RSS-based Node Localization in the Existence of Moving Obstructions

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***Abstract*—In the context of wireless sensor networks, a node's location must be known for its data to be meaningful in many cases. Received signal strength (RSS)-based localization has been widely used because of low complexity and easy deployment. This paper proposes a novel method to localize nodes in the presence of randomly moving obstructions. We introduce background learning to reduce interferences caused by moving obstructions such as people or other objects. Based on our experimental results, each link of data is modeled as a mixture of Gaussians (MoG) and its parameters are updated by background learning. In this way, we can reduce the interferences of moving obstructions from obtained RSS measurements. Then we use least-square (LS) cooperative localization algorithm to implement node localization and the experimental results show good performance.**

***Index Terms*—wireless sensor networks, cooperative localization, MoG, background learning, RSS**

I. INTRODUCTION

Node localization in wireless sensor networks is a key enabling technology in recent years and has been studied extensively [1] [2] [3]. The implementation of locating nodes accurately enables a lot of new applications such as healthcare monitoring, animal tracking and emergency services [4]. The knowledge of a node's location is usually a must to make information communicated by nodes meaningful. For example, if we deploy a sensor network to monitor equipment in a warehouse, the positions of nodes must be known dynamically to find the positions of equipment. In many cases, especially emergency cases, we must deploy sensors randomly and rapidly and it is impractical to record node positions beforehand. In such scenarios, the nodes' positions must be known autonomously.

Cooperative localization [5] is an effective method to localize nodes with high accuracy and coverage. Given a prior knowledge of a few anchor nodes, we estimate positions of the remaining non-located nodes. Several range-based localization techniques have been widely used such as TOA, TDOA, AOA and RSS [1]. Since RSS-based localization is cost-efficient and does not require additional hardware, it is the simplest approach among range-based measurement methods. However, RSS values may deteriorate badly without profound consideration of environmental interferences [6]. In this paper, we use background learning to reduce the effects of random moving obstructions and improve RSS-based node localization accuracy greatly.

Several RSS-based cooperative localization methods have been proposed [7] [8] [9]. However, most of the previously proposed techniques transfer obtained RSS into distance information directly without the consideration of attenuating obstructions. In our previous work [10], we account for RSS changes caused by static attenuating objects with known positions. Unfortunately, when there are random moving obstructions in the environment, RSS will experience high variations and affect localization accuracy greatly. To address this problem, we consider RSS data of each link as a mixture of Gaussians (MoG) and use background learning to update the model. With this method, we can obtain true RSS values which can reflect the real distance between nodes. Then we use the modified pair-wise RSS and a few anchor nodes to localize the non-located nodes.

In this paper, some related works about cooperative localization are introduced in Section II. In Section III, we demonstrate MoG model and use background learning to update the model to find the true RSS data. LS algorithm is presented to estimate the position of non-located nodes. Section IV performs experiments and shows the results of system performance. In Section V, some concluding remarks are presented.

II. RELATED WORKS

The existing node localization techniques can be classified into many categories. To summarize, different approaches vary in two phases: distance/angle estimation and position computation. In this section, we present some related work from these two aspects.

In distance/angle estimation phase, measurement method should be determined to estimate distance/angle between nodes. The Angle of arrival (AoA) methods takes advantage of the relative angle information between the received signals. It can reach high accuracy while with the demand of additional hardware. The Time of Arrival (ToA) and Time Difference of Arrival (TDoA) methods measure the time delay from the transmitting node to the receiving node.However, the estimation is limited by addictive noise and multipath signals. Even there is no multipath signals, addictive noise can affect the estimation accuracy greatly. Methods using received signal strength (RSS) as measurements are based on a simple physical fact: the power of radio signal attenuates along with propagation and the signal strength is inversely proportional to the squared distance between the transmitter and receiver.

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RSS-based measurement is easy to implement and does not need dedicated hardware. In this paper, we limit our researches to RSS-based measurements.

In position computation phase, the critical issue lies in how to transfer range information into the coordinates of non-located nodes. In [8], multidimensional scaling (MDS) is used as an initialization stage for maximum-likelihood estimator (MLE) localization method to improve localization efficiency. [9] presents Bayesian techniques to track primary users in a cognitive radio network to attain greater accuracy. In [11], a node selection method is used to make a tradeoff between accuracy and energy consumption. However, most of these methods concentrate on how to transfer distance information into position efficiently and accurately. When there are obstructions in the environment, it is difficult to locate the nodes without considering the effects of obstructions.

III. System Model

In this section, we discuss the problem to be solved and present our MoG model. Background learning method is then used to update parameters of the model.

A. Problem statement

As discussed above, we use RSS-based method to estimate inter-node distance from measured RSS values. As described in [12], the popular radio-propagation path loss model is usually used. Based on the path loss model, the signal transmitted from node i to node j can be expressed as:

$$P_{ij} = P_0 - 10\beta \log_{10}(\frac{d_{ij}}{d_0}) - v_{i,j} \tag{1}$$

where P_{ij} is measured RSS between node i and node j and P_0 is the RSS value received at reference distance d_0, d_{ij} is the distance between the two nodes and β is the path loss exponent that depends on environments. $v_{i,j} \sim (0, \sigma^2)$ is a random variable which represents shadow-fading effects in multipath environment. As described in [13], distance between node i and node j is usually approximated as δ_{ij}:

$$\delta_{ij} = d_0 10^{\frac{P_0 - P_{ij}}{10\beta}} \tag{2}$$

Obviously, $v_{i,j}$ is not taken into account in the formulation. When there are obstructions in the environment, $v_{i,j}$ shouldn't be ignored as the obstructions can lead to great errors in obtained RSS. In our previous work [10], we introduce A_{ij} to represent attenuation caused by static obstructions. In this paper, we use a novel method to reduce interferences caused by random moving obstructions.

B. MoG model and background learning algorithm

When an object moves into the area of a wireless network, links which pass through that object will experience shadowing losses. When the channel is predominantly line-of-sight(LOS), objects crossing the link will cause a drop in RSS values because of shadowing of the path [14]. In order to know how RSS varies over time when there are random moving obstructions in the network, we set up 2 nodes with a constant distance of $4m$ in an empty area outdoor. People cross randomly between the link and about 7000 measurements are collected. Fig. 1a shows the temporal plot of RSS , we can see RSS values experience three types of fading. When there is no person between the nodes, RSS varies with a range of 1∼2 dBm around the mean power. When people move around the link but do not obstruct the link, RSS values also experience a variance of 3∼4 dBm. However, when people obstruct the link, RSS experiences a high variance which can be as large as 10∼20 dBm. Throughout the whole process, RSS on a fixed link shows a three-part mixture distribution as shown in Fig. 1b. In [15], this statistical feature can be modeled as a Rician distribution. Other experiments show the fading can be regarded as a mixture of log-normal terms [16]. In this paper, we choose mixture of Gaussians to obtain a compromise between computational complexity and localization accuracy.

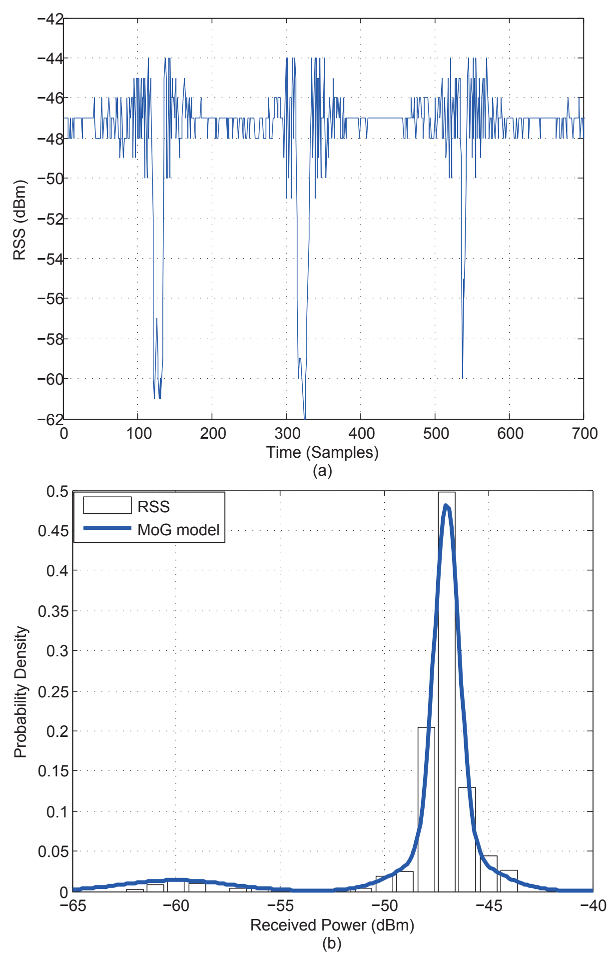


Fig. 1. Temporal fading plot of RSS on a fixed link: (a) Measured RSS; (b) RSS distribution using our MoG model.

Assuming that at time t, the observed RSS is R_t. The probability of current RSS value is expressed as:

$$P(R_t) = \sum_{k=1}^{K} w_k . g(R_t, \mu_k, \delta_k) \tag{3}$$

where w_k is the weight of the K_{th} Gaussian distribution and $\sum_{k=1}^{K} w_k = 1$. g is a normal distribution function with mean μ_k and variance σ_k:

$$g(R_t, \mu_k, \delta_k) = \frac{1}{\sqrt{2\pi\sigma_{k,t}^2}} e^{-\frac{(R_t - \mu_{k,t})^2}{2\sigma_{k,t}^2}} \quad (4)$$

RSS values caused by moving obstructions are considered as "foreground" and RSS reflect the true signal strength of locating nodes are regarded as "background". Since the estimation of Gaussian parameter values using the standard algorithms such as Expectation Maximization (EM) is computationally prohibited, recursive updating using a simple linear adaptive filter is generally given by [17] [18]:

$$\theta_t = \eta_t . \bigtriangledown (R_t; \theta_{t-1}) + (1 - \eta_t)\theta_{t-1} \quad (5)$$

where θ_t is updated by $\bigtriangledown(R_t; \theta_{t-1})$ with learning rate η_t. In [17], $\eta_t = 1/\alpha$ with α ranges between 0 and 1. $1/\alpha$ reflects observation history window with exponent decay. A small value of α results in slow convergence when a Gaussian adapts to background changes. A larger value can improve convergence rate but make the model sensitive to scene changes. In the formulation of [19], $\eta_t = 1/t$ can make the estimate converge quickly at the initial stage. However, it can converge to the local-optimal estimation over observations on a stationary distribution.

In our work, random obstructions will appear in the network. The probable background RSS values are the ones which stay longer and more static. If the first RSS value is a foreground object, it will take long time until the genuine background can be regarded as a background. A proper learning rate is critical to get a tradeoff between convergence and accuracy. Based on standard formulation for the mixture approach [17], Dar-Shyang Lee [18] proposed an effective Gaussian mixture learning algorithm to improve performance. Our basic algorithm follows the the formulation in [18]. The proposed algorithm in pseudocode is shown in Algorithm 1.

A combination of fast convergence and stability is introduced in the proposed algorithm. The most significant modification is the calculation of the learning rate η_k. A new variable c_k is introduced to count the number of effective observations for Gaussian G_k and determine the appropriate learning rate η_k. When the Gaussian is updated, it is incremented. When there is no Gaussian matched, it is reset to 1 since a new Gaussian is started. From our experiments, this modification can improve the convergence speed and model accuracy greatly.

C. Selection of background RSS

The remaining issue is to decide which Gaussians are chosen as background models. When there are moving targets in the environment, the variance will remain larger until the moving object stops. The static environment keeps a comparatively constant value with low variance. Besides, when new object appears, it will hardly match any of the existing distributions and a new distribution with low weight will be produced.

Control variables: K V_0 α T_σ
Initialization: $\forall_{j=1...K}$ $w_j = 0$ μ_j=Inf $\sigma_j = V_0$ $c_j = 0$
while *new* R_t **do**

$$\forall_{j=1...K}, p_j = \begin{cases} w_j . g(R, \mu_j, \delta_j) & \frac{|R-\mu_j|}{\delta_j} < T_\sigma \\ 0 & otherwise \end{cases} \quad (6)$$

```
    // At least one match is found
```
    if $\sum_{k=1}^{K} p_j > 0$ **then**
        for $k = 1; k < K; k++$ **do**
```
            // expected posterior of G_k
```
            $q_k = p_j / \sum_{k=1}^{K} p_j$
            $w_k(t) = (1 - \alpha) w_k(t) + \alpha \cdot q_k$
```
            // For matched Gaussians
```
            if $q_k > 0$ **then**
                $c_k = c_k + q_k, \eta_k = q_k \cdot \alpha + \frac{1-\alpha}{c_k}$
                $\mu_k(t) = (1 - \eta_k)\mu_k(t-1) + \eta_k \cdot R$
                $\sigma_k^2(t) = (1 - \eta_k)\sigma_k(t-1)^2 + \eta_k \cdot (R - \mu_k^2(t))$
            end
        end
    end
```
    // No match found
```
    else
        $\forall_{j=1...K}, w_j(t) = (1 - \alpha) w_j(t-1)$
        $k = argmin_j \{w_j / \sigma_j\}$
        $w_k = \alpha, \mu_k = R, \sigma_j = V_0, c_j = 1$
    end
    $Normalize \quad w$
end

Algorithm 1: Background Learning Algorithm

w reflects the proportion belongs to the background. The K distributions are ordered by w_k/σ_k, the first B distributions are regarded as background models:

$$B = argmin_b \sum_{k=1}^{b} w_k > T \quad (7)$$

where T is the minimum portion of data which are considered as background data. In other words, it is the the minimum prior probability that the background is in the network. Until a certain portion of RSS values have been accounted for we can obtain the best distribution which reflects background. Any RSS value that is less than 2.5 standard deviations away from any of the B distributions is considered as background RSS.

D. Cooperative localization

When we get background RSS, we use formulation (2) to obtain the relative distance between nodes. With all these relative distances calculated, the coordinates **x** of non-located nodes are calculated by minimizing δ(**x**) and the real position matrix $\hat{d}$(**x**). We apply Least Square (LS) algorithm to implement the estimation:

$$C_{LS}(\mathbf{x}) = \sum_{i=1}^{N_2} \sum_{j \in S_i} \parallel \delta_{ij} - \hat{d}_{ij} \parallel^2 \quad (8)$$

where $\hat{d}_{ij} = \parallel x_i - x_j \parallel$ is the distance between node i and node j, calculated with the estimated estimation(or real coordinate if j is anchor node). N_2 is the number of non-located nodes and S_i is the number of nodes communicate with non-located nodes.

At time t, minimization of the cost function (8) is calculated through a distributed gradient descent mechanism expressed as:

$$x_i(t) = x_i(t-1) + \gamma \sum_{j \in S_j} (\delta_{ij} - \hat{d}_{ij}) e_{ij} \quad (9)$$

where $x_i(t)$ is node i's coordinate , $e_{ij} = \frac{x_i(t-1) - x_j(t-1)}{\|x_i(t-1) - x_j(t-1)\|}$ is the unit vector indicating the direction between the estimated coordinates of node i and j. γ is the step size that controls the range of coordinate adjustment. In the following section, we show the performance of locating nodes with our modified RSS data.

IV. EXPERIMENT RESULTS

A. Experimental Testbed

In this section, we present experiments to evaluate the proposed algorithm using measurements from a wireless sensor network. The network contains 20 RF sensor nodes and all the sensor nodes are Crossbow TelosB motes running TinyOS. The IEEE 802.15.4 standard is used for communication in the 2.4 GHz frequency band. A token-ring protocol is developed using nesC. The nodes communicate with each other using data packets which contain the node ID, transmission time and the measured inter-node RSS. The time interval of transmission is set to 5 ms, thus each link of data is recorded every 100 ms.

The sensors were fixed on stands which kept the sensors $1m$ off the ground and the stands were placed with a $7m$ *$7m$ square trajectory. The distance between adjacent nodes is also set at the same interval of $1m$, as shown in Fig 3(a). Firstly, we kept the network vacant to collected 3 groups of RSS data between nodes without obstructions. Then we measured 50 groups of RSS data with the presence of moving people. For each group, a person moved into the network in a random path and speed within $60s$.

B. Experimental Results

Firstly, we use a single link data to perform background learning algorithm. In order to determine the parameters of the proposed system, we make many trials to find the best fitting values. Table 1 shows the final values used in our work. Figure. 2 is the results of background learning, from which we can see the background learning clearly reduces the influence of moving obstructions. The raw interfered data have large and irregular variance. In contrast, the data processed by background learning method are constant with low variance, which are similar to the data in obstruction-free environment.

TABLE I
SYSTEM PARAMETER VALUES

Parameter	Value	Parameter	Value
K	3	T	0.5
V_0	1	P_0	$-33dBm$
α	0.08	β	3
T_σ	2	γ	0.01

The background RSS can obtained quickly and accurately without off-line training. Then we use background RSS to

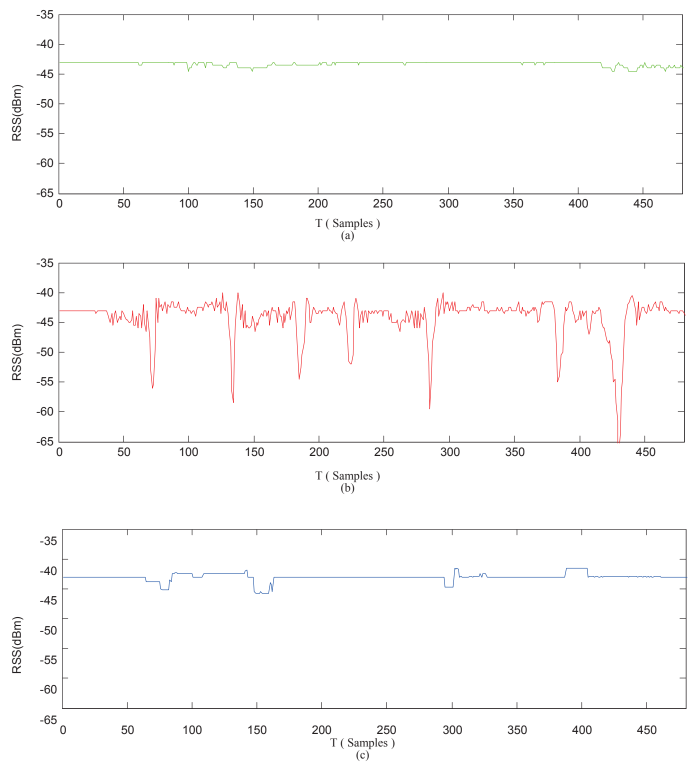
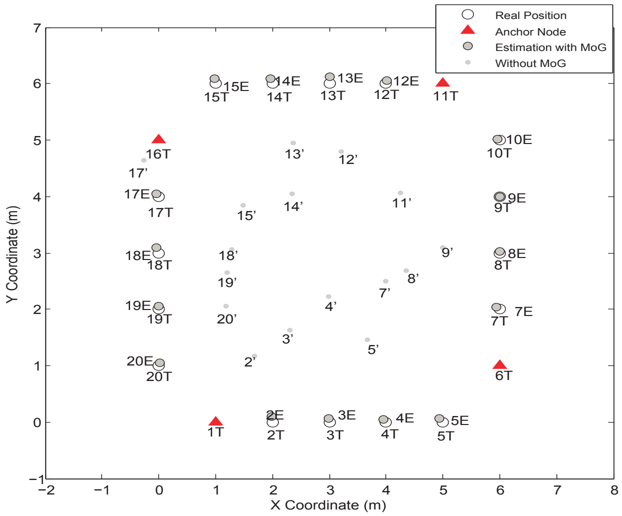


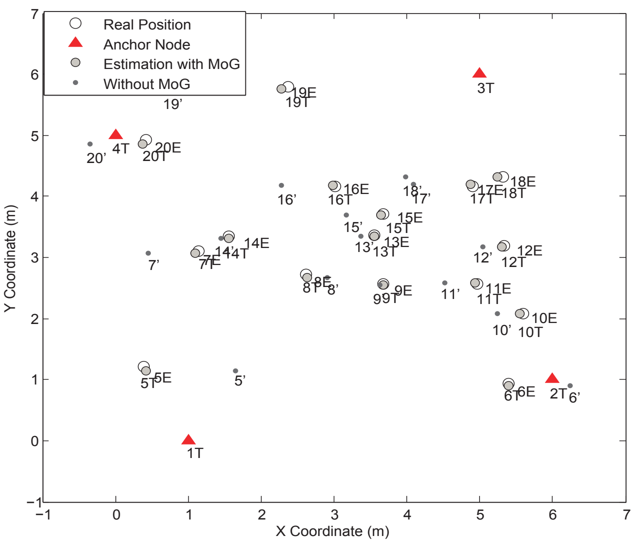
Fig. 2. The results of background learning: (a)Empty RSS without any obstructions; (b)Measured RSS between node 1 and 15 in the presence of moving people; (c)Background RSS extracted by background learning algorithm.

localize the non-located nodes, there are 4 anchor nodes and 16 non-located nodes in our experiment. As the layout of nodes can affect localization results, we then deploy the nodes uniformly in the network area. The results are shown in Fig. 3. The localization results for different layouts have high errors without background learning due to the interference of the moving person.

Figure. 4 shows the plot of the mean-squared error for the localization results when applying background learning method. The MSE keeps at a low level when there is no moving person in the network. When person moves into the network, it becomes higher, but after background learning process,the MSE stays at a constant low level over time.



(a)



(b)

Fig. 3. Localization results: (a) Non-located nodes are deployed regularly in a square; (b) Non-located nodes are deployed uniformly.

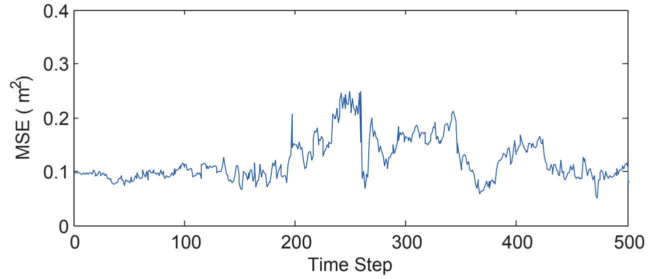


Fig. 4. MSE of localization results using background RSS

V. CONCLUSION

This paper presents an improved cooperative localization system which adopts background learning to solve the problem that the signal is seriously interfered by moving obstructions in the network area. The experimental results show that our method works well under shifty environments. Using MoG method, it is convenient to detect random environmental alterations and reduce the resulting interference. We then use the background RSS to locate nodes, the experiment results of a 20-node WSN demonstrate that this system can perform accurate cooperative localization in the existence of moving obstructions.

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