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Location Estimation of Mobile Devices in CSS WPANs

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Abstract

The location estimation of mobile devices in low rate WPAN is specified as optional function and the devices complied with CSS specification have been used widely in many application of the sensor networks. The performance of location estimation using CSS devices are reported in many researches. We have studied post processing algorithms using extended Kalman filter to improve the accuracy of the locations of mobile devices. We consider a new parameter for frequency offset of device. In case of TOA and TDOA, we experienced and simulated our algorithm, and find that the algorithm show better performance. In this paper, we describe our algorithms and those performances.

Keywords: *Location Estimation, Chirp Spread Spectrum, Extended Kalman filter, TOA, TDOA*

1. Introduction

In many sensor network applications, location based services are frequently required. IEEE 802.15.4 has defined a low data rate, low power consumption, low cost medium access control (MAC) and a physical layer (PHY) specification for Wireless Personal Area Networks (WPANs). Also alternate PHYs employing chirp spread spectrum (CSS) or ultra-wide band (UWB) signaling have been defined in IEEE802.15.4a [1]. The UWB [1, 2] and CSS signals can also be used for data communication and ranging. The specification can be applied to the applications [3, 4] of wireless sensor network (WSN). For the UWB, the ranging function and algorithms are defined in detail. And enhancements of location estimation have been studied in two-way ranging (TWR) [5, 6] and one-way ranging [5] by using frequency offset. In the CSS system, the calculation of the time of flight (TOF) is based on the method of symmetric double-sided two-way ranging (SDS-TWR). With TWR or SDS-TWR, ranging does not require time synchronization between node pairs and decreases the measurement errors caused by clock drift. A localization system based on CSS is suitable for a low-cost indoor localization system. However, the distances measured by CSS ranging are noisy and biased. If the measured distances had only noise, we could obtain the least mean square solution of the coordinates of a mobile node through the least square (LS) algorithm, based on the formulas derived from a trilateration. Although noise modifies a measured distance, the average of these modifications is zero according to the general assumption of zero mean noise. The bias changes a distance to another value on average. Simple location estimation with CSS devices is hard to expect an accuracy of less than a meter in (10m x 10m). Post processing [8, 9] such as Kalman filter may be used to improve the accuracy. The biased ranging algorithm [9] can reduce biased ranging error. Location based service(LBS) has been provided by satellite and it can be deployed indoor and underwater[10] with WPAN. In this paper, we describe our location estimation algorithm using extended

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Kalman filter with frequency offsets of devices. We thought that the trilateration is not sufficient to enhance the localization and the bias is mainly derived from frequency offsets of anchor and mobile nodes. We need a kind of digital filter such as Kalman filter to improve the accuracy. The problem is that how to manage the frequency offset to algorithm. In this paper, we describe enhancement of localization using extended Kalman filter (EKF). The simulation using actual measured data gathered from 10mx10m area is performed with Matlab tool.

2. Positioning System

A pre-installed network can be configured such that the mobile devices within a deployment area can maintain connectivity with anchor devices positioned at known locations. Clock synchronization between anchor devices enables one-way ranging (OWR) in conjunction with the time difference of arrival(TDOA) technique as opposed to time of arrival(TOA). An example of a wireless sensor network supporting LBS is shown in Figure 1.

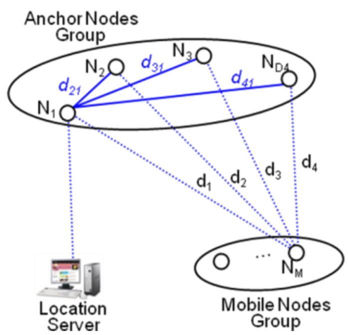


Figure 1. An example of a wireless sensor network supporting LBS

In the figure, the sensor network consists of anchor devices, mobile devices and a location server. Device A is connected to a location server and becomes a reference device to construct device pairs. The locations of devices are (a_{11},a_{12}), (a_{21},a_{22}), (a_{31},a_{32}), (a_{41},a_{42}) and (x_1,x_2) respectively. The distances between a mobile device and the anchor devices are d_1, d_2, d_3 and d_4 respectively. The differences of distances between the anchor devices and a mobile device from a reference anchor device, N_1, are described as d_{21}, d_{31} and d_{41} respectively. We assume that most calculations for ranging and positioning would be performed at the location server which supports extended Kalman filter(EKF) with frequency offsets.

3. Proposed Algorithm

3.1. Extended Kalman Filter

Non-linear state equations are as follow.

$$x_{i+1} = f_i(x_i, w_i) = x_i + w_i$$

$$y_i = h_i(x_i, v_i)$$

Here, x_i, y_i, w_i, v_i, $f_i()$ and $h_i()$ is state vector, measurements vector, process noise vector, measurement noise vector, nonlinear transition matrix and nonlinear measurement matrix respectively. Correlation matrixes of process noise and measurement noise are defined as Q_i and R_i respectively.

$$Q_i = E[w_i w_i^T]$$

$$R_i = E[v_i v_i^T]$$

Correlation matrix of expected error for states is defined as follows.

$$P_{i|i-1} = E[(x_i - \hat{x}_{i|i-1})(x_i - \hat{x}_{i|i-1})^T]$$

Here, $\hat{x}_{i|i-1}$ is a estimated state.

Recursive equations for extended Kalman filter begin with initial values of $x_{1|0}$, $P_{1|0}$ and described shortly below.

$$e_i = y_i - h_i(\hat{x}_{i|i-1}, 0)$$

$$K_i = P_{i|i-1} H_i^T \left[H_i P_{i|i-1} H_i^T + R_i \right]^{-1}$$

Here, H_i is Jacobian matrix of $h_i(x_i, v_i)$.

$$H_i = \frac{\partial h_i(x_i, v_i)}{\partial x_i} \Big|_{x_i = \hat{x}_{i|i-1}}$$

$$\hat{x}_{i|i} = \hat{x}_{i|i-1} + K_i e_i$$

$$P_i = P_{i|i} = \left[I - K_i H_i \right] P_{i|i-1}$$

$$P_{i+1|i} = F_i P_i F_i^T + Q_i$$

Here, F_i is Jacobian matrix of $f_i(x_i, w_i)$.

$$F_i = \frac{\partial f_i(x_i, w_i)}{\partial x_i} \Big|_{x_i = \hat{x}_{i|i}}$$

3.2 Proposed Algorithm for TOA

We assume that there are m anchor devices preinstalled at fixed locations in n dimensional coordinate. To reduce ranging error, frequency offset compensation should be considered. If the frequency offsets of anchor devices are added as states, the system can't make sure controllable or observable. In our Kalman filter model, the frequency offsets of anchor devices are divided into a common variable one and a constant one with respect to each anchor device. As a result, the state vector includes the coordinate of a mobile device and a common frequency offset as states in a proposed model. The state vector x_i at time i and the coordinate of k_{th} anchor device a_k are shown.

$$x_i = \begin{bmatrix} x_1(i) \\ : \\ x_n(i) \\ r(i) \end{bmatrix}, \quad a_k = \begin{bmatrix} a_{k1} \\ : \\ a_{km} \end{bmatrix}$$

here, $[x_1(i),..,x_n(i)]^T$ describes a location of mobile device and $r(i)$ represents a common frequency offset of anchor devices.

In TOA(Time of Arrival) measurement, the distance between the mobile device and k_{th} anchor device, $d_k(i)$, and measurement vector y_i at time i, is shown.

$$d_k(i) = (1 + r(i) + f_k)\sqrt{(x_1(i) - a_{k1})^2 + ... + (x_n(i) - a_{kn})^2}$$

Here, f_k represents the constant frequency offset of k_{th} anchor device.

Therefore, the measurement vector can be described as follows.

$$y_i = \begin{bmatrix} y_1(i) \\ y_2(i) \\ : \\ y_m(i) \end{bmatrix} = h_i(x_i, v_i) = d_i(x_i) + v_i = \begin{bmatrix} d_1(i) \\ d_2(i) \\ : \\ d_m(i) \end{bmatrix} + v_i$$

The distance $d_k(i)$ includes constant frequency offset f_k which represents the frequency offset of k_{th} anchor device with the state of common frequency offset variable $r(i)$. The constant frequency offset of each anchor device can be obtained on the way of ranging and communication. As a result, this proposed model apply individual frequency offset of each anchor device to the state of EKF while the biased ranging model [7] apply a common frequency offset of anchor devices to the state of EKF. The Jacobian matrix of $h_i(x_i, v_i)$, H_i is shown with examples.

$$H_i = \begin{bmatrix} H_{11}(i) & : & H_{1n}(i) & H_{1r}(i) \\ : & : & : & : \\ H_{m1}(i) & : & H_{mn}(i) & H_{mr}(i) \end{bmatrix}$$

$$H_{11}(i) = \frac{\partial d_1(x_i, v_i)}{\partial x_1}\Big|_{x_i = \hat{x}_{i|i-1}}$$

$$H_{1r}(i) = \frac{\partial d_1(x_i, v_i)}{\partial r}\Big|_{x_i = \hat{x}_{i|i-1}}$$

The Jacobian matrix of $f_i(x_i, w_i)$, F_i is shown. Actually $F_i = I$.

$$F_i = \begin{bmatrix} F_{11}(i) & : & F_{1n}(i) & F_{1r}(i) \\ : & : & : & : \\ F_{m1}(i) & : & F_{mn}(i) & F_{mr}(i) \end{bmatrix} = I$$

$$F_{11}(i) = \frac{\partial f_1(x_i, w_i)}{\partial x_1}\Big|_{x_i = \hat{x}_{i|i}}$$

$$H_{1r}(i) = \frac{\partial f_1(x_i, w_i)}{\partial r}\Big|_{x_i = \hat{x}_{i|i}}$$

3.3. Proposed Algorithm for TDOA

As shown in proposed algorithm for TOA, our algorithm can be applied to TDOA (Time Difference of Arrival). The difference of distances between the mobile device and k_{th} anchor device, and the mobile device and reference anchor device may be measured by active or passive one way ranging. In this case, we define the measurement vector y_i at time i as follow.

$$y_i = \begin{bmatrix} y_1(i) \\ y_2(i) \\ : \\ y_m(i) \end{bmatrix} = h_i(x_i, v_i) = D_i(x_i) + v_i = \begin{bmatrix} D_1(i) \\ D_2(i) \\ : \\ D_m(i) \end{bmatrix} + v_i$$

Here, the difference of distances, $D_k(i) = d_k(i) - d_{ref}(i)$, can be described with frequency offsets as follows..

$$D_k(i) = (1 + r(i) + f_k)\sqrt{(x_1(i) - a_{k1})^2 + \ldots + (x_n(i) - a_{kn})^2} - (1 + r(i) + f_{ref})\sqrt{(x_1(i) - a_{ref\cdot 1})^2 + \ldots + (x_n(i) - a_{ref\cdot n})^2}$$

The Jacobian matrix of measurement is shown with examples.

$$H_i = \begin{bmatrix} H_{11}(i) & : & H_{1n}(i) & H_{1r}(i) \\ : & : & : & : \\ H_{m1}(i) & : & H_{mn}(i) & H_{mr}(i) \end{bmatrix}$$

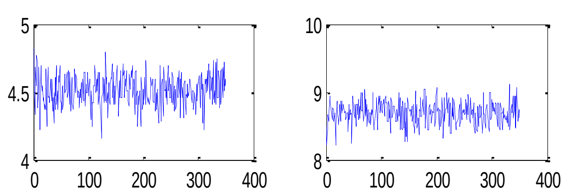
$$H_{11}(i) = \frac{\partial D_1(x_i, v_i)}{\partial x_1}\bigg|_{x_i = \hat{x}_{i|i-1}}$$

$$H_{1r}(i) = \frac{\partial D_1(x_i, v_i)}{\partial r}\bigg|_{x_i = \hat{x}_{i|i-1}}$$

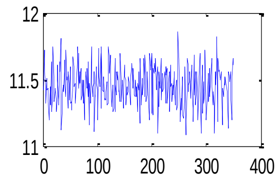
4. Experiment and Simulation

Distance measurement using CSS devices has been experienced with 5 anchor devices and a mobile device in (10m x 10m x 2.5m) space. And we evaluate our proposed Kalman filter model with measured distance data in computer simulation. We simulated algorithms of normal EKF, a biased ranging model with a common frequency offset variable, and our proposed model and compared the performances of 2 dimension EKF(2D only), 2D with a common frequency offset(2D biased), 3D only, 3D with a common frequency offset(3D biased), and 3D with proposed frequency offset compensation (3D foc).

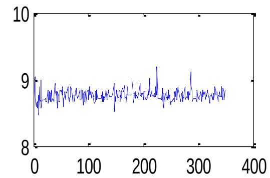
Figure 2 shows actual measured data which are obtained in a good environment. We located the mobile device to a fixed position and measured the distance about 350 times with 5 anchor devices. In this experiment, the coordinate of the mobile device is (2.5, 2.5, 1.8) in meter. The anchor devices are located at (5, 5, 2.5), (-5, 5, 2.5), (-5, -5, 0.5), (5, -5, 0.19) and (0, -4.5, 1.3) in meter. The distances from the mobile device to anchor device 1, anchor device 2, anchor device 3, anchor device 5 and anchor device 5 are shown in (a), (b), (c), (d) and (e) respectively.



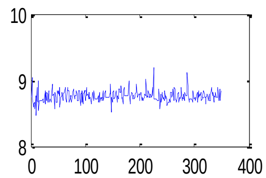
(a) Anchor device 1 (b) Anchor device 2



(c) Anchor device 3



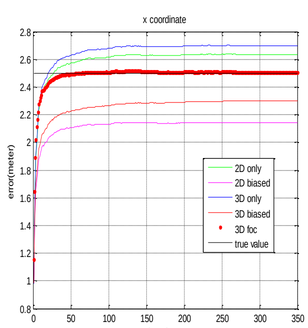
(d) Anchor device 4



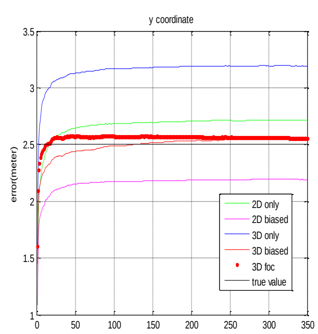
(e) Anchor device 5

Figure 2. Examples of measured data

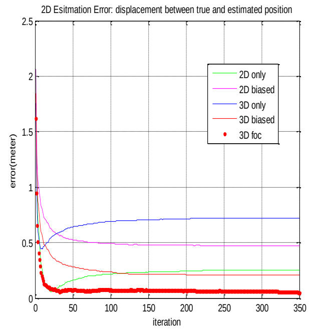
Figure 3 shows parts of TOA results. The errors of x axis, y axis and distance are shown in (a), (b) and (c). The performances are compared with 2 dimension EKF(2D only), 2D with a common frequency offset(2D biased), 3D only, 3D with a common frequency offset(3D biased), 3D with proposed frequency offset compensation(3D foc) and true value. In Figure 3 (a) and (b), the performances of 3D only, 2D only, 3D foc, 3D biased, and 2D biased are shown from top to bottom. The true values are 2.5 meter. In the figure, the normal EKF gives the location error about 30cm, biased ranging EKF gives about 20cm, and our proposed EKF gives less than 10 cm. Proposed model shows better performance which points almost exact location of the mobile device. The states of 2D biased (common biased EKF) and 2D foc (individual biased EKF), which represent a biased ranging parameter or a common frequency offset, show very similar changes in (d). It is shown that the state of 2D foc is close to zero offset.



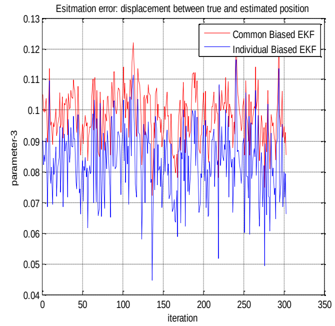
(a) Error of x axis



(b) Error of y axis



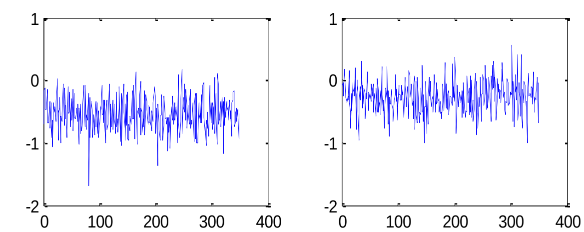
(c) Error of distance



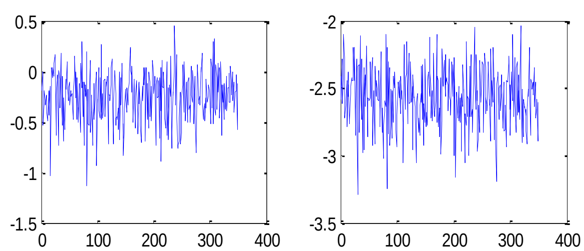
(d) Common state of frequency offset

Figure 3. Errors and a common frequency offset for TOA

Figure 4 and 5 show parts of TDOA results with a mobile device and 5 anchor devices. In this experiment, the coordinate of the mobile device is (0, 0, 1.8) in meter. The anchor devices are located at (5, 5, 2.5), (-5, 5, 2.5), (-5, -5, 0.5), (5, -5, 0.19) and (0, -4.5, 1.3) in meter. Figure 4 shows the difference of distances. The difference of distances from the mobile device to anchor device 2 and from the mobile device to anchor device 1, (distance from the mobile device to anchor device 2) minus (distance from the mobile device to anchor device 1), is shown in (a). Those of anchor device 3 and anchor device 1, anchor device 4 and anchor device 1, anchor device 5 and anchor device 1, are shown in (b), (c) and (d) respectively.



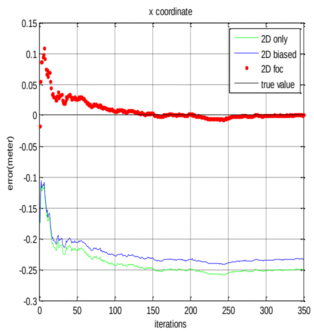
(a) Anchor device 2 and 1 (b) Anchor device 3 and 1



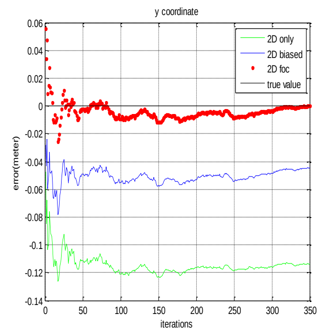
(c) Anchor device 4 and 1 (d) Anchor device 5 and 1

Figure 4. Differences of distances

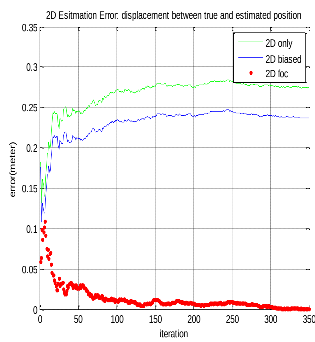
Figure 5 shows parts of TDOA results. The errors of x axis, y axis and distance are shown in (a), (b) and (c). The performances are compared with 2 dimension EKF (2D only), 2D with a common frequency offset (2D biased), 2D with proposed frequency offset compensation (2D foc) and true value. In Figure 5 (a) and (b), the performances of 2D foc, true value, 2D biased, and 2D only are shown from top to bottom. In the figure, our proposed method, 2D foc, shows better performance to point almost exact location. The error of location in 2 dimension is shown in (d). It is shown that the estimated points of 2D foc are scattered very close to true position. The states of 2D biased and 2D foc are shown in (e). It is shown that the state of 2D foc is crossing zero offset.



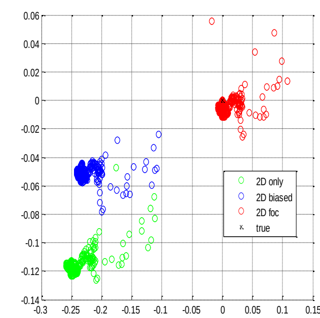
(a) Error of x axis



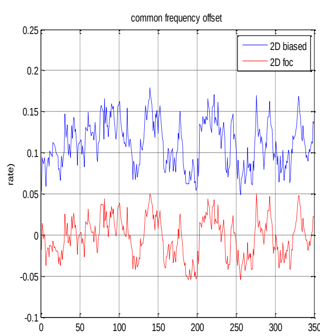
(b) Error of y axis



(c) Error of distance



(d) Error of location (true location is (0, 0)



(e) Common state of frequency offset

Figure 5. Positioning errors for TDOA

5. Conclusions

In this paper, we have studied to enhance the accuracy of location estimation using CSS devices. The post processing with frequency offset compensation using adaptive digital filter such as extended Kalman filter gives outstanding performance. The state parameter of common frequency offset compensates the bias error. Consideration of frequency offset for individual anchor device contributes to estimate accurate location. This result shows that CSS devices may be used for accurate location estimation. The algorithm may be applied to an actual positioning system.

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