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近傍携帯端末群によるばねモデルを用いた協調的屋内位置推定手法の提案

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概要：近年，Wi-Fi モジュールを搭載した高性能携帯端末の普及に伴い，Wi-Fi 電波を用いた屋内位置推定に関する研究が多く行われている．多くの既存研究では，屋内の各座標において予め計測した Wi-Fi 信号強度の分布情報を用いるフィンガープリンティングと呼ばれる手法により，携帯端末の屋内位置を推定する．本研究では，既存手法を基に，近傍に存在する端末群が協調しながら，より高精度に屋内位置を推定する方法を提案する．具体的には，携帯端末に搭載された Wi-Fi と Bluetooth センサを用いて推定されたそれぞれの端末の位置と距離関係の辻褄が合うように、ばねモデルを用いて推定位置を修正する．また，実環境での実験を行い，提案手法の有効性を検証した．

キーワード：屋内位置推定, Wi-Fi 信号強度, フィンガープリンティング, 近傍携帯端末, ばねモデル, 協調的位置推定

Spring Model based Collaborative Indoor Position Estimation with Neighbor Mobile Terminals

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Abstract: Nowadays, as the widespread of smart-phones that equipped with Wi-Fi modules, many researches have studied Wi-Fi based indoor positioning techniques. The existing method makes use of the Wi-Fi received signal strength (RSS) information that collected from several places indoors in advance to estimate the position of mobile device by referring to a fingerprinting algorithm. Base on the existing method above, this paper addresses a high-precision indoor positioning method by coordinating the neighbor mobile terminals. we estimate the position coordinates and distance information of the mobile terminals by using the Wi-Fi and Bluetooth sensors on them. Then, referred to these position and distance information, we utilize the spring model to adjust the estimated positions. In addition, we also performed the evaluation experiment in the real indoor environment, and the feasibility of our proposed method was well proved.

Keywords: Indoor Positioning, RSS, Fingerprinting, Neighbor mobile terminal, Spring model, Collaborative positioning

1. Introduction

Indoor positioning systems (IPSs) have become very popular in recent years. These systems provide a service called automatic object location detection and there are many real-world applications that employ the techniques. For example, product management can consider the locations of products stored in a warehouse, visitors can receive background information about the exhibit they are viewing in a museum, the firemen can know their location in a building on fire to save the people quickly, and emergency medical personnels can locate critical patients or equipments. Given accurate and reliable location information can help people know their positions and where to

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go next.

The widespread proliferation of 802.11x wireless LAN (WLAN) as a common network infrastructure enables Wi-Fi based localization with few additional hardware costs, and has generated commercial and research interest in statistical methods to track people and things. Inside warehouse, museum and hospital, where Global Positioning System devices generally cannot work, IPSs aim to provide location estimates for wireless devices such as smart-phones, laptop computers and handheld digital devices. The Wi-Fi Internet access in stores, hotels, airports, schools, and homes generates Wi-Fi signals which can be used to locate mobile terminals in IPSs.

The existing Wi-Fi based IPSs perform position estimation by using Wi-Fi received signal strength (RSS). There are two main categories of Wi-Fi RSS based techniques for indoor position estimation in WLAN environment [1]. One way called trilateration approach is to use a signal propagation model of Wi-Fi signal and the information of the geometry of the building to convert RSS to a distance measurement. However, this method may be affected by the penetration losses through obstacles, and the multi-path propagation, reflection easily in the condition of an indoor environment. The other way is called fingerprinting, which estimates the position of mobile device with the preset database of position fingerprints that formed by the Wi-Fi RSS features at several reference positions [2].

In general, the IPSs based on fingerprinting techniques can be divided into two phases: training phase and positioning phase [3]. In the training phase, the system builds a location fingerprint database which consists of RSS patterns collected in several reference points (RPs) from multiple Wi-Fi access points (APs) indoors. Then, in the positioning phase, a mobile device measures the RSS sample at target place and sends it to system. The system uses an appropriate matching method (such as nearest neighbor algorithm, Bayesian classifier [4] or other methods) to estimate the position of the mobile device referring to the location fingerprint database of the reference points mentioned above and reports the estimated result back to the mobile device.

However, Wi-Fi RSS based IPSs are much reliant on the condition of the indoor environment. The change of layout, people's movement and electromagnetic interference may affect the final positioning accuracy. Importing some high precision sensor such like ultrasonic tag may be able to solve the problem above, but the deployment cost is too much [5]. Here, [6] brings us some inspirations. That research provides a cooperative position estimation, which is to leverage the variance in positioning accuracies among nodes within a people cluster. The key issue of that method is to identify neighbor nodes with high positioning accuracy, and use their estimated position information to help localize the target nodes with lower positioning accuracy. It consists of 3 major modules: 1) Neighborhood Detection identifies nearby mobile nodes as possible candidates for collaborative positioning; 2) Confidence Estimation computes the confidence score of the position estimation given by the existing Wi-Fi based IPSs; 3) Collaborative Error Correction adjusts the estimated position of the target node by using the neighbor nodes with higher confidence scores in the same cluster. The neighbor nodes with high positioning confidence perform like a magnet with strong magnetic charge and pull the target node which acting as a nail from its original position toward their positions.

Then, based on the related method mentioned above, we intend to address a collaborative positioning method by using not only the estimated positions of the neighbor mobile devices, but also their distance relationship between each other. With our proposed method, we are able to correct the estimated position with low confidence and improve the location accuracy without considering the factors of indoor layout changes and people's affection.

2. Design and Implementation of Proposed Method

2.1 Outline of proposed system

Fig. 1 shows the design of our system structure. In this research, there are some Wi-Fi access points installed indoor in advance. The client is mobile device (MD) such as smart-phone currently, and it continuously obtain the received signal strength (RSS) data from each Wi-Fi access point (AP) at the current place. The Bluetooth sensor on the MD also collects the signal strength (SS) of Bluetooth from the other MDs real-time. All of the information mentioned above will be sent to the server or the master of MDs, which deals with this information in 2 different processes.

One process is shown in the left side of Fig. 1. Referred to the existing Wi-Fi based indoor positioning algorithm, the system estimates the current position of each MD with its RSS data that collected just recently. We estimate how much accurate the estimated position is, i.e., how the estimated position is close to the actual position, and then

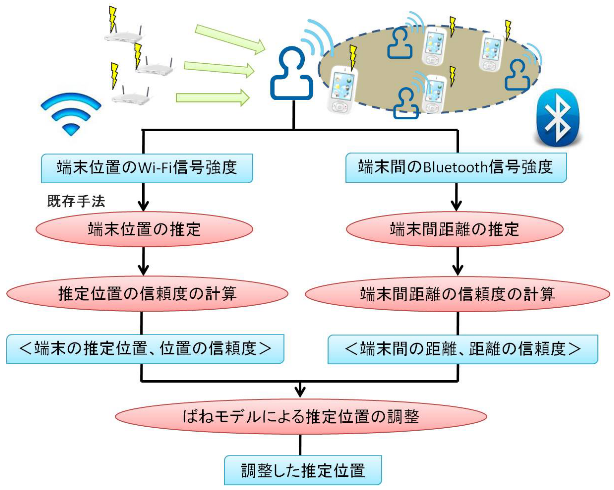

図 1 提案システムの概要
Fig. 1 Outline of proposed method

we determine which MD's position should be corrected with this information. However, as the system does not know the actual position in advance, it shall evaluate the confidence of every estimated position. The confidence evaluation measures the probability of the estimated position whether it being close to its true position. In other words, a high / low confidence score implies that the estimated position has a high / low probability of being the actual position. The output of the left side process is a set of pairs of estimated position of the xth MD and its confidence score ($< Pos(x), Conf_P(x) >$) for every MD.

The other process shown in the right side of Fig. 1 is to estimate the distances between a target MD and the other ones. This time, the system utilizes the characteristic of Bluetooth signal attenuation to estimate the probable distance between two MDs. Then, as the Bluetooth signal propagation will be affected by the blocks such as walls, furniture, and the effect of multi-path propagation, or reflection problems, the estimated distance may have a big error. So, after the distance estimation, we evaluate the confidence of the estimated distance. Just like the left side process, the right side process will also output a set of pair of the estimated distance between 2 MDs and its confidence score ($< Dis(x,y), Conf_D(x,y) >$).

Finally, the data pairs of the position, distance and their confidence score will be input into the spring model, which will be discussed in the Section 3.5. The spring model synthesizes all the information related to the position, distance and their confidence, and then adjusts every mobile node's position in order to improve the positioning accuracy. When the spring model achieves the balanced state, the system outputs the adjusted position as the final estimated position of each mobile node.

In the following sections, we will introduce the position estimation process, distance estimation process and the final collaborative error correction process in detail.

2.2 Wi-Fi based position estimation

2.2.1 Position estimation with existing method

The existing Wi-Fi based indoor positioning method is based on the deployment of location fingerprinting techniques and it utilizes Wi-Fi received signal strength (RSS) information to estimate the position of a target mobile terminal in 2 phases. They are the off-line training phase and the on-line estimation phase.

In the off-line training phase, we should obtain the layout map of the indoor environment and install some Wi-Fi access points (APs) in the appropriate place as to coverage all the rooms. Then, a large number of reference points (RPs) should be set up, where we will collect the Wi-Fi RSS information from APs. The number of the RPs affects the positioning accuracy [7]. This is easy to understand. If there are only few RPs set indoors, the system does not have enough reference information to estimate the position. However, too many RPs will also cause a lot of time to prepare the preset training process. So, in general we set a reference point at every 1 $\sim$ 2 meter intervals. After installing the Wi-Fi APs and some RPs, we employ the collected RSS data of all the RPs to train a classifier that determines which RP (location) a MD is at. The classifier has many different types, such as decision tree, Naive Bayes, support vector machine (SVM) or k nearest neighbor (KNN) search [8]. In our research, we choose Gaussian mixture model (GMM) based KNN search as the classifier. Based on the GMM algorithm, the system builds the model for each RP by using its RSS characteristics, and save this model data in the database of reference position information, including the position coordinates of the RP itself.

Then, in the second phase, which is called as on-line estimation phase, we collect new RSS information in the test point (TP), and send the data to a server or the master MD. The system in the server will compare the RSS characteristics of TP with the models in database, and calculate the log density (LD) value of the reference point model for each TP. After that, the system will sort the reference point models in the database in descending order of their corresponding LD value with TP.

$$Pos(x) = \frac{\sum_{i=1}^{k} LD_i \times Pos(x)^i}{\sum_{i=1}^{k} LD_i} \tag{1}$$

Here, we set a constant k and take the first k RPs with larger LD value to calculate the position coordinate of TP. Then, the coordinate of the first k RPs will be multiplied its corresponding LD as the weight according to the Formula 1.

2.2.2 Positioning confidence calculation

Confidence calculation measures the probability of the estimated position that obtained from the existing method mentioned above, being close to its true location. In general, a high / low confidence score implies that the location estimation has high / low probability of being the true location.

In our research, we make use of Wi-Fi scan series data that contain the RSS information from the Wi-Fi APs to calculate an estimated position by the existing Wi-Fi based positioning method. Every TP (the position that needs to be estimated) has its Wi-Fi scan series data which consists of some Wi-Fi scan data taken in seconds. Each Wi-Fi scan is used to calculate position coordinates and the average of this position coordinates will be set as the final estimated position of the TP. The difference between the final estimated position and actual one is considered as an estimation error.

Generally, the confidence of estimated position is mainly affected by the stability of Wi-Fi signal strength. When Wi-Fi signal strength is stable, each Wi-Fi scan data that obtained at a test point is likely to be the same, and the each estimated position coordinates tend to be centralized, which means the standard deviation of these position coordinates will be small. Conversely, when Wi-Fi signal strength is unstable, we will get the diverse results. So, we may speculate that the estimation error has a relationship with the standard deviation of the estimated position coordinates.

Then, referring to the speculation above, the confidence of an estimated position can be defined and its calculation method is shown in the following formula.

$$Conf_P(x) = e^{-|\sigma_x|}, \tag{2}$$

where the σ_x means the standard deviation of estimated position coordinates of the xth MD.

2.3 Bluetooth based distance estimation

2.3.1 Distance estimation

Bluetooth is a short-range, wireless, cable-replacement protocol operating in the license-free 2.4GHz spectrum. It is characterized by its low power requirements and low-cost transceiver chips. There are millions of Bluetooth devices on mobile phones (currently smartphones), laptop computers and PDAs, providing a ubiquitous mechanism for wireless transfer of relatively small amounts of data.

Because the Bluetooth devices also use a radio (broadcast) communication system, they do not have to be in visual line of sight of each other. The effective range varies due to propagation conditions, material coverage and battery conditions. In general, the Bluetooth device we use in daily life has the maximum permitted power of 2.5mW and the detectable range is around 10 meters [9].

As the Bluetooth signal wave is a type of electromagnetic waves, whose frequency is 2.4GHz, we can make use of the traditional electromagnetic wave attenuation to consider the attenuation of Bluetooth signal [10]. In the ideal space (air temperature is 25°C, 1 standard atmospheric pressure, no object exists), the energy loss of the electromagnetic wave is calculated according to the following formula.

$$A(d) = 20 \times log\frac{4\pi d}{\lambda} \tag{3}$$

In Formula 3, d is the transmission distance (meter) and λ is the length of the electromagnetic wave. The Bluetooth signal frequency is 2.4GHz, so λ here is 0.125 meter. After transforming, we can get the calculation method of Bluetooth signal attenuation and are able to estimate the probable Bluetooth signal strength (SS) of a place according to its transmission distance from Bluetooth devices. After getting the relationship between Bluetooth SS and transmission distance in the ideal space, we collect the Bluetooth SS data at several places where there is no obstacle existing in the real indoor environment, and calculate the average value of SS data by different distance. Then, based on this preset collected data and Formula 3 above, we can estimate distance between 2 mobile terminals in the real indoor environment with the detected Bluetooth SS as the following modified formula.

$$d = 10^{-BS(x,y)-40.35/28.53} \tag{4}$$

$BS(x,y)$ in the Formula 4 represents the Bluetooth SS between two MDs (x and y)

2.3.2 Distance confidence calculation

After obtaining the distance between 2 terminals, we are going to discuss the confidence of the result. As we know that, the Bluetooth signal is not so much stable in the indoor environment. When a barrier such like cabinet, wall or moving people exists, the signal strength may drop sharply, and the electromagnetic interference may also decrease the Bluetooth SS.

However, it is difficult for us to judge whether the long distance, obstacles or electromagnetic interference results in the low detected Bluetooth SS. We just know that the stronger signal strength may lead to the more accurate distance result with high confidence, while the weaker signal strength may cause a result with large deviation and low confidence. Referred to the relationship mentioned above, we can address the calculation method of the confidence of the distance between 2 mobile terminals as follows.

$$Conf_D(x, y) = e^{-|BS(x,y)/C_{dis}|} \tag{5}$$

In the Formula 5, $BS(x, y)$ means the detected Bluetooth signal strength between 2 mobile terminals (x and y), and the constant C_{dis} is always set to be -100 which is the minimum of detectable Bluetooth SS.

2.4 Collaborative position error correction with spring model

2.4.1 Spring model

Spring model is often used for force-directed graph drawing in an aesthetically pleasing way. The most well-known spring algorithm is the Eades spring model [11], and it is a very successful layout creation algorithm for drawing an undirected graph by treating a graph as a mechanical system. In this model, nodes are assumed as ideal objects with the same weight 1 but no volume. The edges linked with 2 nodes are made by springs. All the springs have the same natural length l, and each spring has a current length d. Given a pair of nodes connected by a spring, if $l > d$, the spring attracts the nodes; if $l < d$, then the spring repulses the nodes; if $l = d$, then the nodes are stable. The spring forces will attract or repulse the nodes until the system reaches the minimum energy as the existence of friction. This is called the balanced state.

However, if in an ideal space, as there is no friction, the nodes will keep moving forever. In order to avoid that situation, the string model imports friction to stop these nodes. The direction of friction is opposite to the current moving direction of the node. When all the nodes stop and turn to the balance state, the spring model will output their final positions.

2.4.2 Collaborative positioning error correction

In the last collaborative positioning error correction process, we make use of the spring model mentioned above to adjust the positions of the mobile devices. However, there are still some different places between traditional Eades spring model and the one we used.

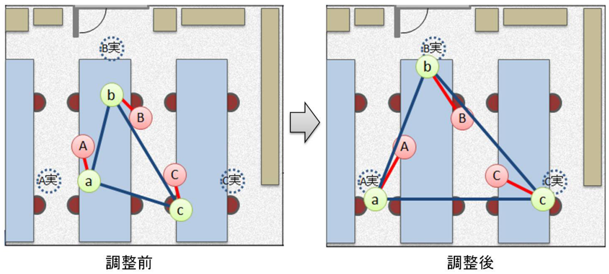

図 2 ばねモデルによる位置の推定
Fig. 2 Position estimation by spring model

Here, we give the setup of our spring model which is shown in Fig. 2. In that model, all the mobile devices are assumed to be nodes. There are 2 types of nodes in the model. As Fig. 2 below shows, the red node shows the estimated position provided by the existing Wi-Fi based indoor positioning system, and the green node is the one that adjusted by the spring model. The former red node is fixed in advance, the green one can be moved freely.

Moreover, there are also 2 types of springs connected with these nodes. The one between red node and green node is zero-length spring, which means the natural length of this spring is 0 and it generates attraction force only. Its spring constant corresponds to the confidence score of the estimated position (red node) of the mobile device. The other spring between 2 green nodes is a common type. It can be compressed or stretched. The natural length of this spring is equal to the estimated distance between the 2 green nodes linked with it, and its spring constant corresponds to the confidence score of the former estimated distance.

When all parameters are set, the spring model releases all the green nodes, and these nodes will be pulled or pushed by the spring force they suffered. After the spring model achieves to the balance state finally, we consider the current positions of the greens nodes as the adjusted estimated positions of the mobile devices.

3. Evaluation experiment

In order to testify the feasibility of our proposed method, we perform the evaluation experiment as follows. In this section, we introduce the experimental environment and scenario in advance. Then, we give the final results that provided by our method and discuss about them. Lastly, we present a way to optimize parameters used in our method to improve the position accuracy further.

3.1 Experimental environment and data

In our experiment, we use five Nexus One (a common smart-phone presented by HTC) as the clients to collect the experimental data. Nexus One is equipped with Wi-Fi and Bluetooth sensors and the operation system (OS) installed in is the well-known Android system, which is very convenient for us to develop other required programs (such as signal strength detection program) on it. Before experiment, we set up 15 Wi-Fi access points (APs) in total in our research lab, and in the experiment area, at least half of them can be detected.

The experimental area contains the meeting room, corridor, and the rest room of our research lab. Fig. 3 shows the layout of the experimental area. In this area, we set 15 reference points (RPs) in different places. The detailed positions of the RPs are shown in Fig. 3. At the RPs, we use Nexus One to collect enough Wi-Fi RSS data from all the APs located in this area, and at least 20 sets of Wi-Fi RSS data at a reference points (RP) is collected (Nexus One scans the Wi-Fi RSS received from the neighbor APs in every 2 seconds). Then, we employ the Wi-Fi RSS data of the 15 RPs to train models for them based on Gaussian Mixture Model (GMM) that mentioned above.

After installing the RPs in the experimental area, we also set 11 test points in Fig. 3 as to simulate the positions of the users with Nexus One in real life. The way to collect Wi-Fi RSS data is just the same as that at the RPs. However, in order to estimate the position of users more quickly, we only take 5 sets of the Wi-Fi RSS data at a test point (TP). In this time, Nexus One scans the Wi-Fi RSS received from the neighbor APs in every 1 seconds and the duration is reduced to 5 seconds. 5 seconds for data collection may be still a little long, but that is the limitation of the mobile device that we used. Besides, the Bluetooth sensor on Nexus One is also used to collect the Bluetooth SS data from the neighbor ones by using the Formula 4 that mentioned in the section 3.4.

We make 6 experimental scenarios for test according to the different experiment areas and the number of MDs in used. They are One-Room with 3 MDs (One-Room-3), 4 MDs (One-Room-4), and 5 MDs (One-Room-5), and the Multi-Room with 3 MDs (Multi-Room -3), 4 MDs (Multi-Room -4), and 5 MDs (Multi-Room 5). Each experimental scenario consists of 10 patterns with the MDs at different places.

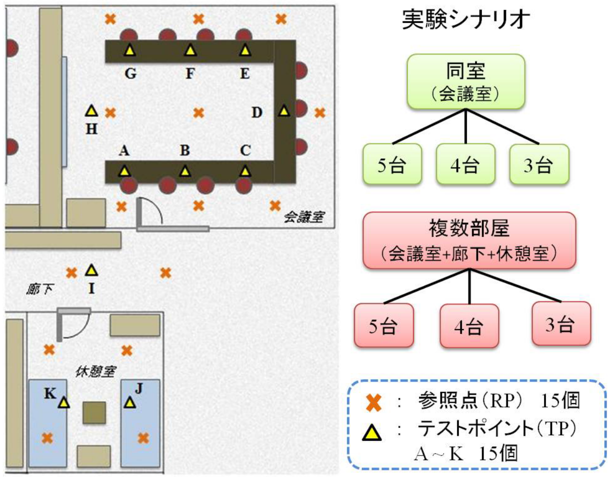

図 3 実験環境と実験シナリオの設定
Fig. 3 Experimental environment and scenarios

表 1 一つの実験パターンの位置推定の結果
Table 1 Positioning results of one experimental pattern

	調整前誤差 (m)	調整後誤差 (m)	変化 (m)
ポイント E	2.21	1.48	-0.73
ポイント G	2.08	1.42	-0.66
ポイント H	2.09	1.36	-0.73
ポイント I	0.23	0.48	0.25
ポイント J	1.48	1.08	-0.4

With the 6 experimental scenarios above, we testify the feasibility of our proposed method in different situations.

3.2 Experimental process and results

In the beginning of the experiment, we make use of the existing Wi-Fi based indoor positioning method to estimate the positions of the MDs in every experimental pattern. Then we estimates the probable distance between 2 MDs when Bluetooth signal can be detected with the Formula 1 above, and calculates the confidence scores of the estimated position and distance referring to the Formula 2 and Formula 5, respectively. After that, all of this data are imported into the spring model and the spring model estimates the final position for each MD. In our experiment, the spring constants of 2 kinds of springs used in model are set as the confidence scores of the estimated position and distance.

Now, let us see the adjustment results provided by our spring model. Firstly, we give the final position result of one experimental pattern in the scenario of Multi-Room-5 when the MDs are placed in Points E, G, H, I and J that shown in Table 1.

Table 1 shows the comparison between the positioning error of the 5 MDs before and after adjustment. We can

表 2 同室の場合推定位置誤差の比較
Table 2 Comparison of positioning errors in One-Room scenarios

端末数	調整前 平均誤差 (m)	調整後 平均誤差 (m)	変化 (m)	向上 精度 (%)
3	2.14	1.99	-0.15	7.0
4	2.25	1.88	-0.37	16.4
5	2.13	1.84	-0.29	13.6

表 3 複数部屋の場合推定位置誤差の比較
Table 3 Comparison of positioning errors in Multi-Room scenarios

端末数	調整前 平均誤差 (m)	調整後 平均誤差 (m)	変化 (m)	向上 精度 (%)
3	1.4	1.36	-0.04	2.9
4	1.57	1.39	-0.18	11.5
5	1.67	1.41	-0.26	15.6

see that almost all of the MDs had higher positioning accuracies after the adjustment by the spring model, expect the MD in Point I which had much little positioning error (0.23 meter) already before adjusting. On the other side, the positioning accuracies of the MDs with larger positioning errors before improved greatly.

Next, we present the comparison of the average positioning error for the 6 experimental scenarios after collaborative adjustment. Table 2 and Table 3 below show the comparison result of them.

In Table 2 and Table 3, we find that after adjustment by the spring model, the average positioning error of MDs in all experimental scenarios is improved, especially the ones of 4 MDs in one-room and 5 MDs in multi-rooms, whose average positioning accuracy has increased by nearly 15%. The average positioning accuracy of the scenarios with 3 MDs has not improved so obviously. Too little information for adjusting by the spring model is one of the possible reasons. Because, more MDs give more position and distance information for adjustment of the spring model, which may lead to a better improvement. In the next section, we will present a parameter optimizing method to improve the current positioning accuracy further.

Here, we also provide the cumulative distribution function (CDF) graphs of the positioning error related to the experimental scenarios with 5 mobile terminals. The CDF shows the positioning precision which considers how consistently the system works. Fig. 4 shows the comparison of the positioning precision of the scenarios with 5 MDs before and after adjustment. We can see that in each scenario, the position precision after adjustment reaches

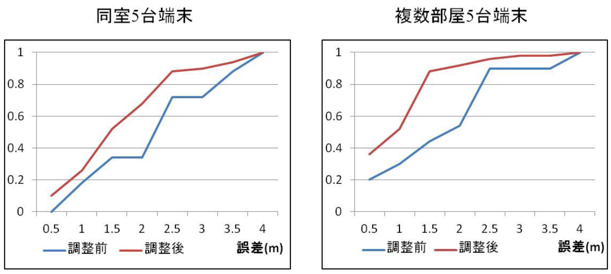

図 4 5 台端末の場合の位置推定誤差の CDF グラフ
Fig. 4 CDFs of positioning error in the scenarios with 5 MDs

high percentile value faster than the one before adjustment, which means the number of the mobile nodes with small positioning error is larger than before and the positioning accuracy in average is well improved.

3.3 Optimization of experimental parameters

As the confidence of the estimated position and distance is the spring constant of the 2 kinds of springs in the model, either of them is too large will break the final balance state. So, we assume that a better balance state generates when 2 confidence scores is at the same level. Besides, the Bluetooth signal is not so stable when obstacle (such as door, wall, or large furniture) exists. When the average distance between mobile devices is far, the confidence of the Bluetooth signal strength becomes low and we should increase the affection of the spring force that is generated by positioning confidence. But, setting adjusting parameter in each confidence estimation process of position is too difficult. We intend to multiply the confidence of the estimated positions with another parameter k to fine-tune the spring constant of the spring associated with the confidence score of the estimated position.

According to the analysis above, we give the calculation method of the parameter k as the following formula.

$$k = \frac{\overline{Conf_P}}{\overline{Conf_D}} \times \frac{\alpha}{\overline{Dis_{BT}}} \quad (6)$$

In Formula 6, $\overline{Conf_P}$ is the average confidence value of the estimated position in an experiment pattern. $\overline{Dis_{BT}}$ means the average estimated distances , and $\overline{Conf_D}$ means the confidence score of them. Besides, α is a constant (we set it 4.5 in this experiment), over which the confidence of the estimated distance becomes low and we should strengthen the spring constant of the spring that directly proportioned to the position confidence.

Table 4 and Table 5 above show the positioning accuracy after optimizing parameter. It is obvious that the average of position error got further improved after setting a

表 4 バネ係数最適化後の同室の場合推定位置誤差の比較
Table 4 Comparison of positioning errors in One-Room scenarios after parameter optimization

端末数	調整前 平均誤差 (m)	調整後 平均誤差 (m)	変化 (m)	向上 精度 (%)
3	2.14	1.62	-0.52	24.3
4	2.25	1.74	-0.51	22.7
5	2.13	1.54	-0.59	27.7

表 5 バネ係数最適化後の複数部屋の場合推定位置誤差の比較
Table 5 Comparison of positioning errors in Multi-Room scenarios after parameter optimization

端末数	調整前 平均誤差 (m)	調整後 平均誤差 (m)	変化 (m)	向上 精度 (%)
3	1.4	1.27	-0.13	9.3
4	1.57	1.13	-0.44	28.0
5	1.67	1.23	-0.44	26.3

more appropriate parameter to adjust the spring constant of the spring associated with the confidence score of the estimated position. And the optimization of experimental parameters is quite required in the following experiment.

Finally, based on the experimental result presented above, the positioning accuracy of our proposal is much better than the one proved by the existing Wi-Fi based indoor positioning method, and get 9.3% ∼ 28.0% improved according to the different experimental scenarios. Therefore, the feasibility of our proposed method is well proved.

4. Conclusion and future work

This paper addresses an enhanced Wi-Fi based indoor positioning method by using the neighbor mobile devices and a spring model. The positioning accuracy of the existing method is easy to be affected by the layout change or human action, and is not suitable for precise positioning requirements.

In order to solve that issue without using any additional beacons, we have designed and implemented a collaborative positioning estimation system, which intends to improve the positioning accuracy of the mobile nodes with lower confidence by referring to the position information and their distance relationships of the neighbor nodes that have higher confidence of accuracy. The proposed method consists of three phases: (1) estimating the position and the distance between mobile nodes with Wi-Fi and Bluetooth signal strengths respectively, (2) measuring the accuracy confidence of the estimated position and distance, and (3) collaborative adjusting the estimated positions by a spring model as to reduce possible positioning errors.

We also testify the feasibility of our system by evaluation experiment. The experimental results have shown that our proposed method provides 9.3% ∼ 28.0% accuracy improvement in several scenarios with different number of rooms and mobile nodes.

As a part of our future work, we plan to improve the accuracy of confidence estimation by using better algorithm or importing some other model such as motion model. And, we also like to fix some anchor nodes in the indoor environment to estimate the position for a target mobile node when there is no neighbor nodes can be detected.

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