### **Research Article**

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## An effective algorithm to overcome the practical hindrance for Wi-Fi based indoor positioning system

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Abstract: Indoor tracking has evolved with various methods. The most popular method is using signal strength measuring techniques like triangulation, trilateration and fingerprinting, etc. Generally, these methods use the internal sensors of the smartphone. All these techniques require an adequate number of access point signals. The estimated positioning accuracy depends on the number of signals received at any point and precision of its signal (Wi-Fi radio waves) strength. In a practical environment, the received signal strength indicator (RSSI) of the access point is hindered by obstacles or blocks in the direct path or Line of sight. Such access points become an anomaly in the calculation of position. By detecting the anomaly access points and neglecting it during the computation of an indoor position will improve the accuracy of the positioning system. The proposed method, Practical Hindrance Avoidance in an Indoor Positioning System (PHA-IPS), eliminate the anomaly nodes while estimating the position, so then enhances the accuracy.

**Keywords:** RSSI anomaly, Indoors tracking, positioning, localization, dead reckoning, Triangulation

## **1** Introduction

With the evolution of the smartphone-based indoor positioning techniques [1] and advancement, numerous applications have been developed based on it, including mapsbased navigation, location-based control, personalized advertisement, emergency evacuation, indoor stock management, hospital routing, etc.

The positioning system based on access point signal strength measuring requires the minimum number of access points available at each point of the indoor system. Even with the careful deployment of access points in an indoor environment concerning the indoor map, the RSSI values will be inherent by non-moving blocks and moving blocks like doors, furniture, new constructions, etc. Those affected access points form as an anomaly node in an indoor positioning system. In this paper, we call these anomalies obstacles/blocks, which weaken RSSI Wi-Fi signals.

The PHA-IPS method comprises the tracking motion of a mobile device for a short range between last known locations using inertial navigation and detecting all the Wi-Fi nodes that are erroneous and avoiding the faulty nodes while calculating the current position.

## 2 Literature Review

The accuracy of current Wi-Fi signal strength-based positioning techniques deteriorates in the practical environment due to the non-line of sight of the signal [2], new constructions, furniture, moving blocks, and even human presence in the line of the RSSI signal [3]. In the Wi-Fi signal strength measuring method (Trilateration), the RSSI is directly proportional to the distance d [4], where d is the distance between the Wi-Fi access point and the RSSI recipient. This technique requires RSSI recipient in the same Line of sight from the access point [5]. The position estimated error increases if the RSSI strength is affected by the non-line of sight or any block in the direct path of the signal [5]. The average position error calculated in the presence of human blocks is 11.34 meters [3]. This error increases with more solid blocks like wall/constructions etc.

The fingerprint technique has an advantage over the Trilateration method. A fingerprint doesn't get affected with the Line of sight or permanent block since it's the

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same as the data collection phase; it has an error range of 1 to 3m [6]. But when the Line of sight is affected by moving a block or new construction in the fingerprinted environment a re-training phase would be called for, which is tedious [7]. Wi-Fi signal fingerprint-based technique required the location & access point not altered from the recording/training phase to the actual position phase [7]. The fingerprinting technique has a drifting error [8], which happens due to the Wi-Fi signal fluctuations at random caused by multipath effects significantly challenging the precision of location estimation [9] and the maintenance of a valid radio map [10]. Location map aware position and fusing of the inertial sensor [8] is used to overcome this challenge in the practical environment. None of the methods discussed were able to find the root cause, which is the affected anomaly node. If the affected nodes are identifiable during the practical hindrance, the system accuracy can be improved efficiently. The PHA-IPS method efficiently identifies the access point hindered by any obstacles and eliminates it completely during the position estimate.

## **3** Positioning Techniques

WLAN and received signal strength indicator (RSSI) based indoor positioning techniques are the most popular among other methods. Because of the variation of Wi-Fi signals, a Wi-Fi based localization system tends to have fluctuations and errors [11–13]. Also, the technique may fail at a random fraction of time due to signal unavailability, temporary blocks, etc. The most typically carried out approach in RSSI-based localization is the Wi-Fi trilateration and Wi-Fi fingerprinting.

### 3.1 Wi-Fi Trilateration Method

Wi-Fi trilateration method depends on measuring the intensity of the received signal, which in turn is used to measure the distance between the devices that receive the signal from the source. This technique calculates the access point position relative to the known position of the access points [14]. Here, the exact location of the access point inside a building and the distance between all the access points need calibration. By using these, the smartphone position can be determined, as shown in Figure 1.

$$RSSI_{AP} = -(10 \times n)log_{10}(d) - A,$$
 (1)

$$d = 10^{((A - RSSI)/20)}.$$
 (2)



Figure 1: Wi-Fi Trilateration using RSSI measured method



Figure 2: Wi-Fi Fingerprinting positioning estimation method

In Equation 1 & 2, *RSSI* is the received strength indicator calculated in dBm, *n* is the signal propagation constant or exponent, *d* is the relative distance between the communicating nodes and the receiver, and *A* is the reference signal strength received in dBm. The reference *RSSI* value is measured when the distance between the receiver and the transmitter is one meter. In this method, any change occurs in the position of the access point will affect the entire positioning system.

#### 3.2 Wi-Fi Fingerprinting Method

Fingerprinting [15] has advantages over trilateration since it takes into account the blocks while doing the training phase of fingerprinting. The fingerprinting technique [16] calls for a manual collection of a large dataset in the training phase (offline phase), and this must be pre-processed [16]. In the online phase, received signal strength is



Figure 3: Position estimation with the inertial sensors of a smartphone

checked against the already captured and stored values to estimate the position as depicted in Figure 2. Furthermore, when there is an alteration within the environment, the fingerprinting method calls for a re-training process, which in turn is tedious. This is the main disadvantage of a fingerprinting based system.

## 4 Pedestrian Dead Reckoning (PDR) - Using Smartphone Inertial Sensor for Positioning

An indoor setting, where the adequate numbers of access point signals are not available, is called a dead zone. In such places, the indoor RSSI based position techniques will fail. In the dead zone, the last known position and inertial sensors of the smartphone are used to estimate the current position of a moving object. But this method has less accuracy when compared with RSSI based positioning. Different inertial sensors like accelerometer, gyroscope, and magnetic compass are used during this process [17]. By calculating the step count, step length [18], and the direction of the steps, the current position of a mobile object can be computed in an indoor environment. This method is known as the Pedestrian dead reckoning (PDR) system.

In this method, number-of-steps denote the number of steps walked determined by accelerometer/step counter, and the step-length indicate the length of each step walked, which can be easily determined by counting the

number of walking steps required for the user to traverse a specified distance. The direction of the user moved is determined by the inertial sensor magnetometer/Compass. The current PDR position is estimated using the distance moved *D*, and the direction of the movement. Dead reckoning position gives excellent accuracy for short distance position estimation. Errors of the traveled distances estimated with the empirical step-length model [19] are in the range of 2.8% to 7% for a travel distance of 150 - 170 meters. Thus the distance error for this method can be of the range 5 to 8m for the distance moved up to 150m. This method has an accuracy above 93%, with an error of 7% for a distance of up to 150m. The threshold (T) value for the PHA-IPS system is fixed based on the error rate of PDR. The distance walked (D) from the last known position is determined by

$$D = Number - of - steps \times step - length.$$
(3)

But, the disadvantage of PDR is that it provides good accuracy only for short range and has a cascading error when deployed to measure the position over long distances. If the fluctuations of the RSSI value are high, even PDR can't produce the exact location because the last known position from any Wi-Fi based positioning algorithm is fed as the input to the PDR. So, to get high accuracy, anomaly nodes need to be eliminated while computing the last known position (LKP) before feeding the PDR system.

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## 5 Practical Hindrance Avoidance -Indoor Positioning System (PHA-IPS)

In the practical scenario, a moving hindrance commonly affects some of the signals from nodes, which take part in estimating the indoor position with the signal measuring techniques. Unsurprisingly, these nodes contribute to more errors and affect accuracy. The efficiency of the system is improved dynamically by detecting the anomaly nodes and avoiding those nodes during the position estimation.







#### Algorithm 1: Pseudo code of PHA-IPS

- Estimate: Current Position based on the LKP Position and the inertial sensors (PDRmethod), this acts as the reference position PDR<sub>(x,y)</sub>
- 2: Scan all Access points at the Current position (*AP*<sub>1</sub>, *AP*<sub>2</sub>, .., *AP*<sub>n</sub>)
- 3: For each  $AP \in AP_{(1,...,n)}$
- 4: Compute :  $D = 10^{((A RSSI_{AP})/20)}$
- 5: Compute : Euclidean distance between  $AP_{(a,b)}$ and  $PDR_{(x,y)} ED = \sqrt{((x-a)^2 + (y-b)^2)}$
- $6: if D > (ED + T_{DR})$
- 7: Anomaly access point
- 8: else
- 9: AP New List(add(AP))

In the PHA-IPS algorithm 1  $(AP_1, AP_2, .., AP_n)$  is the list of scanned access points. And AP - IP is the IP/name of the Access point,  $RSSI_{AP}$  is the Received signal strength indicator of the Access point,  $AP_{(a,b)}$  is the Access point position value, A is a reference received signal strength in dBm. The algorithm scans through all the access point nodes and provides a list of the access points  $AP(AP_{IP}, RSSI_{AP}, AP_{(a,b)})$ . The scanned access point provides details about the access point, like the name/IP  $(AP_{IP})$  of the node, Received signal strength  $(RSSI_{AP})$  of each node, each node preconfigured position  $(AP_{(a,b)})$ . The PDR method continuously calculated the current position using the inertial sensor and from the last known location. The position estimate by the PDR method acts as the reference location, and the threshold (T) is chosen based on the error rate of dead reckoning value [19]. Any AP whose value does not fall within the reference location is detected as the anomaly, and any AP, which does fall with the reference location, is taken as a non-anomaly node, as





Figure 6: RSSI with block & without blocks vs Distance

depicted in Figure 4. Figure 4(A) shows the Anomaly node (access point) detection where the signal strength of the node is affected by the block and Figure 4(B) shows an access point with no block present in the path of the signal. The PHA-IPS method also does sensor fusion with different sensors available on the smartphone. The following sensors in the smartphone were used: Wi-Fi receiver, accelerometer (for step detection), magnetometer (for direction), gyroscope (for the position of a smartphone).



Figure 7: Position estimate by avoiding the anomaly nodes in the system

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Distance(m)	Without blocks (dBm)	With blocks (dBm)						
1	-6.2	-54.3						
2	-15.3	-57.2						
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Table 1: Comparison of RSSI value at a distance with & without

1	-6.2	-54.3
2	-15.3	-57.2
3	-25.1	-65.4
4	-35.2	-75.3
5	-45.4	-76.2
6	-55.3	-79.4
8	-65.2	-82.3
10	-75.2	-85.3
15	-85.1	-90.5
20	-86.2	-93.6
30	-93.1	-95.4

## 6 Experiment design and Results

Figure 5 shows the experimental setup of our test environment. The experiment is conducted to measure the RSSI values from known distance access points (Wi-Fi node)

with blocks and without blocks. We have created temporary blocks in the test environment to block the Wi-Fi signals measured. The experimental setup will show the changes in RSSI value when there is an anomaly node in the environment. To determine the error and compare the RSSI measured with and without a block at a reference distance, the following experiment is conducted. RSSI measured without block forms as a reference curve, and it's compared with the RSSI measured with block. Table 1 and Figure 6 depict the value in our experimental setup with a single block. The error increased based on the thickness and number of blocks. The experiment provides an important observation that the error is cascading with an increase in the number of anomaly nodes present in the calculation of position estimation [20]. Figure 7 shows the experimental setup on our test environment where, in real time, we can detect the anomaly and remove the participation of anomaly node while performing calculation of the position estimates. The experimental setup has several Wi-Fi access points. Access points AP<sub>1</sub>, AP<sub>2</sub>, AP<sub>3</sub>, and AP<sub>4</sub> are the scanned list of the access points from the smartphone whose position needs to be estimated. We have also

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Table 2: Comparison of Trilateration VS PHA-IPS method.

#	Access point (RSSI)				Actual position	Trilatoration	TDE		DDE
	AP1	AP2	AP3	AP4	- Actual position	IIIIateration	IDL	FIAIFS	FDE
1	-85.4	-79.2	-28.2	-82.8	30, 18	21.6, 15.8	8.68	29.2, 17	1.28
2	-82.6	-78.2	-36.2	-76.8	28,18	21.6, 15.0	7.07	27.4,16.8	1.34
3	-81.6	-75.2	-33.2	-73.8	26,18	18.4, 13.8	8.68	25,15.7	2.51
4	-76.6	-73.2	-42.2	-83.8	24,18	17.6, 13.4	7.88	22.4,17.5	1.68
5	-74.6	-70.2	-56.2	-88.8	22,16	15.6, 12.6	7.25	21.5,14.2	1.87
6	-73.6	-71.2	-63.2	-85.8	20,16	14.2, 11.0	7.66	19.1,17	1.35
7	-66.6	-69.2	-73.2	-84.8	18,16	13.6, 10.2	7.28	16.4,15.2	1.79
8	-63.6	-65.2	-72.2	-88.8	16,15	12.4, 10.1	6.08	15,14.2	1.28
9	-61.6	-64.2	-75.2	-89.8	14,14	11.6, 7.8	6.65	13,12.3	1.97
10	-56.6	-63.2	-75.2	-96.8	12,14	9.0, 5.2	9.3	11,11.5	2.69
					Average Distance error		7.653		1.776



Figure 8: Distance Error by Trilateration and PHA-IPS method

calculated the reference position using the PDR method. When the list of the scanned access points and the reference position by PDR is given as an input to the PHA-IPS algorithm, we can separate the list of the good access points ( $AP_1$ ,  $AP_2$ ,  $AP_3$ ) and avoid the anomaly access point ( $AP_4$ ) during the calculation of the position estimate. In the PHA-IPS method, any anomaly node within the 20m of measuring the distance between AP terminals and receiver can be detected. This method can reduce the error up to 90% and improve the system in the practical scenario to bring the accuracy close to that of a system with no hindrance.

# 7 Experimental result and discussions

The experiment was conducted with a minimum of four access points involved in position estimate

( $AP_1$ ,  $AP_2$ ,  $AP_3$ ,  $AP_4$ ) and a single access point ( $AP_4$ ) RSSI affected by block / Line of sight [21] (anomaly node). The position/distance error of an indoor positioning system is in the range of 6m to 17m due to the anomaly node [3]. We have compared the distance error (DE) by trilateration and the PHA-IPS method, which used the fused PDR along with the trilateration method to detect and remove the anomaly node during the calculation of the position estimation. In a positioning system, the distance/position error denotes the error in positioning, which is the difference between the estimated position ( $X_{location}$ ,  $Y_{location}$ ) and the actual position ( $X_{actual}$ ,  $Y_{actual}$ ).

$$DE = |Estimated \ position - Actual \ position| \qquad (4)$$

$$DE = \sqrt{((X_{location} - X_{actual})^2 + (Y_{location} - Y_{actual})^2)}$$
(5)

The average distance error is calculated by averaging the distance errors for all the location points along the entire moving path. As shown in Figure 8, the result shows that the distance error for Trilateration (TDE) is in the range of 6m to 10m, where the distance error for the PHA-IPS method (PDE) is the range of 1m to 3m, which is much less. The distance error increases proportionately with the increase of anomaly nodes present in the system. With the PHA-IPS method, we can identify the anomaly node, which brought down the error in the range of 1m to 4m, which is relatively low. The position error increases proportionately with the anomaly node, which brought the increase of anomaly node present in the system. With the PHA-IPS method, we can identify the anomaly node present in the system. With the PHA-IPS method, we can identify the anomaly node present in the system. With the PHA-IPS method, we can identify the anomaly node present in the system. With the PHA-IPS method, we can identify the anomaly node present in the system. With the PHA-IPS method, we can identify the anomaly node present in the system. With the PHA-IPS method, we can identify the anomaly nodes, which brought down the error in the range of 1m to 4m, which is relatively low.

### 8 Conclusions

An indoor positioning service is an essential service to locate one's position inside a building, where GPS and other satellite technologies lack precision or fail. WLAN based positioning techniques are the most well known and broad techniques with high area coverage. But, due to fluctuations in RSSI values, the tracking errors are high. In this paper, we have developed an algorithm to detect the access points which generate errors and distort RSSI values. By identifying such nodes using geographical distance, the PHA-IPS method avoids these nodes during the position estimation. This can effectively increase the position accuracy. More research focus is needed to characterize the different hindrances of the signals measuring techniques to improve the efficiency of the positioning system.

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