A Novel Localization Scheme Based on RSS Data for Wireless Sensor Networks*

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Abstract. Sensor localization has become an essential requirement for realistic applications over Wireless Sensor Networks (WSN).In this paper, we propose a novel location algorithm based on mean received signal strength (RSS) measurements. It incorporates Chan's hyperbolic position location algorithm and the extended Kalman filtering to achieve an accurate estimation. We have verified the scheme mentioned in the paper performed better than conventional received signal strength indicator (RSSI) location algorithm for the static location estimator in indoor sensor networks.

1 Introduction

Location information plays a crucial role in understanding the application context in Wireless Sensor Networks (WSN), and many localization algorithms for WSN have been proposed to provide per-node location information [1]. With regard to the mechanisms used for estimating location, we divide these localization protocols into two categories: range-based and range-free. Ranging is the process of estimating the distance between two nodes. RSS-based ranging is attractive as a means of distance estimation because it is essentially free, wireless sensor nodes already have radios, and signal strength is often being measured for each radio packet anyway. In contrast, other ranging and localization technologies such as acoustic, AOA, TDOA [2], GPS, and laser require specialized hardware and sometimes sophisticated processing.

As can be seen, each of the localization schemes on its own has their set of weaknesses. Based on the above notes and results it is our opinion that radio localization can play an active role in several indoor applications provided that the accuracy requirement in terms of spatial resolution is not too strict. As such, we will discuss RSSI location algorithm and the performance of the algorithm applied in indoor sensor networks. In the paper we propose a new methodology which using mean value of RSS data to estimate the position of target node with only 3 anchor nodes. This paper makes the following three main contributions. First, we present a practical, fast and easy-to-use localization scheme with relatively high accuracy and

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low cost for indoor wireless sensor networks. Second, we develop a novel Extended Kalman Filter (EKF), based state estimation algorithm for node localization in our indoor WSN. Third, we implement and validate our scheme on the GAINS sensor node platform, which achieves errors of about 1.16 meter as shown in our experiments. (GAINS sensor nodes are all independently developed by our WSN group of Institute of Computing Technology, Chinese Academy of Sciences.)

2 Localization System Model and Parameters Obtain

In the section, we assume an indoor sensor network model as depicted in Fig. 5. The network proposed in the paper consists of sensor nodes (SN), which are located in random, and three anchor nodes, which have a priori knowledge of their own position with respect to some global coordinate system.

One of the most common radio propagation is the log-normal shadowing path loss model which also will be adopted in our system [3]. The model is given by:

$$PL(d) = PL(d_0) - 10n\log_{10}(d / d_0) - X_\sigma \tag{1}$$

Where d is the transmitter-receiver separation distance, d_0 a reference distance, n the path loss exponent, and $X_ó$ a zero-mean Gaussian RV (in dB) with standard deviation ó (multi-path effects). $PL(d_0)$ is the signal power at reference distance d_0 and PL(d) is the signal power at distance d. The value of $PL(d_0)$ can either be derived empirically or obtained from the WSN hardware specifications.

A theoretically accurate model would model RSSI as having logarithmic attenuation over distance. The specifications from our radio indicate that the output voltage V_{RSSI} on the RSSI pin is proportional to the received power as

$$RSSI = -51.3V_{RSSI} -49.2 \text{ [dBm]} \tag{2}$$

The procedure for our scheme to obtain RSSI measurements will be introduced as follows: Anchor node periodically transmits radio frequency (RF) beacon signal to sensor node, which will be located. During this period, sensor node will constantly sample received signal strength from each anchor nodes orderly and store it for later use. After obtains enough information, we can calculate the target sensor node through our localization scheme by the Pentium-based PC rather than sensor node itself. Then we can employ more sophisticated algorithms to improve location performance.

3 Localization Algorithm

In our localization system, we will not adopt traditional RSSI algorithm but present signal strength difference of arrival (SSDOA) algorithm. When RSSI parameters have been obtained, they are converted into range difference measurements and these measurements can be converted into nonlinear hyperbolic equations. Superficially, there doesn't seem to be any advantage in converting RSS measurements into SSDOA measurements, as we can triangulate the position of the target node using the RSS measurements, directly. However, this may give us some increased accuracy when errors due to multiple signal reflections in pairs of RSS measurements are positively correlated because of having a common signal reflector. The more similar the errors in pairs of RSSs are, the more we can gain by changing them into SSDOAs. After compared the location performance of Fang's algorithm with Chan's algorithm, we will calculate the target sensor node using Chan's algorithm based on mean received signal strength (RSS) measurement to improve the location accuracy [4]. In the paper, we named above means improved-Chan algorithm. The mathematical model of traditional RSSI algorithm will not be introduced in detail here. After briefly introduce mathematical model for SSDOA location algorithms, we will focus on our simulation results.

3.1 Mathematical Model for Hyperbolic SSDOA Equations

A general model for two dimensional (2-D) position location estimation of a source using M anchor nodes is developed. Let *(x, y)* be the source node location and (X_i, Y_i) be the known location of the i'th anchor node receiver. The range difference between anchor nodes with respect to the anchor node where the signal arrives first, is

$$d_{i,1} = d_i - d_1 = \sqrt{(X_i - x)^2 + (Y_i - y)^2} - \sqrt{(X_1 - x)^2 + (Y_1 - y)^2} \tag{3}$$

Where $d_{i,1}$ is the range difference between the first anchor node and the i'th anchor node, d_1 is the distance between the first anchor node and the source node. This defines the set of nonlinear hyperbolic equations whose solution gives the 2-D coordinates of the target source node.

3.2 Extended Kalman-Filter (EKF) Algorithm

In order to utilize the KF equations in the non-linear case, the non-linear equation has to be linearized. A KF that linearizes about the current state and covariance is referred to as an extended Kalman filter or EKF. So the paper deals with target sensor node location tracking using the Extended Kalman filtering based on RSS measurements. EKF tends to increase the robustness of the state estimation process and reduce the chance that a small deviation from the Gaussian process in the system noise causes a significant negative impact on the solution. However, we lose optimality and our solution will be just sub-optimal. The detailed mathematical procedure for EKF algorithm is presented in [5] [6].

4 Simulation Results and Performance Analysis

As described in Fig.5, assume the three anchor nodes are located at (0, 0), (200, 0), and (100,173), so the distance between arbitrary two anchors R is 200 meter. The parameters of propagation model adopted for our simulation scenario are n=2.3, $PL(d_0)$=-56.6519dB, ó=2.3875[7]. We average the sensor location results computed from our scheme over 1000 trials, so we will obtain 1000 RSS measurements. We use a sliding window of 10 samples to compute the mean signal strength on a continuous basis which will be adopted in our improved-Chan algorithm. We study the performance of our algorithm based on Gaussian noise environment. Suppose the speed of target sensor node is very low and can be considered as no relative movement, RSS error caused by target node and all network devices is assumed to be Gaussian distributed with mean 0 and variance 1*i dB (where i=1,2,…5).

As can be seen from the simulation results of Fig.1, the Chan's algorithm achieves better performance than RSSI and Fang algorithms based on indoors LOS environment. The root mean square error increases as variance of the RSS measuring errors increase. From Fig.2, we will sure the location accuracy improved when using improved- Chan algorithm compared with using Chan's algorithm. Furthermore, it can be stated that important improvements in the positioning accuracy are obtained using EKF instead of static estimator. The performance of our scheme exceed traditional RSSI location algorithm from our simulation results.

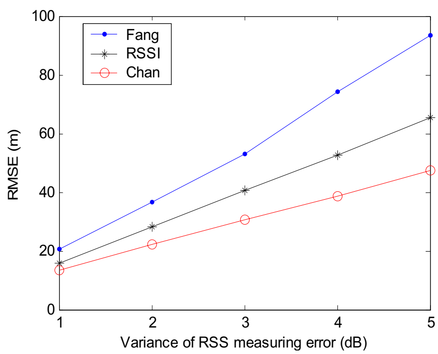

Fig. 1. Position errors of algorithm in LOS environment

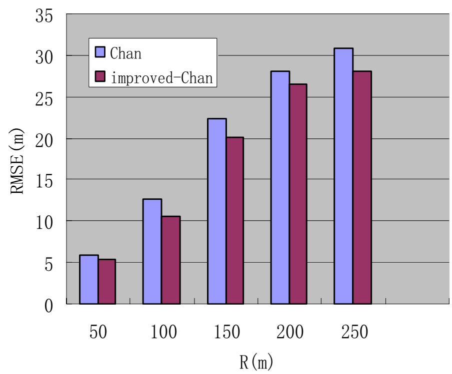

Fig. 2. Analysis localization errors

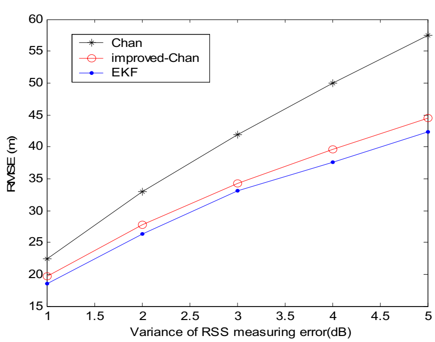

Fig. 3. Comparison of location performance based on different algorithms

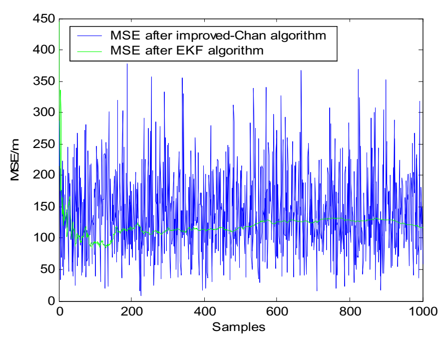

Fig. 4. Comparison of location performance

Absolute Estimation Accuracy: To evaluate estimation accuracy, we report on an experiment with three anchor nodes and one target sensor node, since the visualization of estimation convergence is clearer with a smaller number of sensors.

The three anchor nodes are positioned at (0, *0*) *m*, (10, 0) *m*, (5, 8.6603) *m* in our large boardroom. Fig.6 shows the localization accuracy of our EKF based scheme with approximate 1.16 m. From the observation of our experimental results, we will find when target sensor node close to the center of the triangle which formed by three anchor nodes, the localization accuracy is high. But at some area, the network failed to localize at all.

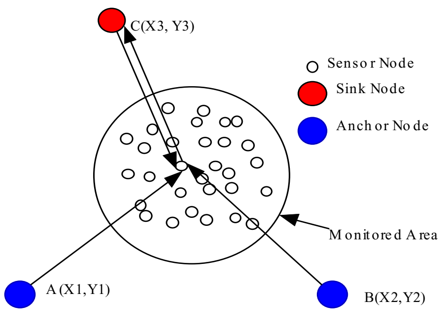

Fig. 5. An example of an indoor sensor networks

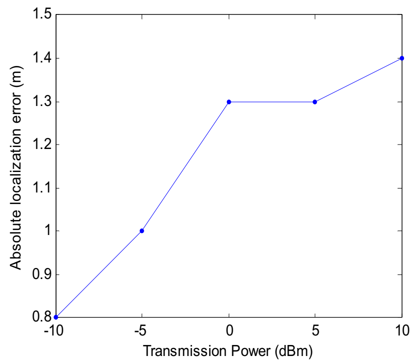

Fig. 6. Localization error for real system

5 Conclusions

In the paper, we presented a novel EKF-based positioning scheme using mean RSS for indoor sensor networks. Our positioning scheme doesn't need sensor node make radio transmission constantly but listen to three beacon signals passively. This efficiently reduces sensor energy cost and also improves using ratio of RF channels. Real experiments in a large indoor boardroom area show that the location accuracy is approximately 1.16m. Now that we have validated our ideas through simulation, implementation and experiment, it can be stated that the approach is effective and obviously has good application foreground in some special indoor sensor networks area.

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