Fusion of Different Height Pyroelectric Infrared Sensors for Person Identification

Ji Xiong, Fangmin Li, and Jian Liu

***Abstract*— Due to the instability and poor identification ability of a single pyroelectric infrared (PIR) detector for human target identification, this paper presents a PIR detection identification system that can collect thermal infrared features from different parts of human targets through multiple PIR sensors for the human identification. First, fast Fourier transform, short-time Fourier transform, and wavelet packet transform algorithms are adopted to extract thermal infrared features of human targets. Then, the canonical correlation analysis algorithm is used to fuse different algorithm features in the feature layer. Finally, using the support vector machine to classify the human targets. In the decision-making layer, the Dempster/Shafer evidence theory is adopted to optimize the recognition results from different PIR sensors that locate at different height positions. Extensive experimental results demonstrate that the fusion of feature layer data could improve the average recognition rate of the human target with closer distance from the single sensor. In addition, the fusion of decision-making layer could improve the recognition ability of the identification system as well. When the detection distance is 6 m, the correct recognition rate of fusion system is still reached 88.75%. Compared with the system using a single sensor, the recognition rate is increased by an average of 22.67%.**

***Index Terms*— Pyroelectric infrared (PIR) sensor, feature extraction, support vector machine (SVM), canonical correlation analysis (CCA), Dempster/Shafer evidence theory (D-S).**

I. Introduction

PIR sensor has a very good ability to detect infrared radiation (8∼14μm) of the human body, and it has the characteristics of small size, low power consumption and low cost. Through the analysis of sensor output signal, the PIR system can realize the identification for different human body. Comparing to the traditional video-based image recognition system, the recognition rate of PIR sensor system is lower than the video system. However, it needs high speed processing equipment in the video system, which is greatly restricted to many external factors such as lighting, angle or clothes. In addition, it usually requires high computational overhead and huge data throughput. The PIR sensor recognition system, therefore, has obvious advantages in some scenes which need less demanding of recognition accuracy. Now more and more researchers have been paying attention to this area, which has become an emerging biometric identification technology.

In recent years, with the sustainable development of the sensor technology, distributed inference and learning technology, human behavioral information can be measured by passive (e.g., "thermal and pressure") or active sensors (e.g., "ultrasound and laser"), spatially distributed sensor nodes with computation and communication capabilities can work together to achieve complex task. Therefore, researchers have attempted to develop many new applications relying on pyroelectric infrared sensor [1]. In order to identify human targets, the pyroelectric infrared sensor has various advantages as follow [2], [3]:

1) Reducing the required number of measurements and sampling frequency for human motion state estimation.
2) Reducing the hardware cost, power consumption, privacy, infringement, computational complexity and networking data throughput.
3) Reducing the time consumption of system deployment and limitations upon applications or application locations (e.g., "long, range or crowded scene").
4) Its performance is independent of illumination and has strong robustness to the color change of background.
5) Its sensitivity range of angular rate is about 0.1 r/s to 3 r/s, and it can cover the walking speeds of most human at around 2 m/s.
6) It can obtain better field of view (FOV) combined with low price Fresnel lens array. Thus, comparing with the traditional video system, the distributed wireless pyroelectric sensor network can provide better spatial coverage and reduce the time and place restrictions of system deployment.

The advantages of the wireless distributed pyroelectric infrared sensor system include the convenient deployment of multiple sensors for collecting measurements from multiple perspectives. By using multiple sensors, the human motion features can be accurately captured and utilized for the higher-security applications where walker verification or open-set identification is required. A typical unmoral biometric system consists of three modules: feature extraction, matching, and decision. Feature extraction is used to describe the most important information of the sensor data (samples). Matching modules compare captured features with templates in the database and output a score to the decision module. Therefore, the information fusion of multiple pyroelectric sensors for

Manuscript received February 8, 2015; revised June 12, 2015; accepted June 12, 2015. Date of publication July 8, 2015; date of current version December 22, 2015. This work was supported by the National Science Foundation of China under Grant 61170090. The associate editor coordinating the review of this paper and approving it for publication was Prof. Jun Ohta.

J. Xiong and F. Li are with the Key Laboratory of Fiber Optical Sensing Technology and Information Processing, School of Information Engineering, Ministry of Education, Wuhan University of Technology, Wuhan 430070, China (e-mail: xiongji@whut.edu.cn; lifangmin@whut.edu.cn).

J. Liu is with the Department of Electrical and Computer Engineering, Stevens Institute of Technology, Hoboken, NJ 07030 USA (e-mail: jliu28@stevens.edu).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/JSEN.2015.2454000

thermal gait biometrics is needed at four different levels: sample, feature, score, and decision.

This paper uses the distributed pyroelectric infrared sensors as a source of information collection in specific environment. Referred to Hao *et al*. [4], our system consists of four PIR sensor modules that locate at different heights, a data processing node, a wireless gateway and a host computer. And each sensor module consists of a pyroelectirc infrared sensor, a Fresnel lens and a signal modulation mask. Each sensor is covered by the Fresnel lens and the signal modulation mask. Once a human target moves in the area of sensor sensing, the infrared radiation of the human target can be captured and transformed into electrical signal which can be transmitted to the host computer to be further processed through the wireless gateway after preliminary noise reduction and data compression.

However, before using the distributed wireless pyroelectric infrared sensor network in the process of identification of motion human target, much attention should be paid to such items as follows:

1) Different Fresnel lens and signal modulation mask can obtain different human pyroelectric infrared information.
2) The four sensors are installed in different heights, which can collect different pyroelectric infrared information from different parts of human body.
3) The effective data is fused by multiple channel signals which are collected from four sensor modules.
4) Extracting different pyroelectric infrared features of human target by different algorithms can help establish different target identification models in database.

In this paper, the major goal of our work is to develop a wireless distributed pyroelectric sensor system and propose a novel way, which can precisely identify human target in a confined area. With the increasing distance between pyroelectric sensor and human target, the target recognition rate of a single sensor module is showed downward trend. Thus, a novel fusion algorithm to fuse the data of pyroelectric sensors of different heights is proposed to improve recognition rate. Firstly, FFT, STFT, and WPT are used to extract the pyroelectric feature of human body, which is detected by a single PIR sensor. Then reduce dimensionality of pyroelectric feature of human target through the PCA. And the preliminary recognition rate of a single sensor module will be obtained by using the SVM algorithm. Finally, The Dempster/Shafer evidence theory is applied to fuse the preliminary recognition rate of four PIR sensor modules, and get the final recognition result. Because the four sensors in different heights, so they have different identification abilities for human target. This paper uses CCA algorithm to fuse different features extraction algorithms and chose the best identification result as input data of the decision-making layer, it overcomes the shortcoming of the single sensor in the collection of the thermal infrared data. The experiment proves that the scheme had stronger robustness for the human height and the detection distance between the human target and the pyroeletric sensor.

The rest of this paper is organized as follows. In Section II, we introduce related work, based on the pyroelectric sensor technology. Section III introduces the sensor module and deployment. Section IV presents a human target recognition system. Section V presents a novel recognition strategy. Section VI presents the experimental results with the collected data. Finally, this paper analyzes experimental results of our methods, and discusses the development direction of our methods at conclusion section.

II. Related Work

The PIR sensors are widely used in surveillance systems and automatic light switching systems as simple but reliable triggers [5], [6]. They also have shown promising capabilities as low-cost camera enhancers in video surveillance systems [7], [8]. Tao *et al*. [9] presents a person localization algorithm using an infrared ceiling sensor network for providing various personalized services in an office environment. This paper demonstrates the benefits of reducing camera deployment in favor of the PIR sensors.

Other works present different approaches to perform people tracking and identifying using PIR sensors. In terms of tracking, Hao *et al*. presents a kind of wireless pyroelectric infrared sensor tracking system which is composed of three modules, namely: sensor modules, an error filtering module and a data fusion module. The pyroelectric infrared sensor module in this system has ability to detect the angular displacement of motion human target in the network. Combined with adjustable FOV, which is realized by the Fresnel lens array, the single human body in the system can be tracked successfully [10].

Shankar *et al*. [11] develops a human tracking system using a low-cost sensor cluster consisting of PIR sensors and Fresnel lens arrays to implement the desired spatial segmentations. They analyze the response characteristics of the sensor cluster, and extract velocity and the direction of motion over large areas of over 12 m. Luo *et al*. [12] uses four sensor modules, each consist of five PIR detectors, are mounted on the ceiling of a monitor field to fix the position of a moving human target. In addition, Kalman filter is adopted to improve the tracking accuracy. Zhao *et al*. [13] presents a novel method which selects the maximum likelihood function of the Bayesian network models as the independent criterion to blindly estimate the number of motion multiple human targets. For the first time, using blind signal separation technology for human pyroelectric signal.

In terms of recognition, Fang *et al*. presents a human identification system using a PIR sensor whose visibility is modulated by a Fresnel lens array and principal components regression method. They also present a method for identifying subjects walking randomly using PIR sensors with modulated visibilities and Hidden Markov Models [14], [15]. Guan *et al*. [16] represents a human motion as a spatio-temporal energy sequence and extract it from an infrared radiation domain, and use a compressive sensing approach for motion classification by the PIR sensors.

Sun *et al*. [17] builds a distributed binary pyroelectric sensor network (PSN) for the purpose of multi-walker recognition and tracking. They accurately extract context features from a hybrid, binary, multi-walker sensor data stream to identify and track multi-walker and achieve good results, the four

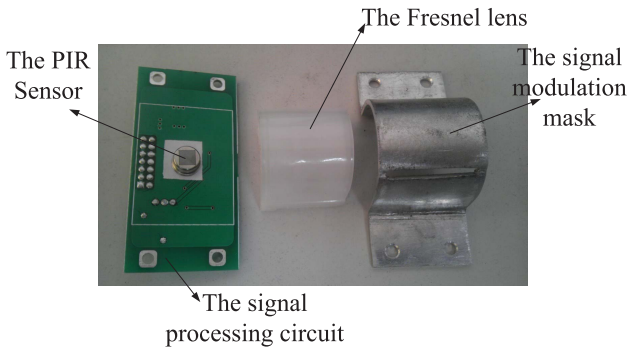


Fig. 1. The pyroelectric infrared sensor module is covered by the Fresnel lens and the signal modulation mask.

scenarios with 100% success rate. Hu *et al*. [18] proposes to use binary principle component analysis (B-PCA) to interpret the relationship between observed sensor data and hidden context patterns, and conducted comprehensive experiments from real sensor data to verify the context detection accuracy. Sun *et al*. [19] proposes a statistical subspace representation model called probabilistic nonnegative matrix factorization (PNMF) to seek the scenario patterns rather than the object characteristics. They also further prove that their PNMF model is a generic model for Nonnegative Matrix Factorization (NMF) based algorithms [20]. Experimental results demonstrate the advantages of their proposed method.

In this paper, a novel application is proposed that multiple pyroelectric infrared (PIR) sensor modules are utilized to collect pyroelectic data from different parts of human body. And various algorithms are applied to extract thermal infrared feature of different parts of the human body, then the decision-making layer algorithm is used to fuse multiple recognition results of the four sensors to get final human identification. Through the experiment, we have analyzed the pyroelectric characteristics of different human targets and different paths. It proves that the proposed characteristic extraction, fusion and recognition methods can effectively remedy recognition deficient of single PIR sensor.

III. Sensor Modules and Deployment

In order to design a wireless network platform based on the PIR sensors, we study the design method for various video sensor platforms. Referring to the system which was set up by Hao in [10], we build a distributed pyroeletric infrared sensor network with several sensors, a wireless gateway and a host computer to detect and identify motion human target.

A. PIR Sensor Module

With relatively stable performance, the LiTaO3 film pyroelectric infrared sensor is chosen as the detecting sensor in our system. Due to the lower receiving sensitivity of the sensor itself, every signal sensor node is covered by a Fresnel lens as shown in Figure 1. It can not only focus the infrared heat of human to the sensor, but also can increase the angle and detectable distance. It is proved in some experiments that the effective detectable range is 2 meters to one of 12-14 meters.

TABLE I

Parameters of D205B Pyroelectric Infrared Sensor

Parameters	Value
IR Receiving Electrode	0.7×2.4 mm, 4 elements
Sensitivity	⩾4300 V/W
Detectivity (D*)	1.6 ×108cmHz$^{1/2}$/W
Supply Voltage	3-15 V
Operating Temp	-30-70 °C
Offset Voltage	0.3-1.2 V
FOV	150°

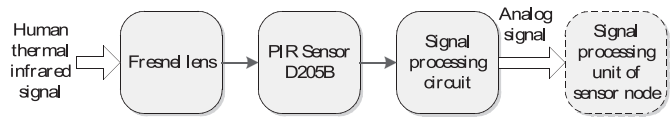


Fig. 2. Human thermal infrared signal processing in a PIR sensor module.

Based on the parameters and characteristics of the D205B sensor are shown in Table I, the PIR sensor module is designed as shown in Fig. 1.

As shown in Fig. 2, the original thermal infrared signal of human target can be converted into analog signal through three steps. Firstly, the original human thermal infrared signal will be focused on the pyroelectric sensor by using Fresnel lens. Then, the infrared signal is converted into weak electrical signal by PIR sensor. Finally, the analog signal can be obtained after the signal processing unit.

B. PIR Sensor Node

The PIR senor node consists of four sensing units (PIR sensor module), a processing unit, and a communication subsystem. The sensing unit is usually composed of a PIR sensor, an amplifier and an actuator. The analog original signal captured by the sensor module is primarily amplified by the amplifier, and then it is converted to digital signal by the ADC (Analog to Digital Converter) module. In the processing unit, the STM32 CPU has embedded 256kB of flash memory and 48kB of RAM for program and data. And all the coordinating sensing and communication tasks are executed by this 32-bit CPU at 72MHz. The memory subunit can store sensing data in a period of time. The communication subsystem interfaces the device to the network composed of a transceiver subunit and a processing circuit.

The processed signal is sent to the wireless gateway by communication subsystem on the basis of Zigbee protocol in the specified interval. Moreover, the whole system is powered by a power unit that may be supported by an energy scavenging unit such as solar cells. The physical device is shown in Fig. 3.

C. Gateway Module

A gateway module is composed of four wireless modules units, a STM32 processor and a gateway unit. The infrared signals of human target, which are detected by each sensor node, are all transmitted to the wireless modules CC1100 in the specified interval. Because the four wireless modules have four kinds of different channels and connect with the

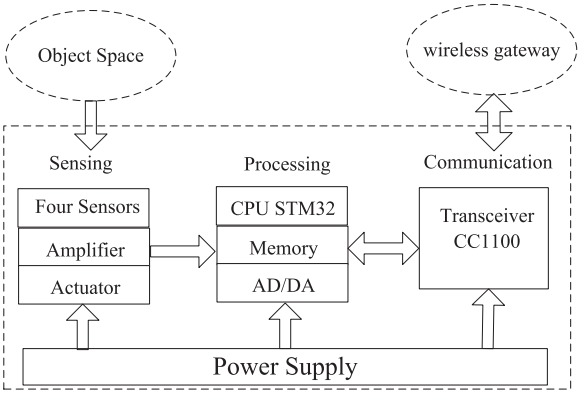


Fig. 3. The composition of the PIR senor node.

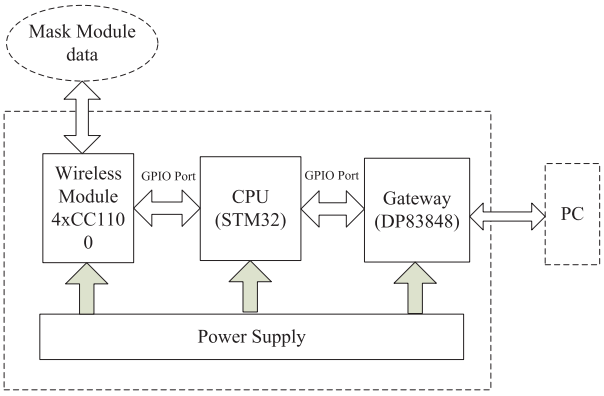


Fig. 4. The composition module of the wireless gateway.

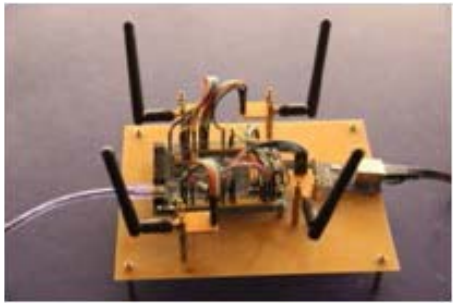


Fig. 5. The wireless gateway module.

STM32 processor by GPIO (General Purpose Input Output), the STM32 processor can independently process the different data from the sensor nodes, and it can also complete wireless data acquisition at the same time. Moreover, the sensed data will be transmitted to the host computer through Ethernet interface for further processing and display. The whole structure and physical photo of the implemented wireless gateway module are shown in Fig. 4 and Fig. 5 respectively. And the whole system is also powered by a power unit.

IV. Target Recognition System

A. System Architecture

The target recognition system consists of two parts, namely a data acquisition part and a data processing part. The data

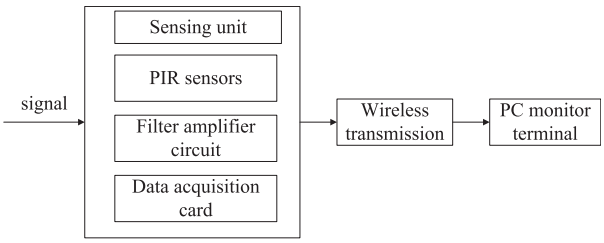


Fig. 6. Data acquisition flow chart.

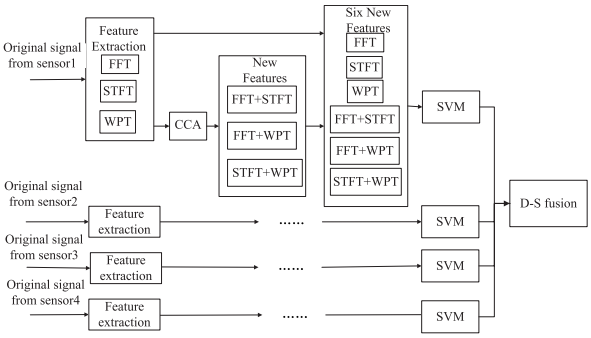


Fig. 7. Algorithms chart.

acquisition part is divided into three units: a sensing unit, a wireless unit, a PC monitor terminal unit. When the target enters the detection area, the infrared signals being emitted by the human body will converge to the PIR sensors through the aluminum mask and the Fresnel lens, and then the signals will be turned into electrical signals. The electrical signals are filtered and amplified, and they would be converted to digital signals by the A/D converter circuit. Through the point to point data transmission between the wireless unit of PIR senor node and the wireless unit of gateway, the data will be transmitted to the PC software by the gateway based on the TCP/IP protocol. In this paper, the QT4.7.4 software platform is used to develop the PC software primarily designed for data reading, storing and waveform drawing. The process of data collection is shown in Fig. 6.

The data process part is mainly composed of three parts: feature extraction, feature matching and feature determination. In the feature extraction unit, this paper adopts FFT, STFT, and WPT, which are used to extract the characteristics of sample data. Then we use SVM algorithm to classify and match the sample data in order to get a preliminary recognition rate and we can also analyze the effect on recognition rate caused by the different installation heights of the sensors and the distance between the human target and the PIR sensor node. Based on these factors, the D-S algorithm is used to fuse the recognition data from four different sensors as the final recognition result.

The data process system is shown in Fig. 7. For the single PIR sensor, the original signal will be separately extracted by three different algorithms, which include FFT, STFT, and WPT, for getting three eigenvectors. Then the CCA is used to fuse the pair feature, and the formation of three new features. The SVM is used to process the data of six different features for the recognition result of the single sensor. Based on the

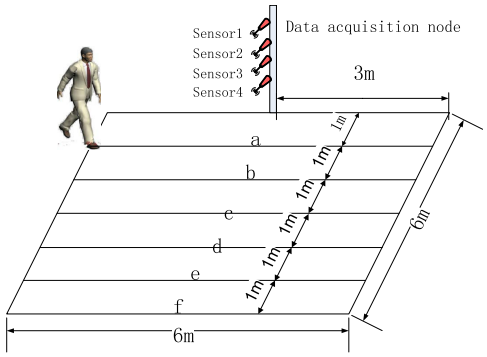


Fig. 8. Experiment scene.

TABLE II
ATTRIBUTE FEATURE OF EXPERIMENT OBJECT

Object	Sexuality	Height	Step distance
A	male	175cm	50cm
B	male	167cm	40cm
C	female	160cm	40cm
D	male	182cm	60cm
E	male	172cm	50cm
F	female	158cm	37cm
G	female	162cm	40cm
H	male	179cm	56cm
I	male	173cm	50cm
J	female	171cm	52cm

output recognition result of the four PIR sensors, different weights will be assigned to the data. Then the D-S theory is used to fuse the recognition result of each single sensor. And we will obtain final recognition rate.

B. Experimental Program

The test model is shown in Fig. 8, in which the size of the area is 6m×6m, and the sensors heights are 0.4m, 0.8m, 1.2m, and 1.6m respectively. The different height sensors aim at obtaining different features of human target. More specifically, the 0.4m corresponds to the part of the human knee, the 0.8m refers to the human hand swing, the 1.2m refers to the human chest and the 1.6m refers to the human head. In the experiment, the test objects are ten health young students aged at 23-24 years old. The heights of different human bodies are shown in table II. Some test objects were respectively asked to walk along the six lines of a, b, c, d, e, and f at the normal speed and walk 10 times per line.

There are two factors to impact on the human recognition rate: the height of sensors location and the vertical distance between the PIR node and walking path. What's more, in order to improve the system recognition result, we use various fusion methods to solve this problem.

V. ALGORITHM DESCRIPTIONS

The proposed algorithm can be divided into three modules: a feature extraction module, a SVM classification module and a D-S Algorithm fusion module [21]. The architecture is shown in Fig. 7. In this paper, firstly, the characteristics of original signal are extracted. Then, through SVM classifier, the signals are further processed and get the recognition result of each sensor. Finally, the D-S Algorithm is used to fuse the preliminary recognition result of the four different sensors to obtain the final results.

In the feature extraction section, the three different algorithms are used, namely FFT, STFT, and WPT. It aims to verify and compare the recognition results of different sensors under the various feature extraction algorithms.

A. Feature Extraction

Because the feature extraction directly affects the final recognition result, this paper uses a variety of algorithms for accurately extracting features.

1) FFT+PCA: From the sample signals, we can obtain the amplitude spectrum through the fast Fourier transform. High spectrum dimension can reduce classifier performance. The PCA (Principal Component Analysis) method is adopted to reduce the dimension of spectrum data.

X is the N times observations of p variable, $X = [x_1, x_2, x_3 ... x_n]^T$, $x_{1:n}$ is a row vector of p dimension which means the spectrum characteristics of each sample, p is the number of the spectrum points. PCA algorithm is described as below [22]:

Standardizing the observation matrix X to obtain matrix Y;

Calculating Z which is the covariance of matrix Y;

Calculating the covariance matrix eigenvalues and eigenvector of Z, and make $\lambda_1 \geq \lambda_2 \geq \lambda_3 \geq \lambda_4 \geq \cdots \geq \lambda_p$, the corresponding eigenvectors are $U_1, U_1, U_1, \cdots, U_p$, covariance matrix Z can be expressed as.

$$Z = U \Lambda U^T \tag{1}$$

Λ is a diagonal matrix, the elements on the diagonal are eigenvalues from large to small. U is a feature vector according to the orthogonal array. Then, computing principal components, namely the new variable matrix.

$$F = Y_{n \times p} U_{p \times m} \tag{2}$$

Each row vector of F matrix means a sample, its dimension drops from p to m.

2) STFT: The time-frequency matrix str is acquired after short time Fourier transform (STFT) of the sample signal. The signal time-frequency matrix describes the characteristic of amplitude distribution in a quite wide range from low frequency to high frequency comprehensively. Each element represents the amplitude on corresponding moment and corresponding frequency. It aims to get the number of singular value from large to small by singular value decomposition (SVD) [23]. A larger singular value contains the larger information of the matrix str. The SVD algorithm is described as follows:

$A_{m \times n}$ is the sample matrix, there are orthogonal matrix $U_{m \times n}$ and $V_{m \times n}$. In this paper, the $m = 20$, $n = 300$.

$$A = U \Sigma V^T \tag{3}$$

Among, $S = diag(\sigma_1, ..., \sigma_r)$, $\sigma_1 \geq \cdots \geq \sigma_r$ is the singular value of A.

3) WPT: The signal will be decomposed with five-layer wavelets for the wavelet packet coefficients [24]. Then we will get the spectrum features of each coefficient-reconstructed signal by FFT algorithm. And the bior wavelet is also chosen to analyze the data.

B. Feature Fusion and Recognition

1) CCA: In the feature level fusion method, we extract feature of the observed signal of each sensor separately in the three kinds of methods to get three different feature vectors. This paper uses the CCA [25] to fuse the three different feature vectors. Using the relationship between the two features characteristics as effective discriminated information, its algorithm steps are as follows:

We extract the three features according to the methods in section A. Here take A and B targets as example.

For the known characteristic signal A and B, the training sample $A_{m\times k}$ and $B_{n\times k}$ calculate the covariance matrix $\sum_{AA}$, $\sum_{BB}$ and $\sum_{AB}$, among them, m is the characteristic dimension of A, k is the number of training samples, n is the characteristic dimension of B.

Calculating the non zero eigenvalues of $\sum_{AA}^{-1}\sum_{AB}\sum_{BB}^{-1}\sum_{BA}$ or $\sum_{BB}^{-1}\sum_{BA}\sum_{AA}^{-1}\sum_{AB}$ and the corresponding standard orthogonal feature vector is u_i and v_i, $i = 1, 2, ..., r$;

Calculating the typical projection vector $\alpha_i = S_{AA}^{-1/2}u_i$ and $\beta_i = S_{BB}^{-1/2}u_i$, take d projection vectors of α_i and β_i to constitute transformation matrix $\sum_A$, $\sum_B$ and $\sum = \left[\sum_A \sum_B\right]$;

Linear transformation matrix $Z = \sum^T \begin{pmatrix} A_{m\times k} \\ B_{n\times k} \end{pmatrix}$ is used to calculate combination characteristic vector for classification.

Whereas achieve information fusion, and eliminate the redundancy between the features. Six groups of unite feature vectors are obtained by fusion these eigenvectors.

2) D-S: In the strategy layer, every sensor completes the transformation to get the independent identity estimates, and fusion of the different properties from each sensor. Fusion method based on the D-S algorithm [26], making a combination of the target identification feature that is obtained by different sensors. The algorithm steps are as follows:

$\mathrm{H} = \{h_i | i = 1, 2, ..., C\}$ is the human body model for testing. The system main consists of the four PIR sensors as $S = \{s_j | j = 1, 2, ..., N\}$, and $m_j^i(h_i) = p(h_i|s_j)$, which as belief function, $0 \le m_j^i(h_i) = m_j^i \le 1$, the larger m_j^i is the possibility of human target attribute which is obtained by the number j sensor, and belong to the number i human target is greater. Definite tags matrix as the human characteristics matrix of the PIR sensor collecting. h_i is the number of collecting output, and using the SVM algorithm as the judgment method. The $sum(i)$ represents the total samples of targets test experiment.

When $x < 0$, sign(x) $= -1$, $x > 0$, sign(x) $= 1$, $x = 0$, sign(x)$= 0$.

$$p(h_i|s_j) = sign(h_i|s_j)/sum(i), \quad i = 1, 2, 3, 4; \quad j = 1, 2, 3, 4 \tag{4}$$

Definition 1: we assume Θ to be the human target sample space, and the human features are mutually exclusive in Θ, calling Θ as identification framework. The target discriminate result of the PIR sensor collecting and processing human body thermal infrared signal as evidence. And as the basic probability assignment (BPA) function, which can be used by the SVM algorithm.

Definition 2: Given a confidence to all targets, the basic probability assignment function m can be mapped in the range of $2^\Theta \rightarrow [0,1]$, and to meet the $m(\Phi) = 0$, $\sum_{A\subseteq\Theta} m(A) = 1$. If $m(A) > 0$, then A is called focal element *Bel*, which represents the total trust degree of A. All focal element of the trust function *Bel* are jointed, which called nuclear, and $Bel(A) = \sum_{B\subseteq A} m_j(B)$.

Definition 3: Assume *Bel1* and *Bel2* to be the trust function, and there are BPA m_1, m_2, $\{A|A_1, A_2, \cdot\cdot\cdot, A_n\}$ and $\{B|B_1, B_2, \cdot\cdot\cdot, B_n\}$, assume that $\sum_{i=j, A_i\cap B_i} m_1(A_i)$ $m_2(B_j) < 1$. Then probability assignment function m is for all non empty A.

Where

$$Bel(A) = m(A) = \begin{cases} \dfrac{\sum_{i=j, A_i\cap B_j = A} m_1(A_i)m_2(B_j)}{1-K}, & \forall A \subset \Theta \text{且} A \neq \phi \\ 0, \quad A = \phi \end{cases} \tag{5}$$

Among them, $K = \sum_{i=j, A_i\cap B_j \neq \phi} m_1(A_i)m_2(B_j) < 1$.

3) SVM: SVM is a classification method based on statistical learning theory [27]. It adopts structural risk minimization principles to solve problems as limited samples, from nonlinearity and high-dimensional pattern recognition to a large extent. Input sample vector can be mapped to a high-dimensional space. Then, optimal linear classification surface can be solved in the new space. A high-dimensional space adopts kernel function, as shown in following formula.

$$f(x) = \mathrm{sgn}(\sum_{i=1}^{l} a_i y_i K(x, x_i) + b) \tag{6}$$

$$K(x, x_i) = \exp(-\frac{|x - x_i|^2}{\sigma^2}) \tag{7}$$

Where x_i is an support vector, x is an unknown vector, $K(x, x_i)$ is a kernel function, a_i is Lagrange multiplier, σ as kernel function width, b is a domain value of the classification and $y_\mathrm{i} \in \{-1,1\}$.

The RBF is selected as the kernel function, the SVM classifier involves two important parameters, that is penalty factor C and kernel parameter σ. When the σ is very small, the training error is very small, and the testing error is close to 1. With the gradual increasing of the σ, the number of support vector is reduced, the training error increases, so the σ can directly affect the performance of the SVM algorithm. The experimental software uses MATLAB platform, and the SVM functions as data classification function in the MATLAB toolbox, the C parameter is set to 100, and the σ is set to 2.

In this thesis, k-fold cross validation is used to optimize classification results of the SVM. Its basic thought is that original training data is divided into training data and test data,

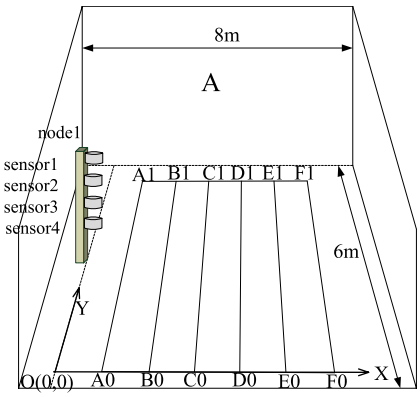


Fig. 9. The experiment scene graph.

$(k-1)n/k$ elements are selected from n sample as the training data and the left n/k acts as the test data to test the SVM classifier, which is repeated for M times. Then obtain average recognition rate of M times, and get final average recognition rate.

In this paper, we use 10-fold cross validation to obtain the parameter of the SVM classifier. All samples are divided into 10 in random, one sample is used to test, the other nine samples are used for training, and then, we take ten times experiment to get average recognition.

VI. Experiments and Results Analysis

A. Experimental Sample Collection

The purpose of this experiment is to use the PIR sensors that are installed at different heights for the human gait recognition. The experimental scene is shown in Fig. 9.

O (0,0) is the original point, and the coordinates of the detection node is (0,3m). The heights of the installed sensors were 0.4m, 0.8m, 1.2m and 1.6m. The numbers of test subjects is ten. The walking paths are A0(1m,0)→A1(1m,6m), B0(2m,0)→B1(2m,6m), C0(3m,0)→C1(3m,6m), D0(4m,0)→D1(4m,6m), E0(5m,0)→E1(5m,6m), F0(6m,0)→F1(6m,6m). And the test subjects were asked to walk 10 times in each line, a total of 0600 samples. The characteristic attributes of each test subjects is shown in table II.

B. Feature Extraction

Before feature extraction, the original data needs to be preprocessed, which include waveform interception and noise canceling. A sample is intercepted 300 points from the first peak of the waveform. The intercepted time-domain waveform of test subject A and B are shown in Figure 10. In this figure, the abscissa represents time(s) and the ordinate represents the voltage value (v). And each column represents different signal from four sensors (Row) for the same path. Each row represents different signal from the same sensor for six paths (Column).

Due to the relatively large amount of sample data, this paper gives the observed signal of target A and target B. The Fig. 10 shows the waveform from the different sensors.

On the one hand, the time-domain waveform of a single target shows that because of the changes in the relative position

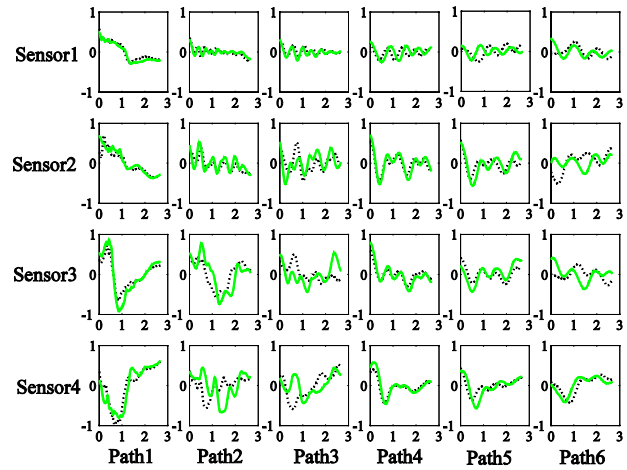


Fig. 10. The figure is the time domain waveform for target A and target B, the green solid line represents the target A, the black dotted line represents the target B, the abscissa represents time, the ordinate represents voltage, each column represents four sensors in different heights, and each row represents six paths.

of the human target, there are some differences between the signal waveform from the same sensor when the target walks in the different paths. And with the increasing of the distance, pyroelectric infrared sensor can get less and less infrared signal of human target, which results in the decrease of amplitude. On the other hand, for the same distance, there are significant differences in the observed signal waveform from different PIR sensors. The reason is that the PIR sensor module locates at different heights would detect the signal from different parts of human target. And that lead to the differences in the final waveform.

For the same distance and the PIR sensor, there is obvious difference between the observed signals, which is caused by the different characteristics of different targets. For the time domain signal, there are three algorithms have been introduced in the Section V, which are used for feature extraction. The result of feature extraction of the two targets waveform is shown in the Fig. 11.

Fig. 11 (a) is feature extraction of the FFT algorithm, the abscissa represents the frequency, the ordinate represents the amplitude, the blue solid line is spectrum feature of the target A, the red dotted line is spectrum feature of the target B.

Fig. 11 (b) is feature extraction of the STFT algorithm, the red line indicates that singular value distribution of time-frequency matrix of the target A, the green line indicates that singular value distribution of time-frequency matrix of the target B.

Fig. 11 (c) is feature extraction of the WPT algorithm, the blue solid line indicates that the WPT energy distribution of the target A, the red dotted line indicates that the WPT energy distribution of the target B.

C. Comparison of Different Algorithms Recognition Rate

In this paper, the CCA algorithm is used to fuse arbitrariness two features from three features, resulting in three new features. So, there are six kinds of features in total. After the

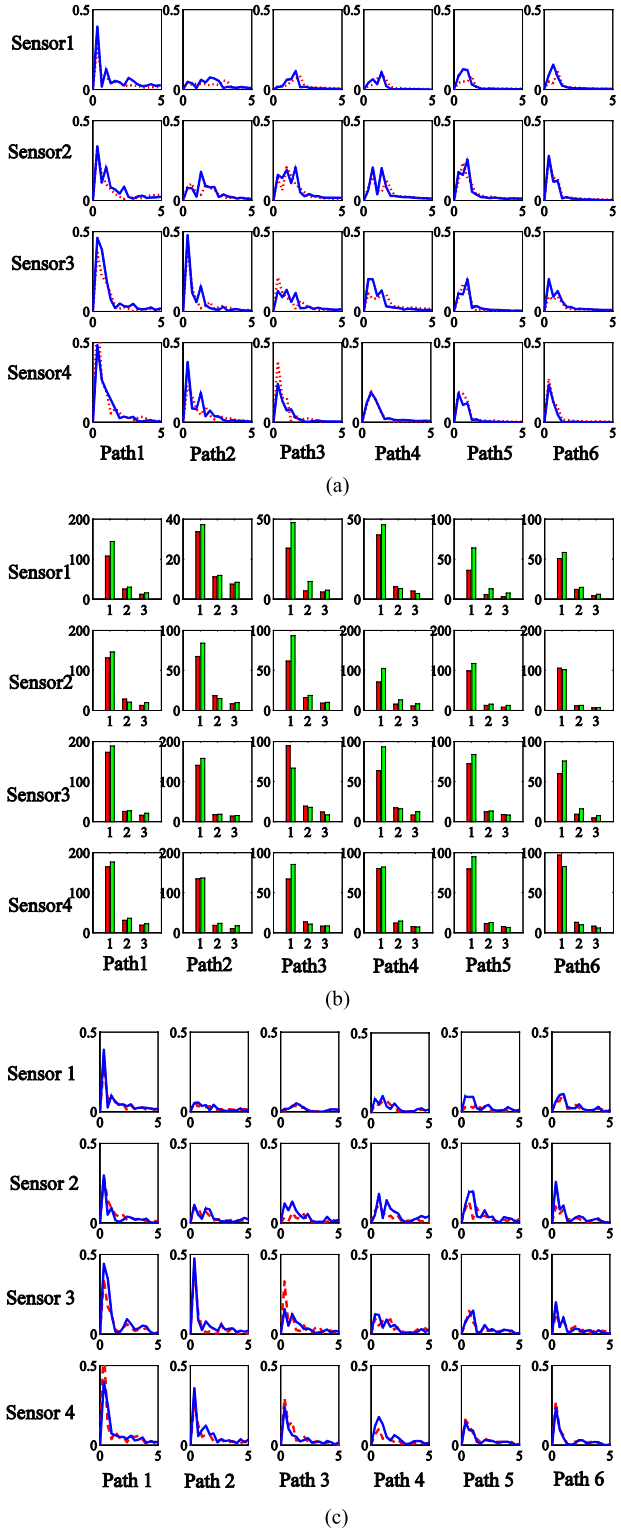


Fig. 11. Feature extraction by different algorithms. (a) Feature extraction by the FFT algorithm. (b) Feature extraction by the STFT algorithm. (c) Feature extraction by the WPT algorithm.

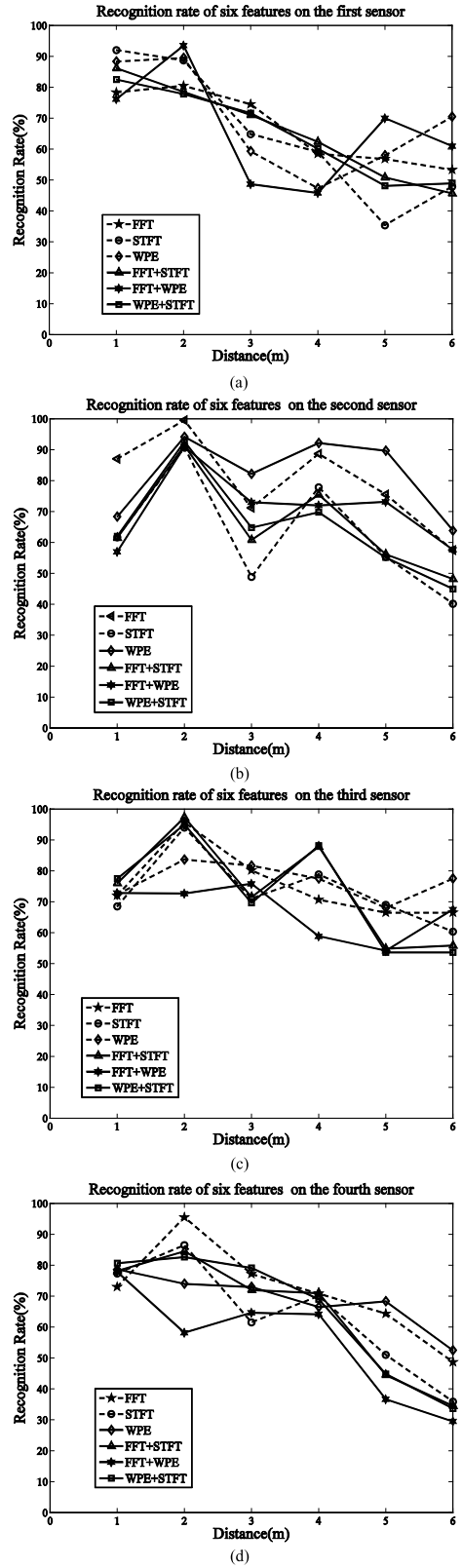


Fig. 12. The average recognition rate of four different sensors. (a) The first sensor. (b) The second sensor. (c) The third sensor. (d) The fourth sensor.

classification for each feature, the optimal feature extraction method is selected as the input data of the follow-up decision-making layer classification. Fig. 12 shows the recognition result of the four sensors.

Fig. 12 shows the recognition rate from the four PIR sensor modules under the independent operation. And the recognition rates are based on six different features. As can be seen in the Fig. 12, we can draw the conclusions as follows:

1) The recognition rate of the sensor which is at the same height for different paths is related to the feature

TABLE III
THE CHARACTERISTICS OF THE HIGHEST RECOGNITION RATE ON DIFFERENT SENSORS IN DIFFERENT DISTANCES

	dis 1	dis 2	dis 3	dis 4	dis 5	dis 6
Sen 1	STFT	FFT+WPT	WPT+STFT	FFT+STFT	FFT+WPT	WPT
Sen 2	FFT	FFT	WPT	WPT	WPT	WPT
Sen 3	STFT+FFT	STFT+FFT	FFT+ WPT	STFT+WPT	STFT	WPT
Sen 4	STFT+WPT	FFT	STFT+WPT	FFT+WPT	WPT	WPT

extraction algorithm. For example, the recognition rate of the first sensor at the path A is up to 92% by using the STFT algorithm. For the path C, it is only up to 74.50% by using the FFT algorithm which is the highest recognition rate from all feature extraction algorithms.

2) The recognition rate of the sensors which are at the different heights for the same path is also related to the feature extraction algorithm. For example, for the path C, the recognition rate of the first sensor has the highest recognition by using the FFT algorithm, whereas the recognition rate of the third sensor has the highest recognition by using the WPT algorithm.
3) The first sensor is mainly used to collect thermal infrared information of human target head. The distance is closer; the thermal infrared information of human target head is richer. So the identification result is better in the A path than other paths.
4) Along with the increase of the distance, the identification rate of the four sensors is tending to reduce.
5) Because of the fourth sensor can collect the thermal infrared radiation of human target leg and foot, so as the distance increases, the identification rate of human target will increase by a large margin.
6) For the same height sensor at the same path, after fusion, some new combination features can improve the recognition rate.

Therefore, in the training phase, if using the best features algorithm from the detecting data of the different sensors at the different paths, it will improve the recognition ability of a single sensor. Table III shows the best recognition effect of various feature extraction algorithms in different paths.

When the human target is walking, different parts of the human body have different thermal infrared features. So, for the same target, the sensors are installed at the different heights will observe different kinds of characteristic signals. What's more, due to the different paths, the signals will be also different for the same height sensor. So we believe those factors will affect the average recognition rate of human targets.

In the table III, on the one hand, the WPT algorithm appears eight times, which indicates that the feature is extracted by the WPT algorithm will have better classification results on the whole. On the other hand, the fusion feature also appears 11 times, and mainly on the beginning four kinds of paths, which describes that the distance is less than 4m, the fusion feature can improve the recognition rate, else not.

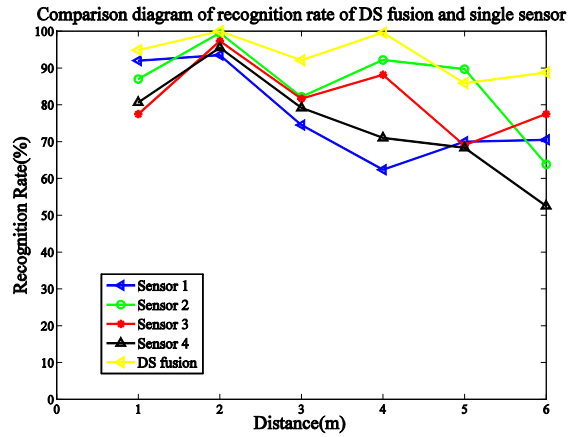


Fig. 13. Comparison diagram of recognition rate of D-S fusion and single sensor.

TABLE IV
TIME FOR FEATURE EXTRACTING, TRAINING AND RECOGNITION

Algorithm combination	Feature extraction time (computer time)	Training time (computer time)	Recognition time (computer time)
FFT+PCA+SVM	1.8	66.0	4.2
STFT+PCA+SVM	1.9	1163.2	5.3
WPT +PCA+SVM	1.8	413.8	4.1
FFT+STFT +PCA+SVM(CCA)	2.5	1728.0	3.7
FFT+WPT+PCA+SVM(CCA)	2.0	358.1	2.4
WPT+STFT +PCA+SVM(CCA)	2.2	1937.6	4.7

According to the table III, optimal feature extraction algorithm is selected for each sensor at different paths. In doing so, recognition capability of a single sensor will be optimal. However, when distance is larger than 4m, the recognition rate is not good, even of the optimal feature extraction algorithm is selected. Thus, decision-making layer integration is introduced. When final decisions are made, D-S theory is used to integrate classification results of the four sensors. A comparison result between the recognition rate of the system after integration and the recognition rate of single senor is shown in Figs. 13–15.

As illustrated above, for the single-sensor recognition, the recognition rate will decrease with the vertical distance increasing between PIR sensors node and human target. And the recognition rate reaches the highest points at the path B, whereas the recognition rates are less than 80% at the path F that the vertical distance between PIR sensors node and human target is 6m. However, after D-S fusion, the recognition rates are generally above 85%. For example, at the path F, the un-fusion recognition rate of the four sensors are 70.5%, 63.83%, 77.5%, 52.5%; after the D-S fusion, the average recognition rate reaches 88.75%, which increases by 22.67%.

Seen from the table IV, the computation time difference is not obvious, which use the CCA algorithm in extraction phase and recognition phase. The training stage will consume large amounts of time, which is not affected the recognition efficiency in the practical work of the whole system. Because the different computing time between the varieties of algorithms is not obvious, we can find that different features have different

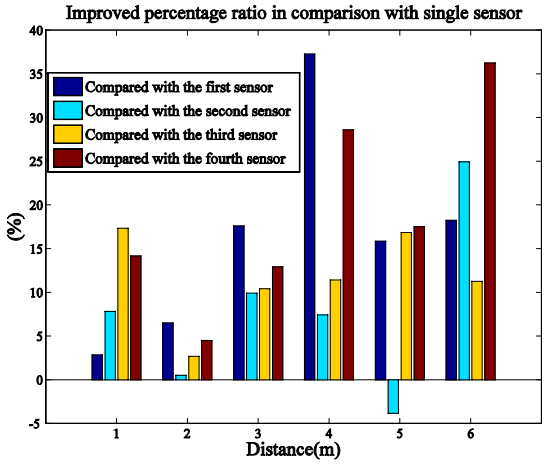


Fig. 14. Improved percentage ratio in comparison with single sensor.

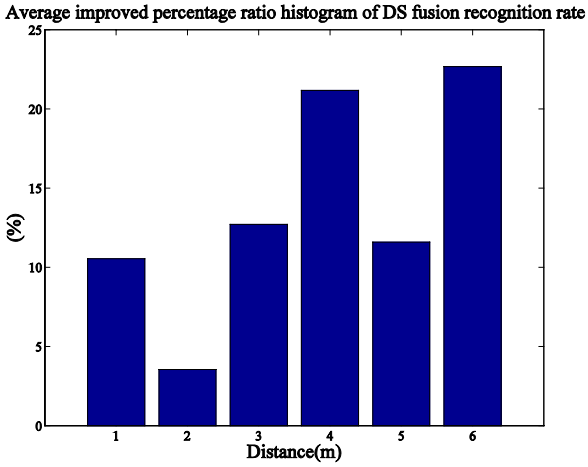


Fig. 15. The average improved percentage ratio histogram of D-S fusion recognition rate.

recognition effect in Fig. 12, so the different feature fusion algorithms are used that can effectively real-time identify the human targets.

VII. Conclusion

We propose the novel methods that integrate classification results of different characteristic extraction methods and pyroelectric sensors, which improve identification ability of the system for motion human target effectively. Specific description is shown as follows:

1) Based on multi-feature fusion algorithm of CCA, recognition rate of a single sensor is improved to some extents. However, fusion of the feature layer has some limitations. When measuring distance exceeds 4m, the recognition rate of the single feature is reducing and fusion of multi-features cannot improve the recognition rate of the single sensor.
2) PIR sensors with different heights have different ability of identifying human targets. The D-S fusion algorithm is classification results of four sensors in decision-making layer which improve the identification ability of the system. Experimental results show that PIR sensors with different heights can improve overall recognition rate of the system. When the distance is larger than 4m, the recognition rate is still over 85%.

Acknowledgment

The authors are extremely grateful to the editors and anonymous reviewers for their works and comments that help us to improve the quality of the paper.

References

[1] Y.-W. Bai, C.-C. Cheng, and Z.-L. Xie, "Use of ultrasonic signal coding and PIR sensors to enhance the sensing reliability of an embedded surveillance system," in *Proc. IEEE Int. Syst. Conf.*, Orlando, FL, USA, Apr. 2013, pp. 287–291.

[2] J. Xiong, F. M. Li, N. Zhao, and N. Jiang, "Tracking and recognition of multiple human targets moving in a wireless pyroelectric infrared sensor network," *Sensors*, vol. 14, no. 4, pp. 7209–7229, 2014.

[3] A. Hossain and M. H. Rashid, "Pyroelectric detectors and their applications," *IEEE Trans. Ind. Appl.*, vol. 27, no. 5, pp. 824–829, Sep./Oct. 1991.

[4] Q. Hao, F. Hu, and Y. Xiao, "Multiple human tracking and identification with wireless distributed pyroelectric sensor systems," *IEEE Syst. J.*, vol. 3, no. 4, pp. 428–439, Dec. 2009.

[5] M. Moghavvemi and L. C. Seng, "Pyroelectric infrared sensor for intruder detection," in *Proc. IEEE Region 10 Conf. (TENCON)*, vol. 4. Nov. 2004, pp. 656–659.

[6] Y.-W. Bai and Y.-T. Ku, "Automatic room light intensity detection and control using a microprocessor and light sensors," *IEEE Trans. Consum. Electron.*, vol. 54, no. 3, pp. 1173–1176, Aug. 2008.

[7] A. Rajgarhia, F. Stann, and J. Heidemann, "Privacy-sensitive monitoring with a mix of IR sensors and cameras," in *Proc. 2nd Int. Workshop Sensor Actor Netw. Protocols Appl.*, Boston, MA, USA, Aug. 2004, pp. 21–29.

[8] F. Erden, A. S. Bingol, and A. E. Cetin, "Hand gesture recognition using two differential PIR sensors and a camera," in *Proc. 22nd IEEE Int. Conf. Signal Process. Commun. Appl.*, Trabzon, Turkey, Apr. 2014, pp. 349–352.

[9] S. Tao, M. Kudo, H. Nonaka, and J. Toyama, "Person authentication and activities analysis in an office environment using a sensor network," in *Constructing Ambient Intelligence*. New York, NY, USA: Springer-Verlag, 2012, pp. 119–127.

[10] Q. Hao, D. J. Brady, B. D. Guenther, J. B. Burchett, M. Shankar, and S. Feller, "Human tracking with wireless distributed pyroelectric sensors," *IEEE Sensors J.*, vol. 6, no. 6, pp. 1683–1696, Dec. 2006.

[11] M. Shankar, J. B. Burchett, Q. Hao, B. D. Guenther, and D. J. Brady, "Human-tracking systems using pyroelectric infrared detectors," *Opt. Eng.*, vol. 45, no. 10, pp. 106401-1–106401-10, Oct. 2006.

[12] X. Luo, B. Shen, X. Guo, G. Luo, and G. Wang, "Human tracking using ceiling pyroelectric infrared sensors," in *Proc. 7th IEEE Int. Conf. Control Autom.*, Christchurch, New Zealand, Dec. 2009, pp. 1716–1721.

[13] N. Zhao, F. M. Li, and X. D. Liu, "Blind estimation of number of motion multi-human targets in wireless pyroelectric infrared sensor networks," *Infr. Phys. Technol.*, vol. 61, pp. 208–215, Nov. 2013.

[14] J.-S. Fang *et al.*, "Path-dependent human identification using a pyroelectric infrared sensor and Fresnel lens arrays," *Opt. Exp.*, vol. 14, no. 2, pp. 609–624, Jan. 2006.

[15] J.-S. Fang, Q. Hao, D. J. Brady, B. D. Guenther, and K. Y. Hsu, "Real-time human identification using a pyroelectric infrared detector array and hidden Markov models," *Opt. Exp.*, vol. 14, no. 15, pp. 6643–6658, Jul. 2006.

[16] Q. J. Guan, C. Y. Li, X. M. Guo, and G. L. Wang, "Compressive classification of human motion using pyroelectric infrared sensors," *Pattern Recognit. Lett.*, vol. 49, no. 1, pp. 231–237, Nov. 2014.

[17] Q. Sun, F. Hu, and H. Qi, "Context awareness emergence for distributed binary pyroelectric sensors," in *Proc. IEEE Int. Conf. Multi-Sensor Fusion Integr. Intell. Syst.*, Salt Lake City, UT, USA, Sep. 2010, pp. 162–167.

[18] F. Hu, Q. Sun, and Q. Hao, "Mobile targets region-of-interest via distributed pyroelectric sensor network: Towards a robust, real-time context reasoning," in *Proc. IEEE Int. Conf. Sensors*, Kona, HI, USA, Nov. 2010, pp. 1832–1836.

[19] Q. Sun, F. Hu, and Q. Hao, "Mobile target scenario recognition via low-cost pyroelectric sensing system: Toward a context-enhanced accurate identification," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 44, no. 3, pp. 375–384, Mar. 2014.

[20] Q. Sun, J. Lu, Y. Wu, H. Qiao, and X. Huang, "Non-informative hierarchical Bayesian inference for non-negative matrix factorization," *Signal Process.*, vol. 108, pp. 309–321, Mar. 2015.

[21] T.-C. Lin and P.-T. Yu, "Thresholding noise-free ordered mean filter based on Dempster–Shafer theory for image restoration," *IEEE Trans. Circuits Syst. I, Reg. Papers*, vol. 53, no. 5, pp. 1057–1064, May 2006.

[22] E. Gumus, N. Kilic, A. Sertbas, and O. N. Ucan, "Evaluation of face recognition techniques using PCA, wavelets and SVM," *Expert Syst. Appl.*, vol. 37, no. 9, pp. 6404–6408, Sep. 2010.

[23] Y. Jiang, B. Tang, Y. Qin, and W. Y. Liu, "Feature extraction method of wind turbine based on adaptive Morlet wavelet and SVD," *Renew. Energy*, vol. 36, no. 8, pp. 2146–2153, Aug. 2011.

[24] Z. Sun and C. C. Chang, "Structural damage assessment based on wavelet packet transform," *J. Struct. Eng.*, vol. 128, no. 10, pp. 1354–1361, 2002.

[25] K. Todros and A. O. Hero, "On measure transformed canonical correlation analysis," *IEEE Trans. Signal Process.*, vol. 60, no. 9, pp. 4570–4585, Sep. 2012.

[26] R. R. Murphy, "Dempster–Shafer theory for sensor fusion in autonomous mobile robots," *IEEE Trans. Robot. Autom.*, vol. 14, no. 2, pp. 197–206, Apr. 1998.

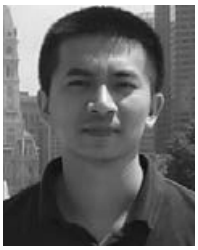
[27] H. M. Qian, Y. Mao, W. B. Xiang, and Z. Q. Wang, "Recognition of human activities using SVM multi-class classifier," *Pattern Recognit. Lett.*, vol. 31, no. 2, pp. 100–111, Jan. 2010.

Ji Xiong received the B.S. and M.S. degrees from the Department of Information Engineering, Wuhan University of Technology, Wuhan, China, in 2006 and 2011, respectively, where he is currently pursuing the Ph.D. degree.

He is with the Key Laboratory of Fiber Optical Sensing Technology and Information Processing, Ministry of Education, and developing a distributed human body monitoring system based on the PIR sensor technology. His research is mostly in the field of information processing and pattern identification. Main topics included implementation of Zigbee-based WSN, smart assistive environment, and human body condition detective based on pyroelectric infrared.

Fangmin Li received the Ph.D. degree in computer specialty from Zhejiang University, Hangzhou, China, in 2001. He is currently a Full Professor with the Wuhan University of Technology. He is the Dean of the School of Information Engineering with the Wuhan University of Technology. His research interests are in the fields of wireless networks, sensor networks, and embedded system.

He has authored over 40 papers in international journals and conferences, one book, and 16 patents. He has been a Senior Member of the China Computer Federation and a Committee Member of the China Computer Federation Technical Committee on Sensor Network.



Jian Liu received the B.E. and M.S. degrees from the Department of Information Engineering, Wuhan University of Technology, Wuhan, China, in 2011 and 2014, respectively. He is currently pursuing the Ph.D. degree with the Department of Electrical and Computer Engineering, Stevens Institute of Technology, Hoboken, NJ, USA.

His current research interests include information security and privacy, mobile computing, and wireless networking.