Wi-Fi RTT based indoor positioning with dynamic weighted multidimensional scaling

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***Abstract*—Indoor positioning methods have appeared to fulfill indoor location-based systems requirements, it is still a great challenge to obtain high precision results of indoor positioning. For example, fingerprint-based methods reach high performances but have a high cost for to survey the environment in order to collect sample and to maintain location fingerprints. Systems based on log-distance path loss model suffer from the multi-path problem and the adjustment of Wi-Fi station powers, and achieve low accuracy in complex environments. The appearance of fine time measurement protocol supported Wi-Fi access points provide a novel way to develop accurate indoor positioning algorithms. Considering the influence of the indoor multi-path effect to the fine time measurement ranging accuracy, we propose a multi-dimensional scaling based positioning algorithm to reduce the impact of ranging errors. We leverage the multidimensional scaling algorithm to estimate the rough position of positioning clients. Successively, adjusting the weight of fine time measurement ranging, we optimize the positioning results with the application of a SMACOF strategy. Through experiments conducted in a complex real-world scenario, we demonstrate that the system proposed reach an accuracy below the 2.5 meters at 80% of the cases.**

Keywords*—*Indoor Positioning, Wi-Fi, Round-trip time, FTM, Multi-Dimensional Scaling

I. INTRODUCTION

Positioning technology is widely used in many aspects of life. Global Navigation Satellite System (GNSS) provides high-precision service on mobile devices and it works effectively in most outdoor environments. However, GNSS is not available or precise enough in most indoor environments due to the fact that signals coming from satellites are not strong enough to cross walls [1]. Since the Wi-Fi network is widely used in many indoor scenes, it replaces GNSS as the main method of indoor positioning. Nowadays, people's demand for high-precision indoor location services is growing, especially in large public places with complex environments such as shopping centers and airports. Consequently, indoor positioning is receiving more and more attention [2, 12-15].

Due to its low-cost and easy-to-deploy feature supported by the IEEE 802.11 WLAN standard [3], Wi-Fi based indoor positioning can be classified approximately into two approaches: fingerprinting-based and range-based. Systems based on fingerprinting generally consists of an offline and an online phase [4][11]. In the offline phase, systems need a large number of samples to form a database of locations and related signals as a radio map. The structure of the wireless network should remain unchanged, otherwise, it will have a great impact during the online positioning. Many researchers have studied how to get high precision estimations through Wi-Fi fingerprint information . In [5], authors propose an indoor position with zone and section estimation based on a Bayesian approach. The Bayesian probability model estimates the probability of current location using the location fingerprint and database. In [6], authors collect Wi-Fi fingerprints at each location to build the fingerprint database, and estimates through a scoring mechanism called FreeLoc. Both of them and others approaches based on fingerprint, require a laborious and time-consuming effort. Moreover, Wi-Fi fingerprint estimations can also be improved with others to improve its accuracy. [8] combines Wi-Fi fingerprints together with magnetic fields and get estimations towards a convolutional neural network (CNN). However, these systems generally use extra information to get high precision, which may not work properly in areas with high geomagnetic interference.

Methods based on range estimation convert Wi-Fi signals into distance information, which is calculated with a log-distance path loss (LDPL) model and considering the received signal strength (RSS). RSS is affected by many factors, such as working power, bandwidth and propagation media. Consequently, the distance estimated with the LDPL model fluctuates with it. Location estimations are usually be solved using a trilateration approach [7]. Traditional ranging methods are greatly affected from the kind of indoor environment and the Wi-Fi fluctuations. In order to reduce these effects, round-trip-time (RTT) is proposed to calculate the distance between the client station (CSTA) and the access points (AP) by mean spread time and propagation speed. IEEE 802.11-2016 standard provides supports for fine time measurements (FTM) protocol, which implements a ranging process based on RTT. Fig.1 illustrates the ranging process of the FTM protocol. An initiator is a CSTA that initiates the process by sending an FTM request to the corresponding AP, which is called responder. In the ranging process, the responder sends an FTM message to the initiator and waits for its ACK. Time drifts at the responder are calculated using transmission or reception timestamp, which is denoted as t_1 and t_4. Those at the initiator are calculated in the same way with t_2 and t_3 [9].

Then the responder sends time drifts back to the initiator and RTT measurements are calculated as follows:

$$\mathrm{RTT} = \mathrm{c} \cdot [(t_4 - t_1) - (t_3 - t_2)] \qquad (1)$$

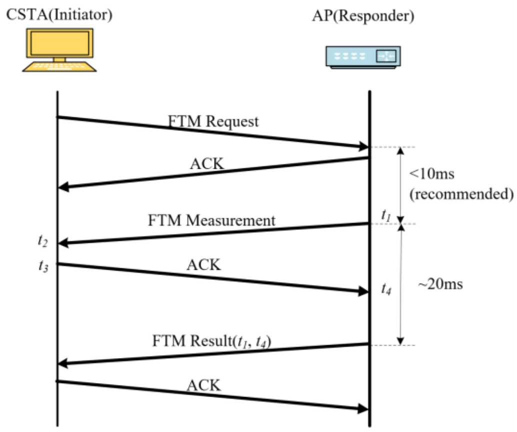


Fig.1 RTT based FTM protocol workflow

Due to the complexity of the indoor environment, multipath propagation occurs commonly during positioning, which greatly interferes with RTT ranging. Existing works are mostly focused on reducing measurement error by estimating probability distribution rather than positioning performances. Authors in [9] discuss ranging performance in various conditions and, in particular, they detect and reduce the impact of non-line-of-sight propagation (NLOS). In [10], authors try to reduce the influence of NLOS applying a probability distribution model in order to evaluate location estimations with least squares (LS).

However, the complexity of the indoor scene leads to different multipath propagation conditions, and the measurement error probability distribution is quite different. The effect of error correction based on the measurement itself is limited. In this paper, we propose a fine positioning method with Huber weighting to reduce the impact of measurement errors. The Huber function defines the mapping between weights and residuals. It maintains a tolerance of the residual to distinguish FTM measurements with large residuals and adapt their impacts with weights during positioning. Base on the weight measurements, the cost function is constructed and fine position estimation is solved iteratively with weights updating. Therefore, the proposed method is able to reduce the influence of multi-path measurements by decreasing their weights, and the positioning result is refined.

The algorithm proposed needs an initial position to perform an iterative optimization process. In order to improve the initial accuracy, we implement a multi-dimensional scaling (MDS) method. It treats FTM observations as high-dimensional variables, and MDS reduces them into 2D coordinates. MDS iteratively optimizes the cost function according to non-convex optimization, which can avoid local optimization in some ways. The MDS method considers both FTM measurement errors and the deployment error of Wi-Fi access points, therefore, it is more robust than the traditional least square method in dealing with multi-path influenced observations.

The contributions of the paper are summarized as follows:

- We propose an indoor positioning algorithm based on SMACOF and Huber to reduce the influence of measurement errors. The method adjusts the weight of FTM ranging measurement with Huber and optimizes positioning results with SMACOF. Therefore, the algorithm is able to improve the positioning performance in complex indoor environments
- An initial position with good accuracy is helpful in improving fine positioning performance. Therefore, we propose an improved MDS to estimate initial positions. Our algorithm is based on a non-convex optimization method, it improves the system's ability to avoid local optimal.
- We conduct extensive experiments to examine the performance of the proposed positioning method, including positioning parameter selection tests as well as positioning accuracy comparisons with several Wi-Fi RTT based positioning methods. Experiments reveal that our algorithm improves positioning accuracy comparing with traditional positioning methods in complex indoor environments.

II. System Architecture

Fig.2 shows the positioning system architecture. Our proposal can be logically divided into two parts: an initial coarse positioning and a fine positioning estimation. The coarse positioning part estimates a rough position of the client based on the FTM ranging measurements. The distances between CSTA and APs are considered as multi-dimensional variables, then are represented with a two-dimensional coordinate matrix. The initial coarse positioning estimation is the results of MDS algorithm and a linear coordinate transformation. In this first phase, the multi-path effect of Wi-Fi signals is ignored and therefore the positioning accuracy drops when this strongly affects the ranging measurements.

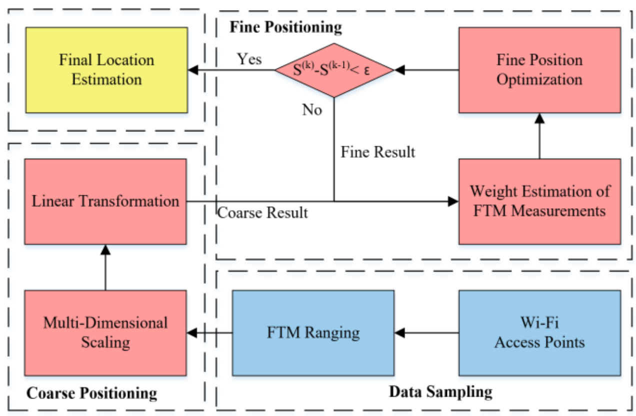


Fig.2 Overview of the indoor positioning system proposed

In order to reduce the effect of the multi-path problem, in the fine positioning part we improve the coarse positioning results applying a Huber-based optimization algorithm. The cost function is constructed to iteratively optimize the coarse estimation. Weights of measurements are updated by Huber function, which is based on the residuals between the iterative position estimations and the ground truth of APs. The client position is initiated by coarse positioning. Then it leverages a SMACOF based method to iteratively refine the coarse positioning results. When the variance of positioning residuals is small enough, the latest optimized positioning result is returned. Symbols adopted in this paper are shown in TABLE I.

TABLE I. Symbols adopted in our methods

Symbol	Meaning
$X=[x_1,\cdots,x_N]$	Coordinates vector of all wireless nodes
$x_i=[x_{i1},\cdots,x_{ik}]$	Coordinates of wireless nodes i, where k equals 2
$x_1,\cdots,x_n$	AP
x_N	Client station
d_{ij}	the Euclidean distance between x_i and x_j
$\hat{d}_{ij}$	the FTM measurement between the CSTA and APs, where i equals N

III. Coarse Position Estimation

A coarse positioning estimation is evaluated with a MDS and a linear transmission model. MDS is a deterministic multivariate data analysis method, which is often used considering a set of ranging results as multi-dimensional spatial research objects and converting them into 2D relative coordinates. An improved linear transmission model is used to convert these relative coordinates into absolute estimations.

A. Relative position estimation with MDS

MDS aims at keeping the relationship between wireless nodes of distance consistent with real environments. The distance d_{ij} satisfy the relation as follows:

$$d_{ij}^2=\begin{cases}\sum_{l=1}^{k}x_{il}^2+\sum_{l=1}^{k}x_{jl}^2-\sum_{l=1}^{k}2x_{il}x_{jl}, & i\neq j\\ 0, & i=j\end{cases} \quad (2)$$

First, we calculate relative solutions of wireless nodes with MDS. According to (2), it can be easily inferred that $d_{ij}^2=d_{ji}^2$. Then we use the Distance Squared Matrix(DSM) to represent the relationship between nodes in N-dimensional space. It is constructed by d_{ij}^2 as follows:

$$D^2(x)=\begin{bmatrix}d_{11}^2 & \cdots & d_{1N}^2\\ \vdots & \ddots & \vdots\\ d_{N1}^2 & \cdots & d_{NN}^2\end{bmatrix} \quad (3)$$

Then we use (2) to decompose (3) as (4):

$$D^2(x)=\mathrm{Z}+Z^T-2\mathrm{B}=\mathrm{z}e'+ez-2xx' \quad (4)$$

where $\mathrm{B}=xx'$, x is the column vector of X, e is N dimensional vector filled with 1, and z is a vector of $\sum_{l=1}^{k}x_{il}^2$.

Distance is considered as observations, so $D^2(x)$ is constructed by using the FTM observations between the CSTA and each AP to represent the distance relationship of wireless nodes. Assuming the relative positions of wireless nodes unchanged, the centering operation can be performed on $D^2(x)$. The high-dimensional coordinate system is linearly transformed considering the mean value of the coordinates of each node in the network equals to 0. Multiplying the centralization matrix H on both sides of $D^2(x)$ we obtain a centralized squared distance matrix $C^2(x)$. It is calculated with (4) as:

$$C^2(x)=-\frac{1}{2}H(\mathrm{z}e'+ez)H+HBH \quad (5)$$

where $\mathrm{H}=I_N-\frac{1}{N}ee'$ and I_N represents N-dimensional unitary matrix. For $\mathrm{H}e'=eH=0$, (5) can be calculated as:

$$C^2(x)=(xH)(xH)^T \quad (6)$$

We perform a singular value decomposition (SVD) on $C^2(x)$ to get the centralized feasible solution of the unknown node, which is expressed as $C^2(x)=U\Lambda U^T$. There are several Singular values of $C^2(x)$, and the value may be positive or 0. Singular values in Λ are sorted from large to small, and the largest k is selected to form a diagonal matrix Λ_k, the corresponding left singular matrix is U_k. The centralized relative positions of wireless nodes are calculated as (7):

$$x^{rel}=U_k\Lambda_k^{1/2} \quad (7)$$

where $x^{rel}=[x_1^{rel},\cdots,x_N^{rel}]$.

B. Absolute position coordinates estimation

Coarse estimations are calculated by the relative positions x^{rel}. Then the linear transformation-based model is established to convert them into navigation frame. It considers a variety of linear transformations, and the optimal linear transformation matrix is solved by LS. Finally, the coarse solution of unknown node CSTA is estimated.

There are four types of linear transformation methods: translation, rotation, scaling, and mirror. Since scaling will change the distance between nodes, it is not considered in this paper. The transformation model T^M is constructed with the other three methods. Translation, rotation, mirror are represented as T_S, T_R, and T_M respectively. Thus, T^M can be represented as $T^M=[T_S,T_R,T_M]$.

Seven-parameter transformation model is always used to convert two different 3-dimensional Cartesian coordinates system. In this paper, we simplify this model to Four-parameters transformation model in 2-dimension without scaling, and the model is shown as:

$$x_i^{abs}=T_R\cdot x_i^{rel}+T_S \quad (8)$$

where $x_i^{abs}=\left[x_{i1}^{abs},x_{i2}^{abs}\right]^T$ represents the absolute estimations of node i, and $x_i^{res}=[x_{i1}^{res},x_{i2}^{res}]^T$ represents relative estimations obtained by (7).

The mirror transformation is considered separately with the other two methods in T^M. It requires to select a particular axis of symmetry before transforming, and results vary with the axis selected. However, these results can be converted to each other by rotating. Thus, in order to reduce the complexity of computation, the mirror transformation operation is performed with the line x=0 as the axis of symmetry, and the corresponding transformation matrix T_M is shown as:

$$T_M=\begin{bmatrix}-1 & 0\\ 0 & 1\end{bmatrix} \quad (9)$$

Translation transformation is determined by the offset Δx, Δy along x, y-axis direction. Rotation transformation depends on the rotation angle $\alpha(\alpha\in[0,2\pi])$. The sine and cosine value of α is simplified as a and b, and matrices are shown as (10) and (11):

$$T_S=\begin{bmatrix}\Delta\mathrm{x}\\ \Delta\mathrm{y}\end{bmatrix} \quad (10)$$

$$T_R = \begin{bmatrix} \cos\alpha & -\sin\alpha \\ \sin\alpha & \cos\alpha \end{bmatrix} = \begin{bmatrix} a & -b \\ b & a \end{bmatrix} \quad (11)$$

All transformation matrices are divided into two parts according to whether there is a mirror transformation in it. We assume that transformation without a mirror is the one with a unitary matrix as T_M, so the model in (8) can be improved as:

$$x_i^{abs} = T_R T_M \cdot x_i^{rel} + T_S \quad (12)$$

Then we use (12) to solve the optimal transformation model T using linear least squares and nodes with prior information.

According to (10), (11) and (12), we can get the linear equations without mirror as follow:

$$\begin{bmatrix} R_1 \\ \vdots \\ R_n \end{bmatrix} \begin{bmatrix} \Delta x \\ \Delta y \\ a \\ b \end{bmatrix} = \begin{bmatrix} x_1^{abs} \\ \vdots \\ x_n^{abs} \end{bmatrix} \quad (13)$$

where $R_i = \begin{bmatrix} 1 & 0 & -x_{i2}^{rel} & x_{i1}^{rel} \\ 0 & 1 & x_{i1}^{rel} & x_{i2}^{rel} \end{bmatrix}$, $x_i^{abs} = \left[x_{i1}^{abs}, x_{i2}^{abs}\right]^T$.

(13) is also shown as (14) simply:

$$RT_X = B \quad (14)$$

Due to the solving process of LS, the transformation model is solved as:

$$T_X = (R^T R)^{-1} R^T B \quad (15)$$

As for each access point, x_i^{abs} is obtained by T_X and x_i^{rel} and the transformed error E_C is calculated as $\sum_{i=1}^{k} \left\| x_i^{abs} - x_i \right\|^2$. The optimal transformation matrix with mirror T_X^M and its transformed error E_C^M is solved in the same way. Finally, the system selects the one with the lower transformed error as the optimal transformation model T and coarse positioning estimations are obtained as:

$$x^C = T_S + T_R T_M \cdot x_N^{rel} \quad (16)$$

IV. Fine Positioning

Fine Positioning module iteratively optimizes the cost function with SMACOF to obtain fine position estimations. Position estimation is initiated with coarse positioning and optimized by a U function. In addition, the Huber function is used to reduce the influence of FTM ranging errors.

A. Huber Based Ranging Weight Estimation

In order to get fine estimations, the cost function is constructed with FTM ranging measurements and the location of APs. $d_i(X)$ depends on the initial position, and the target of the cost function is to minimize the total difference between $\hat{d}_i$ and $d_i(X)$ together with ω_i. The cost function is shown as:

$$S(X) = \sum_{1 \le i \le n} \omega_i \cdot \left(\hat{d}_i - d_i(X)\right)^2 \quad (17)$$

where ω_i represents weights for FTM measurements from wireless node i. If there is no measurement from node i, $\omega_i = 0$. $S(X)$ is chosen to optimize the squared weighed summation of the distance difference $\left|\hat{d}_i - d_i\right|$, which can reduce the impact of RTT ranging errors. However, multi-path occurs frequently indoors, which has a great impact on the accuracy of FTM range. Traditional cost functions use equal weights in $S(X)$ but, in this case, we chose a weighting mechanism to leverage the multi-path effects and to improve the performances.

As for any access points, the confidence of FTM measurement $\hat{d}_i$ is concerned with its relative measurement error or itself. The propagation time of Wi-Fi signals is greatly affected by NLOS, multipath, media and other factors. These factors introduce measurement errors. Fine Positioning introduces the weighting mechanism based on MDS, which can effectively reduce the influence of the gross measurement error on the overall positioning accuracy.

We use residuals to represent the confidence of measurement errors. It is a function of measurement error $\left(\hat{d}_i - d_i\right)$ called the Huber Function, and the equation of residual and weights are shown as (18) and (19):

$$u_i = \begin{cases} \left(d_i - \hat{d}_i\right)/\hat{\sigma}, & |u_i| \le k \\ \left(d_i - \hat{d}_i\right)/med|u_i|, & |u_i| > k \end{cases} \quad (18)$$

$$\omega_i = \begin{cases} 1, & |u_i| \le k \\ 1/|u_i|, & |u_i| > k \end{cases} \quad (19)$$

The graph of ω_i is shown in Fig.3.

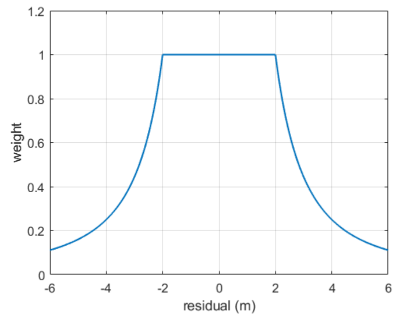


Fig.3 Huber Function

u_i and ω_i are based on the estimations of the last iteration. k is a parameter in Huber that indicates tolerance to the measurement error $\left(\hat{d}_i - d_i\right)$. The residual u_i greater than k will be amplified with the median value of residuals to reduce its weight ω_i in the next iteration. ω_i remains at 1 in tolerance, and it falls rapidly outside the range. This is because measurement in the tolerance range has less error than others, increasing the weight of this part can reduce the influence of the error introduced by others. The algorithm treats these measurements as accurate ones, and the errors introduced are ignored. Measurements with large errors will be given much lower weights, further reducing its influence. However, the weights do not fall to 0. This means that all the FTM measurements from access points are taken into account regardless of the measurement error. In order to avoid a failure in the positioning estimation process, also when the errors of most measurements are large, all the measurements are not discarded. In fact, Huber can always provide effective weights and never fails although most measurements have gross errors. And it can also reduce the weights of those with gross errors rapidly.

B. Optimization with SMACOMF algorithm

Fine positioning process is based on SMACOF algorithm. It is often used to solve the optimization problem in the classical MDS method. In this paper, we consider positioning as a kind of optimization problem. The cost function is constructed according to the wireless network with FTM observations and, iteratively optimized by SMACOF algorithm, the fine estimation is finally obtained.

$d_i(X)$ and ω_i between node i and mobile clients vary with estimations of the current iteration. If the current estimation falls into local optimum, the positioning accuracy will be greatly affected. So we need to optimize the cost function $S(X)$ to get the optimal position node estimation in each iteration.

We propose a U function of the cost function $S(X)$ to get optimal estimations during iteration. The solving process is shown as Algorithm 1.

Algorithm 1: SMACOF based positioning algorithm

inputs: $\{\hat{d}_i\}$, ε, k
construct a distance square matrix $D^2(x)$
coarse location estimation by improved MDS
initialize: $\{u_i^{(0)}\}$, $S^{(0)}$
Repeat
  t = t + 1
  for i = 1 to n
    compute residuals $\{u_i^{(t)}\}$ from (18)
    compute weights of Huber $\{\omega_i^{(t)}\}$ from (19)
    compute $b_i^{(t)}$ from (28)
  end for
  compute $X_N^{(t)}$ from (27)
  compute $S^{(t)}$ from (20) to (23)
until $S^{(t)} - S^{(t-1)} < \varepsilon$

The current estimation is obtained by improved MDS and is updated by U function with iterations. U function is calculated by $S(X)$ to get optimal estimations at each iteration. Huber weights of each measurement are constantly updated during the iteration. Finally, the positioning process ends with $S^{(t)} - S^{(t-1)} < \varepsilon$.

First we calculate U function by $S(X)$. The cost function in (17) can be split into:

$$S(X) = \eta_{\hat{d}}^2 + \eta^2(X) - 2\rho(X) \tag{20}$$

And $\eta_{\hat{d}}^2$, $\eta^2(X)$, $\rho(X)$ are respectively:

$$\eta_{\hat{d}}^2 = \sum_{i=1}^{n} \omega_i \cdot \hat{d}_i^2 \tag{21}$$

$$\eta^2(X) = \sum_{i=1}^{n} \omega_i \cdot d_i^2(X) \tag{22}$$

$$\rho(X) = \sum_{i=1}^{n} \omega_i \cdot \hat{d}_i d_i(X) \tag{23}$$

FTM observations are considered as constant values, and distance between CSTA and APs are seen as the unknown variable. From (20) to (23), we can see that $\eta_{\hat{d}}^2$ is the constant term, $\rho(X)$ and $\eta^2(X)$ are a respectively linear and quadratic term in $S(X)$. Different from MDS, there is no minimum optimized explicit expression of $S(X)$ in Fine Positioning. Thus, we use Cauchy-Schwarz inequality to optimize $\rho(X)$ to $\rho(X,Y)$ as (24):

$$\rho(X,Y) = \sum_{i=1}^{n} \omega_i \cdot \frac{(x_N - x_i)^T (y_N - y_i)}{\|y_N - y_i\|} \tag{24}$$

Then we obtain an optimization function of the cost function $\mathrm{T}(X,Y)$ as:

$$T(X,Y) = \eta_{\hat{d}}^2 + \eta^2(X) - 2\rho(X,Y) \tag{25}$$

From (24) and (25), it is easy to derive that $S(X) \leq T(X,Y)$ for any Y, and the equation is established at $Y = X$. This function can be used to implement iterative minimum optimization. Thus, the optimization process of $S(X)$ is converted into a nonlinear optimization problem of $T(X,Y)$, that is, finding the local minimum of $T(X,Y)$. It is a quadratic function about $d_i(X)$, so the minimum is solved as:

$$\frac{1}{2}\frac{\partial T(X,Y)}{\partial X} = 0 \tag{26}$$

Y stands for the estimations of the last iteration (k-1), and estimations of the current iteration (k) is:

$$X_N^{(k)} = X_N^{(k-1)} \cdot b^{(k)} \tag{27}$$

where $b^{(k)} = [b_1^{(k)}, \cdots, b_N^{(k)}]$, $b_i^{(k)}$ is represented as:

$$b_i^{(k)} = \begin{cases} \omega_i \cdot [1 - \hat{d}_i / d_i(X_N^{(k-1)})], & 1 \leq i \leq n \\ \omega_i \cdot \hat{d}_i / d_i(X_N^{(k-1)}), & i = N \end{cases} \tag{28}$$

After substituting $X_N^{(k)}$ into $S(X)$, the local minimum of $S(X)$ in the current iteration can be calculated as $S^{(k)}$. Then we set a threshold Ɛ together with a compensation c to control the iterations, so as to obtain the fine positioning estimations. The compensation c is initialized to 0. The optimization algorithm is summarized as Algorithm 1.

V. EXPERIMENT

In this section, the ranging performance of the FTM protocol will be analyzed. Then the positioning performance of weighted MDS will be discussed comparing with other methods.

A. Experiment Setup

While several Wi-Fi cards provide FTM standard implementations with support for the 802.11mc protocol, we chose the Intel Dual Band Wireless-AC 8260 Card for FTM measurements ranging. This card obtains open software supports for accessing FTM measurements (a Linux driver with FTM protocol implementations), and it requires further modifications to support for FTM measurements. We select this as client stations and access points. Android Pie System has also provided API supports for FTM Ranging, but we cannot get FTM measurements on Android phones with it, for which Wi-Fi chipsets in it do not support the 802.11mc protocol.

We use laptops as CSTA and PCs as access points with Linux kernel version 3.19.0-61-lowlatency. Though FTM standard and 802.11mc protocol have been implemented in newer kernel versions, it is one of the best versions supported by the backport IWLWIFI Driver (an open-source Linux driver). We use the IWLWIFI Driver version 8000 from the LinuxCore30 release, along with firmware version 31.

CSTA can be configured with the iw (a nl80211 based CLI configuration utility for wireless devices in Linux) at version 4.14. Access points are configured manually with hostapd (an access point management tool in Linux) at version 2.6. We also need to modify the IWLWIFI Driver to activate the responding feature to make the FTM Access Points available.

As for most commercial access points doesn't have the capacity of RTT ranging, our experiments are conducted in our laboratory at 7th Floor in ICT, where we deployed several desktop PCs equipped with FTM Wi-Fi cards. It is a typical indoor official area, and the multi-path problem is serious. In this test, PCs are used as access points, and the client station is carried by a tester. The experimental setup is shown as Fig.4. Several positioning methods are used to compare with weighted MDS in this paper. FTM samples are classified into dynamic and static ones due to their motion state, and the performance will be analyzed according to motion states.

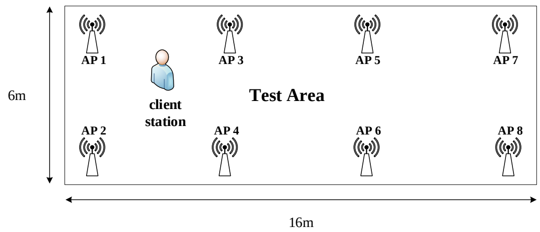
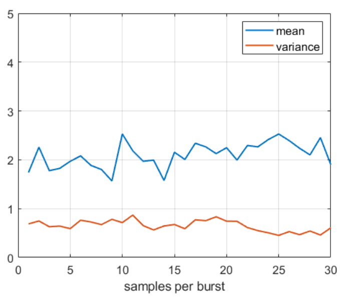


Fig.4 Experimental setup

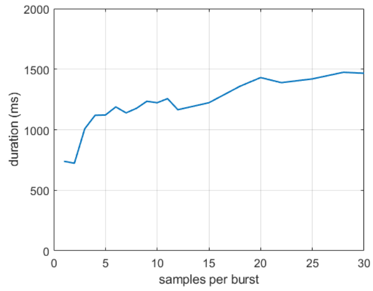
B. Parameters Selection

Due to the motion state, the positioning process is classified as dynamic and static positioning. In dynamic positioning, CSTA moves at a constant speed in the location area, and real positions are obtained by average segmentation. 30 pieces of observations are collected at the interval of 2s at each anchor positions in static positioning. The iw tool supports to set the number of FTM samples per burst, so as to improve the performance of ranging. Thus, we study the effect of it first.

Ranging capabilities of Intel AC 8260 Wi-Fi card is affected by temperature. It cannot work continuously for long. However, the mobile station is limited in performance due to its portability and persistence. It is prone to heat more easily when working continuously for long, resulting in an increase in temperature. In this test, samples per burst (SPB) vary from 1 to 30, which is the maximum number, and PC instead of a laptop is fixed as client station with the distance of 2.7m. 500 pieces of measurements are collected respectively for each burst, and the time interval is set to 5 minutes to keep the Wi-Fi card working normally. Fig.9 shows the mean and variance as a function of SPB. Experiments show that the mean and variance decrease slightly as SPB increases, and the optimal value of SPB is 3.



(a) mean and variances



(b) durations

Fig.9 samples per burst

k in the Huber function represents the tolerance to the estimated errors. It is implemented based on iterations, and the residuals are obtained by the estimated errors in the last iteration.

The Huber function can reduce the impact of ranging error effectively. We investigate the performance of positioning varying k in the Huber function. It is set to 0.01, 1.5, 5 and 10 respectively and errors of estimation in dynamic and static positioning are shown in Fig.10 and 11. When k is much small as 0.01, the residual u_i will be easily amplified, and its tolerance to the residual is very low. Due to the characteristics of the reciprocal function, ω_i of nodes with gross ranging error is always positive. It increases relatively, resulting in an increase in estimation error. However, when k is much bigger as 10, due to the tolerance of Huber, almost all nodes with valid measurements have a weight of 1. In that case, weights make no sense that all nodes have equal weights. Large numbers of experiments show that the Huber function has the best weighting capacity when k equals to 1.5.

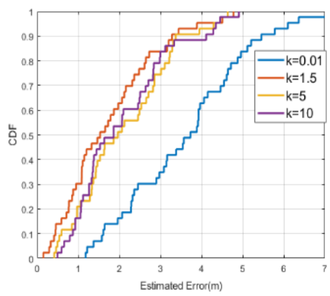


Fig.10 Dynamic Positioning varies with k

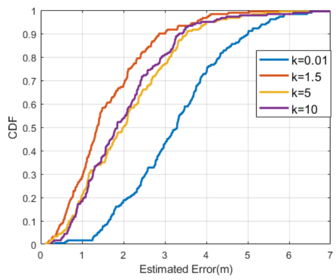


Fig.11 Static Positioning varies with k

C. Comparing with other methods

In order to detect the positioning performance of weighted MDS algorithm, several other methods are used to compare with it. We least squares to implement triangulation, then MLP (Multi-Layer Perception) is proposed to solve the positioning problem. MLP is a forward-structured ANN (Artificial Neural Network) that maps a set of FTM input vectors to a set of output vectors. It consists of several layers with nodes, and adjacent layers are fully connected to each other. Except for the input nodes, each node is a neuron with a nonlinear activation function. MLP is trained by a back-propagation algorithm and locates towards model obtained in the training process. It is used in two ways: regression of estimations or FTM ranging compensation. They both have two hidden layers with n_1 and n_2 nodes, which structures of them are similar to each other and is shown in Fig.12. In estimations regression, FTM measurements are treated as input and the output are location estimations. n_1 and n_2 equal to 9 and 2 respectively. In ranging compensations regression, each AP has its own model, which inputs are FTM measurements of itself. Measurements of missing APs are filled with coarse positioning with LS first, then models are trained to estimate compensations as output. Location results are calculated by LS with compensations. n_1 and n_2 equal to 6 and 2 respectively.

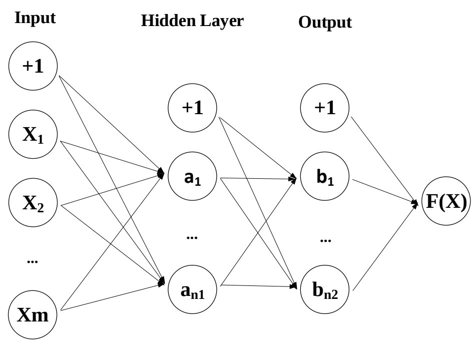


Fig.12 Structure of MLP

All methods mentioned above are used to get estimations with dynamic and static positioning in the location area, so as to compare estimated errors with each other. The sampling interval is set to 2s and CDF results are shown in Fig.13 and 14, where wmds represents the Weighted-MDS, ls represents Least Squares, ap and pos respectively represents ranging compensation regression and estimations regression based MLP. We can see that weighted MDS is better than others obviously. This means that the weighting mechanism makes sense and the SMACOF algorithm can effectively attenuate the ranging error introduced by NLOS and multipath. As for the other three methods, LS is the least one, it has no capacity to the ranging error. Position regression based on MLP behaves better in dynamic positioning, while MLP based ranging compensation regression behaves better in static positioning. This may because filling missing APs with coarse positioning introduces extra error in such method in dynamic positioning and this is particularly small in static positioning.

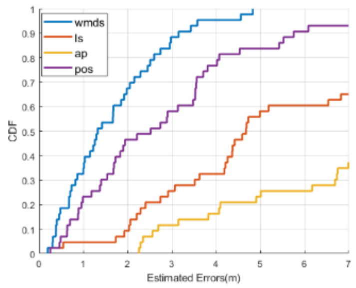


Fig.13 Dynamic Positioning

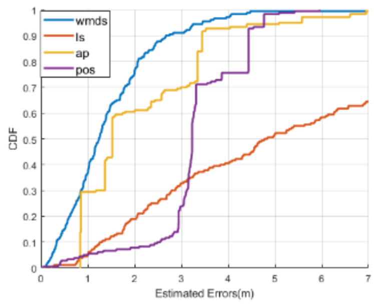


Fig.14 Static Positioning

VI. Conclusion

In this paper, an innovate Wi-Fi RTT positioning method is proposed in this paper. It is based on classical MDS and SMACOF algorithms, which are widely used in psychological analysis.

The proposed method is improved in the following aspects. Firstly, the transformation model is used to convert relative coordinates into absolute ones. It includes translation, rotation, mirror and is solved using LS. Secondly, the Huber weighting mechanism is used to reduce or eliminate the influence of range errors. It can adapt its tolerance to the measurement error range with k, and weights of those with gross errors will decrease rapidly. Finally, the optimization function of $S(X)$ is constructed and the fine estimations are calculated by iterations. Its variation falls rapidly so that it can obtain higher accuracy with it.

The performance of it is described in two parts: ranging and positioning. The mean error of FTM ranging can achieve under 2m. Human bodies and concrete affect more on FTM ranging than glass, and the ranging capacity is similar on different devices. Positioning accuracy of weighted MDS is higher than others, which can achieve under 3m.

Future work will focus on the weighting mechanism and NLOS. We will try some other methods to assign weights more effectively and to eliminate the effect of NLOS during ranging before positioning. In addition, we will also devote to improve coarse positioning based on classical MDS method, so as to optimize the local minimum.

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