Improved fingerprinting performance in indoor positioning by reducing duration of the training phase process

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ABSTRACT

Wireless sensor network (WSN) can be used as a solution to find out the position of an object that cannot be reached by global positioning system (GPS), for example to find out the position of objects in a room known as Indoor Positioning. One method in indoor positioning that can be used is fingerprinting. Inside there are two main work phases, namely training and positioning. The training phase is the process of collecting received signal strength indication (RSSI) data levels from each sensor Node reference that will be used as a reference value for the positioning phase. The more sensor Nodes used, the longer the processing time needed in the training phase. This research focussed on the duration of the training phase, the implementation of which are used 4 sensor Nodes, namely Zigbee (IEEE 802.15.4 protocol) arranged according to mesh network topology, one as Node X (positioning target) and 3 as reference Nodes. There are two methods used in the training phase, namely fixed target parameter (FTP) and moving target parameter (MTP). MTP took 5 seconds faster than FTP in terms of the duration of RSSI data collection from each reference Node.

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1. INTRODUCTION

Wireless network telecommunication is one of the choices of every technology user who needs ease in communication, both in terms of infrastructure, the installation process and its practical use [1]. Wireless network telecommunications are increasingly developing which are characterized by a combination of wireless telecommunications networks with microelectronic technology as sensor Nodes known as wireless sensor networks (WSN). WSN can be used as a solution to find out the position of an object that cannot be reached by global positioning system (GPS), for example to find out the position of objects in a room called indoor positioning [2]. In indoor positioning, each sensor Node installed is expected to provide information needed by other sensors [3], so that with a certain method can infer the position of an object [4]. The sensor Node used should have a small physical size, low power consumption, limited processing power, short range communication, and have a small amount of memory storage, such as that of Zigbee or wireless local area networks [5]-[7]. Initially the use of Zigbee was intended for various types of automation system applications due to energy saving and security factors that are qualified [8].

The one method that can be used for indoor positioning on WSN with Zigbee is fingerprinting [9], [10]. From several other methods that can be used in indoor positioning based on received signal strength indication (RSSI) such as trilateration and triangulation, fingerprinting is a method that is widely adopted

because of its high level of accuracy [11]. The fingerprinting method contains two main work phases, namely training (offline-phase) [2] and positioning (online-phase) [12], [13]. In the first phases (training) is the process of collecting data s (example: RSSI) from each sensor Node that is collected in a database which can later be used as reference data to help infer the position of an object carried out in the second phase (positioning). The more Nodes are used, in which the time needed during training process is much longer which will reduce the performance of the system.

Uradzinski *et al.* [14] did researched on advanced indoor positioning using Zigbee wireless technology with the fingerprinting method. The purpose of his research is to raise the level of accuracy during the positioning phase. To achieve this goal, Uradzinski undertakes two stages of work, the first is filtering out interference signals in the measurement area so that reference data in the database can be more accurate. The second step is to make a combination of the weighted nearest neighbors algorithm with the Bayes algorithm. The sensor Nodes used are 4 Zigbee as reference Nodes with implementation hardware. The measurement area is 42.5x4.96 m with the division of the area/mapping area into 108 reference points at 1.6 m intervals. From his research, there was an increase in accuracy when adding filtering when taking RSSI values in the fingerprinting method. The standard deviation for the measurement area over distances above 40 m is 0.51 m.

Ou *et al.* [15] did researched on indoor positioning with the proximity method which was applied using IEEE 802.15.4 (ZigBee). Zigbee was chosen because it has a low cost, low power consumption, small size and is easy to use compared to WiFi, so it is very suitable for short distance wireless transmission systems. The parameters used as measuring material are time of arrival (TOA), time difference of arrival (TDOA), angle of arrival (AOA), and received signal strength indication (RSSI). When collecting RSSI, ou uses a modification of the proximity method, which is triangulation between the two initial reference Nodes combined so that they intersect to form a new reference Node. The time required is faster and complex calculations are reduced. The resulting average error is 0.42 m.

Fonseka and Sandrasegaran [16] did researched on indoor positioning for IoT applications using the fingerprinting method that is applied using WiFi. The algorithm used is probability and weighted k-nearest neighbor (WKNN), as well as a combination of both. The aim of his research is to improve the performance of the fingerprinting method in terms of precision, accuracy and durability. In the offline phase, all WiFi signals contained in the research area are read information such as signal level (RSS), signal quality, modulation and mediamedia access control (MAC) address. RSS values that have been read are entered into a database that will be used as input in the online phase. In the research area of 6 m x 6 m, 49 reference points were 0.5 m away, with a target target station, line of sight (LOS) conditions, using 5 access points and a combination of probability and WKNN K=3 algorithms obtained an error distance of 0.4757 m, its precision increases to 88%. In the study area of 5 mx3m, the target device moves to non-LOS conditions, with K = 7 an error distance of 0.4025 m is obtained, its precision increases to 99%.

AlShamaa *et al.* [17] did researched on localization of sensors in indoor wireless networks: An observation model using WiFi RSS. The method used is fingerprinting and clustering with hardware implementation in the WLAN living lab environment of Troyes University of Technology, France. The parameter used is the RSS WiFi of each access point (AP) at that location with a research area of 500 m² divided into 19 clusters. When experimenting with combining fingerprinting and clustering methods without AP Selection, obtained an accuracy rate of 88.21% during the training phase and 86.26% during the positioning phase. With the addition of the AP selection method, the accuracy increases to 92.78% during the training phase and 90.42% during the positioning phase. However, with the addition of the AP Selection method, it will add processing time to the training phase. AlShamaa also made a comparison between the methods carried out with methods that others have done such as: K-nearest neighbors, Naive Bayes, multinomial logistic regression, neural networks and SVM. From all the methods carried out experiments on the same environment, scenario and device, to get results with high accuracy, it requires more time during the training phase in fingerprinting.

In this work, we propose a study to improve the performance of the level of speed in terms of processing time on the training phase of the fingerprinting method for indoor positioning with certain algorithms by hardware implementation using Zigbee. The output generated when using certain algorithms can reduce the processing time in the training phase. This research was conducted in an actual room with an area of indoor area that is 3 m x 3.6 m (empty space). The method used is fingerprinting for indoor positioning with WSN. The communication protocol standard used is IEEE 802.15.4 (ZigBee). The parameters taken in the fingerprinting method are RSSI (received strength signal indicator) from each sensor Node. Each sensor Node is placed in an ideal condition/LOS, so that the influence of the human body and furniture can be ignored [18]. This study used two measurement methods which were carried out during the training phase. The results of the duration of the two methods are then compared so we get data to give a conclusion. The paper is organized, section 2 deals with the research strategy performed in this work and

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how the procedures fixed target parameter (FTP) and moving target parameter (MTP) are implemented in fingerprinted method. Section 3 describes the measurement results for various scenario and its analysis. Section 4 gives the conclusion of the paper.

2. RESEARCH METHOD

For the proposed model, we use zigbee devices that are coupled with a mesh network topology to form a wireless sensor network. WSN category used is structure WSN, the sensor Node is placed in a fixed position permanently, so as to reduce network savings and management costs [19]. In general, each sensor Node contains 4 sub-systems, namely: Controller sub-system; Communication sub-system; Sensing subsystem; and Power Supply sub-systems [20], [21]. Zigbee can be used as a sensor Node because each sensor does not require wide bandwidth, but requires low latency and low energy consumption. Zigbee has been introduced by IEEE as an IEEE 802.15.4 communication standard [22] that works at 2,4 Ghz frequency [23]. There are several network topologies that can be used on WSN, one of them is the Mesh Topology that is often used because it has a high redundancy [24]. The parameter used from each Node is RSSI which is applied to indoor positioning. RSSI is short for Received Signal Strength Indicator, which means an indicator of the signal strength possessed by a wireless transmission device between one device and another [25]. RSSI is also a standard parameter in wireless communication that is often used by other researchers [26]. In this study RSSI was chosen because it can be used for the fingerprinting method with the distance from each sensor Node that is close enough. RSSI measurements can reflect a distance between each sensor Node. The farther the distance between the sensor Nodes, the smaller the RSSI value obtained. The main objective of this research is to apply the RSSI data collection method in the training phase which is more effective so as to reduce the duration of the processing time in the training phase. This section will discuss including research focus, research flow, fingerprinting methods in indoor positioning and RSSI data collection methods in the training phase.

2.1. Research strategy

Wireless sensor network (WSN) has many applications that can be applied in it, such as indoor positioning. Determination of the location of objects in an indoor area can be done with a variety of methods, one of which is fingerprinting. There are several methods that can be used for indoor positioning/indoor localization systems (ILS) [27], such as proximity, triangulation, fingerprinting, dead reckoning. In the fingerprinting method, there are two main phases, namely the training phase and the positioning phase. The focus of this research is to optimize the training phase in the fingerprinting method. Inside there are two methods, namely fixed target parameter (FTP) and moving target parameter (MTP) which is a method for retrieving RSSI data in the training phase. After knowing the focus of the research to be conducted, the next step is to make a research flowchart to achieve the objectives of the research. The research flowchart can be seen in Figure 1.



Figure 1. Research flowchart

The research method is carried out with several stages in accordance with Figure 1. First, literature review stage, read some of the references of previous journal/research writers to look for problems that are deemed necessary to develop or continue their research. Configuring WSN hardware with Zigbee stage, determine the position of each sensor Node, in order to obtain an ideal result, namely the line of sight (LOS) to the reference Node (Node X). Application of the fingerprinting method stage. Initially the mapping of the measurement area is carried out according to the conditions in the field. The parameter measured is RSSI (received signal strength indicator) from Node X and all sensor Nodes in each mapping area. RSSI sensor Node reference that is read by Node X is entered into the database which will be used as the next reference value. measurement of RSSI at the training stage in the fingerprinting method is done in two ways, namely fixed target parameter (FTP) and moving target parameter (MTP). From the results of the FTP and MTP method, the duration of the training phase is then compared and analyzed. Then The Analysis and Conclusions stage. from the results of measurements and data processing that has been obtained, will find a conclusion from a study.

2.2. Fingerprinting method

In the fingerprinting method, there are two phases of the process that must be carried out, namely training and positioning. In the training phase, the Node X sensor is first mapped into the smapping scheme in accordance with the measurement location applied. Node X can know the RSSI value of each sensor Node around it, then the values are entered into a database that will be used as a reference value in the next phase. In this study, the implementation was carried out in an indoor room (empty space) ideal condition (sensor Node LOS) with a size of 3 x 3.6 m^2 . The position of the reference Node sensor is placed at a height of 2 meters and Node X is placed on a 60 cm wheeled chair. An illustration of the position of the sensor Node can be seen in Figure 2.



Figure 2. Illustration of sensor Node placement

Node X is a sensor Node as a target location that you want to know its location by collecting RSSI information from the sensor reference Nodes that are around it, namely Node A, Node B, and Node C. Terminals are connected directly to Node X to see the surrounding RSSI in real time. In the FTP method, Node X is in an area that has been mapped first. Node X collects RSSI data from each reference Node alternately in each designated area. The scheme is made in accordance with the dimensions of the space used as a place of research, as shown in Figure 3.

In Figure 3(a), the location mapping scheme was created by dividing the measurement area by 30 mapping areas. Each of these measurement areas is $60 \times 60 \text{ cm}^2$. The division of these areas is expected to improve the positioning results more accurately. After the mapping scheme is created, the next step is to determine the location of the sensor Node that will be used as a reference. The schema sensor reference Node placement is seen in Figure 3(b). The sensor Node used in this study uses 4 sensor Node units, 1 unit as Node X and 3 other units as sensor reference Nodes (Nodes A, B, and C). In the FTP method, Node X in a stationary state in one of the mapping areas measures the RSSI of each sensor Node reference (Nodes A, B and C) against Node X. These measurements are repeated one by one in each mapping area (A1-F5). Then the measured RSSI value is stored in the database which will be used as a reference value.

In the MTP method, Node X in the mapping area is not at rest, but there is movement with an average speed of 0.06 m/s. As Node X moves, the reference Node sensors (Node A, B and C) retrieve data / measure the RSSI Node X value of each sensor Node reference. Illustration of Node X movements performed can be seen in Figure 4.

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Figure 3. Target position and sensor Node reference mapping scheme

Node A	noc	ie x	A2	A3	A4	A5	
	в	1	B2	В3	B4	В5	
	С	1	C2	C3	C4	C5	Node E
	Γ	1	D2	D3	D4	D5	
	E	1	E2	E3	E4	E5	
Node C	F	1	F2	F3	F4	F5	

Figure 4. Illustration of Node X movement on MTP in training phase

Figure 4 illustrates the movement of Node X in the MTP method which simultaneously each sensor Node reference (Node A, B and C) takes the level of RSSI Node X to the sensor Node reference. Later the RSSI value is processed and compared to match the RSSI value in the FTP method. The appropriate RSSI value will be used as the next reference value for the positioning phase.

3. RESULTS AND DISCUSSION

In this testing and measurement phase, it uses two methods as explained in the previous chapter, namely the fixed target parameter (FTP) and moving target parameter (MTP) methods. Both of these methods are used during the training phase in the fingerprinting method to collect RSSI data from each sensor Node reference and its value is entered into the database in the form of a reference value table that will be used at the positioning stage.

3.1. Measurement of the fixed target parameter method

Measuring steps are carried out in accordance with the measurement method planned in the previous chapter. The first measurement method is done by the FTP method. Node X is in one of the areas that has been mapped before (example: area B3) in a stationary condition, as shown in Figure 5.

In Figure 5 is a measurement scheme carried out in the condition of line of sight (LOS), Node X in a stationary condition in Area B3 gets the RSSI value from the reference Node (A, B, and C). Then the RSSI value is entered into the database which will be used as a reference value. The duration of the training phase with FTP in Area B3 takes 10 seconds for each reference Node.

In Figure 6 contains the duration of creating a reference database in the training phase with FTP in each calculation area for 3 reference Nodes (A, B and C). The X-axis shows the list of areas that RSSI measurements have been made by Node X against the reference Node, namely areas A1 to F5. The Y-axis determines the time (in seconds) to take RSSI measurements in each mapping area. The Δt Node A bar chart

shows the duration of the RSSI measurement until input into the database by Node X against Node A. The Δt Node B bar chart shows the duration of the RSSI measurement until the input into the database by Node X against Node B. The Δt Node C bar chart shows the increase in RSSI to input into the database by Node X to Node C. The duration of the training phase with FTP requires an average time of 30 seconds in each area to calculate for the use of 3 reference Nodes. The more sensor Nodes used and the large number of area mappings, the more time it takes to collect references.



Figure 5. RSSI measurement in area B3 scheme



Figure 6. Graph of training phase process duration with FTP

3.2. Measurement of the moving target parameter method

The second method in the training phase is using MTP. In this method, the reference Node takes RSSI data from the moving Node X. In Figure 7 shows the Node X moves from the reference Node (Node A) to other reference Node (Node B). When Node X starts to move, each reference Node (A, B, and C) takes RSSI data from Node X. In Figure 7 is the first Node X movement model on MTP, there are 2 other movement models, namely from area A3 to Area F3 and from Node C to area A4. The results of the RSSI in area B3 can be seen in Table 1.

Table 2 shows lists the duration of the training phase with MTP in area B3. Of the three MTP movement models, 3 times the RSSI measurements were made for Nodes A, B and C in area B3. In the MTP measurement scheme, Node X moves with a speed of 0.06 m/s, so the duration needed for the training phase with MTP is an average time of 25 seconds in each mapping area

Table 1. RSSI m	neasurement result	lts in area B3 wi	th MTP method
Node X	RSSI Node A	RSSI Node B	RSSI Node C
In Area B3	(dBm)	(dBm)	(dBm)
Model - 1	-55 / -64	-55 / -62	-52 / -57
Model - 2	-55 / -65	-54 / -61	-52 / -62
Model - 3	-55 / -62	-55 / -62	-52 / -55

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Node A	node X	A2	A3	A4	A5	
	B1	B2	В3	В4	В5	
	C 1	C2	C3	C4	C5	Node B
	D1	D2	D3	D4	D5	
	E1	E2	E3	E4	E5	
Node C	F1	F2	F3	F4	F5	

Figure 7. Illustration of the movement of Node X from Node A to Node B

Tuble 2. Else of training phase durations with WITT in area D5										
No	Movement Model MTP	Toward A, B an Area I	ls Node nd C in B3 (1)	∆t ABC-1 (second)	Toward A, B an Area I	ls Node nd C in B3 (2)	Δt ABC-2 (second)	Toward A, B an Area I	ls Node nd C in B3 (3)	Δt ABC-3 (second)
		Start	End		Start	End		Start	End	
1	Model 1 (Node A to Node B)	17.19.4 6	17.20.1 3	00.00.27	17.32.5 6	17.33.2 0	00.00.24	17.43.4 0	17.44.0 7	00.00.27
2	Model 2 (Area F3 to Area A3)	17.35.5 5	17.36.2 0	00.00.25	17.36.0 0	17.36.2 6	00.00.26	17.47.2 4	17.47.4 8	00.00.24
3	Model 3 (Node C to Area A4)	17.38.5 4	17.39.1 8	00.00.24	17.38.4 5	17.39.0 9	00.00.24	17.49.2 5	17.49.4 8	00.00.23
Ave Area	rage Durations of each per-3 Nodes (second)			00.00.25			00.00.25			00.00.25

Table 2. List of training phase durations with MTP in area B3

3.3. Data processing and analysis

From the results of RSSI measurements with the fixed target parameter (FTP) and moving target parameter (MTP) methods that have been carried out, sample measurements are taken in Area B3. The RSSI measurement results is showed Table 3. Table 3 shows that the RSSI value measured by FTP is close to the RSSI value measured by MTP. When measuring using the FTP method, an average time of 30 seconds is required in each mapping area, while the MTP method requires an average time of 25 seconds in each mapping area. In the MTP method, it can be seen from several graphs that have been displayed that the range of the lower and upper limits of the RSSI obtained is close to measurement by the FTP method. So that the MTP method can improve the efficiency of the fingerprinting method that is applied to indoor positioning.

Table 3. Comparison of RSSI FTP and MTP measurement results in area B3

~ -	e et eomparison o	russii ii ana		
	Node X	RSSI Node A	RSSI Node B	RSSI Node C
	In Area B3	(dBm)	(dBm)	(dBm)
	FTP	-56 / -62	-52 / -58	-50 / -60
	MTP Model - 1	-55 / -64	-55 / -62	-52 / -57
	MTP Model - 2	-55 / -65	-54 / -61	-52 / -62
	MTP Model - 3	-55 / -62	-55 / -62	-52 / -55

4. CONCLUSION

Indoor positioning with the fingerprinting method is very effective and accurate when used in small indoor areas. Efficiency in the training phase will improve the performance of the fingerprinting method. Two methods have been used during the training phase, namely MTP (moving target parameter) and FTP (fixed targer parameter). The MTP method on the training phase of fingerprinting can increase the efficiency of the process duration in collecting RSSI data from each sensor Node in the mapping area by 16% or 5 seconds faster than using the FTP method.

As a suggestion for further research, for example the Node X movement scheme can be adjusted to the conditions of the mapping area, so that all areas can be exceeded and all RSSI from each sensor Node can be measured in one movement model, such as zig-zag or like a sine wave. For the purposes of precision in the positioning stage, more than 3 units of sensor reference Nodes are needed.

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