Location Estimation of Mobile User in Wireless Sensor Network Based on Unscented Kalman Filter

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***Abstract*—A strength prediction algorithm based on Unscented Kalman Filter (SPKF) is proposed to fuse the mobile localization estimation obtained from received signal strength in wireless sensor network. The algorithm is particularly suitable for indoor applications where the presence of furniture, objects, walls and the induced diffraction, reflection and multi-path effects. The Unscented Kalman Filter is used to predict the tendency of received signal strength, and cooperates with dynamic triangular location algorithm achieves an improved accuracy and provides a lower fluctuation of received signal strength than the grey prediction when mobile user is moving. It is also proved to grey prediction when mobile user is moving. It is also proved to be able to dramatically outperform and reduce the fluctuation of received signal strength when mobile user is moving.**

Keywords- wireless sensor networks; mobile localization; Unscented Kalman Filter;

I. INTRODUCTION

Determining the location of a mobile user is a fundamental problem in wireless sensor network. The outdoor location detection uses Global Positioning System (GPS) and generally is exploited in navigation, but in the building the GPS signal is not available. Wireless sensor network has evolved over last several years, and can easily deploy a number of sensor nodes in the building. It corresponds to the features of low power, low cost, low complexity and small size and provides mobility and flexibility of nodes, so it has many advantages to replace the traditional sensor and control nodes in the building.

The relative localization in mobile sensor networks is accomplished through triangulation of neighbor nodes using a common one-hop neighbor[1], and the authors propose algorithms for building a relative coordinate system based on a central node, while this work estimates positioning in a mobile environment without seed nodes, it is not applicable in mobility scenarios where directed motion is required. A method based on predictions is presented in [2], where nodes in the network use a dead reckoning model to estimate the movements of all other nodes. Position information is adjusted for granularity so that distant pairs of nodes maintain less accurate position information than pairs which are closer to each other. Right now, distance between sensor nodes can be estimated by using Time of Difference of Arrival (TDOA), Time of Arrival (TOA). However, these schemes require energy-consuming electronics and precise synchronization, which make them not feasible and economical for low-cost sensors [3]. Similar as TOA and TDOA technologies, AOA also rely on expensive and energy-consuming hardware which may be inappropriate for sensors with limited capabilities [4]. In the proposed localization schemes based on received signal strength (RSS) technology [5-6], a sensor can estimate its distance to several reference nodes according to the received signal strength from them. Though schemes with RSS technology do not require extensive hardware, common problems in Radio Frequency (RF) systems, such as multi-path fading, background interference and irregular signal propagation, may cause significant errors in estimated distances. Ren C.Luo use grey prediction with weight (WGP) to predict the tendency of RSS at run-time stage and present analysis of predicted RSS when mobile user is moving. Location algorithm with grey prediction method can achieve smaller mean distance [7-8]. Due to the model's dependence on the previous estimates, the location errors are cumulative, each node has to collect many samples before a good estimate can be made.

This paper discusses Unscented Kalman Filter (UKF) based location estimation algorithm for wireless sensor network. we mention only briefly particular location estimation algorithms. Instead, and focus on the accuracy prediction of RSS using UKF [9-10]. The strength prediction based on UKF (SPKF) algorithm can reduce the fluctuation of RSS when mobile is moving, and achieve higher accuracy location estimation than the grey prediction with weight method.

II. RADIO PROPAGATION MODEL

In order to estimate mobile user's location, we must obtain the estimation distance between the mobile user and sensor nodes, and put the estimation distance into localization algorithms to get the coordination of mobile user. The Maximum likelihood (ML) method [11] is often used to find the radio propagation model. Radio signal propagation is easy influenced by diffraction, reflection, and scattering of radio induced obstacles in a building. The Radio signal strength measurement is contaminated by the measuring error and the Non-Line-of-Sight (NLOS) error [12]. The measuring error result from the measuring processes in a noisy channel and can be improved with better signal-to-noise ratio (SNR). NLOS errors depend on the multipath-dominated environments and change from time to time.

We record the *RSS*s and distances between the sensor nodes and mobile user, and use ML method to find a propagation model for fading channel. The Measured signal strength fit Channel Model is obtained the by using the following equation

$$RSS(d) = RSS(d_0) - 10n\log(d/d_0) \tag{1}$$

Where $RSS(d)$ is the mean signal strength that received form the mobile user, $RSS(d_0)$ is the received signal strength in dB at a reference distance, and n is denoted the path loss exponent.

The estimation of the distance is written as

$$\hat{d} = d_0 10^{\frac{RSS(d_0)-RSS(d)}{10n}} \tag{2}$$

The $\hat{d}$ can be rewritten as

$$\hat{d} = d + X_\sigma \tag{3}$$

Where X_σ is the random variable that denoted the estimation error with variance σ, it increases with distance between the sensor node and mobile user.

III. Strength Prediction Based on Unscented Kalman Filter Algorithm

For tracking mobile user, the proposed SPKF approach utilizes the UKF to predict received signal strength. The UKF is an advanced application of the scaled unscented transformation; it is a recursive minimum mean-square-error (RMMSE) estimation to propagate the sigma points through the state equation to obtain some high order information.

The SPKF addresses the problem of trying to estimate the state $\bar{x}_k$ of a discrete-time controlled process that is modeled as a nonlinear auto-regression function

$$\boldsymbol{X_k} = \boldsymbol{F}\left(\boldsymbol{X_{k-1}}, \boldsymbol{w}\right) + \boldsymbol{A}\bullet v_{k-1} \tag{4}$$

Where $X_k = \left(x_{k-M+1}, ..., x_{k-1}, x_k\right)$, $x_k = RSS_k, \left(k = 1, ..., \mathrm{n}\right)$ denotes the true RSS at step k , n is the input number of RSSs. $\boldsymbol{w}$ is the time updating processing weight vector and $\boldsymbol{w} = \left(w_1, w_2, ..., w_k\right)$

The SPKF model the measured dynamic received signal strength of $RSS(d)$ as following equation

$$\boldsymbol{Y_k} = \boldsymbol{H(X_{k-1}, r) + n_k} \tag{5}$$

Where the measurement sequence is $\boldsymbol{Y}_k = (y_1, y_2, ..., y_n)$, y_k denotes the measurement at step k . $\boldsymbol{r}$ is the measure updating processing weight vector and $\boldsymbol{r} = \left(r_1, r_2, ..., r_k\right)$.

The random variables v_k and n_k represent the process and measurement noise (respectively). They are assumed to be independent (of each other), white, and with normal probability distributions which is shown as

$$p(v_k) \sim N(0, \boldsymbol{Q_k}) \tag{6}$$

$$p(n_k) \sim N(0, \boldsymbol{R_k}) \tag{7}$$

Where $\boldsymbol{Q_k}$ is the process noise covariance matrix, and R_k is the measurement noise covariance matrix. The initialization states are

$$\overline{RSS}_0 = \mathrm{E}\left[RSS_0\right] \tag{8}$$

Where $\mathrm{E}\left[\bullet\right]$ denotes the mean value operation and the autocorrelation matrix of RSS_0 can be expressed as

$$P_0 = \mathrm{E}\left[\left(RSS_0 - \overline{RSS}_0\right)\left(RSS_0 - \overline{RSS}_0\right)^{\mathrm{T}}\right] \tag{9}$$

Let

$$\boldsymbol{\bar{X}_0^a} = \mathrm{E}\left[RSS^a\right] = \left[\overline{RSS}_0^{\mathrm{T}} \quad 0 \quad 0\right]^{\mathrm{T}} \tag{10}$$

Where $RSS^a = \left[RSS^{\mathrm{T}} \quad v^{\mathrm{T}} \quad n^{\mathrm{T}}\right]$ and the autocorrelation matrix of RSS_0^a is

$$\boldsymbol{P}_0^a = \mathrm{E}\left[\left(RSS_0^a - \overline{RSS}_0^a\right)\left(RSS_0^a - \overline{RSS}_0^a\right)^{\mathrm{T}}\right] = \begin{bmatrix} P_0 & 0 & 0 \\ 0 & Q_0 & 0 \\ 0 & 0 & R_0 \end{bmatrix} \tag{11}$$

The models of the UKF can be expressed as

$$x_k = f(x_{k-1}, ..., x_{k-M}, w_k) + v_k \tag{12}$$

Where the model f (parameterized by w) was approximated by training a feed-forward neural network on the sequence. The residual error after convergence was taken to be the process noise variance.

Substitute (12)into(4), yields

$$\begin{bmatrix} x_k \\ x_{k-1} \\ \vdots \\ x_{k-M+1} \end{bmatrix} = \begin{bmatrix} f(x_{k-1}, ..., x_{k-M}, w_k) \\ \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & \ddots & 0 & \vdots \\ 0 & 0 & 1 & 0 \end{bmatrix} \bullet \begin{bmatrix} x_{k-1} \\ \vdots \\ x_{k-M} \end{bmatrix} \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \bullet v_{k-1} \tag{13}$$

Where $\boldsymbol{A} = \left[1, 0, ..., 0\right]^{\mathrm{T}}$ denotes the coefficient matrix of process noise.

Substitute (13) into(5), yields

$$y_k = h(x_{k-1}, ..., x_{k-M}, r_k) + n_k = \left[1 \quad 0 \quad \cdots \quad 0\right] \bullet \boldsymbol{X_k} + n_k \tag{14}$$

Where the model h (here parameterized by $r_k = 1$,)was using as a recurrent neural network on the state variable. Updating the iterative counter, let $k = k + 1$ and generate sigma points:

$$\chi_{k-1}^a = \left[\overline{RSS}_{k-1}^a \; \overline{RSS}_{k-1}^a \pm \sqrt{\left(n_a + \lambda\right) P_{k-1}^a}\right] \tag{15}$$

Where $\chi^a = \left[\left(\chi^{RSS}\right)^{\mathrm{T}} \quad \left(\chi^v\right)^{\mathrm{T}} \quad \left(\chi^n\right)^{\mathrm{T}}\right]^{\mathrm{T}}$, n_a is dimension of the random variable RSS , $\lambda = \alpha^2\left(n_a + \kappa\right) - n_a$ is a scaling parameter, α determines the spread of the sigma points around $\overline{RSS}$, κ is a secondary scaling parameter.

The time updating processing is

$$\chi_{k/k-1}^x = f\left(\chi_{k-1}^x, \chi_{k-1}^v\right) \tag{16}$$

Calculate the posteriori state estimates $\overline{RSS}_{k/k-1}$

$$\overline{RSS}_{k/k-1} = \sum_{i=0}^{2n_a} w_i^{(m)} \chi_{i,k/k-1}^x \quad (17)$$

And calculate the covariance estimates $\boldsymbol{P}_{k/k-1}$

$$\boldsymbol{P}_{k/k-1} = \sum_{i=0}^{2n_a} w_i^{(c)} \left[\chi_{i,k/k-1}^x - \overline{RSS}_{k/k-1} \right] \left[\chi_{i,k/k-1}^x - \overline{RSS}_{k/k-1} \right]^{\mathrm{T}} \quad (18)$$

The measure updating processing is

$$y_{k/k-1}^x = h\left(\chi_{k-1}^x, \chi_{k-1}^n \right) \quad (19)$$

$$\overline{y}_{k/k-1} = \sum_{i=0}^{2n_a} w_i^{(m)} y_{i,k/k-1}^x \quad (20)$$

Where $w_0^{(m)} = \lambda / \left(n_a + \lambda \right)$, $w_0^{(c)} = \lambda / \left(n_a + \lambda \right) + \left(1 - \alpha^2 + \beta \right)$, β is used to incorporate prior knowledge of the distribution of RSS (for Gaussian distributions, $\beta = 2$ is optimal). Where $w_{\mathrm{i}}^{(\mathrm{m})} = w_{\mathrm{i}}^{(\mathrm{c})} = 1 / \left[2\left(n_a + \lambda \right) \right]$, $i = 1, \ldots, 2n_a$. Then calculate the UKF gain $\boldsymbol{K}_{\boldsymbol{k}}$:

$$\boldsymbol{P}_{\overline{y}_k \overline{y}_k} = \sum_{i=0}^{2n_a} w_i^{(c)} \left[y_{i,k/k-1} - \overline{RSS}_{k/k-1} \right] \left[y_{i,k/k-1} - \overline{RSS}_{k/k-1} \right]^{\mathrm{T}} \quad (21)$$

$$\boldsymbol{P}_{x_k y_k} = \sum_{i=0}^{2n_a} w_i^{(c)} \left[\chi_{i,k/k-1} - \overline{RSS}_{k/k-1} \right] \left[y_{i,k/k-1} - \overline{y}_{k/k-1} \right]^{\mathrm{T}} \quad (22)$$

$$\boldsymbol{K}_{\boldsymbol{k}} = \boldsymbol{P}_{x_k y_k} \boldsymbol{P}^{-1}{}_{\overline{y}_k \overline{y}_k} \quad (23)$$

Using (23) the posteriori state estimate $\overline{RSS}_k$ can be concluded

$$\overline{RSS}_k = \overline{RSS}_{k/k-1} + \boldsymbol{K}_{\boldsymbol{k}} \left(y_k - \overline{y}_{k/k-1} \right) \quad (24)$$

Calculate the posteriori error covariance estimate $\boldsymbol{P}_k$

$$\boldsymbol{P}_k = \boldsymbol{P}_{k/k-1} - \boldsymbol{K}_{\boldsymbol{k}} \boldsymbol{P}_{\overline{y}_k \overline{y}_k} \boldsymbol{K}_k^{\mathrm{T}} \quad (25)$$

If $k < \mathrm{M}$, where M is the number of iteration, go on iteration. Then output the prediction result $\overline{RSS}_k$ of the moving object at $t = k$ and $RSS_{\mathrm{pred}k}^k = \overline{RSS}_k$

At last input the predicted signal strength $RSS_{\mathrm{pred}k}^k$, use the dynamic triangular (DTN) algorithm to estimate the location of mobile user via from the coordinate system. The DTN algorithm comprises the following steps:

a) Sensor nodes broadcast *RSS*s that receive from mobile user, and the sensor node which receives the strongest strength becomes the master node, the other nodes are called slave node. Then they build the local coordinate system.

b) The location server calculates the cost functions at each angle on the mapping circle and searches the minimum cost function, this angle on the mapping circle is the estimation location of mobile user.

IV. PERFORMANCE ANALYSIS AND COMPARISON

According to the analysis above, we obtained the following advantages of SPKF versus WGP:

First, in SPKF algorithm the UKF leads to more accurate results than the WGP, and in particular it generates much better estimates of the covariance of the states. Unlike other methods, it uses the true nonlinear models and rather approximates the distribution of the state random variable. The state distribution is represented by a Gaussian random variable (GRV). Particularly, the sigma points in UKF are constructed using a specific, deterministic algorithm. However, the WGP is based on grey model (GM) that describing grey system dynamic behavior. In grey theory, system dynamic model can be represented of $\mathrm{GM}\left(m, h \right)$, where m is order of grey differential equation and h is numbers of variable. Although the WGP algorithm has been widely applied to signal prediction, it has led to a general consensus that it is difficult to tune, and only reliable for systems which are almost linear.

Second, UKF is essentially a set of mathematical equations that implement a predictor-corrector type estimator that is optimal in the sense. It minimizes the estimated error covariance when some presumed conditions are met and has a high convergence rates without many iterations. The prediction accuracy can easily be measured by the error covariance matrix. But WGP algorithm has no such function.

The key metric for evaluating a localization technique is the accuracy of the location estimates. In order to illustrate the high accuracy of SPKF algorithm, in this paper the mean square error (MSE) is used to determine the performance of SPKF system and WGP system. At the Run-time stage we put the measured RSSs which generated from mobile user to the SPKF system, and then get the predicted RSS. WGP method used the following equation to obtain

$$RSS_{\mathrm{pred}w} = w_1 \times RSS_{\mathrm{pred}}^i + w_2 \times RSS^{i-1} \quad (26)$$

Where RSS_{pred}^i represents the i^{th} predicted received signal strength in grey prediction system. $RSS^{i\text{-}1}$ represents the $\left(i-1 \right)^{\mathrm{th}}$ original received signal strength. w_1 and w_2 denote the weighting of original and predicted received signal strength, and the other is SPKF. In the experiments, we let $w_1 = 0.5$ and $w_2 = 0.5$ and MSE have best performance.

We compare two methods of prediction, one is strength of weighted grey prediction $RSS_{\mathrm{pred}w}$, and the other is the strength which predicted by SPKF from equation(24), that is $RSS_{\mathrm{pred}k}^k = \overline{RSS}_k$. MSE_k and MSE_w are used to evaluate the accuracy of $RSS_{\mathrm{pred}k}$ and $RSS_{\mathrm{pred}w}$ in SPKF system and WGP system respectively:

$$\mathrm{MSE}_k = \frac{1}{N} \sum_{i=1}^{N} \sqrt{(RSS_{\mathrm{pred}k}^i - RSS^i)^2} \quad (27)$$

$$\mathrm{MSE}_w = \frac{1}{N} \sum_{i=1}^{N} \sqrt{(RSS_{\mathrm{pred}w}^i - RSS^i)^2} \quad (28)$$

Where, N is the number of input. The results are shown in next section.

V. SIMULATION RESULTS

Assuming the $6\mathrm{m} \times 10\mathrm{m}$ indoor environment has already deployed 6 static sensor nodes where the mobile user is placed in. The positions of the static sensor nodes are known. And the mobile user move in the same circle region whose radius is 5m.

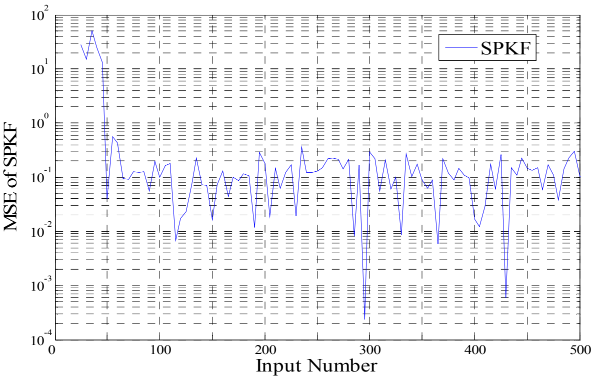

Figure 1. The MSE experiment result

Figure. 1 shows the simulation experiment result of MSE_k versus the input number of RSS. After input 50 RSS, MSE_k is approximately of 0.10, so it is much lower than MSE_w which is 2.49 by inputting 300 RSSs. Obviously SPKF algorithm has a more accuracy prediction result than WGP algorithm.

It displays the value of $\boldsymbol{P}_k$ versus the iteration in Figure 2. UKF has settled from the initial (rough) choice of 1 to approximately 0.1 (dB^2), by the 15th iteration. By the 50th iteration, it has already settled to approximately 0.02 (dB^2). So let the UKF iterate 15 times.

The Figure 3 illustrates the prediction accuracy of comparison among WGP, SPKF and original RSS , this experiment computes 50 RSS samples. And it can be seen from the predicted result that the predicted strength of grey prediction with weight is a little fluctuant, but the predicted RSS of SPKF algorithm is close to original strength. When propagated through the true nonlinear system, in SPKF system the sample points capture the posterior mean and covariance accurately to the 2nd order for any nonlinearity, with errors only introduced in the 3rd and higher orders. So there are few large errors in the estimated statistics of the posterior distributions of the states. But, the WGP algorithm is designed to predict the current estimate on all of the past measurements. It causes cumulated error easily.It can be concluded that SPKF has a better performance in the accuracy aspect of prediction.

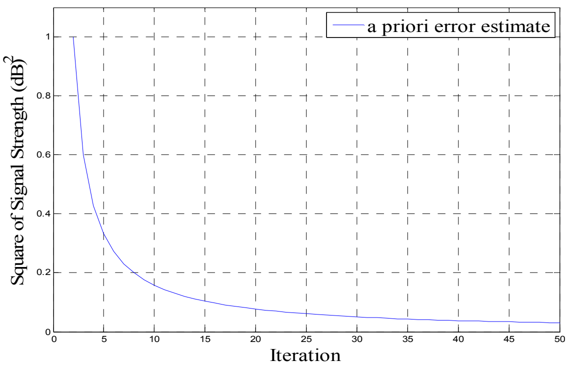

Figure 2. Convergence rates of UKF

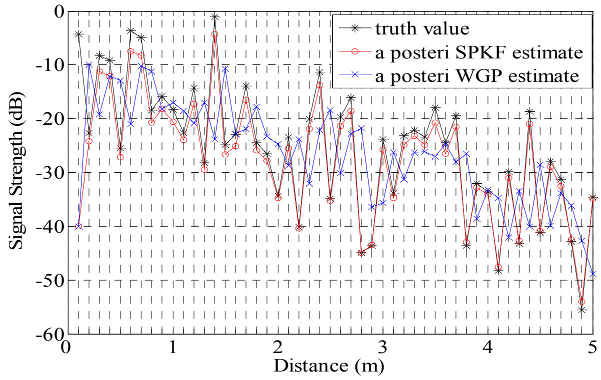

Figure 3. The SPKF, WGP experiments results

VI. CONCLUSION

A Strength Prediction Based on Unscented Kalman Filter algorithm (SPKF) is proposed for attenuation of radio signal strength, it achieves robust mobile localization even in the presence of multipath and NLOS. Compared to WGP algorithm, SPKF allows sensors to estimate the mobile user's location with less storage computation, fluctuation while mobile user is moving. Simulation results show that the proposed algorithm significantly improves the localization accuracy at a comparable level of complexity.

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