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Designing and Implementing a Real time Wi-Fi Indoor Positioning and Route Tracking System Based on RSSI Measurements : Atomic Multri-lateration With Extended Kalman Filter Approach

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***Abstract*— This paper investigates the effectiveness and applicability of using Atomic Multrilateration with an extended Kalman filter (EKF) as a way of refining the position estimation results in near real time indoor positioning systems. It therefore assesses the response speed and the variation of the errors between the actual position and the estimated position. As such, we formulated a two staged process that first investigates the best feasible region through multrilateration and then tries to predict the best feasible point within the best feasible region by filtering position errors and keeping track of the object through continuously iterating the process to obtain up to date retrieved RSSI values from Wi-Fi access points (APs) for localization and positioning purposes in indoor environment were a clear Line of sight (LOS) is not usually guaranteed.**

***Index Terms*— Indoor Positioning, RSSI, Atomic Multri-lateration, Extended Kalman Filter and Real time**

I. INTRODUCTION

For real-time positioning and navigations, the GPS is widely used in open spaces with clear LOS. Indoor spaces however quiet often lack a clear LOS [1]. Therefore, new methods of positioning and localization are exploited.

In recent years, Wi-Fi-based localization systems have shown great promise and researchers have focused on several key challenges in real-time accuracy [1,2].This is due to a large number of Wi-Fi APs installed around indoor spaces and the availability of the technology in most kinds of mobile devices which makes it easily accessible. It has marginal coverage range, is cheap and easily accessible, hence, making it a viable replacement to GPS technology in indoor spaces.

For localisation purposes, methods being tried include; Time of arrival (TOA) where the time obtained for each node is multiplied with speed of light to determine distance [3]. Fingerprinting method which is mainly a two phase process viz. offline training phase which involve creating RSSI-Distance map and the online phase which include matching Wi-Fi RSS fingerprints with respective location co-ordinates prepared [2]. Others are trilateration were, RSSI values from atleast three existing Wi-Fi AP's is related to distance from respective AP's using signal propagation models [1].Our Localisation method will Combine Atomic multrilateration with Kalman filter to first find the best feasible region and then extract the beast feasible point through an iterated refinements of measurements by the filter.

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The goal is to come up with a method that does not involve extensive calibration of a place before a localisation and positioning indoor system can be deemed worthy as is the case in most researches [1, 3, and 5]. This is because the calibration process is laborious and indoor environments differ from place to place .What might work in one area may not work in another. For instance, in the fingerprinting method, the RSSI value corresponding to a certain co-ordinate plane in one indoor space may be different from one environment to another

II. LITERATURE REVIEW

Most wireless communication infrastructure for wireless sensor positioning involve short range unlicensed signals [3]. This process usually requires sensor locations to be known [4]. Wi-Fi methods are inexpensive and require low configuration cost [1,5].Studies have shown though that the received signal strength indicator (RSSI) value has a larger variation over the same distance [5] .This is because it is usually subjected to the delirious effects of fading and shadowing where walls and objects are more prominent and obvious[1]. Therefore, an RSSI-based approach needs more data or a highly effective algorithm than other methods to achieve higher accuracy. In [4] authors have compared three strong indoor propagation models and their suitable environments. Various methods for improving displacement errors in positioning are also suggested. Combination of Trilateration and fingerprints is described in [4]. Reference [3] Proposes many algorithm for indoor positioning using trilateration, RSSI, ultra sound and TOA, TDA for measurements of the position. Reference [5] compares the model with log-distance and free space path loss model. Finally, [1] investigate the relationship between RSSI and distance to suggest an 'accurate' indoor propagation model for 2.4 GHz. Practical and site specific validation of ITU indoor path loss model is explained in [4]. Path loss models with various factors, indices with their values are calculated by authors.

Another common daunting task with positioning involves trilateration, precisely on how to solve inequality equations [3] for position determination with minimal errors.

III. SYSTEM COMPONENT ANALYSIS

The main components of the setup are the transceiver and off the shelf Wi-Fi AP .They are described below.

A. *Transceiver*

The system is based on the Atheros AR2425 Single-Chip Wireless Network card shown in *figure 1*. The transceiver is IEEE 802.11b/g and Wi-Fi compliant with a sensitivity of -127 dBm. Its data is related to the effective incoming power through a calibration formula by the manufacture of the wireless card inserted on a Toshiba A200 laptop.

B. *Access Points*

In this paper, four types of six off the shelf TP-Link Wi-Fi Access Point for 2.4 GHz are used and include the following model: A) one TP-LINK_AD26, B) two TL-WR742, C) one TP-LINK_7DAA, and D) one TL-WR845N .

Further, in an effort to understand the variation of the RSSI value with respect to distance, we also had to review the RF beam power distribution and coverage behaviour of each Access Point and the *figure 2* shows the beam Radiation Patterns of each set of node according to the listed models above. The Wi-Fi nodes all support MIMO which exploits a radio-wave phenomenon called multipath [13]. MIMO harnesses multipath with a technique known as space-division multiplexing whereby a WLAN device actually splits a data stream into multiple parts, called spatial streams, and transmits each spatial stream through separate antennas to corresponding antennas on the receiving end [13].

Therefore the actual geometry arrangement of the anchors' beam in space has a very strong impact on this quantity of the RSSI value, which is an inestimable tool for predicting the limit of the localization performance [6]. We can see from the beam coverage in *figure 2* that the RF beam is not perfectly isotropically radiated. This will partly explain discrepancies in the calculations which assume a perfectly isotropically radiated beam.

Fig. 1. The Nomadic Sensor Components

C. *RSSI Value and Distances*

We calculate the distance using the free space model [6]. To avoid over idealization in for before determining the distance d of the nomadic node from an anchor node, it is reasonable to model the path loss at any value of d at a particular location as a random and log-normally distributed random variable with a distance-dependent mean value [7]. As such, to compensate for power loss due to attenuation, fade margin is added to the basic free space equation. Hence the signal decay model for indoor system can first be given as:

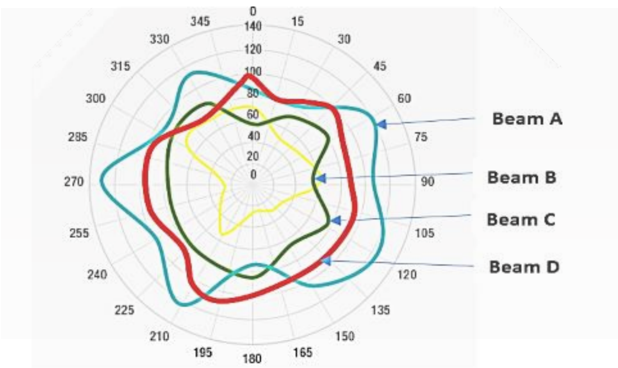

Fig. 2. Wi-Fi Anchor Nodes Estimated RF Radiation Patterns

$$Pr\,(dBm) = Pt\,(dBm) - 10n\log_{10}\left(\frac{d}{do}\right) + X\sigma \qquad (1)$$

Where:

Pr and Pt are power received by transceiver and transmitted by anchor nodes respectively

$X\sigma$ represents the shadow noise modelled as a Gaussian random variable with zero mean and standard deviation σ_{RSS} [6] and is system-specific which has to be calculated empirically for the site. For office buildings, generally the value of $X\sigma$ is 10 dB [4].

The model in equation 1 takes into account the phenomenon referred to as *log-normal shadowing*.in dB, however to have a closer estimate of the path loss PL (d) it is better to first predict the mean path loss values as given below to include other shadowing factors before upgrading it to include height and frequency changing impacts as shown in equation 3.

$$PL\,(d) = PL\,(do) + 10n\log10\,(d/do) + s \qquad (2)$$

Where;

PL (do) is the reference path loss at reference distance (do) in dB and

$PL\,(do) = 20\log_{10}\left(\frac{4\pi do}{\lambda}\right)$

n = is the signal decay exponent.

d = is the distance between transmitter and receiver.

d_o = is the reference distance (say 1m.)

λ = is the wavelength of 2.4GHz signal = 0.125 m

S is the shadowing factor and follows a log normal distribution with a typical shadowing variation of around 6dB.

This model of a path loss works well for a receiver antenna height of 2m and operating a frequency of 2GHz [12]. In order to make it suitable for Wi-Fi Frequencies of 5GHz and 2.4GHz and any other height, a correction factor ought to be considered.

D. *Propagation Model Path loss Tuning*

The purpose of propagation model tuning is to minimize the error between the predicted path loss values and the measurements [12].The modified path loss that considers changes in frequency (f) and height (h) is given below:

$$PL_{mod}(dB)=PL(d)(dB)+PL(f)(dB)+PL(h)(dB) \qquad (3)$$

Where:

PL (d) = is path loss given in equation 4

PL (*f*) = is the frequency correction term is given by $6\log_{10}(f/2000)$, f is the frequency in MHz and

PL (*h*) = is the receiver antenna height correction term given by $-10.8\log_{10}(h/2)$ where h is the antenna height in meters

RSSI will therefore be a modified version of equation (1) with the inclusion of the modified path-loss propagation model is used in equation (3) and given by;

$$RSSI_d\,(dBm) = RSSI_{do}\,(dBm) - PL_{modified}\,(dB) + X\sigma \qquad (4)$$

Where RSSId and RSSIdo represents the received signal strength in dBm at a distance d and do from the transmitter and the reference distance respectively. PLmod represents path loss which depends on several factors: averaged, fast and slow fading, height, frequency of transmission, transmitter gain, receiver gain and transmitted power. Therefore, in practice, its value is usually partially known beforehand and the only unknown value is the path loss at any value of d at a particular location as a random and log-normally distributed random variable with a distance-dependent mean value. n represents the path-loss exponent with typical values between 2 and 6 for indoors.

$$RSSI\,(dBm) = -10n\log 10\,(d) + A \qquad (5)$$

Where;

RSSI (dBm) is the retrieved received signal strength in dBm at a distance d of the wireless card in free space and according to the ITU recommendations for manufacturers.

A include according to equation (4) and (1) all but $-10n\log_{10}$ (d).

d is distance in metres and n is the propagation constant or path-loss exponent ranging between 2.7 to 4.3 in buildings (Free space has n =2 for reference).Based on Equation (7), we managed to calculate the distant of each node from the transceiver installed on the laptop as follows:

$$d = \log^{-1}[(RSSI+A)]/(-10)]$$

$$= 10^{[(RSSI - A)/(-10n)]} \qquad (6)$$

E. Path Loss Error Tuning

Statistical parameters were used in this paper for the purpose of minimizing error between the predicted path loss (PL) values and the measurements. And they include are Mean Error (ME), Root Mean Square Error (RMSE) and Standard deviation σ_{RSS}.

$$ME = \frac{\sum(PL_{Theoritical} - PL_{Estimated})}{Number\ of\ Estimates} \qquad (7)$$

$$RMSE = \sqrt{\frac{\sum(PL_{Theoritical} - PL_{Estimated})^2}{Number\ of\ Estimates}} \qquad (8)$$

$$\sigma_{RSS}(dB) = \sqrt{RMSE - ME^2} \qquad (9)$$

F. Access Points Retrieved Sample Data

The respective nodes passively exchange data with the nomadic node, the Toshiba laptop housing the Transceiver uses our C# program in it that can be called up to *run the sensor app* at the desktop to produce an interface were various measurement such as RSSI [dBm], percentage signal strength, ID name, mac Address and BSS type as can be seen in *figure3*

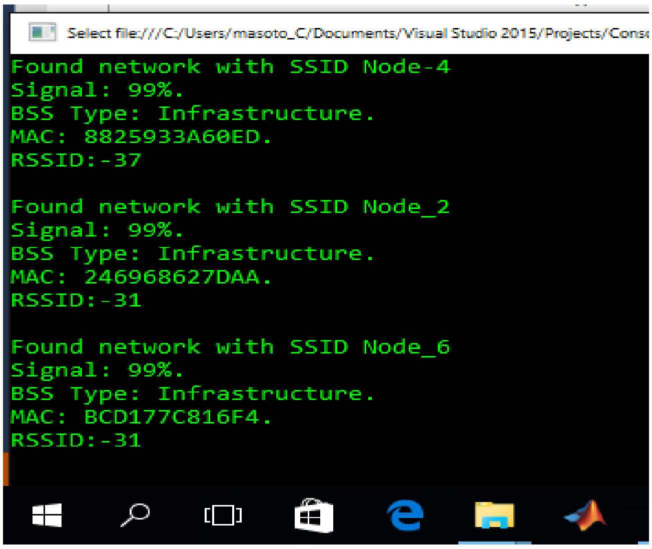

Fig. 3. Wi-Fi Anchor Nodes Estimated RF Radiation Patterns

I. LOCALISATION PROCEDURE

The geometry of the sensor's RF beam as well as the estimated distance between the sensor's signal source and nomadic node's transceiver was vital to finding the position of the nomadic node. Caution was taken on the basis that a large positioning error can arise if the measurement points are located with a bad geometrical distribution of the distance estimates of equation (4) of each node.

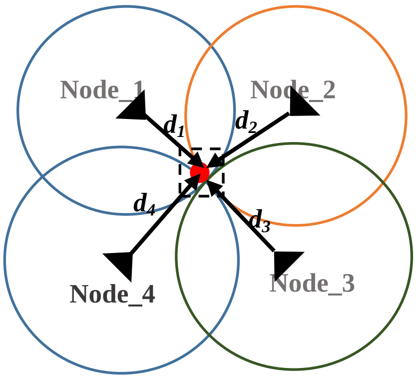

Fig. 4. Illustration of the RSSI based Position estimation Mechanism

In principle, since we have enough constraints information about the position of the anchor nodes and no degeneracies are present, we developed a two staged process algorithm for finding the position based on a system of nonlinear equations that can be solved for the unknown node positions as shown in equation 9. The system has non-linear equations.

In two-dimensional space, the distances to four known beacons returned by a sensor can be related to the position of this sensor (*xi*, *yi*) using the distance formula given in (1),

$$d_i(x, y) = \sqrt{(x_i - x_0)^2 + (y_i - y_0)^2} \qquad (10)$$

The node whose location we seek is named as node_0 and the available Landmark nodes as Node_1, Node_2, Node_3, and Node_4. The position of node_i be (xi, yi) and its measured distance $d_i(x, y)$ between the AP located at $(x_0\ y_0)$ and the measurement point (x_i, y_i) is defined as;

$$d_i(x,\quad y) = \sqrt{(x_i - x_0)^2 + (y_i - y_0)^2} + \epsilon_i(x_0, y_0) \quad (11)$$

Where ϵ_i indicates the error in the i[th] measurement due to noise and other factors.

To increase optimality we implemented a two staged process for our algorithm for localisation purposes by first formulating an information matrix to give us the best feasible region through Atomic Multilateration and then recursively update the likely position of the node by extended Kalman filter within the beast feasible region .The tacit assumption is that the probability distribution (from Atomic Multilateration assumed positions) around the optimal estimates of the nomadic sensor position is a multivariate normal and exhibit multiple peaks (i.e. local optima) of the actual position, however the Extended Kalman filter takes advantage of this variation to find the nomadic node's best feasible point within the beast feasible region estimated by the Atomic Multrilateration process.

II. Atomic Multilateration

Our first goal then is to best estimate x_0, y_0 and Si 's best feasible region so as to minimize the weighted total squared error [3].

$$E(x_0, y_0, Si) = \sum_{i=1}^{4} \alpha_i^2 \epsilon_i^2(x_0, y_0, Si) \quad (12)$$

α_i, indicating how much confidence we want to place in it [3]. Therefore the initial nomadic node positions are estimated using atomic Multilaterated equations and then refined using a Kalman filter technique. Atleast 3 equations are linearized by squaring and subtracting (11) from that of the others, thus obtaining $n - 1$ linear equations of the form (the $x_0^2 + y_0^2$ terms cancel):

$$S_i = di(x,y)^2 - d1(x,y)^2$$

$$u = \begin{pmatrix} x_0 \\ y_0 \\ Si \end{pmatrix} \quad (14)$$

$$v = \begin{pmatrix} -x_2^2 & -y_2^2 + & x_1^2 + y_1^2 \\ -x_3^2 & -y_3^2 + & x_1^2 + y_1^2 \\ -x_4^2 & -y_i^2 + & x_1^2 + y_1^2 \end{pmatrix} \quad (14)$$

$$A = \begin{pmatrix} 2(x_2 - x_1) & 2(y_2 - y_1) & d2(x,y)^2 - d1(x,y)^2 \\ 2(x_3 - x_1) & 2(y_3 - y_1) & d3(x,y)^2 - d1(x,y)^2 \\ 2(x_4 - x_1) & 2(y_4 - y_1) & d4(x,y)^2 - d1(x,y)^2 \end{pmatrix} \quad (15)$$

$v = uA$, and the solution to the system is given by:

$$u = [(A^T A)^{-1} A^T]\, v, [3] \quad (16)$$

Which is the maximum likelihood solution under the assumption of Gaussian measurement noise. The solution fluctuates due to the fluctuation of the RSSI value due to noise. The maximum likelihood estimator solution's principle is based on the mean and the variance whose relationship is shown below [11]:

$$\hat{\theta} = \arg\max_{\theta \subset \Theta} L(\theta, \xi) \quad (17)$$

$\hat{\theta}$, is the parameter that maximizes the likelihood of the sample ξ . $\hat{\theta}$, is called the maximum likelihood estimator of θ .The maximum likelihood estimators of the mean and the variance are for our system was calculated by:

$$\hat{\mu}_n = \frac{1}{n}\sum_{j=1}^{n} x_j$$

$$\hat{\sigma} = \frac{1}{n}\sum_{j=1}^{n}(x_j - \hat{\mu})^2 \quad (18)$$

This was repeated also for the corresponding y_j to find the points of the best fitting region. For estimated distance $d_i(x, y)$, the estimator $\hat{\mu}_n$ is equal to the sample mean and the estimator is equal to the unadjusted sample variance $\hat{\sigma}$ for each iteration that forms a point on the best feasible region. Iterated $\hat{\sigma}$ forms the boundary of the best feasible region with its y_j. Since the linearized state and measurement equations of EKF about the predicted state as an operating point are often inaccurate in practice, by first finding the best feasible region through atomic Multilateration and then estimating the values within the best feasible region by re-evaluating the EKF filter around the new estimated state operating point to refine the value of the best feasible point improves accuracy.

III. Extended Kalman Filter

The EFK was modelled according to the implementation procedure in [9, 10] and the first order Tylor expansion principle were;

EKF Linearization: First Order Taylor Expansion

$$\boldsymbol{f}(x_0, a_t) = \begin{bmatrix} x_{0+1} = x_0 + T\dot{x}_0 + 0 \\ \dot{x}_{0+1} = \dot{x}_0 \\ y_{0+1} = y_0 + T\dot{y}_0 + 0 \\ \dot{y}_{0+1} = \dot{y}_0 \end{bmatrix}$$

Prediction:

$$\begin{bmatrix} x_0 \\ \dot{x}_0 \\ y_0 \\ \dot{y}_0 \end{bmatrix} = \mathbf{C} \cdot \begin{bmatrix} x_{0-1} \\ \dot{x}_{0-1} \\ y_{0-1} \\ \dot{y}_{0-1} \end{bmatrix} + \mathbf{D} \cdot \begin{bmatrix} u_{x0} \\ u_{y0} \end{bmatrix} + \mathbf{Q} \quad (19)$$

When;

$$\mathbf{S_o} = \begin{bmatrix} x_0 \\ \dot{x}_0 \\ y_0 \\ \dot{y}_0 \end{bmatrix} \qquad \mathbf{C} = \frac{\partial f(x_0, a_t)}{\partial x_0} = \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$\mathbf{Q} = \begin{bmatrix} \sigma_a^2 & 0 & small\# & 0 \\ 0 & \sigma_a^2 & 0 & small\# \\ small\# & 0 & \sigma_a^2 & 0 \\ 0 & small\# & 0 & \sigma_a^2 \end{bmatrix}$$

D, is dropped because if known then there would be no need to, "track "the object [8]. σ_a^2, is the standard deviation due to acceleration, dynamic noise covariance Q can be harder to determine. We assume moving at a constant velocity to use a velocity model were dynamic noise is interpreted as acceleration, the known maximum acceleration of the target could be used to calculate 4 sigma σ_a^2 in Q.

Error Correction:

$$\begin{bmatrix} d_1(x,y) \\ d_2(x,y) \\ d_3(x,y) \\ d_4(x,y) \end{bmatrix} = \mathbf{H} \cdot \begin{bmatrix} x_{0-1} \\ \dot{x}_{0-1} \\ y_{0-1} \\ \dot{y}_{0-1} \end{bmatrix} + \begin{bmatrix} \epsilon_1(x_0,y_0) \\ \epsilon_2(x_0,y_0) \\ \epsilon_3(x_0,y_0) \\ \epsilon_4(x_0,y_0) \end{bmatrix} \tag{20}$$

Where:

$$\mathbf{H} = \begin{bmatrix} \frac{\partial d_1(x,y)}{\partial x} & 0 & \frac{\partial d_1(x,y)}{\partial y} & 0 \\ \frac{\partial d_2(x,y)}{\partial x} & 0 & \frac{\partial d_2(x,y)}{\partial y} & 0 \\ \frac{\partial d_3(x,y)}{\partial x} & 0 & \frac{\partial d_3(x,y)}{\partial y} & 0 \\ \frac{\partial d_4(x,y)}{\partial x} & 0 & \frac{\partial d_4(x,y)}{\partial y} & 0 \end{bmatrix}$$

$$\mathbf{R} = \begin{bmatrix} \sigma_{dis}^2 & 0 & 0 & 0 \\ 0 & \sigma_{dis}^2 & 0 & 0 \\ 0 & 0 & \sigma_{dis}^2 & 0 \\ 0 & 0 & 0 & \sigma_{dis}^2 \end{bmatrix}$$

And;

$$\frac{\partial d_i(x,y)}{\partial y} = \frac{y_0 - y_i}{\sqrt{(x_i - x_0)^2 + (y_i - y_0)^2}}$$

$$\frac{\partial d_i(x,y)}{\partial x} = \frac{x_0 - x_i}{\sqrt{(x_i - x_0)^2 + (y_i - y_0)^2}}$$

σ_{dis}^2, is the standard deviation of the measurement noises to anchor nodes in terms of distance and direction, and $small\#$ (hopefully very small) covariances. The inputs to this system are the distance measurements d_i and will be used to update the state of the object. The process noise covariance matrix $\boldsymbol{Q}$ accounts for the unmodeled factors of the system that will be treated the covariance of the dynamic measurement random noise, σ_a^2 and $small\#$ can be considered as the standard deviations of the acceleration velocity and changes noise in the x and y direction, respectively. **R** describes the noise of the motion and this measurement noise covariance R can be calculated via calibration. [9]. Q and R, are constant while the filter is running, hence K and S [11, 8] will converge to a constant due to the gain matrix and state covariance matrix not being affected by the measurements. They assume that the relative noise distributions are given in Q and R. Their job is simply to combine those matrices for use in the estimate of state.

A. Mathematical flow Process

1. Estimate the best feasible region using Atomic multrilateration as stipulated above before deploying the EKF for more refinement and estimation of the best feasible point by following the next few steps

2. Predict next state using a posteriori estimate of the state by using atleast the first few maximum likelihood points of equation as the boundary to ensure that the prediction does not lead to unobservable condition in the early stages when the prediction is less accurate

$$\boldsymbol{X}_{0-1} = \boldsymbol{f}(\boldsymbol{X}_{0-1}, \boldsymbol{u}_{0-1}, 0) \tag{21}$$

$\boldsymbol{f}(\boldsymbol{X}_{0-1}, \boldsymbol{u}_{0-1}, 0)$, is the approximated state

3. Predict next state covariance Use Equation 13

4. Calculates the Kalman gain (weights) where

$$\boldsymbol{K}_0 = \boldsymbol{S}_0 \,.\, \boldsymbol{H}^T\, (\mathbf{H}.\, \boldsymbol{S}_0 \,.\, \boldsymbol{H}^T + \mathbf{R})^{-1} \tag{22}$$

5. Update state using equation 14 and 15

$$\boldsymbol{X}_0 = \mathbf{C} \cdot \boldsymbol{X}_{0-1} + \boldsymbol{K}_0(\boldsymbol{E}_k - \boldsymbol{H}.\boldsymbol{X}_{0-1}) \tag{23}$$

6. Update state covariance

$$\boldsymbol{S}_{0+1} = (\boldsymbol{I} - \boldsymbol{K}_0.\boldsymbol{H}).\boldsymbol{S}_0 \tag{24}$$

7. return $\boldsymbol{S}_{0+1}$ and $\boldsymbol{X}_{0-1}$, compare if x_0 *and* y_0 are within the maxima and minima coordinates of the probability distribution(Best feasible region) points formulated through atomic multrilateration for both the x and y coordinate sets, if yes, keep the estimated point ,if not disregard the position and loop back to update the position.

The irony of this algorithm is that if there is not a one-to-one mapping between the measurement and the state, the Jacobian affects the Kalman gain so that it only magnifies the portion of the residual that does affect the state. If however in the overall measurements there is not a one-to-one mapping between the measurement and the state via, then we expect the filter to quickly diverge. In this case the process is unobservable.

The only input data of the localization is the RSSI embedded in every Wi-Fi packet and retrieved by standard legacy IEEE transceiver. The key of the localization algorithm is based on the geometry provided by the network of anchors' beams and Multilateration and error filtering method. The positioning algorithm estimates the target location of a nomadic node by correlating the real-time RSSI data, collected during the normal exchange of unmodified Wi-Fi packets, to distance

B. Distance Error Tunning

The purpose is to minimize the error between the predicted distances (d) and path loss (PL) values and the measurements. Statistical parameters used in this paper are Mean Error (ME), Root Mean Square Error (RMSE) and Standard deviation (σ^2)[9].

Distance Error evaluation:

$$ME = \frac{\sum\sqrt{(X_{Actual}-X_{Est})^2-(Y_{Actual}-Y_{Est})^2}}{Number\ of\ Estimates} \quad (25)$$

$$RMSE = \sqrt{\frac{\sum(D_{Actual}-D_{Est})^2}{Number\ of\ Estimates}} \quad (26)$$

$$\sigma^2_{dis}(m) = \sqrt{RMSE - ME^2} \quad (27)$$

C. Principle of Operation

Using the formulations described above, the equations can be evaluated iteratively to track the target object. In each iteration, the current state is used to estimate the location at the next time instant. The emphasis is that the landmark estimated rests within the polygon formulated as a result of the best feasible region. The error covariance matrix in the next time step is also projected using the state space model and the process noise in the previous matrix. The current position (x_i, y_i) is a subset of the state vector. The basic idea is to store the prior locations and measured ranges the first few times the anchor node position is estimated and then estimate its position within the intersecting region of the four circles on the plane. Once the estimate of a new landmark is produced, it is added to the Kalman filter where its estimate is then approved along with the estimates of the other landmarks. And once the Kalman gain is computed the distance measurements from the nodes to the target object are obtained and are used to update the state. The keys to this idea are therefore to first find the best feasible region by estimating using a distribution formulated by Atomic Multilateration about the intersection points of the three or four circles formulated through using equation 6 to get the radius and then use the Kalman filter to refine the results. The estimate of the best feasible point is further refined by re-evaluating the filter around the new estimated beast feasible region or state operating points. And because it takes advantage of the special structure of the problem, the resulting approach is less computationally cumbersome and avoids the extrema problems associated with other optimazation techniques.

IV. EXPERIMENTAL SETUP AND TEST RESULTS

We have carried out tests for the signal strengths-distance measurements within the International student dormitory building at South China University of Technology, North campus on the first floor and the map of the test area is shown in *figure 5*.

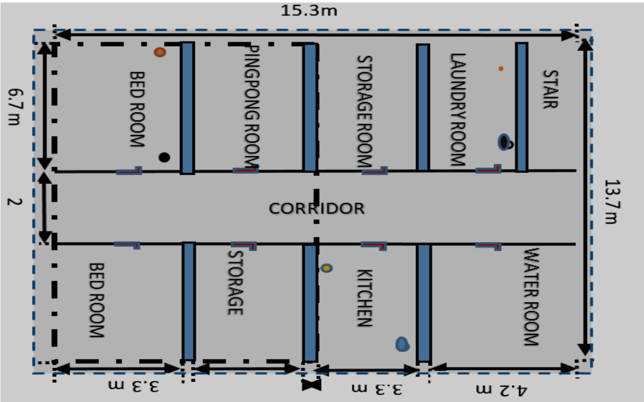

Fig. 5. Test Bed Map

For the measurement of the signals and practical implementation of our localization application, we have used a laptop (A200) running on Window 10. The sensitivity of the transceiver ranges from utmost -15 dBm to about -128 dBm. Nevertheless, values below -90 dBm are generally too inconsistent to be leveraged as reference. Processing this information statistically, we built a Windows application based on C# programming language for localization, and we have tested it in locations where 6 Wi-Fi radios in average were listened to (approximately 4 of them with RSSI above -90 dBm are used in every turn of distance measurement), obtaining accuracies in the order of 2 meters as shown in the *figure 6 and 8*, with real-time dynamicity (refreshment of location information every 5 second).

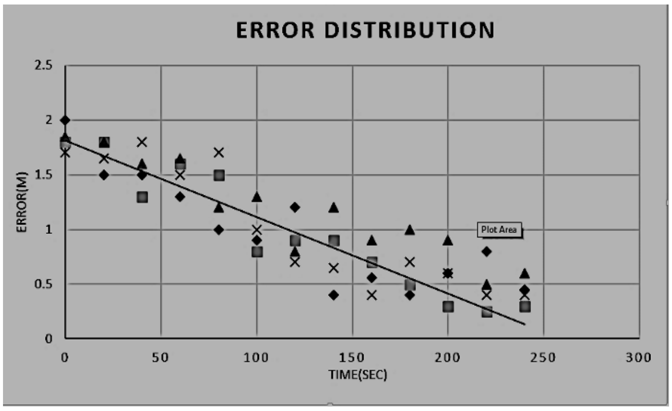

Fig. 6. Error Variation With time

In our experimental setup, the graphical user interface's main display, displays the position of the nomadic node with reference to the 4 corners of our test bed in terms of both angular and linear distance, then on the far right, it displays Access points parameters such as the name of the access point, its percentage signal strength, the RSSI values of the node and its relative distance to the nomadic node and the BSS values as shown in *figure 7* in real time

Access Point can show important standard deviations in between consecutive scans (within the same radio). The estimate can however be refined by re-evaluating the filter around the new estimated state operating point. This refinement procedure can be iterated until little extra improvement is obtained.

Figure 8 shows that the accuracy of the system on average improves approximately after 20 seconds of operation. This is

further clarified by *figure 9* which shows accuracy of individual access points tested over different distances to the nomadic node, that the best first estimate was arrived at between 20 to the 35 seconds of the application's scan operation of APs

The process noise parameter matrix Q was obtained by using varying values of the X and Y process noise parameters, and computing the average distance error for the entire path for that set. *Figure 6* depicts a surface plot of the average distance error against time. It is interesting how the use of inaccurate process noise parameters effects the performance. At the start of the process the resulting error is very high as depicted by *figure 6* and average position estimates in *figure 8*. The minimum average distance error as given in *figure 6*, was found for process noise parameters for all the nodes and the average is shown with a solid line which interestingly implies that the process noise parameters is inversely proportional to time, velocity and acceleration is considered as process noise, and hence the units can be considered as minute.

The maximum distance noise is about 2m error as seen on *Figure 6* and was obtained for the process noise parameters. The benefit of the RMSE given in equation (15) is that the error in localization of the X and Y coordinates is available and X and Y RMSE values can be result in the standard deviation that describes the net error. An interesting characteristics of the RMSE is that it is biased towards large errors. A large error make a larger contribution in RMSE than in average distance error hence indirectly covering up the inaccuracy that might come as a result of varying RSSI values shown in table 1 over the same distance

Access Point can show important standard deviations in between consecutive scans (within the same radio). The estimate can however be refined by re-evaluating the filter around the new estimated state operating point. This refinement procedure can be iterated until little extra improvement is obtained

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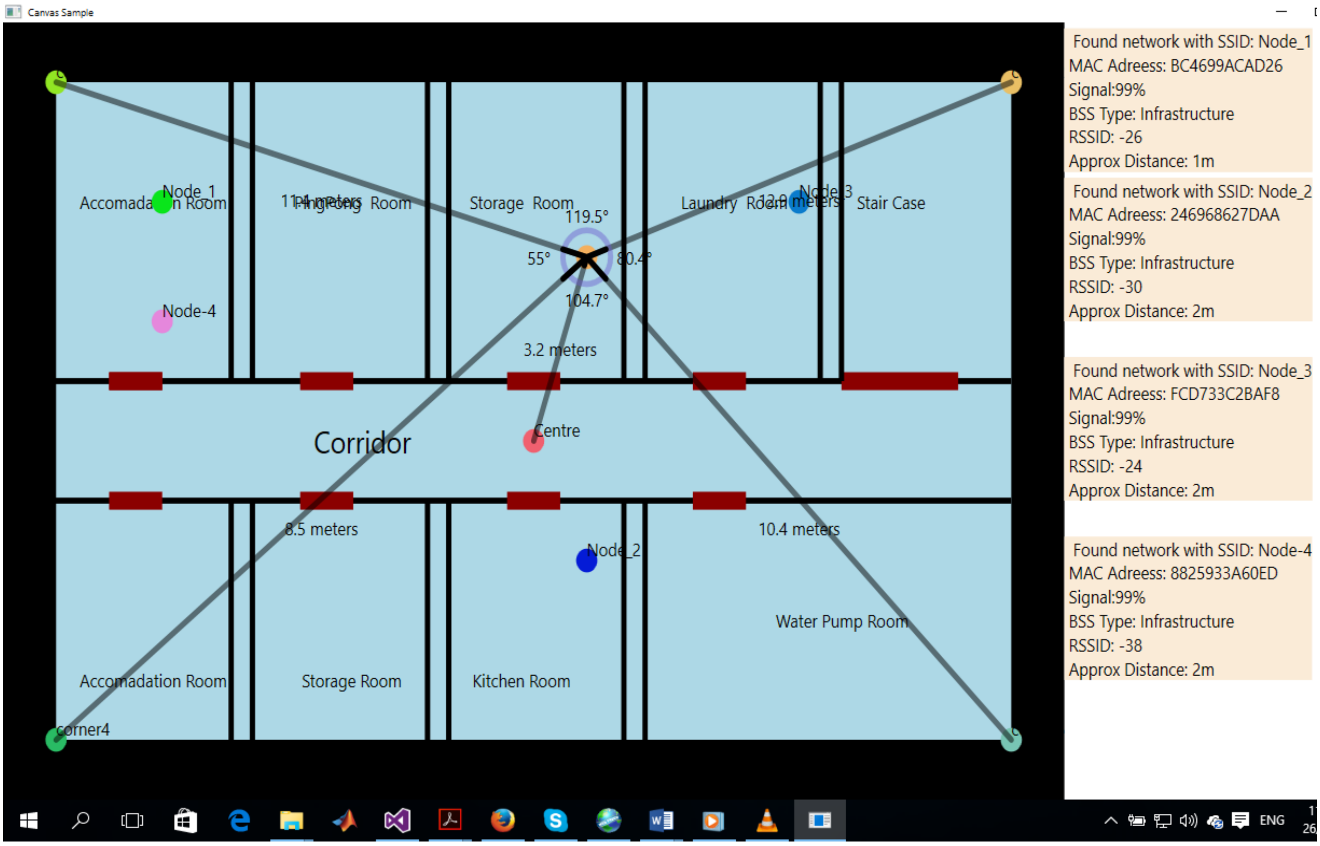

Fig. 7. C# Results Display Interface

process noise parameters effects the performance. At the start of the process the resulting error is very high as depicted by *figure 6* and average position estimates in *figure 8*. The minimum average distance error as given in *figure 6*, was found for process noise parameters for all the nodes and the average is shown with a solid line which interestingly implies that the process noise parameters is inversely proportional to time, velocity and acceleration is considered as process noise, and hence the units can be considered as minute.

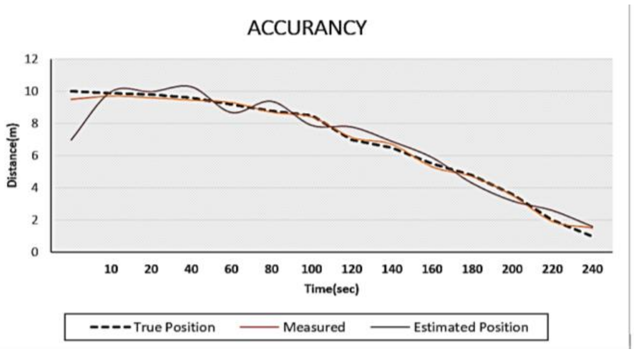

Fig. 8. Accuracy of the System with time

The maximum distance noise is about 2m error as seen on *Figure 6* and was obtained for the process noise parameters. The benefit of the RMSE given in equation (15) is that the error in localization of the X and Y coordinates is available and X and Y RMSE values can be result in the standard deviation that describes the net error. An interesting characteristics of the RMSE is that it is biased towards large errors. A large error make a larger contribution in RMSE than in average distance error hence indirectly covering up the inaccuracy that might come as a result of varying RSSI values sh9own in table 1 over the same distance

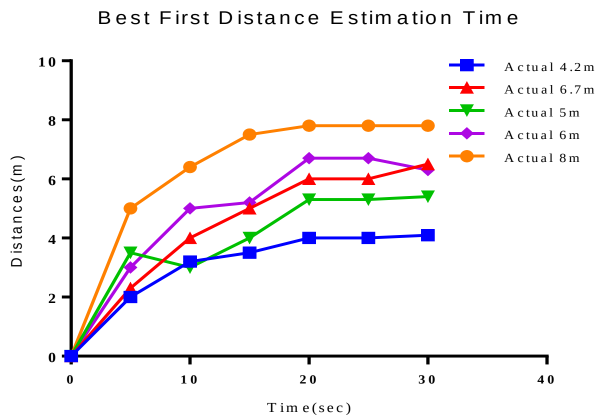

Fig. 9. Time Taken To Make First Best Estimate

As stated earlier, *figure 8*, proves that the process requires many iterative before the Kalman filter can filter out the errors and give the best estimates with the best feasible region

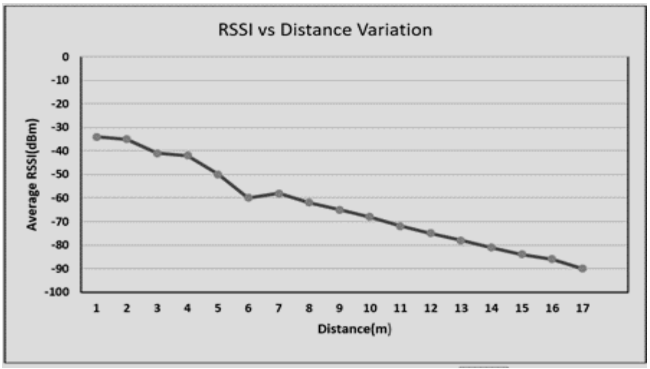

Fig. 10. Total Average values of RSSI versus Distance

TABLE I. 5 INDIVIDUAL ANCHOR NODES' RSSI VALUES RANGES VS DISTANCE

Distance		RSSI Value(dBm)			
Actual (m)	Estimated (m)	Node_1	Node_2	Node_3	Node_4
1	1.5	>-28	>-25	>-24	>-42
2	2.75	-(29 – 40)	-(26 – 33)	-(25 – 33)	-(43 – 46)
3	3.5	-(41 – 45)	-(34 – 35)	-(34 – 35)	-(47 – 50)
4	4.6	-(46 – 53)	-(36 – 40)	-(36 – 40)	-(50- 52)
5	5.8	-(54 – 57)	-(41 - 50)	-(41 - 50)	-(53 – 55)

IV. DISCUSSION

To verify the proposed mathematical models we have implemented a localization system that uses a RSSI Atomic multrilateration approach in a wireless sensor network with a Kalman filter used for position refinement. The system position estimation accuracy was also evaluated. And the results are satisfying in spite of the large error encountered at the beginning of the measurement of roughly about 1.5 to 2 meters as verified in *figure 8* and thereafter a steady improvement. For propagation and distance models tuning, a comparison between predicted path loss and measured path loss data, and actual distance and estimated distance was done, and Statistical parameters such mean error, root mean square error and standard deviation were considered to improve the system performance in terms of position estimation as can be seen in *figure 8's* were there is a steady accuracy improvement over the specified time of running the application. Hence our methodology is viable and leaves room for further improvement of the algorithm combining trilateration and Kalman filter principles.

V. CONCLUSION

The project can further be improved by improving the path loss equation which could be done by adding potential path loss factors and also by improving dynamic and measurement noise predictions in the Kalman filter, and confidence weight in the distance estimates for Multrilateration evaluation error in (10). Overall a maximum error of 2 meters is incredible in spite the laborious tuning involved before the estimations can become more valid and acceptable. I would suggest this methodology over fingerprinting method becomes one doesn't need an extensive calibration of every possible position to improve the estimates but only requires a tune up the system.

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