A 3-D Cooperative base station localization Method applied in Large Complex Indoor Environment

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Abstract. Base stations deployed for localization systems are required to be location aware. Calibrating base stations manually is time-consuming and inconvenient especially in large complex indoor environment. To address this problem, cooperative localization approaches have been developed and mostly focus on the 2-dimensional scenarios. We have proposed a cooperative Localization method to determine the positions of base stations and the corresponding Cramer-Rao lower bounds (CRLB) are derived to ensure localization quality. Simulation results verify that our method can achieve superior performance in terms of accuracy and robustness but sharp decline appears as maximum measurement range(sensing range) decreases. For large error caused by too few connections, prior location information from Barometric Sensors and visually location-specific object is applied in constraint. Meanwhile, we propose an iterative approach in the process of anchor selection and localization, it proves the robustness of cooperative localization to anchor locations. Simulation results show the improvement of localization accuracy by different prior knowledge.

Keywords: Self-Calibration , Sensing Range, Prior Information · Second keyword · Another keyword.

1 Introduction

Base stations in localization systems need to know their own locations in advance. The process of calibration is usually done manually, time-consuming and easily leads to error especially in large complex environment where the number of base stations is enormous. Moreover, if localization systems are deployed in ancient buildings like the Palace Museum, manual calibration of base stations located in the air cannot be implemented. Given accurate positions of few base stations (known as anchors) and pair-wise distance information between anchors and one location-unknown base station (denoted by UB), in large indoor environments, the distances between UB and anchors may exceed the maximum range of communication , i.e., sensing range, which results in insufficient connections with anchors [1] thus noncooperative localization is no longer available, as shown in Fig.1-a. In this event, to compensate for the deficiency of distance constraints, UBs may estimate their locations by taking advantage of other connected UBs, which is called cooperative localization, as illustrated in Fig.1-b.

Cooperative localization is aimed at the situation where some UBs cannot be located using common noncooperative localization method individually. It make use of connected UBs to obtain sufficient distance information constraints. There are two kinds of cooperative localization: Semidefinite Programming [2] and Multidimensional Scaling (MDS) [3] [4]. SDP-based approaches are also developed to determine locations of UBs such that given distance constraints are satisfied, which is a non-convex problem. Relaxation technique [5] is introduced to yield a semidefinite program. Biswas et al. [6] describe a maximum likelihood estimation, and mitigate distance measurement error by formulating it as cost function of a minimization problem. Regarding the SDP solution as an initial point, a gradient-based search method is adopted to further reduce the estimation error [7] [8]. In order to reduce computational complexity and improve real-time performance, [6] also presents a distributed SDP method for large scale problems.

Existing SDP-based methods mainly focus on 2-D scenarios, where base stations can only be deployed on a flat plane. As a result, large errors usually occur while 3-D positioning is implemented. We have proposed a 3-D cooperative algorithm which exhibits superior performance in accuracy and robustness to anchors compared to noncooperative algorithm, however,the fundamental problem of lack of reference data in height has not been solved [9].

In this paper, aimed at the large error caused by too few distance constraints, we propose an iterative approach and take prior estimated distance between UBs and visually location-specific object into consideration. The main contributions of this paper are summarized as follows:

– Prior location information for UBs from barometric sensors and visually location-specific object is added to the constraints of optimization problems, and simulation result proves that appropriate prior information can improve localization accuracy effectively.
– Iterative algorithm is also proposed in the process of anchor selection and localization, and it proves the robustness of 3-D cooperative algorithm to location of anchors.

2 3-D Constraint Model

2.1 3-D constraint model

Suppose we have m anchors $\boldsymbol{\alpha}_k \in \boldsymbol{R}^3$, $k = 1, 2, ..., m$, all the anchors are distributed in lower space for easy installation, and n UBs $\boldsymbol{x}_j$, $j = 1, 2, ..., n$,

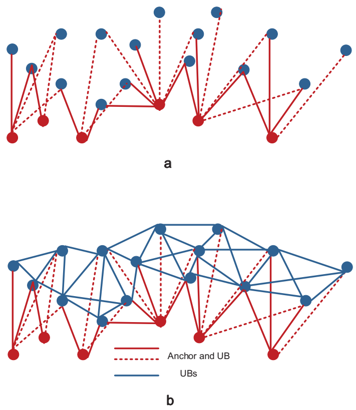

Fig. 1. comparison between cooperative and non-coopetative method

some of them are deployed in higher space for localization accuracy. The euclidean distance between anchor $\boldsymbol{\alpha}_k$ and UB $\boldsymbol{x}_j$ is represented by d_{jk}, the euclidean distance between UBs $\boldsymbol{x}_i$ and $\boldsymbol{x}_j$ is represented by d_{ij}. $\mathcal{M}$ represents distance space of anchors and UBs, $\mathcal{M} = \{d_{j,k} : 1 \leq j \leq n, 1 \leq k \leq m\}$, $\mathcal{N}$ represents distance space of UBs, $\mathcal{N} = \{d_{i,j} : 1 \leq i, j \leq n\}$. We use the $3 \times n$ matrix $\boldsymbol{X} = (\boldsymbol{x}_1, \boldsymbol{x}_2, \boldsymbol{x}_3, ..., \boldsymbol{x}_n) = \begin{pmatrix} x_1 & x_2 & x_3 & \cdots & x_n \\ y_1 & y_2 & y_3 & \cdots & y_n \\ z_1 & z_2 & z_3 & \cdots & z_n \end{pmatrix}$ to represent the locations of UBs, $3 \times m$ matrix $\boldsymbol{\alpha} = (\boldsymbol{\alpha}_1, \boldsymbol{\alpha}_2, \boldsymbol{\alpha}_3, ..., \boldsymbol{\alpha}_m) = \begin{pmatrix} \alpha_{x1} & \alpha_{x2} & \alpha_{x3} & \cdots & \alpha_{xm} \\ \alpha_{y1} & \alpha_{y2} & \alpha_{y3} & \cdots & \alpha_{ym} \\ \alpha_{z1} & \alpha_{z2} & \alpha_{z3} & \cdots & \alpha_{zm} \end{pmatrix}$ to represent the locations of anchors.We define $\boldsymbol{Y} = \boldsymbol{X}^T\boldsymbol{X}$ to derive distance.Relaxation technique is introduced: change $\boldsymbol{Y} = \boldsymbol{X}^T\boldsymbol{X}$ to $\boldsymbol{Y} \geq \boldsymbol{X}^T\boldsymbol{X}$, and thus a feasible region is planned, which is equivalent to

$$\boldsymbol{Z} := \begin{pmatrix} \boldsymbol{I} & \boldsymbol{X} \\ \boldsymbol{X}^T & \boldsymbol{Y} \end{pmatrix} \geq 0. \tag{1}$$

Considering noises in practical scenes, assume that e_{jk}, representing the measurement error between anchor $\boldsymbol{\alpha}_k$ and UB $\boldsymbol{x}_j$ and e_{ij}, the measurement error between UBs $\boldsymbol{x}_i$ and $\boldsymbol{x}_j$, are all independently and identically distributed (i.i.d) Gaussian random variables with zero mean and standard deviation σ. In large complex indoor environment, the distance between UB and anchors may exceed the sensing range. Combining the above conditions, the problem can be formulated as following:

$$\min \left(\sum_{j,k;(j,k)\in\mathcal{M}} \frac{1}{\sigma_{jk}^2} \varepsilon_{jk} + \sum_{i,j;(i,j)\in\mathcal{N}} \frac{1}{\sigma_{ij}^2} \varepsilon_{ij} \right) \tag{2}$$

$$\begin{aligned} s.t.\mathcal{M} &= \left\{(j,k) : \left\|\boldsymbol{x}_j - \boldsymbol{\alpha}_k\right\| \leq R, 1 \leq j \leq n, 1 \leq k \leq m\right\} \\ \mathcal{N} &= \left\{(i,j) : \left\|\boldsymbol{x}_i - \boldsymbol{x}_j\right\| \leq R, 1 \leq i,j \leq n\right\} \end{aligned} \tag{3}$$

$$\begin{aligned} (-d_{jk};1)^T \begin{pmatrix} 1 & \left\|\boldsymbol{x}_j - \boldsymbol{\alpha}_k\right\| \\ \left\|\boldsymbol{x}_j - \boldsymbol{\alpha}_k\right\| & \left\|\boldsymbol{x}_j - \boldsymbol{\alpha}_k\right\|^2 \end{pmatrix} (-d_{jk};1) = \\ \varepsilon_{jk}, \forall\,(j,k) \in \mathcal{M} \end{aligned} \tag{4}$$

$$\begin{aligned} (-d_{ij};1)^T \begin{pmatrix} 1 & \left\|\boldsymbol{x}_i - \boldsymbol{x}_j\right\| \\ \left\|\boldsymbol{x}_i - \boldsymbol{x}_j\right\| & \left\|\boldsymbol{x}_i - \boldsymbol{x}_j\right\|^2 \end{pmatrix} (-d_{ij};1) = \\ \varepsilon_{ij}, \forall\,(i,j) \in \mathcal{N} \end{aligned} \tag{5}$$

$$(0;0;0;\boldsymbol{e}_i - \boldsymbol{e}_j)^T \boldsymbol{Z}\,(0;0;0;\boldsymbol{e}_i - \boldsymbol{e}_j) = d_{ij}^2 \tag{6}$$

$$\left[\boldsymbol{\alpha}_{xk};\boldsymbol{\alpha}_{yk};\boldsymbol{\alpha}_{zk};-\boldsymbol{e}_j\right]^T \boldsymbol{Z}\left[\boldsymbol{\alpha}_{xk};\boldsymbol{\alpha}_{yk};\boldsymbol{\alpha}_{zk};-\boldsymbol{e}_j\right] = d_{jk}^2 \tag{7}$$

$$\boldsymbol{Z} := \begin{pmatrix} \boldsymbol{I} & \boldsymbol{X} \\ \boldsymbol{X}^T & \boldsymbol{Y} \end{pmatrix} \geq 0, \tag{8}$$

The model can be solved by virtue of the CVX and Yalmip toolbox [10].

3 Sensing Range Optimization And Anchor Placement

3.1 Sensing Range Optimization

In large indoor environments, the amount of distance constraints may decrease when the distances between two base stations go beyond the sensing range (denoted by R), which may result in compromises in localization accuracy. In our simulation settings, the maximum distance that can be reached is $r = \sqrt{150^2 + 150^2 + 20^2}m = 213m$, and the sensing range is set from $213m(r)$ to $53m(0.25r)$. As we can observe from Fig.2, with the decrease of the sensing range, RMSD of the thirty UBs increases slowly. But when the sensing range drops to $0.3r$, the RMSD reaches $2m$ quickly. It is proved that 3D-SDP algorithm is robust to R to some extent: it can still achieve high precision when half of the distances constraints between base stations are discarded. However, there exists a critical point of sharp degradation in performance: when R reaches $0.25r$, the precision declines rapidly to about 9.33 meters.

4 Prior Location Constraints

4.1 Constraints By Visual Observations

As we all know, humans can locate themselves according to a location-specific objects object based on their visual observations [11]. The objects can be doors or other objects that have clear and definite location information and are available from the design map of the building, thus prior location information of UBs can be obtained during the process of installation. To verify the feasibility of visual

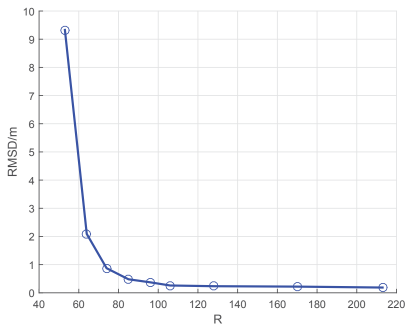

Fig. 2. Relationship between RMSD and R

observation as priori location knowledge, we tested human visual ranging errors on 10 people.

This test is carried out in Room 526, Ninth Teaching Building of Zhejiang University. The area of the field is approximately $6m$ by $15m$. The 15 test points are set on two lines, whose angle with the central axis of the door are $90°$ and $30°$ respectively, as shown in Fig.3. At each test point, 10 testers were asked to estimate the distance with the central axis of the door by themselves. The actual distance increases from $0.759m$ to $6.195m$. The average error, RMSD as well as maximum error of the 10 testers at 15 points are shown in table 1.

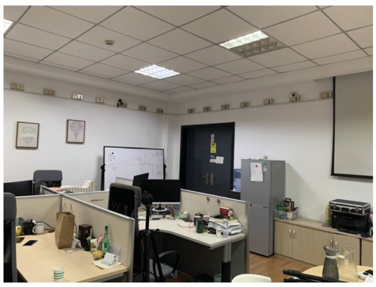

Fig. 3. test scene

Table 1 shows that although the estimated accuracy of tester 5 is weak, the average error is $0.591m$, other people have a good perception of distance. The best of them is tester 6: the average of his estimation error is $0.174m$. In addition, for almost all testers, estimating the position closer to the object is more accurate than that farther away from the object. The test result verifies that visual observation is a reliable prior location knowledge resource, and according to it we can set more appropriate visual error parameter.

Table 1. result of each tester

Tester	average/m	RMSD/m	maximum/m
Tester1	0.255	0.309	0.726
Tester2	0.32	0.444	0.995
Tester3	0.281	0.359	0.826
Tester4	0.343	0.449	0.952
Tester5	0.591	0.654	1.244
Tester6	0.174	0.219	0.544
Tester7	0.190	0.260	0.744
Tester8	0.325	0.471	1.224
Tester9	0.547	0.658	1.395
Tester10	0.247	0.285	0.548

4.2 Prior Location Constraints

In addition, with the popularity of smart phones, micro electromechanical systems (MEMS) sensors are considered as a highly efficient technology that have been applied in business, industrial, medical, and other fields. MEMS barometric sensors is considered a reliable method for height measurement [12]. Differential barometric altimetry is less vulnerable to the variations of atmospheric pressure and can be used in altitude Measurement of high UBs during installation. Thus we restrict the height of UBs firstly, assuming that the measurement errors are Gaussian random variables with zero mean and standard deviation $\sigma = 0.1$. We can see that single constraint on height has little effect on the promotion of accuracy. $RMSD = 2.45m$ and the error of 6th UB is still exceptionally large.

The previous part verifies the reliability of visual observation, experienced installer can pre-estimate positions in x and y directions of each UB by location-specific objects object while deploying. Restrictions are set on x and y directions, assuming that the errors of visual observation are Gaussian random variables with zero mean and standard deviation $\sigma = 0.5$. $RMSD = 1.44m$, half the original $RMSD$. And the errors of all UBs are more balanced.

The cause of sharp decline in accuracy is too large calibration error of the 6th UB. We try to set constraits of all the three axes only on the single 6th UB. It can still be assumed that the errors on x and y are Gaussian random variables with zero mean and standard deviation $\sigma = 0.5$ and $\sigma = 0.1$ on z. The overall localization accuracy has been significantly improved and the $RMSD = 0.63$.

4.3 Spherical Constraint

In most cases, it's inconvenient even unrealistic to pre-estimate one UB's 3-D location by a reference object, and estimating the approximate distance between a UB and a reference object is considered more easier. In the previous section, when sensing range decreases to $64m$, the RMSD reaches about 2m and cause of the sharp decline in accuracy is too large calibration error of the 6th UB.

Thus, we set distance limitation on the 6th base station. By calibrating without prior location information, the initial position of the 6th UB can be obtained. In the meantime, installer can pre-estimate the distance with a close reference object, which can formulate a sphere that the actual position can be, the object is center and the distance is radius of sphere. And the distance is set to be $1m$ in conservative estimation. The intersection of this sphere and line segment between initial position and reference object is considered position of the 6th UB, as shown in Fig.4, 'I' represents the intersection and the location-specific object is a lamp. Thus the calibration error of 6th UB is exactly the visual observation error. $RMSD = 0.66$, the distribution of each UB error is balanced.

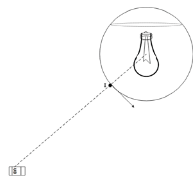

Fig. 4. intersection position

Then we propose an iterative algorithms. The intersection is regarded as the actual position of the 6th UB and act as one of anchors to calibrate the other 29 UBs. And the calibration results will be applied as prior location information to restrict the 29 UBs in the next localization round, where the original 8 anchors are utilized to calculate the original 30 UBs.

The first round RMSD of 30 UBs is 0.48m, and the latter round $RMSD = 1.05m$. The resilt proves the robustness of 3-D cooperative algorithm to location of anchors. The 6th UB still plays a dominant role in RMSD, which is similar to the error distribution with no prior location knowledge. We can see that constraining other UBs with high positioning accuracy can improve the error of base station 6 to some extent, but the number and structure of connections still plays an important role, it's unrealistic to improve position accuracy of one UB by only setting constraints on connected UBs with high accuracy position information.

5 Conclusion

Simulation results show that our 3-D cooperative algorithm is an effective indoor self-calibration method with high-precision and performs closely to the corresponding CRLB under incomplete connections. However, accuracy decreases sharply when more than half of the connections have failed. To solve the fundamental problem of lacking in reference data at altitude in 3-D cooperative localization method, we add prior location information to restrict the initial position when sharp decline in accuracy appears. Simulations show that although the errors mainly come from height, setting only altitude constraint from barometric sensors on UBs has limited effect on accuracy promotion. Visual observation by installer is considered a reliable prior information sources and shows great effect on precision improvement of 3-D cooperative algorithm. We can also see that prior location information constraints only for base stations with large calibration errors can effectively improve the overall positioning accuracy. In addition, we propose an iterative algorithm in the process of anchor selection and localization, it proves the robustness of 3-D cooperative algorithm to location of anchors. And the number and topology structure of connections plays an important role in localization accuracy, it's unrealistic to improve accuracy of one UB by only setting constraints on connected UBs with high accuracy position information.

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