action test sample with training sample of the same kind of action.

In addition, it's obvious that most test samples of action M1-M6 can be recognized correctly by analyzing Fig. 6. However, as for action M7 and M8, the average recognition rate is relatively low and there exists a certain degree of misjudgment. The main reason is that most of the information of such two actions centres on the vertical plane. Since the infrared sensing node of the top view is not sensitive to such motion information, the possibility of misjudgment has been raised. Therefore, it's advisable for us to conduct an infrared motion perception from different perspectives. The action M9 and M10 are relatively complex, which not only include the movement information of hands and legs, but also the rotational information of human body. So there exist some different degrees of misjudgment and the average recognition rate is relatively low.

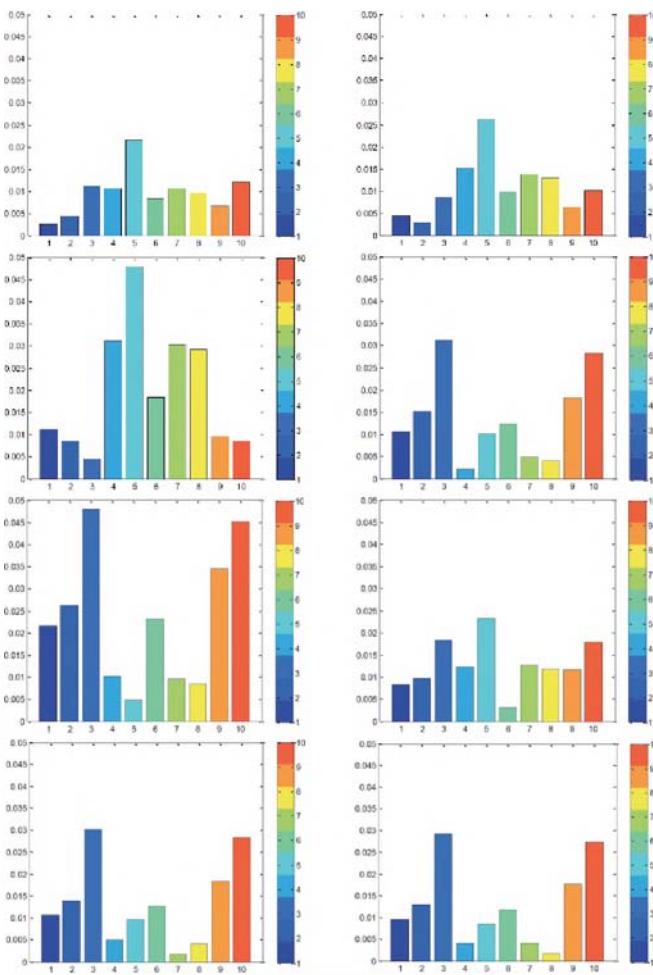


Figure 6: Average modified Hausdorff distance comparison results.

Fig. 7 presents the recognition rate confusion matrix, where each row of the matrix represents a category of action to be detected, and the figure of each column represents the ratios that the testing samples are recognized as corresponding class. Besides, the element of the diagonal indicates the correct recognition rate, while the remains indicate the error rate.

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10
m1	82.28%	4.33%	3.61%	1.33%	1.28%	3.86%	3.79%	3.33%	7.69%	4.13%
m2	5.56%	82.36%	4.22%	0.88%	0.93%	2.22%	2.22%	2.28%	6.22%	5.96%
m3	1.93%	2.47%	80.56%	0.22%	0.22%	0.16%	0.14%	0.18%	3.85%	7.28%
m4	2.15%	1.68%	0.78%	83.55%	4.12%	1.45%	3.55%	3.46%	1.33%	1.47%
m5	0.39%	0.67%	0.32%	1.35%	82.33%	0.12%	1.67%	1.94%	0.56%	0.56%
m6	2.69%	1.19%	1.35%	1.12%	0.53%	81.73%	1.52%	1.28%	2.28%	2.28%
m7	0.83%	1.92%	0.92%	4.88%	4.35%	3.52%	80.04%	5.39%	1.49%	1.41%
m8	0.96%	1.96%	1.03%	5.98%	5.67%	3.46%	5.46%	80.8%	1.59%	1.67%
m9	2.58%	1.59%	3.39%	0.44%	0.31%	3.33%	1.43%	1.16%	71.48%	5.59%
m10	0.63%	1.83%	3.82%	0.25%	0.26%	0.15%	0.18%	0.18%	3.51%	69.65%

Figure 7: Recognition Rate Confusion matrix.

According to the analysis on the confusion matrix: most test samples of action M1-M8 could be recognized correctly, where the average recognition rate is slightly low for action M7, M8. As for action M9 and M10, the average recognition rate is relatively low and there has been a certain degree of misjudgment. Generally speaking, the analysis results are consistent with the histogram analysis.

IV. CONCLUSION

PIR sensor is an effective tool to collect human motion signals. This paper presents a new mention for sleeping position detection which is based on PIR sensing technology. This mention makes full use of the advantages of PIR sensing technology, which could directly extract the targets' motion feature and spatial information, reduce the calculation capacity, simplify configuration and protect user privacy. The experimental results show that, according to the sequential temporal sequence of PIR sensing system output and combination to the nearest neighbor recognition algorithm for modified Hausdorff distance, we can monitor the human sleeping position by analyzing simple sensor voltage signal. However, the method still has a certain gap from actual application requirement in the following aspects such as speed detection and correct recognition rate. As for the follow-up studies, the focus can be put on how to improve the average recognition rate of recognition, and the on-line process to improve the practicability of the sleep position recognition based on PIR sensor.

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