Multiple Human Tracking and Identification With Wireless Distributed Pyroelectric Sensor Systems

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***Abstract*—This paper presents a wireless distributed pyroelectric sensor system for tracking and identifying multiple humans based on their body heat radiation. This study aims to make pyroelectric sensors a low-cost alternative to infrared video sensors in thermal gait biometric applications. In this system, the sensor field of view (FOV) is specifically modulated with Fresnel lens arrays for functionality of tracking or identification, and the sensor deployment is chosen to facilitate the process of data-object-association. An Expectation-Maximization-Bayesian tracking scheme is proposed and implemented among slave, master, and host modules of a prototype system. Information fusion schemes are developed to improve the system identification performance for both individuals and multiple subjects. The fusion of thermal gait biometric information measured by multiple nodes is tested at four levels: sample, feature, score, and decision. Experimentally, the prototype system is able to simultaneously track two individuals in both follow-up and crossover scenarios with average tracking errors less than 0.5 m. The experimental results also demonstrate system's potential to be a reliable biometric system for the verification/identification of a small group of human subjects. The developed wireless distributed infrared sensor system can run as a standalone prisoner/patient monitoring system under any illumination conditions, as well as a complement for conventional video and audio human tracking and identification systems.**

***Index Terms*—Multiple human tracking, walker identification, pyroelectric sensor, wireless sensor network.**

I. Introduction

MANY intelligent environments and secure systems demand collectable, stable and reliable behavioral biometrics to identify individuals and track their actions based on their behavioral attributes. The behavioral biometrics (e.g., gait and habitual trajectory) are advantageous in their capability of recognition at a distance under changing environmental conditions, despite subjects' varying physical appearances. However, establishing identity and tracking actions from distances or in crowded scenes through behavioral biometrics are complex problems due to the intrinsic challenges associated with sensing modalities and feature selections. Focal plane centralized video systems have demonstrated many cases of tracking and identification by post signal processing but at high computational cost and large data throughput. Applications of video systems are usually limited by illumination and power supply conditions, and infrared (multispectral) video systems are expensive.

Continuing advances in sensors and sensing methodologies, wireless transceivers, distributed processing and learning, and embedded networking have allowed distributed alternatives in human tracking and identification. Human behavioral information can be measured by passive (e.g., photonic, thermal and pressure) or active sensors (e.g., ultrasound and laser). Structural innovation and adaptation in sensors, processing architectures, networks and algorithms jointly enable the development of distributed sensor networks (DSNs) that can mediate human-machine interactions. In a typical DSN, small, low-cost, spatially dispersed sensor nodes, with certain computation and communication capabilities, collaborate with each other to achieve complicated tasks [1]–[3].

For most DSN applications, passive sensors are preferred to active ones because of their low costs, low power consumption, and low detectability. The low-cost pyroelectric $LiTaO_3$ passive infrared (PIR) motion detector [4]–[7] is selected for this research. Its performance is independent of illumination conditions and robust to background colors [8]. Its sensitivity to angular velocities ranges from 0.1 to 3 radian/s [9], covering most human walking speeds at a distance of 2–10 m.

The advantages of using wireless distributed pyroelectric sensor networks for multiple human tracking and identification include:

1) reductions in the number of measurements and sampling frequency for human motion state estimation;
2) reductions in hardware cost, power consumption, privacy infringement, computational complexity, communication overhead, and networking data throughput;
3) reductions in the time of system deployment and limitations upon applications or application locations (e.g., long range or crowded scene).

The major goal of our work is to develop a wireless distributed pyroelectric sensor system, which can track multiple humans in a confined area, while maintaining their identities, as illustrated in Fig. 1. The prototype system consists of three types of modules: slave, master, and host. The slave and master modules are based on TI RF micro-controller MP430149-RF6901. The host module is based on a PC. Each slave module contains eight pyroelectric sensors whose field of view (FOV) is modulated by using Fresnel lens arrays and coded masks. The slave module is able to collect the sensor response signals, convert

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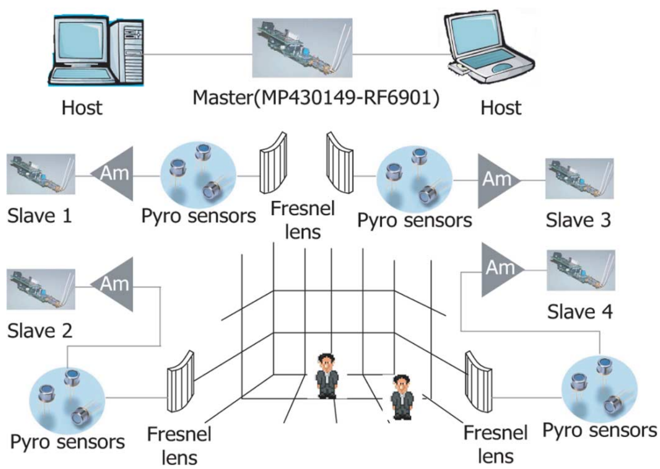


Fig. 1. Setup of the distributed wireless pyroelectric sensor system.

them into event indexes, which are sent to the master module via a wireless channel after the data compression. The master module collects event indexes, rejects false alarms, and provides the host with the processed data, which can be interpreted as local bearing measurements, gait features, and the number of objects. Based on these kinds of information, the host can estimate motion trajectory and identity of the subjects under examination.

The challenges for tracking and identifying multiple humans with distributed pyroelectric sensors include:

1) high variability of human motions and their thermal biometrics;
2) decreased sensitivity of a pyroelectric sensor when its lens apertures are reduced for modulation;
3) errors in geometric optics modeling and system alignment;
4) limits imposed by sensor number, local computation capabilities, and communication bandwidth.

In this paper, we present a framework for tracking and identifying multiple humans using wireless distributed pyroelectric sensors. It extends our previous studies on single human tracking [10] and recognition [11]. The multiple human tracking component includes four parts: detection, localization/data-object association, filtering, and prediction. The multiple human identification component involves: feature selection and modeling, feature-to-object association, and data and decision fusion. The novelty of this work includes: 1) developing pyroelectric sensor nodes suitable for multiple human tracking and identification; 2) utilizing the sensor deployment geometry to facilitate data-to-object association; 3) developing an expectation-maximization (EM) scheme to determine the number of objects under examination; and (4) performing information fusion at different levels for recognition accuracy improvement.

The rest of this paper is organized as follows. Section II reviews the related work. Section III describes the sensor modules and sensor deployment. Section IV presents a mathematical description of the problems and proposed approaches. Section V describes the system implementation. Section VI shows experimental results, and discusses the strength and weakness of the sensor system as well as its potentials. Section VII concludes the paper.

II. Related Work

Multiple human tracking and identification are indeed two aspects of one problem. The *tracking* process provides object locations, helping decouple the signals for multiple object identification. On the other hand, object *identification* facilitates the procedure of data-to-object association in multiple object tracking and reduces the ambiguity and mutual interference among trackers.

Human tracking with multiple sensors is an intrinsic multisensor data fusion problem, which needs to combine readings from different sensor nodes, remove inconsistencies, and pull all the information together into one coherent structure. Multiple human tracking is desirable yet challenging for many applications [12]–[14]. The dynamics of multiple targets can be modeled as coupled hidden Markov chains; it tends to be ambiguous and confusing to perceive and interpret the sensory data generated by multiple targets as some targets are often occluded by others in the FOV of sensors. From the perspective of trackers, the tracking errors of one target may propagate into those of others. Object identification can help reduce such a mutual interference in tracking [1], [15]. Besides, the varying number of targets within object space gives rise to the issue of target number determination and tracker maintenance [16].

Most trackers consist of four components: namely object representation, localization, data-object-association, and motion filtering [17]. The way to implement all these parts in tracking is application dependent and various approaches differ in robustness and efficiency. For real-time applications, the system resource for tracking is limited and the computational complexity of a tracker should be minimized. In video based applications, where the nonrigid aspect of objects is of more interest, object feature extraction and representation play important roles and consume most of the computation resources [17], [18]. For acoustic sensor tracking systems, by contrast, objects are assumed to be rigid and signal-to-noise ratios (SNRs) are low in the noisy and clutter filled environments. Numerous data-object-association and motion filtering techniques have been proposed and developed [19]–[25].

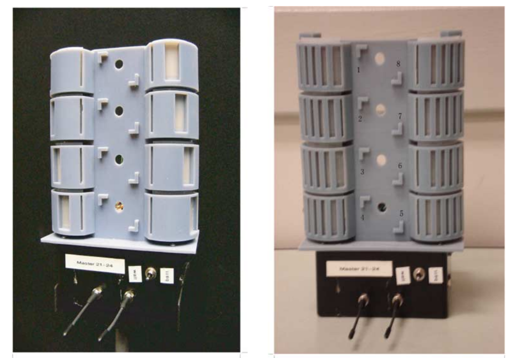
Compared to other biometric modalities (e.g., fingerprints, face, and iris), gait allows noncooperative individuals to be identified at a distance under changing conditions. Despite having many limitations, from clothing changes to viewpoint differences to gait variations under different physical and emotional conditions, the discrimination power of gait can still serve as a unique and useful component in multimodal human-machine interfaces and biometric systems [26], [27].

The techniques for gait recognition in conventional video systems fall into two categories: holistic and model-based [27], [28]. These two methods differ in their ways of dealing with the silhouette extracted from images and forming the feature vector accordingly [29], [30]. Besides, Fourier analysis and dimensionality reduction have been used to increase the efficiency of feature representations. Multiperspective (or multicycle) measurements have also been used to increase the robustness of the feature representation against operational conditions [31], [32]. Usually, the gait features are normalized into one gait cycle, and matched using explicit distance metrics, or using a hidden

Markov model (HMM) that takes into account the sequential coherence of patterns. However, most video-based approaches to walker recognition involve intensive computations, such as edge map extraction and silhouette interpretation. Besides, the main challenge for multiple walker identification is the same as that for tracking, that is, how to associate measurements with the corresponding subjects.

From a thermal perspective, each person acts as a distributed infrared (IR) source. By properly sampling the IR field, the idiosyncrasies in how an individual carries himself/herself and the habits of how he/she moves can generate a statistically unique signature in the signal space. In our previous study on PIR pyroelectric motion detectors, we succeeded in tracking single human object [33], [34], [10], and demonstrating the discriminability among individuals walking along the same path [35], [36], or randomly inside a room [11], by using the multiplex sensing techniques [37] and the concept of geometric sensors [38], [39]. In this study, each pyroelectric sensor works as a binary sensor and only generates logic signals of "1" or "0", indicating a presence, or an absence, of human motion within its FOV. Under the notion of geometric sensors, the FOVs of sensor arrays are modulated in specific ways so that the object space can be segmented into many cells, each characterized by a unique signal pattern of sensors. When a human walks through the FOV modulated object space, the sensor arrays will generate a multidimensional binary signal sequence. Those signal sequences can be utilized to locate and identify human objects [10], [11].

The advantages of the wireless distributed sensor system include the convenient deployment of multiple sensor nodes for collecting measurements from multiple perspectives. By using multiple sensor nodes, the human motion feature can be accurately captured and utilized for the higher-security applications where walker verification or open-set identification is required. A typical unimodal biometric system consists of three modules: feature extraction, matching, and decision [40]. Feature extraction is used to describe the most important information of the sensory data (samples). Matching modules compare features with templates in the database and output a score to the decision module. Therefore, the information fusion of multiple pyroelectric sensor nodes for thermal gait biometrics can happen at four different levels: sample, feature, score, and decision (see [40]).



(a) (b)

Fig. 2. (a) Type I two-column sensor module for multiple walker tracking. (b) Type II two-column sensor module for multiple walker identification.

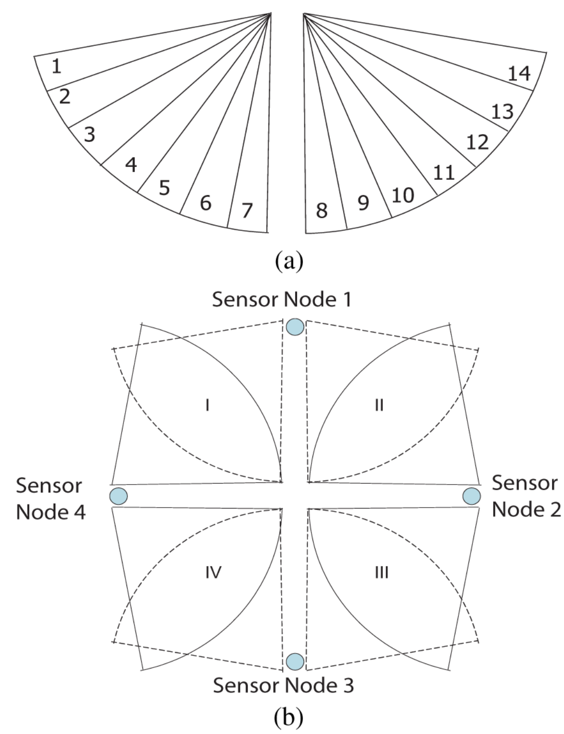


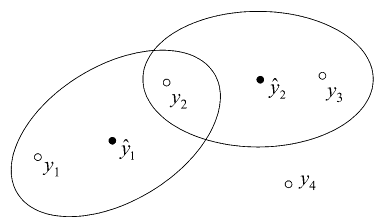
Fig. 3. (a) Detection pattern of a two-column sensor module. (b) FOVs of four two-column sensor nodes. Each FOV contains two separate fan-shaped regions. Four local detection areas are formed by the overlap of these regions. They can be utilized for event validation to reduce false alarms.

III. Sensor Modules and Deployment

We have presented a pyroelectric sensor system model and the technique of FOV modulation with Fresnel lens arrays [10]. In this work, we fabricated two types of two-column radial sensor modules for multiple human tracking and identification, respectively, shown in Fig. 2. Both types of sensor modules have eight pyroelectric detectors with the Fresnel lens arrays arranged in two columns. Such a FOV design can facilitate the process of data-object-association: when sensors of one node associated with two different detection areas fire, it can be concluded that there are at least two objects moving.

For the type I sensor module, shown in Fig. 2(a), the FOV of each sensor spans 24°, by using three Fresnel lenses, with a 16° shift in the FOV between each of the four sensors. Two separate detection areas of 72° are formed by the two columns. The detection pattern of a two-column sensor module is illustrated in Fig. 3(a). Each detection area comprises seven detection regions with different sensor visibility patterns. The average angular resolution of the sensor module is 10°. For the type II sensor module, shown in Fig. 2(b), the FOV of each sensor is modulated by using pseudo-random coded masks. Those coded masks and Fresnel lens arrays work together as a set of spatial filters, helping capture various human motion attributes. There are four sensors in each column, with different FOV modulation schemes. Similarly, two separate detection areas are formed by the two-column structure.

When four sensor nodes (containing either type I or type II sensing module) are deployed in a 9 m $\times$ 9 m room, we have a global FOV distribution shown in Fig. 3(b). It can be seen that



$$\Omega = \left\{ \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 1 & 0 \\ 0 & 0 \\ 0 & 1 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 1 & 0 \\ 0 & 1 \end{bmatrix} \right\}$$

Fig. 4. Typical validation gates and validation matrices.

four local detection areas are formed through such a deployment, marked as areas I, II, III, and IV. In each local area, if only one object moves, those associated sensor modules can provide a high angular resolution. The detection range of each sensor can be reduced to its local areas by increasing the value of the firing threshold set in the embedded signal processor. Given such a sensor deployment, a number of human objects can be tracked or identified when they move inside different local detection areas. The whole data-object-association scheme has two steps: identifying the local area of an object and identifying the sensory data associated with the object. More details can be found in [41].

IV. Problem Formulation and Proposed Approaches

In this section, we present the multiple human tracking problem in terms of object motion dynamics and a sensor observation model. The process of data-to-object association is performed by a Bayesian joint probabilistic data association scheme with validation gates. The varying number of objects is tackled by an EM scheme. The walker identification problem can be formulated as three parts: data learning, hypothesis testing, and data/decision fusion.

A. Multiple Human Tracking

The multiple human tracking includes three problems: object number determination, measurement-to-object association, and object tracking.

1) Bayesian Tracking: For objects under tracking, object state $\mathbf{x}(t)$ is used to represent their spatial-temporal varying radiation, for example, positions, and velocities. The dynamics model of objects is Markov and can be represented by the conditional density $p(\mathbf{x}_{k+1}|\mathbf{x}_k)$. The problem can be stated as, how to determine the object state sequence $\mathbf{x}_{1:k} = [\mathbf{x}_1, \ldots, \mathbf{x}_k]$ with maximum posterior probability from sensor response signals $\mathbf{s}_{1:k} = [\mathbf{s}_1, \ldots, \mathbf{s}_k]$, given the observation model likelihood $p(\mathbf{s}_k|\mathbf{x}_k)$ and state dynamics *priori* $p(\mathbf{x}_{k+1}|\mathbf{x}_k)$

$$\mathbf{x}^*_{1:k} = \arg\max_{\mathbf{x}_{1:k}} p(\mathbf{x}_{1:k}|\mathbf{s}_{1:k}). \tag{1}$$

Note that $p(\mathbf{s}_k|\mathbf{x}_k)$ is derived from the sensor and noise models. It is known as the maximum a *posteriori* (MAP) Bayesian tracking problem.

By using the pre-known FOV modulation scheme, the sensor response signals $\mathbf{s}_{1:k}$ can be digitized into event indexes and then interpreted as angular displacements, with respect to the jth sensor of sensor node i, $z^{(i,j)}_{1:k}$. To handle the possible occlusion of multiple persons, local detection areas are designed for event validation, as shown in Fig. 3. Here, an event is referred to as a detection of human motion. The event validation is referred to as the verification of an event inside one local detection area through checking signal responses of two neighbor sensor nodes. When event indexes (binary logic signals) from four sensor nodes are received, an area-to-object association is made first according to the global sensor FOV geometry. After such a measurement validation, only two measurements are associated with one object, denoted as

$$\mathbf{z}^{(l)}_k = \left\{ z^{(i,j)}_k : P\left(\chi^{(l,i,j)}_k\right) > 0 \right\} \tag{2}$$

where $\chi^{(l,i,j)}_k$ is the event that measurement $z^{(i,j)}_k$ originates from the lth object.

The general sequential Bayesian tracking problem requires that we recursively calculate some degree of belief in the state $\mathbf{x}^l_k$ with validated measurements $\mathbf{z}^{(l)}_{1:k}$. Its solution includes two parts: prediction and filtering, given by

$$\begin{aligned} p\left(\mathbf{x}^l_k \middle| \mathbf{z}^{(l)}_{1:k-1}\right) &= \int p\left(\mathbf{x}^l_k \middle| \mathbf{x}^l_{k-1}\right) p\left(\mathbf{x}^l_{k-1} \middle| \mathbf{z}^{(l)}_{1:k-1}\right) d\mathbf{x}^l_{k-1} \\ p\left(\mathbf{x}^l_k \middle| \mathbf{z}^{(l)}_{1:k}\right) &= \frac{p\left(\mathbf{z}^{(l)}_k \middle| \mathbf{x}^l_k\right) p\left(\mathbf{x}^l_k \middle| \mathbf{z}^{(l)}_{1:k-1}\right)}{p\left(\mathbf{z}^{(l)}_k \middle| \mathbf{z}^{(l)}_{1:k-1}\right)} \end{aligned} \tag{3}$$

where $p(\mathbf{z}^{(l)}_k|\mathbf{z}^{(l)}_{1:k-1})$ can be viewed as a normalizing constant. The probabilistic model of the state evolution $p(\mathbf{x}^l_k|\mathbf{x}^l_{k-1})$ is the state model. The likelihood function $p(\mathbf{z}^{(l)}_k|\mathbf{x}^l_k)$ is the measurement likelihood.

2) Object Number Determination: A more challenging aspect of the multiple object tracking with multiple sensors is the data-to-object association when the number of objects varies. It becomes more intractable for motion sensor systems, which only respond to target motions and generate no signal when targets stand still. We used an EM scheme for object number determination, to initialize new or delete obsolete trackers, accordingly.

1) In each E step, we estimate the probability distribution over object number, $q(n)$, at time $t+1$, given measurements Z and previous data-to-object association probabilities, β, at time t

$$q^{t+1}() = \arg\max_{q()} \mathcal{G}[Z, q(n), \beta^t] \tag{4}$$

where the free energy function $\mathcal{G}[q(n), \beta]$ is [42]

$$\mathcal{G}[Z, q(n), \beta] = \sum_n q(n) \ln p(Z, n|\beta) - \sum_n q(n) \ln q(n). \tag{5}$$

2) In each M step, we optimize the data-object association weights, given the updated object number distribution

$$\beta^{t+1} = \arg\max_{\beta} \mathcal{G}[Z, q^{t+1}(n), \beta]. \quad (6)$$

In other words, we maintain several tracking hypotheses, each of them describing a different number of objects. Over a period, we evaluate all the hypotheses and pick the one with the maximum likelihood for rendering. Compared to the probabilistic multiple hypothesis tracking (PMHT) [43], the proposed EM scheme allows a convenient plug-in of a *priori* on object number and new knowledge on object identity. For example, we can assume the change of object number is a slow process, so when the current object number is N, the possible object number within a preset time window could only be $N-1$, N and $N+1$. In another case, we can use object identification results to shape the probability distribution over object number: if there is a new object present, the object number should be more likely increased.

3) Measurement-to-Object Association: The key concepts of measurement-to-object association for a fixed number of targets are the joint event and the validation matrix [21]. The joint event is denoted as

$$\chi = \bigcap_{j=1}^{m_k} \chi^{jl_j} \quad (7)$$

where χ^{jl_j} is the event that the measurement j originated from object l_j, $0 \le l_j \le N$, and l_j is the index of the object to which measurement j is associated, and m_k is the number of validated measurements at time k.

The validation matrix for a joint event χ is defined

$$\Omega(\chi) = [\omega_{jl}(\chi)] \quad (8)$$

with ω_{jl} indicating if measurement j lies in the validation gate for object l

$$\omega_{jl}(\chi) = \begin{cases} 1, & \text{if } \chi^{jl} \text{occurs} \\ 0, & \text{otherwise.} \end{cases} \quad (9)$$

The construction of each $\Omega(\chi)$ follows the rules [21]:

1) There can be only one origin for a measurement.
2) At most one measurement could have originated from an object.

Those rules might lead to several feasible joint events and validation matrices. To reduce the number of feasible joint events, an individual validation gate can be assumed for each tracker. Only those measurements falling inside the gates will be counted. Fig. 4 illustrates a typical set of validation gates and validation matrices, where $\hat{y}_1$ and $\hat{y}_2$ are estimated object positions, y_1, y_2, and y_3 are position measurements falling insides validation gates, and y_4 is a position measurement outside gates.

By using Bayes' rule, the probability of one joint event conditioned on all the measurements up to the present time k is obtained as [22]

$$p(\chi_k|\mathbf{y}_{1:k}) \propto p(\mathbf{y}_k|\chi_k, \mathbf{y}_{1:k-1}) p(\chi_k|\mathbf{y}_{1:k-1}) \quad (10)$$

where $p(\mathbf{y}_k|\chi_k, \mathbf{y}_{1:k-1})$ is the likelihood of the predicted measurements $\mathbf{y}_k$ for the joint event χ_k, derived from object dynamics and the sensor observation model, and $p(\chi_k|\mathbf{y}_{1:k-1})$ is the prior probability of the joint event, derived from the probability distributions of false measurements and of target detection rates [21].

The association probability β_k^{jl} that measurement j belongs to object l at time k may be obtained by summing over all feasible events for which this condition is true

$$\beta_k^{jl} = \sum_{\chi_k} p(\chi_k|\mathbf{y}_{1:k}) \omega_{jl}(\chi_k). \quad (11)$$

The states of each object can be updated with the measurements weighted by those association probabilities.

After object number determination and measurement-to-object association, the multiple object tracking becomes a set of independent single-object tracking problems. We have summarized the three Bayesian tracking strategies, Kalman, HMM, and Gaussian particle filters, and compared their performances and computation costs in [10]. The Kalman tracking scheme based on a grid approximation [10] is chosen for this real-time implementation.

B. Walker Recognition

The object recognition problem can be divided into two parts: data learning and hypothesis testing. We here use the multidimensional binary event sequence with a fixed length L generated by the type II sensor node as initial gait feature data [11]. We use HMMs to represent the statistics of the feature data. For a multinode sensor system, it involves data fusion and decision fusion.

1) Statistical Feature Models: An HMM can be set up as [44]:

1) $Y = \{y_1, y_2, \ldots, y_T\}$: hidden state sequence;
2) $X = \{x_1, x_2, \ldots, x_T\}$: feature sequence;
3) $\mathbf{A} = \{a_{ij}\}$, $a_{ij} = P(y_{t+1} = j|y_t = i)$: state transition probability matrix;
4) $\mathbf{B} = \{b_{im}\}$, $b_{im} = P(x_t = m|y_t = i)$: emission probability matrix;
5) $\pi = \{\pi_i\}$: initial state distribution;
6) $\theta_H = \{\mathbf{A}, \mathbf{B}, \pi\}$: model's parameters.

For a given parameter vector θ_H, the likelihood of the hidden state sequence Y and the observed data X to associate with the model is [44]

$$p(X, Y|\theta_H) = \left[\prod_{t=1}^{T-1} a_{y_t y_{t+1}}\right] \left[\prod_{t=1}^{T} b_{y_t x_t}\right] \pi_{y_1}. \quad (12)$$

To estimate the membership of one sequence associated with one model, we estimate the hidden state sequence first and use that to calculate the association likelihood.

2) Data Learning: Given the conditional probability density $p(X, Y|\theta)$, the maximum likelihood (ML) estimation of the parameter vector θ from the training data X and their labels Y, known or hidden, is

$$\hat{\theta} = \arg\max_{\theta} \ln p(X|\theta) = \arg\max_{\theta} \ln \sum_{Y} p(X, Y|\theta). \quad (13)$$

For the supervised learning problem, the preset data label distribution is known as $\delta(Y - Y_0)$, so that X is "complete data" for model training. For the unsupervised learning problem, in the case of HMM, the data labels Y are hidden variables, and the EM algorithm has been developed [44].

3) Hypothesis Testing: For a feature sequence, $\mathbf{x}$, we will have $K + 1$ hypotheses for K registered subjects, $\{H_0, \ldots, H_K\}$, to test. The hypothesis H_0 represents "none-of-the-above". The decision rule then is

$$\mathbf{x} \in \begin{cases} H_0, & \text{if } \max_i p(\mathbf{x}|H_i) < \gamma \\ H_i : i = \arg\max_i p(\mathbf{x}|H_i), & \text{otherwise} \end{cases} \tag{14}$$

where $p(\mathbf{x}|H_i)$ is the likelihood of $\mathbf{x}$ associating with the ith hypothesis and γ is a selected acceptance/rejection threshold. There are several special cases of this general statement. For the verification problem, we choose $i = 1$; for the closed-set identification problem, we choose $\gamma = -\infty$.

4) Data, Score and Decision Fusion: For N sensor nodes, each having m sensors, the ensemble data of the sensor system is denoted as $\mathbf{D} = [\mathbf{d}_1^T \cdots \mathbf{d}_N^T]^T$, where $\mathbf{d}_i = [d_{i1} \cdots d_{iL}]$ is an $m \times L$ event sequence from the ith node. The feature sequence selection is to choose M sequences containing more information about the motion of subjects, denoted as $\mathcal{F}(\cdot)$. Therefore, for the sample fusion scheme, $\mathbf{x} = \mathcal{F}(\mathbf{D})$, where $\mathbf{x}$ is an $M \times L$ event sequence. For the feature fusion, we select the l highest frequency sequences as the feature sequence of each node, i.e., $\mathbf{x}_i = \mathcal{F}(\mathbf{d}_i)$, where $\mathbf{x}_i$ is an $l \times L$ event sequence.

For the score fusion, the likelihood of a joint feature vector $\mathbf{x} = [\mathbf{x}^1 \cdots \mathbf{x}^N]$ associated with a joint hypothesis set $[H_k^1 \cdots H_k^N]$ for the kth registered subject is $p(\mathbf{x}|H_k) = \prod_{i=1}^N p(\mathbf{x}^i|H_k^i)$. The decision rule then is the same as described by (14).

For the decision fusion, we first obtain the binary decision vector $[\mathcal{D}_k^1 \cdots \mathcal{D}_k^N]$ for the kth registered subject, and then make the final decision by majority voting. A random decision will be made if there is a tie.

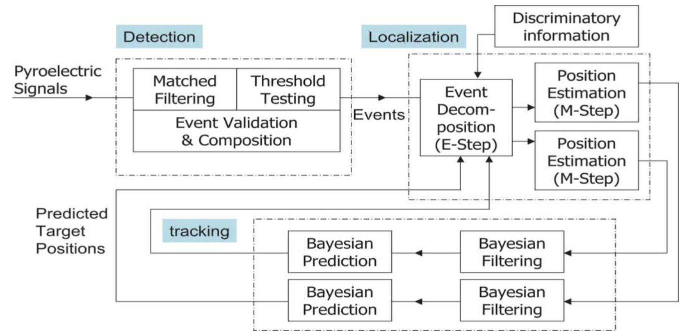


Fig. 5. EM-Bayesian multiple human tracking scheme for distributed pyroelectric sensors.

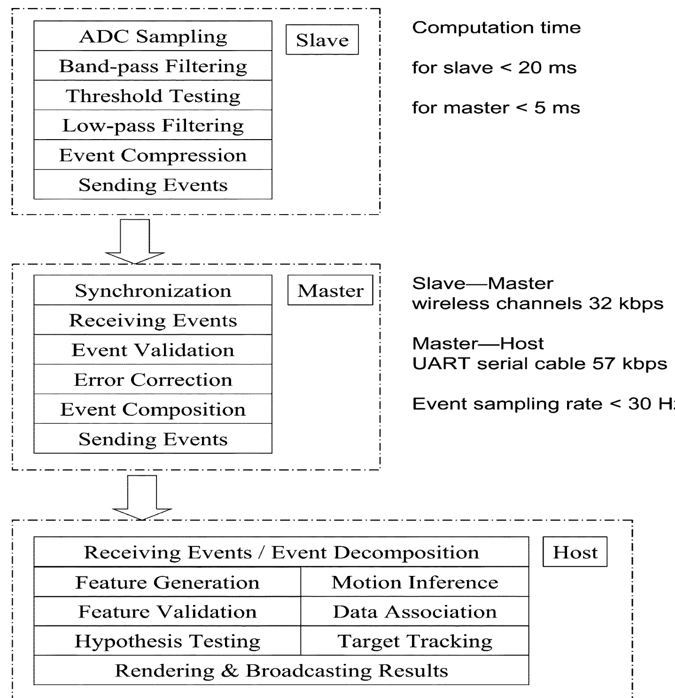


Fig. 6. Computational load distribution among slave, master, and host.

V. System Implementation

Fig. 5 shows the tracking procedure for distributed sensors. In [10], we presented methods for event detection and digitization from pyroelectric sensors and the interpretation of the angular displacement measurements from the events. Through our specific sensor deployment based on sensor FOV geometry, four local detection areas are formed, as shown in Fig. 3. If an object moves inside one of these areas, the sensors associated with that area should fire, forming a valid event. For example, for an object moving in area I, a valid event has the nonzero four higher bits of the event reported by sensor node 1 and the nonzero four lower bits by sensor node 2. If only one of these two sensors reports a nonzero signal, the master will regard it as invalid and clear those bits to zero. After the event validation, the master will package all four event bytes into a single message and send it to the host. The host will localize the objects by interpreting this composite event through the EM steps described in Section IV.

The complete system consists of slave nodes, a master node, and a host computer. We use TRF6901 and MSP430149 as the computation and communication platform. The distribution of computational load is shown in Fig. 6. Each slave node samples the sensor response signals and converts them into event indexes by band-pass filtering, threshold testing, and low-pass filtering. After compressing each event index into a single byte, the slave node broadcasts the data packet to the master node. The master node synchronizes the communications of the nodes, removes the false alarms, and frames a new composite event message. The master sends the event message to the host, which computes local angular displacements or digital features and updates the dynamics states or identities of objects.

Walker identification involves feature extraction, feature modeling, and data testing. In [35], [36], and [11], we studied analog and digital features generated by just one sensor node to recognize walkers in two modalities: path-dependent and path-independent. In this research, we implemented multiple nodes for performance improvement and multiple walker identification. We chose the digital feature modeled by HMMs. The digital feature is based on the multidimensional binary event

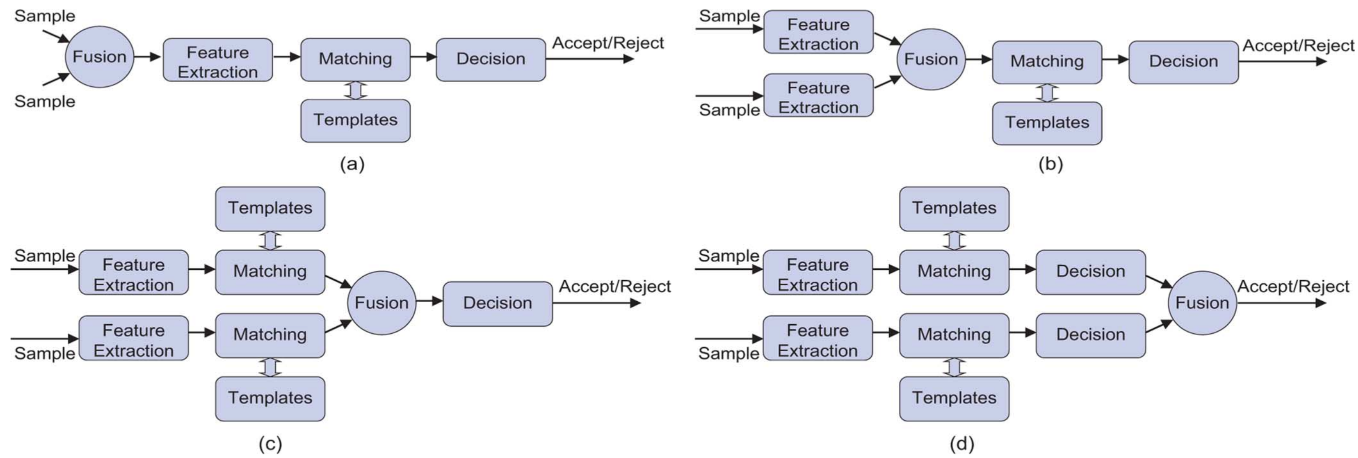


Fig. 7. Sensor fusion schemes: (a) sample fusion; (b) feature fusion; (c) score fusion; and (d) decision fusion [40].

indexes generated by the type II sensor nodes. Each feature consists of a fixed length of binary indexes. HMMs characterize the statistics of those finite-state sequences during training. Their model parameters θ_H are obtained by random initialization and updated after the iterations of expectation-maximization in light of the likelihood of how well the data fit models. By using MATLAB Statistics Toolbox function *hmmtrain*, we can estimate the transition and emission matrices, $\mathbf{A}$ and $\mathbf{B}$, from an initial guess of their values. With another function *hmmdecode*, we can compute the posterior state probabilities of testing sequences generated by different human objects.

The fusion of multiple nodes can happen at four different levels: sample, feature, score, and decision [40], as shown in Fig. 7(a)–(d). Sample level fusion combines multiple sample data sets into a single sample data set. Feature level fusion relies on building a global statistical feature model. Score level fusion combines scores from matching modules, and only one score is outputted to the decision module. Score normalization is important since the likelihood scores from different sensor nodes have different scales. Decision level fusion combines decision from decision modules for different nodes using AND, OR, or majority voting.

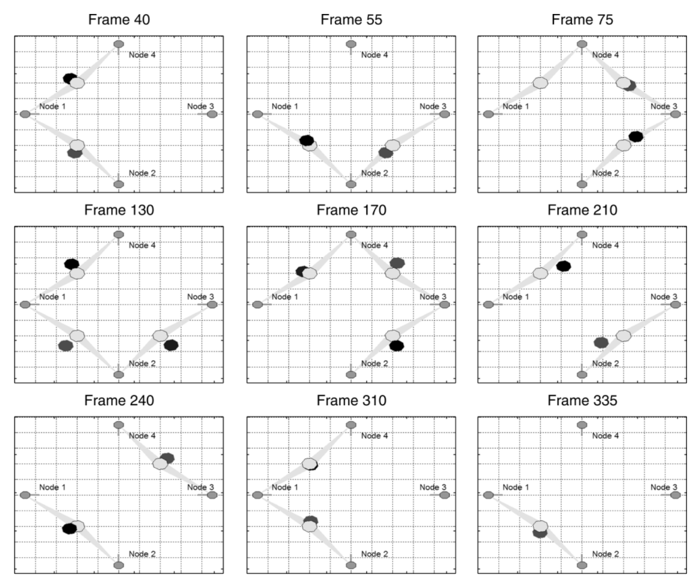


Fig. 8. Snapshots of tracking one, two, and three objects. Four sensor nodes detect the angular displacements of the target, illustrated as the shaded beams. At each iteration, after the data-object-association, the target positions are estimated by a grid approximation and by Kalman filtering.

VI. Results and Discussion

A. Multiple Human Tracking

The tracking system has been implemented in a 9 m $\times$ 9 m room. Two human objects were tracked following both the same path and crossing paths. Fig. 8 displays snapshots of the tracking of one, two, and three human objects, respectively, with four type I sensor nodes. For two walkers following one by another, the four sensor nodes generated four sets of 8-bit event sequences shown in Fig. 9(a). Multiple object tracking involves the process of data-object-association. At each iteration, the association probabilities between measurements and objects were calculated and measurements were assigned to objects accordingly. The tracked trajectories of two human objects following each other along a prescribed rectangular route are illustrated in Fig. 10(a). It can be seen that both initial positions are set as [0 0]. The tracking errors and their histograms are given in Fig. 10(c). The standard deviations of the tracking errors are 0.44 m and 0.45 m for the two objects, respectively.

A more challenging scenario for multiple object tracking is the case when they walk along different paths with a cross-over. There are indeed no effective solutions for the data association problem in general cases without discrimination characteristics available. For some specific cases, such as when objects do not change their velocities abruptly before and after the cross, we can resolve the data-object-association problem by using *a priori* on speeds and their predictions from Bayesian rules. The four sensing nodes generated 8-bit event sequences, as shown in Fig. 9(b). Fig. 10(b) displays the tracking results when two objects walk along two different diagonals of the room. By using the predicted speeds, the trackers can follow the targets after the cross-over. The tracking errors and their histogram are given in Fig. 10(d). The standard deviations of the tracking errors are 0.38 m and 0.7 m for the two objects, respectively.

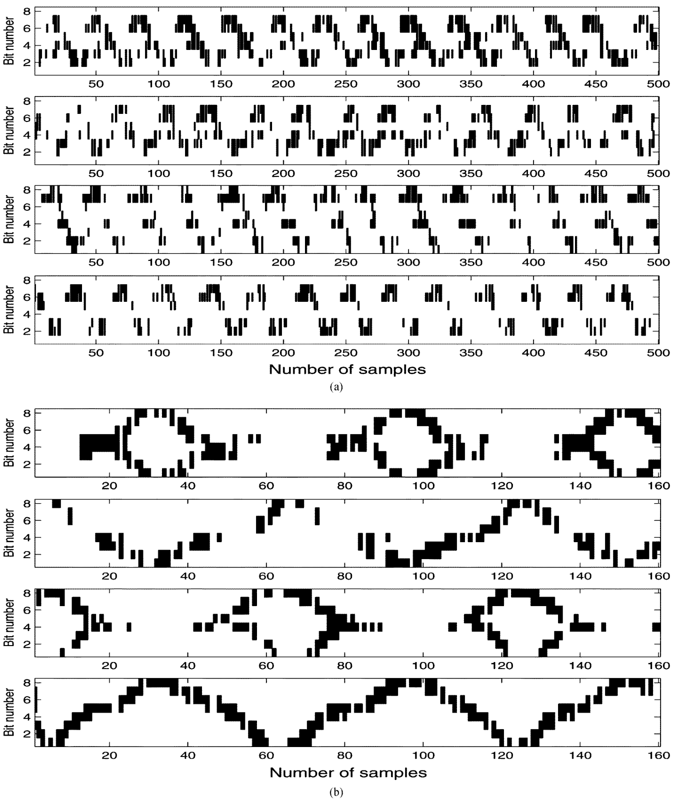


Fig. 9. 8-bit event sequences of four nodes for tracking (a) two objects walking in way of one-follow-another and (b) two objects having crossing paths.

B. Single Walker Identification

For single human subject identification, we used four type II sensor nodes. The human subjects randomly walk inside the room one at a time. Fig. 11(a) illustrates event sequences transmitted by four identification sensor nodes. However, as this 16-bit event sequence has too many possible observations, 2^{16}, to train an HMM model, we need to reduce the dimension of the observation space by extracting the sequences containing more information, that is, feature sequences. For a real-number sequence, one can use principal component analysis (PCA) to extract features. For the binary sequences, we choose those sequences having higher frequency variations as features. Such a feature extraction can be performed at two levels: sample and feature. In the sample fusion scheme, eight most varying binary sequences are selected out of all the sixteen binary event sequences generated by four sensor nodes, as shown in Fig. 11(b). In the feature fusion scheme, a feature sequence that consists of the two most varying binary sequences is extracted first for each node. Then the obtained four feature sequences are put together to form an 8-bit feature sequence, as shown in Fig. 11(c). Each subject generated two sets of data, one for feature model training, another for real time testing. Each set of testing data includes 20 feature sequences generated by one subject. Fig. 12(a) shows the close-set identification results for five walkers using one of four sensor nodes, respectively. Due to the difference in walking habits of human subjects, those four sensor nodes yield different identification performance. The identification rates of some nodes are worse than 50%.

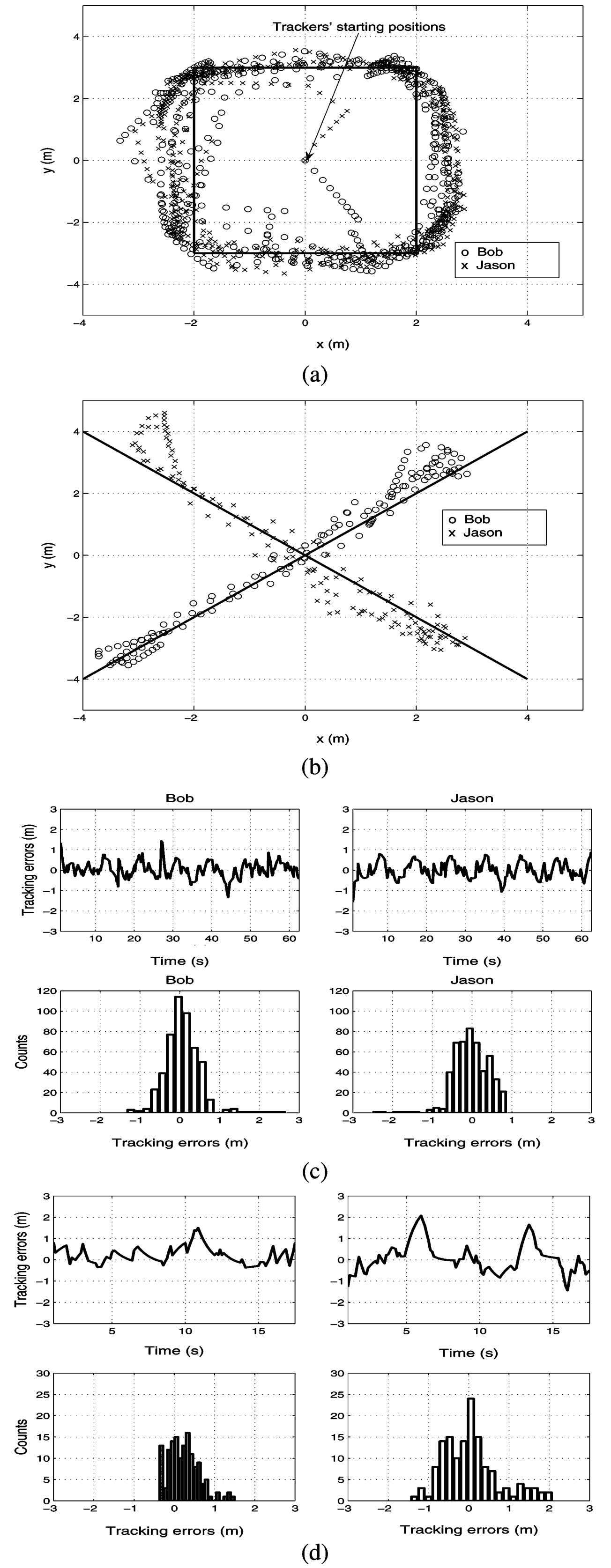


Fig. 10. (a) Tracking errors for: (a) two objects following parallel paths and their histograms and (b) two trackers and their histograms. (c) Estimated parallel trajectories of two human objects walking in five rounds. The tracking results are represented by circles and crosses and the prescribed route by solid lines. (d) Estimated crossing trajectories of two human objects walking in three rounds.

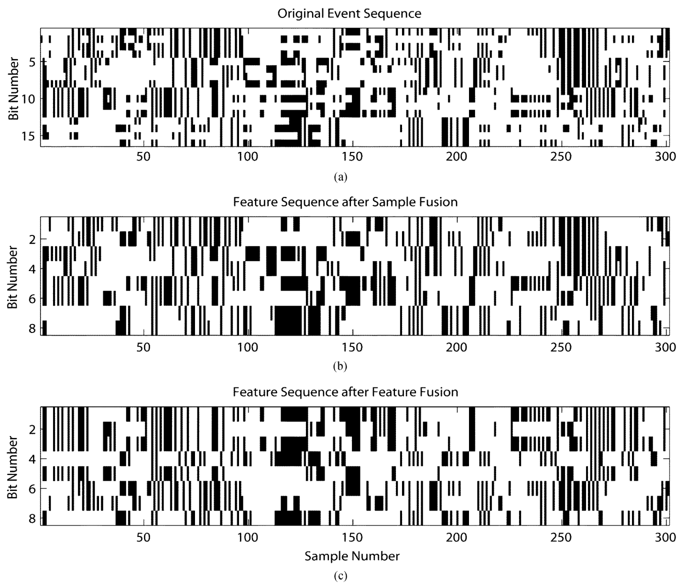


Fig. 11. A 16-bit binary event sequence and two 8-bit feature sequences generated by one random walk. (a) Original 16-bit event sequence from four sensor nodes. (b) 8-bit feature sequence using sample fusion. (c) 8-bit feature sequence using feature fusion.

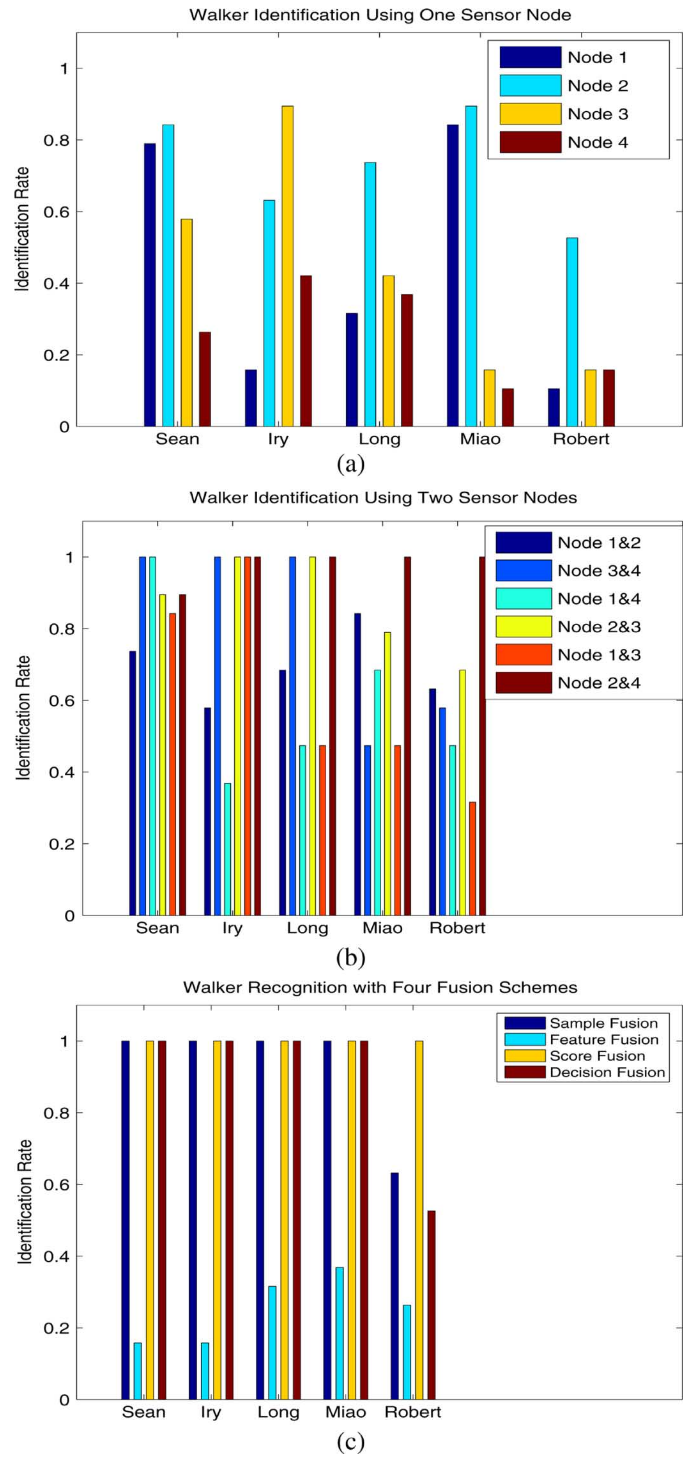


Fig. 12. Single walker identification using: (a) different single sensor nodes, respectively; (b) different pairs of sensor nodes, respectively; and (c) four sensor fusion schemes: sample fusion, feature fusion, score fusion, decision fusion. Multiple walker identification in terms of marginal and joint identification rates.

Fig. 12(b) shows the close-set identification results for five walkers using a pair of four sensor nodes respectively. Due to the geometry of sensor node deployment and room, sensor node combination 2&4 produces the best identification performance. However, for some walkers, such a sensor node pair still can not produce an identification rate of 100%. To improve the identification performance, we applied four sensor fusion schemes, namely sample fusion, feature fusion, score fusion, and decision fusion, to those sensor node pairs. The results are illustrated in Fig. 12(c). It can be seen that the score fusion produces the best result: the identification rates for five walkers are all 100%.

C. Multiple Walker Identification

The main challenge for multiple human subject recognition is the same as that for multiple human subject tracking: how to associate feature sequences with the corresponding subjects. The signals generated by multiple subjects usually interfere and overlap with each other, making it difficult to extract feature sequences for each individual. Our developed approach is to exploit geometric advantages of distributed sensors, which are deployed in a way of forming several nonoverlapped subdetection-regions. The target in each of those subdetection-regions is only detected by a subset of sensors in different sensor nodes, as shown in Fig. 3. When multiple humans walk in different subdetection-regions, it is easy to extract the feature sequences for each subject.

However, when two subjects switch their subdetection-regions, the identification component of the sensor system alone is unable to detect it and keeps processing the signals as if two subjects are still in their original subdetection-regions. It needs an integration of tracking and recognition components. In this paper, we only study simplified cases assuming that each subject stays in their original subdetection-region over the course of identification. Fig. 13 shows the identification results for two walkers. Here, we use the terms of marginal and joint identification rates to describe the multiple human recognition performance. The marginal identification rate refers to the identification rate of each subject when there is a presence of multiple subjects. The joint identification rate refers to the identification rate of all the subjects at the same time. It can be seen, as predicted, that the identification performance for multiple walkers

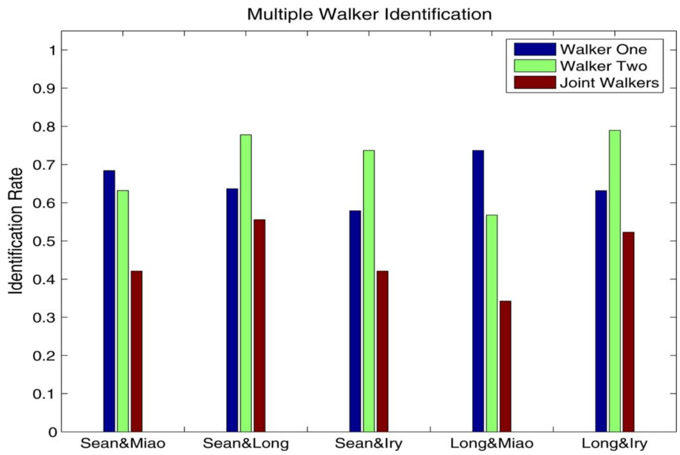


Fig. 13. Multiple walker identification in terms of marginal and joint identification rates.

is worse than that for single walker. The highest marginal identification rate is 80% and the lowest rate is 55%. The highest joint identification rate is 55% and the lowest rate is 33%. One reason is that the signals generated by two walkers inevitably interfere with one another. Another reason is that as the walking range is reduced, the gait information becomes less in the extracted feature sequences.

D. Discussion

The explicit advantages of human tracking with DSNs include better spatial coverage, robustness, survivability, and modularity, compared to focal plane centralized video systems. The advantages of walker identification using pyroelectric sensors include its low cost, low power consumption, independence of illumination, and less privacy infringement. By using multiple sensor nodes, the identification performance in real time for a small group of walkers can be dramatically improved to 100%. According to the reports on gait recognition from video streams [28]–[30], a recognition rate exceeding 95% for 28 subjects has been achieved, each recognition using at least four image sequences. Their result was obtained based on recorded databases instead of real-time tests.

The concept of distributing the computation to multiple low complexity nodes reduces computational requirements of the central processor and the size of data storage. The use of the motion detectors helps maintain the low requirements on data throughput, computational consumption, and communication bandwidth. The characteristics of the pyroelectric sensor give the system the capability to operate under any illumination conditions and the capability to capture human thermal biometrics. The global and local FOV modulation is the most crucial step in developing pyroelectric sensor systems for multiple human tracking and identification. It allows improvement in sensing accuracy, tracking precision and signal discrimination power, and facilitates the process of data-object-association.

The prototype system presented above only employs four sensor nodes to demonstrate the advantages of distributed sensors in tracking (with type I sensor modules) and identifying (with type II sensor modules) multiple objects. It can be extended to more sensor nodes, in order to achieve a higher tracking resolution, larger object number and higher identification rate. A fully functional real-time multiple human tracking and identification system demands short testing event sequences for fast walker identification and the simultaneous identification of multiple objects.

To achieve such a goal, we can 1) improve the sensing resolution by using lens arrays with more elements; 2) adjust the focal length with respect to object space size (the size of the room under examination); and 3) deploy more sensor nodes. With a higher detection resolution, pyroelectric sensor arrays can capture more distinguishable gait information from walkers. When a room is small, the sensor focal length has to be reduced, such that each sensor can detect more motion of subjects in a near-field, small volume object space. Deploying more sensor nodes can help improve the identification performance and yield more effective measurements of subdetection-regions but will incur more complexity on wireless communication/networking, decision fusion, and impose higher requirements on the hardware.

From a signal processing perspective, more advances should be made in 1) distributed signal inference and data learning; 2) tracker initialization and maintenance; and 3) feature representation and modeling. The distributed inference and learning schemes [45], [46] can better utilize the distributed computational resources and achieve the peer-to-peer computation mode. In the crowded scene, robust and intelligent approaches are required to initialize trackers and evaluate their quality. The proposed EM scheme allows a convenient incorporation of prior knowledge into object number estimation but demands closer algorithmic investigations. How to select the best gait biometric feature representation for distributed pyroelectric measurements is still an open question. The multiperspective, multicycle aspects of the thermal gait measurements should be better utilized in feature modeling.

The underlying mechanism and main motivation of developing distributed sensors in multiple target tracking and identification through FOV modulation is the study of reference structure tomography and compressive sensing [47], [48]. Both results recommend choosing random measurement matrices through sensor FOV modulation to achieve efficient information acquisition. As a general FOV design procedure needs a closer investigation, many measurement coding schemes have already been applied in a variety of coded-aperture imaging systems, from Hadamard codes to pseudorandom codes [49], [50]. For a multinode pyroelectric sensor system, measurement coding schemes can differ in nodes to maximize the extracted information.

VII. Conclusion

In this paper, we present a wireless distributed pyroelectric sensor system for multiple human tracking and identification based on TI's micro-controller and RF transceiver combination of MSP430149 and TRF6901. The system consists of host, master, and slave modules. The tracking scheme comprises event detection, object localization, and motion filtering and prediction. The prototype system can track two humans simultaneously in two typical scenarios. By employing multiple sensor nodes and sensor fusion techniques, walker identification performance can be dramatically improved. We approached the multiple walker recognition problem using the concept of subdetection-regions formed by a specific global sensor FOV geometry. The proposed sensor systems can work as a reliable biometric system for a small group of human subjects. From the achieved experimental results, we believe that the pyroelectric sensor will become a mainstream human detection instrument; besides its video and audio counterparts, this sensor offers one more unique modality for all the applications of human-machine interfaces. It can run as a standalone inmate/patient monitoring system under any illumination conditions, as well as a complement for conventional video and audio human tracking and identification systems. Our future work includes sensor module improvement, FOV coding optimization, deployment of a large number of sensor nodes, and integration of multiple human tracking and identification.

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