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A Non-Line-of-Sight mitigation localization algorithm for sensor networks using clustering analysis ☆

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ABSTRACT

Non-Line-of-Sight propagation of wireless signal has an impact on measured distances in range-based localization and will bias the final localization results. A new localization algorithm is proposed in this paper to mitigate Non-Line-of-Sight errors when there are more than enough anchor nodes deployed around the node to be located. This algorithm utilizes multi-round clustering analysis to filter the pre-located estimators which derive from all possible subsets of measured distances. In each round, the method density-based spatial clustering of applications with noise is adopted. Simulations show that the proposed algorithm can effectively improve localization accuracy not only when the measured distances with Non-Line-of-Sight error are minor but also under the condition that all of them suffer random Non-Line-of-Sight error.

1. Introduction

Localization techniques are of great importance to realize a variety of functions in the field of Wireless Networks such as Wireless Sensor Networks (WSN), Mobile adhoc networks (Manet), and Internet of Things (IoT). To obtain the self-location, a node usually utilizes the reference information of neighbor nodes. In this paper, we refer to the nodes with unknown locations as to-be-located nodes, and the reference nodes with pre-known locations as anchor nodes. Among the prevalent localization techniques, the range-based ones are supposed to get higher localization accuracy than range-free ones. The distance measuring techniques includes Time of Arrival (ToA) [1] and Time Difference of Arrival (TDoA) [2] which can measure distances between the to-be-located node and its neighboring anchor nodes. In this paper, our discussion mainly focuses on direct distance measurement techniques. In such a condition, the accuracy of the measured distances using these techniques plays an essential role in obtaining a reliable localization estimator. However, since ToA and TDoA utilize wireless signal for distance measurement, reliable localization can only occur under Line-of-Sight (LoS) propagation. If the signal suffers reflection, diffraction, and scattering, the Non-Line-of-Sight (NLoS) error is introduced [3]. As a result, it will lead to erroneous localization estimator.

NLoS error happens when LoS propagation are not available. While NLoS propagating happens, the received time will be later than that of LoS propagation. Therefore, measured distances derived from these techniques will be consequently much larger than the true value [4]. How to reduce the impact of NLoS error is a research focus in localization work [5,6]. Generally, there are three ways to combat NLoS error [7]. The first one is to detect propagation channels characteristics and then adjust localization method. The second way is giving each measurement a weighting which comes either from the distribution of anchor nodes or from residual error of measurements. However, these two ways are neither feasible nor effective enough in practical application [7]. The third one, which is adopted by several algorithms, is to recognize measurements with NLoS

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error, and exclude them in further calculation. To achieve this, the algorithm in literature [7] requires the knowledge of error information before localization. While the RMIN and RWGH algorithms proposed in [3] can avoid this. In literature [3], the RMIN algorithm adopts the Least Square Estimator (LSE) with least residual error derived from the subsets of measured distances as the final estimator, while RWGH gives each Least Square a weighting factor derived from its residual error. However, although the localization results are satisfactory, both of them have a high computation complexity.

In this paper, we proposed a new localization algorithm to combat NLoS measurement, named as Multi-Round DBSCAN Filtering (MRDF). It is also robust to malicious attack since the attacker also provides biased preference information and its impact is similar to NLoS propagation [8]. By utilizing Multi-Round DBSCAN Filtering Processing, the estimators near the true location can be recognized, and therefore the final estimator derived from these filtered estimators can be with high reliability. There is no need to know the error model beforehand because it utilizes statistic law to perceive error condition. It also has low computation complexity and is more adaptive to different localization scenarios.

The rest of the paper is organized as follows. In Section 2, we present the localization scenario and two effective NLoS mitigation algorithms whose performances will be compared. Then we introduce the new algorithm, MRDF. In Section 3, several simulation results will be presented and analyzed to verify the superiority of the new algorithm. The conclusion of our work will be drawn in Section 4.

2. Related work

2.1. Localization and error model

We assume that in a 2-dimensional field, N_d anchor nodes with known locations are deployed around the to-be-located node. In one localization process, a collection of $\langle x_i, y_i, \widetilde{d}_i\rangle$ can be obtained, where $\widetilde{d}_i$ represents the measured distance between the i_{th} anchor node $\langle x_i, y_i\rangle$ and the to-be-located node, and it can be derived by ToA or TDoA. Let d_i be the true distance, then the relationship between $\widetilde{d}_i$ and d_i is

$$\widetilde{d}_i = d_i + \varepsilon_i + n_i \tag{1}$$

where $n_i \sim N(0, \sigma_i^2)$ is the additive white Gaussian noise (AWGN) with variance σ_i, and ε_i is the potential NLoS error. If the propagation complies with LoS propagation, ε_i is zero.

In multilateration, at least three anchor nodes are required for a 2-dimensional localization when ToA or TDoA is employed [9]. And in practice, there are usually more than three anchor nodes in the neighborhood of the to-be-located node, and the redundancy of these anchor nodes can be utilized for better accurate localization by Least Square (LS), whose estimator for the to-be-located node can be obtained by minimizing the residual square error [10],

$$Res(\hat{\theta}) = \sum \left(d_i - \sqrt{(\hat{x} - x_i)^2 + (\hat{y} - y_i)^2} \right)^2 \tag{2}$$

where $\hat{\theta}(\hat{x}, \hat{y})$ is the estimated location of the to-be-located node.

LS will be effective in estimating the location when there are more than enough distance measurements conducting under LoS propagation. However, since the measured errors brought by NLoS are comparable large, LS estimator will be far more inaccurate when some of the measured distances, which we refer to as corrupted measured distances, are attached with large error due to NLoS propagation [11]. A good strategy to address such a problem is to recognize the corrupted measured distances and exclude them in further LS calculation.

2.2. NLoS error mitigating algorithms

To remove the dependency on the size of each set of measured distances, Normalized Residual Error (NRE) is introduced

$$\overline{Res(\hat{\theta})} = \frac{\sum \left(d_i - \sqrt{(\hat{x} - x_i)^2 + (\hat{y} - y_i)^2} \right)^2}{N_d} \tag{3}$$

This is a good indicator for assessing performance of the LS estimator of each set, regardless the differences in size of them. Intuitively, more reliable measured distances involved in the LS calculation, more accurate the final localization will be [12], so a scheme easy to conceive is to compare the residual errors of all possible subsets taking at least three measured distances, and choose the LS estimator from the subsets with minimum normalized residual error as the final localization estimator. Such algorithm was first proposed in [13] and is named as RMIN.

Rwgh is also proposed in [13]. Its final estimator is the weighted average of the LS estimators of all possible subsets. For a certain subset, its weighted factor is derived from its normalized residual error, so the final estimator of RWGH is,

$$\hat{x}_{rwgh} = \frac{\sum_{k=1}^{N_c} \left(\overline{Res(\hat{x}_k)} \right)^{-1} \cdot \hat{x}_k}{\sum_{k=1}^{N_c} \left(\overline{Res(\hat{x}_k)} \right)^{-1}} \tag{4}$$