ROBUST SEQUENCE-BASED LOCALIZATION IN ACOUSTIC SENSOR NETWORKS

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ABSTRACT

Acoustic source localization in sensor network is a challenging task because of severe constraints on cost, energy, and effective range of sensor devices. To overcome these limitations in existing solutions, this paper formally describes, designs, implements, and evaluates a Half Plane Intersection method to Sequence-Based Localization, i.e., HPI-SBL, in distributed smartphone networks. The localization space can be divided into distinct regions, and each region can be uniquely identified by the node sequence that represents the ranking of distances from the reference nodes to the region. The key idea behind HPI-SBL is to turn the localization problem into half-plane intersection by processing the node sequence. The proposed design is evaluated through extensive simulations and physical experiments in an indoor test-bed with 30 smartphone nodes. Evaluation results show that HPI-SBL can effectively locate the acoustic source with good robustness.

***Index Terms*—** Sequence-based localization, acoustic sensor networks, half plane intersection

1. INTRODUCTION

Acoustic source localization (ASL) is an important signal processing task, and has a wide range of application scenarios, such as speaker-location-aware audio capturing in videoconferencing [1], shooter localization in a battle field [2], and wild biological acoustic studies [3]. The traditional centralized microphone array-based solution to ASL exploited multiple synchronized microphones to simultaneously acquire multiple signals, which had some limitations with regard to the distances between the microphones, and sensing range for the large-scale applications. Wireless acoustic sensor networks (WASNs) can overcome these limitations. A WASN consists of a set of wireless microphone nodes that are spatially distributed over the environment, usually in an ad-hoc fashion. Due to the wireless communication capabilities, the array-size limitations disappear and the microphone nodes can physically cover a much larger area.

Acoustic source localization problem in sensor networks has been widely studied in the literature [4–10]. There is a trade-off between the accuracy of localization and the computational complexity for existing different solutions. Most of localization systems are based on range measurements, such as distance measurements and angle measurements among sensor nodes. Range-based localization methods can achieve good localization performance, however, generally are sensitive to the mesurement errors. There have existed some approaches to range-free localization [11–17]. Yedavalli, *et al.* [18] proposed a range-free Sequence-Based Localization (SBL) method in wireless sensor networks. The heart of SBL is the division of a 2D localization space into distinct regions by the perpendicular bisectors of lines joining pairs of anchor nodes. Each distinct region can be uniquely identified by a node sequence that represents the distance ranks of the acoustic source to that region. Based on the rank of measurements between the acoustic source and the sensor nodes, the location of acoustic source can be estimated by searching through the node sequence table.

In this paper, we present a robust Half Plane Intersection to Sequence-Based Localization (HPI-SBL) by deeply mining the information embedded in the node sequence. As a range-free scheme, our design applies node sequences instead of direct time of arrival (TOA) as the measurement information, and has the following two major advantages: (i) node sequences are more robust to the measurement noise; (ii) node sequences significantly alleviate the accuracy requirement of time synchronization in sensor networks. Compared with earlier works on sequence-based localization in sensor networks (e.g. SBL [18]), the primary contribution of our work is providing a robust approach to solve the sequence-based localization problem with the uncertainty of node position errors and measurement errors. The proposed HPI-SBL system formulates the localization as the probabilistic half-plane intersection problem. The proposed design is evaluated with both test-bed experiments and extensive simulations. Evaluation results show that the proposed HPI-SBL system can provide improved localization robustness.

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2. SYSTEM OVERVIEW

In this section, we focus mainly on the system overview of our HPI-SBL system, which aims at locating an acoustic source with the node sequence. Fig.1 shows a layout of a acoustic sensor network with N sensor nodes and the acoustic source.

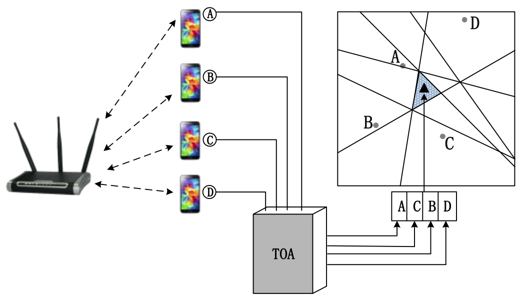

Fig. 1: Overview of HPI-SBL

We use circles and the triangle to stand for sensor nodes and the acoustic source, respectively. Consider any two reference nodes and draw a perpendicular bisector to the line joining their locations. This perpendicular bisector divides the localization space into two different regions that are distinguished by their proximity to either reference nodes, as illustrated in Fig.1. Similarly, if perpendicular bisectors are drawn for all pairs of reference nodes, they can divide the localization space into many regions. All locations inside the same region have the same node sequence, and the node sequence of a given region is unique to that region. If each region in the arrangement is represented by its centroid, then there exists a one-to-one mapping between a node sequence and the centroid of the region that it represents.

Briefly, sequence-based localization system works as follows. Sensor nodes detect the acoustic event sequentially at different time instants, then an order of related nodes, called node sequence, is naturally generated. For instance, in Fig.1, when the acoustic source generates a wave, the node sequence $NodeSeq(ACBD)$ is obtained along the sound propagation. The node sequence implies the location information of the acoustic source. By gathering the TOA measurement data from sensor nodes, the location of the acoustic source can be estimated by processing the node sequence.

Fig.2 shows that $NodeSeq(ACBD)$ can be achieved by TOA measurement of the acoustic event. We can get the distance sequence $SA < SC < SB < SD$ from each node to the acoustic source S. $SA < SC$ shows that the acoustic source S lies in the right half-plane of the perpendicular bisector of A and C. Similarly, $SC < SB$ means that the acoustic source S lies in the left half-plane of the perpendicular bisector of C and B. $SB < SD$ shows that the acoustic source S lies in the left half-plane of the perpendicular bisector of B and D. The intersection of the three half-planes is the final region of the acoustic source.

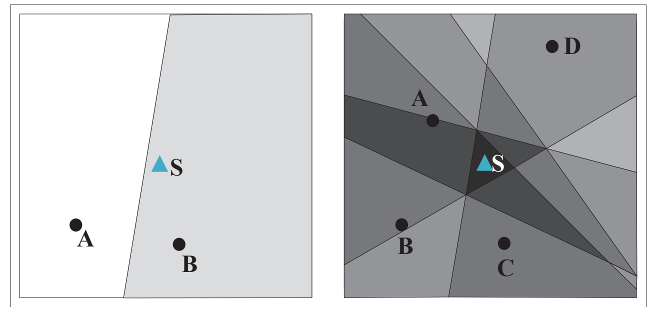

Fig. 2: The basic idea of HPI-SBL

Compared to earlier works on sequence-based localization with brute force searching scheme (SBL [18]), we carefully formulate sequence-based localization as the traditional half-plane intersection problem. To the best of our knowledge, this is the first work to leverage half-plane intersection for solving sequence-based localization problems in sensor networks.

3. DESIGN

In this section, we firstly introduce the basic HPI-SBL method. After the basic HPI-SBL method is proposed, we describe the probabilistic HPI-SBL method in the next subsection. Finally, weighted probabilistic HPI-SBL, the robust version of HPI-SBL is given.

3.1. Basic HPI-SBL

In this section, we introduce the basic sequence-based localization technique based on half-plane intersection.

Considering a sensor network in the 2D space with N nodes, all nodes are $\boldsymbol{X} = \{\boldsymbol{node_1}, \cdots, \boldsymbol{node_i}, \cdots, \boldsymbol{node_N}\}$, where any node $\boldsymbol{node_i}$ has its location coordinate denoted as $[x_i, y_i]$. As showed in Fig. 2, an acoustic event occurs at $\boldsymbol{X_s}= [x_s, y_s]$, d_i is the distance from $\boldsymbol{node_i}$ to the acoustic source $\boldsymbol{S}$. The node sequence is determined by the distances from nodes to the acoustic source $\boldsymbol{S}$.

Basic HPI-SBL turns the localization problem into half-plane intersection by processing the node sequence. The half-planes are constructed by the two adjacent nodes in the node sequences. We can find a solution to narrow the source region by making intersection of these half-planes. Given the following node sequence $NodeSeq(\cdots, i, j, k, \cdots)$ obtained by time of arrival (TOA) information of the acoustic event, we can get the distance sequence $d_i < d_j < d_k$ from the acoustic source to each node. Just considering the adjacent node, we can have the following $N(N-1)/2$ linear constraints: $d_i < d_j$, $d_i < d_k$ and $d_j < d_k$, etc. We construct the corresponding $N(N-1)/2$ half-planes H_{ij}, H_{ik} and H_{jk}, etc. $d_i < d_j$ means that the acoustic source lies in the left half-plane H_{ij} of the perpendicular bisector of $\boldsymbol{node_i}$ and $\boldsymbol{node_j}$. The intersection of the $N(N-1)/2$ half-planes is the final region of the acoustic source.

3.2. Probabilistic HPI-SBL

For the sake of presentation, until now we have described HPI-SBL in an ideal case where a complete and perfect node sequence can be obtained. In this section, we describe how to make HPI-SBL work well under more realistic conditions.

In the practical application, if two nodes are very close to each other along the direction of event propagation, they would detect the event almost simultaneously. In this case, the flip problem of node sequence may occur. Basic HPI-SBL might fail to find a feasible solution that satisfies all the constraints when sequence flip occurs. For example, as shown in Fig.2, the right middle region identifies by the node sequence $NodeSeq(DBCA)$. Once the order of node A and C is flipped in $NodeSeq(DBCA)$, the region corresponding to $NodeSeq(DBAC)$ does not exist, basic HPI-SBL can not give the accurate estimation. In this section, we propose a robust solution to address the problem of sequence flip, called probabilistic HPI-SBL.

Considering the uncertainty of the measurement with the node sequence $NodeSeq(\cdots, i, j, \cdots)$, the probability of $d_i < d_j$ can be described as

$$p(d_i < d_j) > \alpha \tag{1}$$

Eq.1 means that the probability of the acoustic source in the left side of the the half-plane H_{ij} is α, and the right side is $1-\alpha$. After dividing the localization space into some discrete grids, the weight of the grid point in the left side of the the half-plane H_{ij} is α, and the weight of the grid point in the right side of the the half-plane H_{ij} is $1-\alpha$.

Besides these key constraints mentioned in basic HPI-SBL, some relaxed constraints are also provided some localization information. For example, given $NodeSeq(ACBD)$, three key constraints $SA < SC$, $SC < SB$ and $SB < SD$ from the two adjacent nodes, and three relaxed constraints $SA < SB$, $SA < SD$ and $SC < SD$ from the two nonadjacent nodes in the node sequence are achieved, respectively. Given the node sequences with N nodes, all $N(N-1)/2$ constraints can be ultilized to further improve the localization robustness. By processing $N(N-1)/2$ half-planes, we can compute the cumulative weight w of each grid point $\boldsymbol{x}$

$$w(\boldsymbol{x}) = \sum_{k=1}^{N-1} \alpha(k). \tag{2}$$

The region with the highest probability is the final region of the acoustic source

$$\hat{\boldsymbol{X}}_{\boldsymbol{s}} = arg \max_{\boldsymbol{x} \in R} w(\boldsymbol{x}). \tag{3}$$

The centroid of the final region is the estimated location of the acoustic source.

3.3. Weighted Probabilistic HPI-SBL

Considering the uncertainty of the measurement with the node sequence $NodeSeq(1, \cdots, i, j, \cdots, n)$, the probability of $d_i < d_j$ can be described as

$$p(d_i < d_j) > \alpha_{ij} \tag{4}$$

In real condition, we consider the probabilities given by different half-plane exist differences. Here we call the line which divide the space as edge. We believe the edge constructed by i, j, if closer to the acoustic source, the half-plane divided by it is more essential to localization for determining a more accurate area, meawhile, is more likely to occur flip, we give α_{ij} a smaller value. As for the edges further to the source, its function is inferior in localization, but impossible to occur flip so more believable, we set α_{ij} a large value. In this way, utilizing the weighted probability to determine the acoustic source.

As the node sequence $NodeSeq(\cdots, i, j, \cdots)$ is known to us, for every half-plane, the probability change dynamically according to the distance of the edge to the acoustic source. If the node i, j that construct the half-plane in the sequence is 1 and n, as the relative distance is the largest, we set α_{ij} a largest value α, if the relative distance of i, j in the sequence is the smallest 1, we give α_{ij} a smallest probability β. As for other half-planes, we utilize the arithmetic propression between α and β by the relative distance of i, j to set their probabilities.

4. EVALUATION

4.1. Simulation

To verify our method and obtain an intuitive understanding of the localization performance under different conditions, we developed a Monte Carlo simulator that implements both SBL and HPI-SBL using MATLAB. In the simulation, we randomly deployed some smartphones (default 20) in a $10m \times 10m$ area. Considering the impact of the uncertainty of node position and TOA detection, we added a certain amount of node location error (default 0.4m) and TOA measurement error (default 2ms) in all the simulations. Table 1 lists default configurations of major parameters in the simulation. All statistics reported are RMSE over 100 trial runs for high confidence. The results of simulation evaluation are as follows.

1) Impact of the number of anchors: In this experiment, we investigated the localization error and number of anchors with a different number of anchors from 10 to 40 in steps of 3. TOA error is 2ms, and other simulation parameters are default values. With more anchors, the whole space area will be divided into smaller parts, thus more accurate localization estimation could be achieved. The results shown in Fig.3 indicate that, as the number of anchor nodes increases, the localization error decreases for both methods. Fig.3 shows that

Table 1: **Default configuration parameter**

Parameter	Description
Field Area	10m $\times$10m
Number of Anchors	20 (Default)
Node Location Error	0.4m (Default)
TOA Detection Error	2ms (Default)
Random-Seed Loop	500 times (Default)

the localization error of HPI-SBL method is smaller than the SBL method.

2) Impact of the location error: We choosed the location error with the range from 0 to 1m in steps of 0.05m for the three methods. Fig.4 illustrates a comparison of localization errors between the SBL and the proposed HPI-SBL. Fig.4 indicates the location error of anchors has an effect on the localization results. The proposed HPI-SBL method is more accurate than the SBL method. For the SBL method, the localization error changes obviously as location error increases in Fig.4. However, as demonstrated in Fig.4, with the increase location error of nodes, the localization error of HPI-SBL increases relatively slowly, which demonstrates the HPI-SBL method is more robust to the node location error.

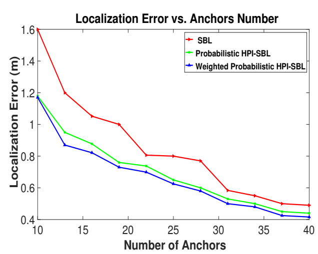

Fig. 3: Localization Error vs. Number of Anchors

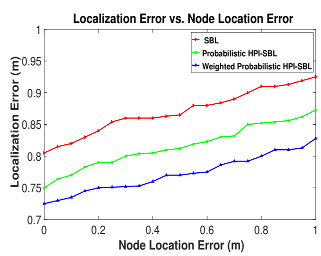

Fig. 4: Localization Error vs. Node Location Error

3) Impact of the TOA measurement error: In this experiment, we performed the impact of the TOA error of anchors for the two methods with the range from 0 to 4ms in steps of 0.25ms. Other simulation parameters keep default. As it is shown in Fig.5, the localization errors of the three methods are increasing as the TOA error growth. Also, the HPI-SBL method has a better result than the SBL method. We can conclude from this figure that HPI-SBL is more robust to TOA measurement error than SBL.

4.2. Emulation

In this section, we reported system implementation of our design based on smartphone arrays. The 30 smartphones are deployed in a size of 16m$\times$10m space and connected by CISCO CVR328W-K9-CN wireless router. TPSN protocol is adapted in the proposed HPI-SBL system to realize time synchronization. In the experiment, smartphones are randomly deployed in the space, and 100 times localization results are shown in Fig. 6. In the figure, blue squares stand for anchor nodes, red circle squares denote the real position of acoustic sources and black dots are the estimated location by HPI-SBL. An arrow origins from the estimated location of each acoustic source and points to its real position. As shown in Fig.6, most of estimated locations are close to the ground truth and the errors between them are very small. In our experiment, the acoustic sources got localized with average and maximum error of 0.84 feet and 3.91 feet, respectively. Fig.6 tells that the proposed HPI-SBL successfully accomplishes acoustic source localization with good robustness.

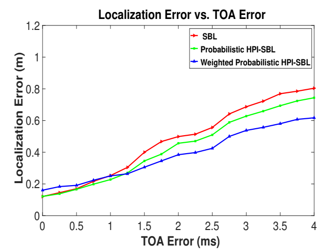

Fig. 5: Localization Error vs. TOA Error

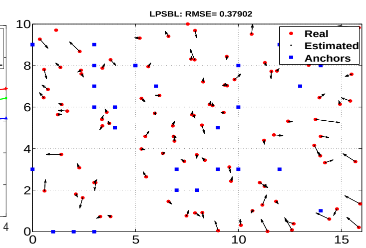

Fig. 6: Test-bed localization result of the Weighted Probabilistic HPI-SBL

Summary: Considering the parameters including the number of anchors, node location error, TOA error and testbed experiment prove that our methods have a great performance. Probabilistic HPI-SBL method introduces the probability, determine a more accurate with error tolerance. Weighted probabilistic HPI-SBL set the half-plane with different weights, further strengthens the localization behavior. Above all, our methods can accomplish localization with robustness.

5. CONCLUSIONS

In this paper, we presented a novel localization technique HPI-SBL. The reference nodes sequence is computed by TOA measurements of acoustic signals between the acoustic source and reference nodes. The half-planes are constructed by processing the node sequence, then turn the localization problem into half-plane intersection problem. Our system runs on COTS smartphones, it has potential to enable a wide range of distributed acoustic localization system. Besides the basic design, robust HPI-SBL is proposed for further enhancing system robustness. Our system is verified and evaluated through extensive simulation and test-bed experimentation. Results have shown that the proposed method can effectively implement acoustic source localization.

6. ACKNOWLEDGE

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