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Enhanced localization for indoor construction

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Abstract

Considerable research work had been conducted in recent years embracing the utilization of wireless technologies in construction with a focus on identification of locations of material, equipment and personnel. A fundamental key for reliable and accurate use of these technologies is path loss models, which are used to estimate distances based on received signal strength (RSSI). This paper introduces a newly developed path loss model accounting for signal de-noising using a Kalman filter. The developed model is tested using four wireless technologies (WLAN, Bluetooth, Zigbee and Synapse SNAP), 20 experiments were carried out in laboratory environment and 1500 data sets were analyzed to investigate the accuracy of distance estimation. The results show an average of 50% enhancement in the distance estimation accuracy, which considered a potential for enhanced localization on indoor construction jobsites.

Keywords: Indoor Localization; Pathloss models; RSSI de-noising; Enhanced localization

1. Introduction

In construction management domain, several researchers have investigated indoor localization with a focus on automating the progress of tracking and control, using a wide range of wireless technologies. The deployment of such tracking technologies are severely impacted by the conditions of the surrounding environment such as the presence of moving resources, metallic objects and extreme weather events [1]. Wireless based tracking technologies utilizes propagation models to convert measured received signal strength (RSSI) into corresponding distances between a transmitter unit and a receiver unit.

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Researchers experimented with multiple wireless technologies specially radio frequency identification (RFID), ultra wide band (UWB) and wireless local area network (WLAN). Each technology has its own inherited advantages and disadvantages, accuracy, cost, coverage range, deployment requirements and scalability [2]. RFID was utilized for object tracking without localization [3, 4], tracking with localization [5, 6] or for outdoor localization supported by GPS [7, 8]. Li and Becerik-Gerber [9] reported that passive RFID tags are a cost effective solution for indoor localization, however they suffer from their short read range, which entails the deployment of a large number of tags and hence additional cost. Researches utilizing ultra wideband (UWB) reported higher localization accuracy of approximately < 1m [10, 11, 12]. However, the measurement accuracy is highly dependent upon the line of sight of the point to be located [13]. Furthermore, cost of commercially available hardware is very high. WLAN is an attractive solution for indoor localization because of the availability of its universal infrastructure [14]. However, several researchers found that its accuracy to be low; approximately 4–7 m with 97% confidence [15, 16, 17, 18, 19, 20]. Jang and Skibniewski [21] implemented combined radio frequency and ultrasound architecture using ZigBee wireless sensor modules for indoor position estimation. However, traditional ultrasound positioning is limited by line of sight, which can be challenging in complicated construction environments [22]. Combinations of RFID and ZigBee based sensor networks have also been experimented with by researchers for material tracking and supply chain management [23, 24]. In these studies, RFID tags were used for identification of construction materials, and ZigBee communication was used for wireless data transfer. While, wireless sensor network (WSN) was only used in these studies for data transfer, they confirmed the positive contribution of WSN to communication efficiency and network flexibility.

The dynamic nature of construction jobsites severely impacts the accuracy of location estimation. In the presence of moving resources, metallic objects and barriers to line of sight, signal propagation models produce poor distance estimates. In order to alleviate such impact, smart and adaptive path loss models are required to filter out inherit noise and to cope with the fast-changing environment on site. This paper is motivated by such need and aimed at the development of enhanced localization method incorporating a Kalman-based path loss model; accounting for filtering and de-noising of RSSI, which contributes to an increased accuracy of location estimation.

Nomenclature

CDF   Cumulative Distribution Function
GPS   Global Positioning System
RFID   Radio Frequency Identification
RSSI   Received Signal Strength Index
SNAP   Synapse Network Appliance Protocol
UWB   Ultra Wide Band
WLAN   Wireless Local Area Network
WSN   Wireless Sensor Network

2. Characteristics of Indoor Environment

Theoretical laws of electromagnetic wave propagation describe propagation losses when waves are travelling in ideal free-space situations, which become very challenging when applied to actual indoor localization situations. These challenges arise from the lack of prediction methods for actual propagation losses on complex and dynamic jobsites. In ideal free-space situations, electromagnetic waves travel or propagate in direct rays from transmitter to receiver. However in actual situations, waves pounce as they are reflected and scattered from surrounding environment such as floor, ceiling, walls and various objects. Which in turn cause multipath waves, which can be either constructive or destructive, resulting in a positive or a negative effect on the received signal strength. Such interference is more complicated in dynamic and continually changing environments such as construction jobsites. Free-space path loss propagation models are not suitable for indoor localization in real world environment due to presents of shadow fading and multipath effects. It is important to investigate signal propagation in real situations in order to design a more

realistic propagation model which is able to handle uncertainties and noise in RSSI measurements. In the following section, real signal propagation scenarios are analyzed in order to provide solutions for indoor localization in construction jobsites environment.

In order to investigate indoor propagation of different radio signals in indoor environment, 21 experiments and 1095 data sets were recorded for more than 2190 minutes [25]. Four wireless technologies (WLAN, Bluetooth, Zigbee and Synapse SNAP) were used in the experimentation. A straight line setup is used to measure the RSSI propagation as shown in Figure 1. The path is 20 m long, straight track with 20 waypoints with a distance of 1 m between two consecutive waypoints. Two stationary sensor nodes are placed next to the track at 0 m and 21 m.
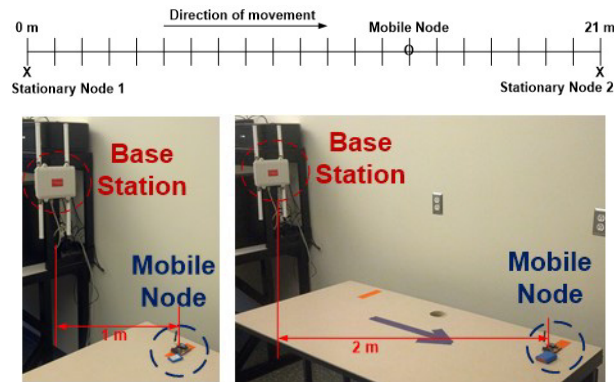
Figure 1. Straight line experimental

The collected RSSI from the above experiments were analyzed to evaluate the variability in measured signal. It was clear that RSSI is affected by random changes in the physical properties of the surrounding environment or even a group of people passing around the transmitter or receiver as shown in figure 2. Such variations in the RSSI readings (even when the node is at standstill) produce huge errors in the estimate distance. A simple moving average could be used to filter out small oscillations in the RSSI, however in order to filter out significantly high frequency noise, the window size of the filter needs to be large. The system latency is highly affected by the size of the filter window, therefore a large filter window is not suitable for real-time applications.
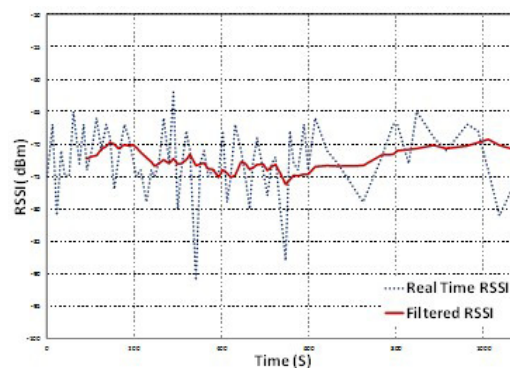
Figure 2. Real-Time RSSI VS Filtered RSSI

3. Developed Method

RSSI measurements presented above are unreliable for distance estimation due to noise interference. The aim of the developed method is to produce a signal which is representative of the original RSSI but less noisy and suppresses interferences caused by surrounding environment, which in turn increases the accuracy of location estimation. The developed method incorporates a Kalman filter to reduce noise in RSSI, while maintaining the shape and height of its waveform peaks as shown in Figure 3. The received RSSI is processed by a Kalman filter to de-noise the signal, and then converted to the corresponding distance using a path loss model designed based on the filtered signal. Once three distance estimations are generated, estimates of tag locations can be produced using a trilateration algorithm.
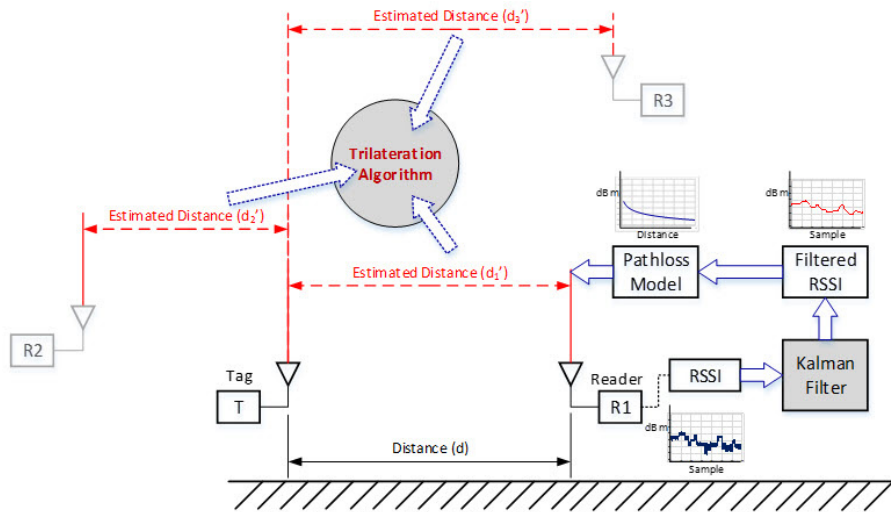
Figure 3. Developed Method Block Diagram

Kalman filter was first introduced in 1960 to present a solution for discrete data linear filtering problem [26]. Since then, extensive research and application had been proposed particularly in the areas of robotics and navigation. The key advantage of the Kalman filter is its simple computational algorithm, adaptive recursive nature, and its status as the optimal estimator for one-dimensional linear systems with Gaussian error statistics [27]. Kalman filter estimation process is based on a feedback loop control system. Which first estimates the process's state at a point in time and then obtains feedback of measurements. This feedback measurement is used to adjust the model parameters for next estimate. The model assumes that the state of a system at a time t evolved from the prior state at time t-1 according to the equation

$$X_t = A_t X_{t-1} + B_t u_{t-1} + w_t \tag{1}$$

where X_t is the process state vector at time t, A_t is the state transition matrix which is applied to the previous state X_{t-1}, u_t is the control input vector, B_t is the control-input model which is applied to the control vector u_t, and w_t is the process noise which is assumed to be drawn from a zero mean multivariate normal distribution with covariance Q_t.

At time t a measurement Z_t of the true state X_t is calculated according to

$$Z_t = H_t X_t + v_t \tag{2}$$

Where H_t is the measurement model for mapping true state space into measurement space and v_t is the measurement noise which is assumed to be zero mean Gaussian white noise with covariance R_t.

The Kalman filter recursive estimator model as shown in Figure 4 has two phases, the prediction phase, which estimates the priori process state at next observation time, and the correction phase, which incorporates a new measurement into the a priori estimate to obtain an improved a posterior estimate.
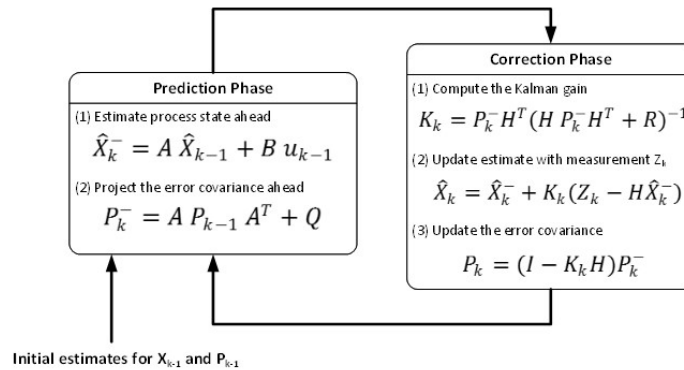

Figure 4. Kalman Filter Recursive Estimator Model

In the context of RSSI de-noising, a simplified version of the above equations will be used. It will be assumed that the process is governed by a linear equation:

$$X_k = X_{k-1} + w_k \tag{3}$$

With a measurement equation:

$$Z_k = X_k + v_k \tag{4}$$

And Hence the Kalman filter prediction phase equation can be rewritten as:

$$\hat{X}_k^- = \hat{X}_{k-1} \tag{5}$$

$$P_k^- = P_{k-1} + Q \tag{6}$$

And the measurement update equations are:

$$K_k = P_k^- (P_k^- + R)^{-1} = \frac{P_k^-}{P_k^- + R} \tag{7}$$

$$\hat{X}_k = \hat{X}_k^- + K_k (Z_k - \hat{X}_k^-) \tag{8}$$

$$P_k = (1 - K_k) P_k^- \tag{9}$$

It is assumed that the process has a very small variance $Q = 1e^{-5}$ (for filter tuning flexibility). The initial seed for the filter, X_{k-1} will be assumed to be zero. Similarly the initial value for P_{k-1}, which is called P_0 will be any value but not

equal to zero. The measurement variance R will be initially assumed very large number in order to express the uncertainty in the measurement accuracy.

The Kalman filtered signal is used to generate the RSSI propagation model, which will be used for distance estimation and hence location estimation. Figure 5 illustrates the Kalman filtered RSSI with respect to the actual distance between the transmitter and receiver nodes. Least square method is used to fit this relation in exponential equation format:

$$d = e^{\left(\frac{RSSI-A}{B}\right)} \tag{10}$$

Where A & B are constant confidents and d is the distance between the transmitter and receiver nodes.
From the Figure 5, the distance can be estimates as:

$$d = e^{\left(\frac{RSSI_{filtered}+38.909}{-8.989}\right)} \tag{11}$$

Based on RSSI measurement and signal propagation model described in sections above, the following section is aimed to test the localization accuracy with the filtered RSSI in comparison to raw RSSI based localization. The trilateration [28] algorithm is applied, where the position of an object (tag) is calculated based on its estimated distances from fix location devices (readers) [29].
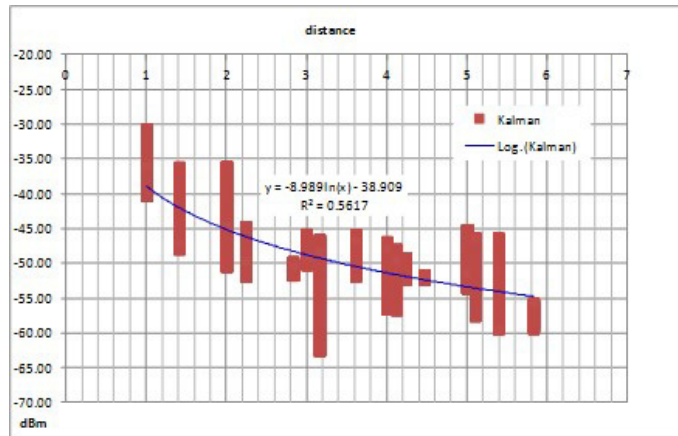

Figure 5. Kalman Filtered RSSI Vs Actual Distance between Tx And Rx Nodes.

4. Testing and Validation

For validating the developed method, experiments were conducted using a grid formation test bed, where readers are installed at the corners of the area, then tags where placed one meter apart in the grid formation shown in Figure 6. Experiments were conducted in indoor lab environment at Concordia University's Construction Automation Lab. Location error is calculated as the distance in meters between the estimated and actual locations using Eq. 12.

$$Distance_{error} = \sqrt{(X-a)^2 + (Y-b)^2} \tag{12}$$

Where: (X, Y) is the actual tag location, and (a, b) is the estimated tag location.
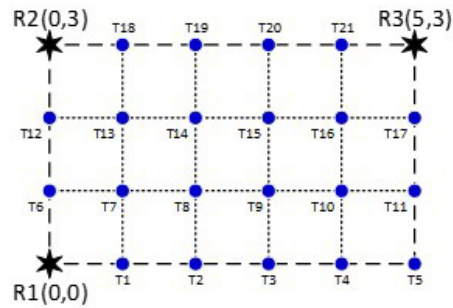
Figure 6. Grid Formation Test Bed

Figure 7 shows graphical display of a sample for actual verses estimated locations of tags using both traditional unfiltered RSSI and the proposed filtered RSSI signals. The orange triangles represent the actual locations, the black crosses represent the calculated locations using raw RSSI and the red circles represent the calculated location using the proposed filtered RSSI method.
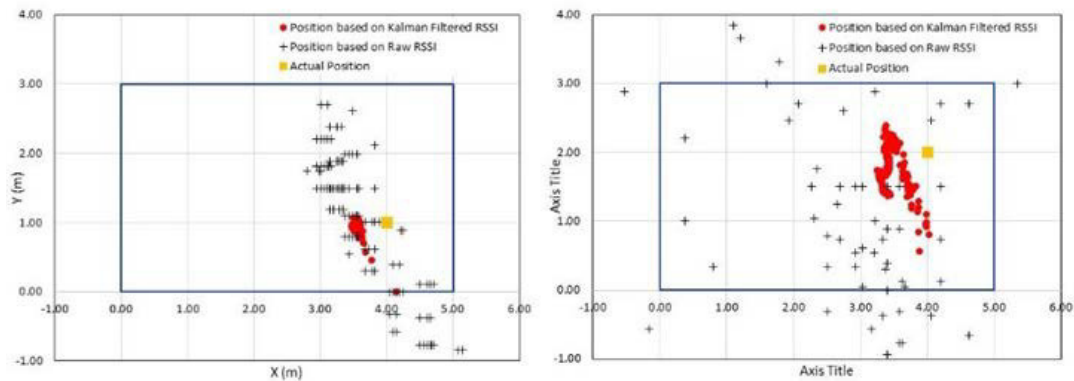

Figure 7. Graphical Representation of Actual vs Estimated Tag's Locations

The results show higher uncertainty and variances in location estimation using raw RSSI, which can be identified from the scattered nature of the calculated location. On the other hand, the locations estimated using the proposed filtered RSSI indicated higher certainty and less variances in the estimated locations. Such higher certainty is translated into less location estimation errors as shown in Figure 8a, where the mean location error using raw RSSI and Kalman filtered RSSI method were 1.67 and 0.66 meters, respectively.

The cumulative probability density functions (CDF) of the distance error are usually used for measuring the precision of a system. To compare two positioning techniques with respect to accuracies and precision, the technique whose CDF graph reaches high probability values faster is more preferable, because its distance error is more concentrated in small values. In order to compare the proposed localization technique to those developed by others, the distance error CDF of the proposed technique is compared to the CDF graph for the system developed by Montaser and Moselhi [6]. The proposed Kalman filtered RSSI localization technique has a location precision of 90% within 1.16 m (the CDF of distance error of 1.16 m is 0.9) and 80% within 0.85 m, while the raw RSSI localization technique has a location precision of 90% within 3.70m and 80% within 2.60m as shown in Figures 8.

(a)   (b)
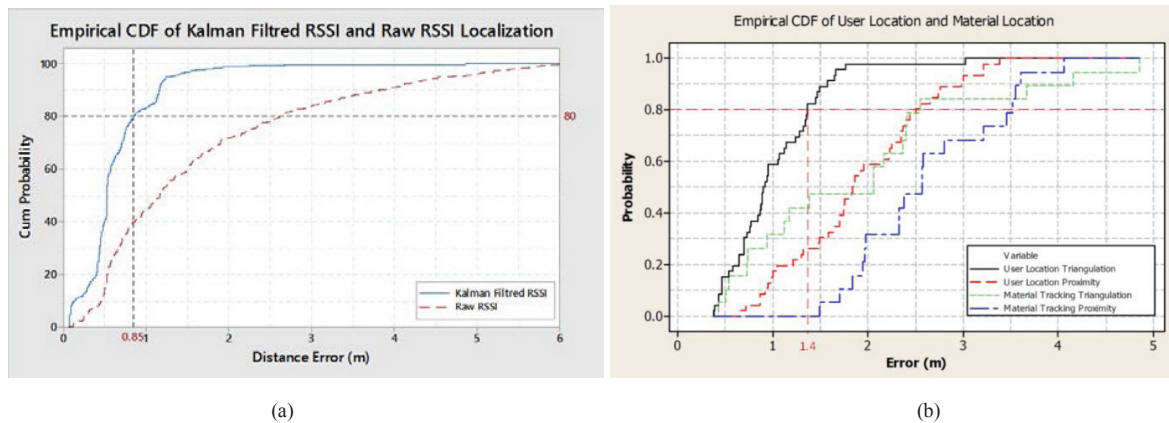
Figure 8. Proposed Method Distance Errors CDF vs Montaser and Moselhi (2014)

Moreover, the system developed by Montaser and Moselhi [6] has a location precision of 90% within 1.60m and 80% within 1.40m as shown in Figures 8. The developed localization yields 306% and 165% accuracy enhancement over that based on unfiltered RSSI and that of Montaser [6], respectively. In addition, the computational time required for that of Montaser [6] is three times the time required for the proposed method due to the three location reading required in Montaser [6], which presents higher advantage for the proposed method in real time localization applications.

5. Conclusion

Despite recent advances in wireless sensor technologies, mobile computing, and tracking techniques, indoor localization remains a technically challenging problem. Modeling indoor radio frequency signal propagation is not a simple task, especially in harsh and dynamic environments such as construction jobsites. This research presented an efficient localization method utilizing low cost radio frequency hardware modules for indoor localization based on RSSI signal smoothing and filtering. The proposed signal smoothing technique, which utilizes Kalman filter, not only increases the certainty in the estimated locations, but also enhanced the localization accuracy by over 300% of that based on the use of unfiltered RSSI. Such enhancement can be attributed to the filtering of the uncorrelated signal noise.

To evaluate the performance of proposed method, several indoor experiments were conducted in lab environment. The proposed method produced location estimates with an average error of 0.66m in comparison to 1.67m using unfiltered RSSI signals. And with a likelihood of 80% the localization error of the proposed method is 0.85m in comparison to 2.60m using unfiltered RSSI signals. Moreover the performance of the proposed method was also compared to that previously developed by Montaser and Moselhi [6] using the cumulative distribution function (CDF) of localization errors. It was found that the proposed method outperformed their method by 138% with a likelihood of 90%. The developed method is expected to improve indoor localization applications in construction such as automated project control and onsite safety.

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