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실내 Wi-Fi 환경에서 가상AP와 칼만필터 기반 위치추정 알고리즘의 성능분석

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Performance Analysis of Localization Algorithm Using Virtual Access Points and Kalman Filter in Indoor Wi-Fi Environment

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요 약

실내 Wi-Fi환경에서 위치추정을 위해서는 먼저 AP의 RSSI를 측정하여 핑거프린트 맵을 구축 한 후 위치추정을 실시하나 잡음등의 영향으로 측정 RSSI의 값들이 불안정해짐에 따라 실제 위치추정 정확도는 매우 하락한다. 본 논문에서는 이러한 문제점을 해결하기 위하여 가상VAP (virtual access point)와 칼만필터 (Kalman Filter)를 사용한 실내 위치추정 알고리즘 (*LA_VAP_KF*)을 제안하고 위치추정 정확도를 분석하였다. 제안 알고리즘의 거리오차 정확도는 3.43m로서 이는 핑거프린트 및 VAP 기반 알고리즘에 비해 각각 0.72m 및 1.75m 더 향상된 것이다.

Key Words : RSSI, Wi-Fi Fingerprinting, Virtual Access Point, Kalman Filter, Indoor Localization

ABSTRACT

In order to estimate the user location in an indoor Wi-Fi environment, the fingerprint map should be firstly constructed by measuring the received signal strength indicator (RSSI) of the existing access points (APs). However, the localization accuracy will be largely decreased because of the unstable RSSI values due to noise. In this paper, we proposed the localization algorithm (*LA_VAP_KF*) using the virtual access point (VAP) and the Kalman filter (KF) in indoor Wi-Fi environment and analyzed the localization accuracy of the proposed algorithm. It is confirmed that the accuracy of the distance error of the *LA_VAP_KF* is 3.43m, and it is increased than that of the fingerprint and VAP based algorithms by as much as 0.72m and 1.75m, respectively.

Ⅰ. Introduction

The indoor localization technologies based on the received signal strength indicator (RSSI) in Wi-Fi environment has been continually evolving. There have been improvements, different approaches and ideas are added to its concept since RADAR[1-2]. One of the main reason of this is the full infrastructure and the readily availability of Wi-Fi environment that exists in almost everywhere. In order to estimate the user location, the RSSI should be firstly measured from access points (APs) that are located away from the source, and the localization algorithm should be secondly

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executed[2].

Increasing accuracy of estimating user location has been the aim in many researches of indoor localization. One way to achieve this improvement in localization accuracy was the use of the virtual access point (VAP)[3-5] where it is used to increase the number of AP in an already existing Wi-Fi network. VAP uses the correlation of APs to statistically create the RSSI to be added in the fingerprint map. The use of VAPs may have improved the localization accuracy but a problem still remained in the system. The presence of noise caused instability in RSSI measurements, which will directly affect the localization calculation. Thus, in order to eliminate the effects of noise, the Kalman Filter (KF) will be added in the system. The purpose of this paper is to propose and analyze the localization algorithm on the VAP and the KF in indoor Wi-Fi environment in improving the localization accuracy. The proposed algorithm, localization algorithm using VAP and KF (LA_VAP_KF), is the advanced model of VAP based algorithm.

Ⅱ. Related Studies

2.1 Virtual Access Point

The information of the physical layer in the VAP scheme can be easily obtained in the Wi-Fi fingerprint map. 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 map. A VAP fingerprint map is built up using this property[6-7].

VAP has proven that it has improvement over fingerprint based algorithm but has concerns with the unstable RSSI from existing APs[3]. The function of VAP is equal to AP with the exception of no existing physical structure. The unique characteristics of VAP is the reading of RSSI value that can be produced from it[6].

After obtaining the RSSI values, the regression coefficient will be computed together with the already existing APs. VAP will be created by the regression coefficient using Eq. (1)

$$VAP = VAP_0 + \alpha AP_n \tag{1}$$

Where, α is the regression coefficient, and VAP_0 is the simulated value of VAP when distance is zero from AP, and AP_n the number of existing AP. After VAP_0 is created from correlation between all other APs, VAP will be computed. It is proven that the higher the absolute value of correlation, the greater the accuracy of determining the user location using Wi-Fi fingerprinting map.

Because VAP placements lead to optimal improvement of localization accuracy, it can be realized by the determination of VAP location through a series of trials and simulations. This work is done during the data collection phase of the proposed localization algorithm using VAP on the fingerprint map[3].

2.2 Kalman Filter

KF in indoor localization algorithm uses the measured value of the user location on a static position based on fingerprint map and produces the predicted value of the location[8]. Noise filtering is essential because of its presence in wireless propagation which is experienced in the measured RSSIs. Upon filtering of noise in the RSSI measurement, it will be revised, and the revised RSSIs will be used in the distance estimation. KF was used to eliminate noise, and a log-distance path loss model was used to revise the measured RSSIs. KF is found to reduce the accumulated errors by 8% relative to the RSSI filter[9].

Ⅲ. Proposed Algorithm

3.1 Problem Analysis

VAP based algorithm has two phases as: the data collection phase and the fingerprint based localization phase[3-5]. Although an average of 4m error distance was achieved, very high error distances were observed. The cause of high error distance was the presence of several factor such as noise, time of day and interferences of obstacles.

Because noise can be seen as the major contributor of instability in RSSI measurements, it will improve the accuracy and reduce the error distance to be less than 4m if noise will be eliminated in the system. Filtering is one way to eliminate noise and KF will be the proposed filter in the system.

In the *LA_VAP_KF*, VAPs are realized by a statistical model with the help of correlation, while KF is used to improve the localization accuracy in VAP. KF is used to optimize the localization accuracy in measured VAPs on the fingerprint map, as lesser noise means higher accuracy.

3.2 Design Considerations

3.2.1 Considerations on VAP

VAP can be realized by a statistical model with correlation to existing APs. It is also needed to know the locations of installed APs in the indoor Wi-Fi environment. AP and VAP placement affects their correlation as observed on previous research on VAP, and the localization accuracy was improved to 4m error distance from traditional fingerprint map as high as 8m[5]. There were three existing APs in the indoor Wi-Fi environment and two VAPs were strategically added with optimal placement and achieved 70% correlation.

3.2.2 Considerations on Kalman Filter

KF is adapted to the proposed algorithm to avoid abrupt changes in the RSSI values from the existing APs. Filtering in noise improves the localization accuracy in wireless localization in indoor environments. KF will filter the noise during the measurement of RSSIs. The main function of KF is to use to measured RSSIs and update it. KF will be performed separately from VAP process, as it will only calculate measured RSSIs eliminating very high or very low values based on its prediction state and update state. The main function of KF is to use to measured RSSIs and update it.

The collaboration with VAP and KF enables not only the stabilization of RSSI level but also the improvement of localization accuracy.

3.3 Proposed Algorithm

The proposed *LA_VAP_KF* is applied for further improvement of VAP based localization algorithm. Filters have been utilized in many sampling algorithms, and KF was chosen for its effectiveness. The overall system architecture of the *LA_VAP_KF* is showed in Fig. 1.

It consists of two modules: *the VAP function module* and *the Kalman Filter function module*. In the *VAP function module,* all the parameters about VAP are initialized in t*he Initialization submodule*. The fingerprint map is built and VAPs are created in *the Creation of VAP submodule*. The acquired RSSI is compared with the existing fingerprint map to estimate the user location in *the Localization submodule*.

The output of this module is a VAP value which will be then used in *the localization submodule* of *the VAP function module*. This *Kalman Filter module* leads to the improvement of localization accuracy in the indoor localization algorithm using VAP proposed in [3].

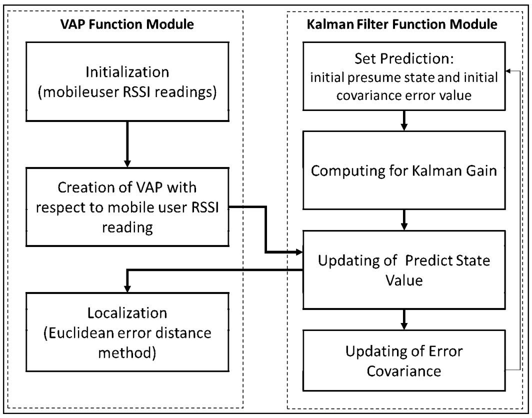

그림 1. 제안 알고리즘의 시스템 구조
Fig. 1. Overall system architecture of the proposed algorithm.

3.3.1 VAP Function Module

VAP function module is divided into three submodules such as *the Initialization*, *the Creation of VAP* and *the Localization*. In order to make the optimal VAP values, a statistical method will be used. The *Initialization submodule* refers to the collection of RSSI data from the existing APs and the creation of the fingerprint map.

The fingerprint map is built up and VAP is created in *the Creation of VAP submodule*. The RSSI value for VAP in the fingerprint map is obtained by making one AP plus some VAPs matrix. The regression coefficient of VAPs with respect to APs can be calculated using the data.

However, the RSSI value for VAPs is dependent on the RSSI value of the collected APs on the creation of VAP, and it is equal to the sum of RSSI value in all existing APs with respect to their corresponding regression coefficient.

Finally, during *the Localization submodule*, these collected RSSI value for APs and VAPs are compared with the matrix of fingerprint map for APs + VAPs collected during *the Creation of VAP submodule*. The final location of VAP can be determined by using Euclidean distance calculation.

3.3.2 Kalman FIlter Function Module

During the Prediction step, x is the predicted state estimate of the object from its observed measurements of RSSI, with changes as $k-1$, or the previous state with k representing time as shown in Eq. (2). x_k will be the present location of the user.

In this step, F_k represents the matrix of set predictions made from the x_{k-1} to x_k. Also computed in this step is the predicted covariance matrix P_k as seen in Eq. (3). P_k is the covariance used to make a set matrix based on Gaussian distribution.

$$\hat{x}_{(k|k-1)} = F_k \hat{x}_{(k-1|k-1)} \tag{2}$$

$$P_{(k|k-1)} = F_k P_{(k-1|k-1)} F_k^T \tag{3}$$

First, Kalman gain K, will be determined to update the measurement date. Kalman gain is the matrix that outputs the minimum mean-square error by combining the variables from the predicted state and the observed measurement with noise covariance R_k, as seen in Eq. (4).

$$K = H_k P_k H_k^T (H_k P_k H_k^T + R_k)^{(-1)} \tag{4}$$

The observed measurement are represented by z_k, with H_k, representing the matrix of it. This is seen in Eq. (5) with v_k, as noise added in the system.

$$z_k = H_k x_k + v_k \tag{5}$$

Update step is represented in Eq. (6)-(8) where the measurement, covariance and Kalman gain is updated based on the Kalman gain of Eq. (4). This updated values will determine the latest or the last known location of the user. This process is computed continually based on the received RSSI measurements.

$$\hat{x}_k = K_k (z_k - H_k \hat{x}_k) + \hat{x}_k \tag{6}$$

$$P_k = P_k - K H_k P_k \tag{7}$$

$$K = P_k H_k^T (H_k P_k H_k^T + R_k)^{(-1)} \tag{8}$$

Ⅳ. Experiments and Result Analysis

4.1 Experimental Environment

The lobby of the 1st floor of the university main building is selected as the testbed for the experiments, the covered area of the building is 32m × 32m. 141 reference points (RPs) are used to build the fingerprint map, and the area of each RP is defined to 2 × 2 m space.

VAPs are strategically placed in the indoor space to provide an optimal coverage together with the

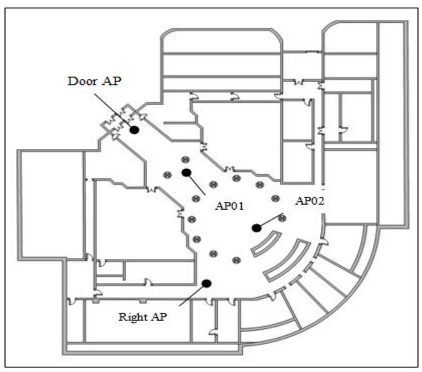

그림 2. 대학 본관 1층에서의 VAP와 AP의 배치관계
Fig. 2. Placement of VAP and AP on 1st floor of main building.

existing two APs, enveloping an area 9.6m × 9.6m around it, without overlapping with other APs. The two APs were in the door and the right wing of the main building. Ap01 and Ap02 are the labels used in the experiments, namely VAP1 and VAP2 respectively.

All VAPs and APs placement can be seen as depicted in Fig. 2. LG G4 was used as the mobile device to obtain RSSI values and for conducting online localization. Random test points were used as the mobile user location to be determined using the localization algorithms.

4.2 Results and Analysis

After computing for regression coefficient, the fingerprint map was created with 2APs and 2VAPs. Correlation was also computed after the creation of fingerprint map as seen in Table 1.

Using Euclidean distance formula, error distance from the mobile user test points to the RPs where determined. Using the three algorithms namely, *LA_FM*, *LA_VAP* and the proposed *LA_VAP_KF* were used to determine the user location. The error distance means the distance of estimated position of user to the RPs.

표 1. AP와 VAP의 상관관계
Table 1. Correlated relations between APs and VAPs

	AP1	*AP2*	*VAP1*	*VAP2*
door/AP1	1	-0.578	0.051	0.580
right/AP2	-0.578	1	-0.019	-0.337
ap01/VAP1	0.051	-0.019	1	0.425
ap02/VAP2	0.580	-0.337	0.425	1

4.2.1 AP and VAP Correlation

Other than the three algorithms, each VAP is also tested individually for its performance. 2APs will be paired with VAP#1, VAP#2 separately and a combination of 2APs with 2VAPs will also be tested. *LA_VAP* and will *LA_VAP_KF* have three different cases each. The overall error distances as measured during the experimentation is summarized in Table 2.

The least error distance of 3.43m was extracted

표 2. 3개의 알고리즘에서의 오류 거리
Table 2. Error distances in three algorithms

Algorithms	Types	Error distances
LA_FM	-	5.18m
LA_VAP	2APs + 2VAPs	4.15m
	2APs + VAP#1	5.25m
	2APs + VAP#2	5.41m
LA_VAP_KF	2APs + 2VAPs	3.43m
	2APs + VAP#1	4.51m
	2APs + VAP#2	3.59m

from the experiment was exhibited by 2APs + 2VAPs of *LA_VAP_KF* among all algorithms and different cases. This result was affected by the high correlation of VAP#2 with other APs as compared to VAP#1 with lower correlation. The low correlation of VAP#1 also resulted to its higher error distance which means a lower accuracy among all cases.

Also seen is the significant difference of three algorithms, where *LA_FM* and *LA_VAP* have error distances almost 1m higher than *LA_VAP_KF*. This proves the improvement in the performance of *LA_VAP_KF* over the two other algorithms.

4.2.2 Average Error Distances

The Fig. 3 shows that the average error distances of the localization algorithm using fingerprint map (*LA_FM*), the localization algorithm using VAPs (*LA_VAP*) and *LA_VAP_KF*. Different cases of *LA_VAP* and *LA_VAP_KF* were also included. The highest overall average error distance is represented by the orange dotted line, this average is from the case of 2APs + VAP#1. While the lowest overall average error is represented by the performance of 2APs + 2VAPs.

The performance of 2APs + VAP#2 was lower, but closely to that of the highest average error distance, as represented of the blue dotted line. The bar graph, also shows the significant difference of *LA_FM* and *LA_VAP* from the proposed algorithm, *LA_VAP_KF*. The role of VAP can be viewed as a significant factor for the improvement

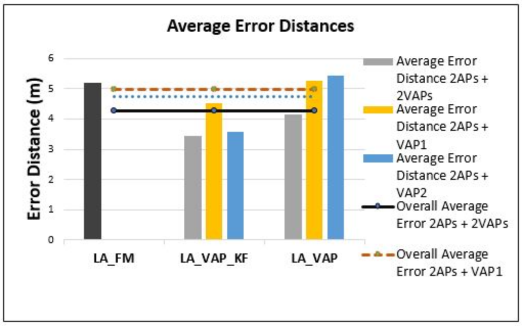

그림 3. 평균 오류거리의 비교
Fig. 3. Comparison of average error distances.

of KF. Individually VAP#1 and VAP#2 shows contrasting results, where VAP#2 has better performance by having lower error distance, while VAP#1 has undesirable performance with its high error distance.

The robustness of KF made it possible to be integrated with VAP algorithm as proven by the very low average error distance of 2APs +2VAPs, an increased performance of the VAP based algorithm.

4.2.3 Cumulative Error Distances.

The cumulative error distances of the moving user on RPs in *LA_VAP_KF* is also compared with that of *LA_FM* and *LA_VAP*. It can be seen that cumulative distribution function (CDF) on RPs in *LA_VAP_KF* is the least than *LA_FM* and *LA_VAP* as shown in Fig. 4. *LA_VAP_KF* depicts that there are higher probability of almost 60% and above for having 2m-3m error distance, and the error distance achieved in any test points

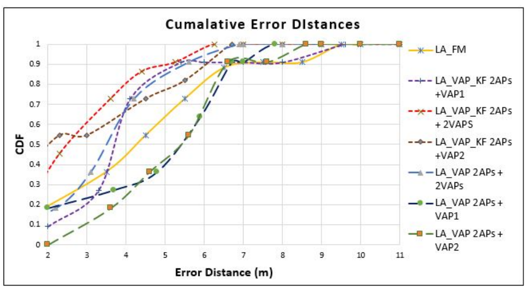

그림 4. 누적 오류거리 비교
Fig. 4. Comparison of cumulative error distances.

will be lesser than that of *LA_FM*. The red dotted line belonging to 2APs + 2VAPs in *LA_VAP_KF* has the noticeable difference among all lines. This represents the higher probability of having an error distance of lesser than 5m by 90%.

Compared to all other probability, it is possible to have an error distance as low as 2m when estimating mobile user location using the algorithm of *LA_VAP* and *LA_VAP_KF*. Despite the decrease on the error distance of the proposed algorithm, the use of VAP based algorithm alone had seen a higher chance of having an error distance of more than 4 meters. This result was highly affected by the maximum or minimum values of RSSI drop in the experiment.

V. Conclusion

It has proved that KF significantly improves RSSI values which, in result, increases the localization accuracy of fingerprint based algorithm. Calibration of RSSI is a very important factor in Wi-Fi localization as seen in the high occurrence of error distance from 4m and above in the CDF of *LA_VAP* without the help of KF.

The integration of KF in VAP based algorithm (*LA_VAP_KF*) improved the results in the experiment to almost 2m and shows the effectiveness of the filter to signal noise and fluctuations. This may be an acceptable value in location estimation on indoor environment with little intervention on the existing Wi-Fi network, and readily available at very low deployment cost.

The error distance in *LA_VAP_KF* is approximately 3.43m, and it is better than that of VAP or fingerprint based algorithms. In the next step, the research for achieving the error distance of the proposed algorithm by decreasing up to 2m will be our challenge.

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