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Indoor Human Dynamic Localization and Tracking Based on Sensory Data Fusion Techniques

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***Abstract*—Within an intelligent building, it is expected to offer various intelligent services by recognizing residents along with their lifestyle and needs. One of the key issues for realizing the intelligent building is how to detect the locations of residents, so that it can provide the interactive services based on the identified need and requests.**

In this work, we develop a wireless pyroelectric sensory system embedded with traditional fire detector, which can be implanted on the ceiling. Both of wireless transmission model and pyroelectric sensor monitoring system can provide the rough information of residents' location respectively. These data can be further improved by reducing the sensory uncertainty through covariance intersection (CI) data fusion method. Pyroelectric localization system suffers from multi target tracking and wireless pyroelectric sensor system works this issue. With the location obtained from wireless pyroelectric sensor system, intelligent building can offer suitable services.

Keyword: Sensor network, pyroelectric sensor, data fusion, location recognition

I. Introduction

THE intelligent building as a way to provide convenient, comfortable, and safe residential environment [1][2]. The intelligent building can offer service for inhabitant such as HVAC (heating, ventilating and air conditioning) system, lighting, humidity control and so on.

The location information of pedestrian is important for these services. According to the record and recognize the living pattern of users, an intelligent building system can anticipate the users' needs and provide appropriate services.

There are a lot of researches discuss the indoor localization systems[3],[4],[5], however, most of them suffer from multi target tracking or expensive implementation cost.

The researches Active Badges[6], Active Bats[7], and Easy Living [8], which use infrared sensors, ultrasonic sensors, and vision sensors, respectively. MotionStar[9] uses a DC magnetic tracker, and RADAR [10] uses wireless local area network for localization. Smart Floor[11] uses pressure sensors to measure proximity to a known set of points.

Indoor localization systems can be classified according to the need of a terminal should be carried by pedestrian. For non-terminal localization methods such as Smart Floor can locate the pedestrian without carrying any devices Terminal-based methods such as Active Badges, which needs human carried a transceiver device or it is not possible to report the location of people without carrying these identification devices.

In this work, we propose an indoor surveillance system which replaces the traditional fire detector with pyroelectric human detector and low power wireless communication device. We also design a low power wireless device, which can replace the traditional badge/indentify card (ID card) which is wore on people. The fact is that pyroelectric sensor system provides the inaccurate position information, and wireless propagation model between the new ceiling implanted fire detector embedded with ZigBee and wireless ID card offers other imprecision location information. The obtained location information from pyroelectric sensor and wireless propagation model can use covariance intersection data fusion algorithm to generate a more reliable coordinate of residents, as shown in Fig. 1.

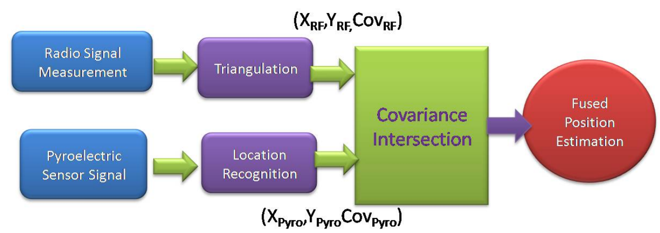


Fig. 1 Architecture of Location Information Obtained from Pyroelectric and Wireless Propagation Model

With such device implanted on the ceiling to replace the original fire detector, the multi target of residents' location information can be obtained. According to the recognized position of people, the intelligent building system can provide appropriate services.

This paper is organized as follow. Section II presents the architecture of our system. Section III describes the position information which obtained from radio propagation model. The pyroelectric location recognition system is discussed in section IV. Section V presents the covariance intersection algorithm. Section VI is our experimental results. Finally, summary and conclusion are presented in section VII.

II. System Architecture

A. Wireless Communication Platform

Our low power wireless device uses CC2431 which produces by Texas Instrument. The CC2431 is a System-On-Chip (SOC) for wireless sensor networking ZigBee/IEEE 802.15.4 solutions. The chip includes a location detection hardware module that can be used in so-called blind nodes (i.e. nodes with unknown location) to receive signals from nodes with known location's. Based on this the location engine calculates an estimate of a blind node's position. The

CC2431 enables ZigBee nodes to be built with very low total costs. The CC2431 combines the performance of the leading CC2420 RF transceiver with an industry standard enhanced 8051 microprocessor control unit (MCU), 128 KB flash memory, 8 KB RAM and many other features.

The CC2431 is highly suited for systems where ultra low power consumption is required. This is achieved by various operating modes. Short transition times between these modes further ensure low power consumption.

B. *Pyroelectric Sensor Module*

According to the datasheet [12], the pyroelectric infrared (PIR) sensor has detection distance of maximum 10m and detection range of 110° in horizontal and 93° in vertical as Fig. 2. The detection region of the PIR sensor is not continuous. Instead, it is divided into several detection zones as shown in Fig. 3. Detection zone is a small region within the whole detection region of the PIR sensor. Objects would not be detected by the PIR sensor if they are not in the detection zone although they are in the detection region. Fig. 3 is a cross-sectional view of detection zones.

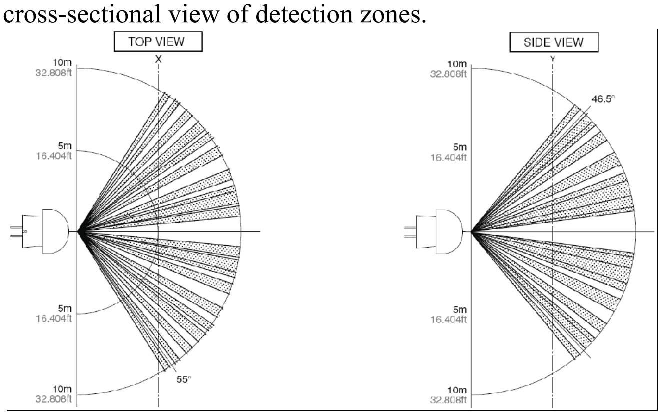


Fig. 2 Horizontal and vertical view of detection zones of the PIR sensor according the datasheet.

As we can see in those figures about detection zones, there is a possibility that the PIR sensor cannot detect human within detection region because detection zones are spatially distributed in the region. In our lab test, this sensor is quite sensitive even human stay still in the detection region are also can be detected.

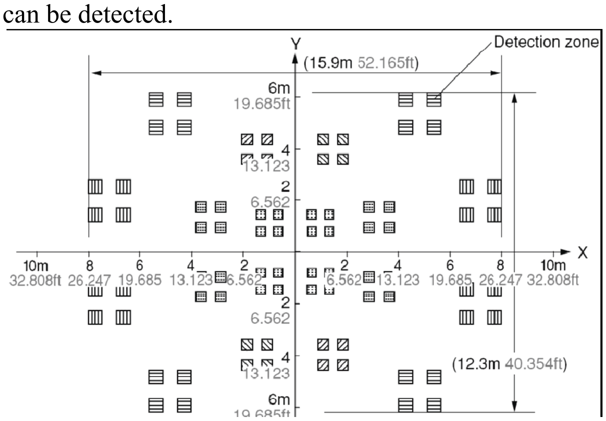


Fig. 3 X-Y cross-sectional view of detection zones of the PIR sensor according the datasheet.

C. *Wireless Pyroelectric Sensor System*

In this work, we use the radio frequency and wireless pyroelectric sensor localization system. We develop this sensor system with CC2431 and Panasonic motion sensor. The algorithms can be installed into flash memory of CC2431.

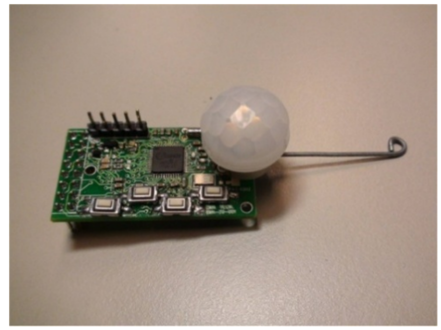


Fig. 4 The experimental platform integrated with CC2431 and pyroelectric sensor

D. *Identification Card System*

Monitoring people in the indoor environment, a wireless transmission device is required for our wireless pyroelectric sensor system. With this device, the location information can be obtained through radio frequency propagation model and triangulation method. The identification card in our system is a simple ZigBee/IEEE 802.15.4 transceiver. The ZigBee protocol can provide unique ID for each device in the same ZigBee environment and can be used to tracking multi targets.

(a) (b)

Fig. 5 (a) Identification card (b) wear on human

III. Radio Frequency Signal

A. *Radio Received Signal Strength Model*

Consider the static environment first, as shown in Fig. 6, where two sensor nodes are mounted on the ceiling with d distance apart and h height from ground. As the dynamic environment, as shown in Fig. 7, one moving object passes through the surveillance environment.

In an indoor static environment, there are two main radio propagation paths between the transmitter and the receiver besides the multi-path reflections of the surroundings. One is the direct transmission path and the other is the ground reflection path as illustrated in Fig. 6. For the direct line of sight propagation path, according to the free space model, the power received by the receiver is given by the Friis free space equation (1) as

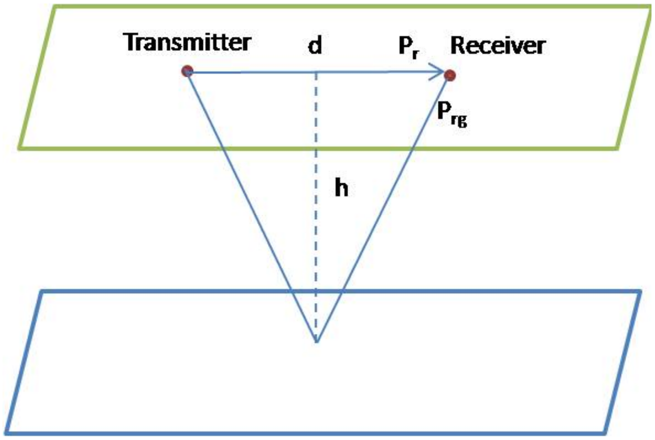


Fig. 6 Static environment

$$P_r = \frac{P_t G_t G_r \lambda^2}{(4\pi)^2 d^2} \quad (1)$$

Where Pt is the transmitted power in watts, Pr is the received power in watts, Gt is the transmitter antenna gain, Gr is the receiver antenna gain, d is the distance from transmitter to receiver and λ is the wavelength in meters.

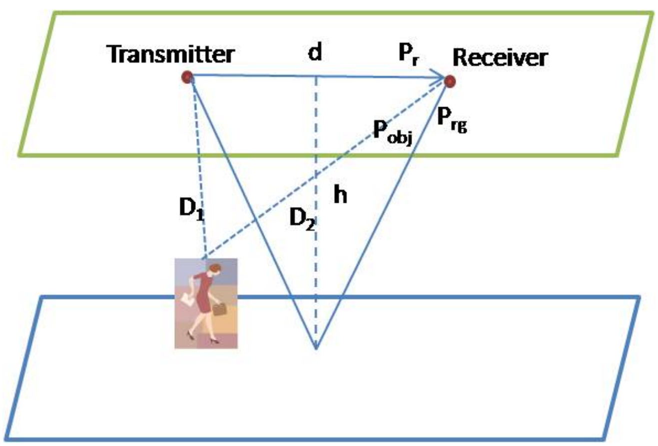


Fig. 7 Dynamic environment

For the ground reflection path, the power received by the receiver can be expressed as

$$P_{rg} = \frac{P_t G_t G_r \lambda^2}{(4\pi)^2 (d^2+4h^2)} \quad (2)$$

Assume that the intensity magnitudes of the direct transmission path and the ground reflection path are E_d and E_g respectively. E_{other} is the intensity magnitude of other radio propagation paths, such as the reflections or diffractions of the surroundings. The total received power by the receiver P_{total} in the indoor static environment is expressed below.

$$P_{total} \propto \left| \, E_d + E_g + E_{other} \, \right|^2 \quad (3)$$

This value is almost stable in a static environment although noise does exist.

When a pedestrian comes into this static environment, the moving target will scatter the incident radio signal in various directions as illustrated in Fig. 7. According to radio equation [15], the received power influenced by the moving target is

$$P_{target} = \frac{P_t G_t G_r \lambda^2 \sigma}{(4\pi)^3 ({r_1}^2 {r_2}^2)} \quad (4)$$

where D_1 is the distance from the transmitter to the target, D_2 is the distance from the target to the receiver, and σ is the radar cross section of the target object. The radar cross section σ is defined as the ratio of scattered to incident power density. According to scattering theory [14], in the dynamic environment, E_d, E_g and E_{other} will remain the same. The total power received by the receiver is the sum of incident and scatted waves as shown below

$$P \propto \left| \, E_d + E_g + E_{other} + E_{obj} \, \right|^2 \quad (5)$$

where Eobj is the intensity of scatted radio wave caused by the moving target.

B. Triangulation Method

Triangulation algorithms are generally used for determining the absolute positions, especially localization problems. Triangulation is the process to find absolute coordinates and distances between ZigBee devices.

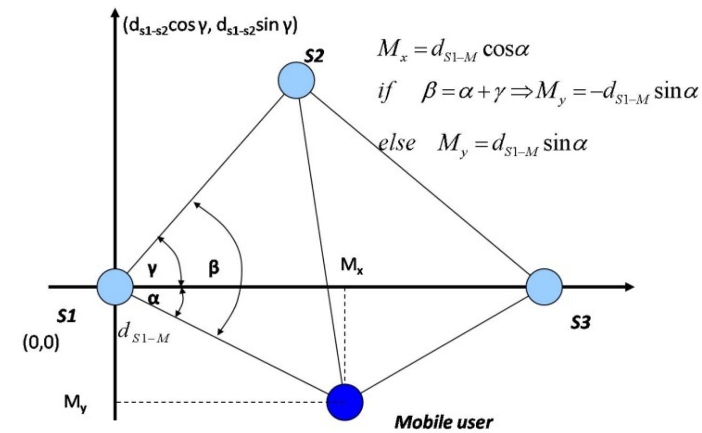


Fig. 8 Basic triangulation method

IV. Pyroelectric Sensor Localization Algorithm

In order to determine the location of pedestrians within the indoor environment, the PIR sensors are used as shown in Fig. 9. In this figure, the sensing area of each PIR sensor is shown as a circle, and some area will have overlap of sensing areas.

The PIR sensors are installed on ceiling, the coordinates of sensors are known. The overlap regions can be calculated from the specification of PIR sensors. When a pedestrian enters the sensing region, the PIR system will collect all sensing information of the PIR sensors and then decide the location of target. For example, a pedestrian enter the PIR sensing system, as Fig. 9, only sensor B reported "ON" and sensors A,C reported "OFF" signal. After collecting all information, the system can locate the target in sensing area B.

If only one sensor reports "ON", the pedestrian will be reported at center of the corresponding sensor as the point 1 in Fig. 9. If two adjacent sensors reports "ON", the coordinate of pedestrian is considered as the center of overlap region such as point 2 in Fig. 9. If three or more sensors report "ON", the pedestrian is located at the centroid of the overlap region of the corresponding sensors.

The numbers, sensing area and location of PIR sensors determine the PIR localization accuracy. The point 3 in Fig. 9 is the maximum value of the localization accuracy.

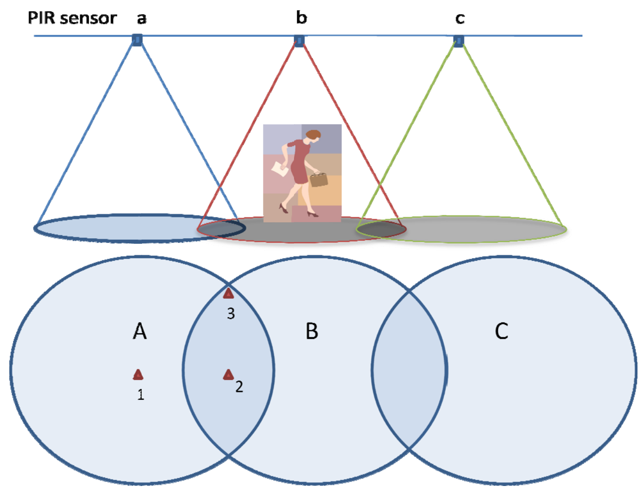
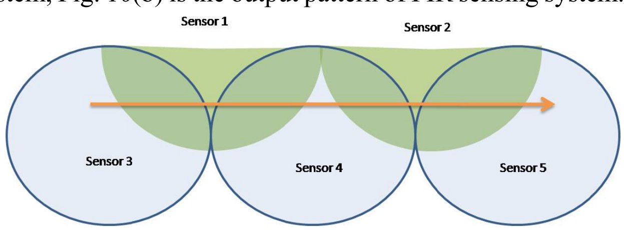
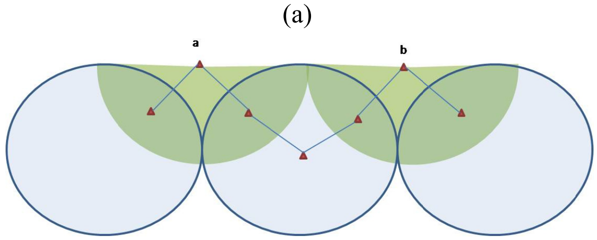


Fig. 9 The localization scheme for PIR sensors.

Fig.10(a) represents a pedestrian enter the PIR sensing system, Fig. 10(b) is the output pattern of PIR sensing system.



(a)



(b)

Fig. 10 (a) Pedestrian's movement (b) Output pattern of PIR localization system.

V. Sensory Data Fusion

A. Covariance Intersection Method

We do not know the degree of redundant information exists in an estimation of a node received. It means that the error between predicted and actual position covariance will be underestimated. The covariance information must keep consistency to avoid the disastrous consequences of redundant data on Kalman filter type estimators. However, it is not possible to maintain cross covariance consistent with distributed. This makes the estimated state based on the assumed state model with little correction from the new measurements. Thus, drifts the state estimate away from the actual state. The Covariance Intersection (CI) can be treated as a generalized Kalman filter. The primary advantage of CI is that it permits filter and data fusion to be performed on probabilistically defined estimates without knowing the degree of correlation among those estimates. Thus CI does not need assumptions of the dependency of the two data of information, when it fuses them. If the cross-variance of the data is unknown, it is not possible to compute the exact covariance matrix of the estimate, but still desirable to have a pair estimate-covariance that is consistent, as defined below.

Set Z a random variable with mean $\bar{z}$ and estimation $\hat{z}$. The estimation error can be given by $\tilde{z} = \hat{z} - \bar{z}$ and the covariance associated with this error is $P_{zz} = E\{\tilde{z}\tilde{z}^T\}$. Let P_{zz}, be an estimation of the covariance of $\hat{z}$, then the pair $\{\hat{z}, P_{zz}\}$ is said to be consistent if

$$P_{zz} \ge \overline{P_{zz}} \tag{6}$$

The proof can be found in [16]. The pair of estimate-covariance is consistent if the estimated covariance matrix is in the upper bound of the actual covariance of the estimate.

Set x and y be two random variables which have means and covariance matrices are E{x}=X, E{y}=Y separately

$$Cov\{x\}=P_{xx},\ Cov\{y\}=P_{yy},\ Cov\{xy\}=P_{xy} \tag{7}$$

Define the estimate Z as a linear combination of **x** and **y:** where **x** and **y** might represent either a prior estimate of ***Z*** with certain covariance matrix or a measurement which has its own uncertainty.

The covariance intersection method is a data fusion algorithm which uses a convex combination of the means and covariances in the information field. This approach is referenced on a geometric interpretation of the Kalman filter process. The general form of the Kalman filter is

$$\hat{z} = W_xX + W_yY \tag{8}$$

$$P_{zz} = W_xP_{xx}W_x^T + W_xP_{xy}W_x^T + W_yP_{yx}W_y^T + W_yP_{yy}W_y^T \tag{9}$$

The weights W_x and W_y are chosen to minimize the trace of P_{zz}. If the estimates are independent (P_{xy}=0), the form of the conventional Kalman filter can be reduce.

The Covariance Intersection method provides estimation and a covariance matrix which their covariance ellipsoid encloses the intersection region. The estimate is consistent independent of the unknown value of P. Given the upper bound $P_{xx} \ge \overline{P_{xx}}$ and $P_{yy} \ge \overline{P_{yy}}$, the covariance intersection estimator are defined as follows:

$$Z = P_{zz}\left\{w_xP_{xx}^{-1}X + w_yP_{yy}^{-1}Y\right\} \tag{10}$$

$$P_{zz}^{-1} = w_xP_{xx}^{-1} + w_yP_{yy}^{-1} \tag{11}$$

$$w_x + w_y = 1,\ 0 \leqq w_x, w_y \leqq 1. \tag{12}$$

The parameter w_i gives the relative weights assigned to **x** and **y.** Different choices of w_i can be used to optimize the covariance estimate with different performance criteria such as minimizing the trace or the determinant of P_{zz}**.**

Let $\alpha \equiv \sqrt{tr\{W_xP_{xx}W_x^T\}}$ (13)

$$\beta \equiv \sqrt{tr\{W_yP_{yy}W_y^T\}} \tag{14}$$

Thus $P_{zz} = (\frac{\alpha}{\alpha+\beta}P_{xx}^{-1} + \frac{\beta}{\alpha+\beta}P_{yy}^{-1})^{-1}$ (15)

and the gains are

$$W_x = \frac{\alpha}{\alpha+\beta}P_{zz}P_{xx}^{-1} \quad W_y = \frac{\alpha}{\alpha+\beta}P_{zz}P_{yy}^{-1} \tag{16}$$

This theorem presents the advantage of the optimality of the best w_i in CI algorithm.

B. Fusion with Pyroelectric Sensor and Wireless Location Information

We can obtain the mean and covariance of human location from pyroelectric sensor and radio frequency propagation localization system respectively. After calculation from the covariance intersection method, the error can be reduced and the results are shown in section VI.

VI. EXPERIMENTAL RESULTS

Fig. 11 Experimental setup

The experimental test with investigation area is 10mx10m. The prototype of wireless pyroelectric sensors is installed on the ceiling. The red circles indicate the sensor units in Fig.1 11.

Fig. 12 shows the relation between radio signal strength (RSS) and the distance from mobile user to reference sensor node. The red line named "regression function" is a linear regression function calculated from mean value of measured data. The distance from mobile user to reference sensor node can be predicted accordingly by entering a measured RSS value to the regression function (17).

$$RSS = c_{m-1} d_{RSS}{}^{m-1} + c_m d_{RSS}{}^{m} + \ldots + c_2 d_{RSS}{}^{2} + c_1 d_{RSS} + c_0 \quad (17)$$

where

$$c = [-0.009\ 0.0944\ -3.2332 - 18.6146]^T$$

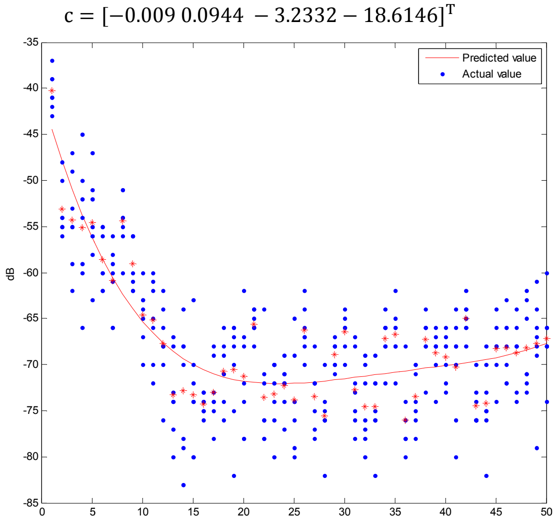


Fig. 12 RSS measured data

Fig. 13 shows that covariance intersection fuses pyroelectric sensor and RSS localization estimation. The maximum mean error of RSS is near to the 19%t and the maximum mean distance error from pyroelectric measurement is near to the 14%. Using covariance intersection algorithm, the mean distance error is below nine percent. The accuracy of locating residents under our system can be improved by using covariance intersection.

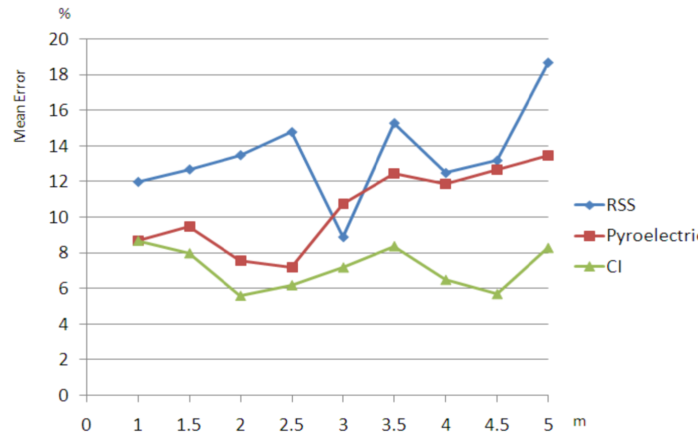


Fig. 13 Covariance intersection with RSS and pyroelectric measurement

In Fig. 14, the circle mark is the actual test trace, square is the measurement through pyroelectric sensor, triangular is the result from RSS and diamond is the fusion result from CI, The tracking error can be reduced through data fusion technique.

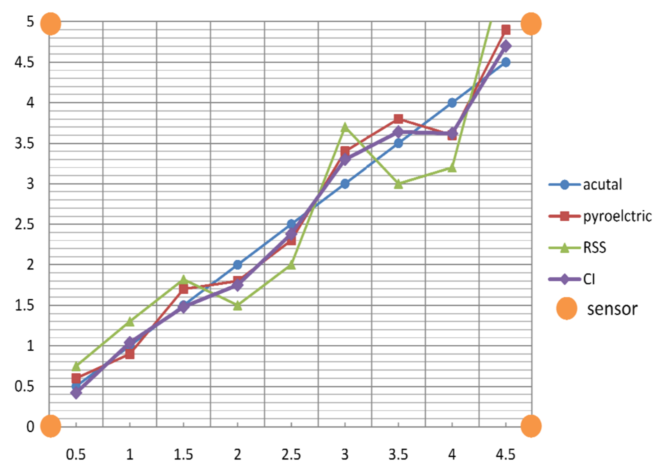


Fig. 14 Moving target tracking

VII. CONCLUSION

This paper presents a wireless multi-functional sensor, which is composed with radio transmission, microprocessor, and pyroelectric sensor. This system can estimate the pedestrian's location from pyroelectric sensor and radio signals respectively. PIR localization system suffers from multi target tracking; however, radio wave signal from ZigBee protocol has identification information which is beneficial to multi target tracking. The measurement error from pyroelectric and radio frequency signal can be reduced through covariance intersection data fusion method. After recognizing the location information of pedestrian, the intelligent building can facilitate appropriate services for people.

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