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Precise Indoor Localization: Rapidly-Converging 2D Surface Correlation-Based Fingerprinting Technology Using LTE Signal

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ABSTRACT This study proposes a 2D surface correlation-based indoor localization technology using LTE fingerprinting with an accuracy of several meters. The most important problem with RF fingerprinting is that the location discernment of signal strength becomes exceedingly low as the distance from the RF signal source increases. Instantaneous RSS measurement based conventional fingerprinting involves the installation of several signal sources to improve location discernment. However, additional installations of LTE base stations (BSs) are impossible. To improve location discernment, the proposed technology utilizes a spatial RSS pattern extracted using the Pedestrian-Dead Reckoning during user movement. The use of the proposed technology greatly improves the accuracy and availability of LTE signals using the pattern. Additionally, the following two points should be considered. First, the spatially accumulated pattern contains location errors that can cause pattern distortion. The proposed technology performs pattern correction through feature matching using RSS mark and crossroad locations. Second, the accuracy of pattern matching may be decreased prior to sufficient pattern accumulation. For the rapid convergence of the pattern matching, the proposed technology performs correlation pattern analysis. This approach detects the point in which the discernment is increased by pattern accumulation and limits the search range around the matching point. To verify the performance, we conducted tests in a shopping mall where only one LTE BS ID is available. Consequently, the convergence distance of pattern matching was improved by 69% after pattern analysis. Furthermore, it was confirmed that the localization error after convergence improved from 4.16 m to 2.82 m.

INDEX TERMS Seamless, indoor navigation, fingerprinting, pattern correlation.

I. INTRODUCTION

Seamless navigation is important for providing location based services (LBS) to users. The Global Navigation Satellite System (GNSS) can be used to provide reliable location information outdoors. However, providing accurate location information indoors is still challenging. Therefore, indoor localization technology is considerably important for providing seamless LBS.

Development of localization technology using Wi-Fi signals to provide accurate location information indoors has been the main focus of existing research. Wi-Fi does not require additional infrastructure because several signal sources are already installed indoors, excluding underground parking lots. However, such a large number of signal sources incurs a high cost in maintaining a database for localization and increases computational complexity. Recently, Google has limited the frequency of Wi-Fi signal scans according to the Android version to improve network performance and battery life. At low Wi-Fi scan frequencies, it is difficult to expect precise localization performance. Therefore, other means are required.

LTE can be a useful means for seamless navigation because LTE signals can be used both outdoors as well as in almost all indoor areas [1]–[3]. In addition, it can be used in all smartphones, and the infrastructure is professionally

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managed using telecom companies. Localization technology using LTE signal is mainly based on Cell-ID (CID) or timing information. The indoor localization performance based on the 3GPP 3D MIMO deployment and propagation model adopted in 3GPP Release 13 were analyzed in [4]. The enhanced CID utilizes round trip time-based distance information for the conventional CID to improve localization accuracy [5], [6]. When placing small cells indoors, it was found that with the use of this technology, horizontal accuracy based on CID was reasonably good, but the additional installation of small cells in the indoor space may increase the maintenance and management costs of the infrastructure. Benedetto *et al.* [7] increased the precision of Time of Arrival (ToA) measurements using parabolic interpolation for cross-correlation samples from different LTE base stations (BSs). Sivers and Fokin [8] proposed a localization method based on the hyperbolic trilateration of the reference signal time difference (RSTD). Specifically, this is an Observed Time Difference of Arrival (OTDOA) technology that performs Time Difference of Arrival (TDoA) using the positioning reference signal of the LTE signal, which is defined in the 3GPP-LTE Release 9 standard. To estimate a location, at least three BSs are required, and therefore, availability is extremely low in an indoor environment. Abdallah *et al.* [9] utilized an LTE signal and a tightly coupled based inertial navigation system (INS) to provide location information without installing additional RF signal sources. In general, a carrier-based software defined receiver (SDR) was used to track LTE signals and provide aiding correction for the inertial measurement unit (IMU). However, a synchronization problem exists in this approach because a precise clock bias between the user's smartphone and the BS must be estimated for high accuracy. Gentner *et al.* [10] proposed a particle filter (PF) with sensors that reflected the 3GPP LTE time difference of arrival (TDoA) error model for more accurate localization performance. Guaranteeing a high accuracy from localization technology that is based on the timing of LTE signals or CID is difficult because of multipath as well as reduced availability in indoor LTE environments. The fingerprinting method places the RF signal information for each location into a database, and compares it directly with the measurements to estimate a location. Therefore, the fingerprinting method can be more effective than the timing-based localization technology in indoor environments because it is possible to perform localization with a small number of RF signal sources. Lembo *et al.* [11] proposed a neural network (NN) based fingerprinting method to determine a user's location by utilizing instantaneous RSS measurements. Pecoraro *et al.* [12] proposed a localization technology using channel state information (CSI), which is a channel gain per subcarrier, to further improve the performance of the RSS-based fingerprinting method. Ye *et al.* [13] proposed a fingerprinting method that utilizes wireless channel characteristics selected through a feature extraction algorithm. The location is estimated using the NN based on the Levenberg–Marquardt learning algorithm. When indoors, several LTE repeaters using the same physical ID are present. LTE coverage is greatly improved, but this factor reduces the discernment of the fingerprinting method. Therefore, it is difficult to predict the precise performance of the conventional fingerprinting method that utilizes instantaneous measurement in the indoor space [14]–[16]. Therefore, methods to improve the accuracy of the fingerprinting method in this indoor LTE environment must be devised.

We have already proposed a precise localization technology based on surface correlation using LTE signals in urban areas [17]. This technology improves the discernment and accuracy of the LTE fingerprinting method in a complex urban area by utilizing 1D spatial RSS patterns accumulated during user movement. For the surface correlation, a spatial RSS pattern on a link that matches a user's movement path must be dynamically generated from a fingerprinting database. However, this requires a more efficient localization technology because the complexity of the localization process is greatly increased in an indoor space composed of complicated and short paths.

In this study, we propose an indoor localization technology based on a 2D surface correlation using LTE fingerprinting. Because the proposed technology utilizes the cumulative spatial RSS pattern, it is possible to improve the availability of LTE signal and accuracy compared to the conventional fingerprinting technology utilizing instantaneous measurements. The contributions of this study are as follows:

- We propose a 2D surface correlation based fingerprinting method that utilizes the spatial RSS pattern accumulated in 2D space, rather than comparing the instantaneous RSS measurement directly with a database.
- Spatial pattern distortion caused by cumulative error through pattern correction is prevented based on feature matching, thus maintaining accurate performance.
- For rapid convergence of pattern matching, the proposed technology detects the point of time when pattern discernment increases through correlation pattern analysis in the correlation process and limits the search area around the matching point at this time.
- Using the proposed technology, it is possible to provide precise location information in an indoor environment where multiple LTE repeaters using the same physical ID exist.

The rest of this article is organized as follows: Section 2 introduces an overview of the proposed fingerprinting method and compares it with the conventional technology. Section 3 describes the details of the 2D surface correlation technology. Section 4 analyzes the performance of the proposed technology, and Section 5 presents the conclusion of this study.

II. OVERVIEW

Two-dimensional surface correlation technology is composed of an offline phase and an online phase similar to the conventional fingerprinting methods [18], [19] as shown in Fig. 1.

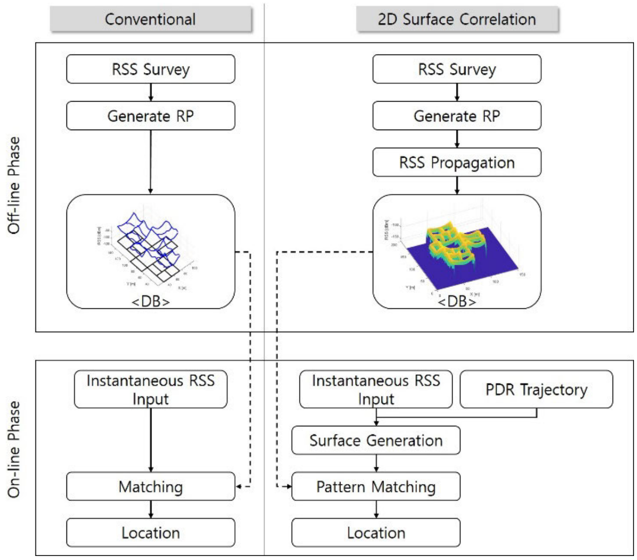

FIGURE 1. Overview of the conventional and the proposed technology.

The offline phase consists of constructing a fingerprinting database through a survey of service areas. The database consists of a collection point (reference point, RP) and RSS information at a given location.

In conventional fingerprinting methods, RSS measurements are compared with RSS on the RP, and the RP having the most similar value is considered as the current location. Therefore, the conventional fingerprinting method defines only the RSS on the collected path [20]. The proposed technology compares the 2D *surface*, a spatial RSS pattern accumulated during the user movement, with the database. Thus, the database must have RSS values for all defined spaces. The proposed technology generates virtual RPs around the RPs present on the collection path. To construct the database, the RSS propagation model is applied to the RP on the collection path to define the RSS for the virtual RPs.

The conventional fingerprinting method directly compares the instantaneous RSS measurement with the database and estimates the location, so the level of discernment is exceedingly poor in an LTE environment where similar RSS patterns may exist. In this study, we use the spatial RSS pattern measured on the 2D path of pedestrian dead-reckoning (PDR) and this pattern is defined as a *surface*, which is the RSS pattern on the PDR trajectory. So, the database must have RSS values for all spaces in the 2D plane, unlike in the conventional fingerprinting method. By directly comparing the 2D RSS pattern with a database, it is possible to estimate the location more easily and simply than the previously proposed technology. However, the spatial RSS pattern can be distorted owing to the drift of the PDR [21]. To prevent this distortion, the proposed technology corrects the PDR trajectory using feature information, crossroads, and RSS marks. Rapid and accurate convergence of pattern matching is highly important in 2D surface correlation technology because it is important to provide users with accurate information quickly. The discernment of the proposed technology can be degraded before sufficient patterns are accumulated. Therefore, it detects when the pattern‘s discernment increases through correlation pattern analysis and limits the correlation area to induce rapid convergence. The proposed 2D surface correlation technology consists of four processes: (1) surface generation; (2) correlation process; (3) feature matching; (4) correlation pattern analysis.

III. PROPOSED TECHNOLOGY

A. 2D SURFACE CORRELATION

The proposed 2D surface correlation technology utilizes the accumulated RSS pattern during a user's movement. The use of the spatial pattern increases accuracy of localization by reducing ambiguity in an indoor environment where a large number of similar RSS patterns exist. The proposed technology utilizes a spatial RSS pattern generated from the PDR. In [22], we proposed a stride estimation algorithm using an accelerometer and a gyroscope. The user trajectory was estimated using the stride information and the heading information based on a gyroscope. The *surface*, a spatial RSS pattern, can be expressed in vector form as in (1) using the user trajectory and RSS information.

$$S^m = \begin{bmatrix} RSS^m_{x_1,y_1} & \cdots & RSS^m_{x_i,y_1} \\ \vdots & \ddots & \vdots \\ RSS^m_{x_1,y_j} & \cdots & RSS^m_{x_i,y_j} \end{bmatrix} \tag{1}$$

where, S^m is a *surface* generated from the m-th physical cell identity (PCI) BS. RSS_{x_i,y_j} is the RSS value at the coordinate (x_i, y_i) estimated from the PDR. The proposed technology selects an RP with the most similar RSS pattern by computing the similarity of the generated *surface* with the database. The similarity in each RP is calculated based on the Euclidian distance as in (2).

$$\mu_{x_k,y_l} = \frac{\sqrt{\sum_{m=1}^{M}\left(S^m - DB^m_{x_k,y_l}\right)^2}}{M} \tag{2}$$

where, μ_{x_k,y_l} is the similarity value at an RP with (x_k, y_l) coordinates on the database. M is the total number of BSs. S^m is the *surface* and $DB^m_{x_k,y_l}$ is the RSS vector from the m-th BS at the (x_k, y_l) coordinate of the database with the same size as the *surface*. Fig. 2 shows the similarity values in each RP calculated through pattern comparison between user *surface* and the database. The RP with a minimum similarity value is determined as the current location as shown in Fig. 2. As mentioned previously, the PDR solely uses a gyroscope to estimate the heading. Therefore, it can estimate only the relative heading change of a user. To estimate the actual heading in comparison with the DB, the proposed technology detects the rotation angle with a minimum similarity value by rotating the *surface* at a specific angle θ.

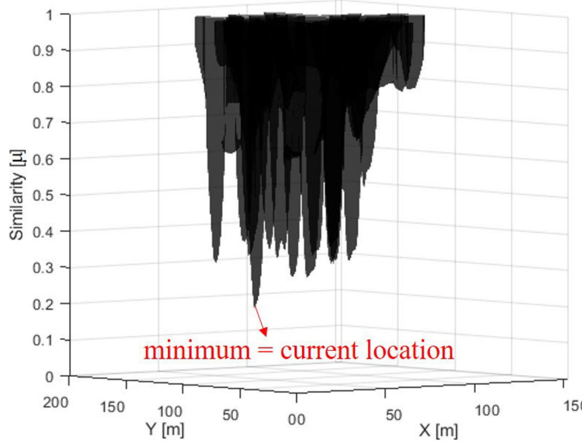

FIGURE 2. Similarity pattern and location determination by selecting a minimum similarity value.

B. FEATURE MATCHING

As mentioned before, the user-side *surface* is generated from the PDR. The drift error of the PDR causes *surface* distortion resulting in a localization error of the proposed technology. The proposed technology maintains high localization accuracy for a longer period of operation by correcting the distorted trajectory on the *surface* using feature information. In this study, the feature information is defined as crossroads and an RSS mark. The feature matching (FM) process is as follows: (1) feature pair detection, (2) pattern correction, and (3) correction update.

In the process of feature pair detection, the proposed technology searches the global minima point (x_p, y_p) with a minimum similarity value on the similarity pattern as shown in Fig. 2. Then a feature pair in the database that minimizes the placement error between the feature coordinates (x_s, y_s) detected on the user *surface* and the feature coordinates (x_f, y_f) in the database is selected. As such, the selected feature coordinates (x_{sel}, y_{sel}) in the database are as follows:

$$d_e = \sqrt{\left(x_p + x_s - x_f\right)^2 + \left(y_p + y_s - y_f\right)^2} \quad (3)$$

$$(x_{sel}, y_{sel}) = arg \sum\nolimits_f d_{e,f} \quad (4)$$

where, d is the distance between the feature on the database and the feature on the user *surface*. The pattern correction and correction update are performed using two features of information in the database matched with the two features detected on the user *surface* as in (5) through (8).

$$\varphi_{ref} = \tan^{-1}\left(\frac{\Delta y_{sel}}{\Delta x_{sel}}\right) \quad (5)$$

$$l_{ref} = \frac{\sqrt{\Delta x_{sel}^2 + \Delta y_{sel}^2}}{step} \quad (6)$$

$$\tilde{x}_k = \tilde{x}_{k-1} + \left(l_k - l_{ref}\right) \cdot \sin\left(\varphi_k - \varphi_{ref}\right) \quad (7)$$

$$\tilde{y}_k = \tilde{y}_{k-1} + \left(l_k - l_{ref}\right) \cdot \cos\left(\varphi_k - \varphi_{ref}\right) \quad (8)$$

φ_{ref} and l_{ref} are the reference heading and stride information calculated from selected database features, respectively. The step is the number of steps measured during the features that are detected. φ_k and l_k are the measured heading and stride at the k-th step. $(\tilde{x}_k, \tilde{y}_k)$ is the corrected PDR coordinates on the *surface*.

C. CORRELATION PATTERN ANALYSIS

There are few LTE BSs indoors, and there are many LTE repeaters that utilize the same physical ID. It is necessary to effectively increase the discernment level for accurate localization using fingerprinting technology in such an LTE environment. The proposed technology is inferior to the discernment much like the conventional fingerprinting method, before sufficient patterns are accumulated. For this reason, rapid convergence of pattern matching point is important in the proposed technology. The proposed technology determines the time when the discernment is clear through correlation pattern analysis. From this time onward, it maintains a high localization accuracy by limiting the similarity correlation area.

The candidate RPs that can be considered as the current location are the local minima points on the similarity pattern as shown in Fig. 3(a). As the pattern accumulates, the discernment increases and localization accuracy also improves. As a result, as shown in Fig. 3(b), the difference between the highest similarity and the other point increases as the pattern accumulates. Based on this result, the proposed technology detects convergence timing through the ratio between similarities as in (9).

$$\mathrm{R} = \frac{\mu_2}{\mu_1} \quad (9)$$

μ_1 and μ_2 represent the similarity values at 1st and 2nd local minima points, respectively. The proposed technology considers when R becomes larger than the threshold as the convergence point. In this study, the threshold is set to 1.2 so that it can be applied in common throughout various tests.

The proposed technology limits the similarity computation area around the location (x_{p1}, y_{p1}) where the 1st minima point was detected from the convergence time as in (10) and (11).

$$x_{p1} - win \leq x_s \leq x_{p1} + win \quad (10)$$

$$y_{p1} - win \leq y_s \leq y_{p1} + win \quad (11)$$

where x_s and y_s are the correlation computation areas on the database. win is the boundary for the limitation. By setting the win for the area limit to 20 m, it is possible to estimate the optimal location within a square range within 40 m. In other areas, the similarity value is considered infinite. Thus, the correlation pattern analysis both improves the discernment level and reduces the computational complexity of similarity by excluding areas where the user is less likely to exist.

D. DATABASE CONSTRUCTION

The fingerprinting database typically consists of the RP coordinates, RSS collection location, and RSS information

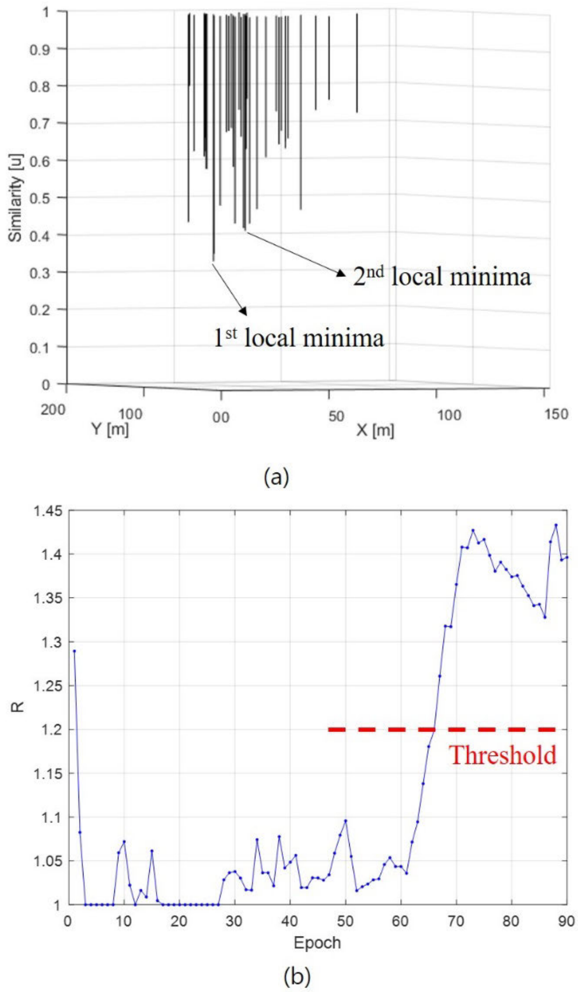

FIGURE 3. Convergence detection (a) local minima points on the similarity pattern, (b) ration between local minima points.

received from the surrounding BSs. In this study, we use the PDR to estimate the approximate location of a database collector moving along a predetermined route. By applying a map-matching algorithm based on the collector's turn information, increasingly accurate location information is calculated. This calculated location is defined as the RP coordinates. The database in the form of the $(i \times j)$ matrix is generated by applying a Gaussian regression to the RSS value for each RP, as in (12).

$$DB^m = \begin{bmatrix} RSS^m_{x_1,y_1} & \cdots & RSS^m_{x_i,y_1} \\ \vdots & \ddots & \vdots \\ RSS^m_{x_1,y_j} & \cdots & RSS^m_{x_i,y_j} \end{bmatrix} \tag{12}$$

(x_i, y_j) is the coordinate of an RP. $RSS^m_{x_i,y_j}$ is the RSS value at (x_i, y_j) received from m-th BS. We must define RSS value for the entire space as well as the collection route to apply 2D surface correlation technology. Thus, the proposed technology generates a virtual RP around the collection route. RSS in this virtual RP is calculated through the RSS propagation model based on the stretched-exponential function as in (13).

$$RSS^l_{vir} = RSS^n_s - \frac{RSS_0}{\alpha + e^{(\beta+\gamma\times d)}} \tag{13}$$

where RSS^l_{vir} is the RSS value at the l-th virtual RP calculated using the nearest n-th RP. RSS^n_s is the RSS value at the n-th sampling RP closest to the virtual RP. RSS_0 is the maximum value of LTE RSS that can be received, and is set to -45 dBm in this study. α and β are values determined through the experiments and are set at 1 and 5, respectively. γ is the attenuation constant and determines the degree of RSS attenuation according to the distance d from the n-th RP, as shown in Fig. 4. The *surface* generated during user movement must match the actual path. Specifically, the pattern should be matched with the RP generated during database collection. To induce this, the RSS attenuation must be large. However, because the RSS pattern generated from the PDR has a drift error, it is necessary to select an attenuation constant that considers this information together. In this study, we set the attenuation constant γ as 1.5.

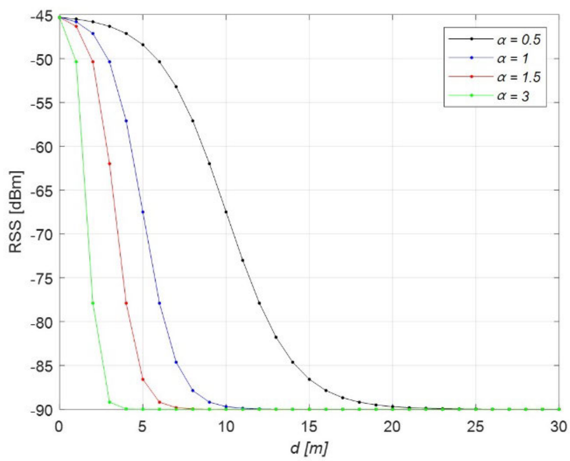

FIGURE 4. RSS propagation model according to the distance from sampling RP.

The proposed technology also requires feature information such as the RSS mark and crossroad information to execute the FM algorithm. The RSS mark and crossroad location information stored in the database are $p_k = \{x_t, y_t\}^k_{t=1}$ and $T_u = \{x_t, y_t\}^u_{t=1}$, respectively. These are sub-matrix satisfying $F_e \ni \{p_k, T_u\}$ and $e = k+u$ for feature information F. k and u are the number of RSS marks and crossroads, respectively.

IV. PERFORMANCE ANALYSIS

A. TEST ENVIRONMENT

To verify the performance of the proposed technology, we conducted tests using a smartphone in an underground shopping mall connected to a subway station as shown in Fig. 5. We surveyed a 130 m × 142 m test area to construct a database before the localization test. A collector was walked several times along the pre-defined collection routes and data was collected from the smartphone as follows:

FIGURE 5. Test site.

- Test smartphone: Samsung Galaxy S10
- Accelerometer and gyroscope output: 40 Hz
- LTE PCI and RSS: 0.5 Hz

We estimated the location of the collector using the PDR, and a more accurate route was generated by applying a map-matching algorithm to the PDR trajectory as shown in Fig. 6(a). As a result, as Fig. 6(b), a 1 m resolution database was generated by applying the Gaussian Regression and RSS propagation model on the map-matched trajectory. At the test site, three LTE PCIs were available. Of these, 110 and 451 PCI were not used for tests because they were intermittently received from the outdoors through the subway entrance. Therefore, only one 469 PCI signal was used for tests. The maximum signal strength from 469 PCI was −51 dBm and the minimum was -94 dBm. Therefore, we set the RSS value below -100 dBm to -160 dBm and excluded it from the computation process of the pattern matching. Specifically, similar spatial RSS patterns were distributed owing to the multiple LTE repeaters that commonly used the 469 PCI. This decreased the discernment level of the fingerprinting method in the test site. The symmetric distribution of the crossroads and RSS marks, as shown in Fig. 6(c), is also a factor that reduces the discernment level of the fingerprinting method.

B. TEST RESULTS

To verify the performance of the proposed technology, we conducted three tests, as shown in Fig. 7(a) through Fig. 7(c). We also compared these results with the conventional k-nearest neighborhood (kNN) based fingerprinting and particle filter (PF) based localization technologies.

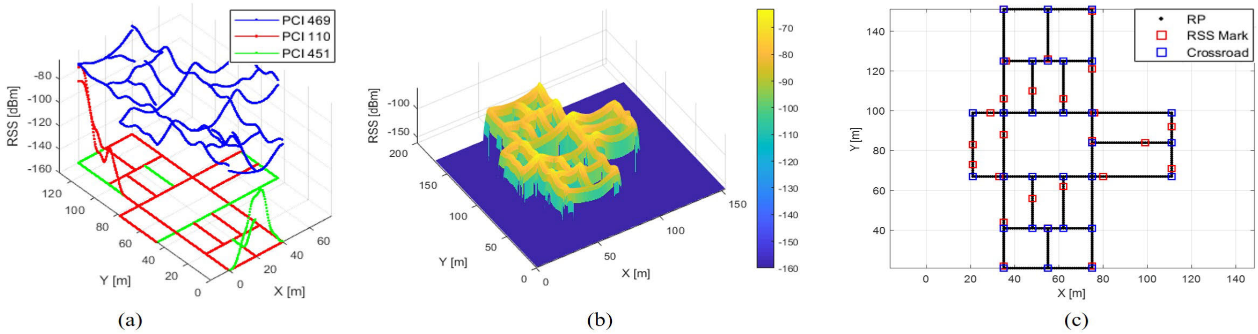

FIGURE 6. Fingerprinting database (a) spatial RSS pattern on each PCI (b) final database applying RSS propagation model (c) feature distribution.

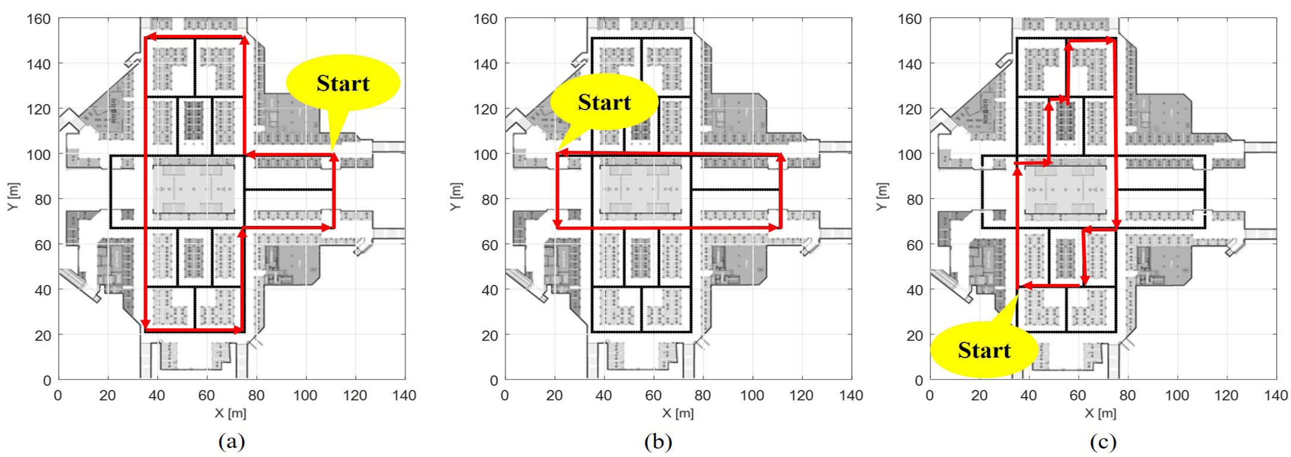

FIGURE 7. Test scenarios (a) first scenario (b) second scenario (c) third scenario.

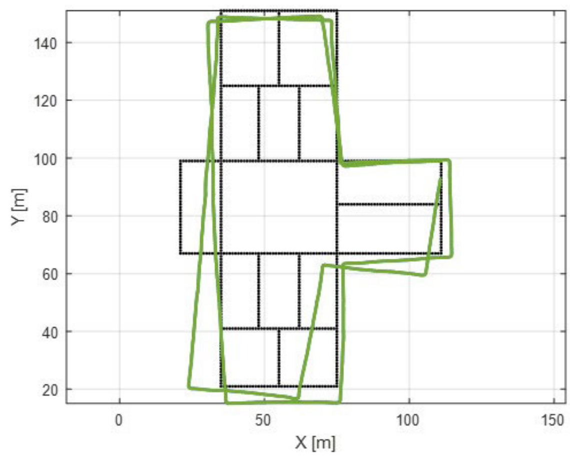

FIGURE 8. PDR trajectory for PF and *Surface* generation.

We generated the true location to calculate the location error through the map-matching algorithm of the roughly estimated PDR trajectory in a similar manner to database generation. In the case of kNN-based fingerprinting technology, we set $k = 5$ to determine a location. PF performs the particle resampling process using the heading and stride information from the PDR. Specifically, the location was estimated through the propagation of 200 particles. The user headings that can be walked at all crossroads are 0°, 90°, 180°, and 270°. Accordingly, the initial heading estimation of the proposed technology was performed in 90° units. The *surface* length was set to maintain a maximum of 150 m. A shorter length can reduce discernment and accuracy. If the length is excessively long, the computational complexity of similarity can increase significantly.

Fig. 8 shows the PDR trajectory of the first test scenario. The initial heading was set to 180° to confirm the PDR drift, but in performing 2D surface correlation technology, the initial heading was set to 0°. We applied the heading and stride information of the PDR to the PF-based localization and *surface* generation for the proposed technology. Fig. 9(a) and Fig. 9(b) show the localization results of kNN-based fingerprinting and PF-based localization technology in the first test scenario, respectively. The results confirmed that localization was impossible in the test environment with exceedingly low discernment because kNN-based fingerprinting technology utilized only the instantaneous RSS measurements. The kNN showed a Root Mean Square (RMS) errors of 55.42 m. The PF showed improved performance compared to kNN in regions where the signal discernment was relatively high because it performed localization in consideration of the PDR information. However, the accuracy was exceedingly low in other regions because of the low discernment problem. The RMSE of the PF was 39.89 m. Fig. 9(c) shows the localization result of the proposed technology without the FM and correlation pattern analysis. This result shows that the proposed technology had a more accurate performance in the indoor LTE environment than conventional technology. Fig. 10 shows the localization error for each step. The localization error was demonstrably low from 46 steps onward after sufficient patterns were accumulated. However, the error increased again because of the symmetric structure of the test area and several similar RSS patterns. In the 2D surface correlation, because the discernment was increased from 150 steps with sufficient patterns accumulated, accurate localization was possible.

Fig. 11 shows the localization result of the proposed technology to which both FM and correlation pattern analysis are applied. The proposed technology showed an inaccurate performance because of the ambiguity during the initial phase. However a more accurate performance was achieved post-convergence. The proposed technology maintained a high accuracy through the FM algorithm despite the PDR drift, as shown in Fig. 8.

Fig. 12 shows the localization error of the tested technologies in every step. In the case of the proposed technology, after the correlation pattern analysis, the convergence point was 46 steps, at 32.33 m in walking distance. Compared with Fig. 10, the convergence of pattern matching was achieved rapidly, with a 69 % improvement over 103 m. The RMSE was 2.82 m after the convergence point of pattern matching. Moreover, the localization error of the proposed technology was bound within 7 m. This meant that the proposed technology was highly available even in the indoor LTE environment.

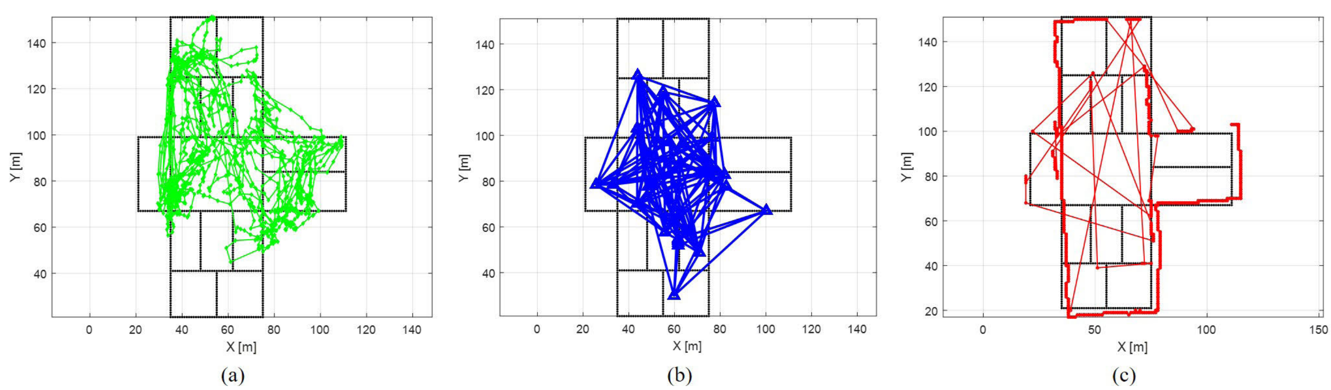

FIGURE 9. Localization results of the first test scenario (a) kNN-based fingerprinting (b) particle filter (c) 2D surface correlation.

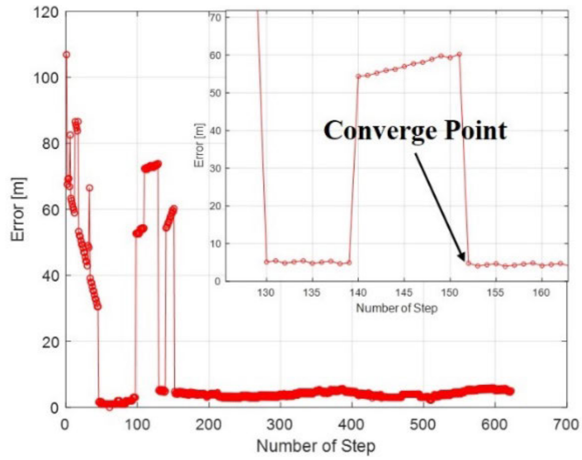

FIGURE 10. Localization error of the 2D surface correlation without the feature-matching and the correlation pattern analysis on the first test scenario.

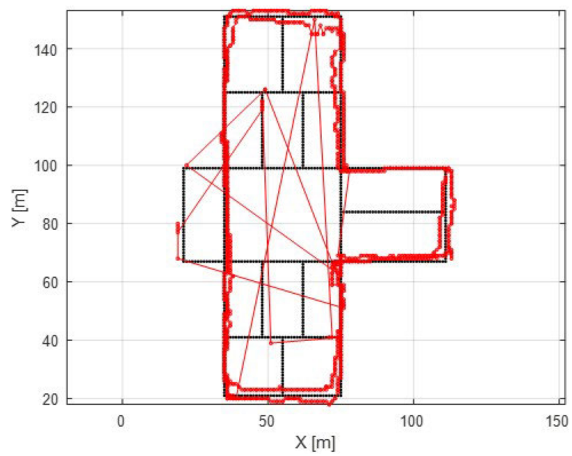

FIGURE 11. Localization result of the proposed technology.

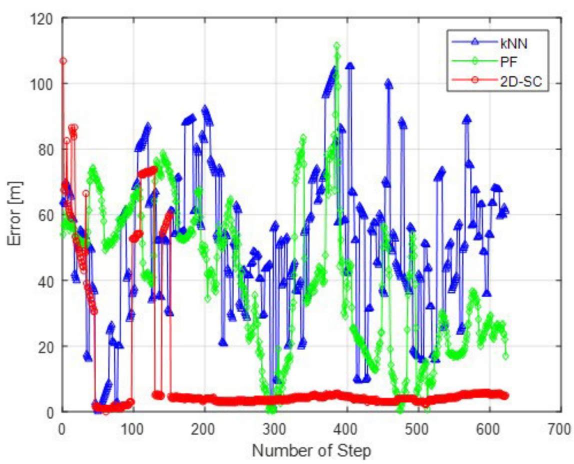

FIGURE 12. Localization errors of each technology on the first test scenario.

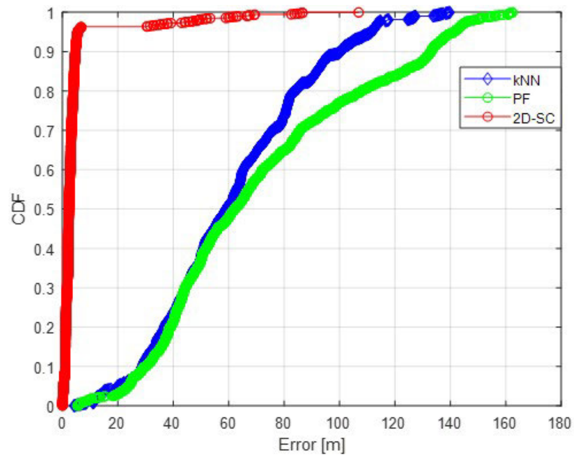

FIGURE 13. CDF errors of each technology on the first test scenario.

TABLE 1. Summarize of the localization error of each technology.

Scenario	Error Type	Technology		
		*k*NN	PF	2D SC (w/o FM)
1	RMSE (m)	55.42	39.89	2.82 (4.16)
	CDF (m)	82.6 (90%)	70.3 (90%)	4.6 (90%)
2	RMSE (m)	43.39	43.28	2.64 (9.02)
	CDF (m)	61.4 (90%)	66.1 (90%)	4.8 (90%)
3	RMSE (m)	45.21	44.49	2.3 (2.31)
	CDF (m)	68.1 (90%)	63.4 (90%)	5.1 (90%)

Fig. 13 shows the cumulative distribution function (CFD) of the localization errors for each technology. The test site was especially challenging for the *k*NN and PF because there were many LTE repeaters, and only PCI was available. As shown in Fig. 13, the conventional technologies could not solve the ambiguity in the test environment, so the CDF curve tended to increase continuously. This result confirmed that it was not preferable to use conventional technologies for localization in indoor LTE environments. On the other hand, the proposed technology maintained a highly accurate performance, except for the initial localization error. Since the proposed technology has an error within 7m after convergence and a larger localization error occurs initially, it can be confirmed that it is a discrete form after 7m. Table 1 summarizes the localization error of each technology for the three test scenarios. Thus, we demonstrated that the proposed technology substantially improved the performance of the conventional fingerprinting method by utilizing the accumulated RSS pattern. Additionally, this approach can also be applied effectively in a challenging indoor environment where multiple LTE repeaters exist.

V. CONCLUSION

In this study, we have proposed a 2D surface correlation-based precise localization technology using LTE fingerprinting for indoor localization, which is the core of seamless navigation. LTE covers outdoor as well as most indoor areas, and its infrastructure is professionally managed by telecom companies. Conventional fingerprinting methods utilize instantaneous measurements, and their location discernment level is exceedingly low. However, this discernment problem can be overcome by increasing the density of RF signal sources. The proposed technology improved the location discernment using the *surface* which presented the spatial RSS pattern generated from the PDR during a user's movement. In addition, it prevented pattern distortion caused by the PDR drift error through a feature matching algorithm using feature information such as the RSS mark and crossroad coordinates. In addition, the proposed technology induced a rapid convergence of the pattern matching point through correlation pattern analysis, and therefore, accurate location information could be served to the user more rapidly. We demonstrated that the proposed technology is highly accurate and can be effectively applied even in an indoor environment where location discernment is low owing to the use of LTE repeaters. We expect that the convergence timing and accuracy of initial pattern matching in 2D surface correlation technology can be further improved if more precise magnetic field information is used in conjunction with LTE.

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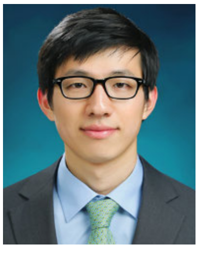

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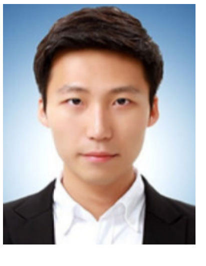

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