Localization of IoT networks: An empirical bayesian approach

Feng Wang\textsuperscript{1,2}, Peng Ma\textsuperscript{2,3}, Jianxin Guo\textsuperscript{4} and Rui Zhu\textsuperscript{1}

\textsuperscript{1}Xijing University, Xi'an, Shaanxi, 710123, China
\textsuperscript{2}Shaanxi Key Laboratory of Integrated and Intelligent Navigation, Xi’an, Shaanxi, 710071, China
\textsuperscript{3}Xi’an Research Institute of Navigation Technology, Xi’an, Shaanxi, 710071, China

Corresponding author and e-mail: Feng Wang, wangfengisn@163.com

Abstract. Location information is an important component of big data, so it has attracted many researchers’ attention to obtain the location of the target based on edge computing. However, in the actual application scenario, due to the influence of non-line-of-sight (NLOS) propagation, relative localization of anchorless networks in complex scenarios is a challenging issue. In this paper, we propose a robust localization framework based on a distributed architecture, which is suitable for the edge computing environment. The proposed framework consists of three steps, firstly, using hierarchical clustering method, the network is divided into several sub-clusters with a small number of nodes. Secondly, in each sub-cluster, outlier detection and low-rank matrix completion algorithms are used to complete the Euclidian distance matrix (EDM), furthermore, MDS is used to calculate the relative coordinates. In the last step, the relative coordinates of all sub-clusters are transformed and stitched to realize the whole network localization. In order to verify the effectiveness of the proposed framework, we carry out a large number of numerical simulations, the results show that our framework can effectively eliminate the outliers caused by NLOS and improve the localization performance in a complex environment.

1. Introduction

The rapid development of internet of things (IoT) ecology has brought new opportunities and challenges, based on this background, location-based service (LBS) is becoming more and more important. In outdoor environment, mobile devices usually rely on global navigation satellite system (GNSS) to obtain location information, in urban or indoor environment, they mainly rely on mobile base stations and Wi-Fi to provide localization services. However, GNSS system like GPS has its inherent defects, such as high cost, high power consumption, and the wireless frequency band it uses is very sensitive to radio obscuration.

In some special complex scenes, such as urban dense buildings, underground mines, mountain ranges, canyons, GNSS signal will be blocked, and there is no mobile base station available. In this scenario, wireless devices need to have (relative) coordinate sensing ability, which can realize self-localization through networking cooperation, obtain the relative position between nodes, and then provide LBS [1,2]. In this paper, we propose a framework for robust cooperative localization in edge computing environment. The proposed framework has a wide range of application prospects, which
can be applied to underground mine workers localization and natural environmental monitoring, and also has an important value for smart cities, industry IoT, driverless vehicles and other fields.

The wireless signals will arrive at the receiving end through different propagation paths, resulting in channel fading, which will lead to large angle measurement and ranging errors, seriously affecting the localization effect. Many NLOS detection and elimination algorithms have been proposed, but in practice, there are some flaws, such as long detection time, low detection success rate, and high computational burden for convex optimization-based localization methods [3-5].

In addition, when the network scale is large, the classical localization method such as multi-dimensional scaling (MDS) algorithm is no longer applicable, because the computational burden of MDS in large-scale network is very high, which will lead to serious localization delay and unnecessary sensor energy waste. We hope to solve these problems through the solutions proposed in this paper, our contributions in this paper are as follows:

- A cluster-based localization framework suitable for edge computing environment is proposed, which can obtain the relative position of sensors in the way of distributed computing.
- In order to eliminate the negative effects caused by NLOS, we introduce outlier detection and matrix completion technology to realize the precise reconstitution of EDM.

The rest of the paper is arranged as follows. In the second section, we give a detailed description of the framework proposed in this paper, and the third section mainly describes the two main innovations of this paper, namely outlier detection and matrix completion methods. In the fourth section, we use numerical simulation to verify the effectiveness of the proposed framework. Finally, the discussion and prospect constitute the fifth section of this paper.

2. Proposed localization framework
Consider an IoT network with $N$ nodes, which is randomly deployed in the indoor environment (a typical GNSS-denied scenario). It is not difficult to observe that EDM will have the form as (1).

$$
E = \begin{bmatrix}
0 & d_{12}^2 & \? & d_{14}^2 \\
\? & d_{21}^2 & 0 & d_{23}^2 \\
\? & \? & d_{32}^2 & 0 \\
\? & \? & \? & d_{43}^2
\end{bmatrix}
$$

(1)

where $d_{ij}$ represents the Euclidean distance between nodes $i$ and $j$, and "?" represents the missing entries, i.e. the distance measurement between corresponding nodes cannot be realized directly. In addition, "?" represents the outliers generated due to NLOS propagation, of course, the exact support of outliers is unknown.

The working process of the proposed cooperative location framework is shown in Figure 1. Firstly, the Symmetrical Double-Sided Two Way Ranging (SDS-TWR) method is used to measure the distance between nodes and get the EDM of the network. This method can overcome the differences in frequency stability and processing delay between different hardware modules. Secondly, the algorithm mentioned above is used to cluster the network, in this step, EDMs corresponding to each sub-cluster can be generated. In order to achieve high-precision localization, in the next step, we implement outlier detection and matrix completion, and then use Sammon mapping [6] to obtain the relative coordinates within all sub-clusters. In the last step, the common nodes in different sub-clusters are used to merge all clusters into a whole network, so as to realize the localization of the whole network.

It should be noted that, due to the space limitation in this paper, we do not introduce the clustering algorithm in detail, in fact, in this paper we use the hierarchical clustering algorithm, the biggest advantage of this algorithm is that it can generate a complete tree of clusters, which is very convenient for us to determine the number of sub-clusters.
3. Outliers detection and matrix completion

As the simulation results show, even a small number of outliers can lead to serious degradation of localization performance, therefore, the detection and correction of outliers is an ongoing research topic. Similarly, incomplete EDM will also affect the localization performance. So, in this section, we study these two technologies respectively, and use them to improve the performance of localization.

3.1. Outliers detection

When applied to localization, the outliers caused by NLOS in EDM are positive errors, that is, the distance between two nodes displayed in the matrix is greater than the actual distance. When the introduced outliers have large amplitude, the triangle relation formed by three nodes in the network may be broken. Intuitively, when the number of broken triangles containing a pair of nodes \((x_i, x_j)\) is large, the probability that ranging data \(d_{ij} = \|x_i - x_j\|\) contains outlier will be high. Based on this observation, [7] implemented outlier detection by counting the number of broken triangles, which is used in our proposed framework.

3.2. Matrix completion

As already known, EDM is naturally low rank, when some entries in the matrix are unknown, they can be reconstructed by matrix completion (MC) algorithm. Recently, a considerable number of MC algorithms have been proposed, such as heuristic greedy algorithm [8], alternating minimization technique [9]. When the rank of the matrix to be completed is known, the low rank can be used as a constraint for the optimization problem to improve the performance of the matrix completion. Here, we chose the relevance singular vector machine (RSVM) [10], which was chosen considering that the rank of EDM that needs to be completed is clearly known.

The essence of low rank matrix completion problem is to determine unknown elements according to known matrix entries, this problem can be formulated mathematically as follows:

$$\min_{X} \text{rank}(X) \quad \text{s. t.} \quad P_{\Omega}(X) = P_{\Omega}(D)$$

(2)
Where $D$ represents the observed EDM, $X$ represents a low rank matrix, and $P_\Omega(D)$ is a projection operator, defined as follows:

$$(P_\Omega(X))_{ij} = \begin{cases} X_{ij} & (i, j) \in \Omega \\ 0 & \text{others} \end{cases}$$ (3)

It is not difficult to see from (x) that our goal is to find a low rank matrix whose known entries should be the same as the observation matrix. Based on empirical Bayesian method, i.e., relevance vector machine (RVM), [10] designs a low-rank matrix completion method. First, the matrix to be completed is represented as a two-sided precision model.

$$X = \alpha_L^{-1/2} U \alpha_R^{-1/2}$$ (4)

By using the EM algorithm to solve (5), it is possible to complement the low-rank matrix.

$$\min_x \beta \| y - \text{vec}(X) \|_2^2 + g_L(\alpha_L^{-1/2} U \alpha_R^{-1/2})$$ (5)

Where $g_L$ is a sparsely constrained function, and $\beta$ is a trade-off parameter for which we set the gamma prior distribution.

3.3. Robust MDS and network stitching

In order to eliminate residual outliers in the completed matrix, weighted MDS, that is, Sammon weighting, is used to perform relative coordinate calculation. This problem can be regarded as a generalized form of classical MDS, and the objective function is shown in (6).

$$\text{Stress}(D) = \sum_{i \neq j} \frac{(D_{ij} - \| x_i - x_j \|)^2}{D_{ij}}$$ (6)

Numerical simulations show that the Sammon method can effectively suppress positive outliers, and this is exactly the situation corresponding to NLOS propagation. What should not be ignored is that the last step of the framework proposed in this paper is to take the common nodes of the sub-clusters as the bridge, and realize the unification of the whole network coordinates through coordinate transformation, the linear transformation involved in it is not very complex, limited by the length of the article, we will not describe it in detail.

4. Numerical simulations

In this section, we use numerical simulations to verify the effectiveness of the proposed localization framework. Firstly, we use an experiment to confirm the adverse effects of outliers and the sensitivity of MDS to outliers. Secondly, the effectiveness of our proposed framework is verified by the analysis of location performance.

4.1. The effect of outliers

The simulation parameters here are set as follows. We randomly deploy 20 nodes in the square range of [-10m, 10m], which is about the number of nodes in a sub-cluster. Then, 3 outliers with large amplitude (about twice of the real data) are added to the ranging data between some nodes, the localization result using classic MDS are shown in Figure 2, which proves that even a few outliers can cause serious localization errors. This experiment indicates the necessity of outlier detection and reveals the defects of classic MDS.

We compare three kinds of matrix completion algorithms, namely, relevance singular vector machine (RSVM) [10], alternative descent algorithm (AD) and rank alternation (RA) algorithm [11]. We can see from Figure 3 that the RSVM algorithm we selected has the advantages that cannot be ignored. Moreover, for a network of 50 nodes, when the missing link is not more than 900, the probability of matrix completion is very high, the successful completion of matrix means that the Frobenius norm of the difference between the completion matrix and the real matrix is less than 100.
4.2. Localization performance evaluation
At the end of the paper, we show the localization performance of the proposed framework through simulation. The simulation system includes 50 randomly deployed nodes, by adjusting the number and magnitude of outliers added, we analyse and compare the impact of different matrix completion algorithms on location performance.

In a network with 50 nodes, 100 outliers are added (the amplitude is not more than twice the real distance), Figure 4 shows the recovery effect based on outliers detection and Sammon mapping, the localization effect of our proposed framework is shown in Figure 5.

5. Conclusions
In this paper, we try to use a hybrid framework to achieve robust localization, our main tools are outlier detection and missing data completion in EDM, as far as we know, the potential of low rank matrix completion in outlier suppression is not fully exploited, the experiments in Section 4 prove that the proposed framework has a good application potential, and can be easily applied to different scenarios of IoT.

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References
[1] Vaghefi R M and Buehrer R M 2015 Cooperative localization in NLOS environments using semidefinite programming IEEE Communications Letters 19(8) pp 1382-1385.
[2] Saeed N and Nam H 2016 Cluster based multidimensional scaling for irregular cognitive radio networks localization IEEE Transactions on Signal Processing 64(10) pp 2649-2659.
[3] Miao H Yu K and Juntti M J 2007 Positioning for NLOS propagation: Algorithm derivations and Cramer–Rao bounds IEEE Transactions on Vehicular Technology 56(5) pp 2568-2580.
[4] Xiao Z Wen H Markham A Trigoni N Blunsom P and Frolik J 2014 Non-line-of-sight identification and mitigation using received signal strength IEEE Transactions on Wireless Communications 14(3) pp 1689-1702.
[5] Momtaz A A Behnia F Amiri R and Marvasti F 2018 NLOS identification in range-based source localization: Statistical approach. IEEE Sensors Journal 18(9) pp 3745-3751.
[6] Sammon J W 1969 A nonlinear mapping for data structure analysis IEEE Transactions on computers 100(5) pp 401-409.
[7] Blouvshtein L and Cohen-Or D 2018 Outlier detection for robust multi-dimensional scaling IEEE transactions on pattern analysis and machine intelligence 41(9) pp 2273-2279.
[8] Lee K and Bresler Y 2010 Admira: Atomic decomposition for minimum rank approximation. IEEE Transactions on Information Theory 56(9) pp 4402-4416.
[9] Tanner J and Wei K 2016 Low rank matrix completion by alternating steepest descent methods. Applied and Computational Harmonic Analysis 40(2) pp 417-429.
[10] Sundin M Rojas C R Jansson M and Chatterjee S 2016 Relevance singular vector machine for low-rank matrix reconstruction IEEE Transactions on Signal Processing 64(20) pp 5327-5339.
[11] Dokmanic I Parhizkar R Ranieri J and Vetterli M 2015 Euclidean distance matrices: essential theory, algorithms, and applications IEEE Signal Processing Magazine 32(6) pp 12-30.