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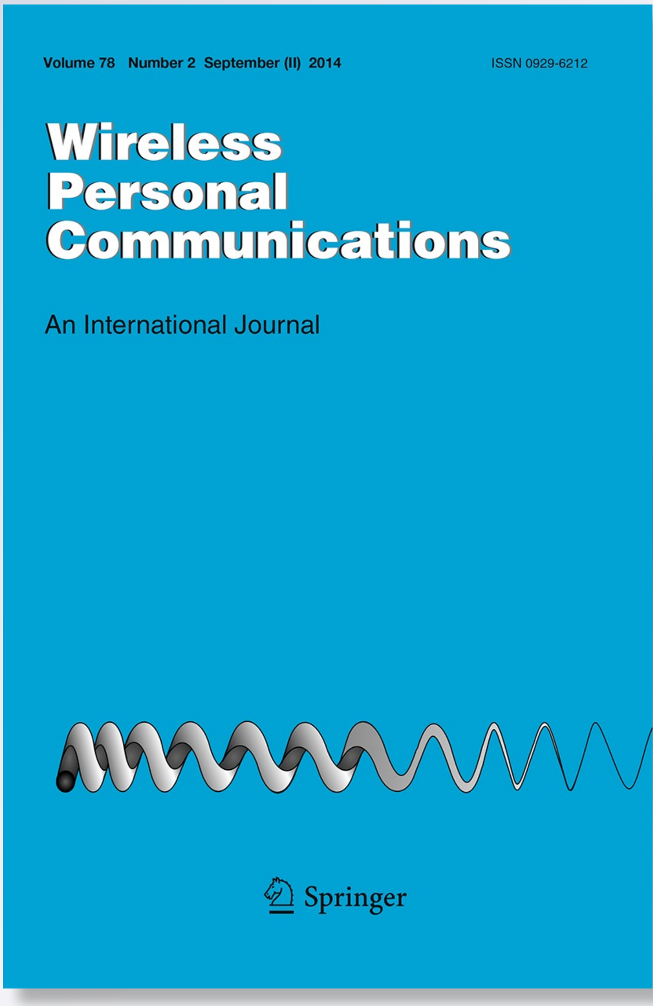

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Low-Cost 3D Bluetooth Indoor Positioning with Least Square

Honggui Li

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Abstract This paper discusses low-cost 3D indoor positioning with Bluetooth smart device and least square methods. 3D indoor location has become more and more attractive and it hasn't been well resolved. Almost each smart phone has a Bluetooth component and it can be used for indoor positioning and navigation in the nature of things. Least square algorithms are the powerful tools for linear and nonlinear parameters estimation. Various linear and nonlinear least square methods and their theoretical basics and application performance for indoor positioning have been studied. Simulation and hardware experiments results prove that nonlinear least square method is suitable for parameters estimation of Bluetooth signal propagation, and generalized least square method has better performance than total least square methods. Simulation and hardware experiments results also show that proposed method has the advantages of low cost, lost power consumption, perfect availability and high location accuracy.

Keywords 3D · Bluetooth · Indoor positioning · Least square

1 Introduction

3D indoor positioning has become more and more important, due to the huge need for navigation in a multi-floor company building, airport, supermarket, entertainment center, conference mansion and etc. Traditional outdoor positioning methods can't work well in indoor environment, for example GPS signal can't be reliably received in a shopping center, and Google Map navigation can't work correctly in a living mall. There are many technologies have used for indoor positioning, such as WIFI [1], Bluetooth, ZigBee [2], RFID [3], UWB [4],

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ultrasound [5], infrared signal [6], computer vision [7], magnetic field [8] and etc. Bluetooth has the advantages of low power consumption, low cost, high availability and high accuracy. Bluetooth accords to the computer wireless personal area network standard—IEEE802.15.1. All smart phones have Bluetooth interfaces, and they can be naturally used for 3D indoor location. Bluetooth is more precise than WIFI, and is more efficient than WIFI in cost and energy. Bluetooth is more convenient than ZigBee and RFID. Bluetooth is more economical in cost and power than UWB, ultrasound, infrared signal, computer vision and magnetic field.

Omar Cruz [9] studied the first and unique 3D indoor location and navigation system based on Bluetooth from now, but he didn't give the theoretical details for 3D indoor location and navigation. Shu Liu [10] found the face-to-face approximate distance with Bluetooth on mobile phone, but she only finished 2D range estimation and didn't locate the mobile phone. Li Zhang [11] researched the Bluetooth fingerprinting-based algorithms for 2D indoor localization, but he must firstly learn the features of indoor environment by machine learning algorithms. In some case, learning is inconvenient, and the features of indoor environment may be changed. Baniukevic [12] investigated the method of hybrid 2D indoor positioning with WiFi and Bluetooth, but WiFi needs higher cost and power consumption, and doesn't provide better location precision.

Classic positioning methods can be divided into range based methods and rangeless methods [9]. Ranged based methods are also known as inference based methods. Inference based positioning algorithms calculate position by distance estimation between two locating devices, such as 2D three border positioning and least square (LS). Inference based algorithms usually use RSSI (received signal strength indicator), TOA (time of arrival), TDOA (time difference of arrival) and AOA (angle of arrival) for distance estimation. RSSI is more suitable for low cost applications than TOA, TDOA and AOA. Rangeless positioning methods are also known as learning based methods. Rangeless positioning algorithms don't depend on the range estimation for location, such as nearest neighbor, centroid, pattern recognition and machine learning. In generally, inference based methods can get higher positioning accuracy than learning based methods, because they rely on the accurate distance estimation. If the features of the positioning environment can be fully learned, learning based methods can achieve flawless location precision.

This paper proposes a new least square based 3D indoor positioning method. This method is inference based, and utilizes the Bluetooth signal propagation model to estimate the distance between two Bluetooth devices, and then locates the target Bluetooth device according to the estimated distance. Least square algorithms are the great facilities for linear and nonlinear parameters estimation. Least square algorithms find the optimal parameters through minimizing the square error. Least square algorithms include: least square , weighted least square (WLS), generalized least square (GLS), total least square (TLS), weighted total least square (TLS), generalized total least square (GTLS), partial least square (PLS), nonlinear least square (NLS) and etc. Nonlinear least square algorithm will be used to estimate the parameters of the Bluetooth signal propagation model. Least square, weighted least square, generalized least square, total least square and weighted total least square algorithms will be utilized to determine the location form coarse to fine.

The rest part of this paper is arranged as follows. Section 2 states the theory foundation for least square based distance and location estimation. Section 3 constructs the experiment framework which verifies the correctness of positioning theory. Section 4 is the conclusions and future works.

2 Theory

2.1 Range Estimation

2.1.1 Bluetooth Signal Propagation Model

Classical wireless signal propagation model (WSPM) is adopted as Bluetooth signal propagation model [10,13].

$$\begin{aligned} r = P_R &= P_T + G_T + G_R + 20\log(\lambda) - 20\log(4\pi) - 10n\log(d) \\ &= -\left(10n\log(d) + (20\log(4\pi) - P_T - G_T - G_R - 20\log(\lambda))\right) \\ &= -\left(10n\log(d) + a\right) \end{aligned} \tag{1}$$

where:

- r is the RSSI;
- P_R is the power level of receiver, which is equal to r;
- P_T is the power level of transmitter;
- G_T is the antenna gains of transmitter;
- G_R is the antenna gains of receiver;
- λ is the wavelength of Bluetooth signal;
- n is the attenuation factor (2 in free space), and denotes influence of walls and other obstacles;
- d is the propagation distance form sender to receiver;
- a is a parameter which is related to P_T, G_T, G_R and λ.

Thus propagation distance can be represented by RSSI as following equation.

$$d = 10^{-\frac{r+a}{10n}} \tag{2}$$

Aforementioned model is a general framework, which is suitable for various wireless signals. Later experimental results will show that this model can't do well in practical propagation environments of Bluetooth signal. More sophisticate Bluetooth signal propagation model may be needed for more precise positioning, such as curve fitting of Bluetooth signal propagation model and etc. A polynominal signal propagation model (PSPM) [14] can be described as following. Later experimental results will also prove its powerful fitting ability for practical data.

$$d = p_n r^n + p_{n-1} r^{n-1} + \cdots + p_1 r + p_0 = \sum_{i=0}^{n} p_i r^i, \quad \forall n \tag{3}$$

Bluetooth works at 2.4 GHz of ISM frequency channel, and Bluetooth signal wave length can be calculated as following.

$$\lambda = \frac{c}{f} = \frac{3.0 \times 10^8}{2.4 \times 10^9} = 0.125\,(m) \tag{4}$$

In TOA based positioning methods, the precision of time measurement is related to the wavelength of signal. For example, TOA based methods for WIFI signal have been already studied [15]. So Bluetooth to some extent can obtain high precision of range estimation with suitable cost and power consumption. For the purpose of low cost and implementation convenience, RSSI based methods, not TOA based methods, are used.

2.1.2 Two-point Parameters Estimation for WSPM

Because there are only two parameters in Bluetooth WSPM, two known points, (r_1, d_1) and (r_2, d_2), can be used to estimate the model parameters. Two-point (TP) parameters estimation method can be described as following.

$$\begin{cases} r_1 = -\left(10n\log_{10} d_1 + a\right) \\ r_2 = -\left(10n\log_{10} d_2 + a\right) \end{cases}$$
$$\begin{bmatrix} n \\ a \end{bmatrix} = \begin{bmatrix} -10\log_{10} d_1 & -1 \\ -10\log_{10} d_2 & -1 \end{bmatrix}^{-1} \begin{bmatrix} r_1 \\ r_2 \end{bmatrix} \tag{5}$$

2.1.3 NLS Parameters Estimation for WSPM

Two-point parameters estimation method has its limitation of only using two known points to estimate the parameters. Two known points' deviation will result in the error of model parameters. Nonlinear least square algorithm is an efficient tool for nonlinear parameters estimation [16], and it minimizes the square error of r depending on m known points. Nonlinear least square algorithm can be depicted as following.

$$\min f(\theta) = \min \frac{1}{2}\sum_{i=1}^{m}\left(r_i - \left(-\left(10n\log_{10} d_i + a\right)\right)\right)^2$$
$$\theta = (n, a)^T \tag{6}$$

2.1.4 NLS Parameters Estimation for PSPM

Nonlinear least square algorithm is also a powerful tool for Bluetooth PSPM. Nonlinear least square algorithm can be described as following.

$$\min f(\theta) = \min \frac{1}{2}\sum_{i=1}^{m}\left(d_i - \sum_{j=0}^{n} p_i r_i^j\right)^2, \forall n$$
$$\theta = (p_n, \hbar, p_0)^T, \forall n \tag{7}$$

2.2 Position Estimation

2.2.1 Four-border Positioning

Let (x, y, z) be the unknown 3D coordinate of target Bluetooth device. Let (x_1, y_1, z_1), (x_2, y_2, z_2), (x_3, y_3, z_3) and (x_4, y_4, z_4) be the known 3D coordinate of the reference Bluetooth devices, whose signal can be received by target Bluetooth device. Let d_1, d_2, d_3 and d_4 be the known distances between target Bluetooth device and the four reference Bluetooth devices. Four-border (FB) positioning method can be described as following.

$$\begin{cases} (x-x_1)^2 + (y-y_1)^2 + (z-z_1)^2 = d_1^2 \\ (x-x_2)^2 + (y-y_2)^2 + (z-z_2)^2 = d_2^2 \\ (x-x_3)^2 + (y-y_3)^2 + (z-z_3)^2 = d_3^2 \\ (x-x_4)^2 + (y-y_4)^2 + (z-z_4)^2 = d_4^2 \end{cases}$$

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 2(x_1 - x_2) & 2(y_1 - y_2) & 2(z_1 - z_2) \\ 2(x_1 - x_3) & 2(y_1 - y_3) & 2(z_1 - z_3) \\ 2(x_1 - x_4) & 2(y_1 - y_4) & 2(z_1 - z_4) \end{bmatrix}^{-1} \times \begin{bmatrix} (x_1^2 - x_2^2) + (y_1^2 - y_2^2) + (z_1^2 - z_2^2) + (d_2^2 - d_1^2) \\ (x_1^2 - x_3^2) + (y_1^2 - y_3^2) + (z_1^2 - z_3^2) + (d_3^2 - d_1^2) \\ (x_1^2 - x_4^2) + (y_1^2 - y_4^2) + (z_1^2 - z_4^2) + (d_4^2 - d_1^2) \end{bmatrix} \quad (8)$$

2.2.2 *Least square*

Four-border positioning method relies on the condition that four spheres intersect in one point—the position of the target Bluetooth device, where the four spheres use four reference Bluetooth device's positions as centers and use the distance between the target Bluetooth device and the reference Bluetooth devices as radius. But the four spheres, which depend on the real observed data, can't always intersect in the same point. Least square algorithm as an efficient parameter estimation tool can be applied to find the proper intersection point. Least square algorithm can be described as following[17].

$$\begin{gathered} Ax = b \\ A = \begin{bmatrix} 2(x_1 - x_2) & 2(y_1 - y_2) & 2(z_1 - z_2) \\ \ldots\ldots & \ldots\ldots & \ldots\ldots \\ 2(x_1 - x_{m+1}) & 2(y_1 - y_{m+1}) & 2(z_1 - z_{m+1}) \end{bmatrix} \\ x = \begin{bmatrix} x & y & z \end{bmatrix}^T \\ b = \begin{bmatrix} (x_1^2 - x_2^2) + (y_1^2 - y_2^2) + (z_1^2 - z_2^2) + (d_2^2 - d_1^2) \\ \ldots\ldots \\ (x_1^2 - x_{m+1}^2) + (y_1^2 - y_{m+1}^2) + (z_1^2 - z_{m+1}^2) + (d_{m+1}^2 - d_1^2) \end{bmatrix} \\ x_{LS} = (A^T A)^{-1} A^T b \end{gathered} \quad (9)$$

Least square algorithm minimizes the following square error.

$$\begin{gathered} Q(x) = e^T e \\ e = Ax - b \end{gathered} \quad (10)$$

2.2.3 *Weighted and Generalized Least Square*

Weighted least square Least square algorithm supposes that all the elements of error vector have the same variance, and all the elements are uncorrelated. This is not true for real situation. So a weight should be added to each element of error vector. Weighted least square algorithm provides the right solution, and it can be depicted as following [18].

$$\begin{gathered} var(e) = W \\ W = CC^T \\ C = diag\left(\sqrt{w_1}, \ldots, \sqrt{w_m}\right) \\ C^{-1} Ax = C^{-1} b \\ x_{WLS} = (A^T W^{-1} A)^{-1} A^T W^{-1} b \end{gathered} \quad (11)$$

Weighted least square algorithm minimizes the following square error.

$$Q(x) = e^T W^{-1} e \quad (12)$$

Generalized least square If $\boldsymbol{W}$ in weighted least square algorithm isn't a diagonal matrix but a generalized symmetric positive definite matrix, it becomes generalized least square algorithm. Generalized least square algorithm can be described as following [19].

$$\begin{gathered} var\,(e) = G \\ G = PP^T \\ P^{-1}Ax = P^{-1}b \\ x_{GLS} = \left(A^T G^{-1} A\right)^{-1} A^T G^{-1} b \end{gathered} \tag{13}$$

Generalized least square algorithm minimizes the following square error.

$$Q\,(x) = e^T G^{-1} e \tag{14}$$

2.2.4 Total Least Square

Weighted least square and generalized least square only consider the error of vector $\boldsymbol{b}$, generally the matrix $\boldsymbol{A}$ also has error. Total least square algorithm offers the right answer, and it can be described as following [20].

$$\begin{gathered} (A + E)\,x = b + e \\ B = \begin{bmatrix} -b & A \end{bmatrix}, \quad D = \begin{bmatrix} -e & E \end{bmatrix}, \quad Z = \begin{bmatrix} 1 & x \end{bmatrix}^T \\ (B + D)\,Z = 0 \\ B = U\Sigma\,(V)^H, \quad U = (u_1, \ldots, u_m)\,, V = (v_1, \ldots, \quad v_{n+1}) \\ \Sigma = \begin{bmatrix} diag\,(\sigma_1, \ldots, \sigma_{n+1}) \\ 0 \end{bmatrix}_{m\times(n+1)} \\ x_{TLS} = \frac{1}{v_{n+1}(1)} \begin{bmatrix} v_{n+1}\,(2) & \cdots & v_{n+1}\,(n+1) \end{bmatrix}^T \end{gathered} \tag{15}$$

Total least square algorithm minimizes the following square error.

$$Q\,(x) = \|D\|_F = \left(\sum_{i=1}^{m}\sum_{j=1}^{n+1} d_{ij}^2\right)^{\frac{1}{2}} \tag{16}$$

2.2.5 Weighted and Extended Total Least Square

Weighted total least square Total least square algorithm assumes that matrix $\boldsymbol{A}$ and vector $\boldsymbol{b}$ have same precision (unit variance), and are uncorrelated, but such condition usually couldn't meet. Weighted total least square algorithm, also known as scaled total least square algorithm, can resolve this problem, and it can be described as following [21].

$$\begin{gathered} (A + E)\,\lambda x = \lambda b + e \\ (A + E)\,\tilde{x} = \tilde{b} + e, \quad \tilde{x} = \lambda x, \quad \tilde{b} = \lambda b \end{gathered} \tag{17}$$

where real factor λ is related to the relationship between the unit variance of $\boldsymbol{A}$ and the variance of $\boldsymbol{b}$. When $\lambda = 1$, weighted total least square algorithm becomes total least square algorithm.

Extended total least square Just as generalized least square is the extension of weighted least square, the weighted total least square is deduced to extended total least square. Extended least square algorithm can be described as following [22].

$$(GA + E)\,x = Gb + e$$
$$\left(\tilde{A} + E\right) x = \tilde{b} + e, \quad \tilde{A} = GA, \quad \tilde{b} = Gb \tag{18}$$

where square matrix $\boldsymbol{G}$ is the general extension of λ in weighted total least square, and confirms that matrix $\boldsymbol{A}$ and vector $\boldsymbol{b}$ have the same precision (unit variance), and are uncorrelated. When $\boldsymbol{G}$ is a unit matrix, extended total least square algorithm becomes to total least square algorithm.

Various linear least square algorithms will be employed to explore the correct location of target Bluetooth form rough to delicate.

3 Experiments

Indoor propagation environment of Bluetooth signal is complicated, such as the reflection and attenuation of floor, ceiling, wall and obstacles. So it is hard to accurately measure the distance according to the unstable signal, and to precisely estimate the 3D position. Three kinds of experiments have been designed to verify the correctness of aforementioned theories, and show the difficulty in practical application. The first experiment is software simulation. The second experiment is hardware experiment. The third experiment is hardware experiment with barometer.

3.1 Simulation Experiment

Simulation experiment is used to prove the correctness of position estimation methods with least square. The step of range estimation is canceled, and the distance with random noise form target node to reference nodes is presumed.

3.1.1 Experimental Conditions

Simulation experiment has been done by Matlab software running on Windows OS and PC. Experimental conditions are showed in Fig. 1. Six reference points, $\boldsymbol{R}_1, \ldots,$ and $\boldsymbol{R}_6$, are placed in three coordinate axes. The distance between each reference point and original point $\boldsymbol{O}$ is $d = 10$ m. Target point is $\boldsymbol{T}$, which is related to a given position. Then the distance form each reference point to $\boldsymbol{T}$ is calculated, and a normal distribution random noise, $\boldsymbol{N}(0, (0.1d)^2)$, is added to each calculated distance. Finally the 3D position of $\boldsymbol{T}$ is estimated using various least square methods.

3.1.2 Experimental Results

The following absolute precision of location estimation method is defined.

$$e_{location} = \sqrt{(x - x_0)^2 + (y - y_0)^2 + (z - z_0)^2} \tag{19}$$

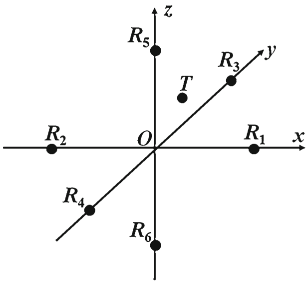

Fig. 1 Conditions of simulation experiment

where:

(x, y, z) is the estimated position;
(x_0, y_0, z_0) is the true position.

Least square algorithm is used to estimate the variance of error vector $\boldsymbol{e}$.

$$var\ (e) = var\ (Ax_{LS} - b) \tag{20}$$

It is supposed that the Matrix $\boldsymbol{W}$ in weighted least square algorithm has the diagonal elements of the estimated variance of $\boldsymbol{e}$.

$$W = var\ (Ax_{LS} - b)|_{diag} \tag{21}$$

It is assumed that the Matrix $\boldsymbol{G}$ in genelized least square algorithm is equal to the estimated variance of $\boldsymbol{e}$.

$$G = var\ (Ax_{LS} - b) \tag{22}$$

According to Eq. (9), the error matrix $\boldsymbol{E}$ of matrix $\boldsymbol{A}$ is zero. This is because, Matrix $\boldsymbol{A}$ actually has no error for the locations of the reference devices are known.

$$E = 0 \tag{23}$$

According to Eq. (23), there is no need to utilize the total least square methods to locate target device. In order to simplify the experiments, it is supposed that $\lambda = 1$ in weighted total least square algorothm, and $\boldsymbol{G}$ is a unit matrix in extended total least square algorithm.

Figures 2 and 3 show the results of 3D position estimation. Figure 2 displays the average of absolute precision of four-border method and various linear least square methods, and

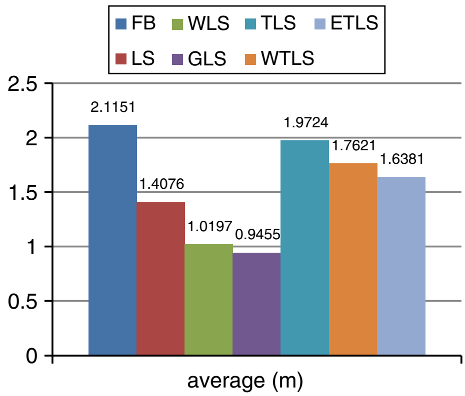

Fig. 2 The average of absolute precision of location estimation for simulation experiment

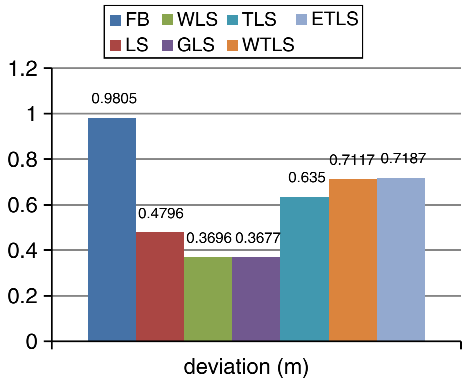

Fig. 3 The standard deviation of absolute precision of location estimation for simulation experiment

Fig. 3 shows the standard deviation of absolute precision of location estimation. Figures 2 and 3 indicate generalized least square method acquires the best accuracy, this is because that it considers the variance of error vector $\boldsymbol{e}$ correctly. Figures 2 and 3 also show total least square methods have higher absolute error than that of least square and weighted least square methods, because there is no error in matrix $\boldsymbol{A}$. Three total least square methods should have the same accuracy theoretically according to the experiments conditions, the different results in Figs. 2 and 3 are the influence of computation errors.

3.2 Hardware Experiment

3.2.1 Experimental Environment

Experimental environment is showed in Figs. 4 and 5. Figure 4 is the sketch map of experimental environment. Four Bluetooth reference devices, marked as white background Bluetooth logo icon, are uniformly deployed on the four 3D positions of a "cubic" room. The four reference devices are placed on four camera stands, and fall in a 9m × 9m square with different height. The target Bluetooth device, marked as black background Bluetooth logo icon, can be in any 3D position of the room. Figure 5 is the hall of our city library, in which hardware experiment has been achieved. Bluetooth Smart (Bluetooth Low-Energy) devices are adopted [23]. The Bluetooth 4.0 component of smart phone is used as target and reference device, and the version of Android OS is 4.3, which supports Bluetooth Smart device. JAMA is a basic

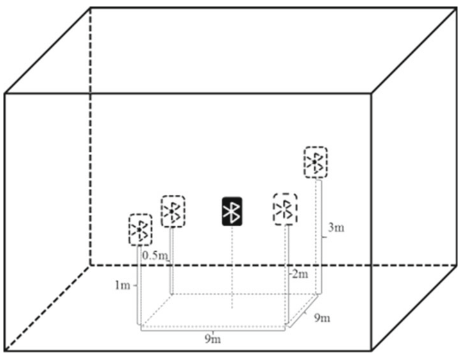

Fig. 4 The sketch map of the experimental environment

Fig. 5 The realistic experiment environment

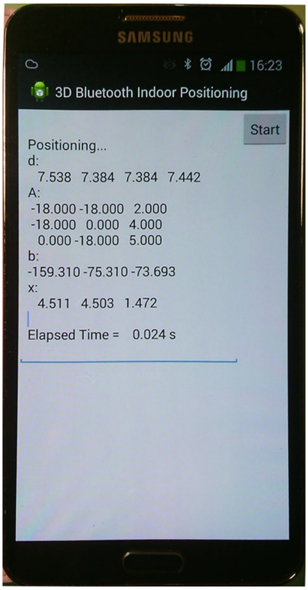

Fig. 6 Android application running on a smart phone

linear algebra package for Java language, and it is used to realize the matrix computing. An Android Application is developed to detect the received signal strength of reference device, estimate the parameters of propagation models, and compute the distances and positions. Android Application is illustrated in Fig. 6. More complex experimental environment may be needed, such as crowded supermarket and multi-floor shopping mall.

3.2.2 RSSI Averaging

Experimental results show that RRSI changes with time and direction of receive antenna. It is owing to the complex indoor propagation environment of Bluetooth signal. In order to decrease the influence of such facts, time-averaging and direction-averaging of RSSI are defined as following.

$$r_{time-averaing} = \frac{1}{n}\sum_{i=1}^{n} r_{time}\left(i\right) \tag{24}$$

$$r_{direction-averaging} = \frac{1}{n}\sum_{i=1}^{n} r_{direction}\left(i\right) \tag{25}$$

For the convenient of implementation, time-averaging of RSSI is used for hardware experiment.

3.2.3 Range Estimation Experiments

Range estimation experiments compare the range estimation precision of two-point method and nonlinear least square methods. Data representing ability of traditional Bluetooth signal propagation model has been compared with that of polynominal model. The following absolute precision of range estimation is defined.

$$e_{range} = |d - d_0| \tag{26}$$

where:

- d is the range estimated by two-point, nonlinear least square methods of wireless model or polynomial model;
- d_0 is the true range.

Figure 7 illustrates the average and standard deviation of absolute precision of range estimation for two-point, nonlinear least square methods of classical model and polynomial model. Figure 7 shows that polynominal model method gains the best accuracy.

3.2.4 Location Estimation Experiments

Experimental results of Location estimation based on weighted least square algorithm are shown in Fig. 8. The average and standard deviation are larger than that of Figs. 2 and 3. This is due to the complicated propagation environment of Bluetooth signal.

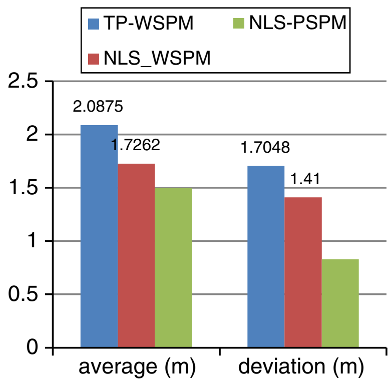

Fig. 7 The average and standard deviation of absolute precision of range estimation for hardware experiment

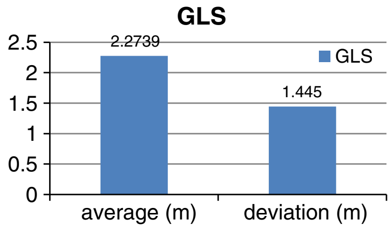

Fig. 8 The average and standard deviation of absolute precision of location estimation for hardware experiment

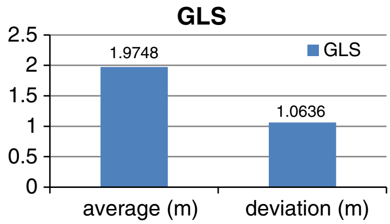

Fig. 9 The average and standard deviation of absolute precision of location estimation for hardware experiment with barometer

3.3 Hardware Experiment with Barometer

Barometer on smart phone can be used to estimate the elevation. z of 3D coordinate (x, y, z) is related to the elevation. So only x and y of coordinate (x, y, z) need to be resolved. 3D positioning precision can be improved obviously. Figure 9 shows the results. The average and standard deviation is lower than that of the results in Fig. 8.

4 Conclusions

This paper is the first one, which provides the theoretical details for 3D indoor position with Bluetooth device. Nonlinear least square method is adopted for parameters estimation of Bluetooth signal propagation model, and various linear least square methods are used for 3D location estimation of target Bluetooth device. 3D indoor positioning will has potential and tremendous business and market requirements. Bluetooth device on smart phone will be the preferred choice for low cost 3D indoor positioning. Simulation and hardware experiments results illustrate that nonlinear least square method is suitable for parameters estimation of Bluetooth signal propagation, and generalized least square method has better performance than total least square methods. Proposed method also has the merits of low cost, low power consumption, high usability and high location precision.

More sophisticate Bluetooth signal propagation model will be studied in our future work. Hardware experiments will also be accomplished in more complicated environment, such as noisy multi-floor building. Indoor navigation with Bluetooth will be one of our next research targets. TOA based method for Bluetooth positioning and navigation will also be investigated.

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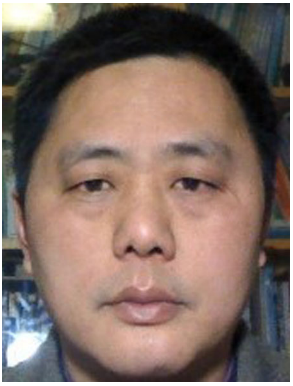

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