Prediction of WiFi Signal using Kalman Filter for Fingerprinting-based Mobile Robot Wireless Positioning System

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***Abstract*—The non-predictive behaviour of wireless signal especially that of 2.4GHz WiFi due to the complex signal propagation is primarily non-usable for mobile robot positioning system. It is fluctuating and prone to error that made positioning accuracy haywires even in stationary location. Therefore, there is a need to estimate the wireless signal to its real value as per fingerprint location. This paper proposed to use the Linear Kalman Filter (LKF) to predict the wireless signal, i.e. the WiFi Received Signal Strength (RSS) to estimate the location using the Weighted K-Nearest Neighbor (WKNN) algorithm that matched the fingerprinting database constructed beforehand. By employing the LKF, the accuracy of the positioning system at any stationary location has improved significantly when compared to the use of raw original WiFi signal.**

***Index Terms*—Positioning Systems; Fingerprinting Technique; Wireless Localization; Kalman Filters; Robotics.**

I. INTRODUCTION

In the recent years, the positioning of subjects or objects such as mobile robot using wireless methods has gained reputable attentions due to ease of deployment as well as cost facilitative. The foundation works using a method known as fingerprinting technique has notched a reasonable accuracy for user tracking in an office environment [1]. Since then, numerous literature has adapted the fingerprinting technique prior to their applications [2-4]. Fingerprinting technique is much favoured than the classical approach of wireless positioning, i.e. the triangulation (or trilateration) technique for their effectiveness and accuracies.

While triangulation technique requires the knowledge of the location of transmitting devices such as the WiFi Access Point (AP) in order to geo-locate the mobile robot [5], fingerprinting technique does not need them. The Received Signal Strength (RSS) from the WiFi AP is usually measured at pre-determined reference locations to construct the signal radio map. Some literature suggested that constructing the signal radio map requires humanly effort [6], but the radio map can also be interpolated by algorithms such as the stochastic Kriging algorithms [7] or using a more deterministic algorithm such as the Modified Shepard's Method [8,9]. The database collecting workload can be further reduced with the aid of autonomous mobile robot fusioned with odometry sensors [10].

Figure 1 shows the commonly used diagram to illustrate the wireless positioning system based on the signal fingerprinting technique. In the training phase, as explained previously the multiple WiFi signals radiated from AP_1 to AP_k are recorded, and the average signal strength is stored in the database. In the positioning phase, the signal measured by the mobile robot is matched to those in the database, and the result is later returned in the form of estimated location, usually in Cartesian spatial space [11].

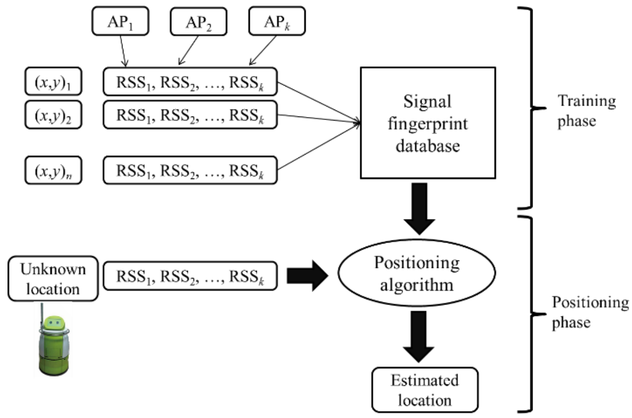

Figure 1: A typical flow of the wireless positioning system based on fingerprinting technique

As simple it might sound, such positioning technique has complex challenges due to the fluctuating behaviour of the wireless signal. Taking examples of using deterministic database matching such as the nearest neighbour (NN) and a stationary mobile robot, the measured WiFi RSS varies unexpectedly over time as depicted in Figure 2. Then the online which matched to the fingerprint database also are varied unexpectedly. Theoretically, the positioning system using such signal will yield different locations. Computation, the average of these locations, is not so beneficial since the 'true' location is unknown. Hence it is perplexing.

Therefore, it is natural to filter in the sense of predicting the incoming signal to the mobile robot. A correct prediction will yield in an accurate positioning result of the mobile robot. In this paper, we discuss the use of the Linear Kalman Filter to predict the WiFi signal in the online phase. As a rule of thumb, the signal fingerprint database has been constructed beforehand having the tuple of reference location coordinate and the average RSS over some sampling period. In addition, the result is also compared with the original WiFi data to observe the effectiveness of the proposed algorithm.

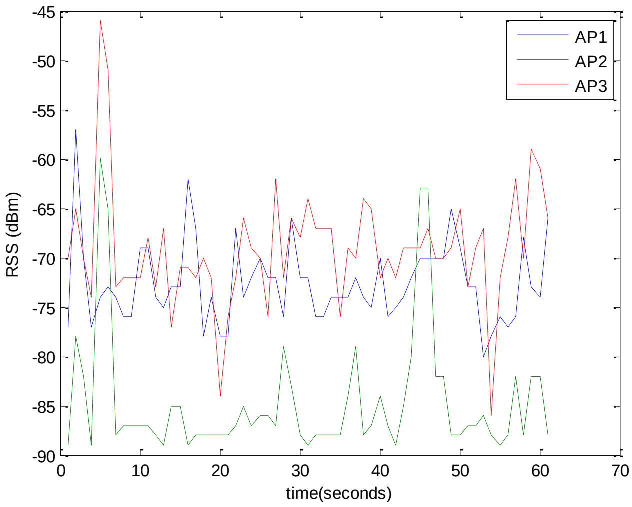

Figure 2: An example of the WiFi signal fluctuation where the mobile robot stays stationary over some period of time.

This paper is organised as follows. Section II introduces the analytical background such as the fingerprinting database and the derivation of the Linear Kalman Filter as well as the Weighted K-Nearest Neighbour (WKNN) positioning algorithm. Then, section III presents the experimental setup including the hardware used in this works. Section IV, on the other hand, discusses the results of the signal prediction from positioning error perspective. Finally, the conclusion and future remarks are drawn in Section V.

II. ANALYTICAL BACKGROUND

A. *Fingerprinting Database*

Figure 3 shows the standard IEEE 802.11 a/c/n Wireless Fidelity (WiFi) channels in the 2.4GHz frequency spectrum. From the nominal 14 channels, there are three non-overlapping channels at channels 1, 6 and 11. This choice of channel is reasonable to avoid interferences between the WiFi APs.

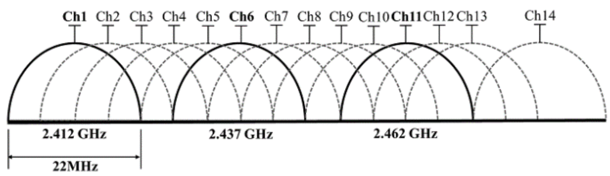

Figure 3: The 802.11 WiFi channels in the 2.4GHz spectrum

At predefined locations, the WiFi signal can be measured over some sampling period. Then it is common to use the signal average as the scalar value to construct the database. It is, in fact, practical to store the database v in vector tuple form given in Equation (1).

$$v = \left[\overline{z}_i^{\,k} \;\; P_i^k \right]^T \tag{1}$$

where $\overline{z}_i^{\,k}$ is the vector of the average of WiFi received signal strength at the *i*-th location of AP *k*. These *i* location can be described as P_i^k in Cartesian space comprising of location coordinate *x* and *y*, respectively. The AP *k* is normally identified using its SSID or BSSID identifier.

B. *Linear Kalman Filter*

In the 60s, Kalman proposed the Kalman filter as a recursive filter to determine the random values of the linear and nonlinear system from lousy and noisy signals [12]. Kalman filter uses the knowledge of current and previous states to track or predict and thus revise the past, present and future states. Kalman filter can plot the system's trajectory, making it suitable to model systems such as radars that anticipate and estimate the next state [13].

This works implemented the classical approach of the Linear Kalman Filter (LKF). If we consider the discrete-time system:

$$\begin{aligned} &\text{Initial state} && : x_0 \\ &\text{State model} && : \hat{x}_k = Ax_{k-1} + Bu_{k-1} + w_k \\ &\text{Measurement model} && : z_k = Hx_k + v_k \end{aligned} \tag{2}$$

where the state variable *x*, *u* and *w* represents the original WiFi signal, control input and the noise at time *k*, and the measurement model pertaining noise variable *v*. The control input is, however, cannot be controlled because the WiFi AP properties are limited by the manufacturers built. Hence, it is assumed to be unity. Intuitively, Equation (2) becomes Equation (3).

$$\begin{aligned} \hat{x}_k &= Ax_{k-1} + w_k \\ z_k &= Hx_k + v_k \end{aligned} \tag{3}$$

Since the LKF is an iterative method, it is easier to illustrate the computation graphically. Figure 4 shows the algorithm of the LKF used in this works.

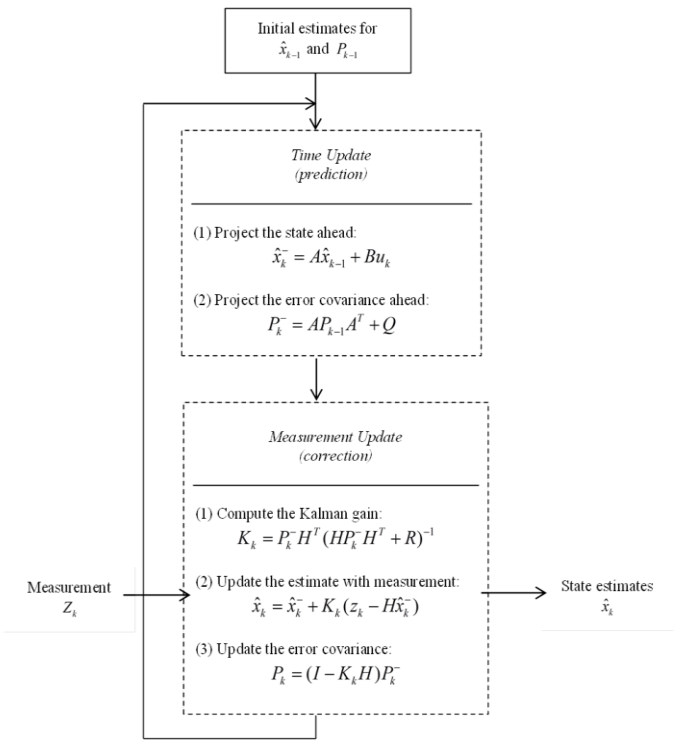

Figure 4: Linear Kalman Filter algorithm

C. WKNN Positioning Algorithm

When an unknown WiFi signal, z_u^k is obtained, it will be matched to those in the database, v. The estimated location is then decided at P_i^k that matched z_i^k. Therefore it is natural to use the data that has the minimum distance between the two, which normally attributed to finding the nearest neighbour (NN) using distance norm p stated in Equation (4).

$$d_j = \frac{1}{N_p}\left(\sum_{i=1}^{M}\left|z_u{}^k - z_i{}^k\right|^p\right)^{\frac{1}{p}} \tag{4}$$

where N_p is the total number of WiFi AP, $z_u{}^k$ is the unknown WiFi RSS data, and z_i^k is the fingerprint database $\{i = 1, 2, \ldots, MN\}$, MN is a total number of the database defined by the level of granularity. However, this idea is somewhat prone to noisy samples which show unpredicted errors. Thus, instead of taking the nearest neighbour, surrounding neighbours around K is taken into consideration. To increase the effectiveness of the matching algorithm, a weightage λ can be included as a function of inverse distance to emphasise the significance of 'close' neighbours while neglecting those 'far' neighbours.

By matching the unknown WiFi signal to the database v, the estimated location can be computed as in Equation (5).

$$\left(\hat{X}, \hat{Y}\right) = \sum_{j=1}^{K}\left[\lambda_j \times (X_j, Y_j)\right] \tag{5}$$

where $(\hat{X}, \hat{Y})$ is the estimated location, λ_j are the weights of the corresponding data, which can be computed merely as Equation (6).

$$\lambda_j = \left(1/d_j\right) \Big/ \left(\sum_{j=1}^{K} 1/d_j\right) \tag{6}$$

III. EXPERIMENTAL SETUP

We conduct our experiments at the second floor of Centre for Human-Robot Symbiosis Research, Toyohashi University of Technology. Figure 5 shows the location of the WiFi AP at their optimised location to ensure the entire wireless coverage within the experimental area[14]. The experimental area is about 11×8.4 meter area highlighted in the black box. The building's surrounding walls are about 20 cm thick dry concrete, and the door is made of steel. A total of 64 sampling locations marked with ' O ' are available in the mobile robot mobility area at one meter sparsity level, considering also space obstruction such as furniture and other placements as well as accommodated space for other works. This one-meter sparsity level is considered suitable since our mobile robot has a base diameter of 0.5 meter that fit well between two reference locations. A details configuration of the mobile robot can be found in [8,9]. Three AP were used, where AP 1 and 2 has a clear, unobstructed line-of-sight (LOS) while AP 3 is obstructed by a cement wall and randomly close and open door. This randomness is resulting from daily used of the experimental area by other research studies. Moreover, such randomness is more nature in real situations. In this works, we used the WiFi AP from Alfa Inc. model number AIP-W525H dual omnidirectional antenna with 5dBi each. The WiFi receiver is also from Alfa Inc. model number AWUS036NHR-V2 with a 5dBi omnidirectional antenna attached on the mobile robot at one meter height from the floor level. For the WiFi APs, the set-ups is built such as none network security, default MAC from Alfa Inc., and network channel set to channel 1, 6 and 11 respectively. The nominal frequency for this AP is 2.4GHz. The recording time per sampling location is set to about three minutes long in order to obtain the generic behaviour of the wireless signal.

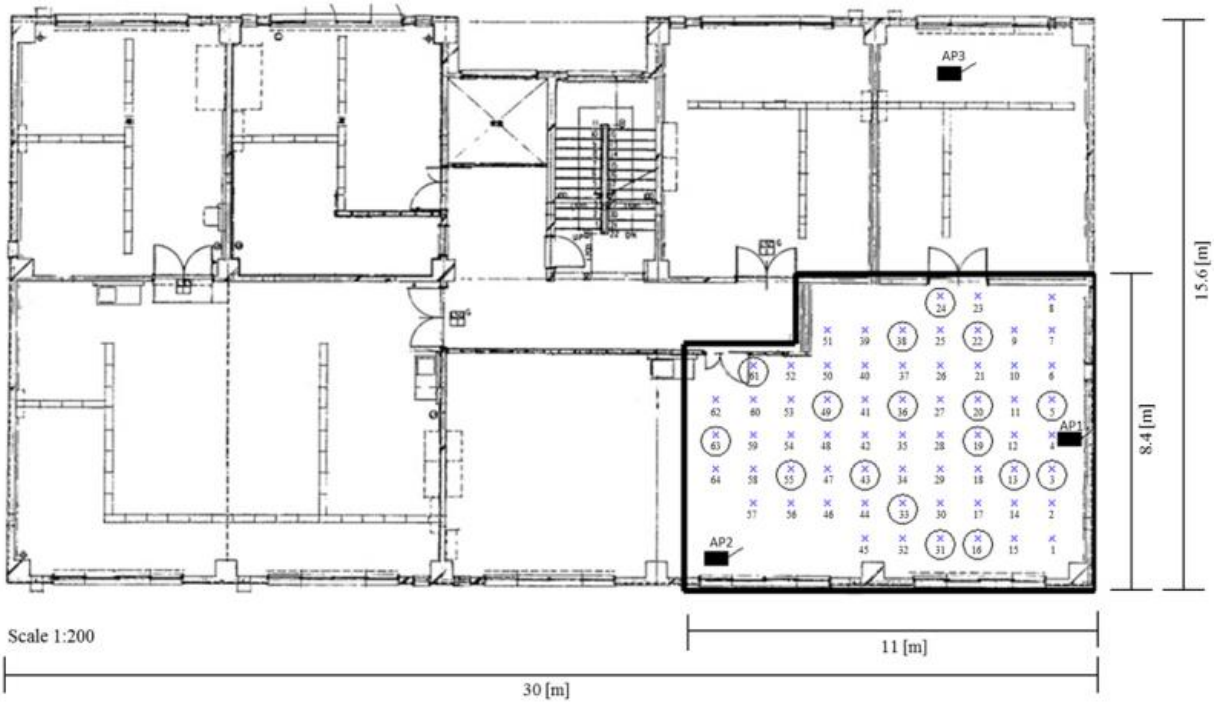

Figure 5: Experimental area showing the location of the WiFi Access Points (AP) and signal fingerprints database [8]

IV. Result and Discussion

The prediction of the WiFi RSS can be accurately forecasted by using the measured WiFi RSS value of the current state as well as the value reflecting the projection from the current state using a recursive algorithm and adaptive Kalman Gain shown as K_K. Moreover, the more we trust our measurement, i.e. smaller value of error covariance estimate, then the system will converge into meaningful value in short period of time. In this paper, a heuristic value of error standard deviation of about 3 dB is used resulting in convergence in a considerable amount of time. Also, the value of K in WKNN algorithm is selected to one which represents the nearest neighbour of the fingerprint database. A thorough analysis of WKNN and its effectiveness is discussed in details in [8,9].

Figure 6 shows the application of LKF towards the fluctuating WiFi sample signals retrieved from three different AP where the mobile robot stays stationary over some period. The stationary location is depicted at Location ID #57 in the experimental map Figure 5, where the strong WiFi signal is received from AP2, the moderate signal from AP1, and the weaker signal from AP3. The continuous straight line over *y*-axis represents the average computation of the RSS signals respective to the APs. By trusting the measurement at aforementioned standard deviation, we can observe that the resulting filtered signals are converged to a respective signal average of about 20s. Then, we can say that the WiFi signal afterwards has been successfully predicted towards its convergence to the signal average before this stationary test location.

Further experiments were conducted from the local positioning of view. The fingerprinting database was initially made using the average of WiFi signal before each test locations. The robot stayed stationary at the test locations, and then it will try to position itself using WKNN matching algorithm. In this sense, the robot did not know its correct location, but it will try to determine his location based only on the obtained WiFi signals.

Referring to the test locations depicted in Figure 5, we experimented the positioning at test location #27, which is located in the central area of the experimental area. This test location is selected in this paper since it is located in the *central* area of the experimental area and represents the location where the robot operates the most. In the first trial, the raw WiFi signal data is fed into the WKNN positioning algorithms, and the estimated position is observed. Later, the same signal is filtered using LKF and re-fed into WKNN positioning system and being observed.

About 120 seconds of sampling data were obtained, and at each individual sampling time, the WiFi signals were fed into the WKNN positioning algorithm to match with the fingerprinting database. Figure 7 shows the result of the positioning system concerning central test location ID #27 using only raw signal. In this case, the average positioning error is recorded at $1.3095 \pm 0.9178\,[\mathrm{m}]$. The highest error is at about 40s with the error of 4.3 [m], and the exact location is obtained only one time roughly at 66s. Figure 8 on the hand shows the positioning accuracy using the unfiltered raw WiFi data in the digitised experimental area. It can be observed that the robot failed to position itself as proved by the scattered estimated locations throughout the experimental area. In addition, there are several locations estimated outside the LOS region of the AP depicted by the triangular notation.

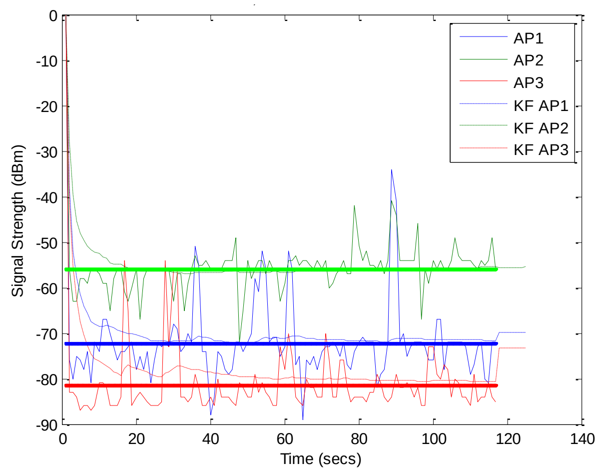

Figure 6: Effectiveness of Linear Kalman Filter towards prediction of the WiFi signal in a stationary location

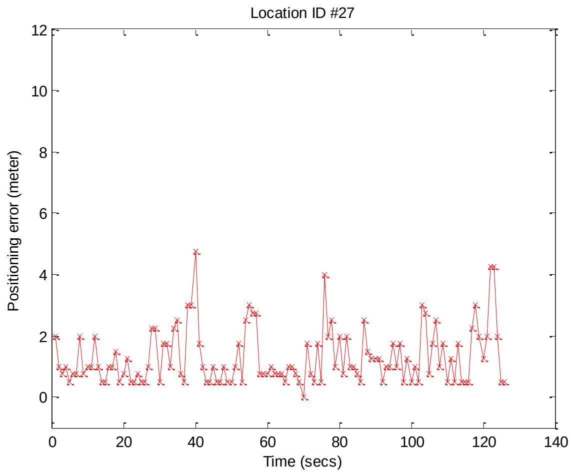

Figure 7: The positioning error the positioning system on using raw data

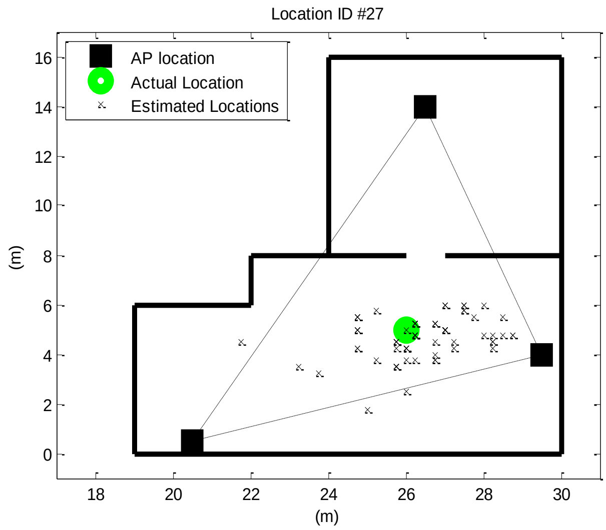

Figure 8: The positioning accuracy of the positioning system on using raw data

Figure 9 presents the positioning error at central test location ID #27 when the WiFi signal is applied to the linear Kalman filter. In the first 10 seconds, the error is at about 1 [m], and afterwards, the error is ultimately reduced to 0 [m] signifies that the robot has successfully determined its true location. The average error at this point is recorded at $0.0635 \pm 0.2448[\mathrm{m}]$ which shown a remarkable 95% improvement from using the raw signal data. Figure 10 shows the accuracy of the wireless positioning system on using the Linear Kalman Filter signal which depicted that the mobile robot has estimated its location exactly on the actual location, most of the time. This is because the signals have successfully converged to the signal average, then the fingerprinting matching system works ideally.

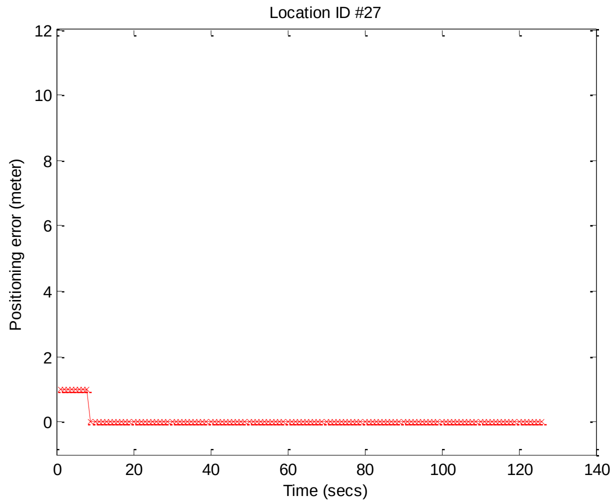

Figure 9: The positioning error the positioning system on using LKF filter

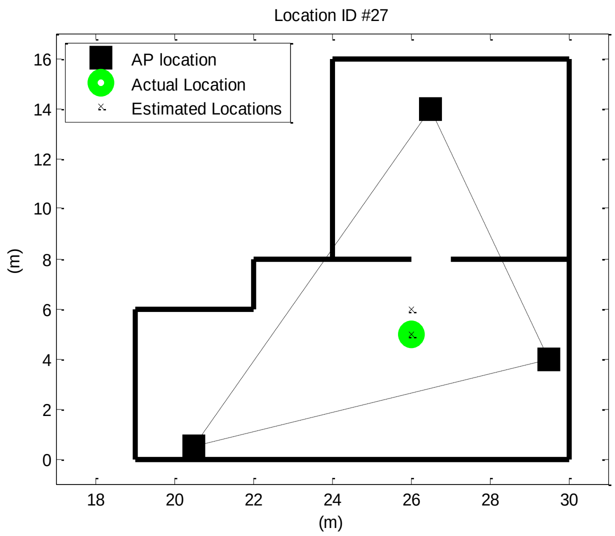

Figure 10: The positioning accuracy of the positioning system on using LKF filter

V. Conclusion

A The stationary positioning system with the use of raw WiFi RSS data may cause bad variation of positioning results due to the signal fluctuation problems. The signal fluctuation caused by complex signal propagation and mechanism is non-deterministic thus controlling them is an ambitious effort. Hence the signal filtering approach is highly desired.

In this paper, the prediction of the WiFi signal specifically used for fingerprinting-based wireless positioning system has been experimented by using the Linear Kalman Filter. With a proper choice of noise standard deviation, the online signal is likely to converge to the signal average which is the reference values in the fingerprinting database. In such cases, the lower noise standard deviation means that the WiFi RSS measurement is much more trustfulness. By using the LKF, the accuracies of the positioning system is improved with remarkable improvement of 95% compared to the use of unfiltered raw data. Moreover, the noises have also been successfully suppressed to the signal average. This correct signal prediction has contributed to the high accuracy WKNN positioning system, specifically at stationary locations. In the future, we are planning to increase the scope this works into mobile tracking with the use of nonlinear Kalman Filters such as the Extended Kalman Filter and Unscented Kalman Filter. Also, spatiotemporal data of robot mobility will also be analysed in order to achieve the ultimate goal of sensor-less mobile robot localisation.

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