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Kalman Filtering For RSSI Based Localization System 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 Kalman filter in order to improve the accuracy in position estimation. 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

Introduction

Most of the location 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. 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 as proposed in [3]-[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 (e.g. [7], [8],[1],[2]).

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 we focus on the Kalman filter implementation on the estimated positions from the RSSI ranging technique. Section 4 is devoted to the algorithm used in this work. Section 5 explains the experimental setup. In Section 6 the results from indoor environment is provided. Conclusion and acknowledgement is provided at the end of paper.

Received Signal Strength

A. Received Signal Strength Indicator(RSSI)

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.

B. Ranging Using RSSI

The strength of received power from a signal can be used to estimate distance because all electromagnetic waves have inverse-square relationship between received power and distance as shown in equation (1)

$$P_r \;\alpha\; \frac{1}{d^2} \tag{1}$$

where Pr is the received power at a distance d from transmitter. This expression clearly states that the distance of signal travelled can be found from received power. In practical measurement, the inverse-square relationship doesn't hold good. In fact, the received power has a dependency on the media through which the signal is transmitted. This leads to environmental characterization using path loss exponent n as below.

$$P_r = \frac{P(d_0)}{(d/d_0)^n} \tag{2}$$

where $P(d_0)$ is the received power measured at distance d_0. Generally, d_0 is fixed as a constant, $d_0 = 1$ m. Path loss exponent n and $P(d_0)$ in the are important parameters for environmental characterization. The distance travelled can be found by comparing the difference between transmission power and received power, or it is called "path loss".

C. RSSI In Indoor Environment

In indoor environment, the signal strength is not linear with distance because of multi-path fading and indoor shadowing effects. This has been verified by the experiments we conducted inside the university building. The RSSI values within 8 meters of the sink were measured with a step size of 1 meter. Fig. 1 shows the result of this experiment with RSSI measurements taken in the presence and absence of obstacles. It is clear from Fig. 1 that the signal strength degrades in the presence of obstacles between transmitter and the receiver.

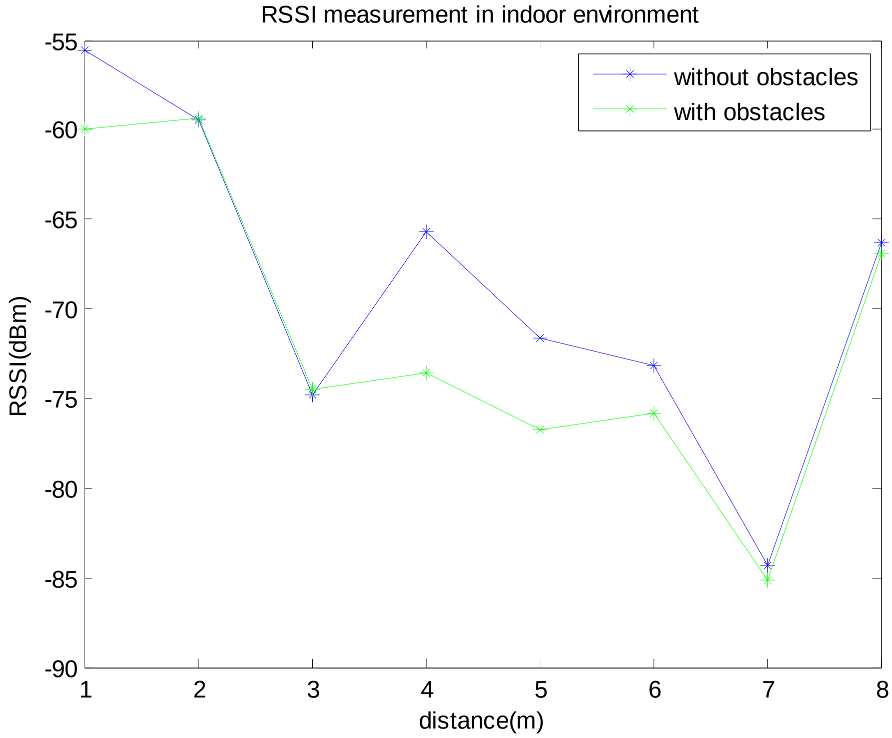

Figure 1: Plot of dependency of RSSI on disturbances in the environment

Fig. 2 and Fig. 3 show the variation of RSSI with distance in indoor and outdoor environments respectively. The readings are taken for various power levels. These measurements were taken using TelosB motes [9] as the transmitter and receiver. Telosb mote uses the Chipcon's CC2420 radio [10]. The power level during transmission can be set by software. The lowest power level is 3 and the highest is 31. Fig. 2 and Fig. 3 show that the RSSI is highly dynamic in nature. This behaviour is due to the severe fading effects and multipath propagation of the radio signal.

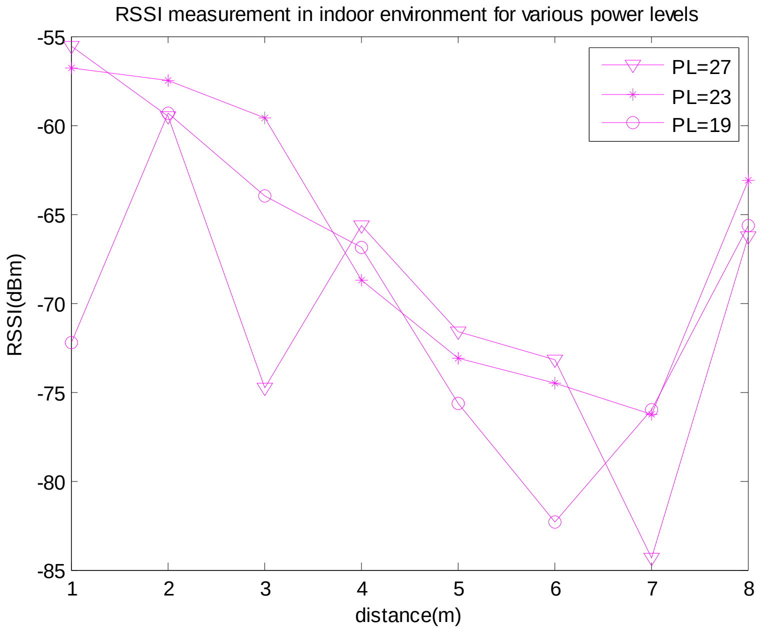

Figure 2: Plot of RSSI Vs distance for various power levels in indoor environment

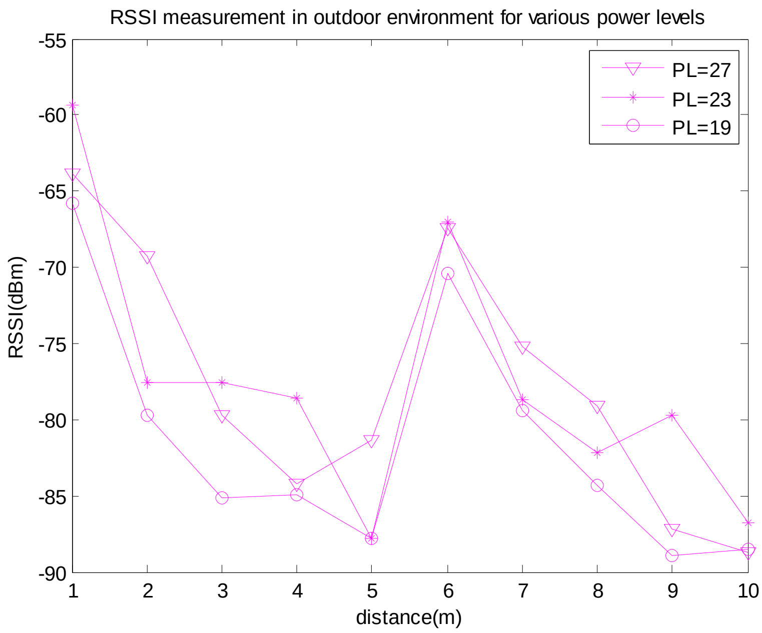

Figure 3: Plot of RSSI Vs distance for various power levels in outdoor environment

The RSSI can be used to find the power P_r of the RF signal in dBm by adding the calibration offset value found empirically during CC2420 system development from the frontend gain. This value was found to be approximately -45 [10]. Hence the power of the received RF signal can be expressed as:

$$P_r = RSSI - 45 (dBm) \tag{3}$$

A realistic way for correlating the RSSI to the distance is by using the log-distance pathloss model (LDPM) [11] which predicts the path loss a signal encounters in an indoor environment to the distance. The received power at a distance d may be expressed as:

$$P_r = P_t - PL(d_0) - 10n\log(\frac{d}{d_0}) \tag{4}$$

where $PL(d_0)$ is the pathloss power in dBm at a reference distance d_0, n is the path loss exponent that depends on the environment. P_t is the transmitted power. By selecting the reference distance to be 1 meter, we can rewrite

$$P_r = A - 10n\log(d) \tag{5}$$

where $A = P_t - PL(1)$. A and n can be found by keeping the target node at a priori known position in the environment. 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.

$$T = (M^T M)^{-1} M^T R \tag{6}$$

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

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

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

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.

$$d = 10^{\frac{(A-P_r)}{10n}} \tag{7}$$

D. 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

$$L=(A_L^T A_L)^{-1} A_L^T B_L \tag{8}$$

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

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

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

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.

A. Localization System Model

The system model for the localization system is constructed based on laws of motion [12]. 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.

1) 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 $X_k=A_{KF}X_{k-1}+B_{KF}U$ (9)

Update error covariance matrix $P_k=A_{KF}P_{k-1}A_{KF}{}^T+Q$ (10)

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

A_{KF} (n×n) matrix that relates the step of k-1 to current state k

A_{KF} 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_{KF} (n×1) matrix that relates U to the state X

B_{KF} 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

2) 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 posteriori state estimate incorporating the measurement. The final step is to obtain an a posteriori error covariance update.

Compute Kalman gain $K_k=P_{k-1}H^T(HP_{k-1}H^T+R)^{-1}$ (11)

Update expected value $X_k=X_{k-1}+K_k(Z_k-HX_{k-1})$ (12)

Update error covariance $P_k=(1-K_kH)P_{k-1}$ (13)

H(m×n) matrix that relates the state X_k to the measurement Z_k by $Z_k = HX_k + R$ (14)

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 posteriori 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.

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,pathloss exponent
   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 $L=(A_L^T A_L)^{-1} A_L^T B_L$

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

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

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

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 = 1 to no_samplingpoints do
        5.4.1 $X_k=A_{KF}X_{k-1}+B_{KF}U$
        5.4.2 $P_k=A_{KF}P_{k-1}A_{KF}^T+Q$
        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

Experimental 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 coordinates (0,0),(2.1,0),(0,7.8),(2.1,7.8).The moving target node is carried by a person. The walking target traverse 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 Fig. 4, 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.

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 a RssiMsg as defined below

```
typedef nx_struct RssiMsg{
        nx_uint16_t rssi;
        } 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.

```
event bool RssiMsgIntercept.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.

Performance Evaluation

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

$$C = \frac{\sum_1^N \sqrt{(x_i - x_{est\,i})^2 + (y_i - y_{est\,i})^2}}{N} \qquad (15)$$

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 C is minimum.

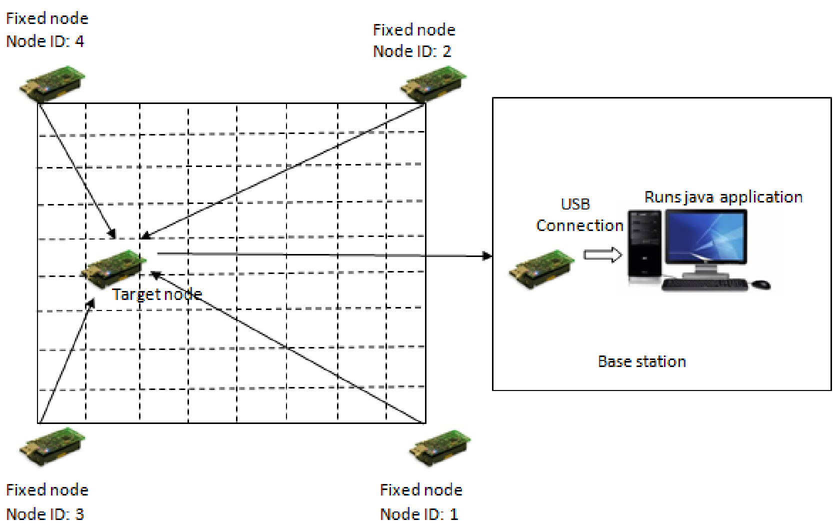

Figure 4: The experimental test bed

Simulation Results

The pathloss 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 pathloss exponent. The average of the five values is found and it is taken as the pathloss exponent .The pathloss exponent was found to be 2.1843.

Fig. 5 and Fig. 6 show 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 Fig. 5 represents the actual path followed by the moving target. Every measurement was carried out on the marked points (cross 1-25) shown in Fig. 5

Left subplot of Fig. 5 shows the tracking without applying the filter. Here the tracking is done only using log-distance pathloss model (LDPM). The average error in the position estimation was found to be 2.2867m. As shown in Fig. 5, the obtained path doesn't draw the actual path. Some of the results go beyond the boundaries.

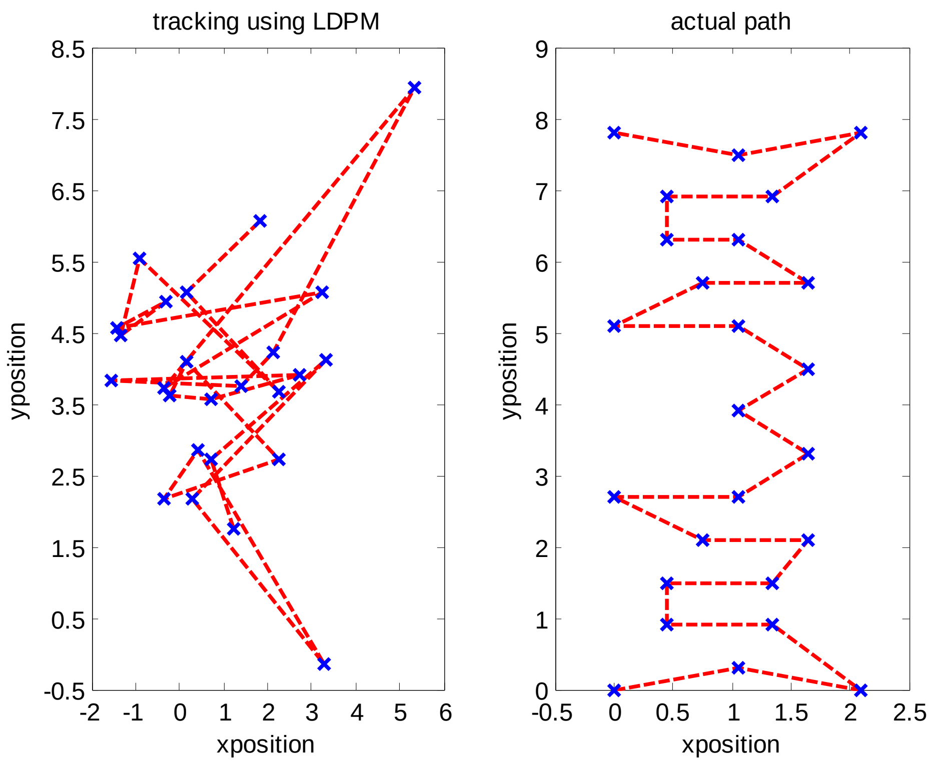

Figure 5: Plot comparing the actual path with estimated path obtained without filtering

Fig. 6 compares the actual path with the one obtained after Kalman filter is implemented. Left subplot of Fig. 6 shows the path obtained after filtering the positions. The Kalman filter smoothens the path as well as reduces the error. The value of the cost function C is found to be 1.0378 which means the average error in the position estimation of the target is 1.0378m. An error reduction of 54.62% in the position estimation is achieved in indoor measurements. It is a satisfactory result.

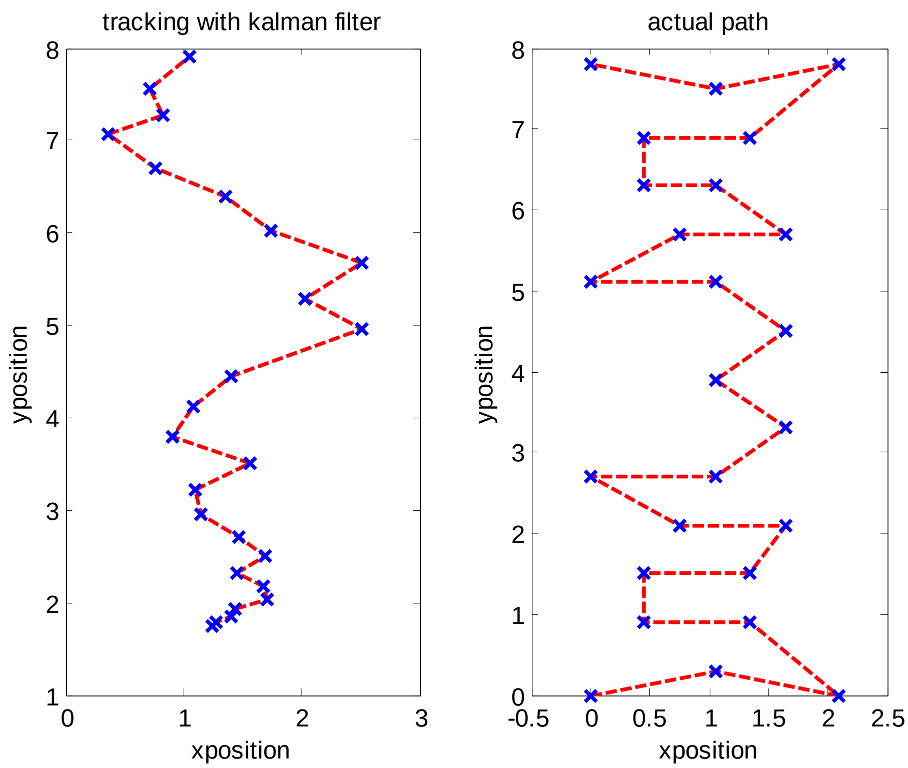

Figure 6: Plot comparing the actual path with estimated path with filtering

Conclusion

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 Kalman filter.

We analyse the relationship between the error in the position estimation and the parameters in Kalman filter. It is found that Kalman gain K_k can influence the localization accuracy. And K_k is a function of variable R, measurement noise covariance. R in Kalman filter is obtained from experiments. Q is the covariance of prediction error can be tuned to get a minimum of the cost function C.

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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