Abstract — Positioning services are increasingly used for applications such as navigation, advertising and social media. While outdoor navigation based on GPS and/or cellular systems works well, indoor navigation is a much tougher challenge. This paper proposes an indoor localization using Wi-Fi received signal strength indicator (RSSI) measurements from existing access points. Using RSSI data from multiple access points, additional access points will be added in the system thru linear regression statistical model to create virtual access points (VAPs). This paper fuses the low-cost and flexible system of fingerprint localization with VAP creation and the improvement in accuracy by adapting Kalman Filter (KF) and Particle Filter (PF). The effectiveness of using KF with VAP has demonstrated positive results in previous research. This paper aims to integrate the use of PF in the system. To improve the performance of indoor localization, the proposed model will be an improved virtual access point localization, proposed filtering (VAP+KF+PF).

Keywords—Wi-Fi, RSSI, Finger printing, Localization, VAP, Kalman Filter, Particle Filter

I. INTRODUCTION

The abundance of Wi-Fi systems gave way to convenient navigation in indoor environments thru location based services. Location estimation has been a part of our daily lives since the Global Positioning System (GPS) has been available in our mobile devices. But GPS has its limitations in the determining our position in an indoor environment. Many approaches have been made in indoor localization aiming for precision, accuracy, complexity, cost and robustness, in [1] a study conducted to compare such techniques considering their implementation and performance. Among known techniques, the use of fingerprint map is still well-known for its low-cost operation and its accurate results. One thing in common among different indoor localization models is the received signal strength indicator (RSSI), radio signals provided by access points (APs) in the indoor environment. But RSSI-based distance estimation requires accurate measurement of radio signals from APs. Different filtering method is used to aid in the removal of noise and fluctuations of these signals.

This paper uses the concept of adding virtual access points (VAPs) [2] in existing indoor wireless local area network (WLAN) system where there is a fixed number and position of APs. The use of VAPs is to add APs without additional AP routers with the use the correlation of RSSI signals of different APs and create a matrix of RSSIs statistically. APs have significant roles in indoor localization such that its position and number affects the radio signal distribution in the environment, on training and online phases of fingerprinting [3].

Additional filters can also be integrated in the VAP algorithm making it compatible with Kalman Filter (KF) that also reduces noise in the measured RSSI by calibrating it during the online phase of localization [4]. It showed to improve the accuracy from standard fingerprinting method. This gave the idea of integrating other filters popularly used in indoor localization where RSSI is used to determine the location of users.

Particle Filter (PF) is known to be used in non-linear Gaussian distribution, which can also be applied in RSSI measurements. Using both KF and PF will be utilized in the improvement of indoor localization with the implementation of VAPs in the fingerprint map.

The rest of this paper is organized as follows. Section 2 discusses processes for measuring RSSIs and estimating indoor distances using virtual access points. Section 3 introduces and describes the proposed algorithm using VAP, KF and PF. Section 4 analyzes the results of the experimental implementation of the proposed method. Finally, the conclusions of the study are presented in Section 5.

II. RELATED WORKS

The use of fingerprinting has led to innovations in indoor localization but is still composed of two fundamental steps that are still being used now. This section discusses the use of
fingerprint map and the addition of VAP in the system to aid in the location estimation and the integration of KF and PF in fingerprint localization.

A. Fingerprint Map and VAP

The indoor positioning techniques using Wi-Fi has seen many approaches with low-cost, high accuracy, low-complexity and robustness. In [4], the information of the physical layer in the scheme can be easily obtained in the Wi-Fi fingerprint scheme. The measured and obtained RSSI reflects the distance information of the transmitter and the receiver. Because each location in an indoor environment receives a unique signal strength due to multi-path effect, the signal property, especially the signal strength, has its own fingerprint. A fingerprint map is built up actually using this property.

Wi-Fi fingerprint scheme has been a popular localization technique since the idea of RADAR [5] and has since been improved with different approaches and ideas added to its concept. It consists of two steps known as the offline phase and the online phase as shown in Fig. 1. The online phase gathers RSSI measurement by use of mobile devices positioned in different Reference Points (RPs) to create a radio map. The radio map represent points in the map with specific RSSI measurements from different APs existing in the system called fingerprints to be stored in a database. During the offline phase the user will measure RSSI from APs and these RSSIs will be compared in the radio map. By the use of Euclidean distance estimation, the least difference from the measured and the stored RSSI will be the nearest location to the user.

<table>
<thead>
<tr>
<th>Offline Phase</th>
<th>Measurement of RSSI \downarrow</th>
<th>Fingerprint Map \downarrow</th>
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<tbody>
<tr>
<td>Online Phase</td>
<td>Received RSSI \downarrow</td>
<td>Comparison to Map \downarrow</td>
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Fig. 1. Conventional fingerprint method.

For the process of creating the VAPs, it is created in an open spaced indoor environment without any obstacles. In [6], two VAPs were added to the existing 3 APs, whereas one VAP was placed in the exact opposite of one existing AP and the other VAP was placed in the middle of the indoor environment. Though the experiments caused the best results, it was done with a series of trials and simulations in order to determine the VAP location. This was done during the data collection phase for the fingerprint map and takes more time than conventional data collection where RSSIs of the existing APs are collected. In the same manner, the creation of the VAP also requires much time as in the case of VAP location.

VAP is created by determining the correlation of APs and taking the regression coefficient of it. The regression coefficient will be used to create the matrix for the RSSI values in assigned RPs in the fingerprint map. Several attempts for seizing the VAP placement was made and some locations has low correlation to existing APs causing low placement accuracy. It is confirmed that the VAP correlation with at least 1 or 2 APs is should be greater than 70% in order to achieve the desired placement accuracy.

\[ VAP_{\text{target}} = VAP_0 + C_{\text{reg}} \cdot AP_n \]  

In Eq. (1), \( VAP_{\text{target}} \) is the VAP RSSI in dBm at distance \( VAP_0 \), with respect to \( AP \), as existing access points. \( n \) is the number of AP available in the indoor environment with \( C_{\text{reg}} \) as the regression coefficient. \( VAP_{\text{target}} \) value will depend on the \( C_{\text{reg}} \) and AP gathered during the data collection phase. \( C_{\text{reg}} \) will be a constant value while \( AP \) will be the RSSI value of \( n \) number of access points. The required number of \( VAP_{\text{target}} \) will be the same as the number of RP per \( M \), which refers to the number of VAPs added in the system. \( VAP_{\text{target}} \) is the RSSI value of a VAP at any RP while \( M \) designates whether it is any VAP among all VAP. The equation is based on the linear regression modeling which assumes two scalar variables are dependent on each other.

B. Kalman Filter

KF is known to be used not just in location estimation but in automatic guidance, navigation and automated control of vehicles. Signal propagation in an open space produced by APs and mobile devices is affected by noise. The presence of noise means irregularity and interferences in measured RSSIs but KF is capable of eliminating this noise. KF was applied in the online phase of the VAP system and was able to minimize the error distance as compared to the conventional fingerprint as well as the previous VAP only applied algorithm [6]. It is also better compared to when using K-nearest neighbor algorithm (KNN) and proved its effectiveness in location estimation using RSSIs [7].

To increase accuracy of estimations [8], KF were used in both the offline and online phase of fingerprinting. This was to detect the maximum and minimum signals and eliminate noise that affects the signal. KF uses two steps in its algorithm; the time update which predicts and the measurement update which corrects variables. The algorithm process works in these two steps. The first step is the prediction step where the filter creates a set of estimated values of the input variables, together with the system noise. The next step is incorporating the measured values, resulting to a calibrated value closer to the actual state of the variable. KF is a known calibration algorithm in many localization papers as well as guidance, control and navigation.

C. Particle Filter

PF represents the density function of estimated position by creating random probabilities that contains weight. This randomly weighted probabilities, particles, will be updated each time new measurements are obtained, continuing the update process into correcting the predicted particles. The most
weighted particle in the form of RSSI measurements will determine the estimated position of the user [8], [10].

\[
P_r[x_t|z_{0:t}] = \sum_{i=1}^{N} \delta w^i_t (x)
\]  

(2)

The prediction and correction steps are the main iteration steps for continuously estimating state. The PF tries to estimate the probability distribution \( P_r[x_t|z_{0:t}] \) where \( x_t \) is the state vector of the device at the time step \( t \), and \( z_{0:t} \) is the set of collected measurements until the \( (t + 1) \)th measurement with the number of particles (position \( x^i_t \), weight \( w^i_t \)) as shown in Eq. (2). \( P_r[x_t|z_{0:t}] \) will be the probability location of user based on the RSSI measurement with \( N \) number of particles.

Then the particle weights will be updated as:

\[
w^i_t = w^i_{t+1}(Pr[x_{t+1}|z_t])
\]  

(3)

Then this weight Eq. (3) is normalized in order to obtain posterior density function. After several iterations, \( N \), at time \( t \) will be considered as the number of particles such that \( w^i_t \) will be greater than zero [9].

III. SYSTEM MODEL

This section describes the system model for improved indoor localization algorithm using VAP algorithm and two filters; KF and PF, which will determine user location based on the received RSSI from APs and VAPs. The performance of using KF algorithm together with VAP algorithm gave positive results of lower error distance [11]. By adding another filter such as PF, it will provide an increase in accuracy as well as deal with non-linear Gaussian data which is more effective compared to KF that is linear in behavior.

A. Design Philosophies

The VAP model will be dependent on the indoor floor plan and structure. The optimal VAP placement will be in accordance with how the floor structure is laid out while the path loss of signal varies on indoor environment. Knowing the number and locations of existing APs should be also considered in making the suggested model because the VAP placement depends on the locations of the existing APs. The RSSI values of VAPs will be generated based on the correlation to existing APs. It is very important that the floor plan of the experimental testbed known as the VAP placement is dependent to the existing APs locations. Several attempts for seizing the VAP placement was made and some locations had low correlation to existing APs causing low placement accuracy. In order to make the VAP model, a statistical method will be used. The VAP related data added in the fingerprint map is the collected data during the data collection phase making APs plus some VAPs matrix. From the collected RSSI data, the regression coefficient of VAPs with respect to APs can be calculated.

RSSI values from existing APs is an important factor in the VAP concept but the variances of the RSSI in indoor environment usually occur. These variances are due to temperature, time of the day and interferences from different devices with Wi-Fi capabilities. The KF and PF is adapted to the proposed algorithm to avoid abrupt changes in the RSSI values from the existing APs. In addition to this, the collaboration with VAP, KF and PF enables not only the stabilization of RSSI level but also the improvement of localization accuracy.

B. System Architecture

The proposed system architecture will be utilizing the two steps of fingerprint localization; offline and online phase as seen in Fig.2. In the online phase, VAP will be created in the fingerprint map while both the KF and the PF algorithms will do calculations in the online phase.

Integrating KF and PF to VAP system will filter the noise during the measurement of RSSIs in the online phase. These RSSIs will be corrected and will be used in the location estimation of VAP. Filtering will be performed separately from the VAP process, as it will only calculate measured RSSIs eliminating very high or very low values based on their different states. The main function of the filters is to use to measured RSSIs and update it. As the system is based on controlled experimental environment, execution on real-time application will take a longer time in constructing the fingerprint map during the offline phase.

1) Offline Phase

Also known as the data collection phase. In this phase, it is required to collect labeled data (fingerprints) to create a fingerprint map. The fingerprints are the measured received signal strength at certain coordinates. During RSSI measurement, the RSSI data can be obtained by war walking using smart phones with pre-installed application capable of detecting RSSI. Any device capable of emitting Wi-Fi signals will act as VAP, placed in strategic locations. These devices will act as if actual APs but will only be used temporarily. RSSI data will be collected from existing APs and the devices acting as VAPs. \( A_{\text{PF}} \) will be the measured RSSI of APs in the WLAN with respect to RPs. \( A_{\text{PF}} \) will be measured in \( dBm \), and in each RP there will be \( N \) number of APs and \( M \) number of VAPs. This measurement will be done manually by the use of a mobile devices capable of detecting Wi-Fi signals. After obtaining all RSSI in RPs, their correlation (\( C_{\text{reg}} \)) will be calculated.
The RSSI correlation refers to the relationship of the measured APs with each other. This determines whether an AP will have a significant effect on the RSSI levels of other APs. This $C_{reg}$ will be used in Eq. (1) to create $VAP_q$ in the fingerprint map. Acquiring $C_{reg}$ will determine how RSSI levels of the APs will impact the value of VAPs. Since VAPs are dependent on the measured RSSI of the APs, it RSSI levels will not greatly deviate from that of existing APs.

Once RSSI of VAPs are completed, next will be the creation of the fingerprint map. The fingerprint map will be composed of the $VAP_q$ and $AP_i$ (dBm), where $M$ refers to the number of VAPs and $N$, to the number of existing APs. The fingerprint map stored in the database will be a matrix composed of APs and VAPs, $(N + M) \times (N + M)$, denoting the number of access points to be used.

This phase is only the 1st stage of the experiment in creating the fingerprint map as the database of different RSSI measured in the experimental testbed.

2) Online Phase

In the fingerprinting localization phase, the devices acting as temporary VAPs will be powered off leaving only the existing APs emitting the Wi-Fi signals. First, the mobile user received RSSI, $AP_i$ will be measured. The user must have a software capable of detecting Wi-Fi signals. With the measured RSSI of existing APs ($AP_i$), $C_{reg}$ can be computed and $VAP_{target_M}$ can be calculated based on this $AP_i$. This will create a matrix of Wi-Fi signals of combined $VAP_{target_M}$ and $AP_i$. Once the matrix of received RSSIs is made, it will be then filtered by KF to remove the noise and result to a filtered RSSI, $x_t$. The $1^{st}$ filter applied will be the KF.

The output of the KF algorithm will be further improved by PF to have a final RSSI value of $[PrX_t]$. A final matrix of $VAP_{target_M}$ and $[PrX_t]$ is created. This matrix of data will be then compared to the fingerprint map database made during the offline phase. Euclidean distance algorithm is used to compare the two matrices (dBm) and have an output of their difference in distance (m) or simply known as the error distance. These collected RSSI value for APs and VAPs are compared with the fingerprint map database matrix for APs + VAPs collected during the offline phase. The estimated location of the user can be determined by using Euclidean distance calculation. This localization process will occur after the 1st algorithm is executed, completing the two stage process of the system.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

A. Experimental Environment

The experiments are executed on the main building of Tongmyong University. Fig. 3 shows the selected experimental setup for the indoor localization with three selected scenarios. The lobby of the first floor of the building is selected as the testbed for the experiments as seen in Fig. 4. 141 RPs are used as the fingerprint map, and the area of each RP is defined to 2m×2m space.

The main building lobby is approximately 30m×30m in dimension. The VAPs are strategically placed in the indoor environment to provide an optimal coverage together with the existing 2 APs. The 2 APs are commercial brand from a local telecommunication company. Access to APs are restricted and RSSI and MAC addresses which can be easily obtained are used. The APs in the experiments are labelled the “Left” and “Right” APs, respectively.

During the data collection phase of the proposed algorithm, 2 devices acting as temporary APs (A1004) are used as VAPs in the experiments. These two devices have a role of VAP are used together with the existing APs to create a 2APs + 2VAPs matrix for computing the correlation after power on. In this situation, the RSSI data is collected from 2APs and 2VAPs in 141 RPs. In addition to this, the fingerprint map is also constructed together with the calculation of the regression coefficient in this phase. This part of the experiment costs the most amount of time. RSSI must be measured in each 141 RPs across the experimental testbed.

During the fingerprinting based localization phase, VAPs will be powered off, leaving only the 2 APs to provide the
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RSSI for the mobile user. Once RSSI is obtained by the user, the measured RSSI of the 2 APs will also be used to calculate the VAP value with the help of the regression coefficient obtained earlier. Once the RSSI of VAP is calculated, it will then be compared with the fingerprint map to determine the least Euclidian distance.

The RP with the least Euclidean error distance is determined to the current location of the user. The real-time application of this will be the collection of data while the analysis and results will be done afterwards. All data acquired by the mobile devices will be done in a separate computer and analyzed.

The experiments were be divided into three scenarios, in which there is a route to follow with specific starts and stops as seen in a, b and c of Fig. 3. The green dot represents the start location and the red dot indicates the location the mobile user will stop. The mobile devices used in the experiments are LG G4 and MacBook Pro notebook.

Initial RSSI readings were gathered using the LG G4 mobile phone with preinstalled RSSI gathering app. After RSSI were gathered on all 141 RPs, the fingerprint map database was created. Computations for the correlation, regression and VAP creation during offline phase were done on the notebook. On the online phase, LG G4 was also used to gather real-time RSSI readings following the trajectory of the three scenarios. KF and PF computations were done after completing the courses.

### B. Experimental Results

Results will be grouped in three scenarios, with error distance differences from 4 techniques used in the experiments. Table 1 shows the differences from using conventional fingerprint localization (FM), VAP fingerprinting (VAP), VAP and KF (VAP+KF), and the use of both KF and PF in the VAP algorithm, proposed filtering of VAP+KF+PF.

The results were based on the average error distance in each scenario. Fig. 5-7 shows the error distance of each data samples gathered during the experiments. In scenario 1, the proposed algorithm has the lowest error distance, which means it has the best performance in the indoor environment with non-line of sight (NLOS) obstacle present during the round trip inside the lobby. KF had an increase in performance of VAP but only very little, as well as the proposed filtering.

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>Average Error Distance (m)</th>
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</thead>
<tbody>
<tr>
<td>FM</td>
<td>VAP</td>
</tr>
<tr>
<td>Scenario 1</td>
<td>6.19</td>
</tr>
<tr>
<td>Scenario 2</td>
<td>8.35</td>
</tr>
<tr>
<td>Scenario 3</td>
<td>6.33</td>
</tr>
<tr>
<td>Average</td>
<td>6.96</td>
</tr>
</tbody>
</table>

But as observed in Fig. 5, VAP+KF+PF decreases from point 2 onwards showing improvement on each point. The 1st point is caused by the estimation done by KF, affecting the output of VAP+KF+PF to be very high as much as 12m.

### Fig. 5. Estimated error distance comparison in each RP on 1st scenario (a round trip trajectory with obstacle).

In Fig. 6, a more consistent and stable result of VAP+KF+PF is observed among all sample data points. This scenario is where a straight line was the trajectory, it was translated in Table 1, where VAP+KF+PF value is the lowest. During the 3rd scenario in Fig. 7, varying peak error distance in FM is seen, but was stabilized by the application of both KF and PF.

### Fig. 6. Estimated error distance comparison in each RP on 2nd scenario (straight path).

Among the four method used in localization, the proposed method has the lowest average error distance with an average of 4.49m. It has about 2m difference with the conventional FM, while having a better performance than VAP and VAP+KF, with approximately 1 and .5m less respectively. This was also observed in previous study with VAP and KF where KF showed improvements when used in several
scenarios, such as noise filtering with the different VAPs used in the experiment [12]. This demonstrates that VAP can still be improved by adding different filters. It can also be seen that VAP+KF+PF has a consistent performance in all three scenarios compared to the other three algorithms.

In scenario 1, VAP+KF+PF has the best performance considering the obstacle present in the environment. In scenario 2, VAP+KF+PF has a significantly improved with almost half the value of error distance in FM. Finally in scenario 3, VAP+KF has the best performance with only .5m difference from VAP+KF+PF. But considering the small difference, VAP+KF+PF still maintains a consistent error distance value as seen in Fig. 5-7. VAP+KF+PF is seen to have less fluctuations in error distance compared to the highly unstable FM.

![Error Distance on 3rd Scenario](image)

Fig. 7. Estimated error distance comparison in each RP on 3rd scenario (similar to the first scenario but without obstacle).

C. Discussions

Error distance values varies on different RPs on three scenarios. Figures 8, 9 and 10 show the occurrences of these error distances and on how many times they were observed in the experiments in a form of a cumulative frequency distribution graph.

The CDF figure compares the error distances of each mobile user in different RPs using four methods such as the FM, the traditional fingerprinting method; VAP, a fingerprinting method using VAPs as additional access points; VAP+KF, which uses KF with VAP; and lastly the proposed filtering algorithm which is the combined filter of VAP+KF+PF.

As seen from Fig. 8-10, VAP, KF and VAP+KF+PF does not have a large gap with each other, approximately 1m, compared to FM with as much as 2.47m, this is due to the improvement made by VAP to FM. And the filters will be making an optimization on the already improved VAP. The experiment achieved its aim in realizing the effect of filters on the already improved VAP.

![Scenario 1](image)

Fig. 8. CDF of error distance observed in different RPs during the experiments in the 1st scenario.

This must be due to the behavior of both filters, where KF works better in linear estimation and PF suits non-linear calculations. Overall, the proposed improvement by filtering gave promising results.

![Scenario 2](image)

Fig. 9. CDF figure of error distance observed in different RPs during the experiments in the 2nd scenario where VAP+KF+PF has very low error distance.

Few researches have been done on VAP and each have different method of developing virtual access points, but all have the common objective of improving error distance by only with the use of existing APs in the indoor environment.

![Scenario 3](image)

Fig. 10. CDF figure of error distance observed in different RPs during the experiments in the 3rd scenario but without obstacles.
Increasing the number of AP in a wireless network demonstrated to have impact with accuracy of fingerprint localization according to [13]. The greater the number of APs in both the offline and online phase gives improvement in its performance to estimate user location.

As achieved in this paper, AP number in the indoor environment was increased by creating VAPs which acts the same as any APs without any changes done in the wireless network. It is more cost-effective and flexible and has an advantage such that, the RSSI values of VAPs our correlated to existing APs. This correlation means very similar values in RSSI. Another improvement made are the addition of both KF and PF. Both of these filters are known to reduce noise in signal propagation.

V. CONCLUSIONS

The experiments were used to determine the effectiveness of filters in the VAP system, making little effort in the creation of an improved fingerprinting localization. VAP system uses no additional hardware to be installed in any WLAN indoor environment and can be created based on a statistical model that uses correlation between existing APs. KF was used in previous papers [11-12] and showed positive results when integrated together with VAP. This motivated the authors to propose a new algorithm using other filters that can be applied in localization.

The proposed model demonstrated that the addition of PF is possible and it further improved the performance of using VAP in localization. Error distance observed when using FM was decreased as high as 4m as observed in one of the scenarios. This also showed that application of proposed algorithm of VAP+KF+PF is seen as possibility in localization accuracy.

Application of filters greatly improves the performance of localization. As seen in figure 5-7, fluctuations in signal strength is minimized resulting to decrease in error distance as well as stability. Between the two applied filters, it can be concluded that PF improved the noise even better together with KF and is applicable in environment with obstacles blocking direct line of sight to APs.

Instances where KF was better than PF or vice versa has also been observed, these instances points out the differences of each filter, in which one is better than the other depending on the situation or environment. Application of other filters are also encouraged to be applied in VAP, KF and PF.

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