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Improvement of Wi-Fi Location Accuracy Using Measurement Node-Filtering Algorithm

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Abstract

In this paper, we propose a new algorithm to improve the accuracy of the Wi-Fi access point (AP) positioning technique. The proposed algorithm based on evaluating the trustworthiness of the signal strength quality of each measurement node is superior to other existing AP positioning algorithms, such as the centroid, weighted centroid, multilateration, and radio distance ratio methods, owing to advantages such as reduction of distance errors during positioning, reduction of complexity, and ease of implementation. To validate the performance of the proposed algorithm, we conducted experiments in a complex indoor environment with multiple walls and obstacles, multiple office rooms, corridors, and lobby, and measured the corresponding AP signal strength value at several specific points based on their coordinates. Using the proposed algorithm, we can obtain more accurate positioning results of the APs for use in research or industrial applications, such as finding rogue APs, creating radio maps, or estimating the radio frequency propagation properties in an area.

Key words : indoor positioning; Wi-Fi signal strength; centroid; weighted centroid; multilateration

Ⅰ. Introduction

Many research fields such as geosciences, computer sciences, wireless communications, and mobile computing are concerned with indoor location techniques because of their wide impact and applications. The main purpose of the existence and development of indoor positioning techniques is to overcome the limitations of global positioning systems (GPSs). Many GPSs have been developed, such as that of the US Army, Glonass (Russia), and Beidou (China), based on satellite positioning technology. All of them support human activities in positioning and navigation for aerospace, marine, traffic vehicle, and general human location utilities. However, the satellite signals are degraded when transmitted to receiver equipment placed in indoor environments, which leads to inaccurate positioning results. Indoor positioning techniques have therefore been researched and developed using multiple methods to improve positioning accuracy.

The best approach from a research point of view is based on Wi-Fi signal measurement and analysis for location prediction because Wi-Fi access point (AP) equipment and Wi-Fi signals are often available in indoor environments; in other words, Wi-Fi-based indoor positioning is

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the most cost-efficient and convenient choice for location-based implementation. With respect to Wi-Fi-based implementation, there are two best approaches: ranging-based and fingerprinting techniques. The traditional ranging-based technique uses the theory of three-circle intersections to determine the position of the target. In an ideal scenario, based on the signal strength measured by user equipment, the propagation model can be used to calculate the distance from the user equipment to the AP location. Each AP signal strength collected from the user equipment ranges over a circle with the central point as its coordinate, and the radius of the circle is equivalent to the estimated distance from the user equipment to the AP. By calculating the intersection point coordinates of three circles, the user location can be determined. The advantage of this method is that it is easy to implement and does not require bulk data collection, which helps conserve labor costs. The disadvantage is that the propagation model is affected significantly by multipath, fading, or reflex effects in a real indoor environment, which is complex with many kinds of obstacles. This causes inaccurate estimation of the distance from the user equipment to the AP or circle radius. Therefore, the estimated user location may also be inaccurate.

Radio fingerprinting techniques have been considered by most previous studies as a better performance solution for indoor positioning [1]. Signal strength data are collected at particular positions from multiple Wi-Fi APs. These collected data at each point form a bulk of vectors of active Wi-Fi signal strengths with their AP ID, or collect physical Wi-Fi signal strength from multiple channels by each access point to extract more signal characteristics, which is called Channel State Information (CSI) [2]. After collecting data in the offline phase, to recognize the user location in the online phase, a machine-learning model is trained from the processed collected data by applying several types of multiclass classification methods, such as weighted K-nearest neighbor [3], multilayer perceptual algorithm [4], and deep learning [5][6]. Then, the trained model must look up the received signal strength vector to determine the user location by selecting the closest reference point. The advantages of this technique include overcoming the effects of signal fluctuations and improving accuracy over the traditional ranging-based techniques. The most significant disadvantage of this technique is that it is labor-intensive to collect data. This method is seemingly impossible to implement in large areas, such as airports, piers, and squares.

To utilize the advantages of each technique and offset the disadvantages, some studies have proposed a hybrid system [7] or the well-known RADAR system [8] using Wi-Fi AP or virtual Wi-Fi AP locations and measured signal strengths to estimate and form radio maps to reduce labor costs on signal strength data collection efforts; re-optimizing ranging-based techniques using the centroid [9-10], statistical access point selection [11], or least-squared weight average multilateration [12] methods have also been suggested to reduce the limitations from obstacles and signal fluctuation. A prerequisite for these techniques is that a Wi-Fi AP location must be recognizable. A greater number of Wi-Fi APs participating in the positioning process ensures better performance accuracy. In a large or complex area, determining the real location of each Wi-Fi AP requires a lot of effort, which is sometimes impossible owing to location access permission. To conserve time and minimize labor costs, several methods have been proposed to find AP locations, such as the advanced weighted centroid [13], least-square multilateration [14], and the received signal strength indicator (RSSI) distance ratio [15]. Similar to user-equipment positioning techniques, to find a Wi-Fi AP location, a system has to address external problems such as dependency on the signal path loss model, signal strength fluctuations caused by obstacles and propagation effects, and AP antenna gain. These kinds of parameters are difficult to measure or estimate accurately in real environments. The RSSI distance ratio method [15] solves the dependency on the path loss model parameters through a distance ratio model from the signal path loss model by calculating the signal attenuation ratio between two reference points. This method helps remove the signal strength parameter at a distance of 1 m in the path loss model. The weight centroid [13] and multilateration [14] algorithms both deal with signal fluctuations caused by physical obstacles in real indoor environments using multiple signal measurement points to determine the best fit locations of the Wi-Fi APs based on the least-square or centroid method. This approach is based on measurement of the point coordinates and their signal strength values. Although these methods are aimed at compensating the signal strength fluctuations using multiple measurement points, the fluctuation effect still remains a problem that needs to be solved. It is easily realized that the more complex the construction of obstacles is in a real environment, the greater is the fluctuation effect on the measurement quality. As noted above, a greater number of Wi-Fi APs participating in the positioning process ensures better performance accuracy. Therefore in many cases, the requirement to detect the access point location is very urgent, The researcher want to enrich the data collection, but the quantity of access point which was detected in real map is limited, while the user equipment receives multiple signal source from unknown access point around, the solution is utilizing the signal from unknown access points around by detecting their location on real map. By detecting unknown access point location, the data source is enriched for indoor positioning, or helping for generating radio map or calculating wireless propagation model in indoor environment; however, a higher proportion of error signal strength values from the measurement points may result in larger errors in the final computation result. Therefore, it is necessary to evaluate reference point signal strength values that are sufficiently reliable. Based on this optimization requirement, this work proposes new algorithm that has ability to filter the "untrustworthy" measurement points containing large deviations of the signal strength values from being included in the computation task, thereby improving the positioning performance significantly. This paper describes the key insights and design of the proposed node-filtering algorithm (Section 2) and compares its real-world performance with those of the existing methods (Section 3).

II. Indoor Positioning Algorithm

The goal of a positioning system is to determine the location of a target on a map. The AP target position can be determined using its coordinate parameters x_{AP} and y_{AP} on the Euclidean plane. To verify the accuracy of the estimated position of the target with respect to its real location, the Euclidean distance equation is applied. Assuming that the estimated target position is defined by coordinate parameters x_e and y_e, the positioning error d_e can be calculated using Equation (1), which is derived from the Euclidean distance equation [16]:

$$d_e = \sqrt{(x_{AP} - x_e)^2 + (y_{AP} - y_e)^2} \tag{1}$$

The Euclidean distance equation is also used to calculate the distance between two locations on a real geolocation map [16]. To measure the distance from the AP location to a measurement position i having coordinates x_i and y_i, the distance d_i is calculated as shown in Equation (2):

$$d_i = \sqrt{(x_{AP} - x_i)^2 + (y_{AP} - y_i)^2} \tag{2}$$

In other studies that propose methods to determine user equipment locations using the radio propagation model, the convention for the experimental scenario is knowledge of the locations of three or more APs, using which the location of the user equipment is determined algorithmically. Estimating the distance between a known AP and the measurement position is one of the primary tasks because it is helpful before applying any optimization algorithm to improve the accuracy of the result. The popular method for distance estimation in this case uses the path loss model as follows:

$$P_r = P_0 - 10n\log 10(d/d_0) + X_\sigma \quad (3)$$

where P_r is the received signal strength at the measurement point in dB, P_0 is the signal strength at a distance of d from the transmitter, and n is the path loss exponent. X_σ represents the shadow noise caused by random obstacle factors in a real environment. In general, d_0 is set to 1m, and the path loss exponent n depends on the complexity of the environment; d is the distance from the measurement to AP nodes. Suppose that r_i is the Wi-Fi signal strength received at location i; from Equation (3), d can be estimated as d_i, as given in Equation (4).

$$d_i = 10^{(P_0 - r_i)/(10n)} \quad (4)$$

Based on Equations (3) and (4), Equation (5) describes the relationship between the radio signal strength and distance between the AP and measurement nodes on the geolocation map.

$$\sqrt{(x_{AP} - x_i)^2 + (y_{AP} - y_i)^2} \approx 10^{(P_0 - r_i)/(10n)} \quad (5)$$

In the multilateration technique, the signal strength values r_i are received from the k measurement nodes and have coordinates $\{x_i, y_i\}$. Applying Equation (5), after squaring, rearranging the terms, and subtracting the kth equation from the ith equation [17], a multilateration model can be obtained as in Equation (6):

$$\begin{bmatrix} -x_1^2 - y_1^2 + x_k^2 + y_k^2 + 10^{\frac{(P_0 - r_1)}{5n}} - 10^{\frac{(P_0 - r_k)}{5n}} \\ -x_2^2 - y_2^2 + x_k^2 + y_k^2 + 10^{\frac{(P_0 - r_2)}{5n}} - 10^{\frac{(P_0 - r_k)}{5n}} \\ \cdots \\ -x_{k-1}^2 - y_{k-1}^2 + x_k^2 + y_k^2 + 10^{\frac{(P_0 - r_{k-1})}{5n}} - 10^{\frac{(P_0 - r_k)}{5n}} \end{bmatrix} = \begin{bmatrix} -2x_1 + 2x_k & -2y_1 + 2y_k \\ -2x_2 + 2x_k & -2y_2 + 2y_k \\ \vdots & \\ -2x_{k-1} + 2x_k & -2y_{k-1} + 2y_k \end{bmatrix} \begin{bmatrix} x_{AP} \\ y_{AP} \end{bmatrix} \quad (6)$$

The multilateration model can be briefly expressed as $y = X \cdot b$. $b = \{x_{AP}, y_{AP}\}$ is defined as the coordinate of the AP. Equation (6) still depends on the parameter P_0, defined as the signal strength received at a distance of 1m. Therefore, Equation (6) was transformed as in [14] to reduce the dependence on parameter P_0, as shown in Equation (7),

$$\begin{bmatrix} -x_1^2 - y_1^2 + x_k^2 + y_k^2 \\ -x_2^2 - y_2^2 + x_k^2 + y_k^2 \\ \cdots \\ -x_{k-1}^2 - y_{k-1}^2 + x_k^2 + y_k^2 \end{bmatrix} = \begin{bmatrix} -2x_1 + 2x_k & -2y_1 + 2y_k & \frac{a_1(r_1 - r_k)}{5} \\ -2x_2 + 2x_k & -2y_2 + 2y_k & \frac{a_1(r_2 - r_k)}{5} \\ & \vdots & \\ -2x_{k-1} + 2x_k & -2y_{k-1} + 2y_k & \frac{a_1(r_{k-1} - r_k)}{5} \end{bmatrix} \begin{bmatrix} x_{AP} \\ y_{AP} \\ \frac{1}{n} \end{bmatrix} \quad (7)$$

The parameter a_1 in Equation (7) is defined as the linearization coefficient; a_1 can be estimated by linearizing the exponential relationship. Assuming a linearization model $y = ax + b$, the linearization coefficient can be estimated using Equation (8):

$$a = \frac{N\sum(xy) - \sum x \sum y}{N\sum(x) - \sum x^2} \quad (8)$$

The linearization of the exponential relationship could be performed as in Equation (9):

$$10^{(P_0 - r_i)/(10n)} \approx a_1\left(\frac{P_0 - r_i}{10n}\right) + b \quad (9)$$

Applying Equation (8), the coefficient a_1 can be estimated by multiple signal strength values r_i from multiple measurement points. As shown by the experimental result in [14], the accuracy is not affected significantly by the coefficient a_1. Therefore, the required input for computation is the measurement point coordinates on the Euclidean geolocation and received signal strength values. Equation (7) is denoted in the form of $y = X \cdot b$; to estimate b, the least-squares estimation method [18] is applied as in Equation (10).

$$b = (X^T X)^{-1} X^T y \tag{10}$$

The AP location is estimated by calculating $\{x_{AP}, y_{AP}\} = b$. To reduce the shadow noise from complex propagations caused by obstacles, a measurement node-filtering method is proposed in this study. Assuming that N measurement nodes are used in the computation task, each node contains the information of coordinate values $\{x_i, y_i\}$ and the corresponding received signal strength values. The method in [14] is referred to as the multilateration linearization function.

Ⅲ. Measurement node-filtering algorithm

In Figure 1, "A" is a collection of measurement point input values, and $A(i)$ is an element in A. In each $A(i)$, X_i is the X-axis coordinate value and Y_i is the Y-axis coordinate value, with R_i being the signal strength received at coordinate $\{X_i, Y_i\}$. Multiple measurement point parameters, including coordinates and signal strength values are used in this computation. First, the multilateration linearization function computes the AP location coordinates from the input values.

Thereafter, the distance from each measurement node to the AP is computed by two methods, namely the Euclidean method [16] and Path-loss distance method of Equation (4). At each node, the deviation between the distances from the two methods are calculated as the absolute difference between them. By calculating the deviation value from all measured nodes, we got the list of deviation values. The maximum, minimum, and total deviation values are then computed from the list of deviation values, and the measurement node with the highest deviation is temporarily removed from the list of nodes. The remaining nodes are then used in the computation as inputs to the multilateration linearization function, and a new value of the AP location is obtained. To verify whether the new value of the AP coordinate is more accurate or optimal than the one in the previous step, the Euclidean and Path-loss distances are computed again, and the minimum, maximum, and total deviation values are computed. To verify the trustworthiness of each node, the old and new values of the minimum and total deviations are compared. In other studies, the measurement node that has the highest value of the received signal strength was concluded to be the node with the highest accuracy; in other words, the measurement node that is closest to the AP location often receives the highest signal strength and has the least effects from the propagation environment. In contrast, measurement nodes with lower received signal strengths were affected to a higher degree by the propagation environment. Therefore, the nearest measurement point is chosen as the anchor to determine the location of the AP.

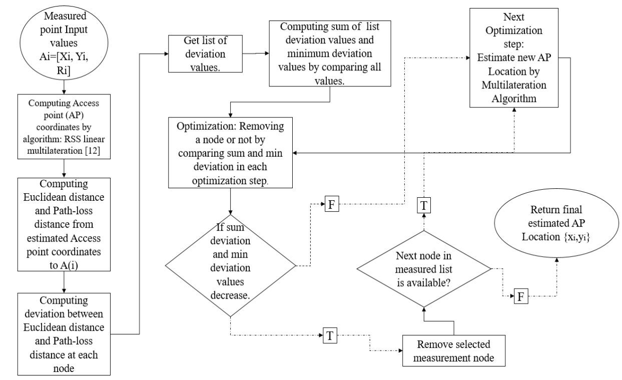


Fig. 1. Measurement node-filter algorithm.

If the new values of the minimum and total deviations are less than their corresponding values in the previous step, the new values of the AP location are considered more optimal. In contrast, if the new AP coordinate values are not more optimal than before, the measurement node that was temporarily removed from the set of inputs is reinstated. In the next step, a measurement node that contains the maximum deviation of the Euclidean and path loss distances but is smaller than the maximum deviation value in the previous step is temporarily removed. The optimality verification for the new result is performed again by comparing the current and last minimum and total distance deviation values. This process is terminated stops when no measurement node remains to be removed or removed temporarily. The final optimized result is also obtained at this point in the process.

Ⅳ. Experiment and Measurement

To verify the above results, we conducted an experiment on the 7th floor of Building. Four Wi-Fi APs in four different positions were chosen for inclusion in the experiment. These four positions were indifferent rooms and under different complex radio propagation conditions. Figure 2 depicts the survey map and the positions of the APs.

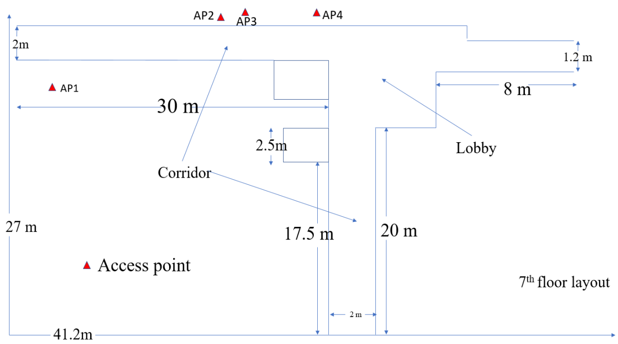


Fig. 2. Building floor layout.

Each measurement node was chosen according to the corridor length and the surrounding lobby square. The space between each pair of measurement nodes ranged from 2 to 2.5 m. To collect data from the experiment, we determined the position of each measurement node as $\{x,y\}$ coordinates based on the dimensions along each direction in units of meters, x value ranges from 0 to 41.2, y value ranges from 0 to 27. Corresponding to each measurement node, we collected the Wi-Fi signal strength value using a self-developed program on an Android smartphone. The program can scan all Wi-Fi APs in its surroundings using their related information, such as the service set identifier (SSID), basic SSID (BSSID), media access control (MAC) address, and signal strength (unit: dB). Each AP has a unique BSSID; therefore, the signal strength values can be determined according to their related BSSIDs in the database. The program has two scanning modes: scanning per touch and non-stop scanning. Owing to fluctuations of the signal during complex propagation, the signal strength data should be collected several times continuously. Then, the signal strength values with the highest appearance proportion were chosen for the computation task. If the signal value set has high diversity and it is difficult to find a signal with a high proportion, then the mean value of each signal is chosen for representation.

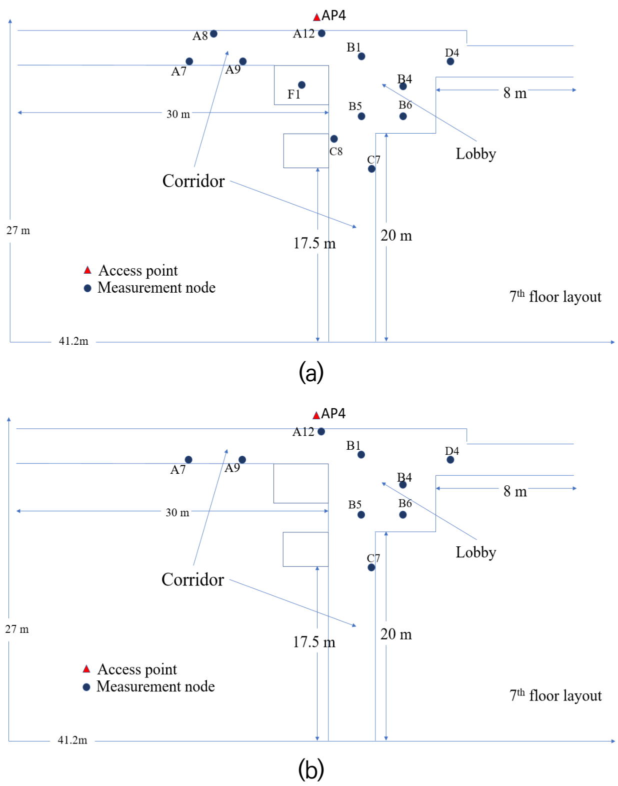


Fig. 3. (a) measured node before optimization
(b) measured node after optimization

When the computation task is complete, the results are optimized by removing several inefficient measurement nodes, as shown in the simulated results of AP4 in Figure 3 below:

In Figure 3, a map of the measurement nodes for AP4 is presented. Before optimization using the measurement node-filter algorithm, a total of 12 measurement points are included in the computation task, as shown in Figure 3a. After optimization, 3 nodes which stay in far from access point or in obstacle position toward access point were removed to optimize the accuracy of the final positioning result, due to the unstable value of RSSI from those measurement node. And the locations of the remaining nodes are as shown in Figure 3b.

To verify the performance of the proposed algorithm, we conducted experiments, collected data, and processed the data using the node-filtering algorithm, as well as other existing algorithms, such as the multilateration linearization, improved weighted centroid, and RSSI distance ratio, for performance comparisons.

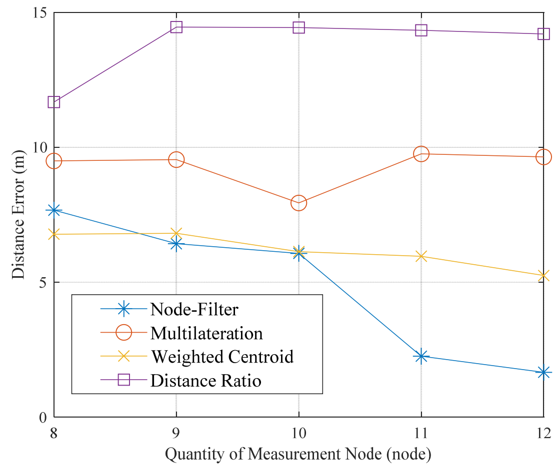
Each algorithm was processed on the given dataset to determine the final results as the estimated coordinates of the APs. By comparing the real coordinates of the APs, we obtained the error distances between the real and estimated results, asshown in Table 1, summary and compare the distance error.

Table 1. Distance error comparisons. (unit: meter)

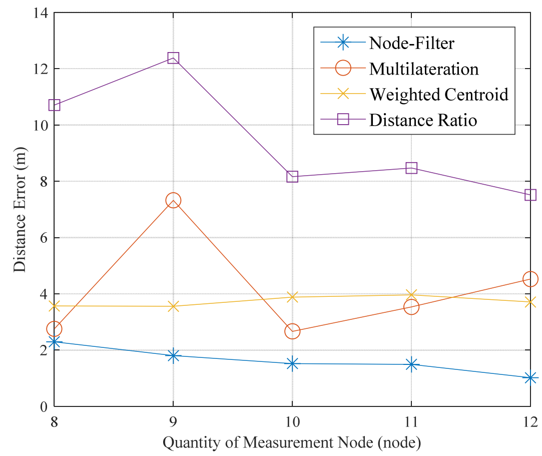
	AP1	AP2	AP3	AP4
Node filter	0.92	0.38	1.66	1.02
Multilateration	11.42	5.46	9.64	4.52
Weighted centroid	3.90	1.85	5.25	3.71
Distance ratio	6.89	2.48	14.20	7.52

As shown in the experimental results in Table 1, the error distance of the node-filtering method is lower than those of the other algorithms at all target APs, while the other methods return higher error distances and higher instability of accuracy.

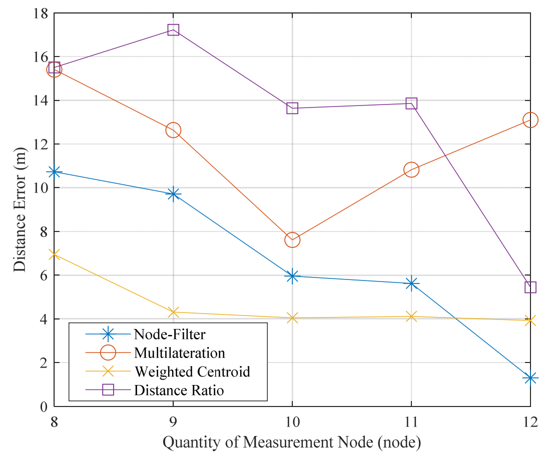
The node-filtering method is thus superior in terms of accuracy and stability improvement over the previous methods.



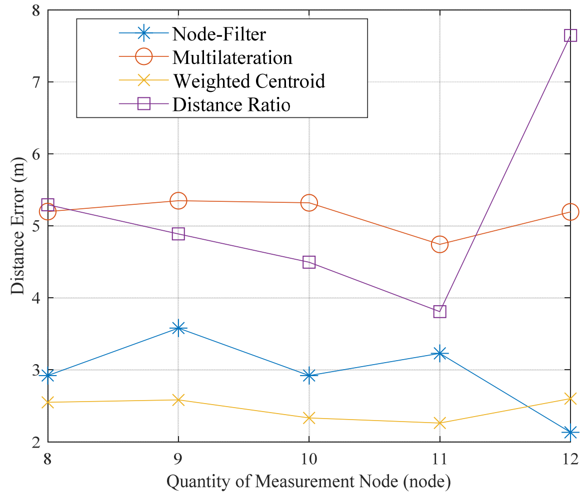
(a)



(b)



(c)



(d)

Fig. 4. Algorithm performance by measurement node quantity (a) AP1 (b) AP2 (c) AP3 (d) AP4.

The performance of the proposed algorithm is compared with those of the other algorithms through the calculated deviation values for different cases with different measurement node quantities. This performance result is shown in Figure 4.

The results shown in Figure 4 indicate that as more measurement nodes are used in the computation task, the performance of the proposed algorithm is improved. The starting number of the measurement nodes is eight to ensure that the proposed algorithm has sufficient number of inputs for selection and optimization. In four cases with four APs, along with an increase in the number of measurement nodes, the weighted centroid algorithm often showed the most stable performance with low distance errors, while the multilateration and distance ratio algorithms had higher distance errors during the experiments. Our proposed algorithm is thus more desirable than the improved multilateration algorithm; therefore, the performance of the proposed algorithm is affected by the performance of the multilateration approach when the number of measurement nodes is lower than necessary or insufficient. Specifically, in the case of AP4 results shown in Figure 4d, the positioning performance with eight nodes in-stead of 11 nodes is worse than that of the weighted centroid method, and the distance error result fluctuates; however, when the node quantity reaches 12, the performance of the proposed algorithm overcomes that of the weighted centroid. By observing other cases from AP1 to AP3 in Figures 4a, 4b, and 4c, the performance of the weighted centroid is stable; however, when it reaches a saturation value, the ability to obtain more optimized results is low. In contrast, the performance of our proposed algorithm has room for be optimization when an additional measurement node is available.

Ⅴ. Conclusion

This paper presents a new method called the node-filtering algorithm and its performance evaluations. The node-filtering approach is based on evaluating the trust-worthiness of the signal strength quality of each measurement node. Then, nodes that affect the accuracy of the entire computation system are removed by comparing the error distances, which are calculated as the differences between the Euclidean and path loss distances from the measurement nodes to the estimated AP locations; this error computation task is iterated until the minimum value of the error distance between the two methods is obtained. As more data from more reference points are included in the computation task, higher performance results may be achieved.

In the future, this method can be improved in several ways: retaining the untrustworthy measurement nodes but calibrating their weights in the computation task, retaining the untrustworthy points and reducing labor-cost to obtain more data from more measurement nodes, or combining the node-filtering method with other methods, such as the weighted centroid and RADAR. Node-filtering is therefore a method that helps evaluate the reliability of each measurement node; hence, we can combine the node-filtering method with any of the other types of positioning methods to obtain better performance of the positioning system.

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