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An investigation of different Wi-Fi signal behaviours and their effects on indoor positioning accuracy

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In recent years, in addition to 2.4 GHz Wi-Fi signals, 5 GHz signals have been introduced making it possible to transmit data at both IEEE 802.11n and 802.11ac standards. Therefore, researchers have increasingly focused on developing indoor positioning applications based on Wi-Fi dual band. This study was conducted in two stages. In the first stage, we investigated the behaviours of 2.4 and 5 GHz Wi-Fi signals by collecting received signal strength (RSS) values from access points and determined the relationship between RSS and distance for each signal frequency using a curve fitting technique. Furthermore, we comparatively analysed signal fluctuations and their effects on positioning accuracy. In the second part of the study, we compared the positioning accuracy of four algorithms; namely, bilateration, trilateration, weighted iterative non-linear least square and extended Kalman filter using 2.4 and 5 GHz Wi-Fi signals. The experimental results revealed that the 5 GHz signals were more stable and had better positioning accuracy than the 2.4 GHz signals. Concerning the positioning algorithms, bilateration had the best positioning accuracy at both frequencies.

Keywords: Wi-Fi, 2.4 GHz, 5 GHz, Bilateration, Trilateration, Weighted iterative nonlinear least square, Extended Kalman filter, Indoor positioning

Introduction

In recent years, indoor positioning has been intensively researched by academic and commercial communities due to the wide demand for it (Subbu *et al.* 2014). Although the main purpose of such research was to provide an effective positioning solution for indoor positioning, there is still no solution that has been agreed on by the community (Caceres *et al.* 2009). In outdoor environments, Global Navigation Satellite Systems (GNSS) provides positioning accuracy at meter-to-millimeter level using several different measurement techniques (Alkan *et al.* 2015). However, this accuracy may be reduced due to several obstructions that prevent the direct line-of-sight between satellites and receivers such as heavy tree cover, ravines and urban canyons (Alkan *et al.* 2015). In addition, other conditions including poor satellite geometry and inadequate number of visible satellites may negatively affect the positioning accuracy of GNSS systems (Alcay and Yigit 2016). Similarly, in indoor areas, several factors; e.g., reflection, scattering, multipath and obstacles (Al-Ammar *et al.* 2014) result in loss of GNSS signals and prevent the achievement of the desired positioning accuracy (Wang *et al.* 2012). In the last decade, a considerable amount of work has been carried out using technologies such as radio frequency identification, Bluetooth, wireless local area network (WLAN), ZigBee and global positioning system (GPS) to eliminate these deficiencies and introduce an accurate indoor positioning solution (Li 2014). Among these, WLAN stands out with its characteristics of not requiring any additional equipment and being cost-effective, which make it easily accessible almost everywhere including hospitals, shopping malls, airports and campuses (Yim *et al.* 2010). Moreover, most mobile devices; e.g., mobile phones, tablets and laptops are equipped with WLAN and therefore they can transmit and receive Wi-Fi signals (Talvitie *et al.* 2015b).

In indoor positioning systems, range-based methods that rely on the determination of the distance between the transmitter and receiver are commonly used. These distances can be obtained using different techniques such as time of arrival, time difference of arrival (Li *et al.* 2011), angle of arrival and RSS. Although the former three methods require specialised equipment to obtain distances, RSS does not have such a requirement and thus is widely preferred for indoor positioning applications (Tarrio *et al.* 2011, Wang *et al.* 2012, Talvitie *et al.* 2015a). However, RSS is affected by certain indoor environmental parameters including obstruction, multipath, shadowing, fading, diffraction and scattering, which reduce the accuracy performance regarding the measurement of distances and positioning (Yim *et al.*

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2010, Wang *et al.* 2012). Typically, two approaches are used in RSS-based positioning systems; fingerprinting and channel model-based. In fingerprinting, first RSS values are collected from all APs to generate a radio map related to the workspace. Then, the position of the receiver can be determined by matching the observed RSS values with the closest RSS values in the radio map (Tarrio *et al.* 2008). The two main disadvantages of this approach are the requirement of an excessive pre-survey to create a radio map and environmental effects on RSS values (Yu *et al.* 2014). Moreover, changes in the working area adversely affect the positioning accuracy of the system and require the repetition of both the labour intensive and time consuming pre-survey and the experimental radio mapping process. In the channel model-based approach, distances between transmitters and the receiver are established using a signal propagation model that reveals the relationship between RSS and distance, and the position of the receiver can be determined using these distances. However, this approach also has two main limitations. First, determination of ranges is more difficult as the distance between the receiver and transmitters increases due to the logarithmic relationship. Second, the position of the transmitters should be known in order to determine the distances between the receiver and transmitters (Mautz 2012).

Until the last few years, WLAN systems mostly provided services in the 2.4 GHz frequency band; thus, this band is commonly used in mobile devices, and WLAN-based indoor positioning research has mostly focused on the investigation of this frequency. However, due to the common use of the 2.4 GHz signals, they are subject to strong interference from other devices such as Bluetooth and microwaves (Li *et al.* 2005b). With the release of new standards in the WLAN technology namely IEEE 802.11n and 802.11ac, in addition to 2.4, 5 GHz frequency band has also been utilised in new generation APs. This has prompted some researchers to explore the use of 5 GHz bands in indoor positioning. Today, a navigation and positioning solution can be offered by the use of smartphones due to their improved microprocessors, operating systems, multi-sensors and radio transceivers such as Wi-Fi (Zhuang *et al.* 2015). Lohan *et al.* (2015) investigated the RSS fluctuations and positioning accuracy of 2.4, 5 GHz Wi-Fi signals and Bluetooth low energy(BLE) for indoor positioning applications. For the comparison of the positioning accuracy of these signals, they used fingerprinting, weighted centroid and path-loss-based algorithms with and without floor loss. The authors reported that the positioning accuracy of 5 GHz frequency bands was slightly lower than that of 2.4 GHz and BLE due to the lower signal in the 5 GHz band. In another study, the 2.4 and 5 GHz Wi-Fi signals were comparatively analysed by means of interpolation and extrapolation using the fingerprinting method (Talvitie *et al.* 2015a). Similarly, the results of that study revealed that the positioning accuracy of the 2.4 GHz signals were much better than that of the 5 GHz signals due to the lower number of 5 GHz fingerprints compared to 2.4 GHz. The authors suggested that the positioning accuracy of the two bands would have been at the same level if they had an equal number of fingerprints. Similar results were obtained by Talvitie *et al.* (2015b), who used the Bayesian fingerprinting method. In addition, Karlsson *et al.* (2015) compared the positioning accuracy of the 2.4 and 5 Wi-Fi signals in an indoor environment using a particle filter. They found that the 2.4 GHz signals provided better results than 5 GHz. Yu *et al.* (2014) implemented an indoor positioning system to analyse and compare the fluctuations and positioning accuracies of 2.4 and 5 GHz signals. They compared the performance of fingerprinting-based methods namely k-nearest neighbour (KNN), weighted KNN, fuzzy logic and histogram algorithms in accurate positioning. They reported that the 5 GHz signals had lower variances and were more stable, and therefore, their positioning accuracy was better than that of the 2.4 GHz signals for all positioning algorithms. A detailed analysis of 2.4 and 5 GHz signal behaviours was performed using a fingerprinting system in an indoor environment (Lui *et al.* 2011). It was concluded that the accuracy of fingerprinting could be improved using 5 GHz signals. Although all these studies analysed the signal behaviours of 2.4 and 5 GHz frequency bands and compared their positioning accuracies using Wi-Fi based fingerprinting algorithms, in this study, we used four channel model-based algorithms in an indoor environment to investigate the two signal behaviours comparatively and determine the location of a mobile device.

In this study, we compared the positioning accuracy of 2.4 and 5 GHz frequency bands for RSS-based indoor localisation. This experiment was conducted in signal propagation and positioning phases. In the signal propagation phase, to investigate and comparatively analyse the behaviours of the Wi-Fi bands, RSS data in the 2.4 and 5 GHz bands were collected using a smart phone at different ranges, and the relationship between the RSS and distance was determined using a CF technique. In the positioning phase, the distances between the smart phone and APs were determined using equations that had been derived from CF for each band. Using these distances, position information was predicted by different localisation algorithms; bilateration, trilateration, WINLSQ and EKF. In brief, the two main contributions of this study were the detailed analysis of 2.4 GHz and 5 GHz Wi-Fi band behaviours and the comparison of the accuracy of two frequency bands in an indoor environment using four positioning algorithms.

Propagation loss model

In channel model-based indoor positioning, the location of a mobile device is determined using the estimated distances from APs; therefore, distance estimation is a crucial step in localisation applications (Wang *et al.* 2015). However, RSS values are very sensitive to the effects of the indoor environment, such as reflection, diffraction, penetration, scattering and fading (Seybold 2005), complicating the distance estimation process (İlçi *et al.* 2015). The relationship between the distance and RSS can be determined using site-general modes such as the log-distance path loss model (Rappaport 1996) or the path loss model developed by the International Telecommunication Union (ITU-R 2015). These models present a simplified solution to determine signal behaviours with only few measurements in the deployment area (Naik and Bapat 2014). However, due to the environmental effects on the signals, these models cannot provide a similar distance estimation solution for the whole area (Li *et al.* 2005a, Wang *et al.* 2015). RSS values depend logarithmically on distance (Rappaport 1996) therefore, in this study, we adopted a logarithmic-based CF approach to estimate the distances. This approach can be formulated as follows:

$$\mathrm{RSS} = -a - \ln(d)b \tag{1}$$

where a and b are the constant values that were obtained from the experimental studies on the application area, and d is the distance between the transmitter and the receiver.

Positioning algorithms

Bilateration

The bilateration algorithm consists of a series of non-iterative geometric formulations that provide high positioning accuracy and low computational complexity (Li *et al*. 2007, 2008); thus, this algorithm is appropriate for constrained devices such as smartphones (Cota-Ruiz *et al*. 2012). The bilateration algorithm is based on the calculation of two circle intersections for every two neighbour APs called candidate points. To determine the appropriate candidate point for both candidate points, the proximity to the other paired candidates is tested using both of these points. After finding all the reasonable candidate points clustered in an area, the final position is determined by calculating the average.

Owing to the inaccurate estimation of distance in indoor environments, three scenarios may arise:

(i) Two intersections may occur at two different points.

(ii) There may not be any intersection due to the circles being away from each other.

(iii) There may not be any intersection due to one of the circles containing the other.

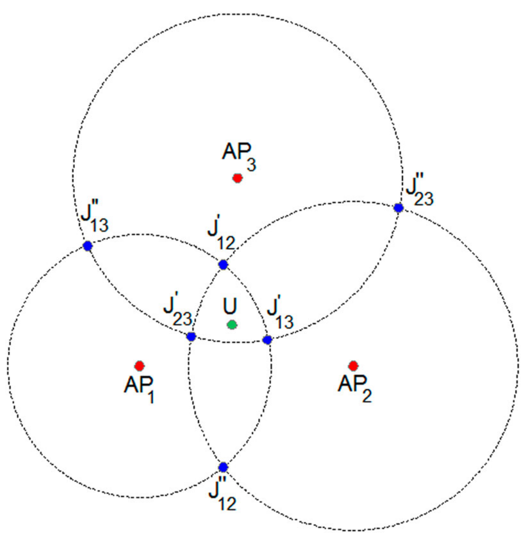
The positions of the APs are indicated as $\mathrm{AP}_N = [\,X_{\mathrm{AP}_N} \quad Y_{\mathrm{AP}_N}\,]^T$ and the position of the mobile device is $U = [\,X_U \quad Y_U\,]^T$. Candidate points that are the reflection of each other with respect to the imaginary line between the position of two APs are symbolised as J'_{12} and J'_{12}.

The minimum Euclidean sum from one of the two candidate points to all of the other candidate points is calculated to determine the logical candidate positions between the two candidate pairs (J'_{12} or J''_{12}; J'_{13} or J''_{13}; J'_{23} or J''_{23}.

$$\begin{aligned}\alpha = {} & \min(J'_{12} - J'^2_{13}, J'_{12} - J''^2_{13}) \\ & + \min(J'_{12} - J'^2_{23}, J'_{12} - J''^2_{23})\end{aligned} \tag{2}$$

$$\begin{aligned}\beta = {} & \min(J''_{12} - J'^2_{13}, J''_{12} - J''^2_{13}) \\ & + \min(J''_{12} - J'^2_{23}, J''_{12} - J''^2_{23})\end{aligned} \tag{3}$$

In Fig. 1, the minimum value between α and β indicate the logical candidate points J'_{12} or J''_{12}. After all the operations are repeated for all the neighbouring AP pairs, the real position of the target is calculated based on the average of all logical candidate points. Detailed information about the bilateration algorithm can be obtained from Li *et al*. (2007) and Cota-Ruiz *et al*. (2012).



1 Bilateration algorithm

Trilateration

Trilateration is one of the simplest and most widely used algorithms in the literature (Khan *et al*. 2014). In this algorithm, the location of a mobile device can be determined using three or more simultaneous range measurements from APs (Koo and Cha 2011, İlçi *et al*. 2015). For the development of 2-D and 3-D solutions, trilateration requires at least 3 and 4 non-coplanar ranges, respectively (Al-Ammar *et al*. 2014). This algorithm can be defined by the following expressions:

$$A\vec{x} = \vec{b} \tag{4}$$

$$A = 2\begin{bmatrix} (X_{\mathrm{AP}_2} - X_{\mathrm{AP}_1}) & (Y_{\mathrm{AP}_2} - Y_{\mathrm{AP}_1}) \\ (X_{\mathrm{AP}_3} - X_{\mathrm{AP}_1}) & (Y_{\mathrm{AP}_3} - Y_{\mathrm{AP}_1}) \\ \vdots & \vdots \\ (X_{\mathrm{AP}_M} - X_{\mathrm{AP}_1}) & (Y_{\mathrm{AP}_M} - Y_{\mathrm{AP}_1}) \end{bmatrix} \tag{5}$$

$$\vec{b} = \begin{bmatrix} (X^2_{\mathrm{AP}_2} - X^2_{\mathrm{AP}_1}) + (Y^2_{\mathrm{AP}_2} - Y^2_{\mathrm{AP}_1}) - (R^2_2 - R^2_1) \\ (X^2_{\mathrm{AP}_3} - X^2_{\mathrm{AP}_1}) + (Y^2_{\mathrm{AP}_3} - Y^2_{\mathrm{AP}_1}) - (R^2_3 - R^2_1) \\ \vdots \\ (X^2_{\mathrm{AP}_M} - X^2_{\mathrm{AP}_1}) + (Y^2_{\mathrm{AP}_M} - Y^2_{\mathrm{AP}_1}) - (R^2_M - R^2_1) \end{bmatrix} \tag{6}$$

$$\vec{x} = (A^T A)^{-1} A^T \vec{b} \tag{7}$$

where AP_1, AP_2, AP_3, and AP_4 are the positions of the reference points, and R_1, R_2, R_3, and R_4 represent the estimated ranges between mobile devices and reference points obtained using RSS values. The known coordinates of APs are represented as $AP_i = [\,X_{\mathrm{AP}_i} \quad Y_{\mathrm{AP}_i}\,]^T$, and x is the coordinate of the mobile phone that can be estimated by applying minimum mean square error.

Weighted iterative nonlinear least squares

Least square algorithms minimise square errors to estimate optimal linear and nonlinear parameters (Li 2014). As known, RSS decreases logarithmically with distance (Rappaport 1996); therefore, high-range estimations could be more affected by RSS-based errors than short ranges (Tarrio *et al*. 2011). Therefore, the weighted form of the least square algorithm can improve positioning accuracy (Wang 2015). In this study, we used the WINLSQ algorithm described by Zhuang *et al*. (2015) to achieve highly accurate positioning. This algorithm requires an initial coordinate to run equations. We also utilised the Taylor equation to minimise computational complexity (Xiao *et al.* 2012). The measurement misclosure vector δz is presented as:

$$\delta z = H\delta x + v \tag{8}$$

Equations (9)–(11) present the solution δx, covariance matrix of the solution $C_{\delta\hat{x}}$, and the new state vector $\hat{x}_{\text{updated}}$, respectively:

$$\delta\hat{x} = (H^T R^{-1} H)^{-1} H^T R^{-1} \delta z \tag{9}$$

$$C_{\delta\hat{x}} = (H^T R^{-1} H)^{-1} \tag{10}$$

$$\hat{x}_{\text{updated}} = \hat{x} + \delta\hat{x} \tag{11}$$

The observation covariance matrix R is expressed as follows:

$$R_{\text{RSS},k=\text{diag}(\sigma^2_{d_{\text{AP1},k}} \quad \cdots \quad \sigma^2_{d_{\text{AP}n,k}})} \tag{12}$$

The design matrix H can be arranged as a Jacobian matrix for the static target as:

$$H_{\text{dist},k} = \begin{bmatrix} \frac{(X_M - X_{\text{AP}_1})}{d_1} & \frac{(Y_M - Y_{\text{AP}_1})}{d_1} \\ \frac{(X_M - X_{\text{AP}_2})}{d_2} & \frac{(Y_M - Y_{\text{AP}_2})}{d_2} \\ \vdots & \vdots \\ \frac{(X_M - X_{\text{AP}_n})}{d_n} & \frac{(X_M - X_{\text{AP}_n})}{d_n} \end{bmatrix} \tag{13}$$

The iteration of this process continues until $|\delta\hat{x}| <$ threshold. Detailed information about the WINLSQ algorithm can be obtained from Zhuang *et al.* (2015).

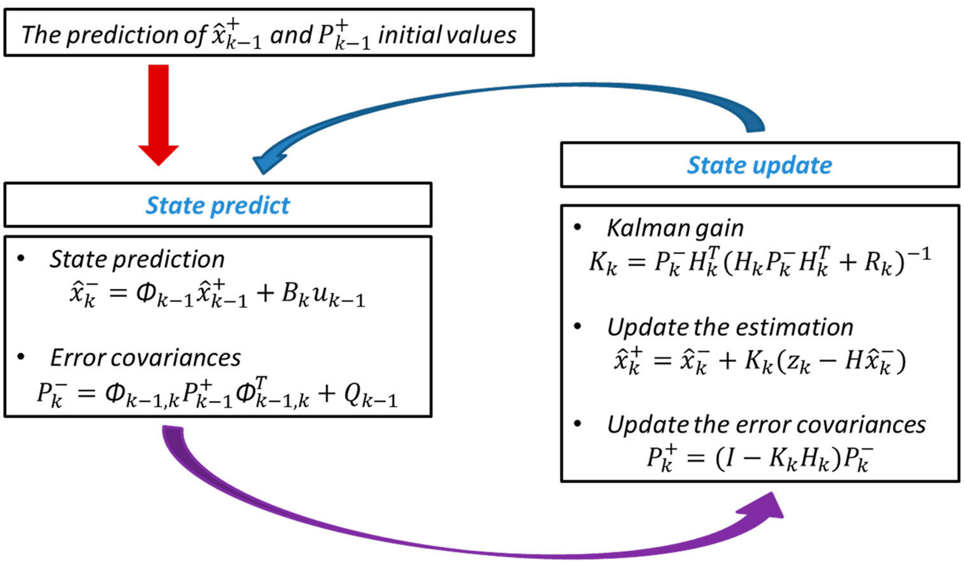
Extended Kalman Filter

The Kalman Filter (KF) algorithm minimises variance estimation errors by determining the status of the process with a series of repetitive mathematical calculations (Welch and Bishop 2006). Although this algorithm provides an efficient solution for linear systems, in which measurements errors have a Gaussian distribution, it does not offer an equally optimal solution for non-linear systems (Khan *et al.* 2013). Therefore, EKF has been proposed to overcome the limitations of KF through the linearisation of non-linear systems. The success of this algorithm depends on the well modelling of system dynamics and measurements (Caceres *et al.* 2009). In this algorithm, current state estimation is predicted based on previous state estimation. EKF is composed of two recursive phases; 'State Predict' and 'State Update' (Fig. 2).

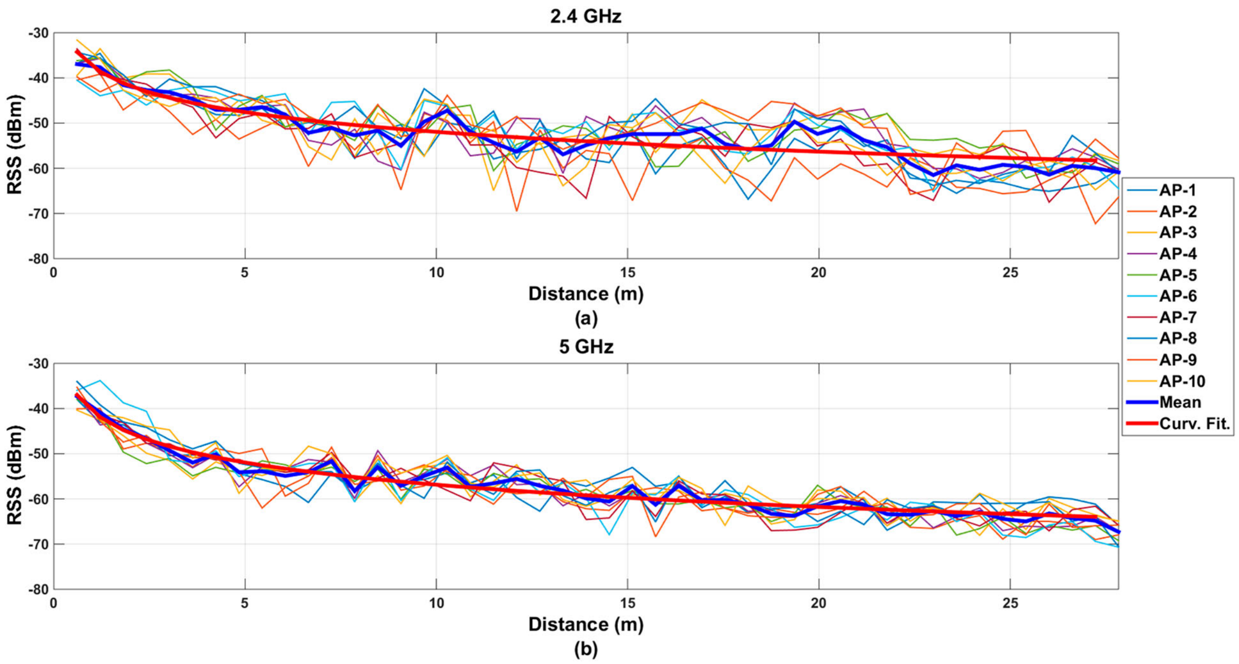
In the state prediction phase, a priori state vector $\hat{x}_k^-$ at time k is predicted using a posteriori state vector $\hat{x}_{k-1}^+$ at time $k-1$. ϕ_{k-1}, B_k and u_{k-1} represent the linearised state transition matrix, input matrix and system input, respectively. P_k^-, P_{k-1}^+, and Q_{k-1} refer to the estimated covariance matrix associated with the a priori state vector $\hat{x}_k^-$, the previous a posteriori covariance matrix and the covariance matrix of the process noise, respectively. In the state update phase, K_k is the Kalman gain computed using the Jacobian matrix of the expected measurements H_k and the covariance matrix of the observation vector R_k. z_k is the measurement vector at time k and I represents the identity matrix. Detailed information about the EKF algorithm can be obtained from Welch and Bishop (2006), Yim *et al.* (2010), (Khan *et al.* 2013) and Khan *et al.* (2014).

Analysis of 2.4 GHz and 5 GHz Wi-Fi frequency bands

This application was conducted in a line-of-sight indoor environment to comparatively analyse the behaviours of 2.4 and 5 GHz Wi-Fi signals. These signals were transmitted by 10 APs of the same brand (ASUS DSL-AC68U). The signals were collected using an Android-based smartphone with the capability to receive Wi-Fi signals at both frequencies. Approximately 150 samples were collected from 10 APs at 0.6 m intervals from 0.6 to 27.8 m in Corridor 3 (Fig. 5). We developed software using the JAVA programming language to collect Wi-Fi signals and estimate distances via a propagation loss model. Figure 3 presents the average values of the



2 EKF algorithm



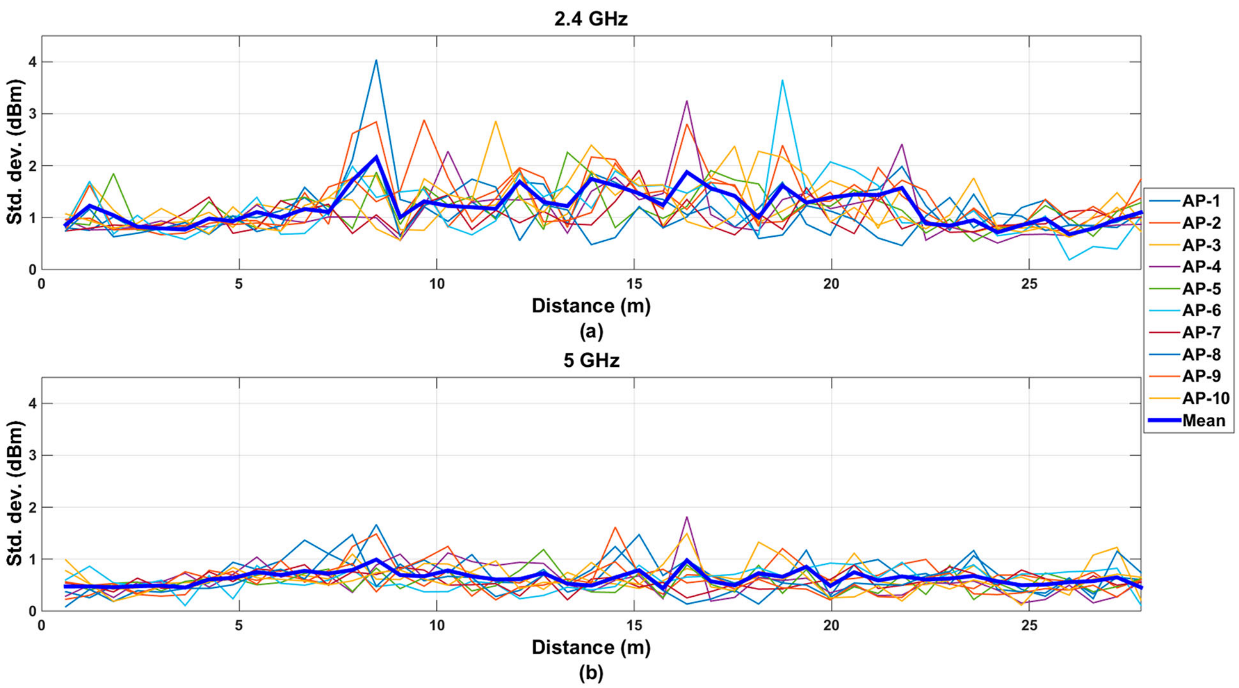
3 The relationship between the RSS and distance *a* 2.4 GHz, and *b* 5 GHz

Table 1 Statistical values of CF

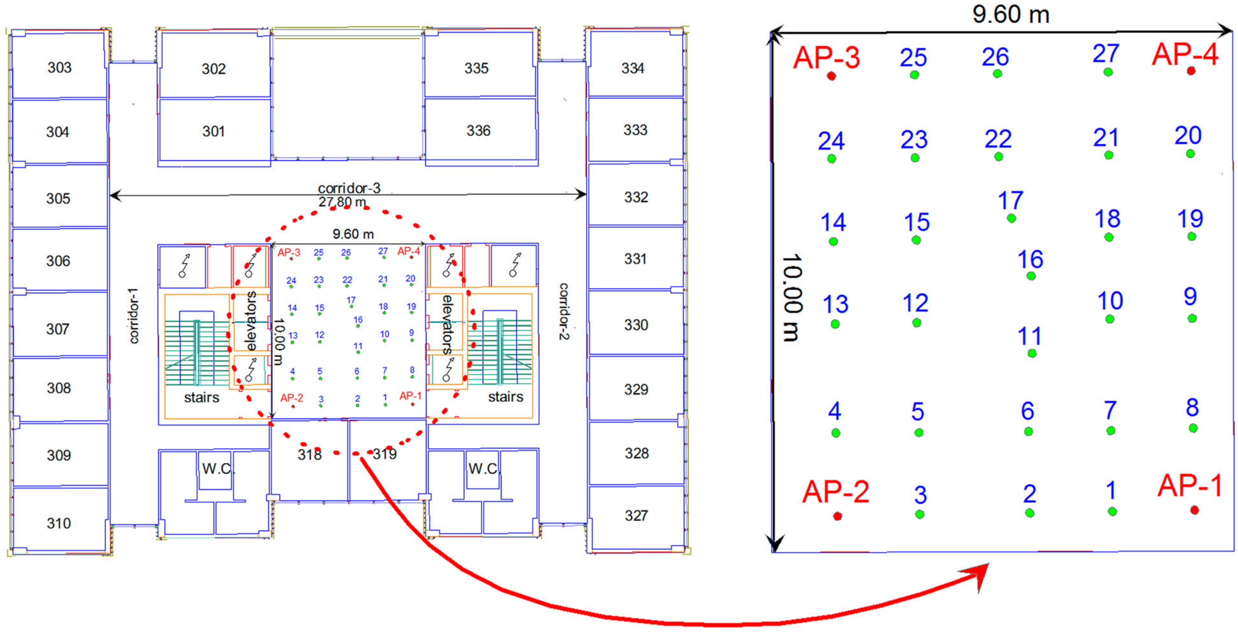
	2.4 GHz	5 GHz
RMSE	2.577	1.685
R-square	0.8238	0.9351

RSS samples obtained from different distances by 10 APs, the mean values of these 10 lines and the logarithmic CF obtained using the MATLAB Curve Fitting Toolbox.

The 2.4 and 5 GHz signals logarithmically lost their effectiveness with the increasing distance, but the signal fluctuations of the 2.4 GHz signals were considerably higher than those of the 5 GHz signals. This is because 2.4 GHz is an unlicensed spectrum that is mostly used by other devices such as microwaves ovens, Bluetooth devices and wireless video devices. This usage causes noise and interference on the 2.4 GHz signals (Yu *et al.* 2014). In the fitting statistics for the 2.4 and 5 GHz signals, the root mean square error (RMSE) value being closer to 0 indicates that the model is useful for prediction and the *R*-square value being closer to 1 show that the model accounts for a greater proportion of variance. Table 1 shows that the fitted curve of the 5 GHz signals



4 Standard deviations of the *a* 2.4 GHz and *b* 5 GHz signals by distance



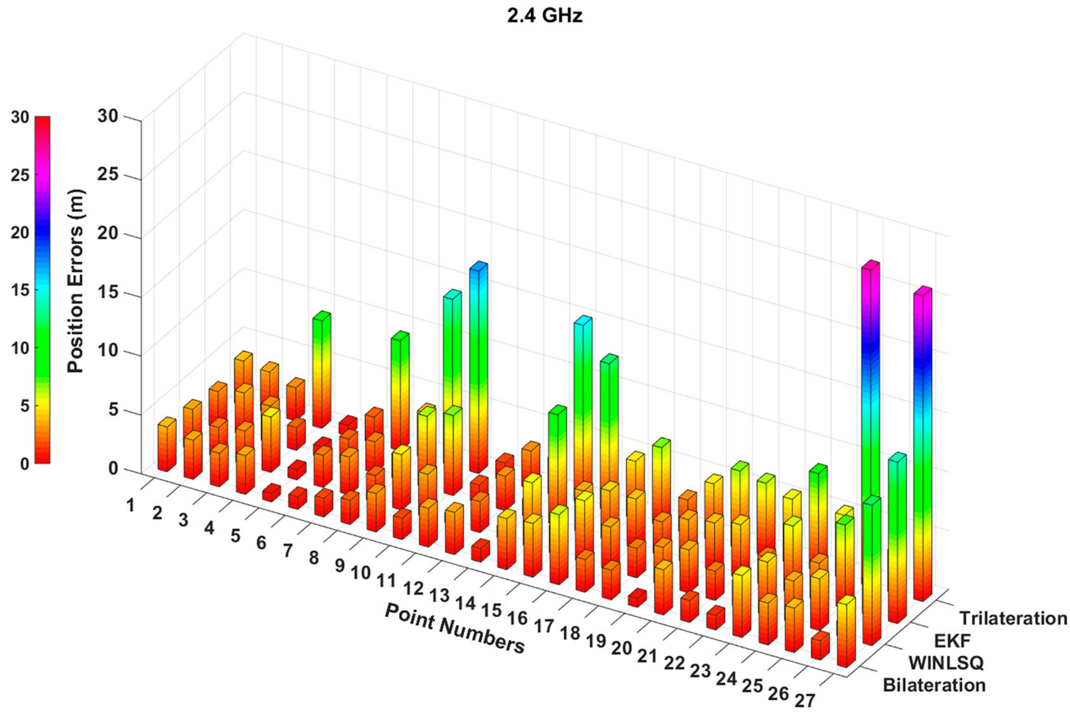
5 Application area

are more representative than the 2.4 GHz signals. This means that there will be fewer distance estimation errors with the 5 GHz signals compared to the 2.4 GHz signals. Furthermore, the mean standard deviations of the RSS values (Fig. 4) were found to be 1.2 and 0.6 dBm for the 2.4 and 5 GHz signals, respectively.

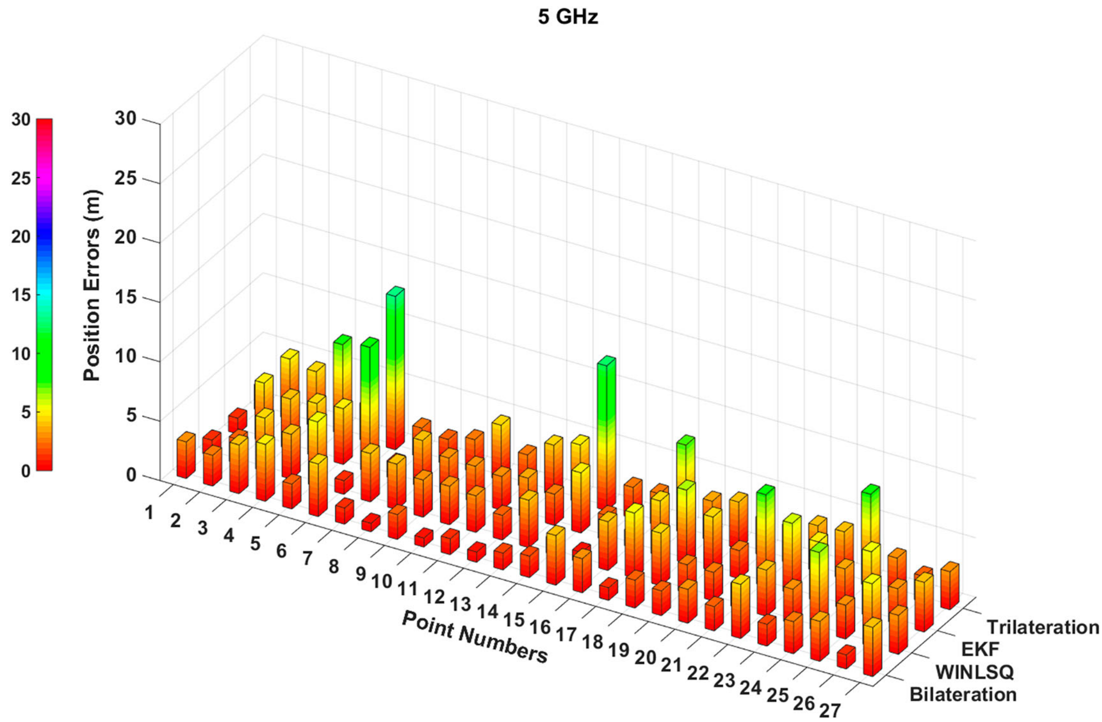
The tests showed that the 5 GHz signals were more appropriate for modelling and more stable with less signal fluctuations and lower standard deviations compared to the 2.4 GHz signals. Therefore, it can be expected that the 5 GHz Wi-Fi signals provide better distance estimation and higher positioning accuracy.

Analysis of positioning algorithms

This study had two main objectives; investigating the effects of signal behaviours on the positioning accuracy of 2.4 and 5 GHz frequency bands, and comparing the positioning accuracy of four algorithms. To this end, first a static test was carried out in a line-of-sight indoor environment of 10 m × 9.6 m size in the main building of the Vocational School of Technical Sciences of Hitit University (Fig. 5). Four ASUS DSL-AC68U APs with the capability to transmit 2.4 and 5 GHz Wi-Fi signals at 802.11ac IEEE standards were located in the corner of the atrium (red dots in Fig. 5). Using an Android-



6 Positioning errors of four positioning algorithms using 2.4 GHz signals



7 Positioning errors of four positioning algorithms using 5 GHz signals

based smartphone, the RSS values transmitted from the APs were collected 150 times at 27 observed points (green dots in Fig. 5). In order to perform distance and positioning calculations on the smartphone, the Java programming language including Jama basic linear algebra package was used. The 2-D reference coordinates of 4 APs and 27 observed points were obtained using traditional geodetic methods. The coordinate values obtained from four positioning algorithms were compared with reference coordinates. Figures 6 and 7 present the positioning error values of the 2.4 and 5 GHz signals, respectively. Moreover, the statistical values of the position errors of the 27 observed points are given in Table 2.

We first compared the results according to the signal frequencies. Although, the minimum positioning errors were very similar in both the 2.4 and 5 GHz signals, the maximum positioning error of the 5 GHz signals were substantially better than those of 2.4 GHz (Table 2). Although the RMSE and mean values obtained from the bilateration, WINLSQ and trilateration algorithms showed that the 5 GHz Wi-Fi signals were better than the 2.4 GHz signals, the results of the EKF algorithm suggested that the 2.4 GHz signals were slightly better than those of 5 GHz. Based on these results, particularly concerning maximum positioning errors, we consider that 5 GHz Wi-Fi signals are more feasible for indoor positioning applications than 2.4 GHz signals. Noise and interference effects were found to cause more fluctuations in the 2.4 GHz signals reducing the positioning accuracy of these signals. .

In the second stage of the study, we compared two non-iterative positioning algorithms (bilateration and trilateration) and two iterative algorithms that require initialisation values (WINLSQ and EKF) in terms of their positioning accuracy. Table 2 clearly indicates that the bilateration algorithm achieved the best positioning accuracy while trilateration provided the worst results. In addition, according to the results of two iterative positioning algorithms, the WINLSQ algorithm produced slightly better results than the EKF algorithm. The main disadvantage of the trilateration algorithm was that weights were not used although the RSS values logarithmically decreased with the increasing distance. This caused greater signal fluctuations and higher number of distance errors as the distance increased, thus resulting in more positioning errors. On the other hand, bilateration provided the best positioning accuracy since this algorithm disposes of incompatible candidate points using a clustering test, and finds the optimal solution for the candidate points. Moreover, the bilateration algorithm presents low computational complexity, which is very important for constrained devices such as mobile phones.

Table 2 Statistical values by positioning algorithm and signal type

	2.4 GHz				5 GHz			
	Bilater. (m)	WINLSQ (m)	EKF (m)	Trilater. (m)	Bilater. (m)	WINLSQ (m)	EKF (m)	Trilater. (m)
min	0.71	0.85	0.93	0.88	0.71	0.88	1.32	2.07
max	5.97	11.95	13.75	26.92	4.79	6.65	10.50	12.91
mean	2.94	3.41	4.09	7.79	2.46	3.32	4.12	4.51
RMSE	3.27	4.00	4.89	10.28	2.75	3.61	4.57	5.29

Conclusions

In this study, we first focused on the comparison of the behaviours of two Wi-Fi signals and their effect on indoor positioning accuracy. In recent years, the availability of dual band Wi-Fi devices has dramatically increased leading us to investigate the similarities and differences between 2.4 and 5 GHz Wi-Fi signals in terms of their efficiency in indoor positioning applications. Today, the 2.4 GHz band is still used by most wireless devices, and the signals from these devices cause interference and fluctuation effects on this band. Since there are no interference effects on the 5 GHz signals, these signals have lower signal fluctuations; thus, they provide better distance estimation and higher positioning accuracies than the 2.4 GHz signals.

Second, the positioning accuracy of four RSS-based algorithms namely bilateration, trilateration, WINLSQ and EKF was compared. Providing highly accurate positioning results and having low computational complexity, bilateration was found to be a superior positioning algorithm for static indoor applications in both 2.4 and 5 GHz frequency bands. Moreover, using bilateration as an initial value for certain positioning algorithms such as WINLSQ and EKF seems to be more suitable than using the trilateration algorithm. This study also demonstrated that the WINLSQ algorithm provide slightly more accurate positioning accuracies than EKF algorithm in a static application. The results of the study reveal that approximately 2.46 m positioning accuracy can be obtained using the bilateration algorithm with the 5 GHz Wi-Fi signals in line-of-sight indoor localisation applications.

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