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ADAPTIVE ESTIMATION AND PI LEARNING SPRING-RELAXATION TECHNIQUE FOR LOCATION ESTIMATION IN WIRELESS SENSOR NETWORKS

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Abstract- In order to reduce the location estimation error in Wireless Sensor Network(WSN). A localization algorithm is proposed combining adaptive estimation, PI-learning and spring-relaxation techniques for wireless sensor networks in this paper. Our proposed method takes the advantages of the spring-relaxation technique, thus it inherits its simplicity. The overall accuracy of the location estimations is improved by introducing adaptive estimation and PI-learning. Moreover, it requires only a few beacons with known locations to compute the location estimates of all sensors. Simulation examples demonstrate the overall accuracy of the proposed method.

Index terms: Wireless Sensor Networks, Location Estimation, Adaptive Estimation, Spring-Relaxation Technique, PI learning.

I. INTRODUCTION

In recent years, research on WSN location has received increasing attention[1-2]. The location methods can be divided into two categories: range-based and range-free schemes. The range-based schemes estimate locations on the basis of either node-to-node distances or angles [3,4]. The first range-based scheme is time based location estimation, e.g., time of arrival (TOA) [5], time difference of arrival (TDOA) [6]. The second range-based scheme is direction based location estimation, such as angle of arrival (AOA) or direction of arrival (DOA) [7].The range-based schemes typically have higher location accuracy than the range-free schemes, but require additional hardware to obtain distances or angles and have weakness in the noisy environments.

The range-free schemes do not need the distance or angle information to the sensor nodes from the anchor nodes for their localization [8,9]. Because the range-free schemes provide more economic and simpler estimates than the range-based ones, it becomes more popularity than the range-based methods, but their results are not as precise as those of the range-based methods.

However, accurate and low-cost autonomous self-localization is a critical requirement of various applications of a distributed wireless sensor network [10]. In order to solve this problem, a lot of researches have been made [10-13].

In [10], a spring-relaxation technique is proposed for location estimation, which uses received signal strength indicators for ranging, light weight distributed algorithms based on the spring-relaxation technique for location computation, and the cooperative approach to achieve certain location estimation accuracy with a low number of nodes with known locations. The two-step indoor location estimation method is presented based on received signal strength in wireless sensor network [11], which measures the received signal strength (RSS) of radio signals transmitted by multiple training points. In [12], NN-based location method is proposed, which constructs a flexible model based on neural network and uses grid sensor training phase for accurate localization of sensors. The NN is trained using the RSS values of the grid sensors. A soft computing technique is proposed for range-free location. It approximates the entire mapping from the anchor node signals to the locations of sensor nodes by a neural network. Lee etc. [13] proposed a self-location estimation scheme using ROA for wireless sensor networks without any special device for location awareness. But in most schemes, lots of RSS samples are required and the reference nodes should broadcast repeatedly to get more accurate location estimation, which is difficult.

Aiming at getting more accurate location estimation without additional hardware, a PI-learning spring-relaxation technique is proposed. The rest of the paper is organized as follows. Section 2 presents our localization method in details. Section 3 provides presents the simulation results covering studies in system design and parameter design. Finally, Section 4 summarizes our conclusions.

II. Localization Algorithms

a. Range measurement scheme

The observation space shown in Fig. 1 is a set of range measurements, and the parameters that need to estimate location are the geographical coordinates of the sensor node. We assume the random variation of RSS is a log normal Gaussian random variable due to shadowing effect. Thus we can describe that RSS in dB is distributed with $X_{\sigma_s} = N\left(E,\sigma^2\right)$ of E mean and σ^2 variance.

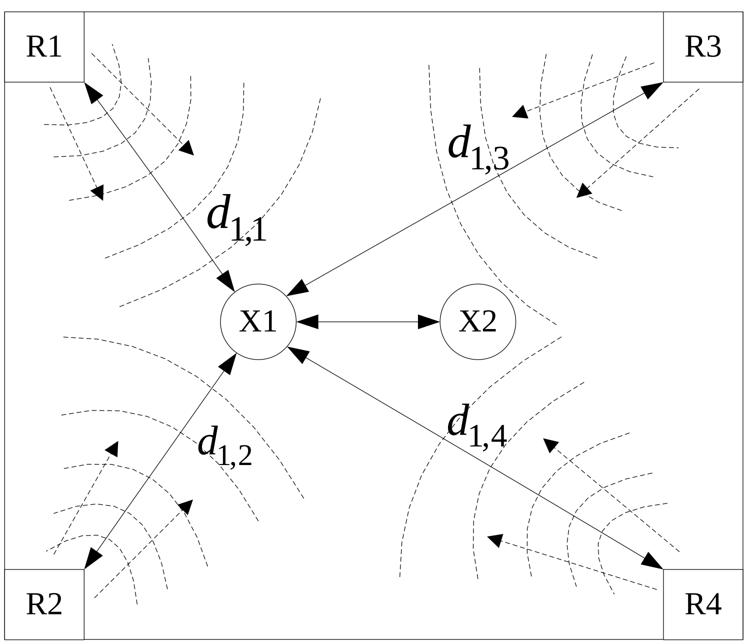


Figure 1. Referenced Network Topology. *Rj* : Reference node *Beacon*$_j$, *Xi*: Sensor node *Sensor*$_i$

In figure 1, the reference nodes (R1~R4) are repeatedly broadcasting data involving its own location information to the sensor node(X1 and X2). After receiving the signals from each reference node the sensor node sorts the received signal strengths and estimates the average received signal strength. And then the sensor node calculates average distances ($d_{i,j}$ in figure 1, $d_{i,j}$ is the estimated distance between $Sensor_i$ and $Beacon_j$) from each reference node to the sensor node through received signal strength.

b. Adaptive estimation and PI learning spring- relaxation technique for localization

We assume that $\vec{V_i}$ is the location of $Sensor_i$, where $i \in$ S; $\vec{V_j}$ is the location of $Beacon_j$, where $j \in$ B; and $d_{i,j}$ is the estimated distance between $Sensor_i$ and $Beacon_j$ according to the measured signal strength. Define $\overrightarrow{F_{i,j}}$ to be the force that the spring between $Sensor_i$ and $Beacon_j$ exerts on $Sensor_i$ .We show that

$$\overrightarrow{F_{i,j}} = \left(d_{i,j} - \left\|\vec{V_i} - \vec{V_j}\right\|\right) \times u\left(\vec{V_i} - \vec{V_j}\right). \qquad (1)$$

The scalar quantity $d_{i,j} - \left\|\vec{V_i} - \vec{V_j}\right\|$ is the displacement of the spring from natural length, which gives the magnitude of the force exerted by the spring between $Sensor_i$ and $Beacon_j$. The unit vector $u\left(\vec{V_i} - \vec{V_j}\right)$ gives the direction of the force on $Sensor_i$. The spring constant is ignored. The net force on $Sensor_i$, defined as $\vec{F_i}$, is the vector sum of all forces

$$\vec{F_i} = \sum_{j \in B}\left(\overrightarrow{F_{i,j}} + \overrightarrow{\Delta F_{i,j}}\right). \qquad (2)$$

$\overrightarrow{\Delta F_{i,j}}$ takes the Gaussian random variable into consideration. To mimic the evolution of the spring network, our algorithm updates the locations of sensors in iterations. In each iteration, the algorithm moves $Sensor_i$ a small distance in the direction of $\vec{F_i}$ and then recomputes all the applied forces. Let δ be the step size of location adjustment. $\overrightarrow{\Delta F_{i,j}}$ is estimated by the following adaptive laws

$$\frac{d\Delta F_{xi,j}}{dt} = -\gamma_{xi} F_{xi} F_{yi}, \qquad (3)$$

$$\frac{d\Delta F_{yi,j}}{dt} = -\gamma_{yi} F_{xi} F_{yi}, \qquad (4)$$

where $\Delta F_{xi,j}$ is the x coordinate of $\overrightarrow{\Delta F_{i,j}}$ and $\Delta F_{yi,j}$ is the y coordinate of $\overrightarrow{\Delta F_{i,j}}$.

Considering a linear relationship between the net force and the displacement, the location of *Sensor*$_i$ is then updated as

$$x_i \leftarrow x_i + \left(\Delta F_{xi} + I_i \sum_{j=1}^{k} F_{xi} \right), (5)$$

$$y_i \leftarrow y_i + \left(\Delta F_{yi} + I_i \sum_{j=1}^{k} F_{yi} \right). (6)$$

where x_i is the x coordinate of $\vec{V_i}$, y_i is the y coordinate of $\vec{V_i}$, F_{xi} the x coordinate of $\vec{F_i}$, F_{yi} the y coordinate of $\vec{F_i}$.

Algorithm 1 Location Estimation

INPUT: received signal strengths $s_{i,j}$, estimated distances $d_{i,j}$, beacon locations x_j, y_j, and initial guess of x_i, y_i

OUTPUT: estimate of x_i, y_i

$$\vec{F_i} = \tau$$

For $k = 1$ to N

  For *Sensor*$_i$, $i \in$ S

    while $\left\|\vec{F_i}\right\| \geq \tau$ **do**

$$\vec{F_i} = 0$$

      for all *Beacon*$_j$ **do**

        if *Beacon*$_j$ is visible to *Sensor*$_i$ then

$$\overrightarrow{F_{i,j}} = \left(d_{i,j} - \left\|\vec{V_i} - \vec{V_j}\right\| \right) \times u\left(\vec{V_i} - \vec{V_j} \right)$$

$$\vec{F_i} = \vec{F_i} + \overrightarrow{F_{i,j}}$$

        end if

      end for

$$x_i \leftarrow x_i + \left(\Delta F_{xi} + I_i \sum_{j=1}^{k} F_{xi} \right)$$

$$y_i \leftarrow y_i + \left(\Delta F_{yi} + I_i \sum_{j=1}^{k} F_{yi} \right)$$

$$\frac{d\Delta F_{xi,j}}{dt} = -\gamma_{xi} F_{xi} F_{yi}$$

$$\frac{d\Delta F_{yi,j}}{dt} = -\gamma_{yi} F_{xi} F_{yi}$$

end while

end for

end for

In the algorithm, there are several design parameters that are used to adjust the algorithm behavior and control the algorithm execution. Threshold, τ, is a constant that used to define the visibility or connectivity.

If the received signal strength $F_{i,j}$ from $Beacon_j$ to $Sensor_i$ is no smaller than the threshold, then $Beacon_j$ is visible to $Sensor_i$. The specific value of the threshold follows the specification for receiver sensitivity defined in [14].

Secondly, we give the location estimation Algorithm 2 with the information about mean of measurement noise.

Algorithm 2 Location Estimation

INPUT: RSSs and $E_{nj_1j_2}$ estimated distances $d_{i,j}$, beacon locations x_j, y_j, and initial guess of x_{is}, y_{is}

OUTPUT: estimate of x_{is}, y_{is}

$E_{nj_1j_2} = \sum_{l=1}^{N_1} \frac{\hat{d}_{j_1j_2c}(l)}{n} - d_{j_1j_2}$, where $E_{nj_1j_2}$ is the mean of measurement noise, $\hat{d}_{j_1j_2c}$ is the measurement distance between $Beacon_{j1}$ and $Beacon_{j2}$, and $d_{j_1j_2}$ is the real distance between $Beacon_{j1}$ and $Beacon_{j2}$.

For $k = 1$ to N

For *Sensor*$_i$, $i \in$ S

$$\text{choose } E_{nj_1 j_2}$$

while $\left\|\overrightarrow{F_i}\right\| \geq \tau$ **do**

$$\overrightarrow{F_i} = 0$$

for all *Beacon*$_j$ **do**

if *Beacon*$_j$ is visible to *Sensor*$_i$ then

$$\overrightarrow{F_{i,j}} = \left(d_{i,j} - \left\|\overrightarrow{V_i} - \overrightarrow{V_j}\right\| \right) \times u \left(\overrightarrow{V_i} - \overrightarrow{V_j} \right)$$

$$\overrightarrow{F_i} = \overrightarrow{F_i} + \overrightarrow{F_{i,j}}$$

end if

end for

$$x_i \leftarrow x_i + \left(\Delta F_{xi} + I_i \sum_{j=1}^{k} F_{xi} \right)$$

$$y_i \leftarrow y_i + \left(\Delta F_{yi} + I_i \sum_{j=1}^{k} F_{yi} \right)$$

$$\frac{d\Delta F_{xi,j}}{dt} = -\gamma_{xi} F_{xi} F_{yi}$$

$$\frac{d\Delta F_{yi,j}}{dt} = -\gamma_{yi} F_{xi} F_{yi}$$

end while

end for

end for

III. SIMULATION STUDY

The simulation model is shown in Fig. 1. Table 1 is the simulation parameters and ranges for the performance evaluation and ranges.

To generate RSS samples as a function of distance the path loss model with the lognormal shadowing effects is used[7]:

$$PL(d) = 30 + 21\log_{10}\left(\frac{d}{d_0}\right) + X_{\sigma_s}, \qquad (7)$$

where $PL(d)$ is the path loss for the distance between reference nodes and the sensor node. To consider indoor environment in the simulation we assumed that the value of d_0 is 1m, the path loss exponent (η) is 2.1 and path loss for a reference distance is 30. And the transmit power (PT) of reference nodes is fixed as 10dBm. The random variation of RSS in dB is expressed as a Gaussian random variable of mean of E and variance of σ^2. All powers are expressed in dBm and all distances in meters.

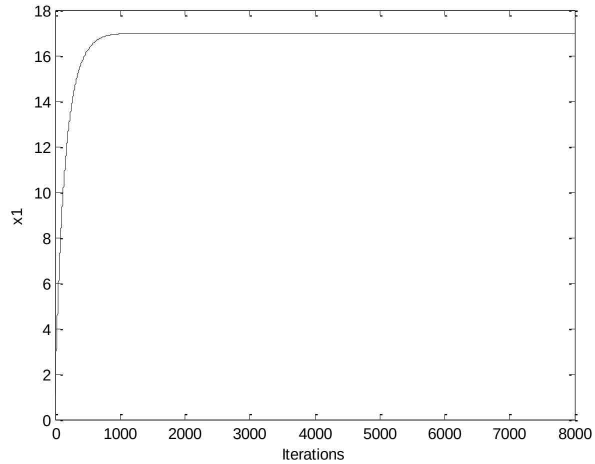
Table 1. Typical values and ranges of simulation parameters [15]

Parameters	Typical Value	Typical Range
P_T	10dBm	NA
$P_L(d_0)$	30dB	NA
η	2.1	NA
σ_s (LOS)	7dB(indoor)	2-4
σ_s (NLOS)	9.7dB(indoor)	2-4
Dimension	25m×25m	{50,40,30.20}
Node placement	Random	NA

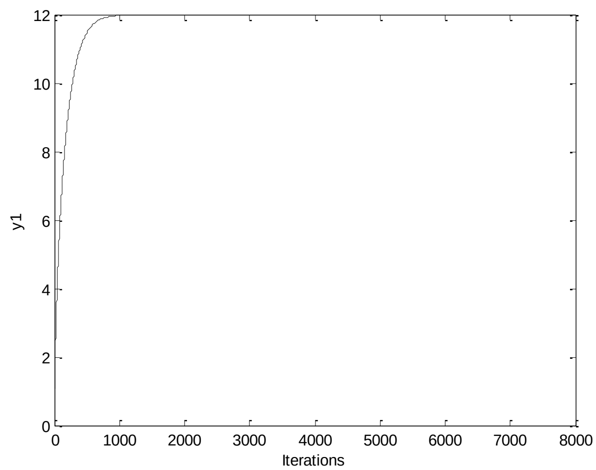
Let the initial conditions be $X_1 = (x_1, y_1) = (17,12)$, $X_2 = (x_2, y_2) = (8,9)$, $E = 2.2$, $\sigma^2 = 0.2$, $R_1 = (0,25)$, $R_2 = (0,0)$, $R_3 = (25,25)$, $R_4 = (25,0)$, the initial guess $\hat{X}_1 = (1,1)$, and the initial guess $\hat{X}_2 = (19,19)$.

The parameters of the proposed algorithm are chosen as follows: $I_1 = I_2 = 0.001$, $\gamma_{x1} = \gamma_{x2} = 0.001$, $\gamma_{y1} = \gamma_{y2} = 0.001$, $\delta = 0.001$.

Figures 2(a)-(d) show the location estimations of the *Sensor₁* and *Sensor₂*. The true value of X_1 is $17,12$, and the true value of X_2 is $8,9$. The estimation value of X_1 is $17.000,12.000$, the true value of X_2 is $8.000,9.000$.



(a)



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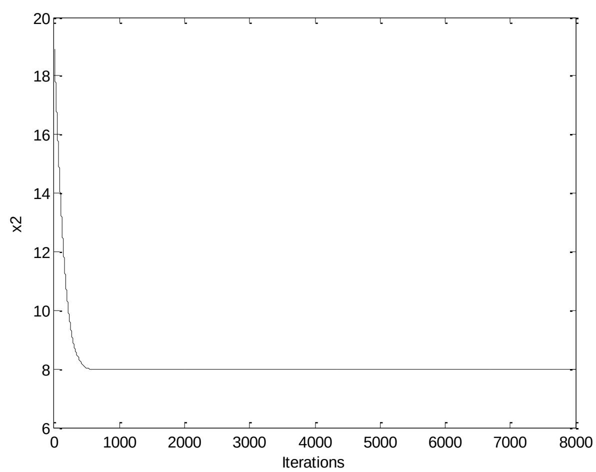

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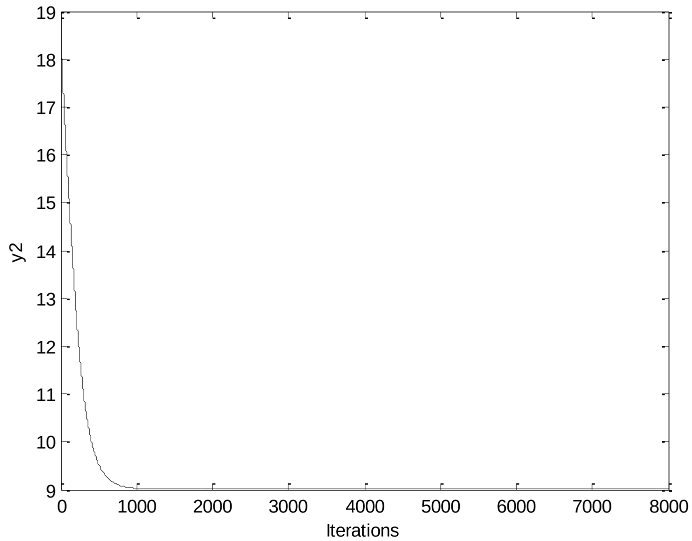
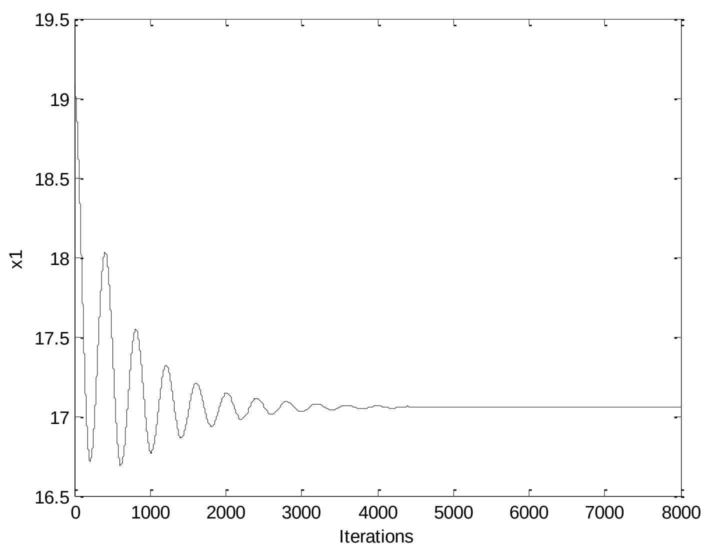


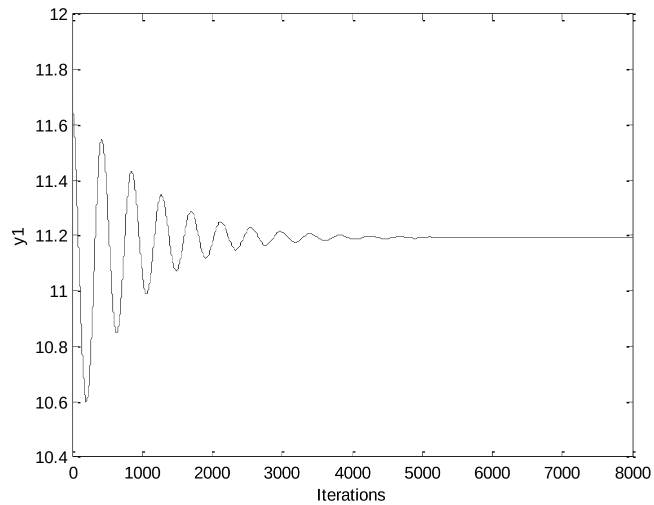
(d)

Figure 2. Location estimations of the proposed method in this paper without noise

Figures 3(a)-(d) show the location estimations of the *Sensor₁* and *Sensor₂*. The true value of X_1 is 17,12 , and the true value of X_2 is 8,9 . The estimation value of X_1 is 17.09,11.19 , the true value of X_2 is 8.975,9.325 .



(a)



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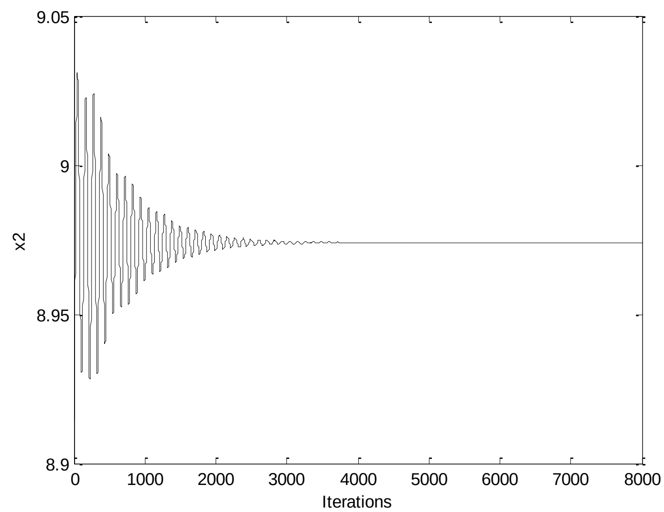

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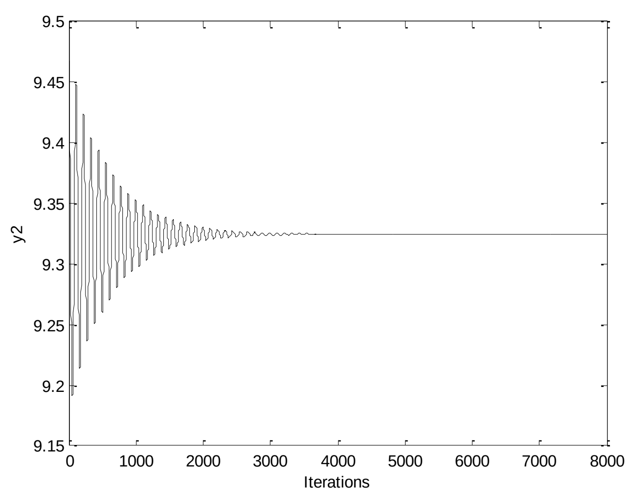
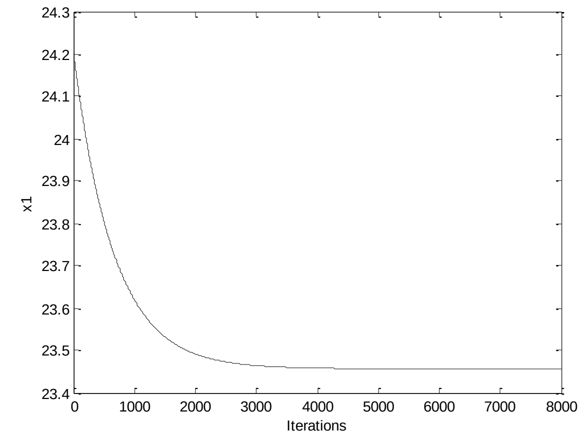


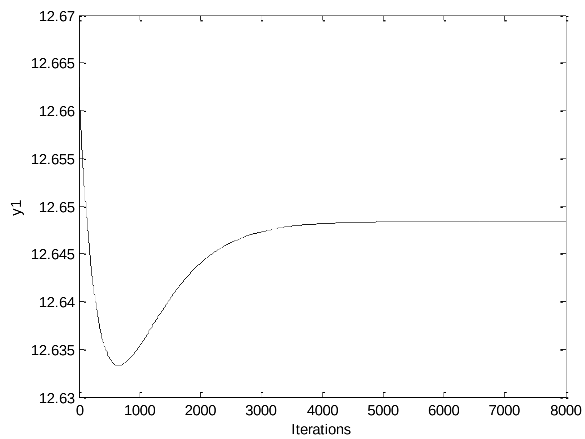
(d)

Figure 3. Location estimations of the proposed method in this paper

Figures 4(a)-(d) show the location estimations of the *Sensor₁* and *Sensor₂*. The true value of X_1 is 17,12 , and the true value of X_2 is 8,9 . The estimation value of X_1 is 23.47,12.648 , the true value of X_2 is 10.988,11.1485 .



(a)



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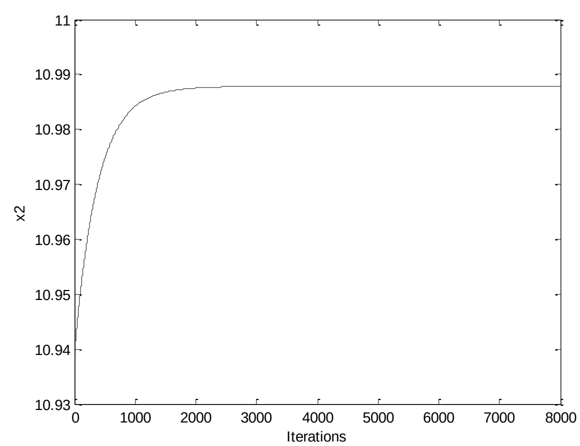

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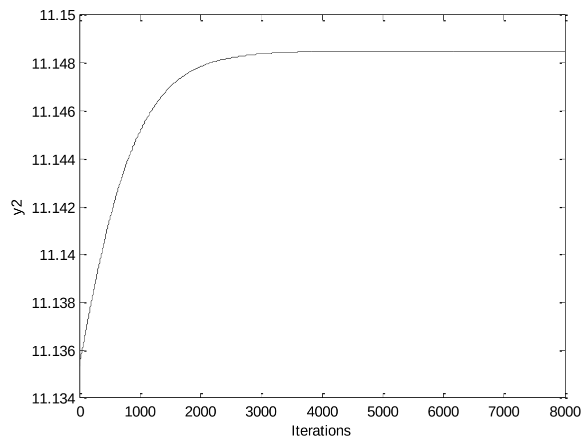
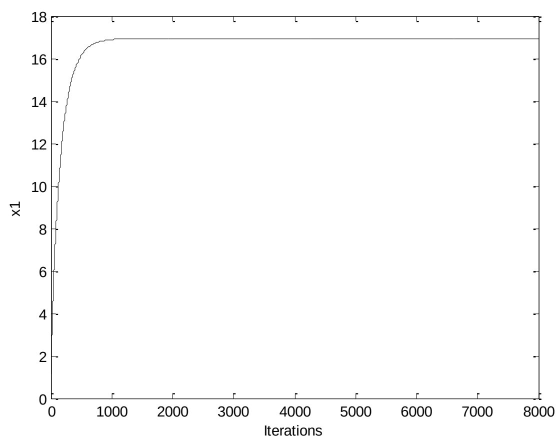


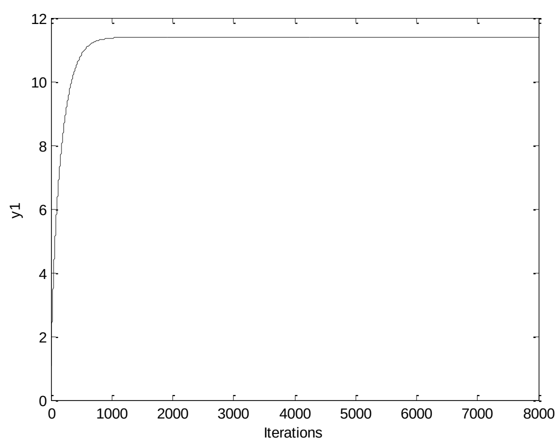
(d)

Figure 4. Location estimations of the proposed method in [10]

Figures 5(a)-(d) show the location estimations of the *Sensor₁* and *Sensor₂*. The true value of X_1 is $17,12$, and the true value of X_2 is $8,9$. The estimation value of X_1 is $16.933,11.389$, the true value of X_2 is $6.841,8.924$.



(a)



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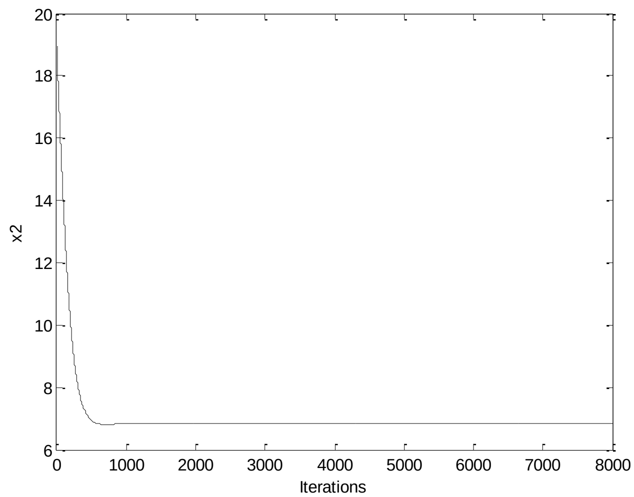

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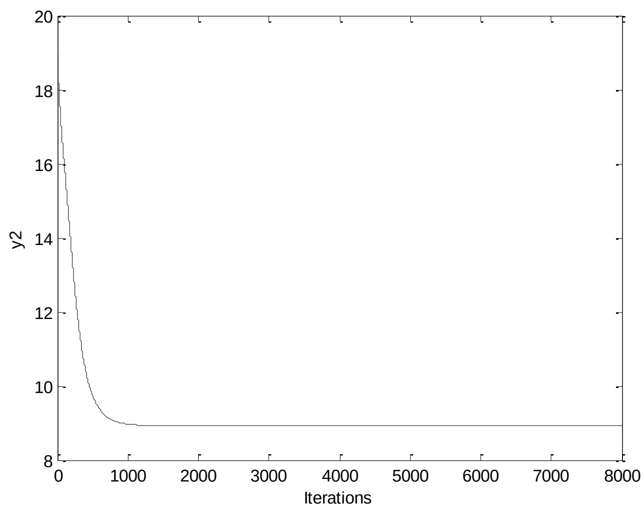

(d)

Figure 5. Location estimations of the proposed Algorithm 2 in this paper

In order to show the advantages of the proposed algorithm, we define the accuracy performance index as

It is obvious that the overall accuracy of the proposed method is improved greatly. With the information about measurement noise, the accuracy of algorithm 2 is better than that of the algorithm 1. The accuracy of algorithm 1 is better than that of the Algorithm proposed by Zhang et al. in Ref.[10].

IV. CONCLUSIONS

In this paper, a localization algorithm is proposed combining adaptive estimation, PI-learning and spring-relaxation techniques for wireless sensor networks. Our proposed method takes the advantages of the spring-relaxation technique, thus it inherits its simplicity. We use the proposed method to obtain higher accuracy of location estimation through introducing adaptive estimation and PI-learning. Moreover, it requires only a few beacons with known locations to compute the location estimates of all sensors. Simulation examples demonstrate the overall accuracy of the proposed method.

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