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Received Signal Strength Indicator-Based Adaptive Localization Algorithm for Indoor Wireless Sensor Networks

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Received: 15 April 2013 /Accepted: 20 June 2013 /Published: 28 June 2013

Abstract: Solutions for indoor localization have become more critical with recent advancement in context and location-aware technologies. When wireless sensor network (WSN) used in complex indoor environment, great propagation loss will be caused and it is very difficult to estimate adaptively the location of target nodes when environment changed. In this paper, an indoor adaptive localization algorithm based on received signal strength indication (RSSI) for wireless sensor networks is proposed. The algorithm utilizes the RSSI of radio signals radiating from two other fixed nodes to generate the local parameters of signal propagation model for each fixed node, and the parameters are updated online according to environmental variation. According to the estimated parameters of the signal propagation model, iteration method is applied to estimate the position of target node. Through actual experimental tests, the validity of the proposed algorithm is demonstrated.

Keywords: Indoor localization, Adaptive localization, Received signal strength indicator, Iteration method, Wireless sensor network.

1. Introduction

Wireless sensor network (WSN) is expected to serve as a key infrastructure to realize rich information services based on sensory data beyond conventional information technology, such as supervising system of human activity, visualization systems of physical status, positioning and navigation, content recommendation based on user's location, automatic detection of emergency states, and so on [1]. WSN brings many challenging research subjects to the scientific and technical field. The network's localization problem is one of them. Accurate and reliable location information can lead to better decision making [2]. In last years, many researchers have investigated various localization techniques, such as global positioning systems (GPS), radio frequency identification (RFID), and laser scanning [3-5]. Much of these researches pertain to location in outdoor environments, resulting in limited performance for indoor environments. So it is urgent and useful to develop the indoor localization system.

In the field of WSN-based indoor localization, many location estimation methods have been proposed in the literature. There are three categories of location estimation algorithms [6]. The first is time based location estimation, e.g., time of arrival (TOA) [7, 8], and time difference of arrival (TDOA) [9]. The second is direction based location estimation, such as angle of arrival (AOA) [10] or direction of arrival (DOA) [11]. A third category of location method is received signal strength indication (RSSI) based location approach [6, 12-15].

Of techniques that use radio-frequency to measure location, TOA techniques have shown great promise. Based on the signal traveling time between target node and fixed nodes in WSN, the distance between them is estimated by TOA (or TDOA) location method. The estimation result derived by this method has good accuracy. However, this performance requires a direct path between sensors, giving a limitation similar to line-of-sight requirements, and precise timing synchronization is needed. The signal direction of transmitted signal from a target node can be estimated by AOA method. This method doesn't need timing synchronization. However, systems based on AOA or TOA techniques require specific hardware and this fact increases the cost and complexity of the localization systems. In the case of AOA the system uses directional antennas with beam forming in order to derive the direction information of target node. Due to limitation of the previously described approaches, recent research has investigated the use of RF technologies that measure the RSSI [16]. Such RF based technologies assume that there are some fixed nodes with known spatial location and act as beacon points to localize other nodes with unknown location. Compare with other location technique, the main drawback of RSS-based method has lower location accuracy [6]. Although this, RSSI-based location method is suitable used in WSN because some system constraints, such as miniature hardware size and lower battery power, should be considered for the practical application in WSN.

It should be noted that there are still a number of challenges to be overcome in the field of RSSI-based indoor localization. The main difficulty lies in the fact that communication signals in an indoor environment face interference and attenuation from multi-path, reflection, channel fading, deflection, and diffraction [12]. In fact, it is quite difficult to establish a reliable signal propagation model in an indoor environment due to difficulties in reliably estimating the signal path-loss parameters.

Recently, many RSSI-based indoor localization algorithms for WSN have been reported. The foundation of these algorithms is path loss regression model. It is calibrated using a set of RSSI values collected at various known sampled points to determine the relationship between RSSI values and the distance from the transmitting node to the receiving node. A regression equation model of this relationship is constructed and used to estimate the distances based on RSSI values and the target's location. Based on the path loss, there are many algorithms for location estimation based on the RSSI value or calculated distances [17]. The two-step indoor location estimation method [6] was proposed. In the algorithm, least-squares approach had been applied to determine parameters of signal propagation model, and, minimum mean squares error (MMSE) method was applied to estimate the position of target node after considering the estimated parameters of the signal propagation model obtained in the first step. The literature [12] addresses a novel method for localizing a stationary object in an indoor office environment. The proposed method utilizes RSSI of radio signals radiating from fixed reference nodes and reference tags placed at known positions to generate a precise signal propagation model. In the proposed approach, the signal propagation model and model parameters were updated online in a closed-loop feedback correction manner. Paul et al. [13] evaluate the feasibility of building an indoor location tracking system that is cost effective for large scale deployments, can operate over existing Wi-Fi networks, and can provide flexibility to accommodate new sensor observations as they become available. The paper also propose a sigma-point Kalman smoother (SPKS)-based location and tracking algorithm as a superior alternative for indoor positioning. The proposed SPKS fuses a dynamic model of human walking with a number of low-cost sensor observations to track 2-D position and velocity. In the literature [14], narrowband measurements at five VHF (Very High Frequency) frequencies are used to evaluate the accuracy of RSSI-based location algorithms. Since shadow fading increases with frequency, location accuracy decreases with frequency. A satisfactory approximation of location accuracy in a given network is obtained by the error estimates that are based on linearization but modified when the receiver is close to one transmitter. In [15], a robust, easy to deploy and flexible indoor localization system based on ZigBee WSN was presented. The localization system consists of two phases: calibration and localization. Anytime a blind node needs to be located, the presented system performs calibration using a matrices system, so that the environment can be characterized, taking into account possible changes on it since the last request. Then, in the localization phase, the central server processes all the information and calculates the blind node's position with the new iterative algorithm.

In this paper, we investigate the most important problems, estimating the signal path-loss parameters in an indoor environment to establish a reliable signal propagation model, and propose a RSSI-based adaptive localization algorithm for indoor WSN. The algorithm utilizes the RSSI of radio signals radiating from two other fixed nodes to generate the local parameters of signal propagation model for each fixed node, and the parameter set of the fixed node is built, and the parameters can be updated online according to environmental variation. In localization phase, each fixed node searches the most suitable parameters of the signal propagation model from its parameter set according to RSSI value that it has received from the target node, and iteration method is applied to estimate the position of target node. The performance of the proposed algorithm is compared with others. The superior accuracy of our approach over a number of trials is demonstrated.

The remainder of this paper is organized as follows. Section 2 gives signal propagation model, and Section 3 analyzes the problems of localization with the signal propagation model. Section 4 describes the indoor adaptive localization algorithm based on RSSI for WSN. Experimental results are given in Section 5, and finally conclusions in Section 6.

2. Signal Propagation Model

In RSSI-based indoor localization algorithms, the receiver computes the signal propagation loss based on RSSI from the sender and finally computes the precise location by converting the signal propagation loss into distance with the help of both theoretical and empirical models. As a result, it is necessary to understand the relationship between RSSI and distance. The following signal propagation model has been widely used for this relationship

$$P(d_0) - P(d) = 10n\log(\frac{d}{d_0}) + v, \tag{1}$$

where d is the distance between fixed node and target node, and d_0 is the distance between target node and reference point. In general, d_0 is assumed to be 1 m. $P(d)$ represents the signal-strength measured at distance d, and $P(d_0)$ is the signal power received at reference point. n is the path-loss parameter, and $v \sim N(0, \sigma_v^2)$ is Gaussian random variable representing lognormal shadowing effects in indoor multipath environments.

3. Problem Analysis

RSSI based traditional approaches aim to calculate the unknown distance d using the measurement $P(d)$ and parameters n and $P(d_0)$ modeled in advance. Thus, in traditional approaches, the distance d is calculated as

$$d = 10^{\frac{P(d_0) - P(d) - v}{10n}}. \tag{2}$$

In actual applications, however, the calculated parameters n and $P(d_0)$ don't match the actual situation because they are environmental- dependent in the presence of signal interference, deflection, and variation of the power radiating from the transmitter [12]. So the traditional approaches may not be efficient and potentially result in numerous errors.

Let us suppose that the calculated model parameters n and $P(d_0)$ have error Δn and $\Delta P(d_0)$. Then the actual model parameters are

$$\begin{cases} n_\Delta = n + \Delta n \\ P_\Delta(d_0) = P(d_0) + \Delta P(d_0) \end{cases}. \tag{3}$$

Thus, it change formula (1) to

$$P_\Delta(d) = P(d_0) + \Delta P(d_0) - 10(n + \Delta n)\log(d) - v. \tag{4}$$

In such case, if the fixed parameters n and $P(d_0)$ are used without modification, the distance d will be evaluated as

$$\begin{aligned} d_\Delta &= 10^{\frac{P(d_0) - P_\Delta(d) - v}{10n}} \\ &= 10^{\frac{P(d_0) - (P(d_0) + \Delta P(d_0) - 10(n+\Delta n)\log d - v) - v}{10n}} \\ &= 10^{\frac{10(n+\Delta n)\log d - \Delta P(d_0)}{10n}} \\ &= d^{1+\frac{\Delta n}{n}} \cdot 10^{\frac{-\Delta P(d_0)}{10n}}. \end{aligned} \tag{5}$$

Therefore, if parameter variations are not considered, then distance errors will certainly exist according to formula (6).

$$\begin{aligned} d - d_\Delta &= d - d^{1+\frac{\Delta n}{n}} \cdot 10^{\frac{-\Delta P(d_0)}{10n}} \\ &= d(1 - d^{\frac{\Delta n}{n}} \cdot 10^{\frac{-\Delta P(d_0)}{10n}}) \end{aligned} \tag{6}$$

From formula (6), it can be seen that there is a big error of the calculated distance between a receiving node and a transmitting node according to the model. So it is necessary to constantly update the parameters of the model with the changes of environment, in order to calculate more accurate distance and to locate a more precise position.

4. Adaptive Localization Algorithm

Recently, RSSI-based localizations have attracted considerable attention due to their simplicity and low cost [18], as well as their lower sensitivity to bandwidth and occurrences of undetected-direct paths [19]. This paper presents an adaptive localization algorithm that is suitable for indoor WSN and it is also based on RSSI. There are the fixed nodes, a master node which is connected to computer, and the target nodes to be located in the algorithm. The fixed nodes receive and send radio signals, and compute the parameter set of the signal propagation model based on RSSI. The master node receives the information sent by fixed nodes, and transmits them to computer for estimating the location of target node.

4.1. The Parameter Set of Signal Propagation Model

Assuming there are N fixed nodes whose position coordinates are (x_i, y_i), $i = 1, \cdots, N$ and $N > 2$. Before target nodes are located, it is necessary to first establish a set of parameters of the signal transmission model. Initially, the fixed node s_i transmits the radio signal with the strength of P_i, and receives the signal of the fixed node s_j ($j = 1, \cdots, N$ and $j \neq i$) with the strength of $P_{ij}(d_{ij})$ where d_{ij} is the distance between the fixed node s_i and s_j, and

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \,. \tag{7}$$

Thus, formula (1) can be changed as

$$P_i(d_0) - P_{ij}(d_{ij}) = 10 n_i \log(\frac{d_{ij}}{d_0}) + v_i \,. \tag{8}$$

In the above formula, the unknown parameters are $P_i(d_0)$ and n_i. The problem is to estimate $P_i(d_0)$ and n_i, according to the measurement $P_{ij}(d_{ij})$ and the known distance d_{ij}. The parameter d_0 is 1 meter, so the two unknown parameters $P_i(d_0)$ and n_i can be calculated if getting two sets of known data $P_{ij}(d_{ij})$ and d_{ij}. Thus, each fixed node will calculate a set of signal transmission model parameters corresponding to the two nodes, according to the data obtained from other two fixed nodes. The used equations are as follows:

$$\begin{cases} P_{i-jk}(d_0) - P_{ij}(d_{ij}) = 10 n_{i-jk} \log(d_{ij}) + v_i \\ P_{i-jk}(d_0) - P_{ik}(d_{ik}) = 10 n_{i-jk} \log(d_{ik}) + v_i \end{cases} \\ i = 1, \cdots, N, j = 1, \cdots, N, \\ k = 1, \cdots, N, i \neq j \neq k \tag{9}$$

where n_{i-jk} and $P_{i-jk}(d_0)$ are the signal model parameters n and $P(d_0)$ of the fixed node s_i that are calculated according to d_{ij}, d_{ik}, $P_{ij}(d_{ij})$ and $P_{ik}(d_{ik})$, respectively.

Here, let us suppose that v_i can be ignored. Therefore, $P_i(d_0)$ and n_i can be calculated as

$$\begin{cases} n_{i-jk} = \dfrac{P_{ik}(d_{ik}) - P_{ij}(d_{ij})}{10(\log d_{ij} - \log d_{ik})} \\ P_{i-jk}(d_0) = P_{ij}(d_{ij}) + \dfrac{\log d_{ij}(P_{ik}(d_{ik}) - P_{ij}(d_{ij}))}{\log d_{ij} - \log d_{ik}} \end{cases} \tag{10}$$

Then, in addition to formula (10), each fixed node begins to compute the parameters of the signal propagation model, and to establish its parameter set that is defined as follows:

$$s_{i-PS} = \{n_{i-jk}, P_{i-jk}(d_0), P_{ij}(d_{ij}), P_{ik}(d_{ik}) \mid \\ j = 1, \cdots, N, k = 1, \cdots, N, i \neq j \neq k\} \\ i = 1, \cdots, N \tag{11}$$

where s_{i-PS} represents the parameter set of the fixed node s_i. Here, the parameter set can be updated according to environmental variation.

4.2. RSSI-Based Localization Algorithm

Based on the estimated parameter set of signal propagation model derived in above step, the location of target node is estimated. As with the literature [6], assuming the sampling duration time for power signal is T (ms), and the number of sampling point in this duration is M. The sample period between each sampling point is Ts. Let the location of target node at mTs is (Xm, Ym), and the distance between target node and i-th fixed node is

$$d_{it}^m = \sqrt{(x_i - X_m)^2 + (y_i - Y_m)^2} \\ i = 1, \cdots, N, \quad m = 1, \cdots, M \tag{12}$$

In localization phase, a target node sends the radio signal at mTs. After the fixed nodes have received the signal of the target node with the strength of $P_{it}^m(d_{it}^m)$, they begin to search the most suitable parameters of the signal propagation model from their parameter set. The fixed nodes search signal strengths of the two closest to the signal strength $P_{it}^m(d_{it}^m)$, and the corresponding parameters n_{i-jk} and $P_{i-jk}(d_0)$ are the most suitable parameters for the target node at mTs. Then, each fixed node sends the data containing its selected parameters and received signal strength $P_{it}^m(d_{it}^m)$ to the master node. The master node receives the information sent by fixed nodes, and transmits them to computer for estimating the location of target node.

In order to clearly explain the localization process of target nodes, we define

$$\begin{cases} P_{it}^m = P_{it}^m(d_0) - P_{it}^m(d_{it}^m) \\ A^m = [X_m \quad Y_m]^T \end{cases} . \tag{13}$$

where $P_{it}^m(d_0)$ represents the most suitable $P_{i-jk}(d_0)$ value of the fixed node s_i for the m-th target node. Thus, formula (1) can be changed as

$$f_{it}(A^m) = P_{it}^m = 10 n_{it}^m \log(d_{it}^m) \tag{14}$$

where $f_{it}(A^m)$ represents the function of vector A^m, and n_{it}^m is the most suitable n_{i-jk} value of the fixed node s_i for the m-th target node.

According to N equations shown in formula (14), the vector form is expressed as

$$P^m = F(A^m) \tag{15}$$

where

$$\begin{cases} P^m = [P_{1t}^m \quad P_{2t}^m \quad \cdots \quad P_{Nt}^m]^T \\ F(A^m) = [f_{1t}(A^m) \quad f_{2t}(A^m) \quad \cdots \quad f_{Nt}(A^m)] \end{cases} \tag{16}$$

$F(A^m)$ is a vector that the elements are non-linear functions. Using the first-order Taylor series expansion at the formula (17), $F(A^m)$ can be expressed as the formula (18).

$$A^m = A_0^m = [X_0^m \quad Y_0^m]^T \tag{17}$$

$$F(A^m) \approx F(A_0^m) + J^m(A^m - A_0^m), \tag{18}$$

where A_0^m is a random initial estimated vector of A^m. The initial estimated location must fall into the cover region of WSN. J^m is a Jacobian matrix. Combining formula (15) and (18), we can obtain the following relationship:

$$P^m - F(A_0^m) + J^m A_0^m = J^m A^m. \tag{19}$$

Let

$$U^m = P^m - F(A_0^m) + J^m A_0^m. \tag{20}$$

Then, the location of target node can be calculated as

$$A^m = ((J^m)^T J^m)^{-1} (J^m)^T U^m. \tag{21}$$

In order to obtain optimum solution of estimated location, the iteration method is used. In the iteration algorithm, the present location estimated vector can be the initial estimated vector for next iteration. The formula is

$$\begin{gathered} J_h^m A_{h+1}^m = P^m - F(A_h^m) + J_h^m A_h^m \\ h = 0,1,2,\cdots, \end{gathered} \tag{22}$$

where A_h^m and J_h^m are the coordinate vector of target nodes and Jacobian matrix at h-th iteration respectively. The error function of the iteration algorithm is shown in formula (23).

$$e_{h+1}^m = \left\| A_{h+1}^m - A_h^m \right\|^2 \tag{23}$$

When the value of the error function satisfies certain conditions, the iteration process is over. The conditions can be decided by the accuracy of localization systems that use the paper's localization algorithm.

5. Experimental Results

In our experiments, WSN is deployed to evaluate the performance of our proposed method. We set the experiment carried out on the Imote2 platform, which is developed by US-based CrossBow Inc. For the software platform, we choose TinyOS as the operating system, which is specially designed for WSN. The experimental environment selected is a 20×20 meters indoor space. There are 16 fixed nodes and a master node distributed in this region. According to the proposed localization algorithm, the master node transmits the information sent by fixed nodes to computer for estimating the location of target node.

The localization algorithm uses the iterative method, and the iteration termination conditions vary depending on the application scenario. In the experiment, the condition that forces the iterative computation procedure to be stopped is

$$\left| e_{k+1}^m - e_k^m \right| < 0.05. \tag{24}$$

When the absolute value of the error function difference between two consecutive iterations is less than 0.05, the iteration is over. At this time, the obtained vector A_{h+1}^m is the coordinates of the target node.

It is very important to analyze the localization error of the algorithm. We randomly deploy 16 target nodes. Performing our proposed algorithm and the method proposed in [6] that is used here as a benchmark for a comparative experimental study, the estimated x and y value results are shown in Fig. 1 and Fig. 2 respectively, and the distance estimation error is given in Fig. 3. In the Fig. 1 and Fig. 2, the squares are the actual x and y values of target nodes, and the asterisks are the calculated x and y values from the proposed method, and the plus signs are calculated x and y values from the method proposed in [6]. From the Fig. 1 and Fig. 2, it can be seen that the coordinates of target nodes evaluated by our proposed adaptive localization algorithm are more accurate than that evaluated by the method proposed in literature [6] both the abscissa and the ordinate.

Fig. 3 shows that the minimum distance between real location and estimated location of target nodes is about 0.02 m, and the maximum distance is not more than 0.35 m. Compare with the algorithms of references [6], our proposed algorithm can achieve the better performance. The reasons are that the average values of the parameters of signal propagation model calculated from all fixed nodes are used by the literature [6] in estimating the location of target nodes. However, we adopt the most suitable parameters of signal propagation model for target nodes in the proposed algorithm. Thus, no matter what location the target node is in, the proposed algorithm is able to use the model parameters of the closest to actual situation to estimate the location of target nodes.

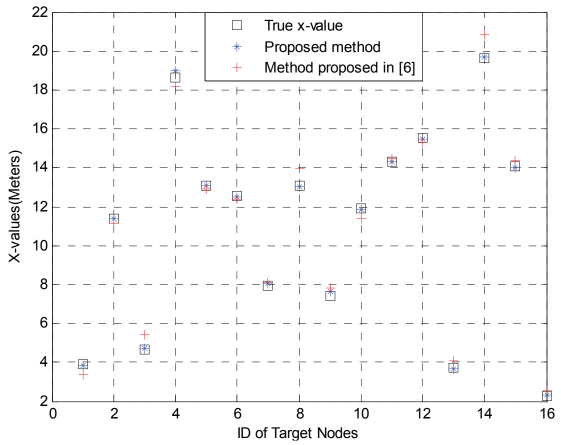

Fig. 1. The real location and estimated location of target nodes.

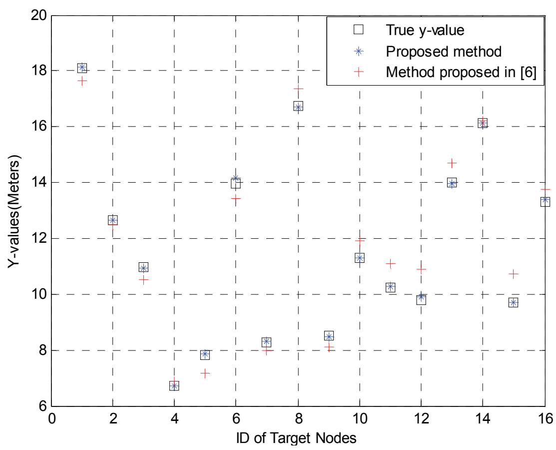

Fig. 2. The real location and estimated location of target nodes.

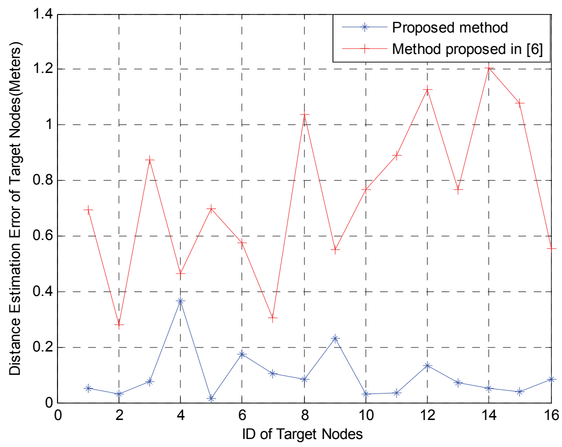

Fig. 3. The distance between real location and estimated location of target nodes.

6. Conclusions

In the paper, a RSSI-based adaptive localization algorithm for indoor WSN is proposed. In the algorithm, each fixed node calculates the local parameters of signal propagation model and sets up its parameter set, according to RSSI of radio signals radiating from two other fixed nodes, and the parameters can be updated online according to environmental variation. In localization phase, each fixed node searches the most suitable parameters of the signal propagation model from its parameter set according to RSSI value that it has received from the target node, and iteration method is applied to estimate the position of target node. The performance of the proposed algorithm is compared with others. The experimental results show that the proposed approach can achieve high location estimation accuracy.

Acknowledgements

This work was supported in part by Major Program of National Natural Science Foundation of China under Grant No. 61131004, and National Natural Science Foundation of China under Grant No. 51108060.

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