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A REAL TIME RSSI BASED NOVEL ALGORITHM TO IMPROVE INDOOR LOCALIZATION ACCURACY FOR TARGET TRACKING IN WIRELESS SENSOR NETWORKS

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ABSTRACT

This paper deals with the development and deployment of a wireless sensor network for monitoring locations of a mobile target in an indoor environment. The system uses received signal strength (RSS) measurements as the baseline for range determination. Although the RSSI based localization technology needs no additional hardware, the accuracy remains a big challenge because of the severe fading effects and multipath propagation in the indoor environments. This paper proposes a new method along with the Kalman filter in order to improve the localization accuracy. The system is tested for indoor environment. An error reduction of more than 50% is achieved in indoor environment.

Keyword: wireless sensor networks, RSSI, localization, Kalman filter.

1. INTRODUCTION

Most of the locations tracking systems are based on Global Positioning System (GPS). But, there are some limitations with the usage of GPS. The major issue is that it cannot be used in indoor environments. And GPS receivers are expensive as well as power intensive.[1] Wireless sensor networks provide us with a better alternate for location tracking since they are much more viable when considering economic and convenience constraints. It has wide scope of applications in the fields of medical, surveillance, intrusion detection applications and automatic tracking or location estimation systems [2-5].

There are numerous of techniques available to track a moving target in an indoor environment. One can estimate absolute or relative positions of target mobile node against the reference ones. These reference nodes can process the radio signal from the target node in different ways on the basis of the received radio waves properties. The radio wave properties like received angle, propagation time, and signal strength are usually used for localization purpose [6-7].

In this paper we have proposed and analysed RSS based methods for distance estimation. Radio signal strength (RSS) is an ideal modality for range estimation in wireless networks because RSS information can be obtained at no additional cost with each radio message sent and received. Although RSSI-based approach is frequently applied in target localization, its performance degrades due to the inaccurate estimates caused by measurement noises. Motivated by this observation, this paper proposes to filter the estimated positions with Kalman filter to obtain smooth trajectories. This study is focused on how to improve localization estimates in the tracking of moving objects in a cost effective manner.

The rest of the paper is organized as follows: Section 2 presents RSSI fundamentals and explains the ranging method using RSSI measurements. In Section 3 describes about log normal shadowing model. Section 5 focuses on the Kalman filter implementation on the estimated positions from the RSSI ranging technique. Section 6 describes a proposed method. Section 7 is devoted to the algorithm used in this work. Section 8 explains the experimental setup. In Section 9 the results from indoor environment is provided. Conclusion and acknowledgement is provided at the end of paper.

2. RECEIVED SIGNAL STRENGTH

Signal strength can be measured at receiver when it receives the packet sent from transmitter. RSSI is a unit less metric used to measure the power of the received radio signal that are equipped with an onboard CC2420 transceiver, operating at the 2.4 GHz band and deploying the 801.15.4/zigbee wireless communication protocol. The RSSI is a relative indicator and the higher the value of the RSSI, the stronger is the signal. The measured value provided by the module may not be exactly the received power in dBm. However, received signal strength indicator (RSSI) is used to represent the condition of received power level. This can be easily converted to a received power by applying offset to calibrate to the correct level. TelosB motes are used to measure RSSI [14-15].

3. LOG NORMAL SHADOWING MODEL (LNSM)

The RSSI signal propagation model is currently of three types; Free Space propagation model, Two-ray ground Model and Log Normal Shadowing Model (LNSM).The first two models have special requirements for the application environment while the third model which is considered in this chapter is a more general signal propagation model [11-12].

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

P_L = Total path loss in dB;

P_t- Transmitted power in dBm;
P_r = Received power in dBm.

Propagation model used in indoor wireless sensor network is given by

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

$P_L(d_0)$ = Path loss at the reference distance $d_0$in dB
d_0 = Reference distance (≈ 1m)
d = distance from sender
n = Path loss exponent
X_σ= 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.

A, B and σ can computed from measured data using linear regression. B= 10n

The RSSI values are collected at the target node which is at known distances away from the anchor nodes. Crammer's rule can be used to find the values of A and n.

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

$$T = \begin{bmatrix} A \\ n \end{bmatrix} \quad M = \begin{bmatrix} 1 & 10\log d_1 \\ 1 & 10\log d_2 \\ 1 & 10\log d_3 \\ 1 & 10\log d_4 \end{bmatrix} R = \begin{bmatrix} RSSI_1 \\ RSSI_2 \\ RSSI_3 \\ RSSI_4 \end{bmatrix}$$

Where d_1, d_2, d_3, d_4 represent the distances between the target and the respective anchor nodes and $RSSI_1$, $RSSI_2$, $RSSI_3$, $RSSI_4$ are the RSSI mean values collected from the anchor nodes. There is also assumption that environment will have constant properties for the whole time. Later the properties are used to estimate the distance d (in meters) between the transmitting and receiving node as follows.

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

4. POSITION ESTIMATION

Multilateration is accepted as the most appropriate way to determine the location of a sensor node based on locations of beacons [6]. The procedure attempts to estimate the position of a node by minimizing the error and discrepancies between the measured values.

Once the distances between a target node and all reference nodes based on the RSSI of the received packets are found, the position of the target node is calculated using the multilateration method. The multilateration method has been selected due to its good computational cost-accuracy trade-off [6].

If the anchor 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) (L) can be obtained as

$$L=(A^T A)^{-1} A^T B \quad (6)$$

$$L = \begin{bmatrix} x \\ y \end{bmatrix}$$

$$A = 2\begin{bmatrix} (x_1 - x_2) & (y_1 - y_2) \\ (x_1 - x_3) & (y_1 - y_3) \\ (x_1 - x_4) & (y_1 - y_4) \end{bmatrix}$$

$$B = \begin{bmatrix} d_2{}^2 - d_1{}^2 - (x_2{}^2 + y_2{}^2) + (x_1{}^2 + y_1{}^2) \\ d_3{}^2 - d_1{}^2 - (x_3{}^2 + y_3{}^2) + (x_1{}^2 + y_1{}^2) \\ d_4{}^2 - d_1{}^2 - (x_4{}^2 + y_4{}^2) + (x_1{}^2 + y_1{}^2) \end{bmatrix}$$

5. THE KALMAN FILTER

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. Kalman filter estimates the states of a process in two steps, time update step and measurement update state [8-10].

A. Localization system model

The system model for the localization system is constructed based on laws of motion [16-17]. The model is described as a time discrete state space by means of a state and an observation. The state equation is governed by the linear stochastic difference equation.

a) Time update state: In this step, the algorithm calculates an estimate of the future state of the system from the previous state estimate.

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

Update error covariance matrix $P_k=AP_{k-1}A^T+Q$ (8)

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

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

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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×1) matrix that relates U to the state X

B is taken as $\begin{bmatrix} \Delta t^2/2 \\ \Delta t^2/2 \\ \Delta t \\ \Delta t \end{bmatrix}$

U optional control input

P_k is the error covariance

Q process noise covariance

b) Measurement update: The first task during the measurement update is to compute the Kalman gain. The next step is to actually measure the process to generate a posterior state estimate incorporating the measurement. The final step is to obtain an a posterior error covariance update.

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

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

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

H(m×n) matrix that relates the state X_k to the measurement $Z_k$by

$$Z_k = HX_k + R \qquad (12)$$

R is a random variable which represents measurement noise covariance. Q and R are assumed to be independent (of each other), white, 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 a 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. PROPOSED METHOD

The distance between the beacon node and unknown node calculated using Log-normal shadowing model depends on the parameters A and n. In order to reduce the measurement error further, the following algorithm is developed. Figure-1 shows the flow diagram of localization after applied proposed method and Kalman filter. Proposed method reduces the position error and then it is given to Kalman filter to track the target.

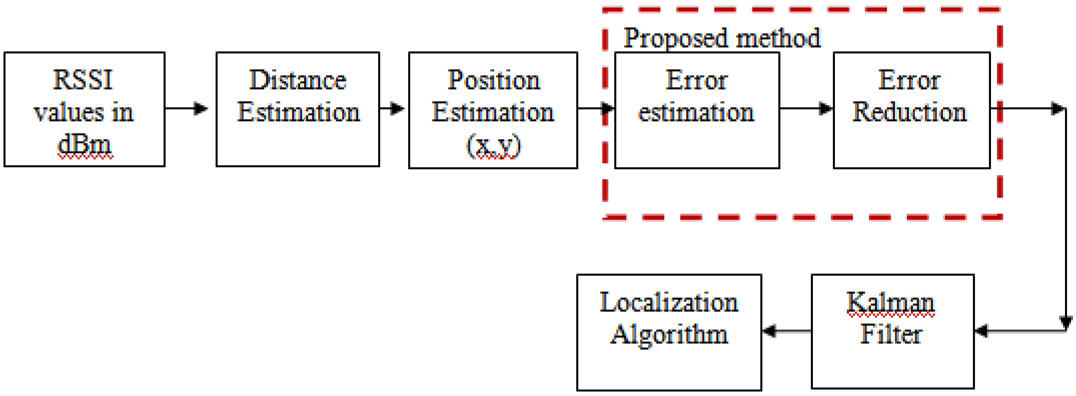

Figure-1. Proposed method along with the Kalman filter.

Algorithm steps

a. Get RSSI values from TelosB motes.
b. Find the mean of RSSI values of each anchor node.
c. Find A and path-loss exponent n.
d. Calculate distance from log normal shadowing model (LNSM).
e. Estimate position(x,y) using multilateration.
f. Estimate error (E) from the measured and calculated values.
g. Calculate mean error (M_E).

$$M_E = \frac{\sum_1^N \sqrt{(x_i - x_{est_i})^2 + (y_i - y_{est_i})^2}}{N} \qquad (13)$$

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Mean error M_E is positive value,

a) If the error (E) is negative, M_E will be added to E. Resultant is an error reduction(E_R). $E_R = -E + M_E$
b) If the error (E) is positive, M_E will be subtracted from E. Resultant is an error reduction(E_R). $E_R = E - M_E$.

h. Mean error M_E is negative value,

a) If the error (E) is positive, M_E will be added to E. Resultant is an error reduction(E_R). $E_R = E + (- M_E)$
b) If the error (E) is negative, M_E will be subtracted from E. Resultant is an error reduction(E_R). $E_R = -E - (-M_E)$.

i. If the E_R is greater than the E value, then E is considered as E_R.
j. Calculate mean error reduction (ME_R).
k. From ME_R and M_E, calculate the percentage of error reduction.

In order to evaluate the localization performance we use the average. Distance error per estimate (m) which is calculated as follows:

$$M_E = \frac{\sum_1^N \sqrt{(x_i - x_{est_i})^2 + (y_i - y_{est_i})^2}}{N}$$

where N is the total number of measurements taken. $(x_{est_i}, y_{est_i})$is the estimated coordinate and (x_i, y_i) is the actual coordinate of the target at i^{th}position. Better performance of the localization system is achieved when the value of the function $M_E$is minimum.

7. LOCALIZATION ALGORITHM

The localization system works upon the following algorithm.

1. Collect RSSI values from anchor nodes
2. Find the mean of RSSI values of each anchor node, R after sampling period
3. Find A, path-loss exponent n.
3.1 Initialize the distance matrix, $d = [d_1\ d_2\ d_3\ d_4]$
3.2 $T= (M^T M)^{-1} M^T R$

$$T = \begin{bmatrix} A \\ n \end{bmatrix}$$

$$M = \begin{bmatrix} 1 & 10\log d_1 \\ 1 & 10\log d_2 \\ 1 & 10\log d_3 \\ 1 & 10\log d_4 \end{bmatrix}$$

$$R = \begin{bmatrix} RSSI_1 \\ RSSI_2 \\ RSSI_3 \\ RSSI_4 \end{bmatrix}$$

4. Find x, y coordinates of the target
4.1 $L= (A^T A)^{-1} A^T B$

$$L = \begin{bmatrix} x \\ y \end{bmatrix}$$

$$A = 2\begin{bmatrix} (x_1 - x_2) & (y_1 - y_2) \\ (x_1 - x_3) & (y_1 - y_3) \\ (x_1 - x_4) & (y_1 - y_4) \end{bmatrix}$$

$$B = \begin{bmatrix} {d_2}^2 - {d_1}^2 - ({x_2}^2 + {y_2}^2) + ({x_1}^2 + {y_1}^2) \\ {d_3}^2 - {d_1}^2 - ({x_3}^2 + {y_3}^2) + ({x_1}^2 + {y_1}^2) \\ {d_4}^2 - {d_1}^2 - ({x_4}^2 + {y_4}^2) + ({x_1}^2 + {y_1}^2) \end{bmatrix}$$

5. Implement Kalman Filter
5.1 Initialize the matrices A, B, C of the state equation
5.2 Set the initial position
5.3 Set the initial velocity to zero
5.4 for k = 1to no_sampling points do
5.4.1 $X_k=AX_{k-1}+BU$
5.4.2 $P_k=AP_{k-1}A^T+Q$
5.4.3 $K_k=P_{k-1}H^T(HP_{k-1}H^T+R)^{-1}$
5.4.4 $X_k=X_{k-1}+K_k(Z_k-HX_k)$
5.4.5 $P_k=(1-K_kH)P_{k-1}$
5.5 end for
6. Plot the localization graph

8. TEST BED SETUP

The indoor experiments were conducted in a corridor which is 2.1 m wide and 7.8 m long. This involved four anchor nodes and a moving node. The anchor nodes are fixed at corners of the corridor with co-ordinates (0, 0), (2.1, 0), (0, 7.8), (2.1, 7.8).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.

As shown in Figure-2, the base station consists of a PC and a TelosB mote attached to it through USB connection. The PC runs a java application which is used to display the real time RSSI values from the anchor nodes and plot the same.

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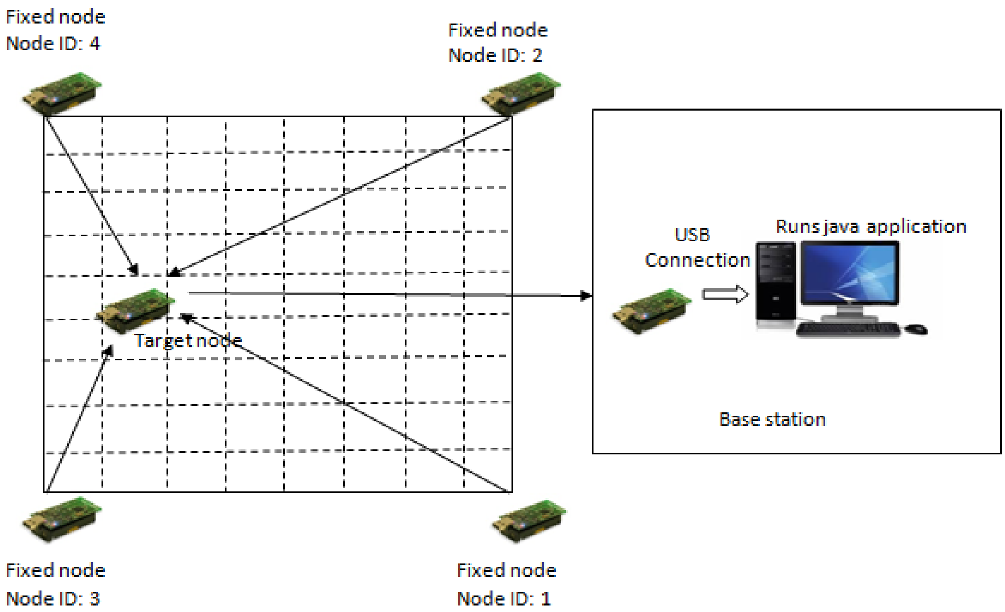

Figure-2. The experimental test bed.

Every anchor mote sends message whose RSSI will be read by the base. The application in the anchor mote contains a simple logic to periodically send aRssiMsg as defined below

```
typedefnx_structRssiMsg{
nx_uint16_trssi;
  } RssiMsg;
```

The RssiMsg is sent empty; it is the target that will include the RSSI value in the message. The target mote includes the RSSI values in the message and forwards them over the radio to the base station.

```
eventboolRssiMsgIntercept.forward (message_t *msg,
void *payload, uint8_t len) {
RssiMsg *rssiMsg = (RssiMsg*) payload;
rssiMsg->rssi = getRssi(msg);
return TRUE;
}
```

Base station mote is connected to the serial port of the PC and will effectively read the RSSI.

9. RESULTS

The path-loss exponent, n is found by keeping the target at known distance away from the anchor nodes. The target was kept at five different priori locations in the field to find path-loss exponent. The average of the five values is found and it is taken as the path-loss exponent.The path-loss exponent was found to be 2.231.

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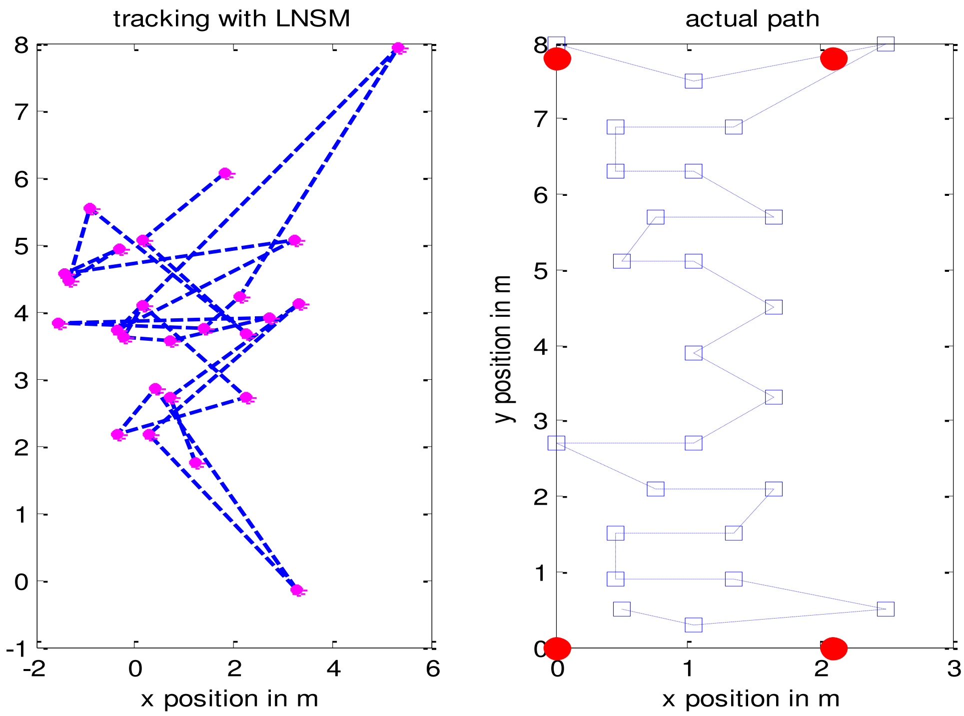

Figure-3. Target tracking using LNSM.

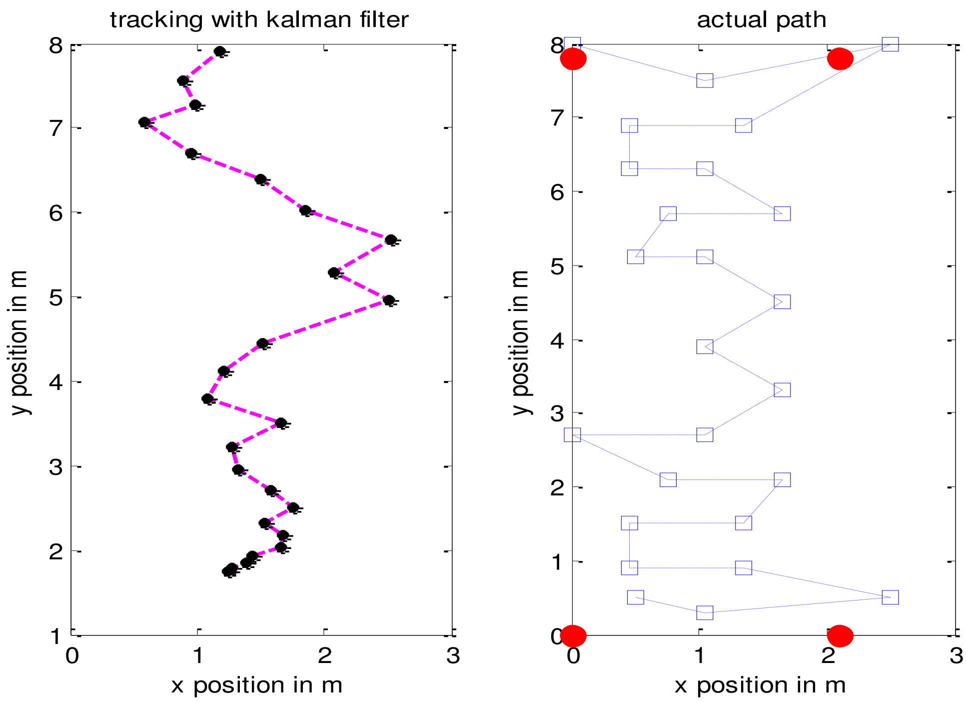

Figure-4. Target tracking using Kalman filter.

Figure-3 to and Figure-6 shows the final simulation results of the localization system. The algorithm is implemented using MATLAB. 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 (cross 1-25).

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 error in the position estimation per measurement was found to be 2.231m. 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 per measurement is reduced to 1.007m.

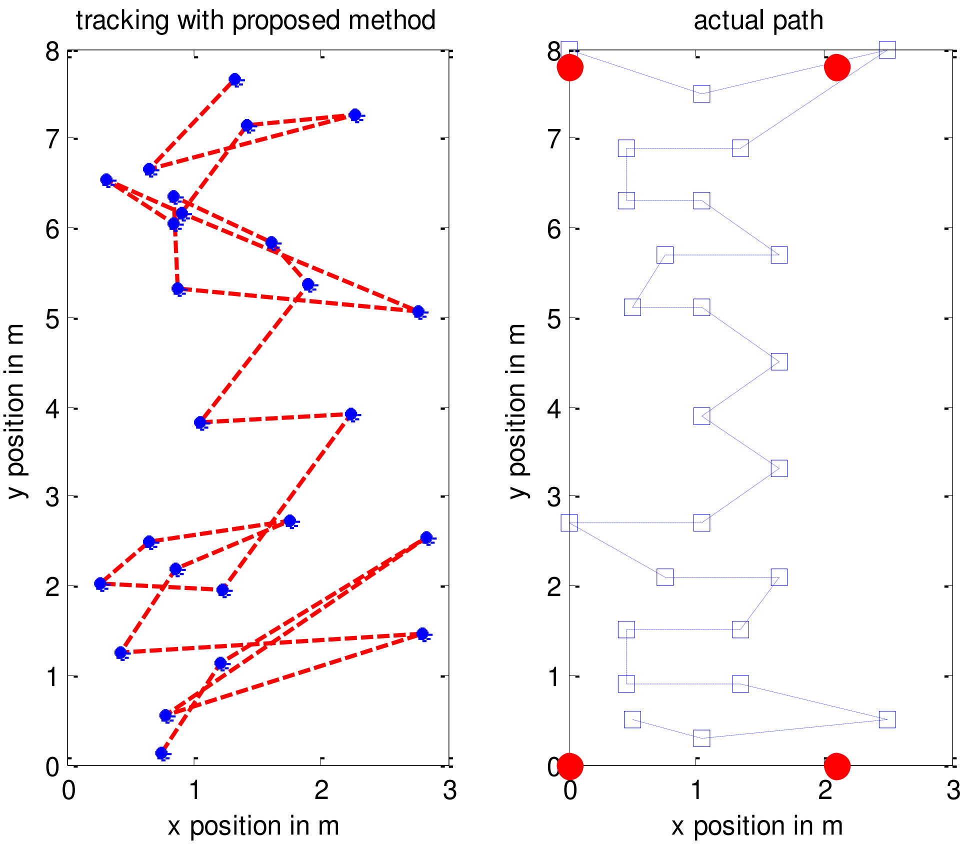

Figure-5. Target tracking using proposed method.

Figure-5 compares the actual path with the one obtained after proposed method without kalman filter is implemented. Left subplot of Figure-5 shows the path obtained after reduced the position errors. The proposed method smoothen the path as well as reduces the error than kalman filter but overlapping of path. The error in the estimation of the target per measurement is reduced to 0.818m.

Figure-6 compares the actual path with the one obtained after proposed method with kalman filter is implemented. Left subplot of Figure-6 shows the path obtained after reduced the position errors. The proposed method along with the kalman filter smoothen the path as well as reduces the error. The error in the estimation of the target per measurement is reduced to 0.570m.

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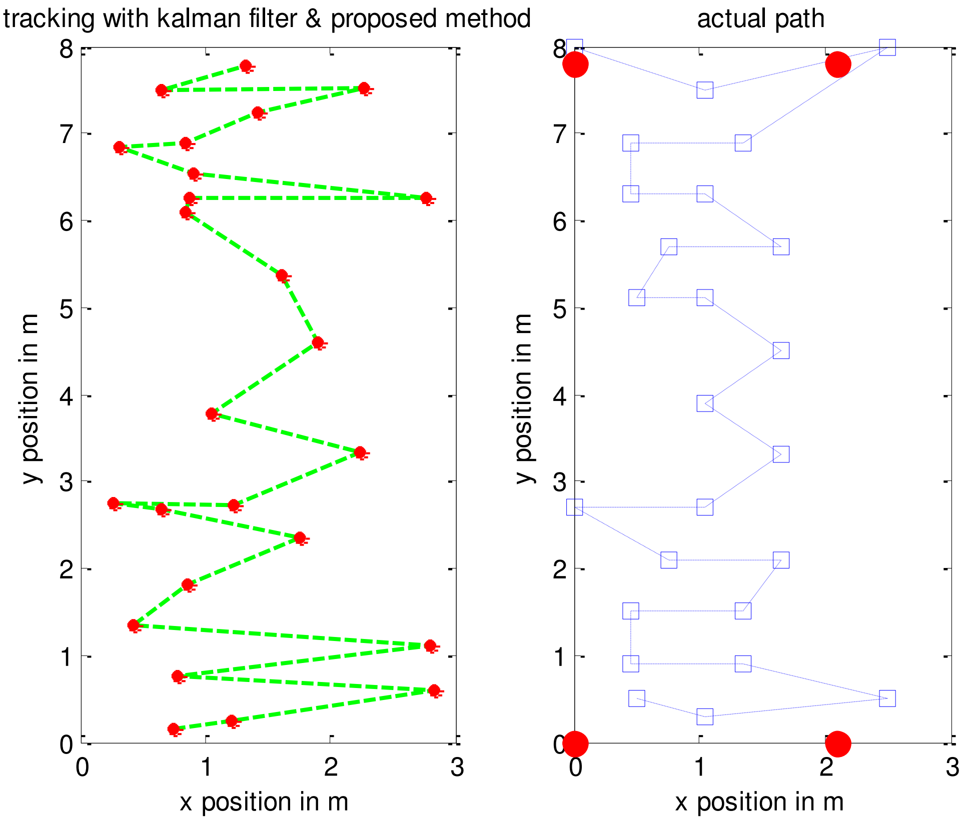

Figure-6. Target tracking using proposed method with Kalman filter.

Table-1. Comparison of four methods.

Method	**Error** (m per measurement)
LNSM	2.231
Kalman filter	1.007
Proposed method	0.818
Proposed method with the Kalman filter	0.570

Table-1 shows that comparison of all the four methods and it's found that proposed method along with the Kalman filter gives better results.

10.CONCLUSIONS

The ideal case of RSSI ranging contains no error. But in practice, ranging using RSSI doesn't produce a satisfactory result for localization systems. It is because of the various effects like multipath fading and shadowing effect which cause the RSSI to fluctuate. The RSSI based localization system can be made more reliable by using proposed method along with the Kalman filter. The relationship between the error in the position estimation and the parameters in Kalman filter is analysed. It is found that Kalman gain K_k can influence the localization accuracy. The Error using proposed method with the Kalman Filter is found to be 0.570meters per measurement. Since this system involves environmental characterization, it can be used in various types of environments, where obstacles and dynamical changes are present.

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