

Investigations on real time RSSI based outdoor target tracking using kalman filter in wireless sensor networks

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ABSTRACT

Target tracking is essential for localization and many other applications in Wireless Sensor Networks (WSNs). Kalman filter is used to reduce measurement noise in target tracking. In this research TelosB motes are used to measure Received Signal Strength Indication (RSSI). RSSI measurement doesn't require any external hardware compare to other distance estimation methods such as Time of Arrival (TOA), Time Difference of Arrival (TDOA) and Angle of Arrival (AoA). Distances between beacon and non-anchor nodes are estimated using the measured RSSI values. Position of the non-anchor node is estimated after finding the distance between beacon and non-anchor nodes. A new algorithm is proposed with Kalman filter for location estimation and target tracking in order to improve localization accuracy called as MoteTrack In/Out system. This system is implemented in real time for indoor and outdoor tracking. Localization error reduction obtained in an outdoor environment is 75%.

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1. INTRODUCTION

A wireless sensor network is composed of a large number of inexpensive, low-power and tiny sensors, which are randomly and densely deployed in the surveillance area [1]. These tiny sensors, which consist of sensing, data processing, and communicating components, collaboratively monitor the event of interest, process the sensed data, and provide resultant information about the monitored events for a number of potential applications, ranging from battlefield monitoring and environmental surveillance to health care [2-5]. Object tracking and localization are the important problems of WSNs [6, 7]. Energy consumption and accuracy enhancement are the recent concerns in WSN. Localization algorithms are classified as range based and range free localization. Range free localization does not require distance estimation. There are four basic range based techniques in WSN, namely AOA, TOA, TDOA and RSSI. RSSI based localization is the cost-effective implementation because no extra hardware required for distance measurement compare to other ranging techniques. But the drawback of RSSI based localization is the relatively lower accuracy. Many localization algorithms have been introduced to improve the localization accuracy [8-10].

The rest of the paper is organized as follows: Section 2 gives the Literature review. Section 3 presents overview of MoteTrack In/Out system and it explains the experimental setup used in this work. In Section 4 describes about distance and position estimation methods respectively. Section 5 introduces Kalman filter and section 6 focuses on MoteTrack In/Out system algorithm. Section 7 the results from outdoor environment is provided. Conclusion is provided at the end of paper.

2. RELATED WORK

In [11], an enhanced version of Disk Overlapping localization scheme is proposed by attaching mass coefficients to each point of the possible locations in the region. The position estimation is derived in [12], as weighted least square problem and the location estimates are computed in a decentralized manner. Location estimation may also be defined in a dynamic scenario with the help of location tracking of a single mobile node (MN). With the information provided by previous locations and the mobility of nodes enable us to gain better estimation accuracy and a smoother trajectory in this approach of location tracking. Kalman Filter (KF) has been widely utilized for modeling the tracking of mobile nodes in the literature.

A Unified Kalman Tracking (UKT) algorithm is introduced in [13]. As this algorithm combines the previously proposed two-step least square method into KF state formulation and provides a simultaneous solution to the location estimation and tracking problems. Considering RSS variations, [14] has the SNRs at sensor nodes by a 2nd order polynomial function for their specific experimental setup. Later, KF applied to the predicted SNRs to track position changes. In [15] the tracking task of a mobile node is also modeled by KF. Lateralization with nearest three estimated nodes gives advantage to estimate the coordinates of the object. This has been experimented for straight or circular movements of the mobile nodes. Another proposed method in [16] has improved the performance of KF by renovating the estimated velocity in state equations through a direction finding process. In this paper, an adaptive Mote Track InOut tracking technique is developed to track the variations of the location estimations obtained. The initially modeled KF has been modified to account for the convergence requirement, uncertainties about system dynamic model and noise description. The proposed adaptive Kalman tracking scheme can well adapt to the rapid changes of movement and environment [17-19].

3. EXPERIMENTAL SET UP OF MOTE TRACK INOUT SYSTEM

In an indoor environment, for a moving target the localization error using Log Normal Shadowing Model (LNSM), Kalman filter and proposed method is 2.231m, 1.007m and 0.818m respectively. The localization error is reduced using proposed method but over lapping occurred in the tracking path. MoteTrack InOut is used and it is found that localization error is 0.570m and there is no overlapping in tracking path. Localization error reduction obtained using the proposed method along with the Kalman filter for a moving target is 1.66m when compared to LNSM [20]. The outdoor experiments are conducted in an open play ground. Ground is surrounded by number of trees and plants. Figure 1 show the experimental test bed set up of MoteTrack InOut system. It consists of four beacon nodes and one mobile node.

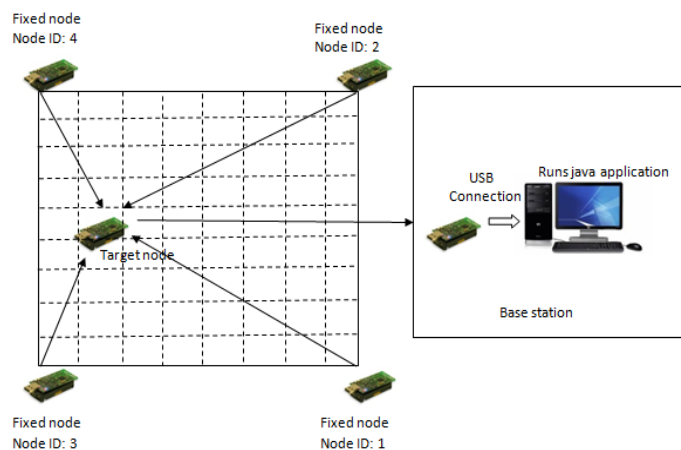


Figure 1. The experimental test bed

As a node TelosB mote is employed. It is a low power embedded device with chipcon CC2420 [21, 22]. It provides a digital received signal strength indicator (RSSI) that may be read any time. TelosB mote has a USB port, applying that it is connected to PC or laptop. Operating system for this mote is Tiny OS. We can develop a program in PC or laptop applying NesC language and upload a program into the TelosB mote as well as erase a program and load a new program. Beacon node will send a empty packet periodically to the mobile node. This periodic message consists of two information's such as source ID and

power level. There are eight power levels used in TelosB mote. The highest and default power level is 31 and its equivalent value in dBm (decibel-mill watt) and mill watts is 0 and 1 respectively. The beacon nodes are fixed at the four places of the ground with coordinates (0, 1), (0, 2.5), (1, 7.1), (2.5, 7.1). The moving target node is carried by a person. The walking target traverses the corridor at a varying velocity. The RSSI measurements from the anchor nodes are collected and forwarded to the sink node. The sink node is connected to PC where the localization algorithm is implemented.

4. DISTANCE AND POSITION ESTIMATION

Log normal shadowing model (LNSM) is used to estimate distance between beacon node and unknown node. The measured RSSI values are used in LNSM to find distance [23, 24].

$$P_L(d) = P_t(\text{dBm}) - P_r(d)(\text{dBm}) \quad (1)$$

P_L - Total path loss in dB; P_t - Transmitted power in dBm; P_r - Received power in dBm. Propagation model used in wireless sensor network is given by

$$P_L(d) = P_L(d_0) + 10n \log(d/d_0) + X_\sigma \quad (2)$$

Where ' $P_L(d_0)$ ' is the path loss at the reference distance d_0 in dB, For this experiment ' d_0 ' is taken as 1m, ' d ' is the distance from sender, ' n ' is the path loss exponent, ' X_σ ' is the zero-mean Gaussian random variable. Path loss exponent measures the rate at which the RSS decreases with distance, and its value depends on the specific propagation environment

$$P_r(d) = A - 10n \log(d) \quad (3)$$

Where $A = P_t - P_L(d_0)$ is the received signal at 1m distance. Linear regression analysis is used to compute ' A ' and σ value based on the measured data. The RSSI values are collected at the target node which is at known distances away from the Beacon nodes. Cramer's rule can be used to find the values of A and n .

$$T = (M^T M)^{-1} M^T R \quad (4)$$

$$T = \begin{bmatrix} A \\ n \end{bmatrix}, M = \begin{bmatrix} 1 & 10 \log d_1 \\ 1 & 10 \log d_2 \\ 1 & 10 \log d_3 \\ 1 & 10 \log d_4 \end{bmatrix}, R = \begin{bmatrix} \text{RSSI}_1 \\ \text{RSSI}_2 \\ \text{RSSI}_3 \\ \text{RSSI}_4 \end{bmatrix}$$

Where d_1, d_2, d_3, d_4 represent the distances between the target and the respective beacon nodes and $\text{RSSI}_1, \text{RSSI}_2, \text{RSSI}_3, \text{RSSI}_4$ are the RSSI mean values collected from the beacon nodes. The below equation is used to calculate distance from RSSI measurements.

$$d = 10^{\frac{(A - P_r)}{10n}} \quad (5)$$

The above equation is used to calculate distance from RSSI measurements. Where ' n ' - Path loss exponent; P_r - Received power in dBm; Multilateration is implemented to find the position of a unknown node. Four beacon nodes positions are kept at reference to find the unknown node's position. The multilateration method has been selected due to its good computational cost-accuracy trade-off [25]. If the beacon nodes are located at $(x_1, y_1), (x_2, y_2), (x_3, y_3), (x_4, y_4)$ then the position of the target (x, y) can be obtained using (6) as

$$\begin{aligned} d_1^2 &= (x - x_1)^2 + (y - y_1)^2 \\ d_2^2 &= (x - x_2)^2 + (y - y_2)^2 \\ d_n^2 &= (x - x_n)^2 + (y - y_n)^2 \end{aligned} \quad (6)$$

5. KALMAN FILTER

The objective of the Kalman filter is to minimize the mean square error between the actual and estimated data. It estimates the states of a process in two steps, predictor state and corrector state [26, 27]. Predictor state: This state calculates an estimate of the future state of the system from the previous state estimate.

$$\text{Update expected value of } X \quad X_k = AX_{k-1} + BU \quad (7)$$

Update error covariance matrix

$$P_k = AP_{k-1}A^T + Q \quad (8)$$

Where, X_k is state estimate at step $k = \begin{bmatrix} \text{positionX} \\ \text{positionY} \\ \text{velocityX} \\ \text{velocityY} \end{bmatrix}$

A ($n \times n$) matrix that relates the step of $k-1$ to current state k

A is taken as $\begin{bmatrix} 1 & 0 & \Delta t & 0 \\ 0 & 1 & 0 & \Delta t \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$, Δt represents the sampling period, B ($n \times 1$) matrix that relates U to the state

X , B is taken as $\begin{bmatrix} \Delta t^2/2 \\ \Delta t^2/2 \\ \Delta t \\ \Delta t \end{bmatrix}$, Where ' U ' is the optional control input; ' P_k ' is the error covariance; ' Q ' is

the process noise covariance.

Corrector (Measurement update) state: First step in this state is calculation of Kalman gain. The second step is to update expected value and the final step is updation of error covariance matrix.

$$\text{Compute Kalman gain } K_k = P_{k-1}H^T(HP_{k-1}H^T + R)^{-1} \quad (9)$$

$$\text{Update expected value } X_k = X_{k-1} + K_k(Z_k - HX_{k-1}) \quad (10)$$

$$\text{Update error covariance } P_k = (1 - K_kH)P_{k-1} \quad (11)$$

$$H(m \times n) \text{ matrix that relates the state } X_k \text{ to the measurement } Z_k \text{ by } Z_k = HX_k + G \quad (12)$$

Measurement noise covariance is represented by random variable ' G '. Q and G are assumed to be independent (of each other), and with normal probability distributions. In practice, the process noise covariance and measurement noise covariance matrices might change with each time step or measurement, however here we assume they are constant. The time update projects the current state estimate ahead in time. The measurement update adjusts the projected estimate by an actual measurement at that time. The filter works in a recursive manner. After each time and measurement update, the steps are repeated with the previous posterior estimates used to project or predict the new a priori estimates. The Kalman filter recursively generate a current estimate based on all of the past measurements.

6. MOTE TRACK IN-OUT SYSTEM

Flow diagram of target tracking using MoteTrack InOut system is shown in Figure 2. TelosB motes are used to measure real time RSSI values in an outdoor environment. After distance and position estimation using these measurements, position error is calculated. In order to reduce position error a new algorithm is developed. Kalman filter is applied after this algorithm to track the target and to reduce the measurement error. The MoteTrack InOut system works upon the following algorithm.

- 1) Collect RSSI values from beacon nodes and calculate the average of RSSI measurements of each beacon node. Find path-loss exponent ' n ' and ' A '.
- 2) Estimate distance from log normal shadowing model
- 3) Find distance error (D_E).
 $D_E = \text{Actual distance } (d_A) - \text{Calculated distance } (d_C)$
- 4) Find average distance error (A_{DE}).

$$A_{DE} = \frac{\text{Actual distance } (d_A) - \text{Calculated distance } (d_C)}{\text{Total number of measurements taken } (N)}$$

- 5) Average distance error A_{DE} is negative value,
 - a. If the distance error (D_E) is positive, A_{DE} will be added to D_E . Then the Resultant error reduction (RE_R) is
 $RE_R = D_E + (-A_{DE})$
 - b. If D_E is negative, A_{DE} will be subtracted from D_E . Then the RE_R is
 $RE_R = -D_E - (-A_{DE})$.
- 6) A_{DE} is positive value,
 - a. If D_E is negative, A_{DE} will be added to D_E . Then the RE_R is
 $RE_R = -D_E + A_{DE}$
 - b. If D_E is positive, A_{DE} will be subtracted from D_E .
 $RE_R = D_E - A_{DE}$.
- 7) If RE_R is greater than the D_E value, then D_E is considered as RE_R . Calculate average distance error reduction (AE_R).
- 8) Calculate the percentage of error reduction from AE_R and A_{DE} .
- 9) Find node's position and position error P_E

$$P_E = \frac{\sum_{k=1}^N \sqrt{(x_k - x_{cal_k})^2 + (y_k - y_{cal_k})^2}}{N}$$

(x_{cal_k}, y_{cal_k}) is the calculated position and (x_k, y_k) is the actual position of the target at k^{th} position.

When position error (P_E) is minimum better performance of the localization system is achieved.

- 10) Repeat steps from 1 to 9 for various beacon positions.
- 11) Implement Kalman Filter
 - a. Initialize the matrices A, B, C of the state equation
 - b. Set the initial velocity to zero and set the initial position
 - c. for $k = 1$ to 25 do
 - i. $X_k = AX_{k-1} + BU$
 - ii. $P_k = AP_{k-1}A^T + Q$
 - iii. $K_k = P_{k-1}H^T (HP_{k-1}H^T + G)^{-1}$
 - iv. $X_k = X_{k-1} + K_k(Z_k - HX_k)$
 - v. $P_k = (1 - K_kH)P_{k-1}$
 - d. end for

- 12) Plot the localization graph.

This algorithm is used to reduce the position error in indoor and outdoor environments.

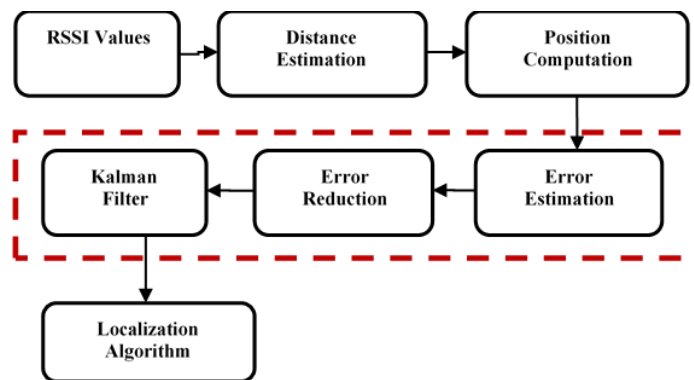


Figure 2. Flow diagram of motetrack inout system

7. TARGET TRACKING COMPARED WITH OTHER METHODS

Kalman filter is widely used in control systems to estimate the state of a process in presence of noisy measurements. It estimates the states of a process by minimizing mean square error between the ideal and real system states.

7.1. Outdoor Environment System Model

Table 1 shows the parameters involved for the RSSI measurements in an outdoor environment. Four anchor nodes are used for this experiment and it is named as N_1 , N_2 , N_3 and N_4 . Readings are taken in 128 different positions using non-anchor node. From Figure 3 to Figure 6 show the final simulation results of the localization system. The result compares the actual path with the estimated path. Right subplot of Figure 3 represents the actual path followed by the moving target. Every measurement was carried out on the marked points (blue colour square boxes). Anchor node positions are shown in red colour small circle. Left subplot of Figure 3 shows the tracking without applying the filter. Here the tracking is done only using log-normal shadowing model (LNSM). The average position error per position is 3.425m. As shown in Figure 3, the obtained path doesn't draw the actual path. Some of the results go beyond the boundaries.

Figure 4 compares the actual path with the one obtained after Kalman filter is implemented. Left subplot of Figure 4 shows the path obtained after filtering the positions. The Kalman Filter smoothen the path as well as reduces the error. The error in the estimation of the target is reduced to 2.112m. Figure 5 compares the actual path with the one obtained after proposed method before applying Kalman filter is implemented. Left subplot of Figure 5 shows the path obtained after filtering the positions. The proposed method reduces the error as well as smoothen the path but in some places overlapping occurred. The error in the estimation of the target is reduced to 1.251m.

Table 1. Real time outdoor parameters

Number of Anchor nodes used	Anchor node positions(N_1,N_2,N_3,N_4)	Number of mobile nodes used	Mote	Number of positions used	Operating System	Simulation
4	(0,1),(0,2.5),(1,7.1),(2,5,7.1)	6	TelosB	128	TinyOS	MATLAB

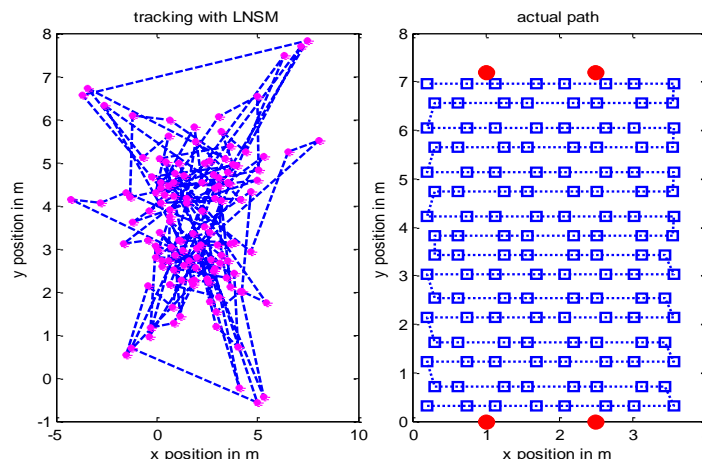


Figure 3. Plot comparing the actual path with estimated path obtained using LNSM

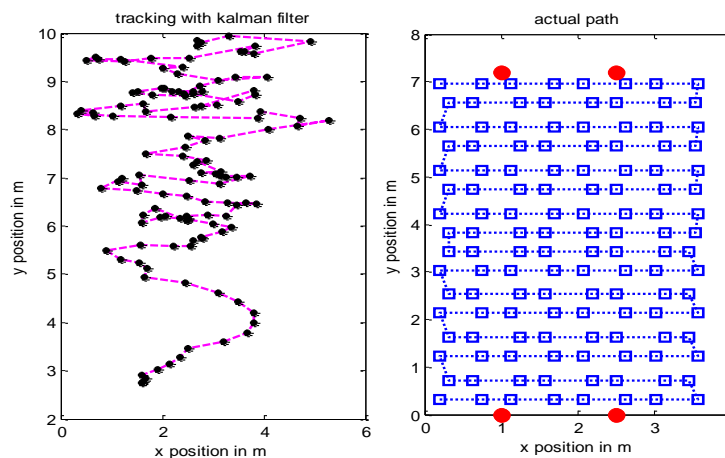


Figure 4. Plot comparing the actual path with estimated path using kalman filter

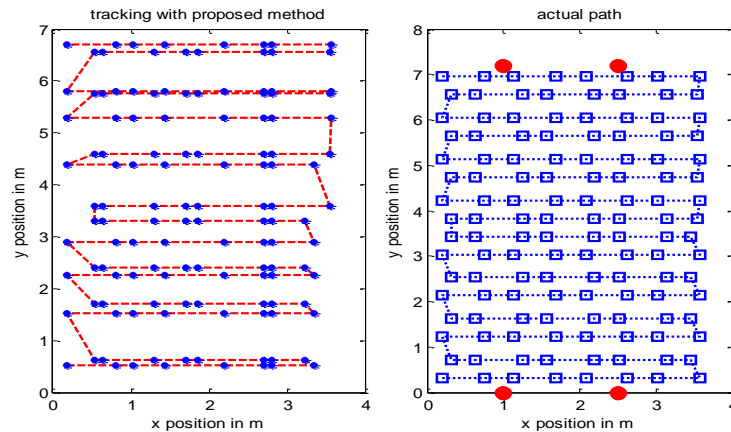


Figure 5. Plot comparing the actual path with estimated path obtained using proposed method before applying kalman filter

Figure 6 compares the actual path with the one obtained after MoteTrack InOut is implemented. It is found that localization error is 0.834m and there is no overlapping in the tracking path. The Localization errors obtained using the proposed method and various other methods are shown in the Table 2.

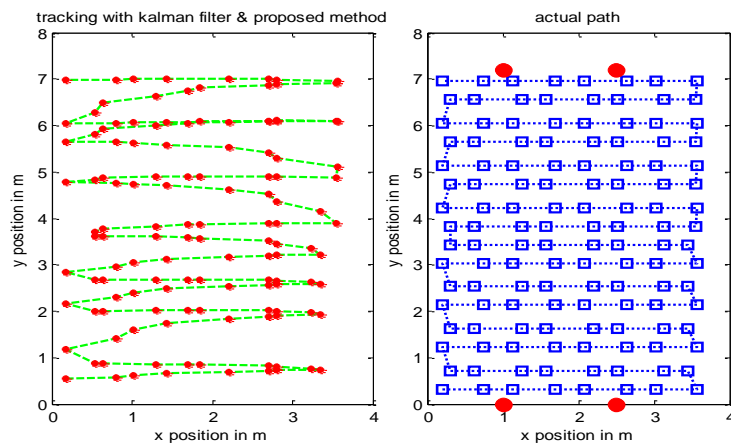


Figure 6. Plot comparing the actual path with estimated path obtained using motetrack inout system

Table 2. Localization error calculated for the real time RSSI values under different methods

Method	Localization Error((m)
LNSM	3.425
Kalman filter	2.112
Proposed method without Kalman filter	1.251
MoteTrack InOut System	0.834

8. CONCLUSION

In an outdoor environment, for a moving target the localization error using LNSM, Kalman filter and proposed method before implementing Kalman filter is 3.425m, 2.112m and 1.251m respectively. The localization error is reduced using proposed method but over lapping occurred in the tracking path. Proposed algorithm with the Kalman Filter is used and it is found that localization error is 0.834m and there is no overlapping in tracking path. Localization error reduction obtained using the MoteTrack InOut system for a moving target is 2.51m when compared to LNSM. Localization error reduction of 74.5% and 75.6% are obtained for indoor and outdoor respectively using Motetrack InOut system for a moving target compared to LNSM.

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