Performance Analysis of Location Estimation Algorithm in ZigBee Networks using Received Signal Strength

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Abstract *This paper presents a Maximum Likelihood Estimator (MLE) for the ZigBee networks. We propose a deployment of cluster-tree topology in the ZigBee networks and derive the MLE under the log-normal models for the Received Signal Strength (RSS) measurements. The ZiLA algorithm is also proposed to apply the MLE to ZigBee networks. To validate the RSS measurement model, we have conducted exhaustive experiments. Testbed experiments are also conducted to validate the effectiveness of ZiLA algorithm.*

1. Introduction

In the past decade, we have witnessed a burgeoning amount of research and commercial interest in the area of ubiquitous computing and location-aware computing. These growth of interest provides a strong motivation to develop techniques for estimation the location of devices in home network environments. To achieve this goal, such wireless networking techniques as IrDA, WLAN, Bluetooth, UWB and ZigBee can be used as infrastructure. Among those ZigBee is remarked as a promising open standard. ZigBee is a new industrial standard for ad hoc networks based on IEEE 802.15.4 PHY and MAC[1]. The specification for network and higher layers are defined at ZigBee Alliance[2]. It is used for low data rate, low power, and cost effective wirelessly networked products. Thus, expected applications for ZigBee include remote monitoring, home control, industrial automation, and localization.

To be sure, the RSS-based localization is a fascinating research topic. The RSS is traditionally notorious for its irregularity model of its measurements[3]. However, it has an attractive feature from the point of view of device complexity. In addition, the cost of a node is relatively cheap because no extra hardware is required. Due to its attractiveness, the research community in wireless sensor networks (WSN) has extensively studied and proposed several RSS-based algorithms. Despite rapidly-increasing popularity of ZigBee and RSS-based localization in WSN, there is lack of studies about application localization algorithms to ZigBee networks. In the paper, we focus on a location estimation method using received signal strength (RSS) of RF hardware in ZigBee networks.

We begin with Section 2 by providing a short survey of localization schemes using RSS. Section 3 considers a deployment of ZigBee networks in home networking environments. In Section 4, we formulate the location estimation problem in cluster-tree topology so as to derive maximum likelihood estimator (MLE). In Section 5, we present experimental results to validate our channel model and the performance of developed algorithm. The paper concludes with Section 6.

2. Related Works

The problem of location estimation is very important for many engineering fields and has been researched for many years. In [4] a comparative study of many RSS based localization techniques is presented. Among them, Ecolocation[5], MoteTrack and Probability Grid[6] are three of the few localization algorithms that have been evaluated on a real sensor network that uses a low power wireless radio. Ecolocation reports a location error of 3.04m for a quite small outdoor network deployment area (7.92m x 14.93m) while probability Grid reports a location error that is equal to the 70%-80% of the communication range for a 125m x 125m outdoor network deployment. MoteTrack reports a location error of approximately 3.96m for an indoor network deployment area of 41.75m x 41.75m. Other work on RSS-based localization algorithms has been developed in the context of two broad categories: map based such as [7] and distance (or area) prediction based [8],[9].

3. A Deployment of ZigBee networks

The proper deployment of ZigBee networks in home environments does not only affect efficiency and flexibility of devices but also plays an important role for the location estimation algorithm. The ZigBee specifications permit three different network topologies to be implemented depending on the application; star, cluster-tree, and mesh. In the star topology, one device acts as the Personal Area Network (PAN) coordinator, through which all communications on a given radio channel takes place. The PAN coordinator should be capable of communicating with any other device on the network. The configuration is quite simple bu

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not scalable. In the mesh topology, there is full connectivity among all devices participating in the network. Thus, the primary advantages of the mesh topology are reliability and network throughput provided via multiple paths. The cluster-tree topology is formed by modifying the star topology. One or more of the ZigBee End Devices (ZED) connected to the PAN coordinator is replaced with a ZigBee Router (ZR), from which more devices may be attached. One advantage of the cluster-tree is that it may be used to extend the geographical spread of the network. Configuring a network of the entire home environments only using a star topology has a intrinsic problem which limits capability as well as operating flexibility of the network. The mesh topology also meets a problem that all devices within the network should be ZR. Additionally, it is difficult to operate at low power consumption. To overcome these problems, we propose a deployment of ZigBee networks to home environments using a cluster-tree topology. In the cluster-tree topology, network addresses of all devices are assigned using a distributed addressing scheme that is designed to provide every potential parent with a finite sub-block of network addresses. These addresses depend on both network rules and *Cskip(d)* function of ZigBee specification. It is essentially the size of the address sub-block being distributed by each parent at that depth to its router-capable child devices for a given network depth, *d*, which is described as follows:

$$\mathrm{Cskip}(d)=\begin{cases}1+\mathrm{Cm}\cdot(\mathrm{Lm}-d-1), \text{if } \mathrm{Rm}=1\\ \dfrac{1+\mathrm{Cm}-\mathrm{Rm}-\mathrm{Cm}\cdot\mathrm{Rm}^{\mathrm{Lm}-d-1}}{1-\mathrm{Rm}}, \text{otherwise}\end{cases} \quad (3.1)$$

where *Cm(nwkMaxChildren)*, *Lm (nwkMaxDepth),* and *Rm (nwkMaxRouters)* are the maximum number of children a parent may have, the maximum depth in the network, and the maximum number of routers which a parent may have as children, respectively. The *Cskip(d)* values for an example network having *nwkMaxChildren*=20, *nwkMaxRouters*=6 and *nwkMaxDepth*=5 are calculated and listed in Table 1. Fig.1 generically illustrates the example network.

Table 1. CSkip(d) values for each given depth

Network Depth , *d*	***Cskip(d)***
0	5181
1	861
2	141
3	21
4	1
5	0

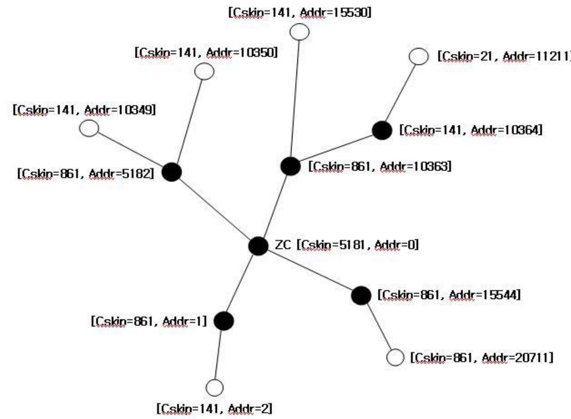

Fig.1 Address assignment in the cluster-tree topology

4. Location Estimation Algorithm in ZigBee

In this section, we now specialize for the location estimation algorithm using pair-wise RSS measurements in the cluster-tree topology. Consider a ZigBee network described in the Fig. 1 with *n* ZR, and a mobile ZED whose location is estimated. Because a vector of device parameters is $\theta = [\theta_{zed}, ..., \theta_{n+1}]$ and we assume 2-dimensional coordinate, the parameter of the *i*th ZigBee device is $\theta_i = [x_i, y_i]^T$. Thus, the location estimation problem for a mobile ZED is equivalent to finding the estimate of the coordinate, $\hat{\theta}_{zed}$, given the coordinate vector of the reference ZR locations $\theta_{zr} = [\theta_1, ..., \theta_n]$.

4.1 Statistical Model and MLE

The RSS measurements are commonly modeled as log-normal random variables [8]. We define $P_{zed,i}$ as the measured received power at a mobile ZED transmitted by ZR *i* (in milliwatts). Thus, the random variable $P_{zed,i}(dBm) = 10\log_{10}(P_{zed,i})$ is Gaussian

$$\begin{aligned} &P_{zed,i}(dBm) \sim N(\overline{P}_{zed,i}(dBm), \sigma^2{}_{sh}) \\ &\overline{P}_{zed,i}(dBm) = P_0(dBm) - 10 n_p \log_{10}(d_{zed,i}/d_0) \end{aligned} \quad (4.1)$$

where $\overline{P}_{zed,i}(dBm)$ and $\overline{P}_0(dBm)$ are the mean received power and the received power at a reference distance d_0, respectively. Typically, d_0 is 1m. n_p is the propagation exponent. σ^2_{sh} is the variance of the lognormal shadowing. Based on this statistical model, the log of the joint conditional pdf is obtained as follows:

$$\begin{aligned} &l(P|\theta) = \sum_{i=1}^{n} l_{zed,i} \\ &l_{zed,i} = \log f_{P|\theta}(P_{zed,i}|\theta_{zed}, \theta_i) \end{aligned} \quad (4.2)$$

Before deriving the location estimators, it is important to know a lower bound on the variance achievable by those. The Cramer-Rao Bound (CRB) provides a means for calculating such a lower bound. Researchers who are testing localization algorithms can use the CRB as a benchmark for a particular algorithm. It is assumed that a vector parameter which is estimated is $\theta = [\theta_1 \theta_2 ... \theta_p]^T$ and the estimator $\hat{\theta}$ is unbiased. Then, the CRB is found as the [i,i] element of the inverse of a matrix, which is described by

$$\mathrm{var}(\hat{\theta}) \geq [F^{-1}(\theta)]_{ii}, \tag{4.3}$$

where $F(\theta)$ is the $p \times p$ Fisher Information Matrix (FIM). The latter is defined by

$$[F^{-1}(\theta)]_{ij} = -E\left[\frac{\partial^2 \ln p(x;\theta)}{\partial \theta_i \partial \theta_j}\right], \tag{4.4}$$

for $i = 1,2,...,p;\ j = 1,2,...,p$. In our estimation problem, the parameter which is estimated is $\theta = [x_{zed}, y_{zed}]^T$. Therefore, the FIM is derived as follows.

$$F(\theta) = \tag{4.5}$$
$$\begin{bmatrix} b\sum_{i=1}^{n}\frac{(x_{zed}-x_i)^2}{\|z_{zed}-z_i\|^4} & b\sum_{i=1}^{n}\frac{(x_{zed}-x_i)(y_{zed}-y_i)}{\|z_{zed}-z_i\|^4} \\ b\sum_{i=1}^{n}\frac{(x_{zed}-x_i)(y_{zed}-y_i)}{\|z_{zed}-z_i\|^4} & b\sum_{i=1}^{n}\frac{(y_{zed}-y_i)^2}{\|z_{zed}-z_i\|^4} \end{bmatrix}$$

In general, the MLE finds the parameters which maximizes the likelihood function, or equivalently, minimizes the negative of the log-likelihood function. Thus, the MLE of θ is derived by

$$\hat{\theta} = \arg\min_{\{z_{zed}, z_i\}} \sum_{i=1}^{n}\left(\log\frac{\hat{d}^2{}_{zed,i}/C^2}{\|z_{zed}-z_i\|^2}\right)^2, \tag{4.6}$$
$$C = \exp\left[\frac{1}{2}\left(\frac{\log 10}{10}\frac{\sigma_{sh}}{n_p}\right)^2\right]$$

where $z_i = [x_i, y_i]^T$ and C is the multiplicative bias factor.

4.2 ZigBee Location Algorithm

In ZigBee networks, information about the current link quality is not only measured at IEEE 802.15.4 PHY layer but also employed to measure a pair-wise RSS. It can be the received power, the estimated signal-to-noise ratio (SNR), or a combination of both. In our hardware and MAC software, the link quality indication (LQI) value is generated by simple scaling of the RSS value. Thus, we can compute the RSS value by appropriate inverse scaling. Using the information, the MLE, which is described in 4.1, can be calculated. It takes too much time to calculate the MLE in the 8-bit microcontroller. Thus, the mobile ZED collects RSS data in the beacon frame received from the ZRs and transmit those to a central “listening” device, ZC. Also, ZC uploads RSS data to a laptop computer, which calculate the minimum of the MLE using the optimization algorithm. Due to the resource constraints in ZigBee networks, we have the following assumptions.

- The ZigBee network operates in a beacon-enabled mode, and ZC covers the whole home environments.
- Transmission power is fixed.
- The beacon frames of all ZRs should not collide one another in the period of beacon order (BO).
- The time of joining/leaving a network should be less than 2 seconds.

In the ZigBee tree topology, we define the application object between a mobile ZED and a ZC for the location estimation. A mobile ZED should carry out the following ZigBee location algorithm (ZiLA). To the end, the modification of ZDO of the mobile ZED is inevitable.

STEP1 If it is the first time to start location algorithm, initiate the network discovery procedure in the period of n * BO.
STEP2 If the received beacon frames exist, push the network descriptors of ZRs to stack in the order of RSS measurement.
STEP3 Join a network through association to ZR in the top of the stack.
STEP4 Report the RSS measurement data which are pairs of {address, LQI} to ZC.

5. Experimental Results

5.1 Channel Measurement Experiment

In this section, we describe the ZigBee based measurement device and validate the RSS measurement model made at the beginning of subsection 4.1. The centerpiece of our system is the CC2420DB board which is developed using t he Atmega128 microcontroller from ATMEL and CC2420 RF transceiver from Chipcon. The Chip con Z-Stack is used for ZigBee protocol stack. To evaluate the basic characteristics of wireless link, we conducted several kinds of experiments:

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RSS vs. Direction and RSS vs. Distance tests. The two CC2420DBs were placed in a vacant indoor office 2m away from the each other. One of them configured to send beacon packets continuously while the other was measuring the RSS value of each received packet. RSS value was measured in four different geographical directions by sampling 100 beacons received in each direction.

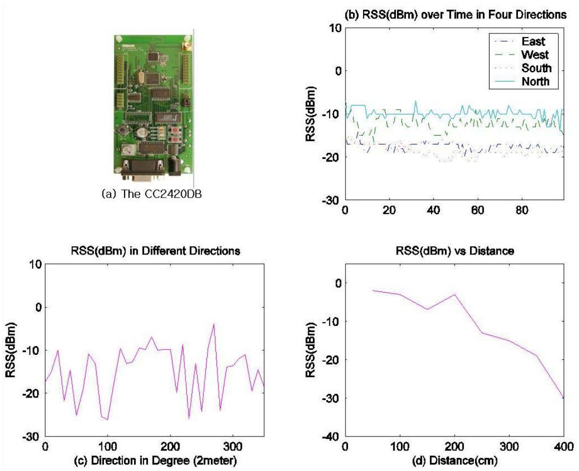

Fig.2. (a) The CC2420DB board. (b) RSS(dBm) over Time in Four Directions. (c) RSS(dBm) in Different Directions. (d) RSS(dBm) vs. Distance Plot

Fig. 2(b) shows that the RSS value in each direction is relatively stable over time. However, the RSS value received in the north is much higher than that received in the south, although devices have the same distance from the sender. We also measure the variation of RSS value with the changes in the angular direction of the receiver with respect to the sender. Fig. 2(c) shows the variation of the RSS value as a function of the angular direction with respect to the sender. These results show that the RSS value varies continuously with the direction. In other words, incremental changes in direction result in incremental variation in the RSS value. Fig. 2(d) shows the RSS vs Distance plot which means RSS value changes almost linearly with the log of the distance.

We verify the log-normal distribution of the RSS measurements by scrutinizing the RSS vs. Distance experimental data via chi-square test. Several thousands of RSS data are collected at the distance of 1m, 2m, 3m, and 4m and chi-square statistics are calculated to determine the goodness of fit of the distribution to a set of experimental data. Fig. 3 shows both probability distribution from RSS measurement model and histogram from observed data at each distance. The chi-square values for the four histograms are 22.8, 23.2, 27.6, and 25.7, respectively. Each of them does not exceed the threshold value for chi-square test at a 10% significance level, so we conclude that the experimental data is consistent with that of a RSS measurement model.

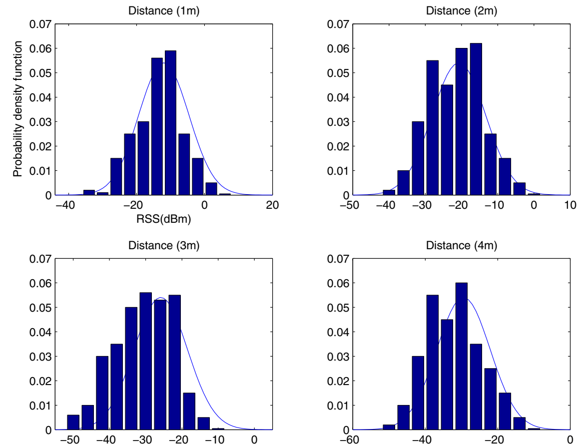

Fig.3. Goodness-Of-Fit Test
(a) Distance (1m). (b) 2m. (c) 3m. (d) 4m.

5.2 Testbed Experiment

To evaluate the effective performance of the proposed algorithm, we construct a testbed of ZigBee networks. Our experimental testbed is Brandon's home(8m x 9m), which is located on the third floor of a four-story apartment house. This is a typical home environment that includes indoor walls, furnishings, appliances, and exterior walls. The floor map and cluster-tree topology of a ZigBee network are depicted in Fig. 4.

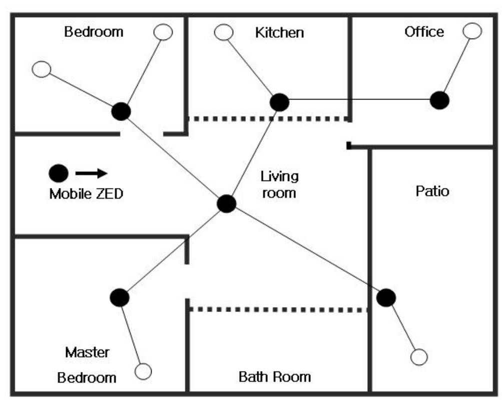

Fig.4 The floor map and deployment of a ZigBee network

First of all, in testbed one ZigBee Coordinator (ZC), five ZRs, six static ZEDs, and one mobile ZED are deployed using the cluster-tree topology. Next, after fixing the mobile ZED location, we estimate the propagation exponent n_p, which is 2.9. Finally, we divide the 8m x 9m testbed by the unit grid with 1m x 1m while putting the mobile ZED on the selected 16 points to estimate its location. The minimum of

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the MLE mentioned in subsection 4.1 is calculated using a conjugate gradient algorithm. The estimated locations are shown in Fig. 5. The mean distance error is 1.8m. These results demonstrate the accuracy of estimation.

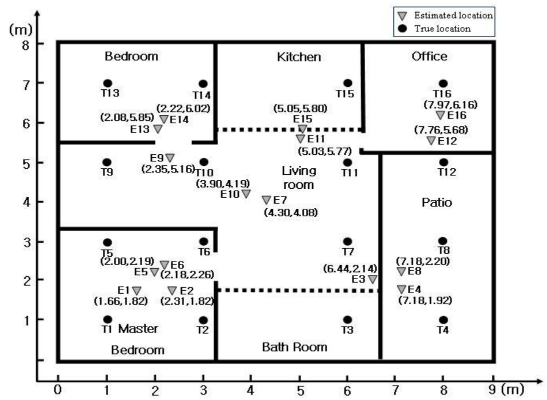

Fig.5 Location Estimation Results of ZiLA Algorithm

6. Conclusion

In this paper, we proposed a maximum likelihood location estimation algorithm which is applied to ZigBee networks. Based on the cluster-tree topology, the MLE under log-normal models for the RSS was derived, and the ZiLA algorithm also was proposed. We testified the RSS measurement model by using the chi-square test. The performance of the proposed algorithm is validated through a testbed of ZigBee networks supporting the home environments. We implement our algorithm while evaluating it by utilizing commercially available ZigBee hardware and protocol stack. According to the experimental results, it shows a reasonable estimation accuracy enough to support intelligent services for the home networking environments.

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