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A Light Solution for Device Diversity Problem in a Wireless Local Area Network Fingerprint Indoor Positioning System

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A B S T R A C T

The development of location-based services requires an increasingly accurate positioning system technology. Research on outdoor positioning systems has achieved satisfactory accuracy and has been commonly used in various location-based services. The research trend is now shifting toward the Indoor Positioning System (IPS). One technique that is widely used in Wi-Fi-based IPS is fingerprinting. The fingerprinting technique on Wi-Fi uses the Received Signal Strength Indicator (RSSI) value. The problem that occurs is that the results of RSSI measurements on smartphones of different brands will produce different RSSI values, also known as device diversity. Device diversity will cause a decrease in system accuracy. This study aims to offer a solution to the problem of device diversity in Wi-Fi IPS based on RSSI Fingerprinting, i.e., to get a minor distance error. The proposed solution is to modify the original database radio map into two new databases: the difference database and the ratio database. The Difference Database Radiomap was able to reduce the average value of distance errors by 24.3% in Meizu and 28% in OPPO. Then, using the Radiomap database ratio, the average value of distance errors could be reduced by 13% in Meizu and 24% in OPPO. From the calculation, Radiomap database ratio can provide solutions to the problem of device diversity for an Indoor Positioning System better than the difference database radiomap if we looked at reduced distance error.

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NOMENCLATURE

d	Euclidean distance	(xe, ye)	The estimated location (IPS measurement results)
S_{m_n}	Value of RSSI (Received Signal Strength Indicator) from the AP (Access Point) to-n at a known location	(RR1, RR2, RR3)	New database and the new test point for the ratio method
S_{i_n}	value of RSSI from the AP to-n at the unknown location	Ea	Initial error, which uses the original database from the results of the RSSI measured value
(xa, ya)	The actual location	Eb	New error, using the results of the proposed database modification of the difference or ratio

1. INTRODUCTION

Along with the increasingly widespread development of location-based services, the positioning system technology is developing rapidly such that there is now a need for high standards in the system [1]. Research on the outdoor positioning system is considered to have achieved satisfactory accuracy and has met these standards, so the system is now commonly used by the general public in various location-based services such as navigation and mapping [2]. The research trend is now shifting toward the indoor positioning system (IPS).

Human activity today tends to be done more in-room; the community generally spends about 80%–90% of all their time in rooms. This situation translates to 80% of data communication being carried out indoors.

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Therefore, location-based services in the room have high market potential. Location-based services have led to an increase in IPS research trends in the past decade. However, research on existing IPS has not produced generally optimal, reliable, or ready-to-use methods like the Global Positioning System (GPS) technique for the outdoor positioning system [3]. A good IPS is expected to meet the following aspects: ease of accessibility, simple calculation, and high scalability [4].

One of the devices that can support the ease of accessibility in IPS is the smartphone. In the modern era today, the use of smartphones has drastically increased, supported by various sophisticated smart sensors such as biometric, odometry [5] etc., making smartphones high-potential instruments for IPS. Studies on IPS using smartphones have also been carried out. Subsequently, one by one, research has begun to develop smartphones with built-in sensors for IPS planning. One of these devices involves Wi-Fi data sending technology, which has now become famous in IPS planning.

Positioning system-based Wi-Fi is profitable because it is easily found in various public places and requires relatively cheaper costs. In addition, the Wi-Fi-based positioning system is compatible with outdoor use and various indoor environments to support the high scalability aspects that IPS needs.

Specific techniques must be applied to use Wi-Fi as an instrument in IPS planning. Some commonly-used techniques for positioning systems in indoor-based Wi-Fi are triangulation, trilateration [6], proximity matching, and fingerprinting. Of all the techniques that have been mentioned, fingerprinting techniques are the most widely used because they have high accuracy as they conduct positioning based on references in the original environment [7]. Besides, this method does not require any additional device or tool [8-10]. There are several types of fingerprinting techniques, one of which is the Wi-Fi Received Signal Strength Indicator (RSSI), which matches the Wi-Fi signal strength data received in determining positions. The RSSI-based Wi-Fi fingerprinting technique is the most suitable technique for positioning a system in a room [1].

However, position determination can result in poor precision, when using measurements based on the Wi-Fi RSSI fingerprinting technique involving small cell sizes [7]. The measurement error that appears can worsen if the measurement is made using a smartphone of a different brand due to the manufacturing differences from the Wi-Fi transceiver used by each smartphone [1]. Thus, the main problem with this method is the measurement of RSSI Wi-Fi on smartphones of different brands in the same condition and location, which can produce different RSSI data. The term commonly used for this problem is device diversity. Device diversity can affect the accuracy of the Indoor Positioning System (IPS) that has been built [11]. Therefore, a solution is needed to solve the problem of device diversity so that the accuracy of IPS can be maintained and the measurement results remain precise; although it is used in a variety of Android smartphones.

2. LITERATURE REVIEW

2. 1. Wi-Fi-based Indoor Positioning System Technology The indoor positioning system (IPS) has two main objectives: tracking and navigation [8]. Several studies have summarized and examined the performance of various principles and methods that have been proposed in building an IPS [12-14]. The measurement principle uses internal range, signal strength, acceleration, or angles for location determination, along with specific schemes such as triangulation [15], trilateration, hyperbolic location determination, and data matching [12, 16]. The principle of measurement using radio signal technology is divided into several parts; one of which is to use the Wireless Local Area Network (WLAN). To produce an effective and efficient IPS, some measurement principles are combined with one or a combination of two schemes to determine positions.

2. 2. Fingerprinting Technique Based on the standard provisions in the IEEE 802.11 Standard, Wi-Fi cards and Access Point (AP) wireless networks measure the intensity of radio frequency signals [17]. The fingerprinting technique used for IPS is classified as a data matching scheme, which generally uses signal strength [18] for location mapping where the signal is obtained [1, 19]. One of the most common types of fingerprinting techniques is the Received Signal Strength Indicator (RSSI) [20]. Another type is visual fingerprinting, which uses images from camera sensors, and motion fingerprinting, which utilizes displacement sensors such as accelerometers [1].

2. 3. Wi-Fi IPS Positioning System based on RSSI Fingerprinting In general, a positioning system using Wi-Fi fingerprinting consists of two phases; the offline phase, where the RSSI measurement from several Access Points (AP) is collected to map a Wi-Fi radio fingerprinting model called the fingerprinting database [13, 21]; and the online phase, which can also be referred to as the location determination phase to determine the position of the device used by matching the Wi-Fi signal received from that location with a database that has been built previously [22, 23]. Figure 1 shows the framework of a Wi-Fi positioning system based on RSSI fingerprinting.

2. 4. Positioning Algorithm: K-Nearest Neighbor (kNN) Algorithm The kNN algorithm is a method for classifying objects based on learning data closest to the object [24] and to solve user orientation problem [25].

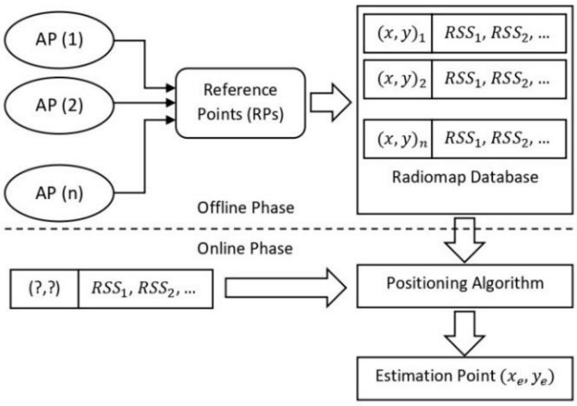

Figure 1. Wi-Fi IPS Positioning System Technology based on RSSI Fingerprinting

The value of K is the smallest amount of Euclidean distance between each AP and the point of location that was not known beforehand. The kNN algorithm is one of the classification methods that are included in the instance-based learning category. That is, this method uses a supervised learning approach, so it requires training known data or labeling. Unknown values will be compared with the known value, and then classified based on the closeness or distance of both values. This algorithm follows the fingerprinting method used in IPS.

The Euclidean distance is calculated using Equation (1) given below [24]:

$$d = \sqrt{(S_{m_1} - S_{i_1})^2 + (S_{m_2} - S_{i_2})^2 + \cdots + (S_{m_n} - S_{i_n})^2} \quad (1)$$

where S_{m_n} is the value of RSSI from the AP to-n at a known location, while S_{i_n} is the value of RSSI from the AP to-n at the unknown location.

2. 5. Device Diversity Device diversity (also often referred to as device heterogeneity) is a difference in the results of reading the strong Wi-Fi signals received from different devices [26-27]. This situation generally occurs due to differences in antennas, antenna attenuation, different sensor specifications and [29] chip designs on different devices [27]; note that the difference in the results of this reading can also be found with the same type of device [28].

Park et al. [30] stated that device diversity is an exciting problem to resolve in the design and application of indoor positioning. However, standardization and calibration are not the right solutions for an environment in which the brand of devices varies because these would require sophisticated and expensive equipment. Therefore, one of the calibration efforts is to use detailed signal maps that are robust for use. Several different devices have been proposed, but this effort is less effective in dealing with new types of devices and still requires special equipment and high costs. The other method is the pre-calibration method; translates the RSS of heterogeneous devices into the benchmark device by a set of conversion formulae. But this method impractical and time-consuming with the increasing number of new mobile devices because formulae must be found and validated in the lab [31].

Therefore, the methods that have been proposed to overcome the problem of device diversity in an indoor positioning system are generally mathematical. Device heterogeneity is eliminated by applying a linear mapping between fingerprints from different devices [29]. Some of these methods are the Unsupervised Learning Algorithm [32], linear regression [33], and hyperbolic location fingerprinting (HLF).

3. MATERIALS AND METHODS

This research was conducted in a computer and simulation laboratory at the Department of Electrical Engineering, Faculty of Industrial Technology, Islamic University of Indonesia. This laboratory has five rooms and one alley. The devices used in the study are smartphones and laptops. Smartphones were chosen from three different brands: Redmi Series 3, Meizu Series Note 5, and Oppo Series F1 Plus, to show device diversity. The laptop was used for data processing and calculating the distance errors used in the study.

This study consists of several stages: determining the number of access points (APs) used, making a database radiomap for each Android. Radiomap is model of network characteristics in a deployment area to estimate a position [34]. Then determining the test point and calculating the approximate location, and then calculating the distance error to examine the differences in the devices. The last step calculates a distance error with a proposed database modification, as shown in Figure 2.

According to the problem limit, the number of access points (APs) used to determine the distance error should be 4; 2 APs were available in the laboratory so 2 additional APs were added. The number of reference points used was 234 based on the length and width of the room, with a distance between one reference point and another reference point being 1 meter. All the rooms and the single hallway/alley in the laboratory were first measured in length and width before the reference point was determined. The layout of the Laboratory is shown in Figure 3.

The next step was to create a database radiomap using three selected Android brands: Redmi Series 3, Meizu Series Note 5, and Oppo Series F1 Plus. The database radiomap is the measurement result at the reference point stored in the database, consisting of the identification of the reference point, the position of each reference point, and the measured data. The most important information

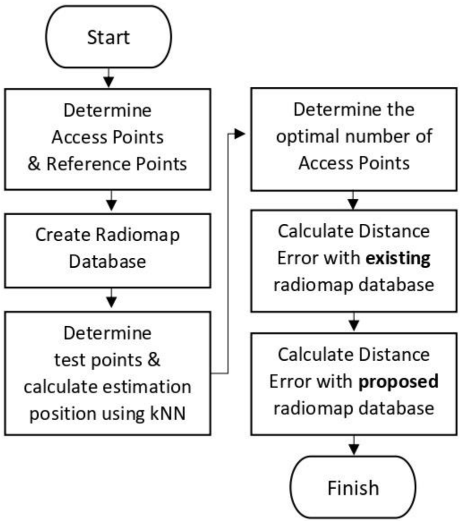

Figure 2. Research Flowchart

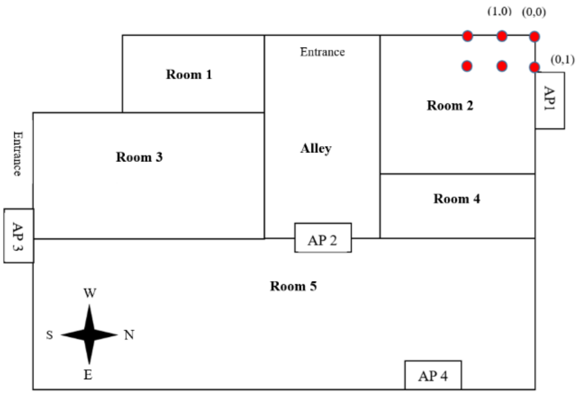

Figure 3. Computer and Simulation Laboratory Layout

in the database radiomap is the result of the Received Signal Strength Indicator (RSSI) value measured from all the available APs.

The radiomap database was created by measuring the RSSI values at each reference point, totaling 234 points, and the number of APs used. Before taking the measurements from each Android, special applications were first installed on the devices to take the RSSI value. The application was also given a Mac Address based on the 4 types of APs used in the study. The application used was Using Wi-Fi developed by Alshami et al. [23].

RSSI indicates the strength of the incoming (received) signal in a receiver. The closer to 0 dBm, the stronger the signal is. The RSSI value is very fluctuating (not constant) depending on multipath fading, environmental conditions, and the distance between the sender and receiver [25]. On IPS fingerprint, each coordinate point (x, y) is represented by a set of RSSI values from several access points (radiomap database). Each access point is represented by an RSSI value, to obtain this value it is necessary to measure several RSSI values and choose a representative value. In this study, 20 RSSI values will be measured at each point using smartphone, and the mode value will be selected [9]. If at each coordinate point only one RSSI is measured, then the RSSI cannot represent the coordinates so that the accuracy of the IPS system will decrease.

In case of designing of Wi-Fi networks, RSSI values are classified into several groups: -50 dBm is excellent, -70 dBm is good, -80 dBm is low, and -100 dBm is no signal. But in IPS fingerprint there is no such classification, what is important is that each coordinate point has a unique set of RSSI values. That value becomes the difference between one coordinate point and another. The higher the variant value of the RSSI data in radiomap database, the higher the accuracy of the IPS Fingerprint system. High variance in the RSSI data is usually obtained in buildings that have many rooms or have many partitions with various materials.

The RSSI values were measured simultaneously using 3 Android brands at a height of 1 meter from the measured point, as shown in Figure 4. For one reference point, there would be 4 RSSI measured values. For AP1, the measured RSSI value was labelled RSSI1, whereas the RSSI value for AP2 was named RSSI2, and so on. The database radiomap format is summarized in Table 1.

The measurement of the RSSI value starts at the coordinates of x, y (0.0), which means it starts at the corner of one of the rooms in the laboratory, which can be seen in Figure 3 so that later, it would be easier to name each point that has been measured (based on their respective coordinate points). For each coordinate, there are 234 RSSI values, of 4 different types, namely RSSI1, RSSI2, RSSI3, and RSSI4, according to the number of APs used.

The test point was determined after measuring the RSSI and Radiomap database values obtained from the 3 Android brands. The test point taken was 10% of the 234 reference points, and the total test points used were 24 points. These 24 test points were determined randomly and evenly in all rooms in the laboratory by re-measuring the RSSI value at a predetermined point.

Distance error was calculated using the kNN algorithm (k = 3) based on the Redmi Android database with the Redmi test point. At this stage, the distance error could also be calculated using another Android brand, as

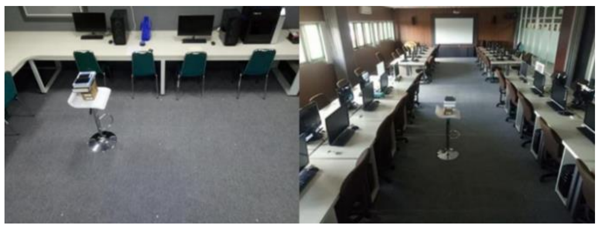

Figure 4. RSSI Value Measurement Process

TABLE 1. Format of The Radiomap Database

Coordinates		**Redmi**				**Meizu**				**Oppo**			
x	y	RSSI1	RSSI2	RSSI3	RSSI4	RSSI1	RSSI2	RSSI3	RSSI4	RSSI1	RSSI2	RSSI3	RSSI4

long as the database and test point were sourced from the same Android brand. The purpose of the calculation at this stage was to choose the optimal number of APs to be used in the next stage because the number of APs used will affect the computing load, i.e., the more APs used, the more complex the calculation.

The author used Microsoft Excel software to get a distance error value; the calculation scheme at this stage was to vary the number of APs:

- Scheme 1 used 4 APs
- Scheme 2 used 3 APs
- Scheme 3 used 2 APs

The distance error values in each of the smallest schemes and other considerations were chosen for the optimal use of AP, which would then be used as a reference for the following distance error calculation. The formula for calculating distance errors is given by Equation (2):

$$Distance\ Error = \sqrt{\Delta x^2 + \Delta y^2} \tag{2}$$

Remark:

Δx	=	x_a - x_e
Δy	=	y_a - y_e
(x_a,y_a)	=	the actual location
(x_e,y_e)	=	the estimated location (IPS measurement results)

Distance error values were calculated using kNN (k = 3). The database was the Android Redmi series, and the test point was Android Redmi, Meizu, and Oppo. The calculation at this stage aimed to examine the effect of the different devices on the distance error value. Calculations were carried out sequentially to produce distance error values for the Android Redmi, Meizu, and Oppo:

- Redmi Series 3 database with the Redmi Series 3 test point
- Redmi Series 3 database with the Meizu Series Note 5 test point
- Redmi Series 3 database with the Oppo F1 Plus Test Point

Once the distance error of each Android brand had been obtained, the next step was to observe and compare the results of the distance error obtained. Differences in the value of the distance errors for each Android brand will point to a solution on how to use the database and test points with different Android brands, so the value of the resulting distance error is not so significant.

At this stage, a solution will be given to overcome the problem of device diversity, that is, by calculating the distance error using the kNN algorithm (k = 3) with the proposed database modification using the difference method and ratio method to improve performance, namely by reducing distance error when using different devices. Before making the calculation, the original database of each Android brand was modified into 2 types of new databases: the difference database and the ratio database.

The number of APs used at this stage was 3 pieces, so the RSSI values were divided into 3 parts: RSSI1, RSSI2, and RSSI3, for each Android brand. The database and test point in the different methods must be modified by way of reducing each other, i.e., reducing the value of one RSSI with another RSSI value, for example, SR1 = |RSSI1 – RSSI2|, SR2 = |RSSI1 – RSSI3| dan SR3 = |RSSI2 – RSSI3|. A new database radio map (SR1, SR2, SR3) is thus formed. At the test point, the same thing was done for creating a new database, which is to reduce the value of RSSI with one another, and a new test point was formed for the difference method.

In the ratio method (comparison), the database and test point were modified per Equations (3), (4), and (5) given below:

$$RR1 = \frac{RSSI1}{(RSSI1+RSSI2+RSS3)} \tag{3}$$

$$RR2 = \frac{RSSI2}{(RSSI1+RSSI2+RSS3)} \tag{4}$$

$$RR3 = \frac{RSSI3}{(RSSI1+RSSI2+RSS3)} \tag{5}$$

This way, the new database and the new test point for the ratio method are (RR1, RR2, RR3). Once the new database and test point with the different methods and ratios have been obtained, the next step is to calculate the distance error using the kNN algorithm (k = 3) for each Android brand and series. The expected outcome in the difference method and this ratio is to reduce the value of distance error when using a different device compared to the original database so that the problem of device diversity can be overcome.

4. RESULTS AND DISCUSSION

Before taking the data to the laboratory, the necessary tools were first prepared, namely 2 additional access points (APs), 2 electric terminals, and a meter measuring device. The next step was to prepare a laboratory and name a location plan at each point. Each point's general location can be seen in Figure 5, where the red points indicate randomly determined test points. Then, for data collection, the RSSI value for each point marked in the laboratory room was taken. The results of the RSSI value measurements can be observed in Table 2.

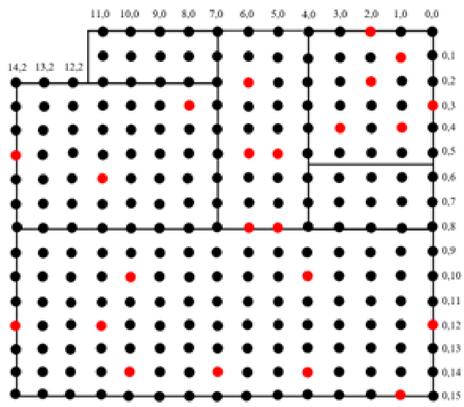

Figure 5. Test Point Location

TABLE 2. RSSI Value Data Retrieval Results

Mac Address			
cc: 16:7e:b5:e0:51	**cc: 16:7e:d2:67:c1**	**74: 4d:28:f1:6c:44**	**74: 4d:28:f1:6d:39**
-67	-68	-39	-54
-67	-68	-39	-54
-67	-68	-39	-54
-67	-68	-39	-54
-67	-68	-39	-54
-79	-73	-34	-66
-79	-73	-34	-66
-79	-73	-34	-66
-79	-73	-34	-66
-79	-73	-34	-66
-78	-74	-33	-66
-78	-74	-33	-66
-78	-74	-33	-66
-78	-74	-33	-66
-78	-74	-33	-66
-79	-74	-34	-65
-79	-74	-34	-65
-79	-74	-34	-65
-79	-74	-34	-65
-79	-74	-34	-65
Median			
-78	-73	-34	-65

Table 2 summarized the results of the RSSI value taken from the Android Meizu Series Note 5 at point (2,0). The top column shows the Mac Address of the 4 APs used. Mac addresses cc:16:7e:b5:e0:51 and cc:16:7e:d2:67:c1 indicate the Mac address from the APs that are already in the laboratory. Mac addresses 74:4d:28;f1:6c:44 and 74:4d:28:f1:6d:39 are the Mac Address of the additional APs that were included in this research. The RSSI value for each point was taken 20 times for the data collection, and then the median value of each AP was determined. The RSSI value of these median results was then entered into the database radiomap.

In this experiment, the number of APs used was 4 pieces, but the distance error calculation consists of quite complex stages, especially because the data must be processed according to the number of test points used, which amounts to 24 test points. Therefore, to reduce the difficulty in further calculations, the number of APs was varied and the value of the distance error was calculated using the kNN algorithm (k = 3) for a total of 4 APs, 3 APs, and 2 APs.

This calculation used the RSSI value that had been processed in the database radiomap; the database used was from the Redmi Android brand with the Redmi test point. The distance error value obtained using the kNN algorithm (k = 3) with 24 test points for each number of AP was calculated according to the average value. The results of the average distance error obtained is shown in Figure 6.

From the graph in Figure 6 above, using 4 AP average values and a distance error with k = 3 produced an error of 1.59, for 3 APs, the average value distance error with k = 3 was 1.61 and 2 APs resulted in an average distance error with k = 3 of 1.93. The smallest average distance error for k = 3 was with 4 APs used. The distance error value when using 2 APs was very large compared to using 3 APs and 4 APs. The distance error value when 3 APs were used compared to 4 APs was not so large. Therefore, the authors chose 3 APs as the optimal number of APs to use for further calculations.

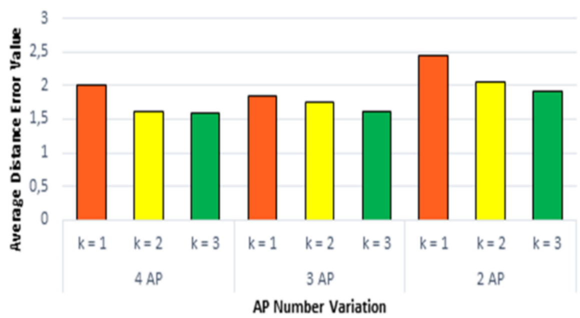

Figure 6. Graph of Average Distance Error with Variation in the number of AP (radiomap database : Redmi)

The calculation at this stage was to find the average value of the distance error via kNN (k = 3) using 3 Aps, with the test point consisting of the Redmi 3 test point, Meizu Note 5, and Oppo F1 Plus. The average value of the distance error produced by the Redmi test point was expected to be smaller than when using the Meizu and Oppo test points because the database is the Redmi database itself.

The average value of the distance error would be taken as it is calculated using the kNN algorithm (k = 3) with 24 test points from the three types of Android brands. The results of the average distance error that was obtained is shown in Figure 7.

From the results of the graph as shown in Figure 7, the average value of the distance error for k = 3 obtained with the Redmi Android test point was 2.7, whereas the android Test Point Meizu produced an average distance error of 3.2, and the test point using Android OPPO produced an average distance error of 3.68. From the obtained results, the assumption from the start, before the calculation, is proven—namely, that the average value of the distance error produced by the Android Redmi test point will be smaller compared to the average value of the distance error using the Android Meizu and Oppo test points. This concept proves the notion of device diversity, where, by using a different device, the average value of the distance error produced will also be different. The use of the Meizu and OPPO devices resulted in an increase in the average distance error by 18.5% and 36.3%, respectively.

Given the problem of device diversity seen in the calculation as a result of using a different test point, a proposal was made to overcome it, namely via database modification using the difference and ratio methods; then, 2 types of new databases were created and used in the calculation for each method.

Both of these methods use the same previous calculation: to find distance error using the kNN algorithm (k = 3) to improve performance so that the distance error generated by the different devices would be smaller than before.

The distance error results obtained after calculating the difference method and the ratio method showed a reduced distance error produced by each Android brand, as shown in Figure 8 below. The decrease in the average distance error (%) by using this proposed database modification is calculated using Equation (6).

$$Decreased\ Error = \frac{(Ea - Eb)}{Ea} \times 100\% \qquad (6)$$

Ea is Initial error, which uses the original database from the results of the RSSI measured value. Eb is new error, using the results of the proposed database modification of the difference or ratio.

From the graph shown in Figure 8, the Android Redmi Series 3 results in a distance error value, using the original database, of 2.7, while for the difference database, the resulting error value is 2.17. Moreover, the ratio database also produced a smaller error compared to the original database, which is 2.56. Using equation (6), the average value of the distance error for the difference database decreased by 19.6%. As for the original database, the average distance error decreased in value by 5.2%.

On the Android Meizu Note 5 Series using the difference database, the ratio database produced an error that was smaller than the original database. The difference database produced a distance error of 2.42, while the ratio database produced a distance error of 2.78. This result is significantly different from the distance error generated using the original database, which was 3.2. The decrease in the average distance error in the difference database is 24.3%, whereas the ratio database was 13%.

The Android Oppo F1 Plus series produced a smaller distance error value when using the ratio database with a difference of 2.8 and 2.65. The original database of the distance error produced an error of 3.68. The decrease in average distance error using the difference database was 28%. Meanwhile, in the original database, the average decrease in the distance error was 24%.

Previous research preformed also used the kNN algorithm on IPS Fingerprint resulted in an accuracy of

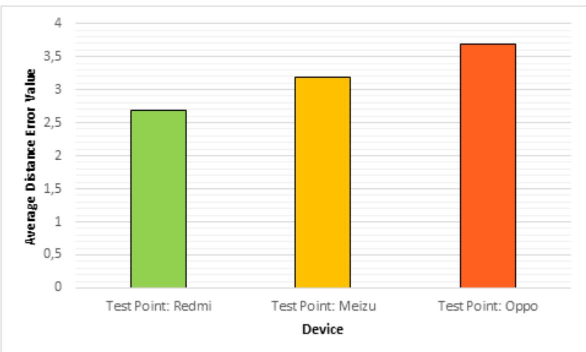

Figure 7. Graph of Average Distance Error for 3 Different Devices (radiomap database : Redmi)

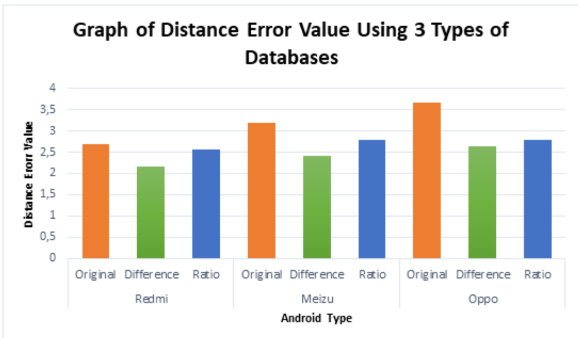

Figure 8. Graph of Comparison of Distance Error (radiomap database: Redmi)

2.94 m. Research conducted by Xia et al. [1] which uses a more complex algorithm (a multi-layer perceptron for indoor positioning), with a positioning accuracy of 2.3 m. The two studies have not paid attention to the aspect of device diversity. In the data reported by Nguyen et al. [4] stated that the IPS Fingerprint technique that uses Wi-Fi proposed by Zhou et al. [27], He et al. [6] and Korayem et al. [5] each can achieve an accuracy of 3.2m and 5.3m. While in research conducted by Choi and Jang [7], the accuracy that can be achieved is 86% in a cell with a size of 2.7 x 2.8 meters. The best accuracy in this study was 2.17m, still better than the previous studies mentioned above. This research has also overcome the problem of device diversity which has not been discussed in previous studies.

RSSI data collection on a building to create a radiomap database is low cost because it only requires a smartphone and an operator. It is just that manually collecting RSSI data requires quite a long time. Then several solutions have been proposed using the indoor propagation model to create a radiomap database in short time [9]. This research does not touch on RSSI data collection techniques, but on processing RSSI data to create a new database radiomap. Data processing is also only carried out by calculating the difference in RSSI (reduction operation), so that the additional computational needs will not be high either.

5. CONCLUSION

The results of calculating the average value of the distance error using the proposed modification, the Difference Database Radiomap and the ratio database, can provide solutions to the problem of device diversity for an Indoor Positioning System (IPS) using fingerprinting techniques, which only require a light computing system. The decrease in the distance error that occurred with the Redmi 3 Series Android smartphones using the modified difference database was 19.6%, while for the ratio database, the decreased distance error was 5.2%. On Android smartphones, Meizu Note 5 Series showed a decreased average distance error, with a difference database, of 24.3%, and using a ratio database, the average distance error decreased by 13%. As for the Android smartphone, Oppo F1 Plus, using the difference database and ratio database, the decrease in the average distance error was 28% and 24%, respectively.

Based on the research above, several suggestions to improve future research are to use devices that have not been used in this study so that more devices can be compared. Besides, the test location could include more than one location, and the number of original databases can be increased to more than one to compare the distance error value.

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Persian Abstract

چکیده

توسعه خدمات مبتنی بر مکان مستلزم یک فناوری سیستم موقعیت یابی دقیق و فزاینده است. تحقیقات در مورد سیستم های موقعیت یابی در فضای باز به دقت رضایت بخشی دست یافته است و معمولاً در خدمات مختلف مبتنی بر مکان استفاده می شود. روند تحقیقات اکنون به سمت سیستم موقعیت یابی داخلی (IPS)در حال تغییر است. یکی از تکنیک هایی که به طور گسترده در IPS مبتنی بر Wi-Fi استفاده می شود، اثر انگشت است. تکنیک انگشت نگاری در Wi-Fi از مقدار نشانگر قدرت سیگنال دریافتی (RSSI)استفاده می کند. مشکلی که رخ می‌دهد این است که نتایج اندازه‌گیری‌های RSSI در گوشی‌های هوشمند برندهای مختلف، مقادیر RSSI متفاوتی را تولید می‌کند که به عنوان تنوع دستگاه نیز شناخته می‌شود. تنوع دستگاه باعث کاهش دقت سیستم می شود. این مطالعه با هدف ارائه راه حلی برای مشکل تنوع دستگاه در Wi-Fi IPS بر اساس اثر انگشت RSSI، یعنی دریافت یک خطای فاصله جزئی است. راه حل پیشنهادی اصلاح نقشه رادیویی پایگاه داده اصلی به دو پایگاه داده جدید است: پایگاه داده تفاوت و پایگاه داده نسبت. نقشه رادیویی پایگاه داده تفاوت توانست میانگین خطاهای فاصله را ۲٤.۳ درصد در Meizu و ۲۸ درصد در OPPO کاهش دهد. سپس، با استفاده از نسبت پایگاه داده Radiomap، مقدار متوسط خطاهای فاصله را می توان ۱۳٪ در Meizu و ۲٤٪ در OPPO کاهش داد. از محاسبات، نسبت پایگاه داده Radiomap می تواند راه حل هایی را برای مشکل تنوع دستگاه برای یک سیستم موقعیت یابی داخلی بهتر از نقشه رادیویی پایگاه داده تفاوت ارائه دهد، اگر به کاهش خطای فاصله نگاه کنیم.