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Indoor Positioning Technique applying new RSSI Correction method optimized by Genetic Algorithm

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Abstract

In this paper, we propose a new algorithm to improve the accuracy of indoor positioning techniques using Wi-Fi access points as beacon nodes. The proposed algorithm is based on the Weighted Centroid algorithm, a popular method widely used for indoor positioning, however, it improves some disadvantages of the Weighted Centroid method and also for other kinds of indoor positioning methods, by using the received signal strength correction method and genetic algorithm to prevent the signal strength fluctuation phenomenon, which is caused by the complex propagation environment. To validate the performance of the proposed algorithm, we conducted experiments in a complex indoor environment, and collect a list of Wi-Fi signal strength data from several access points around the standing user location. By utilizing this kind of algorithm, we can obtain a high accuracy positioning system, which can be used in any building environment with an available Wi-Fi access point setup as a beacon node.

Key words : indoor positioning; Wi-Fi signal strength; weighted centroid; RSSI correction, genetic algorithm

Ⅰ. Introduction

Indoor positioning technique is concerned in many research fields such as geosciences, computer sciences, wireless communications, and mobile computing because of their wide impact and applications. For years, research and innovations in this area are invested and developed continuously. Global positioning systems (GPSs) technology supports human activities in positioning and navigation for aerospace, marine, traffic vehicle, and general human location utilities. Although many systems or applications today rely on GPS for positioning utilities, they cannot receive satellite signals when transmitted to receiver equipment deployed in an indoor environment, resulting in inaccurate positioning results. Therefore, indoor positioning technology is being proposed as a possible solution to this problem.

Many indoor positioning algorithms or methods have been researched and developed. While GPS signals have signal attenuation problems in indoor environments, indoor positioning also has its problems in indoor environments, causing

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inaccuracies. The problem mainly comes from fluctuations in the received signal. There are several reasons for this to be caused by a third factor: unstable or poor quality of the signal receiver sensor of your equipment, unstable power of the signal transmitter beacon, or a complex propagation environment.

Many studies spent time and workforce to develop the method to improve the limitation of indoor positioning techniques. Some studies focused on improving hardware and data quality. For several methods such as: improving antennas performance [1], applying frequency selective surface for indoor positioning [2], or implementing FPGA for indoor positioning [3]. Other teams approached the method of enriching the data source to enhance the prediction ability of the system, such as the techniques: CSI technique [4], utilizing magnetic data map for indoor positioning [5] and ultrasonic application [6]. Different from the above approach, in this study, we approach the method which helps improve the limitation of indoor positioning, but the cost for equipment investment or data collection workforce is saved. Firstly, we choose a Wi-Fi access point to be the beacon node for collecting the signal, due to its availability in an indoor building for the experiment. Using Wi-Fi signal for indoor positioning system is the most popular method for most indoor positioning systems nowadays due to its advantage mentioned above. Besides the advantages of Wi-Fi signal application in positioning such as the availability and cost-efficient implementation, the most significant disadvantage of Wi-Fi signal is the instability and noise interference characteristics from propagation environment, Therefore, multiple type of researche were deployed to find out how to optimize the accuracy of a positioning system using Wi-Fi signal as the material. a well-known method RADAR was developed and referred to by many other studies later in the research in [7], this method uses the nearest neighbor method combined with the Wi-Fi signal propagation model to estimate the user location. To make the Wi-Fi signal strength series to be smooth or eliminate noise from the signal, a Kalman Filter is applied in [8]. Horus [9] is introduced to be a lightweight method that is based on probabilistic techniques and suitable for implementation in energy-constrained devices. Another approach that is energy consuming but provides high precision of positioning performance is SpotFi [10], this method utilized high resolution data from scanning the channel state information of the Wi-Fi access point signal spectrum, this kind of data is extracted directly from the device hardware. Another method that also directly accessed or modified hardware is ArrayTrack, introduced in [11]. This method was implemented by multiple antenna array design and collecting signal strength, arrival angle data from multiple antennas then finding out the user location by the angle of arrival method.

Other kinds of beacon nodes like: Ultra-Wideband [12] or Bluetooth Low Energy [13] require hardware investment. The method applied in this study is developed from a popular method named: Weighted Centroid [14]. The basic idea of the Weighted Centroid method is calculating the user location by getting the signal strength data from beacon nodes around, then based on beacon node's position and signal strength value. The position of each beacon node has been known, the signal strength data help estimate the distance from the user location to each beacon node, then the user location will be estimated by the Weighted Centroid method proposed in [14].

This method can utilize data from all signal sources around to find out the current user equipment, moreover, this method does not require the step of data collection like the radio fingerprint method to predict the user location [15]. The step of data collection requires time and workforce for collecting data in each point of location on a real map, however, in a large area, we cannot take a survey in any restricted area. Although the radio fingerprint based method is considered to be more accurate recently, all the limitations above are still a problem, then the Weighted Centroid method is a proper solution for improvement.

Despite the advantages of the Weighted Centroid method, there are some limitations to this method. Weighted Centroid depends much on collected signal strength data to calculate the distance from user location to beacon node or compute the weight of detected beacon node when joining in positioning task. As usual, the unstable quality of the signal and the effect of the complex propagation environment make the result to be inaccurate. Other studies proposed several methods for correcting signal strength value, such as anchor optimized modified weighted centroid algorithm [16], RSSI Real-time correction [17], Difference Correction RSSI Location Algorithm of Double Reference Nodes [18]. In this study, we also proposed our own signal strength correction method developed from Weight Centroid and the path-loss model. By signal strength correction algorithm, the system might recognize which beacon node's signal should be correct. The signal strength correction method helps calculate the offset to correct the value of signal strength from a beacon. However, other RSSI correction methods only calibrate the RSSI value of the beacon node by directly adding or subtracting the offset value from the RSSI value. It's hard to say that the calculated offset value has high accuracy for all cases, we need one more process for optimizing the result. In this study, to optimize the result for improvement of positioning performance, we proposed a genetic algorithm as the optimization method to find out the most proper offset value from the signal strength offset range was calculated.

II. Indoor Positioning Algorithm

One of the pioneer algorithms applied in the indoor positioning technique is Weighted Centroid, besides other kinds of algorithms such as Trilateration and Radio Fingerprint method. As mentioned above, each kind of algorithm has its pros and cons. However, they still play a role as the ground for further development of indoor positioning research. Due to the simplicity and easy to implement characteristics but the performance is still ensured, we continue to choose the Weighted Centroid algorithm for development.

In general scenario, in a building environment, there are several Wi-Fi access point setup in multiple areas. Utilizing Wi-Fi signal is an economical solution. Not only by the availability of Wi-Fi access point, but also the WLAN connection ability of consumer electronics products. When a user need support from indoor positioning system, he/she just need personal communication device like smartphone, pad, or notebook. Wi-Fi signal strength data would be connect by the device and send to the system for computing. Based on the coordinates of every beacon node setup on real map was record on the system, combine to received signal strength data, user coordinates result would be return to the user.

Assume the user location coordinates is $\{x,y\}$, the result from Weighted Centroid algorithm can be estimate by equation (1) and (2)

$$x=\frac{\sum_{i=1}^{n}\frac{1}{\left[\frac{d_i}{\sum_{i=1}^{n}d_i-d_i}\right]^2}x_{AP_i}}{\sum_{i=1}^{n}\frac{1}{\left[\frac{d_i}{\sum_{i=1}^{n}d_i-d_i}\right]^2}} \tag{1}$$

$$y=\frac{\sum_{i=1}^{n}\frac{1}{\left[\frac{d_i}{\sum_{i=1}^{n}d_i-d_i}\right]^2}y_{AP_i}}{\sum_{i=1}^{n}\frac{1}{\left[\frac{d_i}{\sum_{i=1}^{n}d_i-d_i}\right]^2}} \tag{2}$$

n is total number of beacon node, i is the sequence of each beacon node. $\{x_{AP_i}, y_{AP_i}\}$ is coordinates of beacon node i on the real map, which was recorded on the system. d_i is the distance from user equipment to beacon node by using path-loss model, based on received signal strength value, follow equation (3)

$$d_i = 10^{(P_0 - r_i)/(10n)} \tag{3}$$

In equation (3), n is the path-loss exponent, in this study we set $n = 3.2$. P_0 is signal strength at the distance 1 meter from beacon node, r_i is signal strength collected from beacon node i.

In real indoor environment, there are many factor which can affect the accuracy of received signal strength. They are the obstacles like wall, door or other building construction, that cause the reflex or attenuation effect for received signal. This is the reason why the distance estimate from user location to beacon node location by path-loss model is just relative result. Recently, there are more superior method like ToA using Ultra-Wideband technology [19] that provide more credible result, however, this method require investment of new kind of equipment and there are some kinds of device in old version are not supported by this technology. To deal with this problem, we choose the solution to correct the received signal strength, called RSSI correction. Every step of RSSI correction method is described in Algorithm I below.

<u>Algorithm I: RSSI Correction</u>

① Assume there are N beacon nodes scanned by user equipment, evaluating the accuracy of a beacon node i ($i = 0 \rightarrow N$) in list of scanned beacon node.

② Temporarily remove beacon node i from beacon node list when executing Weighted Centroid computation task, a temporary user location is calculated from Weighted Centroid computation.

③ Estimate the distance from estimated user location to beacon node location by two methods: path-loss model in equation (3). And estimating Euclid distance in equation (4) below.

$$d_i = \sqrt{(x_{AP_i} - x_i)^2 + (y_{AP_i} - y_i)^2} \tag{4}$$

in equation (4), $\{x_{AP_i}, y_{AP_i}\}$ is the coordinates beacon node i, $\{x_i, y_i\}$ is coordinates of temporary estimated user location from step ②.

④ In this step, the range of offset value (RC) for RSSI correction is calculated by equation (5) below

$$RC = 10n\log_{10}\frac{d_1}{d_2} \tag{5}$$

To demonstrate equation (5), from equation (3): $d_1 = 10^{(P_0 - r_i)/(10n)}$, and equation (4): $d_2 = \sqrt{(x_{AP_i} - x_i)^2 + (y_{AP_i} - y_i)^2}$, from the deviation between d_1 and d_2, we need to calculate an offset value from range RC for correcting r_i to make the value of d_2 and d_1 to be equal approximately, for the ideal condition $d_2 = \sqrt{(x_{AP_i} - x_i)^2 + (y_{AP_i} - y_i)^2} \approx 10^{(P_0 - r_i)/(10n)}$. We rewrite Euclid distance d_2 following path-loss model, set the new signal strength value to be r_j: $d_2 = 10^{(P_0 - r_j)/(10n)}$. The deviation between d_1 and d_2 is calculated below

$$d_2 - d_1 = 10^{(P_0 - r_j)/(10n)} - 10^{(P_0 - r_i)/(10n)} \tag{6}$$

The equation (3) can be rewritten into logarithm formula

$$\log_{10}d_1 = \frac{P_0 - r_i}{(10n)} \tag{7}$$

$$\log_{10}d_2 = \frac{P_0 - r_j}{(10n)} \tag{8}$$

Following logarithm theory, we take equation subtraction: (7)~(8), then we have

$$10n\log_{10}\frac{d_1}{d_2} = r_j - r_i = RC \tag{9}$$

The difference between r_i and r_j (RC) was estimated by equation (9), where d_1 and d_2 were known.

⑤ The difference between r_i and r_j is the offset range for RSSI correction. Each beacon node i has its own offset range (RC_i). A collection of RC_i will be used for the optimization process by a Genetic Algorithm. The optimization task by Genetic Algorithm is depicted in Algorithm II below.

<u>Algorithm II: Genetic Algorithm Optimization</u>

① From the RSSI Correction process in Algorithm I, a collection of offset values for each beacon node is established.

② Initial population: firstly, set up the population number. In this study, we set up the population number is 100. To initial the population for each quantity, an offset value would be divided into quantity numbers.
For example, assume an offset value is O, quantity number is Q, the RSSI value would be calibrated by subtracting by a step number which is calculated by

$$S = O/Q \tag{10}$$

The value of RSSI will be calibrated by the increasing of S

$$S = S + O/Q \tag{11}$$

For clearer detail, the value of S increases Q times, until $S = O$. Assuming $Q = 100$, every time S increases its value, a new value of RSSI is generated by subtracting RSSI to S There are 8 access points joined in the positioning task in the experiment in this study as the beacon nodes. With the value of $Q = 100$, there are 100 individuals, each individual is a collection of RSSI values from eight beacon nodes, which means each individual contains eight genes.
Assume individual $A = [a_1, a_2, a_3, a_4, a_5, a_6, a_7, a_8]$, each element in A is an RSSI value from beacon node 1 to beacon node 8. For example, a_1 is the RSSI value for beacon node 1. Value of a_1 will stay in range from collected RSSI value to RSSI-O.

③ Evaluation fitness: we propose the standard to evaluate the fitness of an individual based on the convergence of positioning results. The convergence computing process will be presented in Algorithm III.

④ Selection: After step ③, any individual who contains a higher convergence point is kept. On the contrary, any individual who contains a lower convergence point is removed.

⑤ Crossover: from the selected individuals in the Selection step, select randomly a pair of individuals and execute the crossover task. There are eight genes in an individual, we execute crossover from gene at position 4th. For example, select two individual A and B. Assume $A = [a_1, a_2, a_3, a_4, a_5, a_6, a_7, a_8]$, $B = [b_1, b_2, b_3, b_4, b_5, b_6, b_7, b_8]$. The elements in array A is genes collection for individual A, and similar to individual B, the elements in array B is genes collection for individual B.

Before Crossover

$$A = [a_1, a_2, a_3, a_4, a_5, a_6, a_7, a_8]$$
$$B = [b_1, b_2, b_3, b_4, b_5, b_6, b_7, b_8]$$

After Crossover

$$A = [a_1, a_2, a_3, a_4, b_5, b_6, b_7, b_8]$$
$$B = [b_1, b_2, b_3, b_4, a_5, a_6, a_7, a_8]$$

⑥ Mutation: an element (gen) in an individual will be mutated to be a new value to generate a new individual. The New individuals in a new generation would be evaluated how fitness it is by a repeat of step ③. If the result of convergence for an individual is higher than the old generation, it could be kept, on the contrary, that individual may be removed.

Before Mutation

$$A=[a_1,a_2,a_3,a_4,b_5,\boxed{b_6},b_7,b_8]$$

After Mutation at gene 6^{th}

$$A=[a_1,a_2,a_3,a_4,b_5,\boxed{c},b_7,b_8]$$

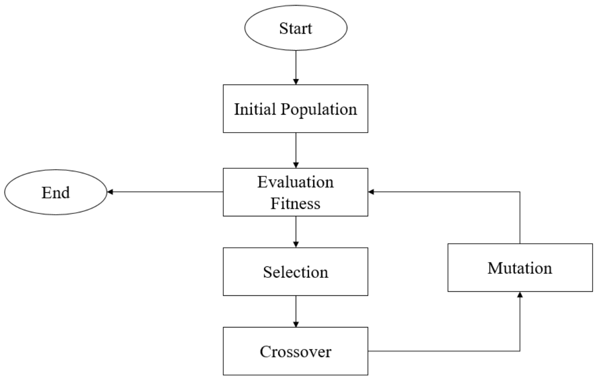


Fig. 1. Genetic Algorithm.

Algorithm III: Evaluation Fitness

This step is the evaluation of the fitness step for the genetic algorithm in Algorithm II, by evaluating the convergence of user location L.

① For an individual $A=[a_1,a_2,a_3,a_4,a_5,a_6,a_7,a_8]$, each element is an RSSI value from beacon nodes, calibrated by offset value calculated in Algorithm I.

② Similar to Algorithm I, we will temporarily remove each value of RSSI from each beacon node then execute the positioning task by Weighted Centroid Algorithm. There are 8 beacon nodes, we will temporarily remove the beacon nodes one by one then the positioning task would return eight results of user location. We call the collection of user location result is $L=[l_1,l_2,l_3,l_4,l_5,l_6,l_7,l_8]$, element in array L is user location result from each positioning task, contains value $\{x,y\}$ is the coordinates values of user location.

③ Computing Euclid distance from each element to others. The sum of Euclid distance from one user location point to others is considered to be the convergence evaluation point in next step.
For example: in collection L, calculate Euclid distance from l_1 to $l_2,l_3,l_4,l_5,l_6,l_7,l_8$, then calculate the sum of all Euclid distance value, return value s_1.
This process loops for all next elements from l_2 to l_8. Then we get the collection of Euclid distance sum $S=[s_1,s_2,s_3,s_4,s_5,s_6,s_7,s_8]$.

④ Select the minimum value from collection S. The selected value is considered to be the convergence evaluation point, also to be the standard for evaluation fitness. If the selected value from S is smaller, the convergence evaluation point is higher, and the evaluation fitness is higher, so that the individual in Algorithm II is a higher ability to be kept for the next generation.
The reason for applying this method for fitness evaluation is based on the convergence of user location results. If the value of all the offset is selected or calibrated more properly, all of the user location results should be more concentrated, and the ideal case happens when after calibration, all of the user location results become consolidated in one location.
The final result is calculated by getting the centroid result F between all user location results. Assume that N user location results contained coordinate values $\{x_i,y_i\}$, i is in a range from 1 to N (N is the quantity of user location result following the quantity of measured beacon node), the final centroid F value is calculated by

$$X_{final}=\frac{\sum_{i=1}^{N}x_i}{N} \qquad (12)$$

$$Y_{final}=\frac{\sum_{i=1}^{N}y_i}{N}$$

$F=\{X_{final},Y_{final}\}$ is the final result for user location estimation. Therefore, the accuracy and trustworthy of final result is based on the convergence of estimated user location result in each sub process. The higher convergence of user location result, the higher accuracy location result achieved.

Ⅲ. Experiment and Measurement

For the experiment scenario, we execute our experiment in floor 7th of building 8, Kongju National University in Cheonan Campus, Republic of Korea.

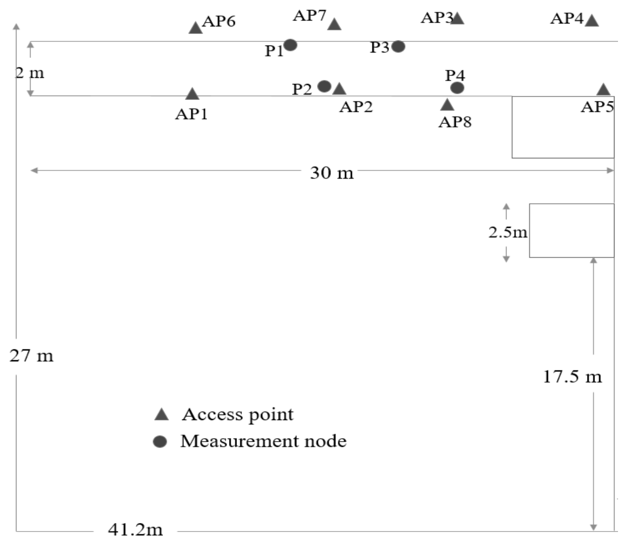
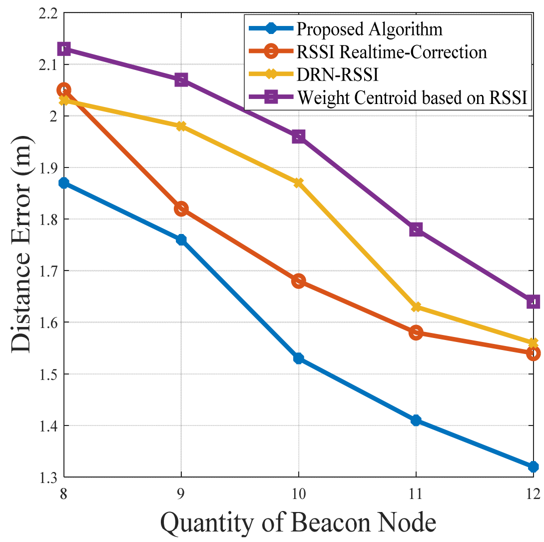


Fig. 2. Experiment Scenario.

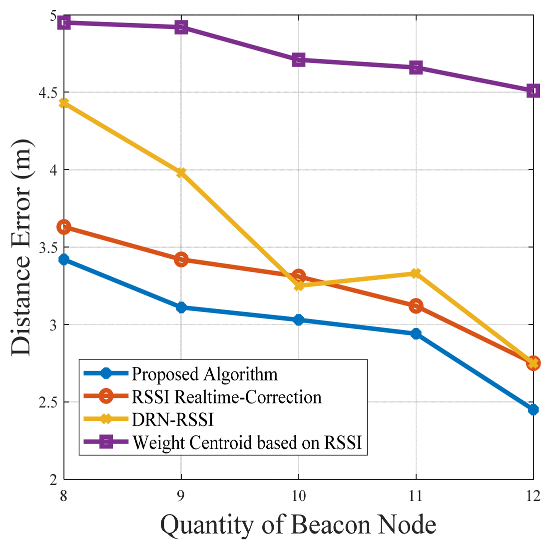
In Figure 2, we utilize eight access point along the corridor as the beacon nodes, then the user brings a wireless signal receiver equipment, such as smartphone for collecting and processing Wi-Fi signal from eight beacon nodes around. As depiction in Figure 3, the dimension of floor layout is 27 meters × 41.2 meters. The coordinates of every point on map are based on the real map dimension. In detail, the map coordinates layout follow {x, y} coordinates system, with X-axis ranges from 0 to 41.2, and Y-axis ranges from 0 to 27.

We measure Wi-Fi signal in 4 measurement points from P1 to P4. The signal strength data is collect, analyzed and processed to estimate user location by 4 algorithm for comparing the performance. In this experiment, other RSSI corrections algorithms from other research project [11], [12], [13] are executed concurrently and evaluated the performance compare with our proposed algorithm performance.

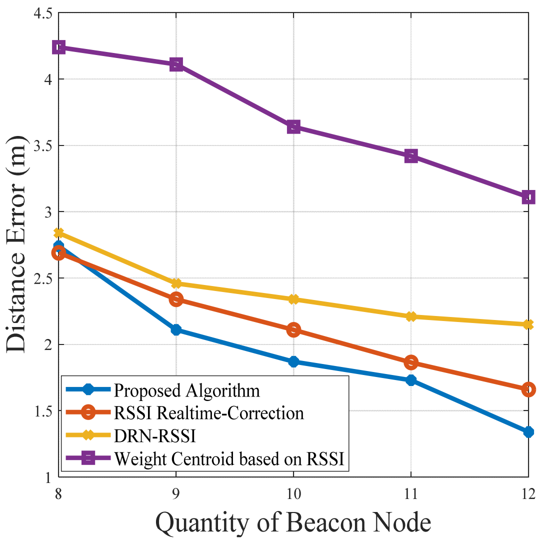
We comparing performance between four RSSI correction algorithms by increasing the quantity of beacon nodes. The least quantity of beacon nodes is 4, the least number of beacon node which is necessary for positioning in any case, then the quantity of beacon nodes increases to 8. Figure 3 below is the performance of four algorithms in four measurement point:



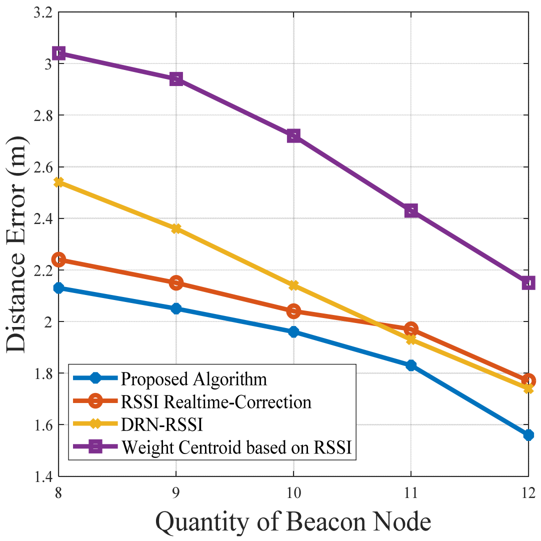
(a)



(b)



(c)



(d)

Fig. 3. Algorithm performance in (a) Position P1; (b) Position P2; (c) Position P3; (d) Position P4.

Through four measurement points and along the increasing of beacon node quantity, Figure 4 shows the result of positioning performance by comparing the distance error, this parameter is calculated based on the distance between the final estimated user location result to the real user location on the real map. The smaller distance error proves the higher performance of the algorithm. As Figure 3 pointed out, the distance error calculated from my algorithm lower than distance error results estimated by other RSSI Correction algorithm.

In this study, the optimization like genetic algorithm is also applied for optimizing the accuracy of final result, therefore accuracy or the performance of research method also depends on the optimization algorithm. To verify the accuracy of genetic algorithm, we evaluating the performance by increasing the generation parameter in genetic algorithm. Figure 4 below depicts the algorithm performance along the increasing of generation number. The distance error decreases along the increasing of generation in genetic algorithm. That means the performance of proposed algorithm improved based on the generation quantity of genetic algorithm. However, the performance reach the saturation point at 1500 generation, from this point, the performance is not improved significantly along the generation increasing.

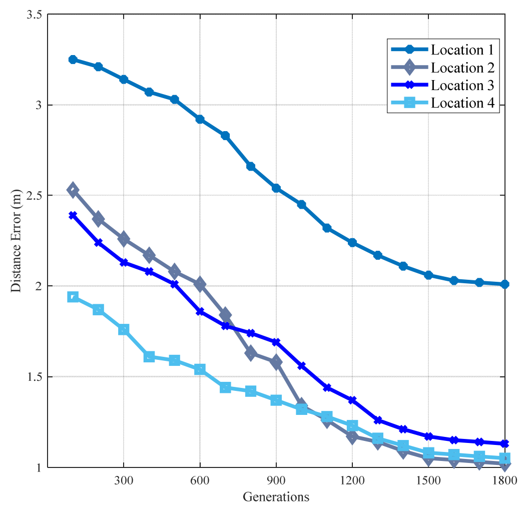


Fig. 4. Proposed algorithm performance through increasing of generation quantity in genetic algorithm.

Ⅳ. Conclusion

This paper presents a new RSSI correction method and its performance evaluations. The RSSI correction 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 re-corrected RSSI value by our developed RSSI correction algorithm, which are calculated by isolated each beacon node in each positioning task and evaluating the accuracy of RSSI value from beacon node by calculating the deviation between Euclid and path-loss distance, finally applying genetic algorithm for optimizing the result. As more data from more reference points, or more optimization task like generation in genetic algorithm executed in the computation task, higher performance results may be achieved.

In the future, this method can be improved in several approaching ways: optimizing RSSI correction methods by other optimization algorithm, such as Particle Swarm Optimization, or create other method for choosing a population and making standard for fitness evaluation in genetic algorithm, they are two most important factor for a good performance genetic algorithm model. Further study also consider about integrating new method to evaluate the performance, stability or trustworthy from any signal source or beacon node. Any poor signal source need to be identified and evaluate its role or decrease its weight in positioning task, for the purpose to decrease the bad affect from any untrustworthy signal source. Other kind of research approaching is utilizing the user movement tracking data combine with the deviation of RSSI data collected from user equipment for generating Wi-Fi map passively. These new approaching method also utilizes the collected RSSI data from user for statistical analysis, makes the system more adaptable and intelligent.

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