COMPRESSIVE GAIT BIOMETRIC WITH WIRELESS DISTRIBUTED PYROELECTRIC SENSORS

by

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A THESIS

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LIST OF ABBREVIATIONS AND SYMBOLS

FOV	Field of View.
WSN	Wireless Sensor Network.
*	Convolution.
KHz	Kilo (10^3) Hertz. Unit of frequency.
MHz	Mega (10^6) Hertz. Unit of frequency.
$\sum_i$	Summation over i.
h(t)	Impulse Response
$V(r)$	Modulated Visibility Function
$s(t)$	Response Signal of Sensor
ψ	Radiation Function from Object
ϵ	Belong to
μm	Micro(10^{-6}) Meter. Unit of Length.
D_{KL}	Kullback–Leibler divergence
=	Equal to
log	Logrithm

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CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

Human tracking and recognition are desirable yet challenging for many applications including surveillance, computer vision, robotics, virtual reality, etc. Many biometric modalities have been used on these applications. Compared to other biometric modalities, such as fingerprints, face, and iris, gait biometrics are advantageous in their capability of recognition at a distance under changing environmental and cosmetic conditions. Despite having many limitations, from clothing changes to gait variation due to different physical and emotional conditions, the discrimination power of gait can still serve as a unique and useful component in human tracking and recognition systems.

The work presented in this thesis aims at developing a distributed wireless sensor human recognition and tracking system, in order to improve the performance of previously established centralized pyroelectric sensor system. Our final goal is to provide wireless distributed pyroelectric sensor nodes as an alternative to the centralized infrared video sensors, with lower cost, lower detectability, lower power consumption and computation, and less privacy infringement. In previous related study, the system was able to succeed in identifying individuals walking along the same path, or just randomly inside a room, with an identification rate higher than 80% for around 10 subjects.

For the human recognition system, innovations and adaptations are developed in: (1) sampling structure, multiple modified two-column sensor nodes are engaged to leverage the ability of effective acquisition of both the shape and dynamic gait attribution. (2) sensing protocols, different compressive measurement functions are

provided for accomplishing the central task of compressive sensing protocol - choosing a proper scheme of the random projection encoding. (3) processing architecture, different levels of fusion schemes performed at data level, feature level, score level, and decision level constitute the processing architecture. Along with the advent of several new digital features, a higher recognition rate for both path dependent human recognition and path independent human recognition is achieved. For the human tracking system, a distributed tracking method was proposed to replace the previous centralized algorithm. Both recognition and tracking system will eventually be combined together and work cooperatively to form the human tracking and identification system.

Real time implementation results are presented in the thesis. Moreover, experimental work and the related results are also discussed.

CHAPTER 1

INTRODUCTION

1.1 Overview

Biometric systems have been researched and tested for a few decades, but have only recently entered into the public consciousness because of high profile applications and increased usage by the public in day-to-day activities. [26, 45] Example deployments within the United States Government include the FBI's Integrated Automated Fingerprint Identification System (IAFIS), the US-VISIT program, and the Registered Traveler program. Many companies are also implementing biometric technologies to secure areas, maintain time records and enhance user convenience. For example, for many years Disney World has employed biometric devices for season ticket holder to expedite and simplify the process of entering its parks, while ensuring that the ticket is used only by the individual to whom it was issued.

A typical biometric system is comprised of five integrated components: 1, a sensor is used to collect the data and convert the information to a digital format; 2, signal processing algorithms perform quality control activities and develop the biometric template; 3, a data storage component keeps information that new biometric templates will be compare to; 4, a matching algorithm compares the new biometric template to one or more templates kept in data storage; 5, a decision process uses the results from the matching component to make a system-level decision.

Over the years, many biometric modalities, such as fingerprints, face, voice, iris and gait have been studied and applied to human recognition application. Following are some examples:

- Fingerprints have an uneven surface of ridges and valleys that form a unique pattern for each individual. For most applications, the primary interest is in the ridge patterns on the top joint of the finger.
- Many face recognition approaches have existed for several years using low resolution 2D images. Recent work in high resolution 2D and 3D shows the potential to greatly improve face recognition. Despite the volumes of research, there are no agreed-upon methods for automated face recognition as there are for fingerprints.
- The concept of using the iris for recognition purposes dates back to 1936. To obtain a good image of the iris, identification systems typically illuminate the iris with near-infrared light. A common misconception is that iris recognition shines a laser on the eye to "scan" it. This is incorrect untrue. Iris recognition simply takes an illuminated picture of the iris without causing any discomfort to the individual.
- Speaker recognition uses an individual's speech, a feature influenced by both the physical structure of an individual's vocal tract and the behavioral characteristics of the individual, for recognition purposes. [36, 37, 38, 39]

Despite having many limitations, from clothing changes to gait variation due to different physical and emotional conditions, gait based human recognition has drawn more and more attention because of its unique advantages over other biometric modalities such as less private infringement, less detecbility and so on. [27, 28, 33, 34] Gait information contains a unique biological or behavioral identification characteristic, such as a fingerprint or a face. Most studies are addressing issues of gait recognition by computer vision that is usually limited for real time application due to the requirement of intensive computations. Others are exploring a novel approach -- gait recognition with a sensor system, which usually have the advantages over the computer vision on cost, power consumption and computation.

On the other hand, recent advances in micro-processors, radio frequency transceivers, sensors, and networking techniques enable traditional centralized multiple sensor systems to evolve into new generations of distributed sensor network. Such networks can provide an immense raw sensing capability in many different modalities, thus create a good environment for distributed human tracking methods to be implemented. As objects move around the sensor field, they affect the observations at nearby nodes. The key to collaboration across nodes is to work out if and how the observations at different nodes are related, and then use these related observations to form more accurate estimates for the objects existence, track and type.

In the previous study [46-50] for human target tracking and recognition using wireless pysoelectric sensors, results from experiments, data analysis and algorithm

design are promising. The main idea is when a human walks through the visibility modulated object space, the sensors will generate a binary signal sequence that contains gait information as well as location information of the walker. By finding the pattern hidden in the signal sequences, the human objects can be located and recognized. The work presented in this thesis suggested several new methods, which improves the performance of the human tracking and recognition system.

1.2 Trend and future of biometrics

The terms "Biometrics" and "Biometry" have been used since early in the 20th century to refer to the field of development of statistical and mathematical methods applicable to data analysis of problems in the biological sciences. Depending on the application, the benefit of using or deploying biometrics may be increased security, increased convenience, reduced fraud, or delivery of enhanced services. In some applications, the biometric serves only as a deterrent; in others, it is central to system operation.

Currently the principal use of the hardware and software dedicated to human biometrics is for identification purposes. This requires recording in some fashion a kind of data of the subject that can later be utilized as a template to identify another data frame of the same part of that subject. It depends upon a digital form of matching.

Biometrics can provide a greater degree of security than traditional authentication methods, meaning that resources are accessible only to authorized users and are kept

protected from unauthorized users. Traditional passwords and PINs are easily guessed or compromised; tokens can be stolen. By contrast, biometrics data cannot be guessed or stolen in the same fashion as a password or token. Although some biometric systems can be broken under certain conditions, today's biometric systems are highly unlikely to be fooled by a picture of a face, an impression of a fingerprint, or a recording of a voice. This assumes, of course, that the imposter has been able to gather these physiological characteristics—unlikely in most cases. Because biometrics are difficult if not impossible to forget, they can offer much greater convenience than systems based on remembering multiple passwords or on keeping possession of an authentication token. For PC applications in which a user must access multiple resources, biometrics can greatly simplify the authentication process—the biometric replaces multiple passwords, in theory reducing the burden on both the user and the system administrator. Applications such as point-of-sale transactions have also begun to see the use of biometrics to authorize purchases from prefunded accounts, eliminating the need for cards. Biometric authentication also allows for association of higher levels of rights and privileges with a successful authentication.

Just as leading biometric technologies differ in fundamental ways, the major biometric applications differ substantially in terms of security and convenience requirements, process flow of enrollment and verification, and system design.

Nowadays, biometric applications are mainly divided into just three categories:

- Applications in which biometrics provide logical access to data or information.

- Applications in which biometrics provide physical *access* to tangible materials or to controlled areas.
- Applications in which biometrics identify or verify the identity of an individual from a database.

In the future, behavioral and medical diagnostics will keep drawing more attention and many promising projects will be put to application. For example, a full home health care appliances and software are possible long range future markets, either in modules or as complete units, probably directly interfacing with primary care organizations. This advance could follow the clinical and institutional market saturation of medical history and diagnostic applications. Another good example is a full surveillance home safety system can be applied using biometric, no password or PIN is needed. It offers residents both more reliable and convenient safety system.

1.3 Compressive human recognition

There are two topics included in the compressive human recognition:1, how to implement data condensing while maintaining essential integrity of each individual feature, which is also known as a problem of compressing sensing. Successful compressing sensing scheme enable us to implement our recognition system at the physical layer where the processing speed can be greatly improved when using MAC layer protocol. 2, how to further keep or enhance if possible the identification/verification

performance, in another word, given the digital patter from different walker, we are trying to find a stable and unique feature belongs to different individual.

To address the first problem, we tried to increase the sensing range hoping to capture more gait information. Firstly we modified our identification node from one-column to two-column with the visibility coding listed in Table 1.1, thus each sensor node can hold 8 sensors as shown in Figure 1.1.

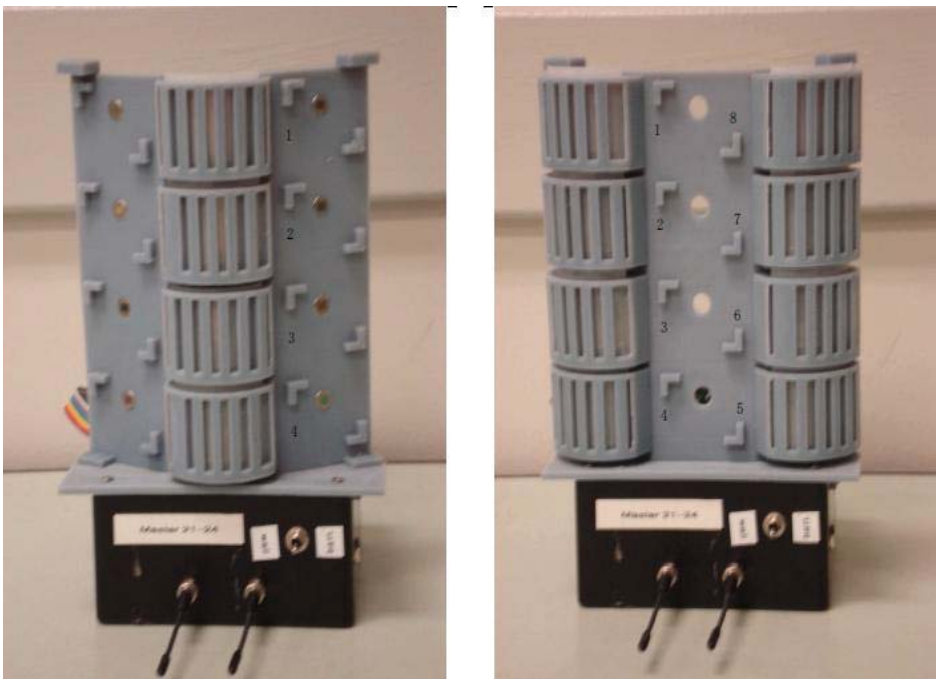

Fig 1.1: Identification sensor node modification

Two more such identification nodes are added to our system, and all 3 nodes are put in 3 different positions as shown in figure 1.2. In such case, the digital data would

contain more detail information about the walker features. For example, when walking along the fixed path 1 as the black line shown in Figure 1.2, sensor node 3 can capture the front motion of the walker while the other two can collect the silhouette dynamics. Then we evaluated the information quality of each bit and apply the bits with best quality for compressive sensing. Several criterions were considered, and self-correlation and entropy value are found to be useful for this purpose.

Table 1.1 Visibility coding scheme of the recognition node

LENS ARRAY	OLD VISIBILITY	LENS ARRAY	NEW VISIBITILTY
1	[1 0 1 0 1 0 1 0 1 0 1]	1	[1 0 1 0 1 0 1 0 1 0 1]
2	[0 1 0 1 0 1 0 1 0 1 0]	2	[0 1 0 1 0 1 0 1 0 1 0]
3	[1 0 1 0 1 0 1 0 1 0 1]	3	[1 0 1 0 1 0 1 0 1 0 1]
4	[0 1 0 1 0 1 0 1 0 1 0]	4	[0 1 0 1 0 1 0 1 0 1 0]
		5	[1 0 1 0 1 0 1 0 1 0 1]
		6	[0 1 0 1 0 1 0 1 0 1 0]
		7	[1 0 1 0 1 0 1 0 1 0 1]
		8	[0 1 0 1 0 1 0 1 0 1 0]

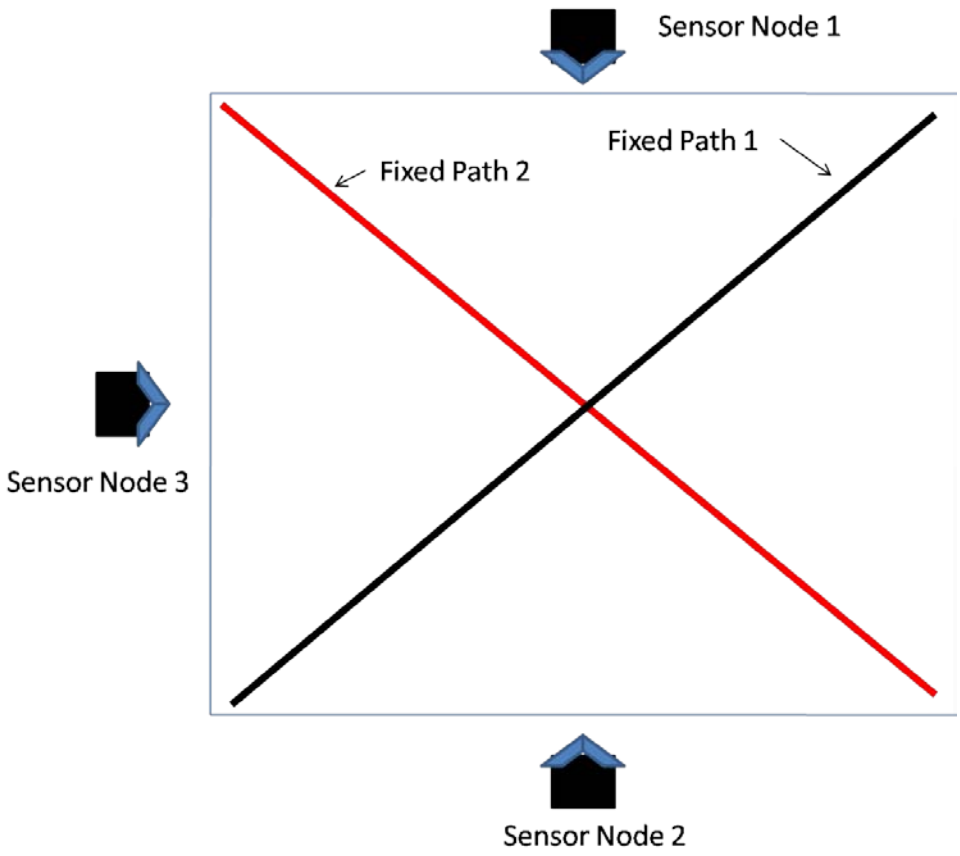

Fig 1.2: Recognition system setup

For the second problem, we introduced compressive sensing idea to our system, meanwhile we designed different sequence mining schemes hope to find the best dynamic feature as well as statistic feature that can efficiently and robustly represent the walker characters. At the same time, we continued the previous work about HMM model and tried to use the Variational Bayesian Hidden Markov Models in our recognition system.

1.4 Distributed human tracking

In sensor networks, distributed processing is becoming more popular than centralized approaches. This is because centralized networks with only one processing node are vulnerable if that particular node is incapacitated. The communication overhead is also significant because if all the sensing nodes are trying to transmit raw data to the central processing node, the required bandwidth increases significantly with the number of nodes. To overcome these drawbacks, a distributed processing approach is attractive.

Distributed processing stipulates processing capabilities at individual sensors. We denote a sensor that has the ability to process data and communicate with neighboring sensors in addition to sensing the environment as a smart sensor. Distributed processing eliminates the need for a central processing node. Since a smart sensor can process its own data, it need only transmit sufficient statistics in the communication channel, minimizing the communication among sensors. Communication consumes more battery power than computation; hence smart sensor networks with distributed processing have additional advantages.

In distributed tracking system, object detection and tracking has been explored in on an individual node basis. There is very little research on distributed detection and tracking within networks of wireless sensors. Object tracking is a topic that has been studied and developed extensively but primarily in the domain of active and passive radar. Graphical modeling techniques such as Kalman filtering and HMMs have been employed very successfully in this domain. Complex multiple hypothesis testing techniques are incorporated into their frameworks that rigorously evaluate every possible origin of the

measurements received. However, they assume that all the measurements are available for processing at a centralized node. In order to develop a distributed tracking sensor system, a generic algorithm that can be applied to the modality available is essential. The figure below shows the sensor node deployed in the tracking system and the system setup during the experiment.

Fig 1.3: Distributed tracking sensor node

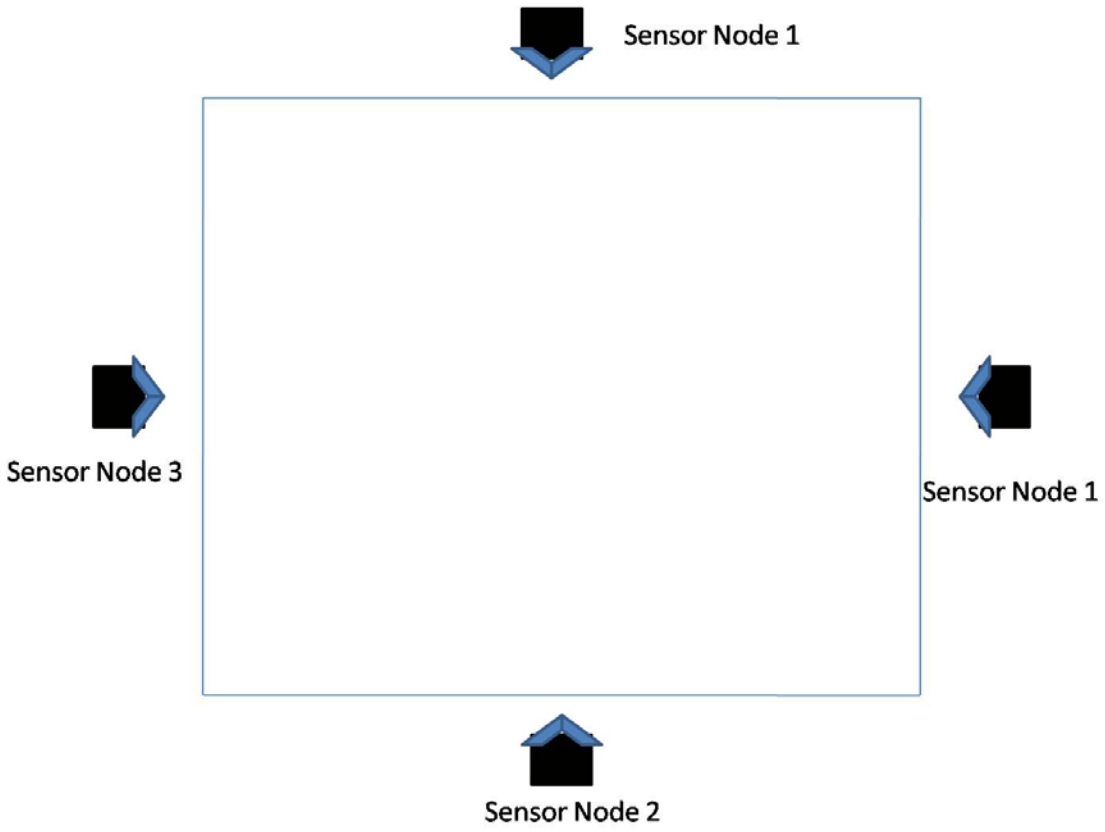

Fig 1.4: Distributed tracking system setup

Table below shows the visibility coding mask for distributed tracking sensor node.

Table 1.2 Visibility coding scheme of distributed tracking node

LENS ARRAY	VISIBITILTY
1	[0 1 1 0 0 0 0 0 0 0 0]
2	[0 0 1 1 0 0 0 0 0 0 0]
3	[0 0 0 0 1 1 0 0 0 0 0]

4	[0 0 0 0 0 1 1 0 0 0 0]
5	[0 0 0 0 0 1 1 0 0 0 0]
6	[0 0 0 0 0 0 1 1 0 0 0]
7	[0 0 0 0 0 0 0 0 1 1 0]
8	[0 0 0 0 0 0 0 0 0 1 1]

1.5: Thesis outline

The next chapter briefly discusses preliminary knowledge, including data recovery, compressive sensing, sequence mining, distance function and sensor model and visibility modulation. Given these preliminary factors, based on which our research was carried on, Chapter 3 describes the detail development of the compressive human recognition and presents the results form of plots. Chapter 4 introduces the distributed tracking scheme as well as implementation. The experimental setup is presented in Chapter 5 and the results are presented in Chapter 6. Chapter 7 summarizes the work and presents possible future direction of the work.

CHAPTER 2

PRELIMINARY

2.1 Introduction

This chapter discusses several issues we had during the research and the solution as well as the backgrounds to those solutions. In Sensor model and visibility modulation, we give a illustration about the sensor model and how the visibility modulation influence the result of sensory data. The ideas of compressive sensing, sequence mining and distance function are also presented here. Compressive sensing plays promising roles in the tradeoff between the high information gain in expectation out of distributed sensor systems and the bottleneck in reality of their narrow data throughput and limited computation power. [41] Sequence mining is concerned with finding statistically relevant patters between data examples where values are delivered in a sequence. In our case, since the sensory data are presented in the form of binary sequence, it is critical for us to explore the field of sequence mining in order to find and evaluate the patter hidden in each sequence. Sequence distance functions are designed to measure sequence similarity. How to evaluate similarity between sequences belong to different human target the central idea for identification and recognition. Given the feature, the feature based sequence distance allows us to use the measureable quantity to make the recognition decision.

2.2 Sensor model and visibility modulation

In this section, we present a pyroelectric sensor system model, including sensor node architecture, sensor visibility and its modulation by a Fresnel lens array. The design of sensor modules is also described.

Figure 2.1 shows the architecture of the sensor node in our system. Robust collaborative signal processing techniques can map the signal states, measured by the distributed sensors, through low-level local computation at each node, into configuration state sequences, which after decision fusion constitute the final identities of targets. A suitable networking protocol guarantees reliable information routing and data dissemination. We employed the master/slave communication mode. Once the master/slave relationship is established, the direction of control is always from the master to the slave(s).

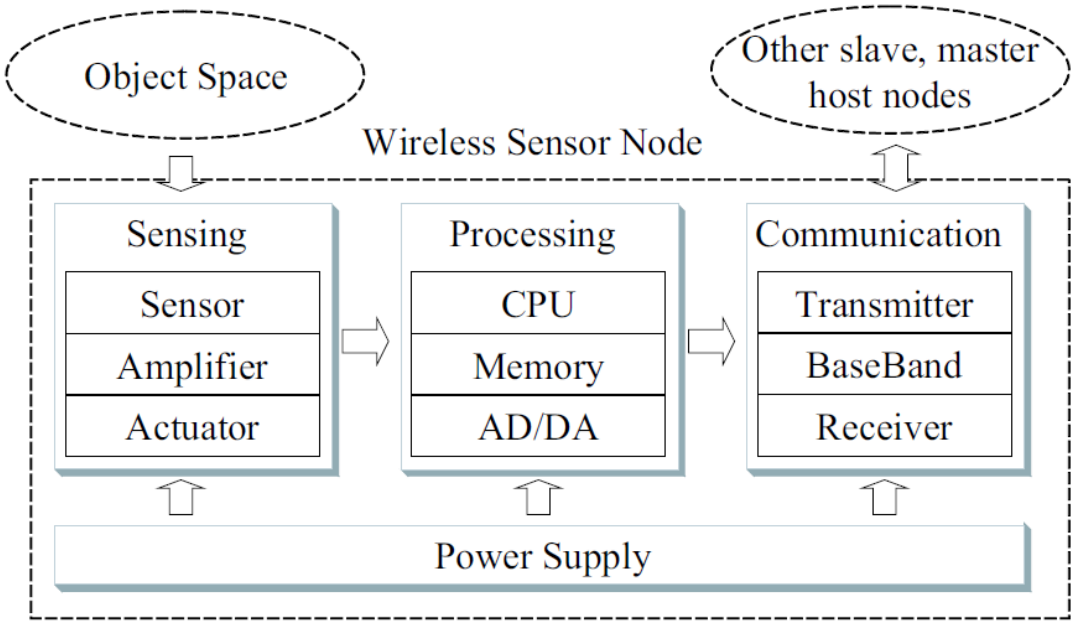

Figure 2.1: Sensor node architecture

The pyroelectric sensing circuits create the signal space, Fresnel lens arrays produce the visibility modulation, and human thermal sources form the object space.

Under the linearity assumption, the response signal of *m* sensors, $s(t) \in R^m$ is given by

$$\boldsymbol{s}(t) = h(t) * \int_{\Omega} \boldsymbol{v}(\boldsymbol{r})\psi(\boldsymbol{r}, t)d\boldsymbol{r}$$

Where "*" denotes convolution, *h(t)* is the impulse response of one sensor, Ω is the object space, $\boldsymbol{V}(\boldsymbol{r}) \epsilon [0,1]^m$ is the modulated visibility function between *m* sensors and the object space, $\psi(\boldsymbol{r}, t)$ is the radiation from the object.

The Fresnel lens we employ is made of a light-weight, low-cost plastic material with good transmission characteristics in the 8~10 μm range. We first utilize the Fresnel lens array to modulate the visibility of our sensors, such that each sensor can observe events uniformly distributed over 11 angles as shown in Figure 2.2. Coded masks are then used to differentiate the sensors' FOVs, such that each sensor can measure different combinations of thermal variation in space caused by motion of human subjects. The underlying mechanism and main motivation of developing geometric sensors in identification is the study of reference structure tomography and compressive sensing. It suggests that multi-dimensional features of a radiation source could be captured at an arbitrary level, once there exists a set of base functions that structurally pose and numerically condition the reconstruction procedure, by fine tuning the multi-dimensional visibilities of distributed sensors. Through its scan-free multi-dimensional imaging, the feature abstraction, shape parameterization, and even characteristic classification of radiation sources under examination can be achieved in a data-efficient and computation-efficient way.

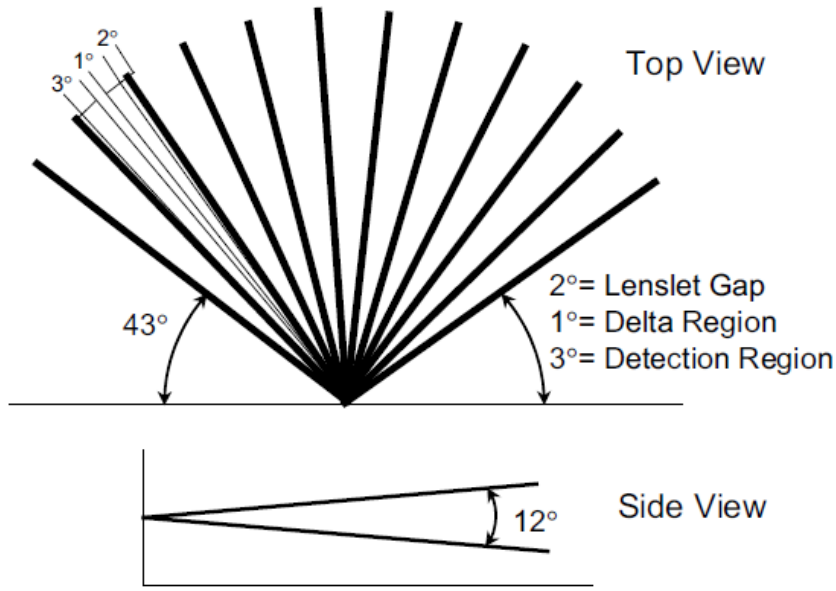

Figure 2.2: Top and side Fresnel lens visible zone

2.3 Compressive sensing

Using multiple sensor nodes described in 1.3 allows enhancing the performance of the distributed sensor system. However, doing so also introduces huge amount noise, redundancy as well as increases the computational complexity. In absence of compressive sensing, one would have to directly use the 24 bits data, then the 2^24=16777216 possible states have to be calculated, which would make the implementation impossible.

Compressive sensing, also known as sparse sensing and compressive sampling, is a technique for acquiring and reconstructing a signal utilizing the prior knowledge that it

is sparse or compressible. The field has existed for at least four decades, but recently the field has exploded.

The main idea behind compressed sensing is to exploit that there is some structure and redundancy in most interesting signals—they are not pure noise. In particular, most signals are redundant. It plays promising roles in the tradeoff between the high information gain in expectation out of distributed sensor systems and the bottleneck in reality of their narrow data throughput and limited computation power.

In our system, the implementation of compressive sensing originates from the efforts to improve data collection efficiency–one sensor can sense different type of events, to capture main components of both motions and radiation features of human objects at the stage of sensory data acquisition, to increase the robustness of the mapping between measurement states of sensors and configuration states of human objects by properly exploiting the sensor redundancy, and to achieve high data processing efficacy and efficiency, which would allow us eventually to implement data processing in the physical layer.

Enabled by multiplex sensing and multichannel, guided by the data evaluation criterions, inspired by the modern compressive sensing technology, we deployed several random compressive methods in our experiment, even thought the results might not be as good as we expected, several interesting aspects drew our attention:

The first random compressive method is random bit data selection from selected bits. In this case compressive sensing in our application starts with taking a randomized

sample in each frame from different preselected channels, bit 6, 9 and 20, respectively. These channels are selected based on data evaluation discussed in the next chapter. Then the result sequence which contains partial information of each of the 3 channels would be used to form a new model for walker. To compare analyze the effect of bit random selection compressive sensing, we replace the single channel bit data sequence with the compressed one bit data sequence, draw the ROC curve using the same method as before. The result is shown below.

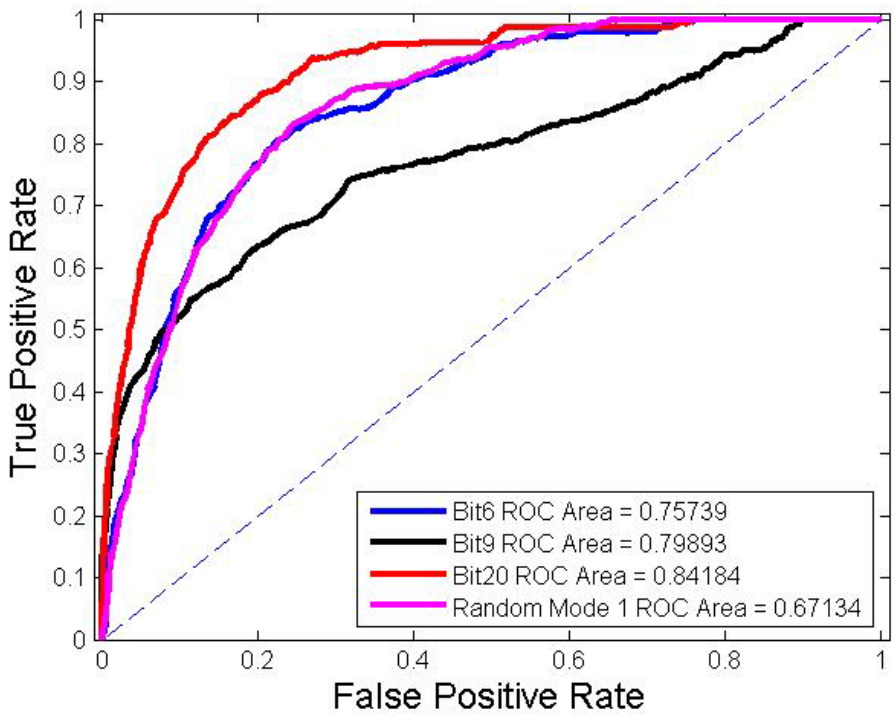

Figure 2.3: ROC curve for bit random selection using direct data

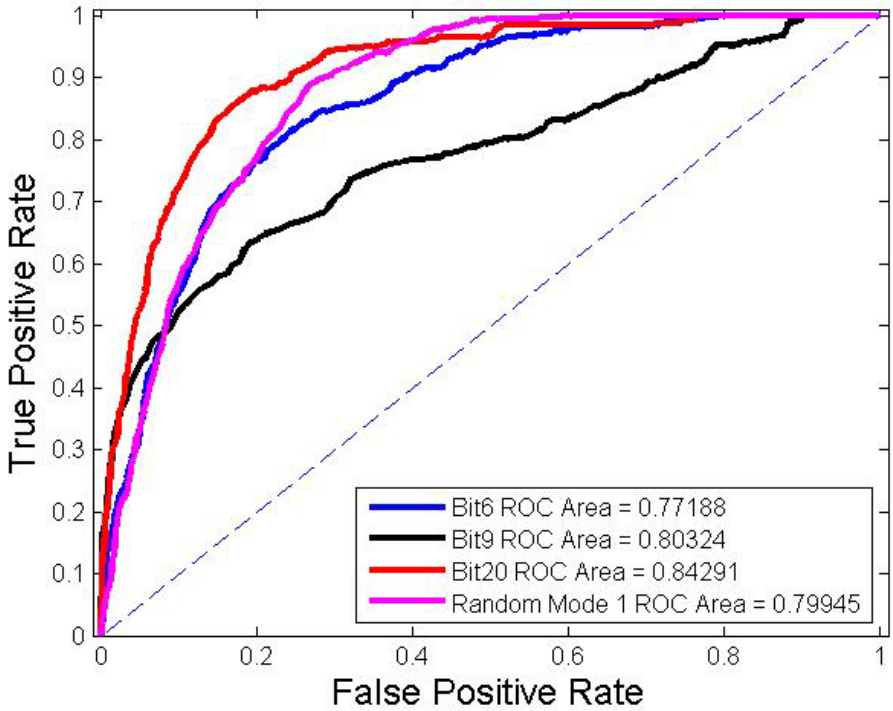

Figure 2.4: ROC curve for bit random selection using transition data

From the plot, we can see that the performance of random bit selection lies between the performance of the best individual channel and the worst individual channel. This is because the random selection scheme is executed at each frame, the task of maintaining essential integrity of each individual feature would involve sacrificing the dynamic information – that is, the dynamic changes, 2nd level, 3rd level and 4th level data transitions, that belong to individual channel might be lost due to switch between channels. At the same time, we believe this random scheme can also reveal some hidden feature by switch between the channels. It is like playing peg-tops with pictures on it,

when the peg-tops is spinning, it is actually has same effect as one constantly change the point of view to the peg-tops, and usually the new pattern appears.

To compare with the first random compressive scheme, we introduced the second compressive sensing method, the frame random selection compress. The difference between this method and the previous one is the length of sample, in the bit random selection method, we start the random selection at each frame, but here we only start random selection after a given fixed frame length. That is, when the fixed frame length is equal to 1, both of these methods have same effect. To see the effect of this compressive method, we set the frame length to 40 and draw the ROC using the same method as before.

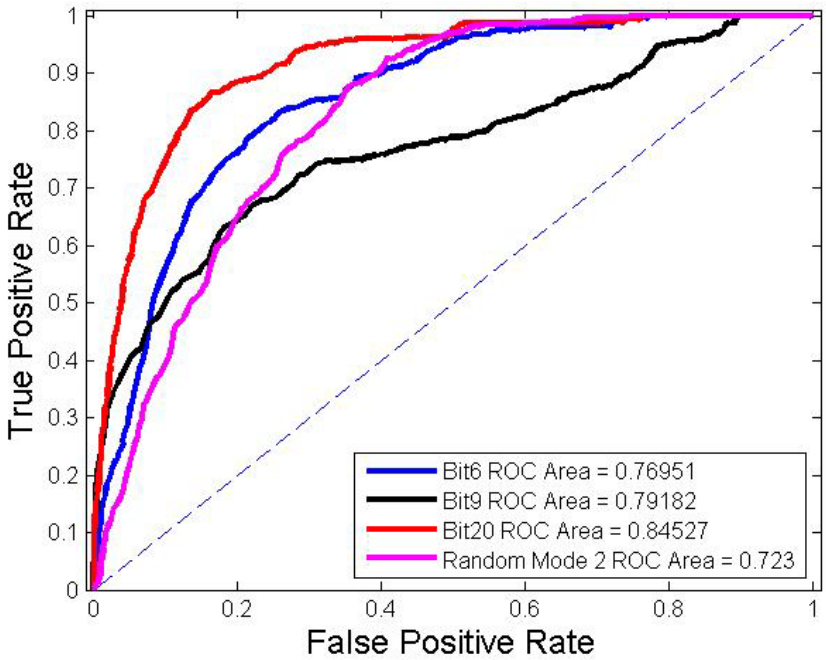

Figure 2.5: ROC curve for frame random selection using direct data

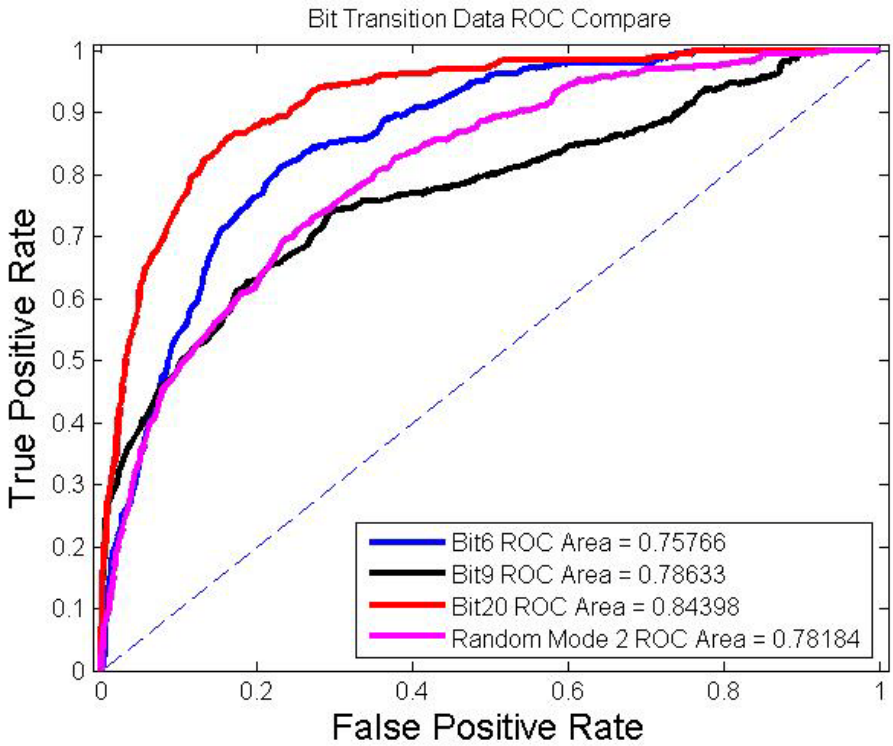

Figure 2.6: ROC curve for frame random selection using transition data

From the figure, we can tell that the frame random selection method does not bring a better effect to the result when compare with bit selection method. In this case, the longer the frame length is set, the more individual channel pattern can be reserved. However, when switching channels, a new channel pattern is introduced. As a result, a sequence contains some patter of each individual but not strong enough to represent any of them is generated. As a result the recognition ability is reduced by the frame random selection. To verify our thoughts, we plot the ROC curve using different frame length as shown below. We can see that as the length of the frame length is increasing, the ROC area is reducing.

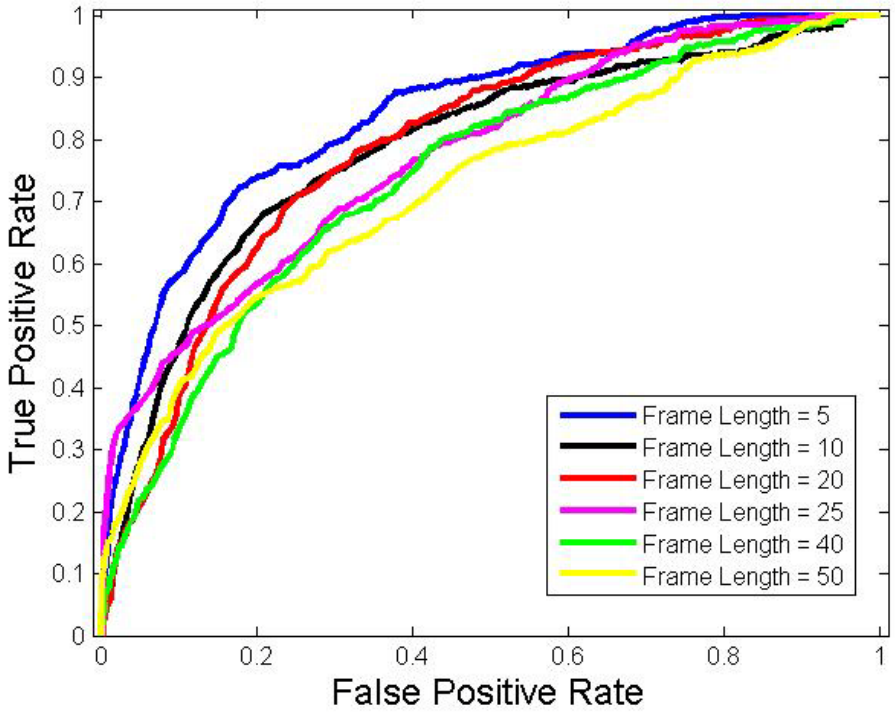

Figure 2.7: ROC curve frame using random selection with different frame length

One problem with compressive sensing using bit random selection is the sources should hold similar information. For example, assume there are 5 people keep talking about the same topic using their own expression and the sixth person wants to know about the topic but he/she is only allowed to listen to one of the 5 people at one time. Common sense tells us that the sixth person should still be able to understand the topic after listening for a while. However, if the 2 of 3 of the 5 people only talk occasionally, then the sixth person will have to listen more in order to understand the topic. In our system, due to the assigned location differences, few sensors rarely collect the information. Using these channels will no longer maintain the integrity of the target

information. That is why we introduced data evaluation in the next chapter to guarantee the reliability of channels.

2.4 Sequence mining

Sequence mining is concerned with finding statistically relevant patters between data examples where values are delivered in a sequence. Roughly speaking, a sequence pattern consists of a number of single-position patterns plus some inter-positional constrains. A single position pattern is essentially a condition on the underlying element type. A sequence pattern may contain zero, one, or multiple single-position patterns. For each position, where the single-position patterns for a given position are perhaps associated with a probability distribution; inter-position constraints specify certain linkage between positions; such linkage can include conditions on position distance and perhaps also include transition probabilities from position to position when two or more single-position patterns are present for some position.

Sequence pattern, also referred as sequence features, can be considered along the following perspectives:

Explicit versus implicit: some features are patterns that occur in the sequence while others are constructed from properties of the sequences or objects underlying the sequences.

Presence versus count: A pattern can generate two types of features. In the first, one uses the pattern as a Boolean feature, by simply considering the presence/absence of

the pattern in the sequence. In the second, one uses the pattern as a numerical feature, by considering the count of the pattern in the sequence.

Frequency based feature selection: the features with high frequencies namely those having frequency over a given threshold, are selected.

Discrimination based feature selection: features with relatively higher frequency at a desired site or in some selected classes than elsewhere are preferred. To find features for identifying a desired site, one prefers features which occurs quire frequently around the site than elsewhere.

2.5 Distance function

Sequence distance functions are designed to measure sequence similarities. Roughly speaking, distance functions can be character based, feature based, and information theoretic based, conditional probability distribution etc. In feature based approach, one would first extract features from the sequences, and then compute the distance between the sequences by computing the distance between the feature vectors of the sequences.

There are several distance functions for sequence. The edit distance, also called Levenshtein distance, between two sequences S1 and S2, is defined to be the minimum number of edit operations to transform S1 to S2. The edit operations include changing a letter to another, inserting a letter and deleting a letter. The hamming distance between two sequences is limited to cases when the two sequences have identical lengths, and is

defined to be the number of positions where the two sequences are different. For conditional probability distribution based distance, the idea is to use the CPD of the next symbol to characterize the structural properties of a given sequence. The distance between two sequences is then defined in terms of the difference between the two CPDs of the two sequences. The similarity between two CPDs can be measure by the variational distance or the Kullback-Leibler divergence between the CPDs. In probability theory and information theory, the Kullback–Leibler divergence (also information divergence, information gain, or relative entropy) is a non-commutative measure of the difference between two probability distributions P and Q. KL measures the expected number of extra bits required to code samples from P when using a code based on Q, rather than using a code based on P. Typically *P* represents the "true" distribution of data, observations, or a precise calculated theoretical distribution. The measure *Q* typically represents a theory, model, description, or approximation of *P*. It is a special case of a broader class of divergences called *f*-divergences. Although it is often intuited as a distance metric, the KL divergence is not a true metric since it is not symmetric (hence 'divergence' rather than 'distance') and does not satisfy the triangle inequality. For probability distributions *P* and *Q* of a discrete random variable the K–L divergence of *Q* from *P* is defined to be

$$D_{KL}(P||Q) = \sum_i P(i)\, log \frac{P(i)}{Q(i)}$$

CHAPTER 3

COMPRESSIVE HUMAN RECOGNITION

3.1 Introduction

Identity recognition is becoming increasingly important in many applications including access control and e-commerce. Current approaches for identity recognition are based on passcards or PIN numbers that can be stolen or forgotten. The use of biometrics (e.g., face, fingerprints, voice patterns, palmprints, iris images, etc.) will improve security, since biometrics is integral to a person. Recognition includes verification (authenticating or rejecting a claimed identity) and identification (matching a presented biometric to one of several in a database). Over the past decade, significant advances have been made in biometric recognition.

In this chapter, the compressive human recognition is introduced. But before we continue to the detail, there are several important concepts of the human recognition need to be addressed.

The human recognition can be performed in two ways:

1) Closed-Set Walker Identification.

The automatic system must determine who is walking. The condition for the system to work correctly is that the walker belongs to a predefined set of known walkers. However, if the set of known walkers do not cover the current target, the system will not

be able to give the correct result. The system performance is evaluated using identification rate.

2) Open-Set Walker Identification.

Open Set operates under the assumption that not all the test probes have mates in the gallery. It either detects the presence of some biometric signature within the gallery and finds its identity or rejects it, i.e., it can provide for the "none of the above" answer. In this approach, the system accepts or rejects the users according to a successful or unsuccessful verification. Sometimes this operation mode is also called as verification or authentication. The system performance is evaluated using the False Acceptance Rate (FAR, those situations where an impostor is accepted) and the False Rejection Rate (FRR, those situations where a walker is incorrectly rejected), also known in detection theory as False Alarm and Miss, respectively. This framework gives us the possibility of distinguishing between the discriminability of the system and the decision bias. The performance can be plotted in a Receiver Operator Characteristic (ROC) plot, where the Detection Rate (DR = 1-FRR) is instead used in most cases.

Despite the different requirements of open-set and closed-set walker identification, they are intrinsically related to one another. For an open-set identification system, the optimal decision threshold has to be obtained from the ROC curves generated from verification testing results. For the verification problem, the unknown walker's data sample is compared to the database. If the claimed walker is among the best matches, the

walker is accepted and otherwise rejected. In both cases (identification and verification), walker recognition techniques can be split into two main modalities:

1) Path Independent.

This is the general case, where the system does not know the path walked by the person. This operation mode is mandatory for those applications where the user does not know that he/she is being evaluated. This allows more flexibility, but it also increases the difficulty of the problem. From the signal processing viewpoint, one must extract a specific statistical pattern for each person.

2) Path Dependent.

This operation mode implies that the same path is taken by everyone. The recognition relies on the comparison of the measured signals. Given that the response signals are usually speed dependent, there are two solutions. Our objective is to develop features that are less sensitive to the speed. This mode is useful for those applications with strong control over user input similar to its text dependent speaker recognition counterpart.

This chapter describes the compressive human recognition, which includes: event and feature, recognition strategies, data evaluation, digital feature extraction and fusion scheme.

3.2 Event and feature

An event could be defined as an occurrence of interest in spatial-temporal space distinguishable from its environment and repeatable in multiple trials. In our case, as shown in figure 3.1, it is an instance in which the thermal flux collected by a pyroelectric sensor is above a threshold and its response data can be associated with one or several specific human motions, such as moving across one detection region.

Features are the individual measurable heuristic properties of the phenomena being observed. Choosing discriminating features is key to any pattern recognition algorithm being successful in classification. Two kinds of features can be extracted from pyroelectric sensor (array) signals, the binary event index sequence of a sensor array and the spectral segment of the data of one event. The first one is defined as the digital feature; the second one as the analog feature. We focus on the former one, which are extracted from event indexes sequences.

Both the event and feature are defined in the pyroelectric signal space. Signal processing techniques such as Kalman filtering, FFT, and band-pass sine filtering are proposed to detect the events embedded in the sensory data.

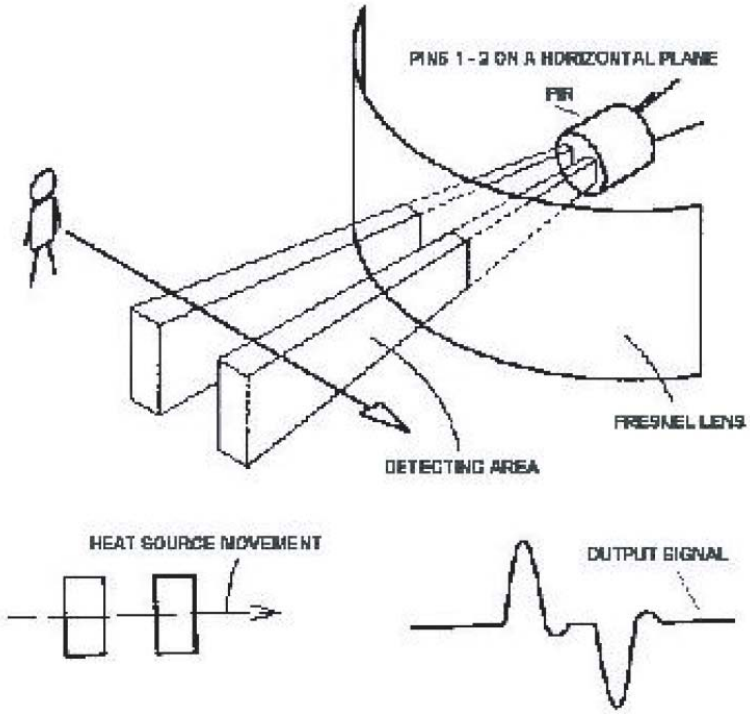

Figure 3.1: Illustration of motion detection by the pyroelectric sensor

3.3 Recognition strategies

Given the definition of event and feature, the identification strategy for the distributed sensors, as shown in Figure 5, includes: event detection; event data acquisition, to acquire the data inside a event window after that event is validated; feature extraction, to extract the feature out of the event data based on the predefined feature-to-event association; membership estimation, to estimate the membership of one feature with respect to all the feature models of enrolled individuals; and object identification, to make

a decision on the identity of the human object under testing according to the estimated membership likelihood vector and the inference rule.

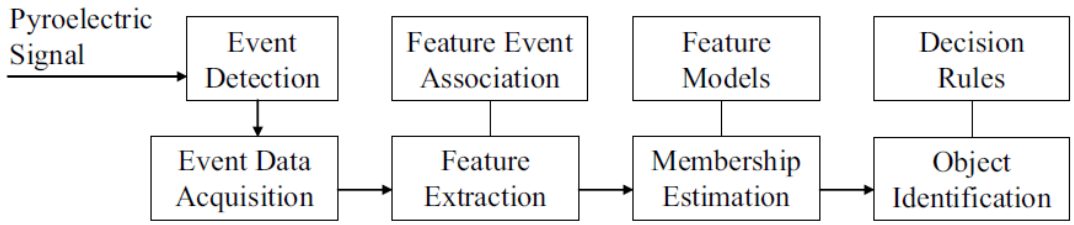

Figure 3.2: General recognition scheme for distributed pyroelectric sensors

3.4 Data evaluation

Due to different signal response and spatial location of each sensor, the event extracted from the sensors varies. Some sensors might contain more useful information while others might introduce noise. Data evaluation is an indispensible step which helps us to tell the two apart, thus improve the performance of our system. Our goal is to obtain credible information that can correctly represent the walker's gait signature. Being credible here consists of two elements: repeatability and uniqueness. Repeatability is the variation in measurements taken by the sensor nodes on the same walker and under the same conditions. A measurement may be said to be repeatable when this variation is smaller than some agreed limit. Especially for fix path walker recognition, since target walker walks along the same path back and forth, so we should expect to capture the period signal that can at least depict this dynamic procedure. Uniqueness can be regards

as the phrase "there is one and only one", which is used to indicate that exactly one object with a certain property exists.

Given the collected data, how to decide if the data contains sufficient information, how to tell if this sequence data is repeatable, is there any uniqueness contained in the data? The answers to these questions are essential to improve the system performance. To answer the above issues, we investigated two traditional signal-processing approaches: entropy analyzes and self-correlation analyze.

Entropy has often been loosely associated with the amount of order, disorder, and/or chaos in a thermodynamic system. We use entropy to evaluate the repeatability of the data. The traditional qualitative description of entropy is that it refers to changes in the status quo of the system and is a measure of "molecular disorder" and the amount of wasted energy in a dynamical energy transformation from one state or form to another. The definition of entropy is given by the following equation:

$$S = -\sum_{i} P_i ln P_i$$

where S is the conventional symbol for entropy. The sum runs over all microstates consistent with the given macro-state and P_i is the probability of the ith microstate. For each bit data, we evaluate the 1st, 2nd, 3rd and 4th level data transition entropy. They are defined as below:

1st level data transition has only two states: '0' and '1'. It represents the spatial occurrences state when a walker passes through.

2nd level data transition has four states: ‘00’, ’01’,’10’, and ’11’. It contains the 1st order dynamic transition information as the walker pass by in certain spatial area.

3rd level data transition has 8 states: ‘000’, ’001’, ’010’, ’011’, ’100’, ’101’, ’110’, and ’111’. It contains the 1.5nd order dynamic transition information.

4th level data transition has 16 states: ‘0000’, ’0001’, ’0010’, ’0011’, ’0100’, ’0101’, ’0110’, ’0111’, ’1000’, ’1001’, ’1010’, ’1011’, ’1100’, ’1101’, ’1110’ and ‘1111’. It has the 2nd order dynamic character.

So given the 24 bits data as shown in the figure below, the entropy can be calculated as listed in table 2.

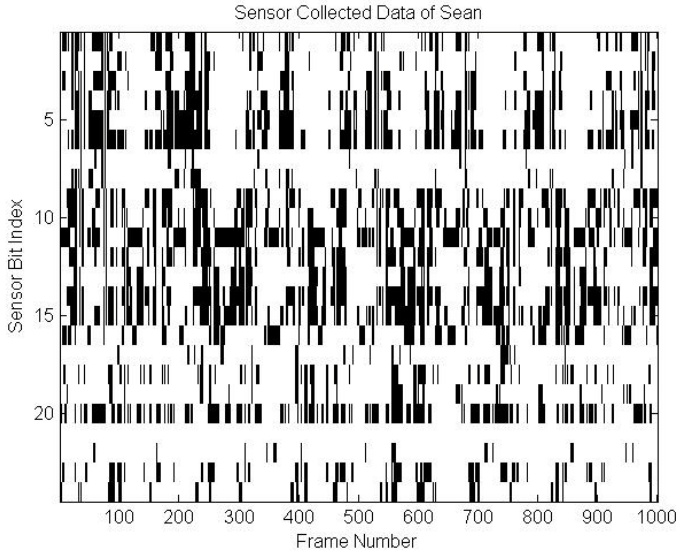

Figure 3.3: 1000 frame 24 bits data collected by the sensors

Table 3.1 Different level of entropy for binary data in Figure 3.3

BIT INDEX	1st LEVEL	2nd LEVEL	3rd LEVEL	4th LEVEL
1	0.8127	1.4152	1.9823	2.5412
2	0.6406	1.0899	1.5071	1.9226
3	0.7531	1.2701	1.7448	2.2126
4	0.8825	1.5165	2.1047	2.6822
5	0.9111	1.4715	1.9921	2.4975
6	0.9986	1.7419	2.4229	3.0931
7	0.2799	0.4741	.6587	.8391
8	0.4817	0.8188	1.1384	1.4526
9	0.9448	1.6230	2.2466	2.8589
10	0.9271	1.6248	2.3092	2.9757
11	0.9990	1.7001	2.3786	3.0537
12	0.9100	1.5503	2.1547	2.7488
13	0.8105	1.2626	1.6915	2.1170
14	0.9991	1.7066	2.3490	2.9755
15	0.9926	1.7149	2.4160	3.1068
16	0.8468	1.3290	1.7867	2.2382
17	0.2970	0.5173	0.7347	0.9511
18	0.7055	1.2419	1.7615	2.2772

19	0.5063	0.8638	1.2031	1.5398
20	0.9901	1.7988	2.5698	3.3329
21	0	0	0	0
22	0.2533	0.4181	0.5794	0.7358
23	0.7219	1.2789	1.7837	2.2781
24	0.5932	0.9787	1.3481	1.7106

If we sort the bit index according to 5 different entropy criterions, we can get 5 similar sorting results. To get the results without losing the general information, we use the summation of all 5 entropy values for evaluating the bit data repeatability, bit 21, 7, 8, 24 and13 are among the bits with small entropy value, it is obvious that the binary data of these bits contain high periodicity. Thus we believe this could be a very way to find the repeatability of sensor data. Notice that bit 21 does not have any value for the walker so we assign 0 for its entropy.

Self-correlation, also known as Autocorrelation, is a mathematical tool for finding repeating patterns, such as the presence of a periodic signal which has been buried under noise, or identifying the missing fundamental frequency in a signal implied by its harmonic frequencies. However, we used self-correlation as a method to find out if the sensor data is unique. Based on the strong assumption that the uniqueness should be lying under the intricate dynamic process, the more transition the bit data has, the more likely it contains the uniqueness with respect to the individual walker. So the idea is to calculate

the self-correlation of the distribution of the 4th level data transition; we can expect to see more peaks in results if the distribution contains more dynamic transitions. As a result, it will also increase the area the self-correlation result plot covers. Here is the result based on the same data image presented in figure 3.3.

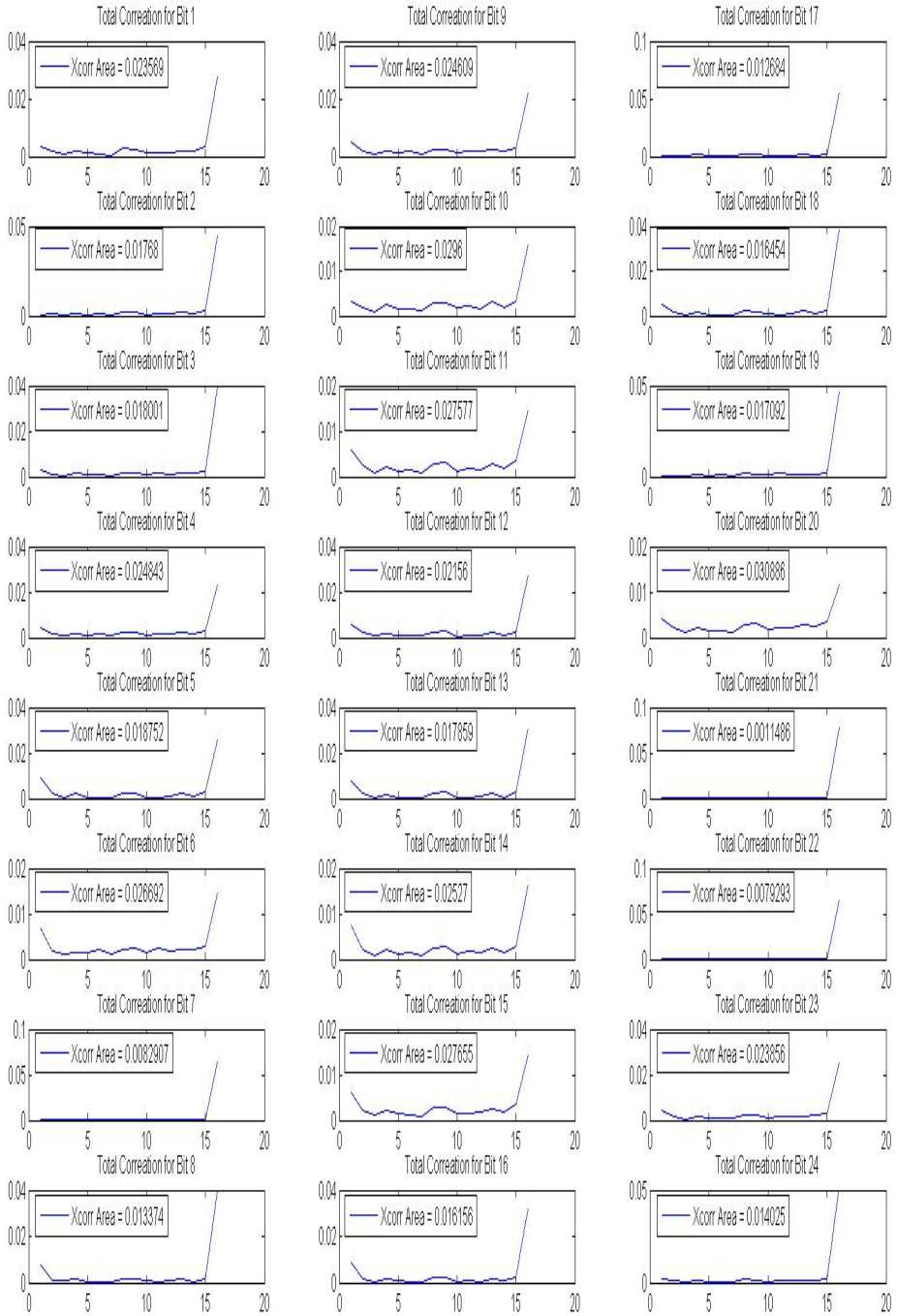

Figure 3.4: Self-correlation of 24 bits data in figure 3.3

We can see that bit 21, which has very low entropy value, also has very low self-correlation area. It will not get a positive evaluation after this step.

Using the above evaluation approaches, one bit was chosen from each sensor node, bit 6, 9 and 20 respectively. To assess the evaluation results, we collected the data from 5 different walker and implemented the closed set recognition test using both 1 bit direct data and 1 bit transition data with KL Distance feature. (The feature extraction will be discussed later) 2 ROC curves were generated as shown below:

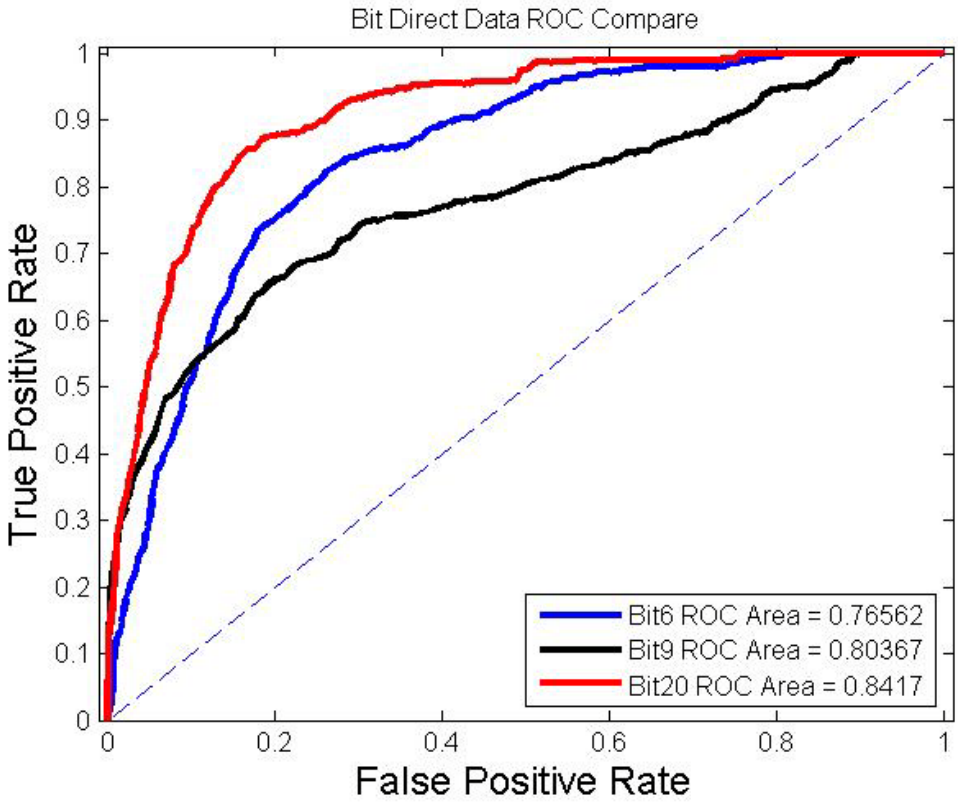

Figure 3.5: ROC curve for single bit 6, 9 and 20 using direct data

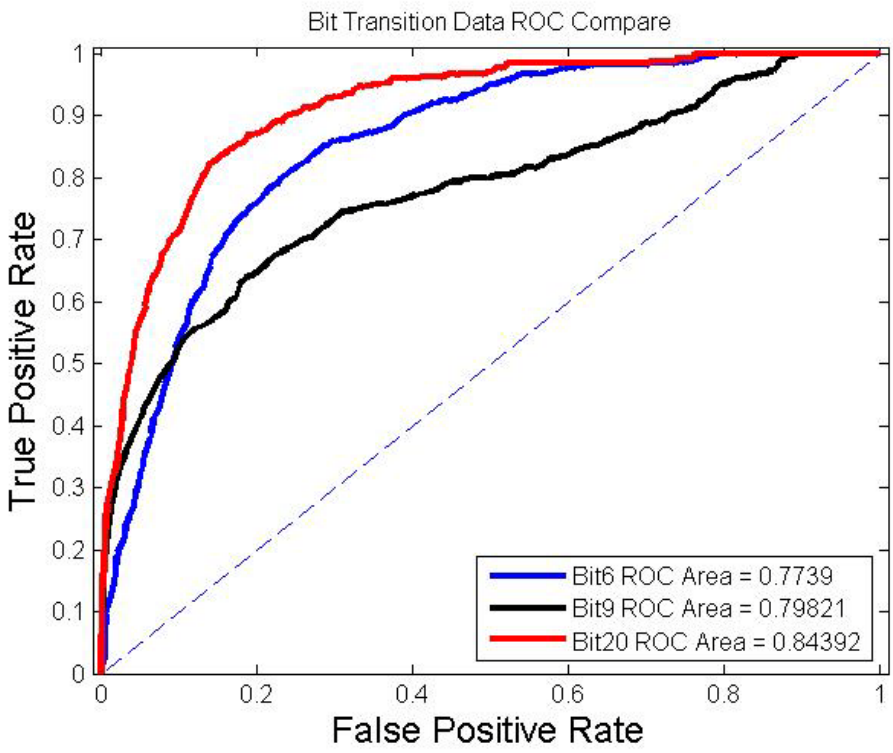

Figure 3.6: ROC curve for single bit 6, 9 and 20 using transition data

Results show us that each of the three bits has individual discriminate ability. To compare, we also plot the bit ROC using transition data for bit 1, 2 and 4. It is clear that these 3 bits has less ROC area than the previous 3 bits.

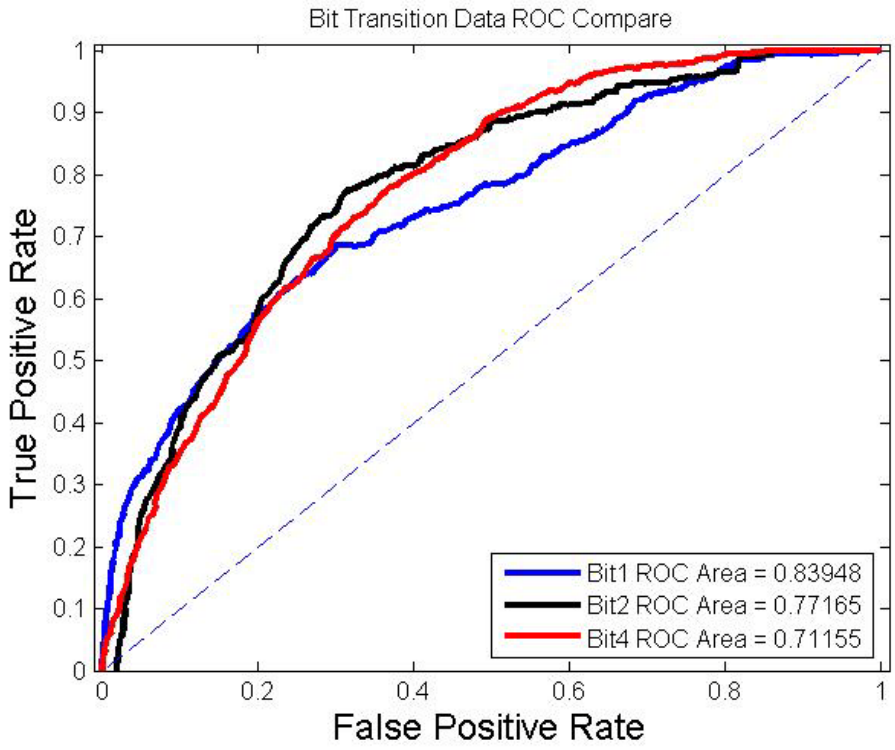

Figure 3.7: ROC curve for single bit 1, 2 and 4 using transition data

In conclusion, the two approaches: entropy and self-correlation will help us find out the bit data that contains ample transitions while maintain periodicity, hence evaluate the data quality before compressive sensing or feature extraction.

3.5 Digital feature extraction

Any functional feature in recognition should be characterized by its universality over all objects under testing, distinctiveness between any two individuals, invariance over a period of time, and feasibility for quantitative measures. As mentioned early, there

are two types of features: the spectral vectors gathered from the analog event data and the digital event sequences produced as a walker crossed individual beams in the modulated object space. In our research, we only focus on digital event sequence, upon which our walker recognition algorithms were based. Our study on pyroelectric signal feature is chosen as statistical characterization of digital event index sequences.

In general, digitalized features should be very simple, easy to compute, and robust to background noise, so that walker recognition detection can take place in real time and perform well. According to the system setup as described in figure 1.2, figure 3.3 illustrates event index sequences transmitted by four wireless sensor nodes, with the visibility codes in Table 1, when one human subject walks along fix path 1 inside a room. With the help of data evaluation, we can choose one bit channel that can best maintain repeatability and uniqueness of the walker from each of the 3 sensor nodes, thus leave us with 3 bits data. To find the measurable heuristic properties hidden in the sequence, we have to extract the sequences using sequence mining methods.

The heuristic properties hidden in the sequence can be also referred as sequence pattern. A sequence pattern is a finite set of single-position patterns of the form $\{c_1, \ldots, c_k\}$, together with a description of the positional distance relationships on the c_i's and some other optional specifications. Roughly speaking, a sequence pattern consists of a number of single-position patterns plus some inter-positional constrains. A single position pattern is essentially a condition on the underlying element type. A sequence pattern may contain zero, one, or multiple single-position patterns. For each position,

where the single-position patterns for a given position are perhaps associated with a probability distribution; inter-position constraints specify certain linkage between positions; such linkage can include conditions on position distance and perhaps also include transition probabilities from position to position when two or more single-position patterns are present for some position.

The first representative sequence pattern type is the frequent sequence patterns. Each such a pattern consists of one single-position pattern for each position. Frequent sequence patterns can be viewed as periodic sequence patterns. In our research this type sequence pattern can be regard as the shape information of each walker, it is one of the static features generated according the walker's thermal distribution.

The second representative sequence pattern type is the sequence profile patterns. Such a pattern is over a set of positions, and it consists of a set of single-position pattern plus a probability distribution. Here we can think of this type of pattern as the dynamic feature produced by the walker's walking habit.

The third representative sequence pattern type is Markov models. Such a model consists of a number of states plus probabilistic transitions between states. In some cases each state is also associated with a symbol emission probability distribution. This is the feature used in our previous work, specifically Hidden Markov Model.

In an effort to build the stable and unique statistical feature model with respect to each individual, we analyzed the digital event sequence in the following perspectives: Explicit versus implicit, some features are patterns that occur in the sequence while

others are constructed from properties of the sequences or objects underlying the sequences. Presence versus count: A pattern can generate two types of features. In the first, one uses the pattern as a Boolean feature, by simply considering the presence/absence of the pattern in the sequence. In the second, one uses the pattern as a numerical feature, by considering the count of the pattern in the sequence. Frequency based feature selection: the features with high frequencies namely those having frequency over a given threshold, are selected.

We took the following steps to find and evaluate the feature:

1, Understand the data.

2, Preprocessing of the data with feature selection and feature construction. Feature selection is concerned with selecting the more useful features from a large number of candidate features. Feature construction is about producing new features from existing features.

3, mine the patterns.

4, evaluate mining results. In this step various measures to evaluate the patterns, mainly focusing on repeatable and uniqueness.

Several features were considered and two of these features appear to work very well with the sensor event sequence: States Distribution and Most frequent States. As stated earlier, the data sequence captured by the sensors with the visibility codes in Table 1, is associated with one or several specific human motions. The distribution of the states contained in the sequence can represent certain characters of the walker such as the

height of the walker, the arm span when the walker walks, and so on. For example, tall people tend to trigger certain spatial areas that short people could not reach; walkers with big arm span would trigger more spatial areas than those who don't swing arms when they walk. By looking into the distribution of different states in the sequence, we can get the information about the walker figure, usually also regarded as shape. When considering the distribution of state transition in the sequence, we can get the information about the dynamic of the walker's walking habit. The figure below shows us the distribution of both state and state transition of the same walker using 3 preselected channels in different 3 trials.

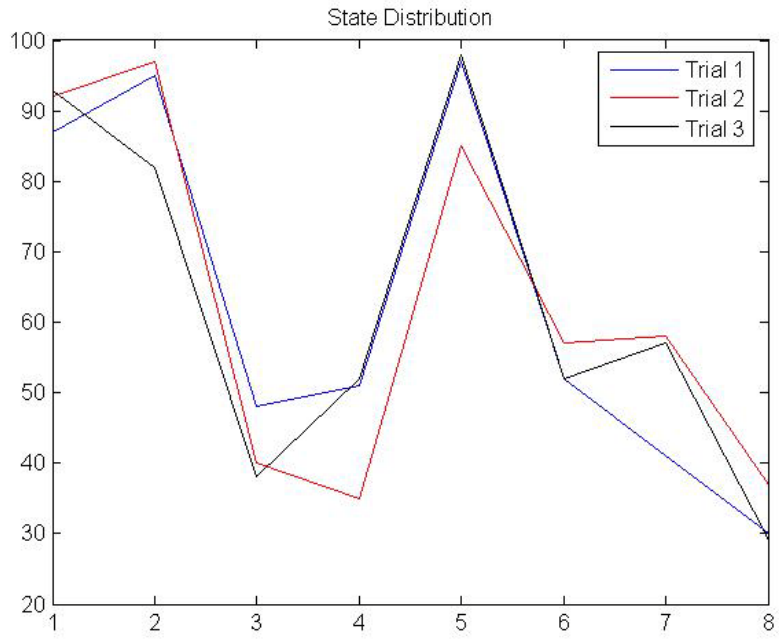

Figure 3.8: State distribution of same target in 3 different trials

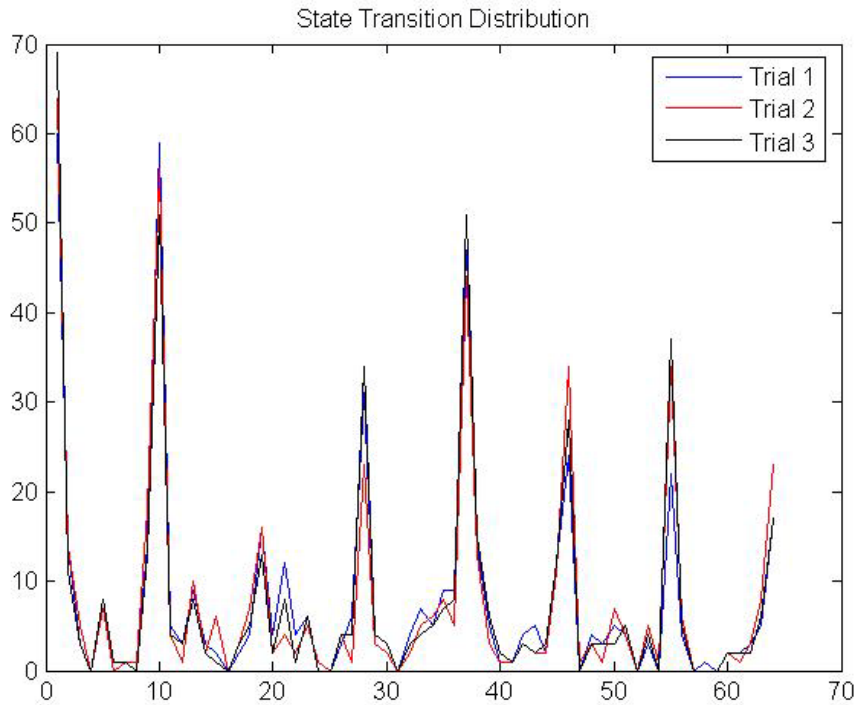

Figure 3.9: State transition distribution of same target in 3 different trials

One issue about using the sequence state distribution is to choose the length of training and testing sequences. As a common problem of all statistic methods, large samples are always required. As shown in the following figure, as the length of the sequence increases, the distribution of both states and states transition becomes stable.

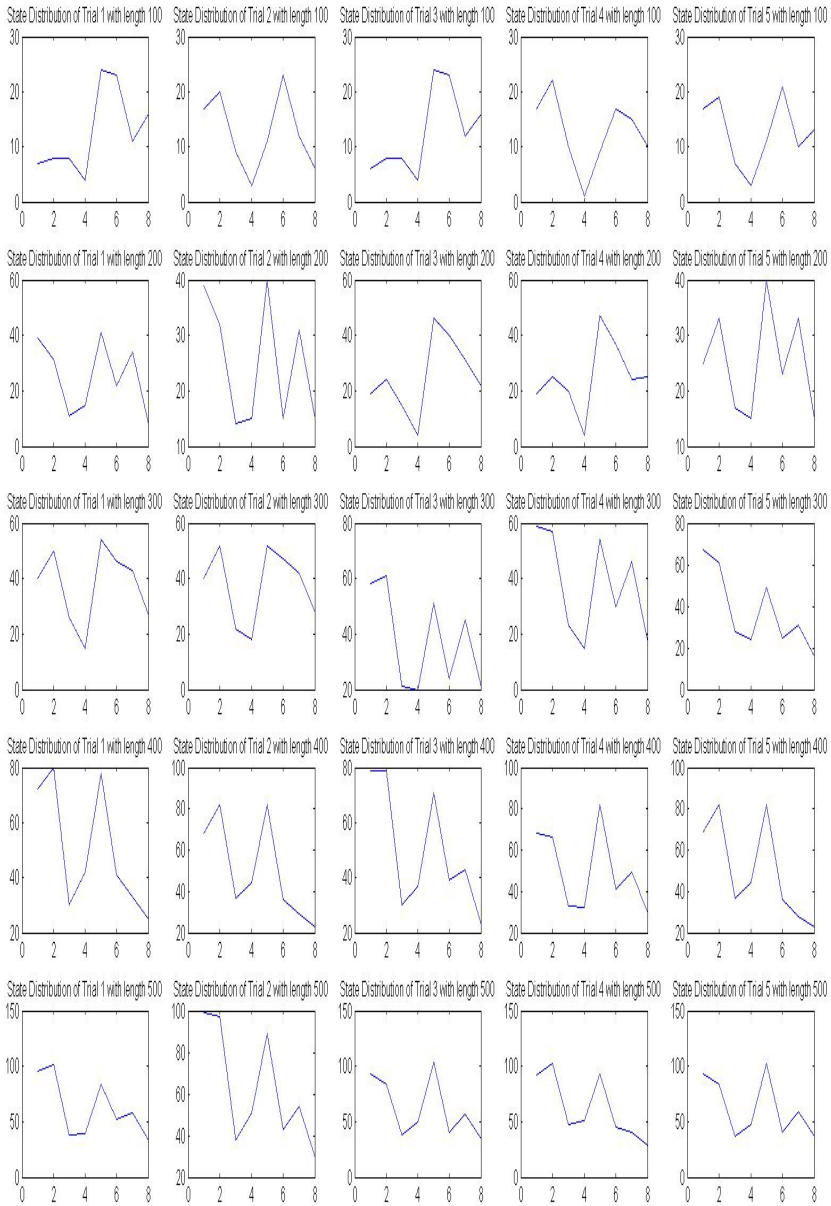

Figure 3.10: The distribution of states in 5 test sample with length 100,200,300,400 and 500 respectively.

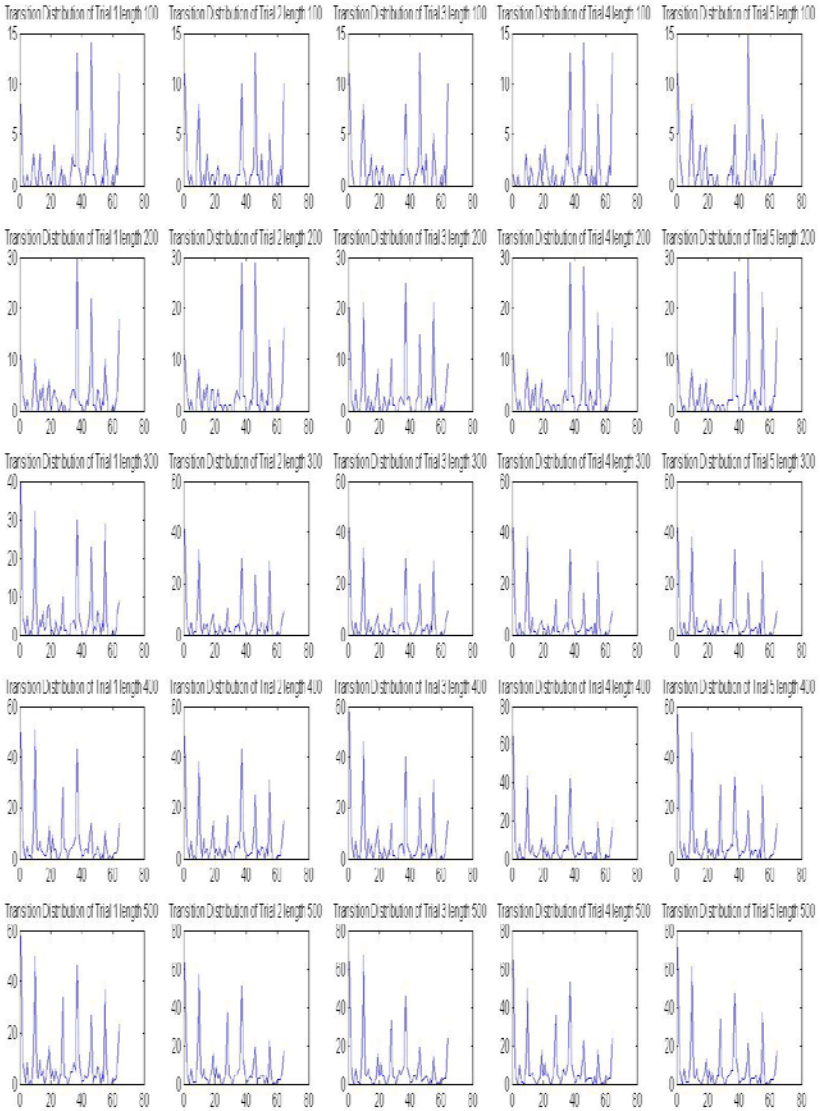

Figure 3.11: The distribution of states transitions in 5 test sample with length 100,200,300,400 and 500 respectively.

This is a big challenge when we want to implement walker recognition in real time. To collect enough data for a stable recognition test, the walker usually need to walk at least for 30 seconds, which make this method less applicable. That is why we introduce the second feature: Most frequent States. Based on the same idea as using distribution, we want to reduce the differences between the samples due to the accident movement of walker and noise, which would be represented by some rare seen states of the walker in the state sequence. What we did is we do not take those signals into account for the distribution, doing so would leave us with the most frequent states; we call it most frequent states. In the test, we consider the 10 most frequently frequent states. Despite the difference between the order of the most frequent states, we found this to be a stable feature belongs to different individuals. The following table shows us the index of the 10 most frequent states of 3 different walkers. We can see that it does not change too much with respect to different individual in 7 different tests using preselected 3 channels data sequence.

Table 3.2 The similarity feature of 3 different targets in 7 tests

Test 1 Feature Matrix: Target 1: 1 22 43 32 11 24 3 19 38 2 Target 2: 1 43 22 64 5 38 3 19 27 62 Target 3: 1 32 4 29 8 57 64 2 3 5
Test 2 Feature Matrix:

Target 1:	1	22	43	3	19	2	32	10	11	5
Target 2:	1	43	5	19	3	64	38	41	22	24
Target 3:	1	32	4	29	64	8	57	2	3	5
Test 3 Feature Matrix:										
Target 1:	1	22	43	3	19	11	5	38	2	24
Target 2:	1	43	5	19	3	64	38	41	22	24
Target 3:	1	32	4	29	64	8	57	2	3	5
Test 4 Feature Matrix:										
Target 1:	1	22	43	3	2	10	19	38	64	11
Target 2:	1	43	5	3	19	22	38	64	41	2
Target 3:	1	32	4	29	64	8	57	2	3	5
Test 5 Feature Matrix:										
Target 1:	1	43	22	32	11	3	24	2	19	38
Target 2:	1	22	64	5	38	43	3	19	62	11
Target 3:	1	32	4	29	8	57	64	2	3	5
Test 6 Feature Matrix:										
Target 1:	1	19	55	37	17	3	21	10	11	23
Target 2:	1	38	19	17	3	34	5	21	54	56
Target 3:	1	32	4	29	64	8	57	2	3	5
Test 7 Feature Matrix:										

Target 1:	1	19	57	38	17	3	10	11	21	24
Target 2:	1	43	22	64	5	38	3	19	46	62
Target 3:	1	32	4	29	16	64	2	8	15	57

3.6 Fusion scheme

To improve the identification performance, we applied four sensor fusion schemes, namely data fusion, feature fusion, score fusion, and decision fusion, to each channel. Feature extraction is used to describe the most important information of the sample data. Matching modules compares features with templates in the database and output a score to the decision module.

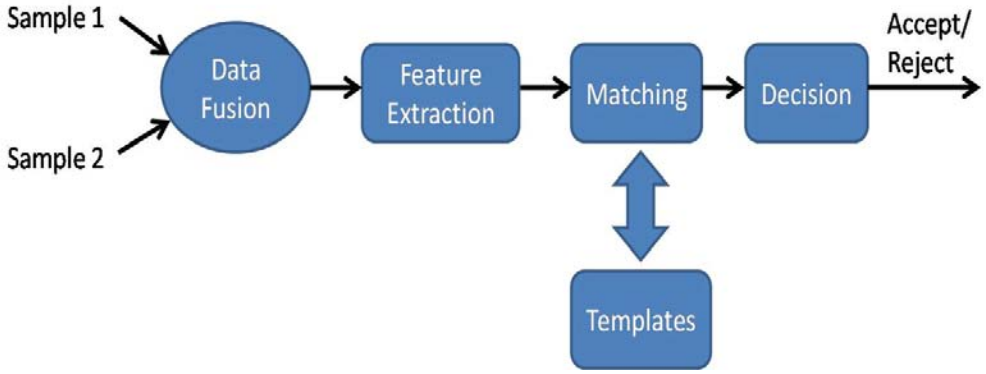

Figure 3.12: Data level fusion

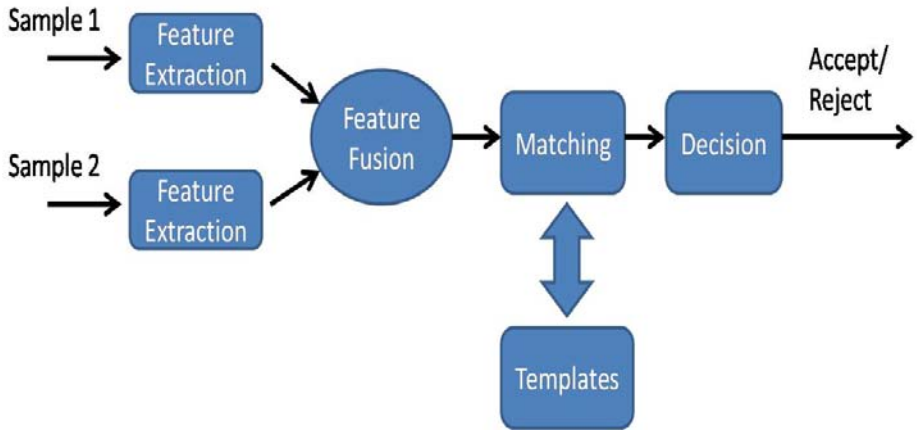

Figure 3.13: Feature level fusion

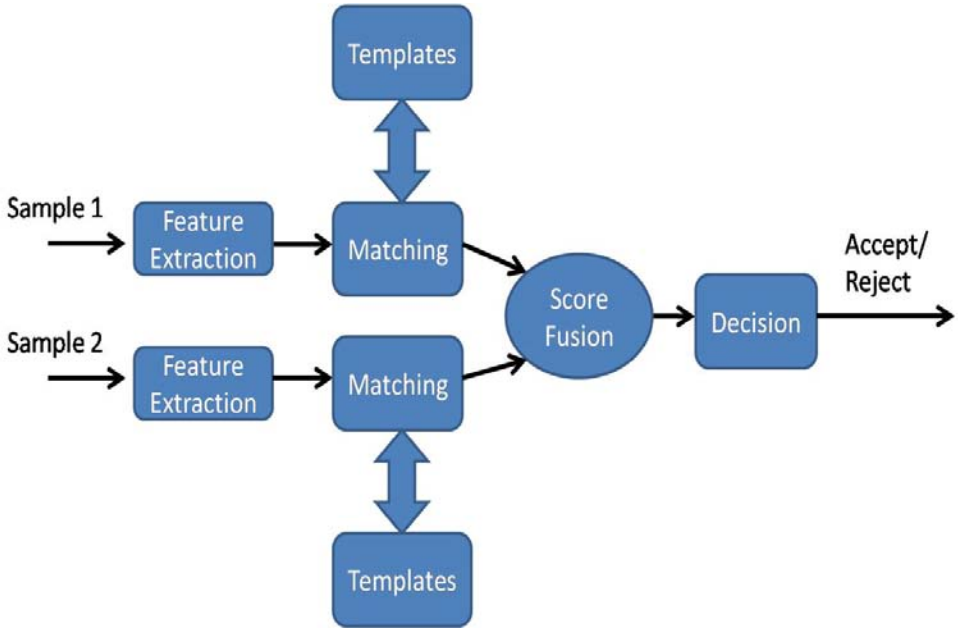

Figure 3.14: Score level fusion

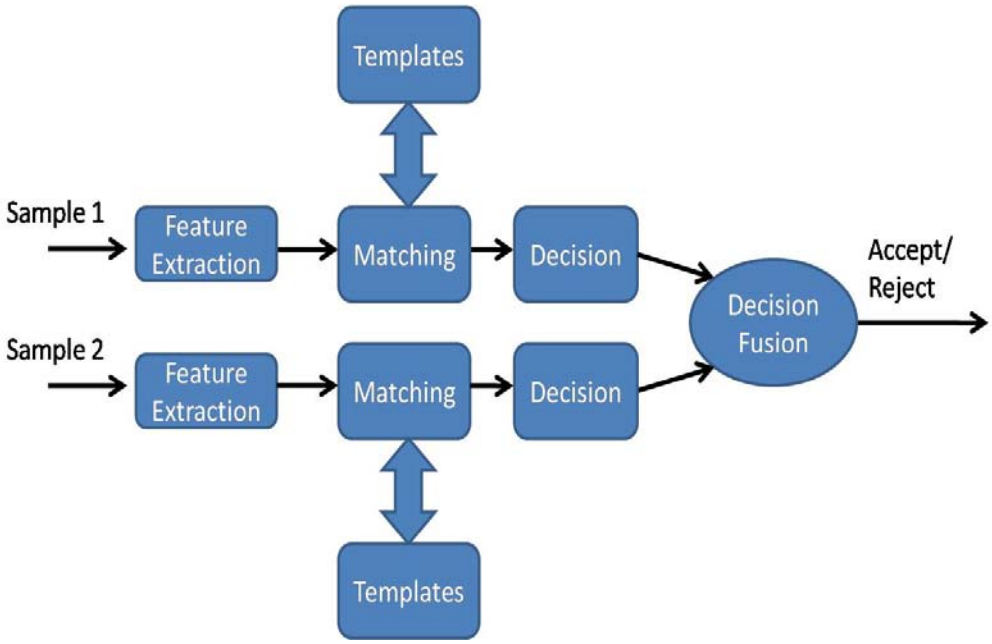

Figure 3.15: Decision level fusion

Data 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. Decision level fusion combines decision from decision modules for different nodes using AND, OR, or majority voting.

CHAPTER 4

DISTRIBUTED HUMAN TRACKING

4.1 Introduction

The emerging technology of wireless sensor networks provides many exciting and interesting applications. Such networks can provide an immense raw sensing capability in many different modalities. The huge difficulty in harnessing these networks lies in trying to process all the sensed data in a meaningful and power-efficient manner. Many studies have been put to solve this problem; one of them is distributed processing in sensor network.

In sensor networks, distributed processing is becoming more popular than centralized approaches. This is because centralized networks with only one processing node are vulnerable if that particular node is incapacitated. The communication overhead is also significant because if all the sensing nodes are trying to transmit raw data to the central processing node, the required bandwidth increases significantly with the number of nodes. To overcome these drawbacks, a distributed processing approach is attractive. .

The problem of object detection and tracking has been explored in on an individual node basis. There is very little research on distributed detection and tracking within networks of wireless sensors. Object tracking is a topic that has been studied and developed extensively but primarily in the domain of active and passive radar. Graphical

modeling techniques such as Kalman filtering and HMMs have been employed very successfully in this domain. Complex multiple hypothesis testing techniques are incorporated into their frameworks that rigorously evaluate every possible origin of the measurements received. However, they assume that all the measurements are available for processing at a centralized node. Distributed processing stipulates processing capabilities at individual sensors. [2, 3, 8, 9, 10, 11, 12, 13, 15, 16]

We denote a sensor that has the ability to process data and communicate with neighboring sensors in addition to sensing the environment as a smart sensor. Distributed processing eliminates the need for a central processing node. Since a smart sensor can process its own data, it need only transmit sufficient statistics in the communication channel, minimizing the communication among sensors. Communication consumes more battery power than computation; hence smart sensor networks with distributed processing have additional advantages.

Here we will outline some key design criteria for our designed distributed tracking algorithms in the domain of wireless sensor networks:

1. Decentralized processing - While it is easier to consider and design algorithms in an architecture where the sensor outputs are communicated back to a central processing unit, this is generally not feasible. When dealing with a network of un-tethered nodes, a finite amount of energy is a factor that must be taken into consideration. Communication is the primary energy consumer. The key is to process the sensor outputs as much as possible

within the network, so as to avoid communicating large amounts of information over large distances.

2. Processing sensed data at the nodes - There are many levels in which the sensed data can be shared and processed among nodes- e.g. signal level, feature level and decision level. At each of these levels, the information content is reduced, but this in turn reduces the required amount of data to be communicated between nodes. In short, processing is cheap and communication is expensive.

3. Dealing with uncertainty - Typically, the nodes are typically very low-cost, low-power throwaway devices that might be prone to noise, increasing the chance of false measurements. A method of estimated the data loss and data recovery is required for robust distributed human tracking application

4. Generic algorithms for different modalities - Nodes might be equipped to record signals from many different modalities. These might include acoustic, optical, IR, temperature, radioactive or seismic modalities. Devising a generic algorithm that can be applied to the modality available is preferred.

4.2 Data recovery

Data missing is a common phenomenon in wireless transmission; it could cause huge impact on applications such as distributed tracking, where the results strongly relies on continuous trustworthy data. For most application in wireless network, how to prevent data loss and how to retrieve the lost data has been a long coming challenge. Usually the

application layer generates the data to be sent over the network and processes the corresponding data received over the network.

One of the issues we discovered when testing our system is the data robustness. While the experiment was conducted under very controlled circumstances, in a real application many detected events unrelated to moving objects might occur. These false events might be due to background phenomena, other types of objects not of interest or perhaps faulty sensors. Data corruptions are often observed especially for tracking system. Since tracking is a sequential process, regardless the robustness of tracking algorithm, several lost data frames might cause the tracking to be interrupted, thus cause the results wrong. Principle causes of the problem may be characterized into two categories: Detector malfunction and data transmission failure between the slave and master node. Since we deployed robust transmission protocol for our transmission, the problem is mostly caused by the first case.

The following diagram illustrates our data recovery scheme, which mainly contains two parts: data lost detection and data reconstruction.

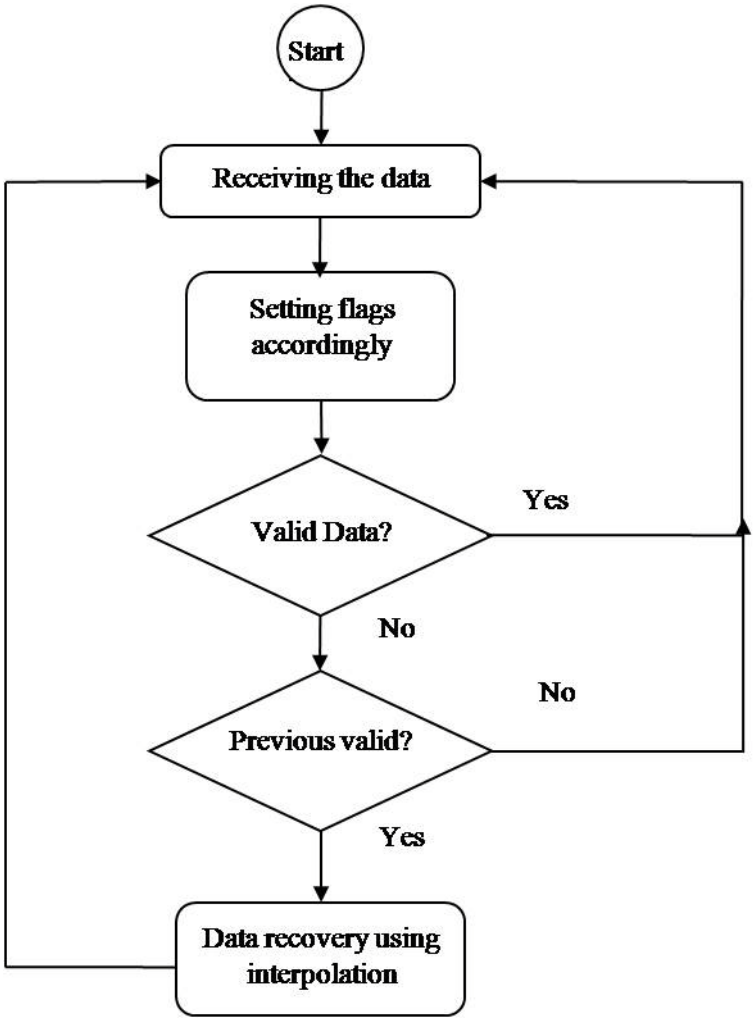

Figure 4.1: Data recovery flowchart

A simple data reconstruction method using interpolation has been implemented to replace missing or invalid data. Figure 2.2 shows the sensor collected data before and after data recovery.

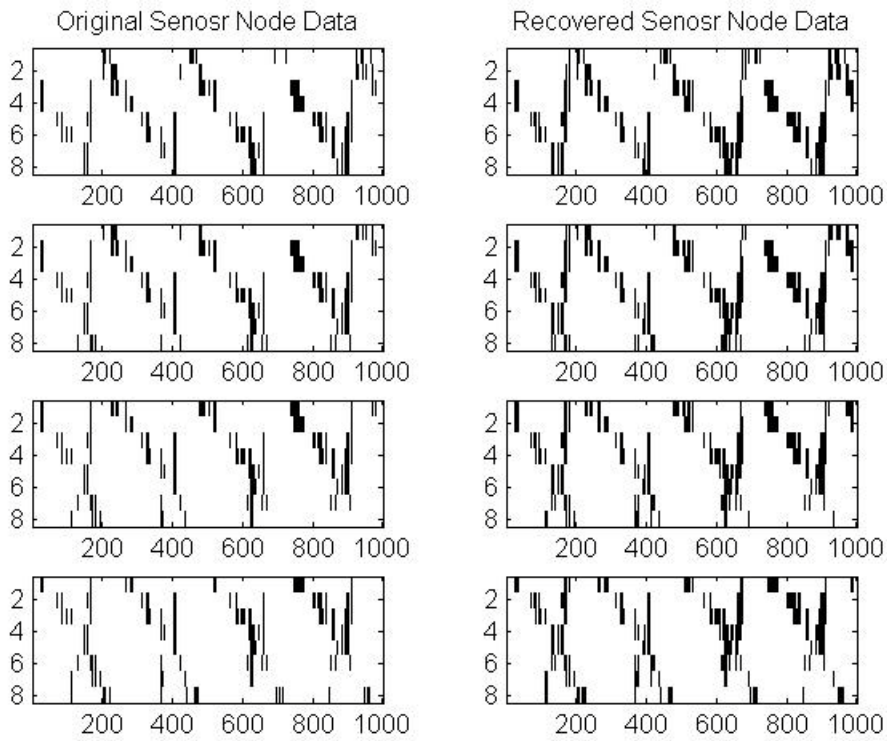

Figure 4.2: Sensor data before and after data recovery

4.3 Tracking strategies

In our distributed tracking design, as shown in the figure below, The sensor network consists of 4 sensing nodes of one modality that have a finite sensing radius due to signal attenuation. Objects will pass through the sensor field, which is indicated by the red line.

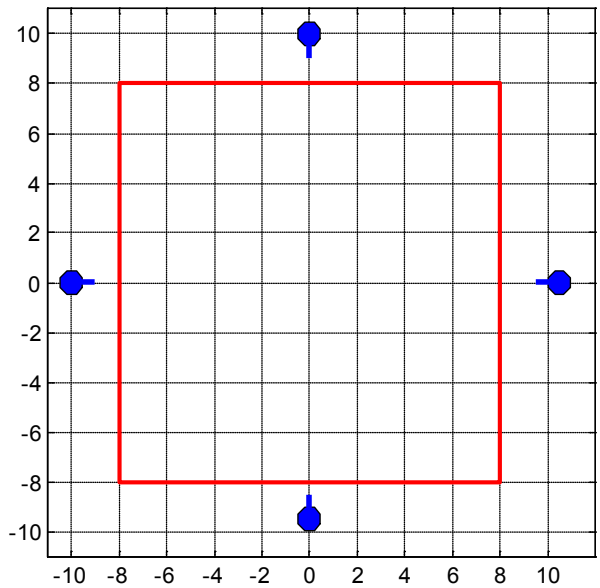

Figure 4.3: Tracking system setup

In previous study, when sensor detect a target moving and generate events, they are report back each event to a distant central node, it would be logical to share the evidence among neighboring nodes and then report any useful results with the central node. If several correlated events are associated together, a more accurate hypothesis as to whether the object is present can be formed, along with an increasingly accurate estimate of its position and velocity. This idea implicitly performs distributed tracking and can be extended to that application.

It can be implemented in such way: each sensor's local observation to produce sensor measurements, and then communicates to the assigned local processors, the local processors compute track estimates and transmit results to the neighbor sensor

processors, and the global fuser merges the local estimates to provide a single global estimate of the targets to be tracked. Track-to-track fusion is an important issue in multi-sensor data fusion. Regardless the independent measurement errors of each sensor node, due to the correlation of sensor node, the tracking results could be greatly impacted by noise. Figure below shows the local detection area of each node. Each local detection area is divided into 16 grids, and different sensor data pair is mapped into one of this 16 grids. Table 4.1 shows the index of the 16 grids to the left side of the sensor. Table 4.2 shows the index of the 16 grids to the left side of the sensor. Table 4.3 and Table 4.4 give the mapping function between the pair sensor data and its result grid index.

Table 4.1 The grid index in the left local detection area of sensor node

1	2	3	4
5	6	7	8
9	10	11	12
13	14	15	16

Table 4.2 The grid index in the right local detection area of sensor node

4	8	12	16
3	7	11	15
2	6	10	14
1	5	9	13

Table 4.3 The data grid index look up table for the left local detection area

Sensor Data	Grid Index
0001	3 4 7 8 12 16
0010	2 3 6 7 11 12
0011	3 6 7 4 12 16
0100	1 5 6 10 11 15
0101	6 10 11 4 8 12
0110	2 5 6 7 10 11
0111	2 3 7 11 12 16
1000	9 10 13 14 15 16
1001	4 8 12 13 14 15
1010	2 7 11 9 14 15
1011	3 7 8 11 9 14
1100	9 10 13 6 15 14
1101	9 10 11 14 3 8
1110	5 10 9 13 11 14
1111	3 7 8 9 10 14

Table 4.4 The data grid index look up table for the right local detection area

Sensor Data	Grid Index
0001	1 5 9 13 14
0010	5 6 10 11 15 16
0011	1 5 9 14 11 13
0100	6 7 12 10 11 14
0101	5 6 7 9 12 14
0110	10 7 14 11 12 15
0111	14 6 7 10 11 13
1000	1 2 3 4 7 8
1001	2 3 4 5 13
1010	2 3 4 6 11 14
1011	3 6 8 9 10 14
1100	2 3 4 6 8 11
1101	2 3 7 8 10 11
1110	1 2 6 7 8 12
1111	2 4 7 10 13 15

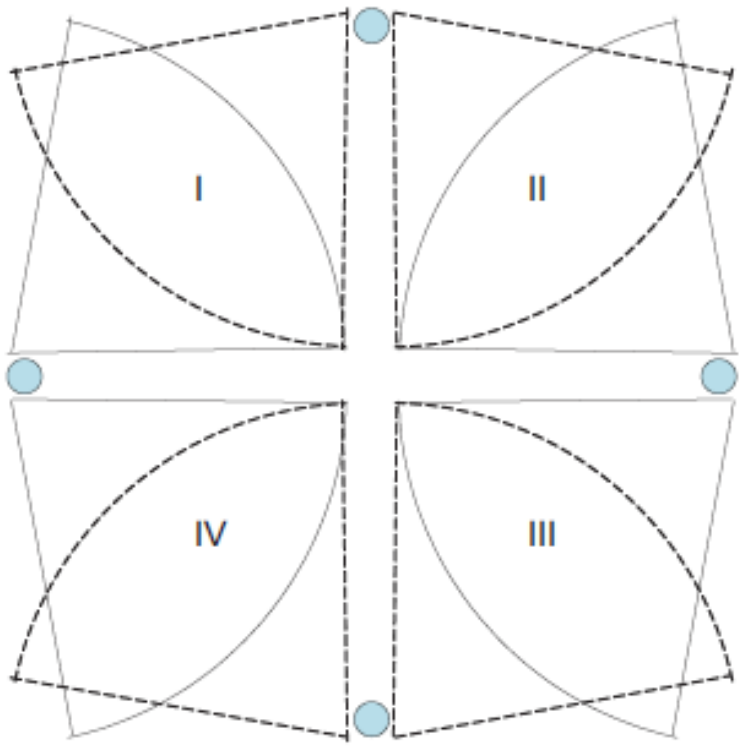

Figure 4.4: Tracking node local detection area

Figure 4.4 shows the tracking strategies of distributed tracking scheme. For each sensor, it only contains the information

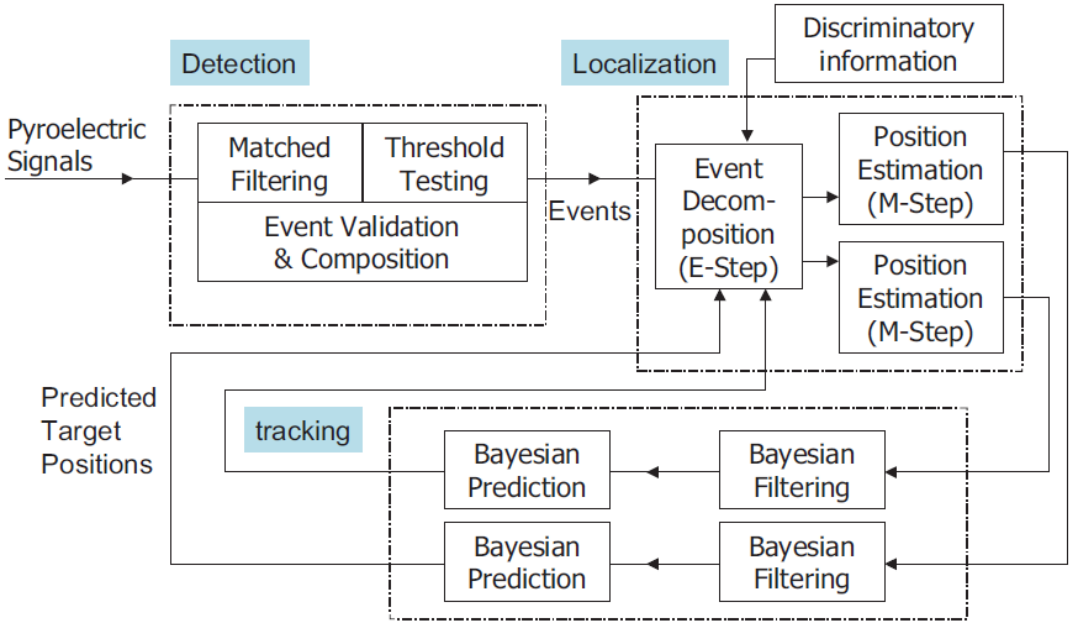

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Figure 4.5: Tracking strategies

4.4 Event association and object state estimation

There are many algorithms that have been developed for tracking over time using a continuous set of noisy measurements. The previous work applies the standard Kalman filtering algorithm to the tracking of objects with a linear model. The algorithm receives continual measurements at fixed time intervals from the sensor. In the domain, measurements are only available when the objects pass the nodes, and more importantly the measurements themselves are only available at the nodes. Despite the asynchronous measurement intervals, the Kalman filtering approach is very appealing due to its

sequential convergence properties and the 'prediction step' that provides a means for associating new measurements.

4.5 Distributed event association and object estimation

A distributed detection algorithm is proposed that operates as follows. Whenever an event occurs at a node in the network, it carries out the following algorithm:

1. Check if the event occurs within the prediction gates of any previous 'time-updated' hypotheses received from the surrounding nodes.
2. Check if the convergence criterion is met. If so, report the confirmed object to the central node. A distributed tracking algorithm takes over at this point.
3. Initiate a new hypothesis starting at this event
4. Broadcast the hypotheses to the surrounding nodes

In the proposed algorithm, the processing that occurs at each node in the sequence when an event occurs is outlined.

CHAPTER 5

SYSTEM IMPLEMENTATION

Both the recognition and tracking wireless sensor systems are based on TI's micro-controller and RF transceiver combination of MSP430149 and TRF6901. The tracking system consists of one host, one master, four slave tracking slave node, while the recognition system consists of one host, one master and three slave recognition slave node. We use the combination of TRF6901 and MSP430149 as the computation and communication platform. Each slave node containing pyroelectric sensors and Fresnel lens arrays, employs an amplifier board that amplifies eight channel signals in the frequency band 1~10 Hz. Each MSP43019 contains an 8-channel, 12-bit A/D converter, whose sampling rate is set as 19.5 KHz, conversion rate as 96 KHz, with 5 MHz internal ADC clock. One data package for an event includes 48 bits, i.e. 6 bytes. It means that the sampling rate of wireless sensor system, from 10 to 80 Hz in terms of events, is virtually determined by the embedded computation time. The TRF6901 is an integrated circuit intended for use as a low cost FSK or OOK transceiver to establish a frequency-programmable, half-duplex, bidirectional RF link. The multichannel FM transceiver is intended for digital (FSK, OOK) modulated applications in the new 868-MHz European band and the North American 915-MHz ISM band. The single-chip transceiver operates down to 1.8 V and is designed for low power consumption. The synthesizer has a typical channel spacing of approximately 200 kHz and uses a fully-integrated VCO.

To ensure the communication stability, the RF data rate between slave nodes and master nodes is set as 32 kbps, despite its maximum of 76 kbps, the UART serial port transmission rate between master and host is set as 57.4 kbps, less than its maximum of 69.4 kbps. The TRF6901 ISM-band RF transceiver is used to establish multichannel, bidirectional wireless communication, link between 888 MHz and 928 MHz, in programmable data transmission rates from 19 to 76 Kbps. The paired baseband processor MSP430F149 FLASH micro-controller comes programmed with baseband communication routines to implement an RS-232 link protocol. Each server node is assigned a certain operation frequency calculated as follow: the base channel width is 370.7 kHz, and the bandwidth of carried signal may be up to 1 MHz, that is, four times base channel width; we hence divide the usable base channel number of 105 by 4, and obtain 26 channels without mutual interference.

We employed the master/slave communication mode. The direction of control is always from master to the slave(s). Table5.1 shows the data packet structure, including two bytes of FF as “header”, two bytes of 10 as “tail”, and one byte for node ID and another byte for event index. Table 5.2 describes the program initialized in the master, slave and host sensor node.

Table 5.1 Data package structure

FF	FF	ID	Event	10	10

Table 5.2 Communication interface

Slave Node

Initialization RF(size of packet, sub bandwidth assigned, baud rate)
while(1)
  Sampling and Processing()
  Send RF(sub bandwidth assigned, &packet, size of packet)
end

Master Node

Synchronization RF(size of packet, all bandwidth assigned, baud rate)
while(1)
  for i=1:number of sub bandwidth broadcasting
  Receive RF (sub bandwidth(i), &packet, size of packet)
  Error Rejection Event Smoothing()
  Send Serial(node ID, &packet, size of packet, baud rate)
  end
end

Host

Initialization Serial(com#, size of buffer, baud rate)
while(1)
  Find Packet Header()
  Read Data()
  Data Fusion Target Tracking()
end

CHAPTER 6

EXPERIMENTAL WORK

6.1 Introduction

This chapter describes the experiment setup and experimental results. Both path dependent and path independent recognition results obtained by using the compressive human recognition scheme introduced in chapter2 and chapter 3 are given. The distributed tracking results are also given.

6.2 System setup

For path dependent human subject recognition, we used 3 two-column sensor nodes, as shown in Figure 1.1. The sensor node deployment is shown in Figure 1.2. The human subjects randomly walk inside a $4m \times 4m$ room one at a time. Each subject generated one set of data, first half of which would be used for feature model training while the other half for real time testing. The same setting is also used for path independent. Regardless whether it is path dependent or path independent, close-set walker recognition and open-set walker recognition are performed. For close-set recognition, the system performance is evaluated using identification rate. For open-set walker recognition, the performance can be plotted in a Receiver Operator Characteristic (ROC) plot, usually is known as ROC curve.

For distributed human subject tracking, 4 tracking sensor nodes shown in Figure 1.3 are used. They are arranged in each of the 4 sides of a $4m \times 4m$ room as shown in Figure 1.4.

6.3 Path dependent recognition results

For single human subject fixed path recognition, the human subjects walk along a prescribed path back and forth inside a $4m \times 4m$ room one at a time. By using the selection method proposed in the previous chapter 2 and chapter 3, 1 bit data is selected from each of the sensor node, thus the total 3 bits data would be used for building model. In order to compare the fusion effect, the fusion results are also shown in the same figures. The close-set identification rate and open-set ROC curve results for 5 targets is shown below. The results are based on 200 tests of 5 different targets.

Here are some notations that need to be explained first in order to understand the result plots. In the plot below, S stands for Similarity; SD stands for Similarity Distance; TS stands for State Transition Similarity; TSD stands for State Transition Similarity Distance; KL stands for KL Distance; TKL stands for State Transition KL Distance; Set 1 indicate the results is based on the first preselected 3 channels – channel 5, 10 and 22, one from each node; Set 2 stands for another set of preselected 3 channels – channel 2 10 19. Both sets are selected through the data evaluation methods introduced in 3.4.

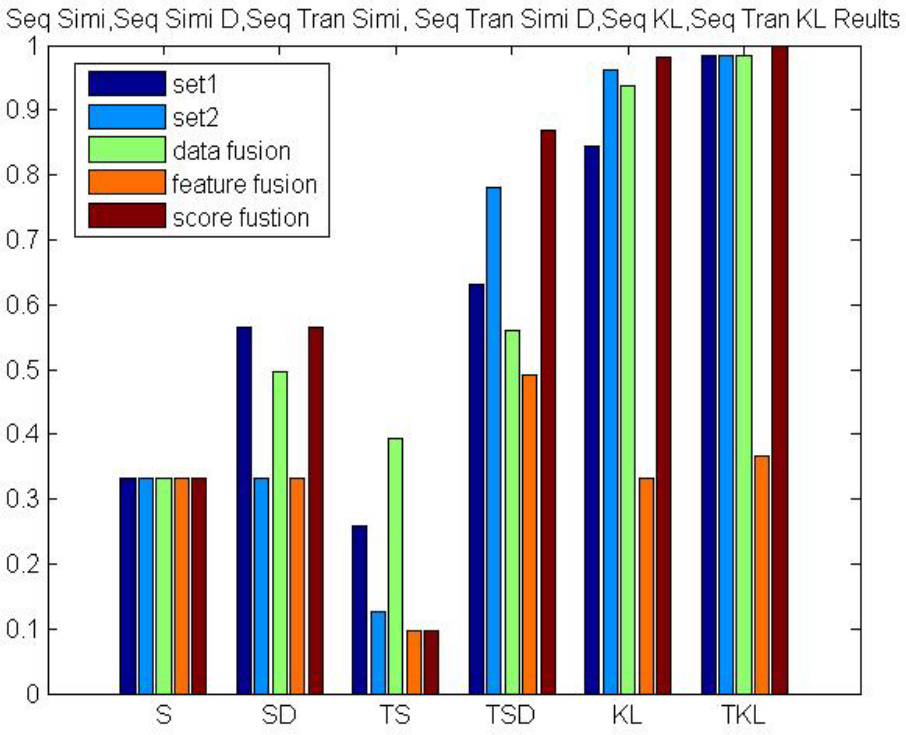

Fig 6.1: Close set recognition rate for path dependent recognition using 2 preselected channels, data fusion, feature fusion and score fusion.

From the figure below, we can see that when using score fusion scheme with the KL distance feature to capture the state transition distribution feature of targets, 100 percent identification rate is achieved. It is not hard to see that when set 1 and set 2 can individually achieve a good performance, the score fusion and help improve the performance. It can also be seen that the state transition data contains more useful information than the state data, since the recognition rate is higher for both similarity distance and KL divergence when using transition data. The open-set ROC curve shown below also shows the similar results.

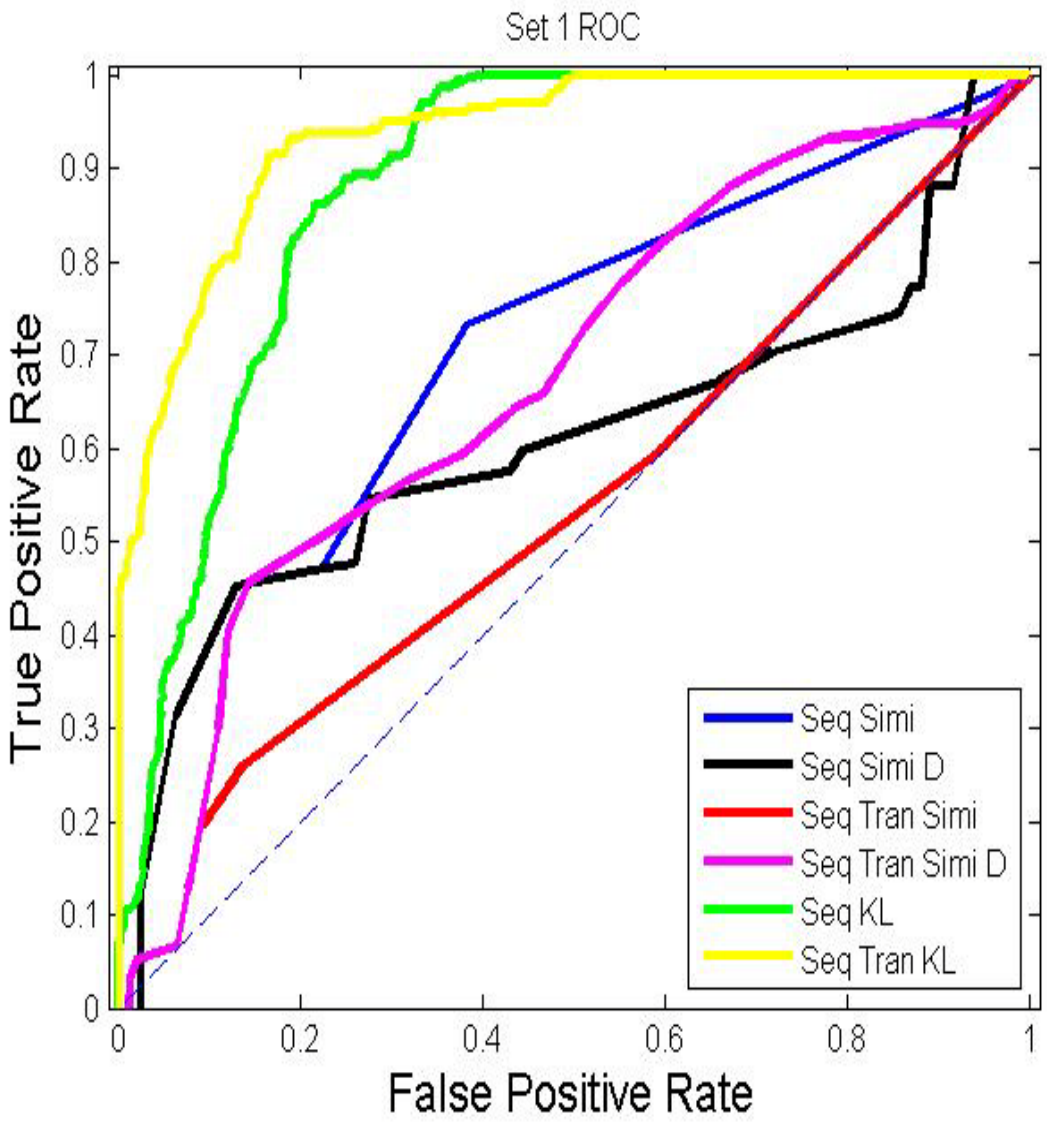

Fig 6.2: Open set ROC curve for path dependent recognition using set 1 preselected channels using different features

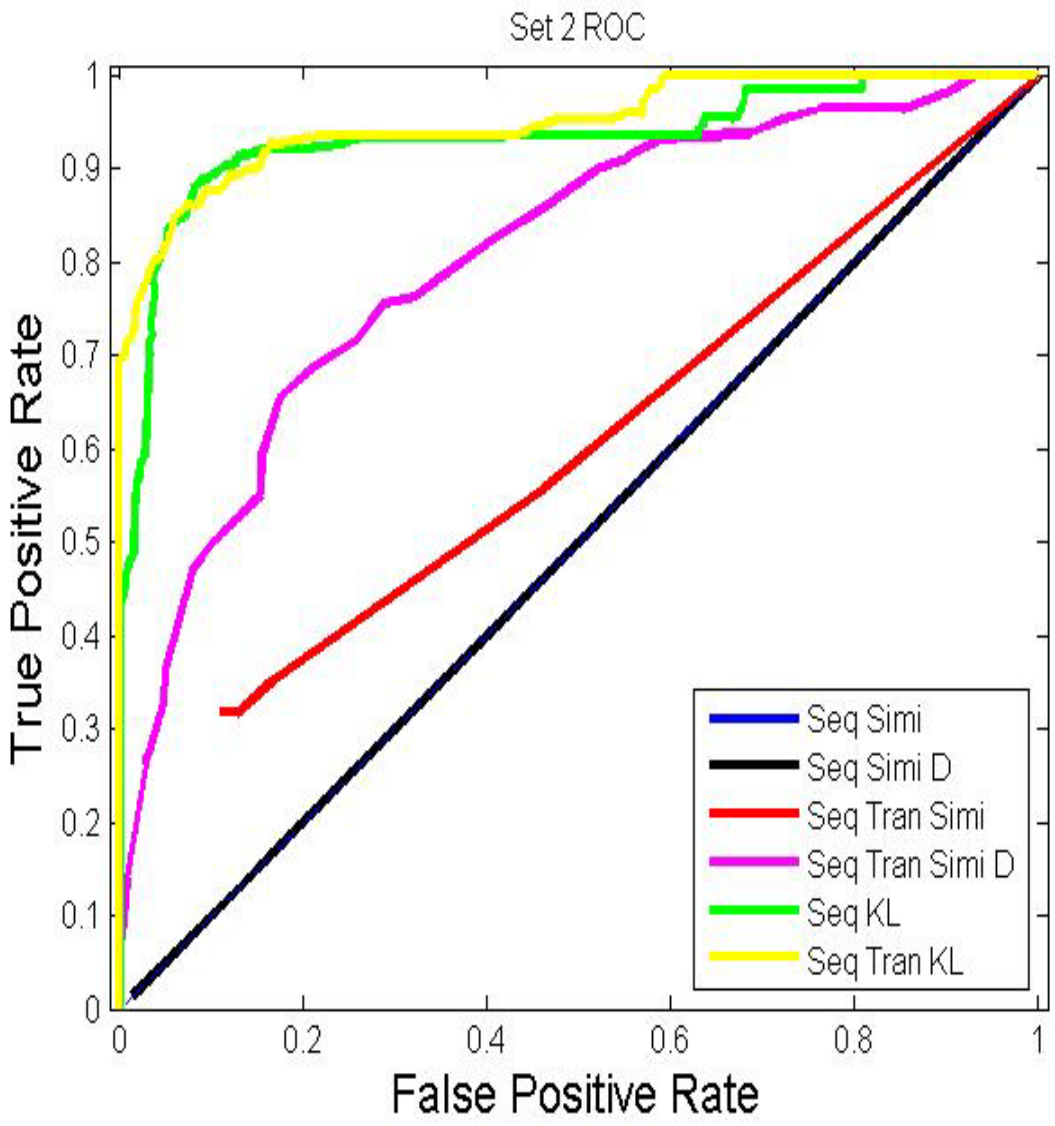

Fig 6.3: Open set ROC curve for path dependent recognition using set 2 preselected channels using different features

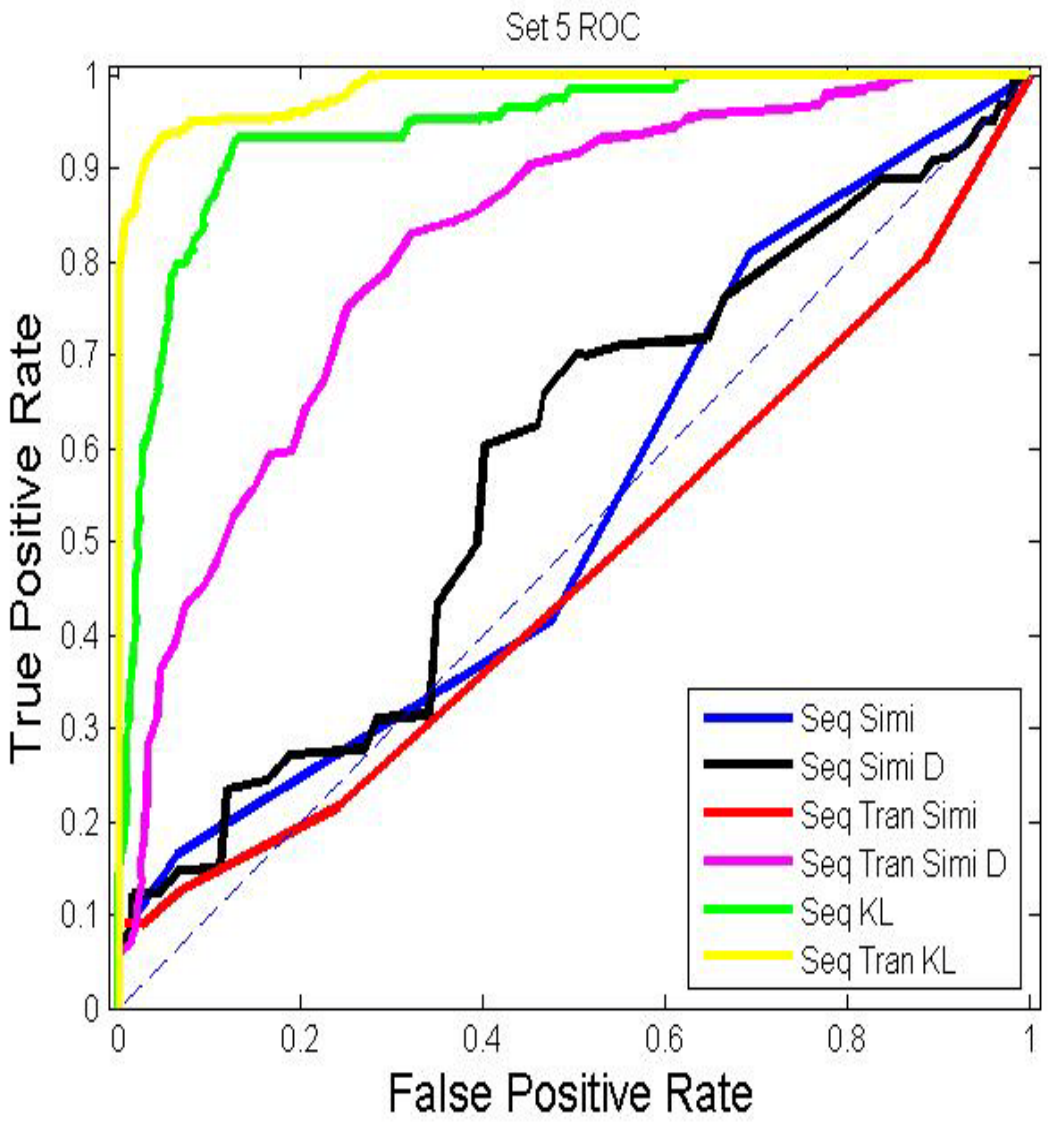

Fig 6.4: Open set ROC curve for path dependent recognition using score fusion preselected channels using different features

6.4 Path independent recognition results

The challenge for path independent recognition is that the random path walk can generate less regular sequence pattern when compared with fixed path walk, makes it hard to extract the feature or find the pattern with respect to each individual. Using the similar process as fixed path could be a solution. That is, we collect the random walk sample of each human target and use the random walk sequence data to extract the feature as well as test.

However, in an effort to develop a more general scheme for path independent recognition, the approach we developed here is to use 2 fixed path patterns as a base, the random walk sequence feature will be mapped into these two bases and the distances to both of them are considered for the decision. The main idea behind this is that we believe no matter which direction the walker walks towards, the 3 sensor nodes should be able to pick up part of the information that is similar to those contained in the pre-designed fix path, the diagonal lines in this case. Human brain has the similar function, as one usually does not need a particular point of view to recognize a person he/she knows is walking. In computer vision recognition schemes, the same idea is used by finding the static feature in different images of the same target.

Table 6.1 shows us the recognition rate of 5 targets in 100 tests. Figures below show us the ROC curve of 200 tests using the idea described above. To compare the

recognition results using the traditional random training scheme, the recognition rate under this scheme is also plotted.

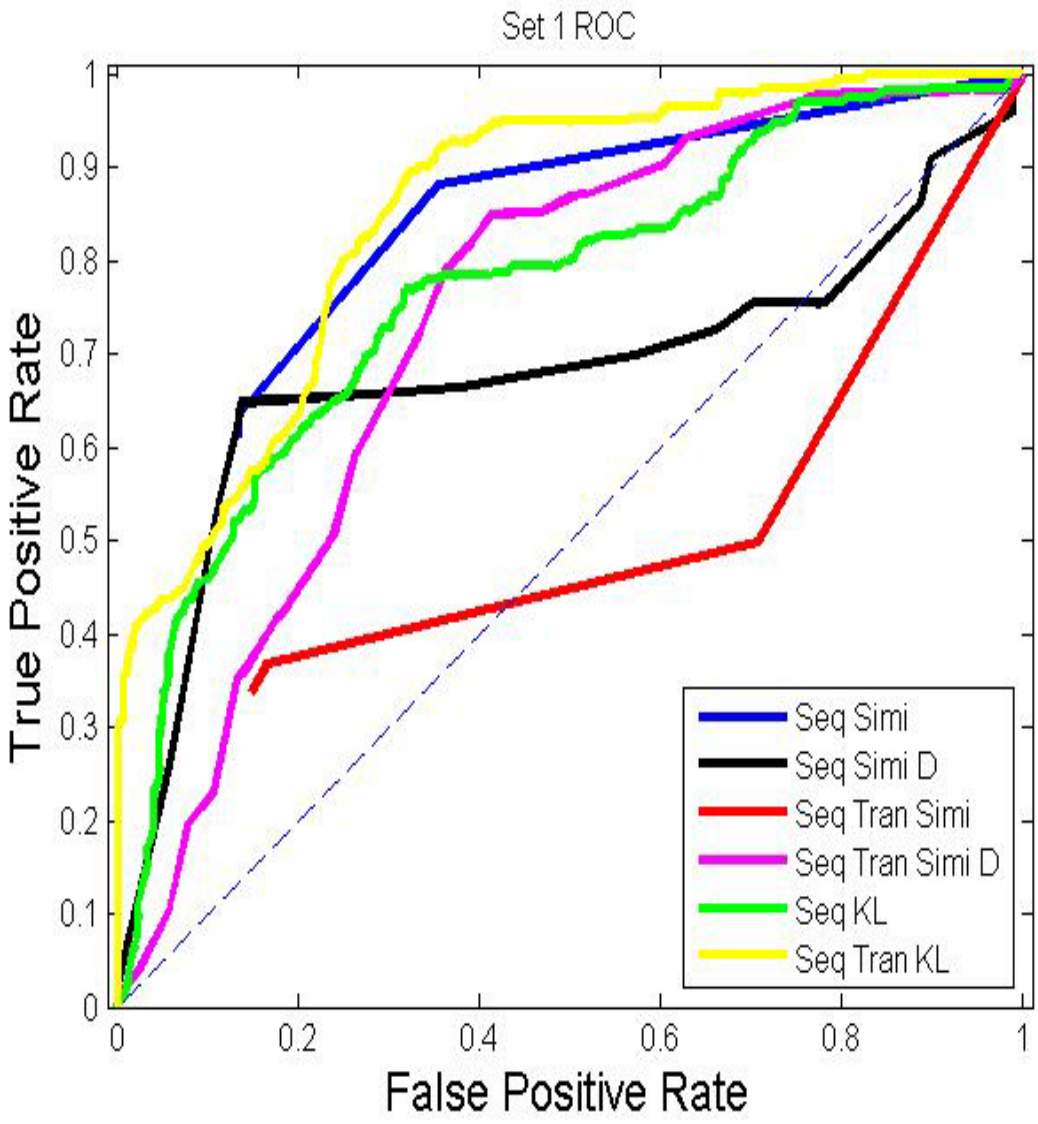

Fig 6.5: Open set ROC curve for path independent recognition using set 1 preselected channels using different features

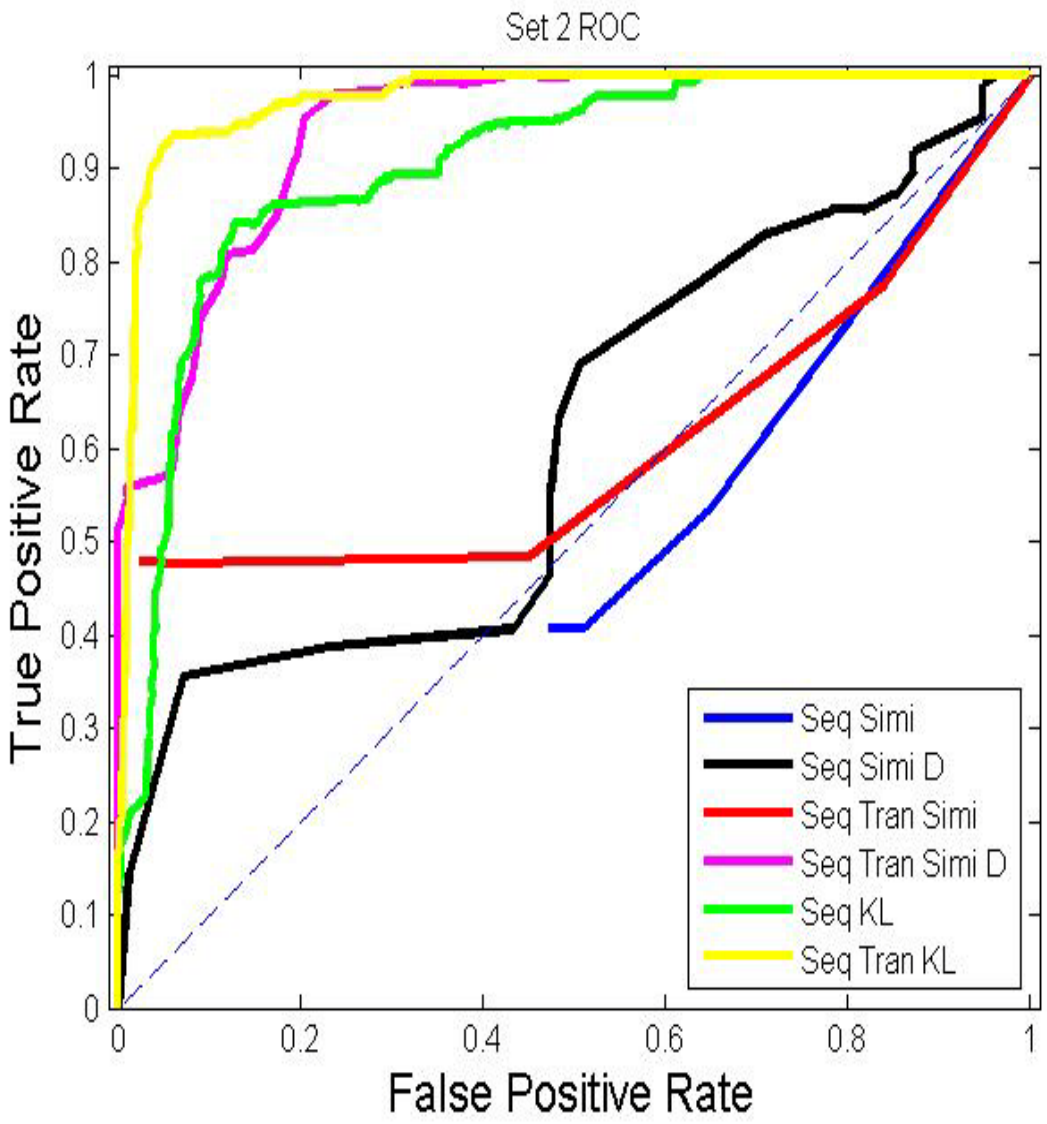

Fig 6.6: Open set ROC curve for path independent recognition using set 2 preselected channels using different features

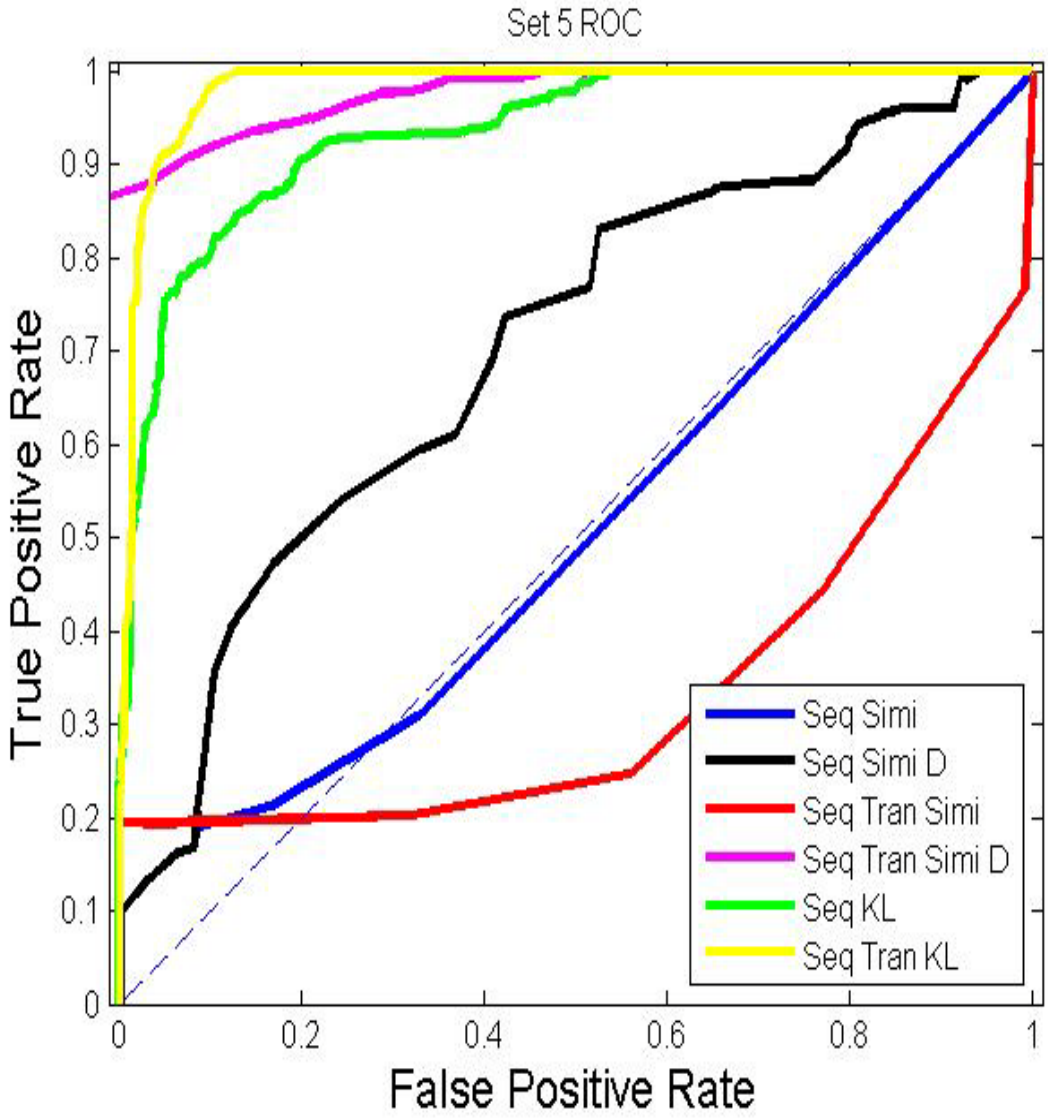

Fig 6.7: Open set ROC curve for path independent recognition with score fusion using different features

Table 6.1 Path independent recognition rate using 2 paths based mapping scheme

	Sean	Alina	Nanda	Robin	Yuan
Sean	83%		1%	4%	12%
Alina	3%	67%	24%	6%	
Nanda	2%	21%	71%	6%	
Robin				78%	22%
Yuan	2%	3%		11%	84%

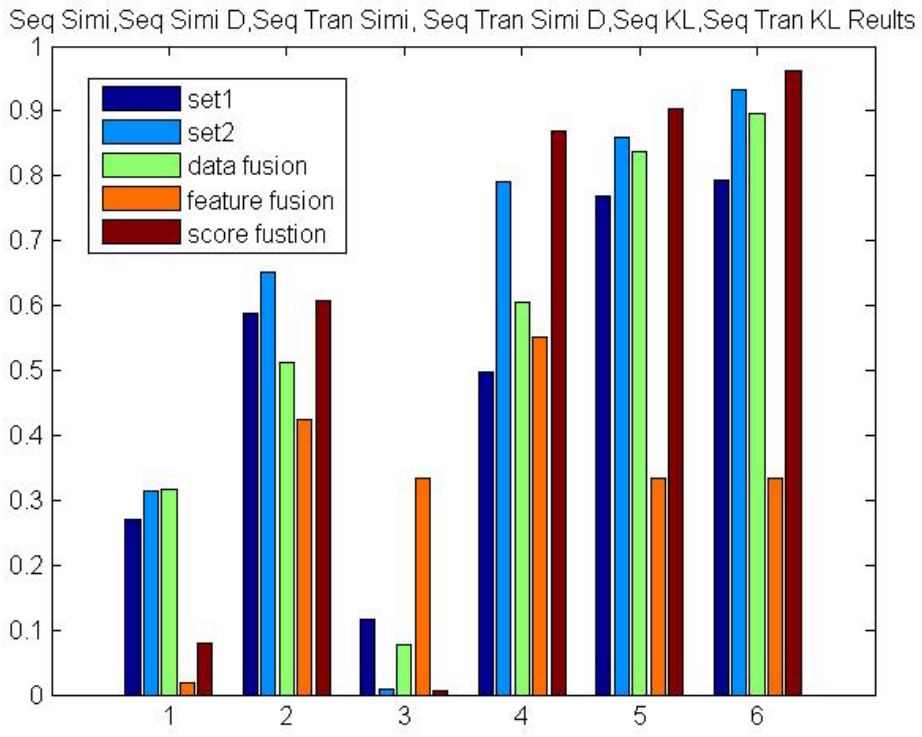

Fig 6.8: Close set recognition rate for path independent recognition using random training scheme with 2 preselected channels, data fusion, feature fusion and score fusion.

6.5 Tracking results

4 tracking sensor nodes shown in Figure 1.3 are used. They are arranged in each of the 4 sides of a $4m \times 4m$ room as shown in Figure 1.4. The figures shown below show the distributed tracking results capture during a cycle of a single human target walking in circles clockwise around the room. The black mark in the figures indicate the tracking target result and the small marks show us the sensor detection beam and detection area according the sensor response.

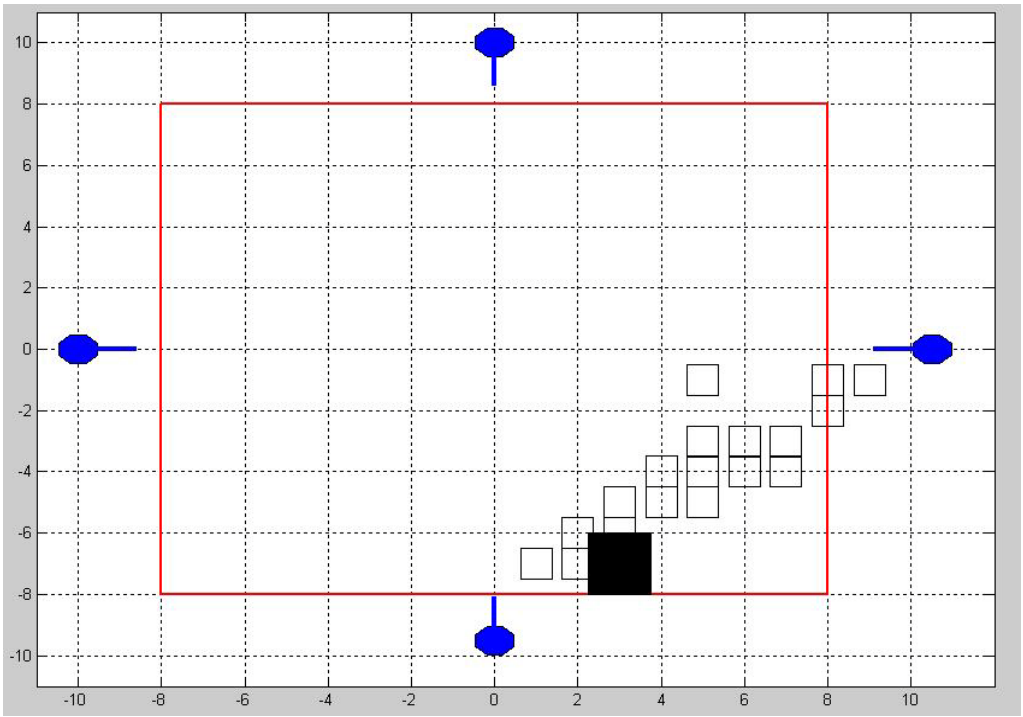

Fig 6.9: Snapshot of tracking one human target walking in a circle in a room. (Frame 15)

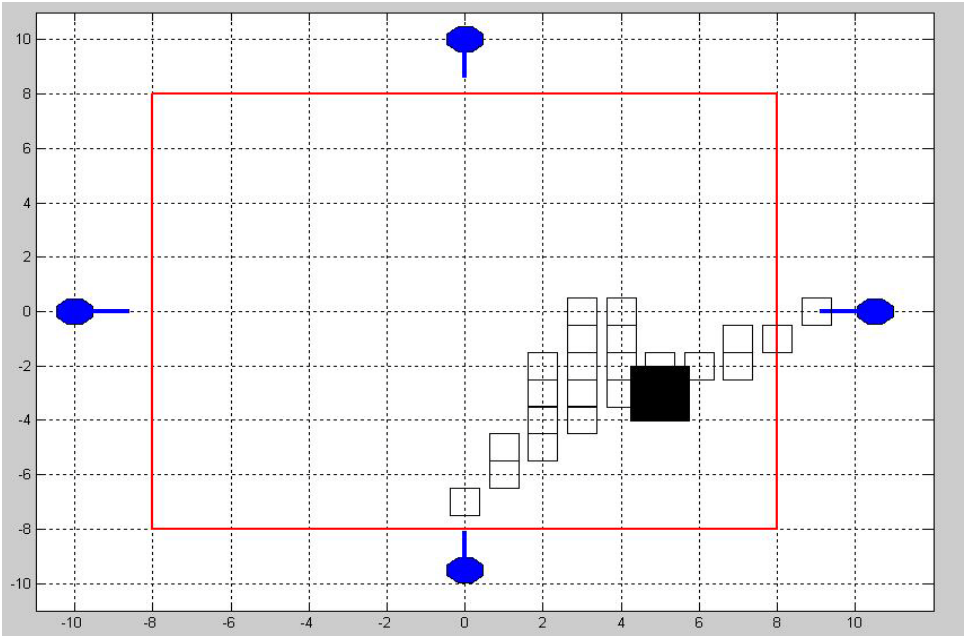

Fig 6.10: Snapshot of tracking one human target walking in a circle in a room. (Frame 23)

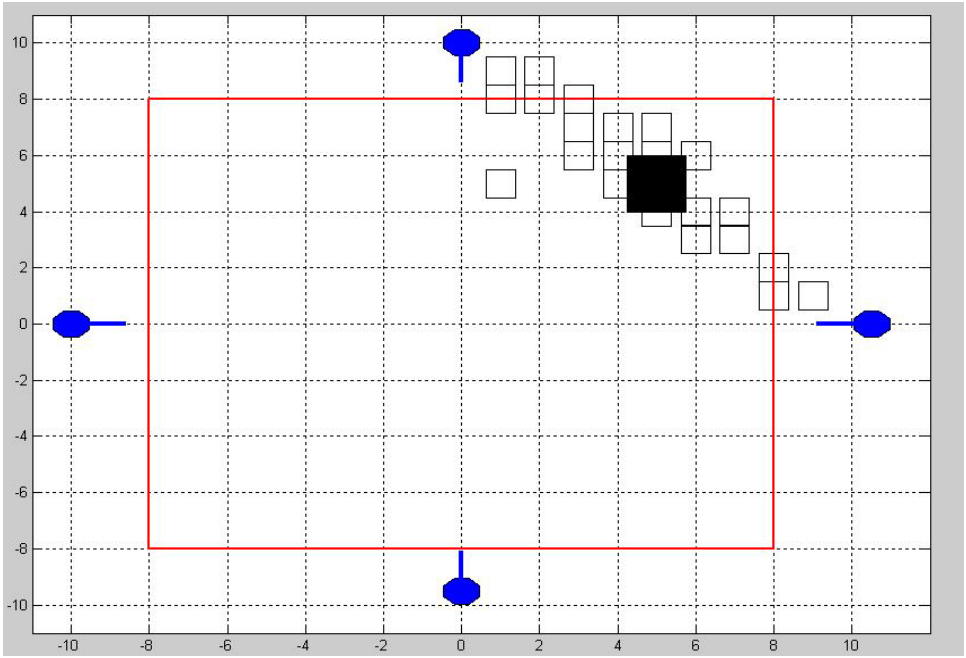

Fig 6.11: Snapshot of tracking one human target walking in a circle in a room. (Frame 36)

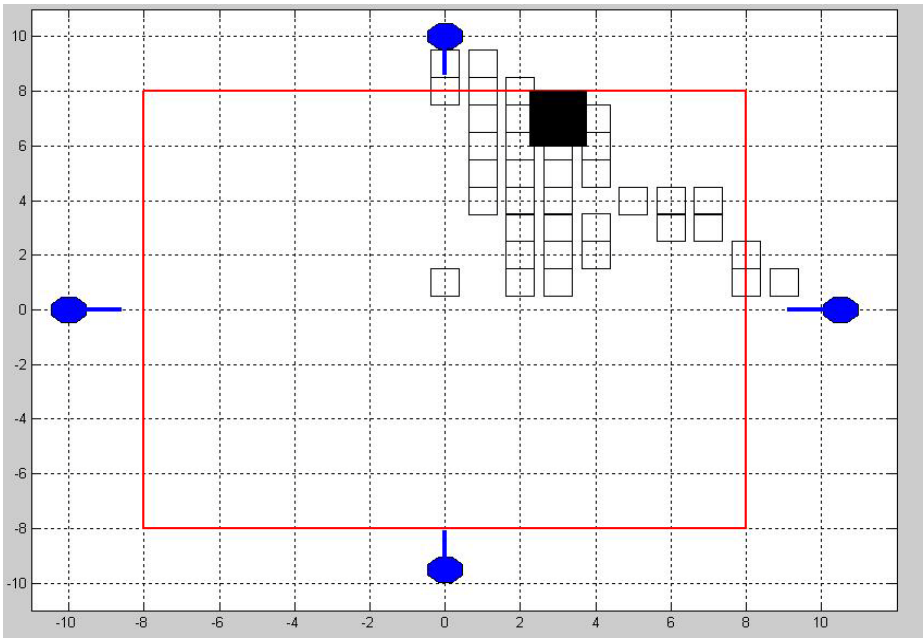

Fig 6.12: Snapshot of tracking one human target walking in a circle in a room. (Frame 42)

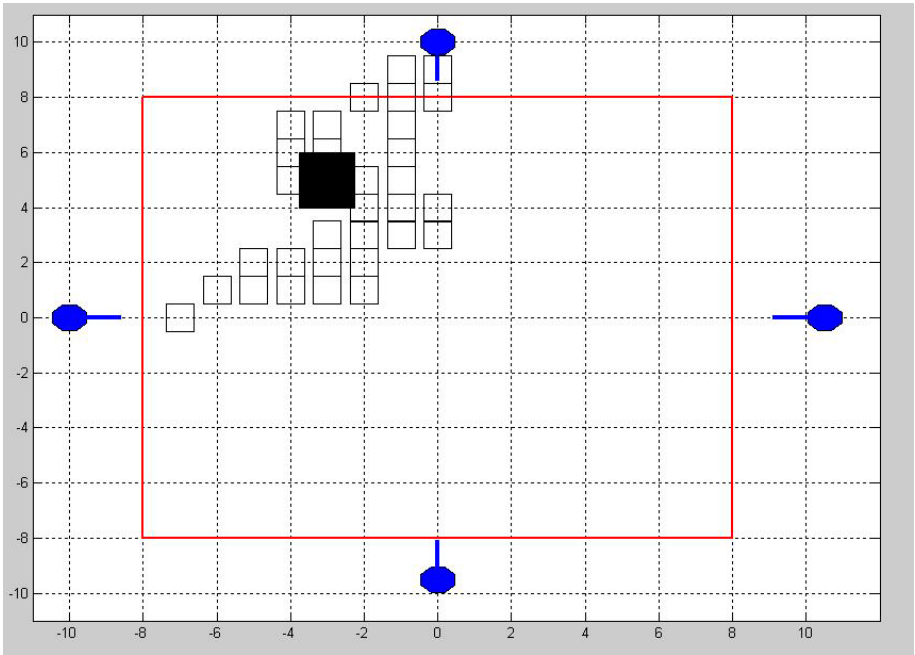

Fig 6.13: Snapshot of tracking one human target walking in a circle in a room. (Frame 50)

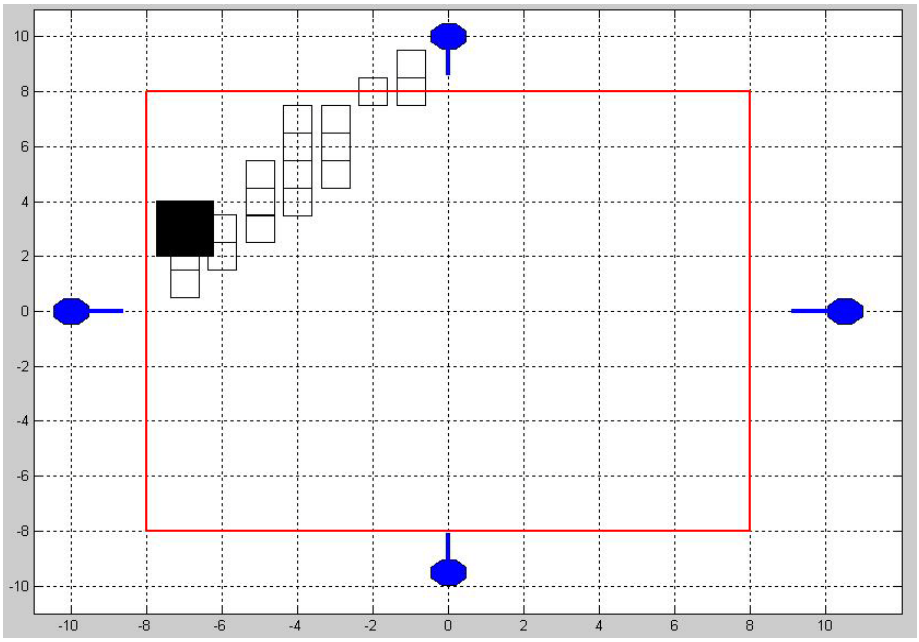

Fig 6.14: Snapshot of tracking one human target walking in a circle in a room. (Frame 55)

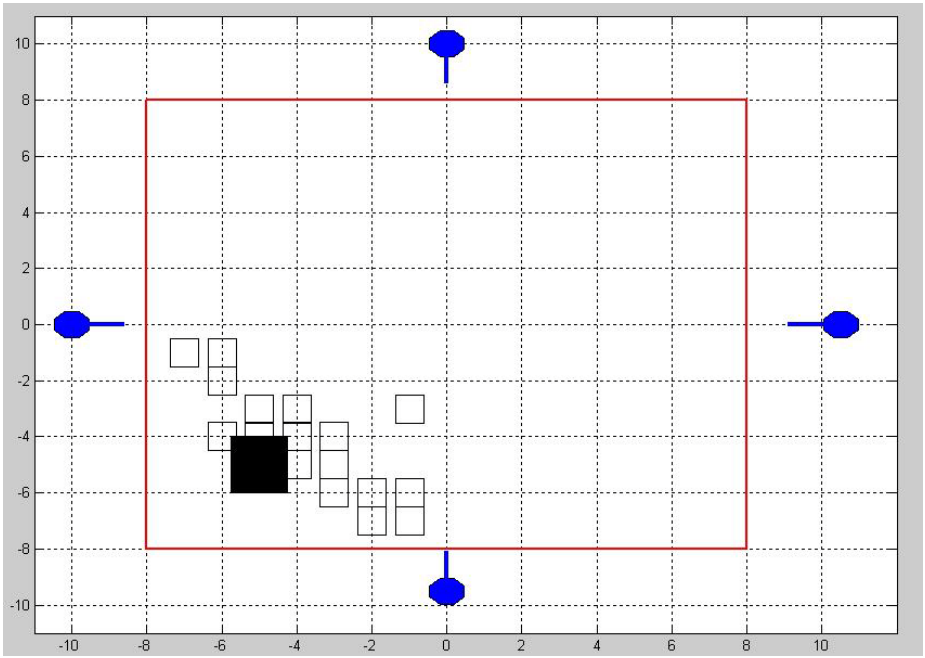

Fig 6.15: Snapshot of tracking one human target walking in a circle in a room. (Frame 63)

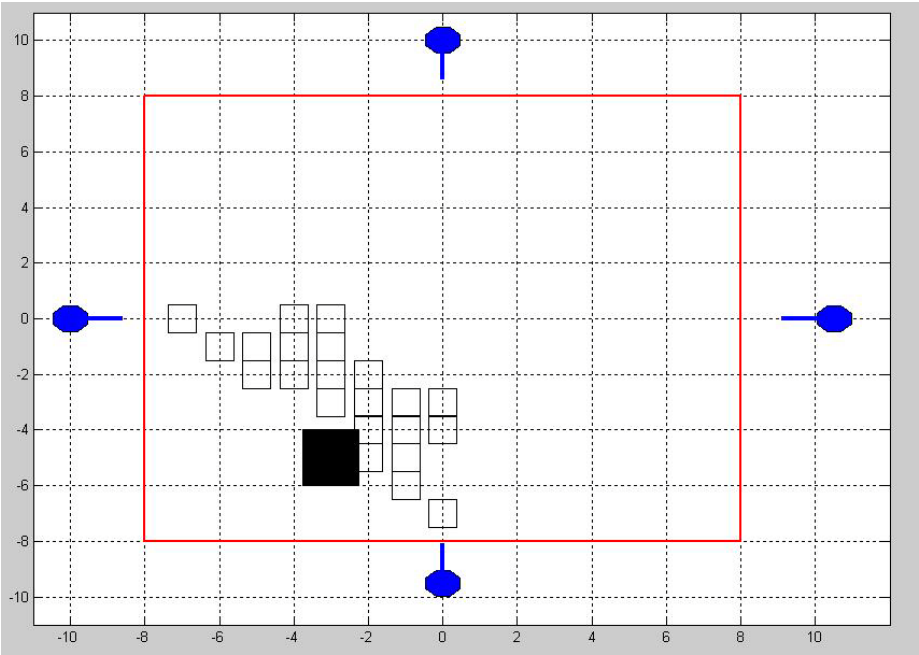

Fig 6.16: Snapshot of tracking one human target walking in a circle in a room. (Frame 68)

CHAPTER 7

CONCLUSION AND FUTURE SCOPE

With the increasing use of biometric and sensor network and their increasing impact on the industrial application, it is important to understand the disciplines in this area. Adopting tools used in these different disciplines, methods of inquiry can be formulated that allow for the interpretation of works that are both technically sound and sociologically insightful.

This thesis presented a compressive gait biometrics. Based on previous work, we developed an integrated sensing and processing framework for compressive gait biometrics. Gait biometrics is advantageous in their capability of recognition at a distance under changing environmental and cosmetic conditions. Gait-based human recognition tolerates low resolution of sensory data and allows for non-cooperative subjects under examination. The central issue of our research is the selection of representative features that describe the specific way one carries the body or makes gestures, idiosyncratic rhythms of arm swing, leg crossing or utterance, and possibility distribution of habitual trajectories. To conquer this problem, we developed a scheme includes data evaluation, feature extraction and feature fusion, which enable us to achieve a high recognition rate of the system.

The main contributions for our work are:

1. We proposed a distributed compressive sampling structure for gait information acquisition includes multiplex field of view modulation of sensors and object space segmentation with distributed sensor deployment. The former refers to the use of coded masks (obscurants) that allows or blocks one sensor to detect motions with several regions in the object space, the latter refers to the deployment of sensor that segments the object space into many cells, each characterized by its Boolean visibility to sensors.
2. We developed an incoherent sensing protocol for gait feature extraction, which allow us to further reduce the redundant sensory data amount and extract feature data in concise forms. This is achieved by multichannel sampling and switching, as well as sparse gait feature representation in terms of logic parameters of probability distributions of signal states and their transitions. The central task of compressive sensing protocol development is to choose a proper scheme of the random projection encoding and linear program decoding. It involves two steps: finding a set of proper temporal spatial bases and choosing a set of measurement functions accordingly. In our study, we studied the non-adaptive random measurement functions, in both spatial and temporal domains for preprocessed sequence data. Through compressive sensing protocols, the gait attributes will be transformed into compressed sensory signals. Sensory data feature will be further extracted from those compressed signals as far as the spatial/ temporal coherence and statistical properties are preserved.

3. We investigated several decentralized information aggregation schemes for distributed sensors. With the help of information aggregation among sensor groups, which can happen at data, feature, score and decision levels, we further improve the performance of the recognition system. Data level fusion accepts high quality samples and rejects poor quality ones. Feature level fusion relies on building inclusive feature models. Score level fusion combines distributed scores. Decision level fusion combines decisions from different processing units by logic rules. Given the prior knowledge about the sensor head information and the physical space resource allocation, compressive sensors convert the raw information into a feature field, which can be reduced by low-level processing and transformed through fusion into a feature pattern representation. Finally, the logic parameters of feature patterns are statistically analyzed for computing similarity and making recognition decisions.
4. We implemented a distributed tracking scheme in real system. From the achieved experimental results, we believe that the pyroelectric sensor will rise to one mainstream human detection instrument, besides its video and audio counterparts, and offer one more dimension for all the applications of human-machine interfaces. It can not only run as a stand-alone inmate/patient monitoring system under all illumination conditions, but also serve as a complement for conventional video and audio human tracking systems.

Several interesting questions appeared during this research are still remain to be unsolved. These questions are likely to be our future work.

(1) The most important one among them is what limitation in clothing, physical, medical and emotional biometrics is on the gait biometric in our system? The following figure shows the sensor data and the data state transition of the same target under different speed conditions and different clothing conditions. The feature we currently used in our system is not stable for this problem, thus will lead the system to a failure recognition decision result.

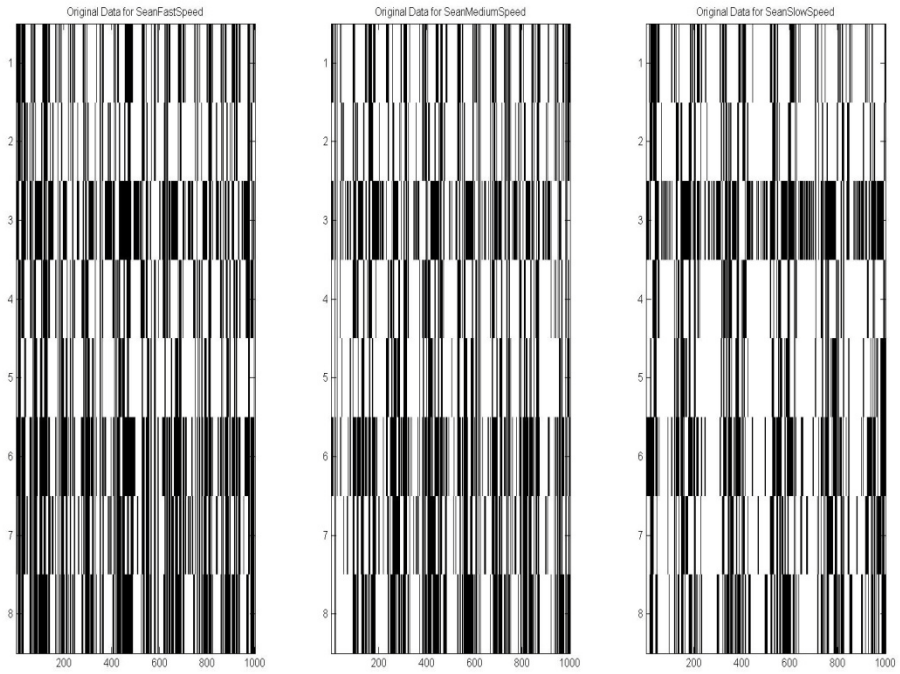

Fig 7.1: Sensory data for same human target under different speed conditions

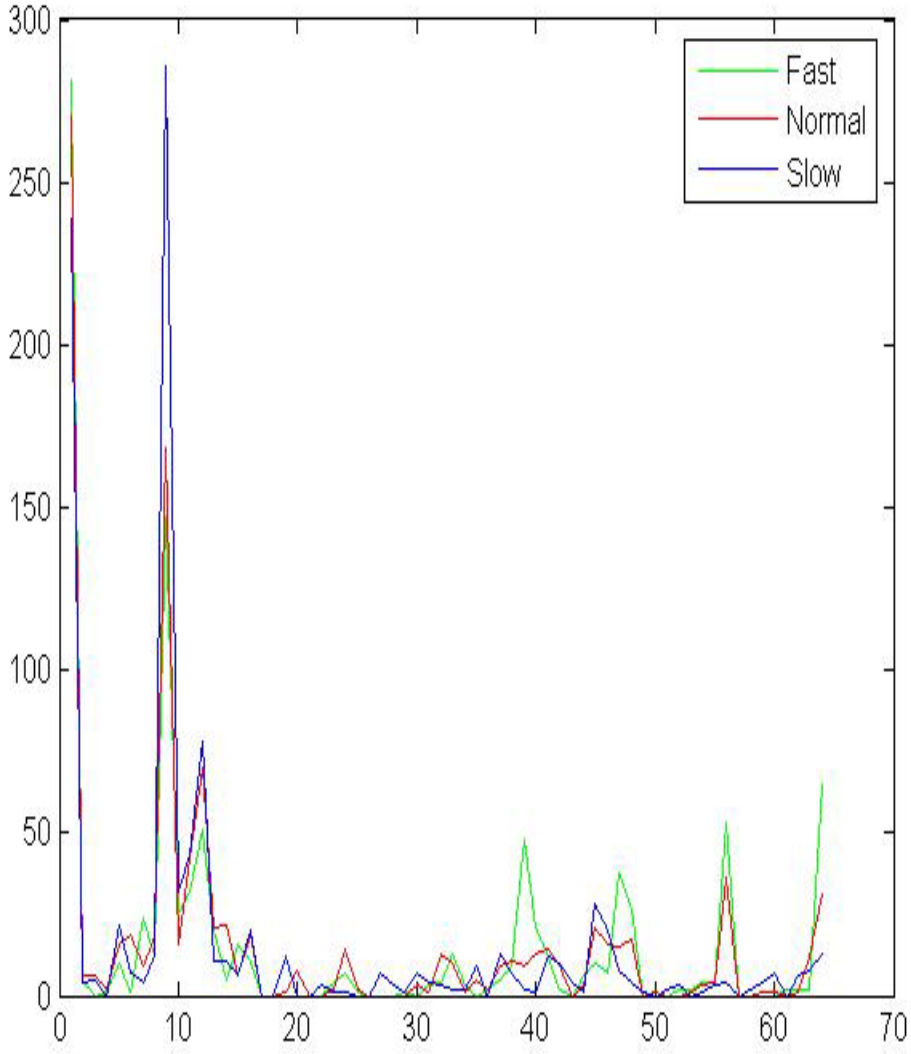

Fig 7.2: State distribution for same human target under different speed conditions

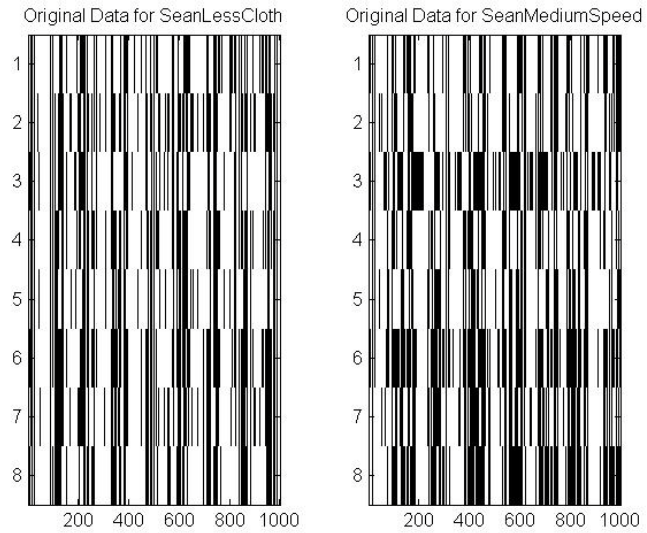

Fig 7.3: Sensory data for same human target under different cloth conditions

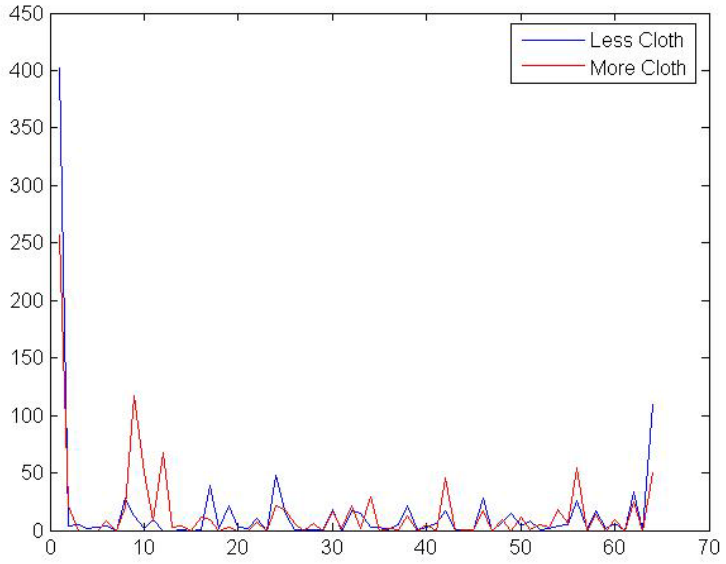

Fig 7.4: State transition for same human target under different cloth conditions

(2) What is the optimal field of view mask design for our system? Different visibility layouts will create pyroelectric sensor systems with different capabilities: one good for motion detection, another for feature extraction. To the human identification, two types of visibility modulation can be further tested, namely the periodic and the random. In capturing motions of the human body along the vertical direction, a periodic visibility modulation of a sensor array functions as spatial filters with a specific passing band. A (pseudo-)random visibility modulation of a sensor array yields a set of spatial filters with orthogonal passing bands. The study of these two types visibility modulation would improve human identification rates.

(3) What is the optimal random multi-channel sampling scheme in both spatial and temporal domain for gait attributed acquisition?

(4) What are the proper sparse representations of shape and dynamic features of gait biometrics in our system?

(5) The distributed tracking algorithm discussed here is only based the predefined setting including sensor nodes position and so on. How to generate a self calibration scheme to automatically calculate the position is also a very challenging problem.

The scope of future work will also include advanced Integration of Tracking and Identification. A fully functional real-time multiple human tracking and identification system demands the ability to discriminate the sensory data source, it will also require

short testing event sequences for fast walker identification and multiple object recognition at the same time.

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