Lila Rana\textsuperscript{1}, Jiabin Dong\textsuperscript{1}, and Joon Goo Park\textsuperscript{1}

\textsuperscript{1}Responder Wall Scenario LOS Scenario

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An Enhanced Indoor Positioning Method based on RTT and RSS Measurements under LOS/NLOS Environment

Lila Rana, Jiabin Dong, Joon Goo Park

Abstract—In recent years, Indoor Positioning Systems (IPS) have gained significance across various applications, including asset tracking, monitoring, interior navigation, and location-based services. The use of Wi-Fi-based technology is a popular choice for IPS due to its cost-effectiveness and widespread accessibility. The WiFi signal's Round Trip Time (RTT) measurement, using the Fine Time Measurement (FTM) protocol, offers fewer ranging errors in Line of Sight (LOS) conditions. However, Wi-Fi RTT ranging measurements encounter higher-ranging errors in Non-Line of Sight (NLOS), multipath, and interference scenarios. This study examines the error in ranging measurements for different scenarios such as LOS, Glass, Metal, and Wall blocking scenarios. To address these challenges, we propose a method that combines calibrated RTT range and processed Received Signal Strength (RSS) feature values in constructing a fingerprinting map to enhance positioning accuracy. The methodology includes the development of a range compensation model for RTT range calibration, utilizing a Gaussian Filter for RSS measurement values processing, and creating a classifier model to distinguish between LOS and Wall scenarios. This integrated approach reduces noise in measurement values, and the Gaussian Process Regression (GPR) algorithm is utilized to predict the final location of the user. Our proposed method achieved a positioning error of 0.79 m, surpassing the performance of RTT fingerprinting by 17.71%, RSS fingerprinting by 49.68%, and trilateration methods by 29.46%.

Index Terms—LOS/NLOS Classification, range compensation model, Wi-Fi-based indoor positioning, Wi-Fi RSS fingerprinting, Wi-Fi RTT-RSS hybrid fingerprinting

I. INTRODUCTION

The demand for IPS and their research has increased with modern wireless communication technological advancements and internet service penetration. A user’s position information is important for implementing IPS for various indoor-based services, such as navigation, monitoring, tracking, and other services in daily human applications. The number of indoor application users has also increased because people spend most of their daily lives indoors using smart devices. Therefore, accurate IPS is essential for humans’ daily lives to provide positioning services using smart devices. As the number of indoor application users increases, the expected market value of global indoor locations is projected to achieve US $32.70 billion by 2033 [1]. The Global Navigation Satellite System (GNSS), which uses satellite signals, has been used for outdoor positioning using the Global Positioning System (GPS) module of smartphones for many years with fewer positioning errors and high-precision navigation services [2]. However, the use of GNSS in an indoor environment is limited due to satellite signal blockage and reflection problems. So, an accurate satellite signal can not be received, and good indoor positioning is impossible using GNSS.

Researchers have used several technologies, such as Wi-Fi [4]–[12], [14]–[34], Bluetooth [35], ultra-wideband [36], radio frequency identification [37], ZigBee [38], ultrasonic [39], computer vision [40], etc., to solve indoor positioning problems. The Bluetooth Low Energy (BLE) is easier to install, but it has less coverage range than Wi-Fi. The computer vision technique uses visual information captured by cameras to locate the user locations, but it suffers from processing delay, high computational cost, and depends on the lighting condition. UWB-based technology can lower positioning errors but has a higher cost, which is similar to ultrasonic-based technology. RFID-based technology is low-cost but has a shorter coverage range, and ZigBee technology is not expensive and exhibits low power consumption but lacks stability. Conversely, Wi-Fi-based technology has low positioning costs without needing extra equipment, as in other technologies. The easy implementation in existing indoor environments attracted significant research attention for using Wi-Fi-based technology, among other technologies.

Wi-Fi-based technology is mainly divided into two positioning methods: fingerprinting and the range-based positioning...
method. The fingerprinting positioning method has two main phases: the training phase (offline phase) and the positioning phase (online phase). In the training phase, the collected RSS [4]–[12] or channel state information (CSI) [34] input feature at each reference point (RP) from all access points (APs) is used to construct the fingerprint database, and the collected input feature from all APs is matched using a positioning algorithm with the training fingerprint database to predict the final location of the user during positioning phase. The matching algorithm is classical K-nearest neighbor (KNN) [7], weighted KNN (WKNN) [8], GPR [9], deep neural network (DNN) [10], [11], Spectral Normalization for Generative Adversarial Networks (SNGAN) [12]. In the fingerprinting positioning method, the signal measurement deviation in the training and positioning phase is due to various environmental changes and device hardware, leading to high positioning errors. Recently, the fingerprinting-based positioning method using crowdsourcing [41] and transfer learning algorithms [42] has been used to lower costs. However, the signal measurements at the same RPs are different due to interference and noise in between the transmitter and receiver. The approach of a three-step robust adversarial framework has been used to address these interference challenges where maximum-minimum adversarial training is employed [43]. The cost of collecting the labeled sample measurements is high in real time for the fingerprinting method. So, unsupervised methods for positioning using unlabeled crowdsourcing samples have also been implemented to address the environment and hardware changes [44]. The deep learning-based fingerprinting method has been widely used and successful for high positioning accuracy; however, the changes in the environment make it less feasible for the generalization of the model. So, meta-learning approaches have been used to address these issues [45].

In the range-based method, the final location of an unknown user is predicted using trilateration [4], multilateration based on least square [5], and weighted least square method [6] via the estimated distance based on RSS. This method does not require collecting the Wi-Fi data like the fingerprinting positioning method. It uses a path loss model established using RSS and distance values. However, it has high positioning error and computational cost in complex indoor environments. The use of CSI can have higher-ranging accuracy and stability, but it requires special equipment to perform the positioning. The FTM protocol in Wi-Fi technology, standardized by IEEE 802.11-2016 [13] in 2016, could theoretically give high precision estimates ranging between a Wi-Fi RTT-enabled smartphone and APs using RTT. This FTM protocol can give the range values between an AP and a Wi-Fi RTT-enabled smartphone by sending ranging requests from smartphone to APs without establishing a connection between them. It can collect the RSS and RTT ranging results within a short-ranging period. The clock synchronization between a smartphone and APs is not required as it is required in time of flight (TOF), which makes the positioning system more reliable.

However, the Wi-Fi RTT ranging measurements and positioning under NLOS conditions suffer in a real indoor environment due to signal reflection, blockage, and multipath propagation. The noise of hardware and software can be filtered out by taking multiple measurements in the same location, but it cannot remove the errors due to NLOS conditions [14]. The longer indirect path results in signal disturbance in the final RTT ranging measurement, which impacts the final positioning performance [15]. The NLOS error arises due to complex environmental conditions, and clock drift error should be considered while constructing the positioning model. So, the identification of LOS and NLOS conditions of APs from smartphones is advantageous for lowering positioning errors in complex environments. Some research has been done that identifies conditions and removes the NLOS signal between the user and APs. These approaches are ineffective when all the conditions between the user and APs are NLOS conditions and estimating the final position is impossible [16], [17]. Trilateration and fingerprinting-based methods using raw measurements without calibration or eliminating Wi-Fi signals have less positioning accuracy in complex indoor environments.

The indoor positioning model’s effectiveness can be enhanced if we consider Wi-Fi signal calibration and processing based on the Wi-Fi signal condition. Therefore, we propose indoor positioning based on a fingerprinting method using a calibrated Wi-Fi RTT range and processed Wi-Fi RSS hybrid features. The primary contributions of our research work are as follows:

- We evaluate the Wi-Fi RTT ranging errors in different Ranging Periods (≥ 200 ms) and scenarios: LOS and NLOS (Glass, Metal, and Wall) and analyze possible reasons behind them.
- We construct a range compensation model for LOS and NLOS (Wall) to calibrate Wi-Fi RTT ranging based on their scenario using a non-linear 3-degree polynomial model. Additionally, we pre-process the raw Wi-Fi RSS values using the Gaussian Filter, which is de-noised.
- We propose a LOS/NLOS condition classification model based on logistic regression to reduce the ranging error in different scenarios.
- We propose an indoor positioning based on a fingerprinting method using a hybrid of calibrated Wi-Fi RTT and processed Wi-Fi RSS input features, which improves the ranging error in LOS/NLOS environments, which can be used in complex indoor environments.

This research work has the following sections: Section II describes the related work. Wi-Fi RTT ranging, Ranging Compensation Model, Wi-Fi RSS Processing, Proposed Fingerprinting Positioning Method, LOS/NLOS Classifier Model, and Gaussian Process Regression model are described in section III. Section IV explains the experiment setup and evaluation of the algorithm. Lastly, Section V is the conclusion and future work of this research work.

II. RELATED WORK

The use of Wi-Fi RSS values for indoor positioning is popular, but it has some drawbacks due to its lower accuracy in complex environments where noise data and NLOS Wi-Fi signals are present. The research work [7]–[12] used
fingerprinting techniques to mitigate the problems in complex environments. Alternatively, many researchers have started to use Wi-Fi RTT for indoor positioning. The positioning error of 2.13 m in 95-th percentiles was achieved by the authors of [18] using Unscented Kalman Filter in range filtering and fingerprinting methods. The authors of [19] have also leveraged the use of ranging and fingerprinting methods using Wi-Fi RTT and achieved sub-meter positioning error for two experiment sites. The authors of [10] utilized DNN for training and reported a 2.13 m positioning error for the 95-th deviation. A 3-D indoor localization with high precision was proposed using Wi-Fi FTM technology and smartphone sensor measurements in article [20], achieving meter-level positioning accuracy.

The author of [21] used an approach of hybrid Wi-Fi RTT and RSS features for more accurate indoor positioning. However, the positioning algorithm does not perform similarly in complex environments where NLOS and LOS signals are present. The classification of Wi-Fi signals in different conditions is a crucial part of the good performance of positioning systems in complex environments. The ranging method using Wi-Fi RSS and RTT signal was used for addressing NLOS and other challenges in [22]. Moreover, the authors in [23] used Wi-Fi RTT and RSS features and classified the LOS and NLOS conditions using machine learning algorithms. This method needs a sequence of Wi-Fi measurements for the classification of signal conditions. The authors in [15] proposed an approach for detecting LOS Wi-Fi APs based on statistical features such as mean, standard deviation, variance, etc. This method may have problems in smartphones due to computation time. An NLOS and LOS distance identification idea was used and estimated the final location in [16]. However, the NLOS distance is discarded in this method, which makes low positioning accuracy. The authors of [24] showed a 1.097 m mean error using Wi-Fi RTT via GPR algorithm in complex environments. However, the model training time is longer, and performance may be poorer for generalized use. The study of ranging analysis of different properties of Wi-Fi RTT and RSS and their performances was performed in [25]. Some other studies related to Wi-Fi RTT offset calculation were performed and calibrated using different calibration models, such as linear polynomial, quadratic polynomial [26], and double exponential [27]. Research related to the ranging model construction has been done to deal with ranging errors due to clock drift in [28]. The authors calibrated the ranging results based on the error difference between the true and estimated ranges and filtered using the Kalman and Average filter to deal with the clock drift errors. The performance of this method depends on the equipment used and has less accuracy if the clock drift is large. They analyzed the ranging error in different NLOS conditions using metallic, non-metallic, and pedestrian NLOS blockers. However, this work has not considered the error analysis for user movement and status of motion. The authors in [29] have investigated the different error categories of Wi-Fi RTT by using fixed and varied modes of distance measurement and location of the user. It summarized the Wi-Fi RTT errors for different categories, such as LOS, wood, glass, and metal blockers, using four different companies’ smartphones.

The authors in [30] proposed a ranging model to deal with the NLOS ranging errors, but it is challenging to use in smartphones due to original time measurement requirements. The LOS and NLOS identification has been done using a model based on GPR, and the LOS range is calibrated accordingly for final positioning and achieved sub-meter positioning error in the research work of [31]. The authors of [32] used a range compensation model to lessen the error in NLOS conditions by using the weighted LS positioning method, which can work in complete NLOS conditions. However, the material of blockage in NLOS condition plays a big role in positioning, which is not analyzed.

We can conclude that the calibration of the Wi-Fi RTT ranging measurements value positively impacts ranging errors for clock drift, random, and NLOS errors. Moreover, we believe that the Wi-Fi RSS combination with Wi-Fi RTT ranging measurements assists positively in the final positioning after considering Wi-Fi signal conditions. The fluctuation of the Wi-Fi RSS measurement values may have disadvantages for positioning results with higher error, but it can be processed using Gaussian filtering as in the work of [33]. We use the hybrid of calibrated Wi-Fi RTT range and processed Wi-Fi RSS feature values to propose an indoor positioning method that can work in a LOS/NLOS complex environment.

A. Wi-Fi FTM Protocol

The Wi-Fi FTM protocol is able to measure the ranging measurements between an initiator (Wi-Fi RTT-enabled smartphone) and responders (Wi-Fi RTT-enabled APs). An initial FTM request is sent by an initiator first, and the responder responds to the initiator’s acknowledgment (ACK) when it is ready. Figure 1 shows two FTM interchanges and one burst measuring containing multiple FTM interchanges at most 32 FTMs, including the initial FTM request, and 8 FTMs are used in our research work.

Fig. 1: FTM protocol ranging principle

The estimated RTT for f FTM interchanges in a burst can
be measured as:

\[ \text{rtt} = \frac{(t_{4,f} - t_{1,f}) - (t_{3,f} - t_{2,f})}{2} \quad (1) \]

where \((t_{3,f} - t_{2,f})\) is a processing time delay at the initiator side and \((t_{4,f} - t_{1,f})\) is the time taken for measurement of one RTT. The final RTT range measurements between initiators and responders can be calculated by taking the average value of all estimated RTT range measurements of FTM request and ACK process a burst, which can be expressed as follows:

\[ \hat{d} = \frac{\text{rtt} \times c}{2} \quad (2) \]

where \(c = 3 \times 10^8 \text{ m/s}\), is the speed of light. A total of 31 FTM measurements in a single burst, excluding the initial FTM request. The Wi-Fi RTT ranging and RSS values are measured from one successful ranging request and took multiple samples at RPs. The clock drift error increases as the response time from the initiator end increases [32]. Some minor clock drift from both the initiator and responder sides impacts the RTT range value, and it can be expressed as follows:

\[ \text{rtt} = \frac{(t_{4,f} - t_{1,f})(1 + e_{\text{init}}) - (t_{3,f} - t_{2,f})(1 + e_{\text{resp}})}{2} \quad (3) \]

where \(e_{\text{init}}\) and \(e_{\text{resp}}\) are clock drift errors at the initiator end and responder end. The clock drift error can be written as follows [32]:

\[ e_{\text{clockdrift}} = \hat{d} - \text{rtt} \quad (4) \]

The total error includes clock drift error, random error, and error due to NLOS. It should be subtracted from the measurement of RTT ranging. We can compensate for these errors by constructing a range compensation model that uses the range difference between the true range and measurement range at known points and scenarios.

### III. Methodology

In this research work, we have proposed an indoor hybrid fingerprinting positioning method based on Wi-Fi RTT and RSS feature values in the LOS/NLOS environment. The raw measurement data can not be directly used due to the multipath, interference, and random error in a real-world scenario. This paper conducts the relevant pre-processing analysis of Wi-Fi RTT range measurements in different environments and the processing of Wi-Fi RSS measurements for fingerprinting construction.

#### A. Wi-Fi RTT Ranging

This section presents an error analysis of Wi-Fi RTT range measurements in various conditions, including LOS and NLOS conditions, taking into account different obstruction materials such as glass, metal, and wall materials. The ranging error primarily varies due to technical and environmental factors. Technical factors, encompassing the specifications of the smartphone and Wi-Fi router, the ranging period, and the operating RF bands, contribute to different errors and stability. On the other hand, environmental factors, such as the absence of obstacles and the presence of different types of materials obstructing the path between the initiator and responder, significantly influence ranging errors.

The technical and environmental factors affect signal degradation in each scenario, leading to higher errors in range and less stability in raw measurement data of Wi-Fi RTT data. Considering these factors and analyzing the raw measurement data in different scenarios can enhance the accuracy of range measurements. To assess the accuracy of the ranging measurements against the true distance, we employed the MSE as the evaluation metric, which can be expressed as follows for the ‘n’ number of samples:

\[ \text{MSE} = \frac{1}{n} \sum_{i=1}^{n} (d_{m,i} - d_{t,i})^2 \quad (5) \]

where \(d_{m,i}\) stands for the \(i\)th measurement range, and \(d_{t,i}\) denotes the \(i\)th true range from the router to the measurement points.

The raw Wi-Fi RTT ranging measurement values exhibit varying errors across different scenarios, owing to time delays known as Wi-Fi RTT bias affecting their true range. Signal variations caused by reflections and obstructions lead to differing propagation times, resulting in measured ranges deviating from the actual range. It is crucial to correct this bias value to enhance the accuracy of positioning. This correction involves adjusting logged ranges to align more closely with ground truth values. A range compensation model, based on ranging at known distances, becomes essential since the offset is not constant across all scenarios. This model ensures a more accurate estimation of range by accounting for variations in bias under different conditions.

Moreover, there may be the presence of outliers in the raw measurement of ranging data due to several environmental factors, which should be identified and eliminated from the ranging data before processing for the compensation model to ensure reliability. In this work, Hampel filtering is used for this purpose so that the input to the compensation model will be outlier-free. Mathematically, it uses median-based statistics and threshold values to identify and eliminate outliers from the sample. It involves a multi-step process: initially, the K-length sample’s median value and the median absolute deviation (MAD) are calculated based on the raw measurement ranging data. Outliers are then identified by comparing deviations from the median against the standard deviation and detected outliers are replaced with median values. The measurement ranges outside of the interval \([\mu + h \times \sigma, \mu - h \times \sigma]\) are identified as non-outlier samples where \(\mu\) is median, \(h\) is a scale factor to standard deviation, which is 3 in common choice, and \(\sigma\) is the standard deviation. The relationship of \(\sigma\) with MAD for normally distributed sample measurement of ranging can be shown in the following equation,

\[ \sigma = 1.4826 \times \text{MAD} \quad (6) \]

#### B. Range Compensation Model

The Wi-Fi RTT ranging results reveal a non-linear relationship between the true range and the estimated range within
each scenario. To capture this relationship, a non-linear polynomial compensation model can be employed, which is shown in Figure 2. This model effectively represents the intricate connection between each scenario’s true and measured ranges. The compensation model utilizes the measured ranges and the ranging error derived from the disparity between measured and true ranges. Specifically constructed for each scenario (e.g., LOS, glass, metal, and wall), the non-linear polynomial aims to identify the optimal non-linear relationship between ranging error and measured ranges. Each measurement contributes to determining a calibrated value intended to minimize ranging errors. The ultimate objective is to apply these calibration values to the measurements, aiming to ideally reduce or eliminate the gap between ranging errors and the true range values to the measurements, ideally reducing or compensating ranging errors.

To construct the compensation model, collected ranging results at each true range are used for analyzing random error and multipath factors. The non-linear model for each scenario can be written as follows:

\[ f(\hat{d}) = p_1 \cdot \hat{d}^3 + p_2 \cdot \hat{d}^2 + p_3 \cdot \hat{d} + p_4 \]  

where \( f(\hat{d}) \) is the estimated ranging error for measured RTT ranging \( \hat{d} \) between the initiator and responder, \( (p_1, p_2, p_3, \) and \( p_4) \) are the coefficients for the 3-degree polynomial.

A non-linear least square solution can be employed to determine the parameter values of a given non-linear function, minimizing the sum of squared differences between the predicted value from the model and the observed values. This process can be represented by Equation (10).

\[ \text{min}(SSR) = \text{min}\left(\sum_{i=1}^{n}(y_i - f(\hat{d}_i, p))^2\right) \]  

where \( y_i \) represents the observed value for the \( i^{th} \) sample \( d_i \), \( f(\hat{d}_i, p) \) represents the model’s predicted values based on the input \( \hat{d}_i \) and parameters \( p \), which represent the group of parameters that minimize the SSR.

The calibrated range \( d \) using the range compensation model with polynomial coefficient will be,

\[ d = \hat{d} - (p_1 \cdot \hat{d}^3 + p_2 \cdot \hat{d}^2 + p_3 \cdot \hat{d} + p_4) \]  

The value of \( d \) may sometimes be a negative value, which can be solved by a piecewise function,

\[ d = \begin{cases} 0 & \text{if } \hat{d} < 0 \\ \hat{d} - (p_1 \cdot \hat{d}^3 + p_2 \cdot \hat{d}^2 + p_3 \cdot \hat{d} + p_4) & \text{if } \hat{d} \geq 0 \end{cases} \]  

The range compensation model, incorporating 3-degree non-linear polynomial coefficient values specific to LOS, glass, metal, and wall scenarios, is constructed to calibrate and evaluate the measurement ranging data. Specifically, we have developed a range compensation model for both LOS and wall scenarios in our study. This model serves as the foundation for constructing the fingerprinting database, which will be utilized for further positioning using multiple access points.

C. Wi-Fi RSS Processing

This section introduces the preprocessing of Wi-Fi RSS measurements in the experiment area, which is described in detail in section V. The raw Wi-Fi RSS measurement values exhibit instability in indoor environments due to environmental factors, such as multipath effects in both LOS and NLOS scenarios. Directly using these raw RSS values for constructing the fingerprint database can lead to low positioning accuracy.

To address this problem, we applied a Gaussian filter to preprocess the raw RSS values, effectively filtering out deviated RSS values from the true ones [33]. This process obtains a stable and smooth RSS value by eliminating noise data, consequently reducing positioning errors. The RSS measurement values at different reference points can be modeled as a Gaussian distribution, and the Gaussian function ‘P’ can be expressed as follows,

\[ P(R) = \frac{1}{\sqrt{2\pi}\sigma_r} e^{-\frac{(R-\mu)^2}{2\sigma_r^2}} \]  

\[ \mu = \frac{1}{n} \sum_{i=1}^{n} R_i \]  

\[ \sigma_r = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (R_i - \mu)^2} \]  

where \( \sigma_r \) is the standard deviation and \( \mu \) is the mean of \( R_i \), RSS values for \( n \) numbers of total values.
D. Proposed Fingerprinting Positioning Method

The proposed fingerprinting positioning method comprises the training and positioning phases, as shown in Figure 3. In the training phase, RTT and RSS measurement values are collected under LOS and NLOS conditions using a smartphone from all access points at each reference point. Notably, the NLOS condition in our experiment site involves a wall, as discussed in Section V. The training set associated with LOS is labeled 0, whereas that belonging to NLOS is labeled 1. The collected data undergo calibration and filtering based on our proposed range compensation model and Gaussian filter. The combination of Wi-Fi RTT with RSS serves to overcome the limitations of Wi-Fi RTT for positioning. During the positioning phase, the final position is predicted using a model trained in the offline phase. The two primary components of post-fingerprinting database construction are the NLOS/LOS classifier model and the training Gaussian Process Regression (GPR) model. The NLOS/LOS classifier model is trained to apply different calibrations on Wi-Fi RTT data in the online phase, providing precise indoor position estimation based on the training scenario.

The calibrated RTT range and processed RSS feature values are utilized to construct the fingerprinting database, with a 1x1 dimensional pair representing each reference point. For multiple access points (APs), the above equation can be expressed as [14],

$$V_n = \begin{bmatrix} d_{n}, & R_{n} \end{bmatrix}^T \tag{15}$$

where $d_n$ and $R_n$ are the respective average calibrated RTT range values and processed RSS values for each n-th reference point. For multiple access points (APs), the above equation can be expressed as [14],

$$V_n = \begin{bmatrix} d_{n,1}, & R_{n,1}, & d_{n,2}, & R_{n,2}, & \ldots & d_{n,m}, & R_{n,m} \end{bmatrix}^T \tag{16}$$

where $d_{n,m}$ and $R_{n,m}$ are the respective average calibrated RTT range values and processed RSS values at the n-th reference point for m numbers of APs, which is 3 in this work. All the information is collected during the training phase.

E. NLOS/LOS Classifier Model

This section introduces our proposed method’s classifier model distinguishing between LOS and NLOS conditions. In the fingerprinting database construction process, the training set associated with LOS is labeled as 0, and that corresponding to NLOS is labeled as 1. A misclassification by the classification model can lead to higher positioning errors in the corresponding training point position estimation. Therefore, the NLOS/LOS condition classification component holds significance before the final position estimation.

In our experiment site, two conditions are present: APs are inside or outside the wall from RPs. The signal transmission is obstructed by the wall, leading to signal delays. To address this, we employed logistic regression to classify the smartphone’s condition in relation to the APs. The logistic regression leverages the sigmoid function, and the fundamental equation is defined as follows:

$$p(y|(d_1, \ldots, d_m)) = \frac{1}{1 + e^{-z}}, \quad z = \sum_{i=1}^{m} w_i d_i + b_0 \tag{17}$$

where $p(y|(d_1, \ldots, d_m))$ represents the probability of the output class $y$ given input features $(d_1, \ldots, d_m)$, utilizing sigmoid function, and $z$ is computed based on weights $w_i$ associated with the input features $d_i$ and bias term $b_0$. $z$ is then passed through the sigmoid function to produce probability between 0 and 1. The threshold value is set at 0.5; if the output probability is greater than or equal to 0.5, the model classifies the input as NLOS or vice versa.

F. Gaussian Process Regression Model

We employed GPR to estimate the final location using the training dataset from the fingerprinting database. GPR
is a non-parametric regression technique capable of handling complex models. Given the intricate indoor environment in our experiment, characterized by several pieces of furniture and walls between the APs and RPs, a complex nonlinear relationship exists between RTT, RSS values, and their true coordinates. In such a scenario, GPR proves to be a suitable option for predicting the final position during the positioning phase, as it captures the complexities and noise in the input values. The scaled fingerprint data at the nth reference point in the model training can be expressed as follows,

\[ V = [v_1, v_2, \ldots, v_n]^T \]  

\[ v_i = [d_{i,1}, R_{i,1}, \ldots, d_{i,m}, R_{i,m}] \]  

The Gaussian Process can be defined by mean function \( m(V) \) and covariance functions \( k(v_i, v_j) \) that follow a joint Gaussian distribution.

\[ m(V) = \mathbb{E}[f(V)] \]  

\[ K(V, V) = \text{cov}(f(V), f(V)) \]  

\[ k(v_i, v_j) = \mathbb{E}[(f(v_i) - m(v_i))(f(v_j) - m(v_j))] \]  

\[ g(V) \sim \text{GP}(m(V), K(V, V)) \]  

where \( \mathbb{E}(\cdot) \) denotes the expectation operator, \( f(V) \) is Gaussian process, and \( K(V, V) \) is the covariance matrix. The output of the training model, which corresponds to the RTT range and RSS fingerprint from each reference point, can be shown as \( F = [f_1, f_2, \ldots, f_n]^T \) and \( f_i = (x_i, y_i) \). It can also be written in simple form as follows.

\[ f_i = g(v_i) + \omega \]  

where \( \omega \sim \mathcal{N}(0, \sigma^2) \) is an additive Gaussian noise with zero mean and variance \( \sigma_n^2 \). The hyperparameters to be solved for our purpose are \( \sigma \), standard deviation of input vector \( s_f \), and length of scale parameter \( l \). We have used three kernels: the Constant kernel, the Gaussian kernel, and the White kernel function. The constant Kernel introduces a constant term denoted by \( s_n^2 \) and can be expressed as follows.

\[ k_c (v_i, v_j) = s_n^2 \]  

The Gaussian Kernel, also known as the Radial Basis Function Kernel(RBF), is equivalent to the squared exponential Kernel covariance function, which employs the \( ||v_i - v_j|| \) Euclidean distance and can be expressed as follows.

\[ k_{se} (v_i, v_j) = s_n^2 \exp\left(-\frac{||v_i - v_j||^2}{2l^2}\right) \]  

The White Kernel represents uncorrelated noise and introduces a constant diagonal term denoted by \( s_n^2 \).

\[ k_w (v_i, v_j) = s_n^2 \delta(v_i, v_j) \]  

where \( \delta(v_i, v_j) \) is the Kronecker delta function, which is 1 if \( v_i = v_j \) and 0 otherwise. The overall combined kernel is the sum of these individual kernels:

\[ k(v_i, v_j) = k_c (v_i, v_j) * k_{se} (v_i, v_j) + k_w (v_i, v_j) \]  

This combined kernel is then used in the GPR model for capturing different types of patterns and noise in the data. We try to predict the position \( f_* \) of testing input vectors and reference point position \( F \) jointly obeys a multivariate Gaussian distribution.

\[ \begin{bmatrix} f_* \end{bmatrix} \sim \mathcal{N} \left( 0, \begin{bmatrix} K(V, V) + \sigma^2 I & K(V, V) \\ K(V, V) & K(V, V) \end{bmatrix} \right) \]  

where \( V \) are the training data and \( V_* \) are the testing data, \( K(V, V) \) is the kernel function and \( I \) is the identical matrix. The posterior mean and posterior covariance can be written as follows.

\[ \mu_{post} = K(V, V)[K(V, V) + \sigma^2 I]^{-1}F \]  

\[ \Sigma_{post} = K(V, V) - K(V, V)[K(V, V) + \sigma^2 I]^{-1}K(V, V) \]  

The trained GPR model is utilized to predict the unknown position of the user during the positioning phase.

IV. Experiment Evaluation

This section describes the experiment setup for ranging and fingerprinting purposes and the technical specifications of the devices used in experiments I and II. Next, we delve into error analysis and LOS/Wall NLOS classification. The final sub-section covers the details of the positioning evaluation.

A. Experiment Setup

In this work, the experiment setup were conducted in two steps. The first step involved collecting training samples from one AP in various scenarios, including LOS, Glass, Metal, and Wall, to analyze errors and construct a range compensation model based on the findings. The second step included collecting samples from reference points and testing points using three different APs. The ‘Google Pixel Nest Wi-Fi router served as the AP, whereas a ‘Google Pixel 2’ was used as the initiator. The router operated in dual bands of 2.4 and 5 GHz, but only the 5 GHz band supported RTT in this experiment setup. For data collection and processing, we utilized the ‘WifiRttScan’ mobile application developed by Google.
TABLE I: Experiment II Details

<table>
<thead>
<tr>
<th>Data</th>
<th>Details</th>
</tr>
</thead>
<tbody>
<tr>
<td>Area of Testbed (m²)</td>
<td>112.5</td>
</tr>
<tr>
<td>Grid size (m × m)</td>
<td>1.5 × 1.5</td>
</tr>
<tr>
<td>Total Reference Points</td>
<td>38</td>
</tr>
<tr>
<td>Total Training Samples</td>
<td>11400</td>
</tr>
<tr>
<td>Total Testing Points</td>
<td>14</td>
</tr>
<tr>
<td>Total Testing Samples</td>
<td>4200</td>
</tr>
<tr>
<td>Feature Values</td>
<td>Wi-Fi RTT, Wi-Fi RSS</td>
</tr>
<tr>
<td>Labels</td>
<td>x, y and NLOS</td>
</tr>
</tbody>
</table>

1) Experiment I: The experiment was conducted in both a passage and a classroom environment, as shown in Figure 4. Ranging measurements were collected without any blockage at first, which is LOS, and collected in the same area using real-world blockages such as a glass door, a metal door in a passage, and wall separation between two classrooms. In the NLOS condition, a physical obstruction completely separated the initiator and responder. Subsequently, samples were collected from at least 200 datasets in 1-meter intervals up to 14 meters for each scenario, with a ranging period of 200 ms. The router and smartphone were positioned at the same height of 1.5 meters.

2) Experiment II: This experiment was conducted in the classroom using three APs installed inside the classroom, as shown in Figure 5. The environment is complex, featuring chairs and occupying an area of 7.5 m × 15 m. LOS samples were collected, amounting to at least 200 datasets from each RP within the classroom, considering all APs. In contrast, NLOS samples were collected in the passage with a 1.5 m × 12 m area at each RP from all APs. A 4 cm concrete wall separates the passage and classroom, consistent with the setup in Experiment I. The ground-truth distance ranged from 1.5 m to 15 m, and the height setting remained consistent with that of Experiment I. For this experiment, only the wall scenario was considered. Testing points were collected at random locations without overlapping with the RPs. The details of Experiment II are explained in Table I.

B. Wi-Fi RTT Ranging Analysis

The effective operation of an IPS relies on the sampling rate of collected samples, a crucial factor in assessing the less error final positioning. Before conducting Experiments I and II, we conducted a preliminary test involving different ranging periods—specifically, 200 ms, 250 ms, 333 ms, and 500 ms. This test was conducted for a 2 m distance gap between an AP and a smartphone, whereas the theoretical ranging period for collecting Round-Trip Time (RTT) ranging samples on a smartphone is 100 ms, including avoiding collisions and potential software problems, which led us to set the ranging period to not less than 200 ms, as recommended by Google. We obtained readings from a router in a smartphone, analyzed the ranging error using equation (5), and presented the results in Figure 6. For a ranging period of 500 ms, it gives four ranging samples every two seconds in successful cases of all the requests between smartphone and AP. After careful consideration, we selected a 200 ms ranging period for faster sampling and lower error, facilitating a shorter test trial period. Figure 7 illustrates the Wi-Fi RTT ranging results in different scenarios at varying distances by considering this ranging period.

As detailed in the experiment setup, we employed various scenarios to analyze errors across different ranges. Figure 8 illustrates each scenario’s Mean Squared Error (MSE) at different true ranges. The MSE for the LOS scenario is stable for all the true range points compared to other scenarios. Conversely, the wall scenario exhibits the highest instability and a higher MSE among the four scenarios. The metal and glass scenarios demonstrate less impact than the wall scenario but more than the LOS scenario. The absolute ranging errors for all scenarios are summarized in Table II.

The ranging errors observed in Wi-Fi RTT in various scenarios highlight the significant influence of material hardware, blockage hardware, and the overall experiment environment. The presence of outliers, attributed to signal fluctuation and bias values inherent in each scenario, contributes to distinctive ranging errors. The bias of Wi-Fi signals varies with the conductivity of different blocking materials. Wi-Fi signals, functioning as electromagnetic waves traveling at the speed of light, encounter a variety of objects in indoor scenarios, including chairs, desks, doors, windows, and walls. These objects introduce reflections and diffractions, altering the propagation...
of electromagnetic waves. The number and type of obstacle materials impact this propagation, and the phenomenon known as the skin effect plays a crucial role.

**TABLE II: Ranging Errors in Different Scenarios**

<table>
<thead>
<tr>
<th>Scenario</th>
<th>LOS</th>
<th>NLOS (Glass)</th>
<th>NLOS (Metal)</th>
<th>NLOS (Wall)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ranging Error</td>
<td>0.22 m</td>
<td>0.47 m</td>
<td>1.13 m</td>
<td>1.57 m</td>
</tr>
</tbody>
</table>

The skin effect involves the distribution of current density within a conductor, concentrating near the surface and decreasing with depth. This effect influences the flow of Wi-Fi signals carried by electromagnetic waves, particularly when encountering obstacle materials. Skin effects occur as electromagnetic waves pass through materials, preventing some waves from passing through based on the material’s conductivity. The attenuation of Wi-Fi signals is contingent on the conductivity of the material, with better conductivity resulting in more significant signal attenuation. Understanding these principles and the relationship between ranging errors and true range allows us to construct a range compensation model tailored to address these errors in each scenario.

**C. Wi-Fi RSS Analysis**

In this research work, a Gaussian filter is applied to all RSS measurement values of reference points. Figure 9 illustrates the raw RSS readings from three different Access Points (APs) at the reference point (2.5, 3) in experiment II. The processed RSS values obtained through the Gaussian filter, characterized by smoother values with reduced noise, are presented. This processing approach effectively addresses the signal mutation problem in raw RSS fingerprint data. In essence, the processed RSS data is now smoother and more accurate, facilitating the construction of a precise fingerprint database and consequently reducing positioning errors.

**D. Range Compensation Model Analysis**

The raw RTT range samples obtained at various distances underwent Hampel filtering as a preprocessing step before constructing the range compensation model. This filtering method...
enhances reliability and accuracy by identifying outliers and smoothing the range measurements. The ranging errors between the estimated range measurements and true ranges are the output of the range compensation model, and the filtered measurement data are the input of the range compensation model. We have constructed the range compensation model for the LOS and wall scenario as our experiment II is in this scenario. A non-linear polynomial relationship can be built using the 3-degree coefficient and calibrating the range on the basis of the scenario.

Table III: Range compensation model parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Parameter</th>
<th>Parameter</th>
<th>Parameter</th>
</tr>
</thead>
<tbody>
<tr>
<td>LOS</td>
<td>0.0003</td>
<td>-0.0043</td>
<td>-0.0083</td>
</tr>
<tr>
<td>Wall</td>
<td>0.0044</td>
<td>-0.0936</td>
<td>0.5329</td>
</tr>
</tbody>
</table>

![Graph of range error before and after calibration](image)

**Fig. 10:** Comparison of compensation effects for (a) LOS scenario and (b) Wall scenario

The calibrated ranges for each scenario can be calculated using the model parameters as shown in Table III and Equation 12. To assess the effectiveness of our range compensation model, we conducted tests on 10% of the total sample collection, employing the same model parameters. The impact of the ranging compensation model is illustrated in Figures 10. In the LOS scenario, the mean ranging error reduced from 0.22 m to 0.18 m before and after the implementation of the range compensation model, respectively. Similarly, in the wall scenario, the mean ranging error reduced from 1.57 m to 0.55 m after applying the range compensation model. This reduction represents a substantial improvement, with mean ranging errors decreasing by 18.18% for LOS ranging and 64.97% for wall blockage ranging. The promising performance of the range compensation model suggests its potential to improve our positioning model, offering calibrated ranges for both LOS and wall scenarios.

The error associated with every sample can result from a combination of [36] delay, random, and scenario errors. These errors can be minimized through range calibration using a non-linear polynomial compensation model, which aims to minimize the Sum of Squared Residuals (SSR) values between predicted and observed values. After classification, the range compensation model is selected for LOS and wall scenarios using a trained classifier model.

**E. LOS/ Wall NLOS Classification**

The classification of LOS and Wall scenarios is a critical part, contributing to the refinement of the search area and achieving precise position during the positioning phase. In our experiment, the LOS scenario involved collecting data in the classroom from all APs, whereas the Wall NLOS scenario was based on data collected in the passage from Experiment II. WiFi RTT ranging measurements were collected at each RP, and logistic regression was employed for scenario classification in our experiment data.

Table IV: Classification performance of different methods

<table>
<thead>
<tr>
<th>Classification</th>
<th>Accuracy</th>
<th>Precision</th>
<th>Recall</th>
<th>FNR</th>
<th>FPR</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVM</td>
<td>0.9247</td>
<td>0.8677</td>
<td>0.9985</td>
<td>0.0015</td>
<td>0.1460</td>
</tr>
<tr>
<td>Logistic Regression</td>
<td>0.9982</td>
<td>0.999</td>
<td>0.9974</td>
<td>0.0026</td>
<td>0.0010</td>
</tr>
<tr>
<td>RF</td>
<td>0.9872</td>
<td>0.9948</td>
<td>0.9789</td>
<td>0.0211</td>
<td>0.0049</td>
</tr>
<tr>
<td>k-NN</td>
<td>0.9816</td>
<td>0.9694</td>
<td>0.9938</td>
<td>0.0062</td>
<td>0.0301</td>
</tr>
</tbody>
</table>

Logistic regression, known for its effectiveness in binary classification, utilizes a threshold value between two classes based on the sigmoid function. We employed several metrics to evaluate our method: Accuracy, Precision, Recall, False Negative Rate (FNR), and False Positive Rate (FPR). Accuracy: the proportion of correctly classified LOS and NLOS scenarios from the total samples; precision: measuring the proportion of true positive predictions (correctly identified NLOS scenarios) out of all scenarios predicted as NLOS by the classifier; Recall: Measures the effectiveness of NLOS classification in capturing all actual NLOS scenarios in the NLOS scenario, FNR: Represents the rate of missed NLOS scenarios in the NLOS scenario, FPR: Indicates the rate of falsely detected NLOS scenarios in the LOS scenario. Comparative analysis of these metric values with other methods of testing data points demonstrated the superior performance of logistic regression over SVM, Random Forest, and k-NN classifiers, as illustrated in Table IV.
of the actual feature values, meaning it only accounts for the noise level in the observations and does not consider any relationships between the features. Therefore, we verified only two combinations of kernels.

**TABLE VI:** Comparison of Methods- RTT only

<table>
<thead>
<tr>
<th>Method</th>
<th>50% RMSE (m)</th>
<th>75% RMSE (m)</th>
<th>90% RMSE (m)</th>
<th>Time (ms)</th>
</tr>
</thead>
<tbody>
<tr>
<td>GPR</td>
<td>1.15</td>
<td>1.24</td>
<td>2.34</td>
<td>23</td>
</tr>
<tr>
<td>RF</td>
<td>0.96</td>
<td>1.20</td>
<td>1.51</td>
<td>12</td>
</tr>
<tr>
<td>KNN</td>
<td>0.94</td>
<td>1.09</td>
<td>1.39</td>
<td>10</td>
</tr>
</tbody>
</table>

The comparison of positioning errors using different methods is presented in Table VI when only the RTT input feature is utilized. It shows that when employing the GPR algorithm, the positioning errors are significantly reduced. Specifically, for GPR, the 50%, 75%, 90% positioning errors, along with the overall Positioning RMSE, are 0.94 m, 0.99 m, 1.41 m, and 0.96 m, respectively. Prior to calibrating the data, the same GPR method yields higher errors: 1.15 m, 1.24 m, 2.34 m, and 1.39 m for 50%, 75%, 90% of the positioning error, and overall positioning RMSE. Comparatively, the fingerprinting method utilizing the RF and KNN algorithms exhibits higher errors in both cases than the GPR algorithms. Although the positioning error obtained using the GPR algorithm is initially higher than that obtained using the RF and KNN before calibrating and processing, the GPR demonstrates a notable reduction in positioning error after applying the calibrating and processing model.

**TABLE VII:** Comparison of Methods- RSS only

<table>
<thead>
<tr>
<th>Method</th>
<th>50% RMSE (m)</th>
<th>75% RMSE (m)</th>
<th>90% RMSE (m)</th>
<th>Time (ms)</th>
</tr>
</thead>
<tbody>
<tr>
<td>GPR</td>
<td>1.66</td>
<td>1.92</td>
<td>2.23</td>
<td>28</td>
</tr>
<tr>
<td>RF</td>
<td>1.37</td>
<td>2.06</td>
<td>2.43</td>
<td>73</td>
</tr>
<tr>
<td>KNN</td>
<td>1.68</td>
<td>2.09</td>
<td>2.54</td>
<td>10</td>
</tr>
</tbody>
</table>

Table VII presents the positioning errors for different methods using only the RSS input feature. A comparison of positioning errors before and after processing RSS measurements reveals that KNN demonstrates lower positioning errors than other methods. Specifically, after data processing, GPR exhibits 1.22 m, 1.92 m, 2.42 m, and 1.57 m in 90%, 75%, and 50% of positioning error, respectively. In contrast, KNN and RF exhibit positioning errors of 1.67 m and 1.69 m, respectively. The impact of the processed RSS feature is evident in the ‘before’ and ‘after’ columns for each method. GPR consistently exhibited lower errors, suggesting its efficacy in leveraging the processed RSS input feature for accurate positioning.

**TABLE VIII:** Comparison of Methods- RTT and RSS

<table>
<thead>
<tr>
<th>Method</th>
<th>50% RMSE (m)</th>
<th>75% RMSE (m)</th>
<th>90% RMSE (m)</th>
<th>Time (ms)</th>
</tr>
</thead>
<tbody>
<tr>
<td>GPR</td>
<td>1.06</td>
<td>1.60</td>
<td>1.99</td>
<td>22</td>
</tr>
<tr>
<td>RF</td>
<td>0.90</td>
<td>1.15</td>
<td>1.57</td>
<td>77</td>
</tr>
<tr>
<td>KNN</td>
<td>0.98</td>
<td>1.40</td>
<td>2.26</td>
<td>10</td>
</tr>
</tbody>
</table>

Subsequently, we explored the performance of hybrid input features, combining RTT and RSS, and compared them using.
the same algorithms. The results are detailed in Table VIII. The fingerprinting method using GPR stands out with a 0.79 m positioning error, whereas RF and KNN exhibit higher positioning errors of 0.85 m and 1.32 m, respectively. Notably, the input feature of calibrated RTT range and processed RSS hybrid outperforms separate RTT and RSS features across all algorithms. For our proposed method, we have adopted the GPR algorithm, showcasing positioning errors of 0.52 m, 0.92 m, and 1.18 m in 50%, 75%, and 90% of positioning error, respectively.

We conducted a comparative analysis of training times for three algorithms in an indoor environment: GPR, RF, and KNN, yielding approximately 20 ms, 70 ms, and 10 ms, respectively. Despite KNN demonstrating a shorter training time, it exhibited a higher RMSE than the other algorithms, as evidenced by the comparison tables. Notably, we observed a discernible relationship between RMSE and training time. While GPR and KNN showed comparable training times, GPR yielded lower RMSE than KNN. Therefore, from a complexity standpoint, GPR was selected as the preferred algorithm. Additionally, GPR offers distinct advantages over KNN. Notably, it provides probabilistic output, enabling predictions while quantifying uncertainty. Moreover, despite its potential computational intensity with large datasets, GPR can effectively handle such data volumes, ensuring scalability. Furthermore, GPR’s inherent robustness to noise enhances its reliability in handling noisy measurements and outliers, a characteristic that may not be as pronounced in deterministic methods like KNN, which are more susceptible to noise.

The CDF for the proposed algorithm, RTT-based algorithm, RSS-based algorithm, and hybrid RTT and RSS-based algorithm is shown in Figure 12. The positioning error of the proposed algorithm significantly outperforms other input feature-based algorithms, demonstrating superior performance 1.15 m positioning error 90% of the time. This improvement is attributed to the calibrated RTT and the processing of RSS measurements, achieved through a range compensation model and Gaussian filtering process, respectively. GPR, a nonparametric regression technique, particularly excels in complex scenarios. The proposed method effectively handles Wi-Fi signal reflection, mitigating errors in LOS and NLOS scenarios caused by obstacles such as chairs, tables, and walls. This is achieved by classifying LOS and NLOS scenarios and preprocessing the Wi-Fi signal. The reduction in significant positioning error underscores the effectiveness of our proposed method.

Our proposed method positively affects the positioning result for the LOS/NLOS complex environment based on our results from different experiments compared to traditional trilateration and fingerprinting methods using raw input features only. So, using a range compensation model based on their scenario classification is a good option for complex environments. We can use the same input features to classify scenarios, making implementation easier for our proposed method. However, this method needs to do data collection work for different environments, requires more training time, and increases the computation time with increased training data in a wider indoor environment.

V. CONCLUSION

This research introduced an indoor positioning system that combines ranging-based and fingerprinting-based methods. An analysis was conducted to understand the effect of different block materials on ranging errors of Wi-Fi RTT, leading to the proposal of a ranging compensation model. Raw Wi-Fi RSS measurements underwent filtering to eliminate noise, and a LOS/NLOS classification model was trained for condition classification, enabling calibration of estimated Wi-Fi RTT ranging. The hybrid use of Wi-Fi RTT and RSS input features in the proposed positioning system addressed challenges in complex indoor environments, including NLOS, multipath, and signal interference.

The results demonstrated the superior performance of the proposed indoor positioning fingerprinting method compared to trilateration and fingerprinting methods using raw Wi-Fi measurements. Following the application of the range compensation model, a notable improvement of 18.18% in LOS and 64.97% in the wall scenario ranging errors was observed. The positioning RMSE for the proposed method measured 0.79 m, significantly outperforming the 1.31 m RMSE associated with raw measurements. Comparative analysis with Wi-Fi RTT fingerprinting, Wi-Fi RSS fingerprinting, and trilateration positioning methods revealed that the proposed system achieved a positioning error improvement of 17.71% compared to Wi-Fi RTT fingerprinting, 49.68% compared to Wi-Fi RSS fingerprinting, and 29.46% compared to trilateration positioning. The study specifically focused on the Wi-Fi signal condition in reference points, distinguishing between LOS and NLOS conditions from access points. Future research will involve further validation of the proposed method across diverse experimental settings and applications.

REFERENCES


**Lila Rana** was born in Palpa, Nepal in 1998. He received the B.E. degree in electronics and communication engineering from Tribhuvan University, Kathmandu, Nepal, in 2018. He is currently pursuing the M.S. degree in electronic and electrical engineering at the Kyungpook National University, Daegu, South Korea. From 2019 to 2021, he was an Associate Broadcast Engineer with the Dish Media Network Ltd., Lalitpur, Nepal. His research includes wireless communication systems and networks, Wi-Fi based indoor positioning and Use of machine learning for wireless communication.

Mr. Lila received the Global Korea Scholarship (GKS) 2021, awarded by the National Institute for International Education Development (NIED), Republic of Korea.

**Jiabin Dong** was born in Luoyang, China, in 1997. She received the B.S. degree in electronic engineering from Kyungpook National University, Daegu, South Korea, in 2022, and she is currently pursuing the M.S. degree in electronic engineering, Kyungpook National University, Daegu, South Korea. Her research interests include wireless communication, indoor ranging method and application of machine learning techniques to indoor positioning.

**Joon Goo Park** received the B.S., M.S., and Ph.D. degrees in electrical and computer engineering from Seoul National University, Seoul, South Korea, in 1994, 1996, and 2001. Since 2005, he has been a professor with the School of Electronics Engineering at Kyungpook National University, Daegu, South Korea.