A Calibration-free RSS-based Mobile Positioning System

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***Abstract*—Received power in cellular networks is commonly employed in mobile localization systems. However, uncertainties in power-distance mapping and dynamics of propagation models challenge the performance of the positioning system. Although collecting realistic data in the target area may reduce the uncertainties, it requires a time-consuming site survey and high-cost labor efforts. This study proposes a novel algorithm to enhance the performance of mobile localization without the need of additional calibration effort. The proposed algorithm utilizes the pairwise information between base stations (BSs), which is assumed to be available, and then localizes the user based on multidimensional scaling. Unlike traditional methods, the proposed approach further considers the geometric structure between BSs to compensate for the problem of distance estimation, thus achieving more accurate location estimations. We applied this approach in a realistic GSM network and experimental results demonstrate the effectiveness of our approach. The proposed algorithm outperforms previous calibration-free positioning methods, including Cell-ID and enhanced Cell-ID, in reducing the mean error by 16.74%-38.56% and 18.22%-20.96%, respectively.**

***Index Terms*—mobile positioning, multidimesional scaling, Cell-ID, GSM networks, wireless localization**

I. Introduction

Localization has gained considerable attention in the last several years because position estimations are often required for useful applications. An example is locating a mobile phone user who is in emergency. Thus, researchers have developed various location systems to compensate for the drawbacks of GPS (Global Position System) such unsatisfactory positioning time and insufficient coverage. Some methods use the time of arrival (TOA) or angle of arrival (AOA) to estimate the mobile position. However, many of these approaches require additional hardware, and are sensitive to the range measurements error caused by non-line-of-sight (NLOS) propagation [1], [2]. An alternative physical characteristic to positioning is the use of receive signal strength (RSS) where line-of-sight (LOS) propagation between transmitter and receiver is not necessary [3], [4]. The popular RSS sensing function also allows location systems to reuse existing wireless infrastructure such as Wi-Fi and GSM networks [5], [6].

One of the most popular RSS-based positioning technique is the location fingerprinting method, which uses a radio map to determine user locations. When a mobile station (BS) requests services, it maps the on-line RSS to its geographic location through the previously constructed radio map. The literature also refers to these methods as scene matching or database correlation methods [7], [8], [9]. However, the accuracy of fingerprinting methods is highly relevant to the density of the radio map. Some researchers try to build a propagation model to describe the relationship between RSS and distance. Unfortunately, there is not a universally-good propagation model due to the dynamic environments. Although collecting data in local regions may construct a better model, it requires a time-consuming site survey and high-cost labor efforts. This inspires us to build a calibration-free localization system by applying multidimensional scaling (MDS).

MDS is a method that represents similarity or dissimilarity among pairs of objects as distances between points in a low-dimensional space [10], [11]. It describes the structure of a set of objects from distances between pairs of these objects. In recent years, MDS is widely used for positioning in wireless sensor networks [12], [13]. By exploring the network connectivity between nodes, some studies utilized MDS-based technique to find the relative positions among the deployed sensor nodes [12], [14]. However, MDS cannot be directly applied to the mobile localization in cellular networks. In sensor networks, each node plays the same role, containing both receiving and transmitting functions. In cellular networks, the mobile station (MS) is different with the BS that the former contains only the receiving function. Because of this unsymmetrical property, some modifications of the classical MDS theory is necessary.

This study focus on the mobile localization based on MDS. We proposed a MDS-based mobile positioning ap-

978-1-4673-0990-5/12/$31.00

proach that requires only the pairwise information from BSs-to-BSs. Although the MS-BS distance is missing, we utilize the propagation model to obtain a rough distance estimation. Given the pairwise distances from BSs-to-BSs and the estimated MS-to-BSs distances, MDS can represent the dissimilarity among these BSs and MS as distances between points in a 2D-coordinate space. The relative location between MS and BSs is determined in this step. Afterwards, we transform the relative location to an absolute coordinate space using a transformation matrix. Unlike previous works, which consider only the MS-BSs distances, the proposed algorithm further takes the BSs-to-BSs structure into account, thus achieving more accurate location estimations.

The experiments reported in this study applied the proposed positioning algorithm to a real GSM environment at the Yuan-Ze University (YZU) campus. The experiment shows that MDS outperformed conventional Cell-ID and the enhanced Cell-ID method, reducing the mean localization errors by 16.74%-38.56% and 18.22%-20.96%, respectively. This improvement can be explained by the MDS's ability to embed the geometrical structure of BSs into to the location estimation. The experiments in this study also investigate the noisy effects to the proposed MDS-based mechanism.

The rest of the paper is structured as follows. Section II illustrates the related works. Section III describes the proposed positioning system. In section IV, we explain the experimental setup and results. Finally, the conclusion is given in Section V.

II. Related work

With growing wireless techniques, there has been an increasing need to capture the location information and to figure it into applications. To compensate for the drawbacks of GPS, some location systems are developed in mobile cellular networks. The Cell-ID algorithm [15] is probably the most common method, which equates the BS with the strongest RSS as mobile station's location. To improve accuracy, Yamamoto et al. proposed an enhanced Cell-ID algorithm that combines the locations from multiple BSs by interpolating the RSS values [16]. Although the accuracy is limited due to the limited number of BSs, the main advantage of these approaches is that the massive data collection is not required.

Recently, MDS is widely used for finding a bunch of nodes' position in sensor networks. The main idea is to use the intra-sensor distance obtained from TOA or RSS to estimate the relative positions between sensors [12], [14]. This inspires us to apply MDS on mobile phone positioning in cellular networks. The proposed algorithm regards BSs as reference nodes and mobile device as a single blind node, as illustrated in the following section.

III. Proposed Localization System

In this section, we describe the theory of multidimensional scaling (MDS) and how we apply MDS to the mobile localization system.

A. Multidimensional Scaling - MDS

Given the distances between pairs of points and we do not know the exact of coordinates of the points, Multidimensional scaling (MDS) is a method for placing these points in a low-dimensional space such that the Euclidean distances between them is as close as possible to the given distances in the original space. In other words, MDS describes the structure of a set of objects from distances between pairs of these objects. Since similarities or dissimilarities between physical locations are usually treated as the Euclidean distances, we assume there are N objects in the Euclidean space as

$$\mathbf{X} = \begin{bmatrix} \mathbf{x}_1 \\ \mathbf{x}_2 \\ \vdots \\ \mathbf{x}_N \end{bmatrix}_{N*2} \tag{1}$$

where $\mathbf{x_i}$ presents the coordinate of an object in a two-dimensional space. We then have the matrix $\mathbf{D}$ referring to the pairwise distance in a square form

$$\mathbf{D} = \begin{bmatrix} d_{11}^2 & d_{12}^2 & \cdots & d_{1N}^2 \\ d_{21}^2 & d_{22}^2 & \cdots & d_{2N}^2 \\ \vdots & \vdots & \ddots & \vdots \\ d_{N1}^2 & d_{N2}^2 & \cdots & d_{NN}^2 \end{bmatrix}_{N*N} \tag{2}$$

where $d_{ij} = d(\mathbf{x}_i, \mathbf{x}_j)$ is the distance between the i-th and the j-th object. The goal of MDS is to find a new assignment of $\mathbf{X}$ in a low-dimensional space that minimizes a stress function. The stress function measuring the goodness of fit is defined as

$$\text{Stress}(\mathbf{X}) = \sqrt{\frac{\sum\limits_{i<j\le N} \left(d_{ij} - \|\mathbf{x}_i - \mathbf{x}_j\|\right)^2}{\sum\limits_{i<j\le N} \|\mathbf{x}_i - \mathbf{x}_j\|^2}} \tag{3}$$

where $\|\mathbf{x}_i - \mathbf{x}_j\|$ is the Euclidean distance between $\mathbf{x}_i$ and $\mathbf{x}_j$. In sensor networks, the nodes' relative position can be obtained from $\mathbf{X}$ by minimizing the stress function. However, this approach cannot be directly applied to the mobile localization in cellular networks because the distances from MS to BSs are missing.

B. MDS-based localization

For the problem of mobile localization, we have total $N+1$ objects, including N base stations (BSs) and one mobile device. Note that the locations of BSs are given and the location of a mobile device is unknown in this problem. We denote $\mathbf{X} = [\mathbf{x}_1, \mathbf{x}_2, \cdots, \mathbf{x}_{N+1}]^T$ as the position of all nodes in Euclidean space with dimension $(N+1)\times 2$, where the first row $\mathbf{x}_1$ represents the location of mobile device. According to the coordinate of BSs, we have the distances between pairwise BSs. That means that $[\mathbf{x}_2, \cdots, \mathbf{x}_{N+1}]^T$ is given.

To apply MDS, we need the distance between MS and BSs to construct the matrix $\mathbf{D}$. This study adopts the Hata propagation model to transform RSS values into distances because it is widely used in cellular networks [17] [18]. Assuming the distance information is given, we can set the Euclidean distances among all BSs and mobile device as the input matrix $\mathbf{D}$, where $\mathbf{D} = [d_{ij}^2(\mathbf{X})]_{ij}^{N+1}$ denotes the matrix of pairwise distance in a square form with dimensions $(N+1)\times(N+1)$. In MDS, the elements of $\mathbf{X}$ can be obtained using eigenvalue decomposition of the double centered the squared distance matrix $\mathbf{D}$. Thus, double centering is then apply to $\mathbf{D}$ to obtain a scalar inner product matrix

$$\mathbf{B} = -\frac{1}{2}\mathbf{J}_{N+1}\mathbf{D}\mathbf{J}_{N+1} \tag{4}$$

where $\mathbf{J}_{n+1} = \mathbf{I}_{N+1} - \frac{1}{N+1}1_{N+1}1_{N+1}^T$ is the centering matrix, $\mathbf{I}_{N+1}$ and 1_{N+1} denote the $(N+1)\times(N+1)$ identity matrix and $(N+1)\times 1$ column vector of all ones, respectively. Note that $\mathbf{B} = \mathbf{X}\mathbf{X}^T$. Then, to recover all relative coordinates, we compute the eigenvectors and eigenvalues of $\mathbf{B}$

$$\mathbf{B} = \mathbf{U}\mathbf{\Lambda}\mathbf{U}^{\mathbf{T}} \tag{5}$$

where $\mathbf{\Lambda} = diag(\lambda_1, \lambda_2, \cdots, \lambda_{n+1})$ is the diagonal matrix of eigenvalues of $\mathbf{B}$ and $\mathbf{U} = [\mathbf{u}_1, \mathbf{u}_2, \cdots, \mathbf{u}_{N+1}]$ is an orthogonal matrix whose columns are the corresponding eigenvectors. Finally, we can obtain the solution $\mathbf{X}$ as

$$\mathbf{X} = \mathbf{U}\mathbf{\Lambda}^{1/2} \tag{6}$$

Since the objects is set in a two-dimensional space, the coordinate matrix can be computed by $\mathbf{X} = \mathbf{U}_2\mathbf{\Lambda}_2^{1/2}$.

The estimated points represent the dissimilarities given by the pairwise information. Since the optimized function in Eq.3 contains the pairwise BSs-to-BSs distances and this information is assumed to be true, the uncertainties in power-distance mapping would be reduced. Then, a transform matrix is required to recover the relative geometric space to an absolute space. We apply a linear transformation (rotation and scaling) which can best transform the estimation results of BSs to the absolute locations in Euclidean space using the true locations of BSs. Applying the same linear transformation to the estimated $\mathbf{x}_1$, we obtain the final result, the absolute coordinate of MS.

IV. Experimental Results

A. Experimental Setup

The experiments in this study applied MDS to an actual GSM network at Yuan-Ze University (YZU) to collect realistic RSS measurements using commercially available phones. The mobile phones were fitted with the Subscriber Identification Module (SIM) cards from FET (Far Eastone Telecommunication) company, which is one of the largest GSM network providers in Taiwan. The mobile phone was able to report the cell IDs and the received power in dBm from sensed BSs. Figure 1 shows the experimental test area. The marks show the nearest five BSs (A, B, C, D and E) in this area. Realistic pairwise RSS data was collected at these locations to obtain the initial data to build the proposed calibration-free localization system. We collected 200 testing RSS measurements from 25 distinct locations in this test field. We assume that the pairwise BS-to-BS information, including the distance and RSS, is available. This assumption makes senses because a telecommunication company knows the positions of BSs and a BS usually contains RSS receiving functions. To obtain the pairwise distance matrix in Eq. 2, we transform RSS into distance by applying Hata propagation model with shadowing path loss factor as $L_U = 69.55 + 26.16\log f + 13.82 h_B - C_H + (44.9 - 6.55\log h_B)\log d$, where L_U is the path loss, d presents the distance, h_B is height of BSs, and f is the frequency of transmission in megahertz (MHz). The antenna height correction factor C_H is computed by $0.8 + (1.1\log f - 0.7)h_M - 1.56\log f$ [19], where h_M is the height of mobile device and is set as one meter in the experiment.

B. Performance Evaluation

This section compares the performance of the proposed approach with that of two Cell-ID-based algorithms in terms of the mean positioning error. Figure 2 shows the mean error of three algorithms, including the Cell-ID, enhanced Cell-ID and MDS-based methods with different number of BSs. Since we have five BSs in the experiments, this figure reports the average values from five and ten different combinations, respectively, for the three-BS and four-BS cases. Figure 2 shows that MDS-based approach outperforms Cell-ID and enhanced

Fig. 1. The YZU campus at which the experiments were performed. The alphabets indicate the locations of FET's BSs in this test-bed.

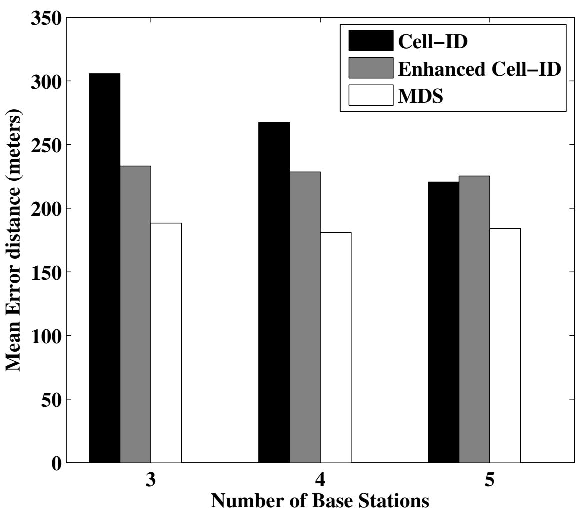

Fig. 2. The mean error comparison of three algorithms with different number of BSs.

Cell-ID with different number of BSs. The improvement of MDS is more significant in the three-BS case. Specifically, MDS reduces the mean localization error by 16.74%-38.56% and 18.22%-20.96%, respectively, compared to the Cell-ID method and enhanced Cell-ID method at different number of BSs. This improvement can be explained by the MDS's ability to embed the geometrical structure of BSs into to the location estimation. Compared to traditional methods, the proposed algorithm further considers the BS-to-BS information, thus achieving more accurate performance. The results in Fig. 2 also show that the enhanced Cell-ID perform better than Cell-ID at three-BS and four-BS cases whereas it shows a similar performance with Cell-ID at the five-BS case. This may be explained by that some testing locations are close to BSs in this scenario.

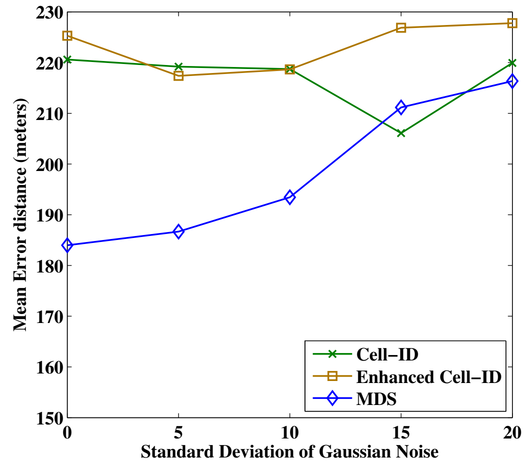

Fig. 3. The impact of noise on different algorithms with different standard deviations of the Gaussian noise.

The next experiment analyzes the impact of the temporal variation of RSS on different algorithms by adding simulated Gaussian noise. We added the random Gaussian noise to the testing data with different standard deviations. Since the maximum RSS variation was 20 dBm from the same BS at a fixed location in our experimental data, the standard deviation of the added noise ranged from zero to 20 dBm. Figure 3 shows the impact of the noisy effect on different algorithms. It is observed that the mean error of MDS clearly increases as the standard deviation of Gaussian noise increases. Compared to traditional methods, MDS seems to be more sensitive to the additive noise. Nevertheless, the performance of MDS is still better than the conventional methods. The results in Fig. 3 also show the robustness of the Cell-ID method. It is because the noise would not change the estimated results unless some corrupted RSS values is greater than that from the strongest BS.

V. Conclusion

This paper established the theoretical base and developed a calibration-free RSS-based localization system based on MDS. We applied MDS to improve mobile localization by taking the geometric structures between BSs into account. In the proposed positioning system, the propagation model is utilized to obtain rough estimates of MS-to-BS distances and form a full dissimilarity matrix. Giving this matrix as input to MDS, we obtain a relative location between MS and BSs, and then transform the relative geometric space to an absolute space using the true locations of BSs. This study applies the proposed algorithm to an actual GSM network, collecting realistic measurements across YZU using mobile phones. Experimental results demonstrate that the proposed algorithm outperforms previous calibration-free positioning methods, including Cell-ID and enhanced Cell-ID, in reducing the mean error by 16.59%-20.94% and 18.33%–38.42%, respectively. This is because the optimized function of MDS contains the pairwise BSs-to-BSs distances and this information is assumed to be true. In other words, the uncertainties in traditional methods are reduced by incorporating this additional information. The experiments also analyzes the impact of the temporal variation of RSS on different algorithms. The results show that the performance of MDS is still better than conventional methods despite the sensitiveness to noise.

ACKNOWLEDGMENT

The authors would like to thank the financial support provided by National Science Council (NSC100-2221-E-155-058-MY3, NSC100-2221-E-155-057).

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