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Signal processing for a positioning system with binary sensory outputs

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ABSTRACT

Energy based localization method for source localization has attracted considerable attention in recent years. The binary sensor is a low-power and bandwidth-efficient solution for positioning system since the node provides only binary information about the sources. Most of the existing acoustic source localization methods assume there only exists a single source and may fail with the presence of multiple sources. In contrast, we directly consider the case when the node is influenced by multiple sources. A maximum likelihood estimation method is applicable to the multiple sources localization problems, but is at the cost of high computational complexity. To tackle these problems, this paper proposes a novel likelihood matrix based multiple acoustic sources localization algorithm for binary sensor. The fuzzy c-means algorithm is firstly employed to calculate the membership degrees of the alarmed nodes associated with the sources, and then a likelihood matrix is proposed for multiple acoustic sources localization. Simulation and experiment results show that the proposed algorithm provides accurate location estimations.

1. Introduction

Due to the availability of low cost and energy efficient sensors, micro-processors and radio frequency circuits for information transmission, there is a rapid development of wireless sensor network (WSN). WSN is composed of a large number of inexpensive nodes which are densely deployed in a region of interests to measure certain quantity. WSN have received significant attention due to its potential applications such as health surveillance, battle field surveillance and environmental monitoring [1].

The source localization is one of the key techniques in WSN. There are several ways to estimate the source location: energy-based [2], angle of arrival (AOA) [3], time difference of arrival (TDOA) [4]. As an inexpensive approach, energy-based method is an attractive method because it requires low hardware configuration. In this paper, we investigate the energy-based sources localization method. The source localization methods have a wide range of possible applications. Applications include vehicle or aircraft localization in outdoor environments, indoor human speaker localization and sea animal or ship localization in underwater environments.

The source localization can be categorized as: single source localization and multiple sources localization [5]. For single source localization: since the objective function of single source localization method has multiple local optima and saddle points [6], the authors formulate the problem as a convex feasibility problem and propose a distributed version of the projection onto convex sets method. A weighted direct/one-step least squares based algorithm is investigated in [7] to reduce the computational complexity. In comparison with quadratic elimination method, these methods are amenable to a correction technique which incorporates the dependence of unknown parameters leading to further performance gains. In [8], the authors propose normalized incremental sub-gradient algorithm to solve the energy based sensor network source localization problem while the selection of the decay factor in this method is still an unsolved problem.

For multiple sources localization: A maximum likelihood estimator [9] is used for the multiple source localization. An efficient expectation maximization algorithm [10] is proposed to improve the estimation accuracy and to avoid trapping into local optima through the effective sequential dominant-source initialization and incremental search schemes. An alternating projection [11] algorithm is proposed to decompose the multiple source localization into a number of simpler, yet also non-convex, optimization steps. This method decreases the computation complexity. And an optimal parametric maximum likelihood solution [12] to locate wideband sources in the near field is proposed. However, this method turns to the solution of a nonlinear optimization problem and thus is still hard to solve. A robust expectation maximization algorithm [13] based on the assumption that the sources are corrupted by the noises with non-uniform variances is proposed. This algorithm is much more computa tionally efficient

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and robust than the existing stepwise-concentrated maximum-likelihood and approximately-concentrated maximum-likelihood algorithms. Most of the source localization methods focus on the signal strength, i.e. the fusion center knows the measurements of the nodes. In order to obtain the accurate measurements, the node needs a complex calculating process. The above methods require transmission of a large amount of data from sensors, which may not be feasible under communication constraints. The binary sensors sense signals (infrared, acoustic, light, etc.) from their vicinity, and they are activated to transmit signals when the strength of the sensed signal is above a threshold. The binary sensor makes a binary decision (detection or non-detection) based on the measurement, and only its ID is sent to the fusion center when it detects the target, otherwise it remains silent. So the binary sensor is a low-power and bandwidth-efficient solution for wireless sensor network.

For binary sensor network (BSN), existing work is concerned with the location estimation of a single source. In [14], the authors propose a maximum likelihood source location estimator in BSN. A low complexity source localization method [15] based on the intersection of detection areas of sensors is introduced in noisy binary sensor networks. A subtract on negative add on positive (SNAP) [16] algorithm is proposed to identify the source location using the binary sensor networks. This is a fault-tolerant algorithm that is slightly less accurate but computationally less demanding in comparison with maximum likelihood estimation. In [17], the authors propose a trust index based subtract on negative add on positive (TISNAP) method to improve the accuracy for the multiple event source localization. This algorithm reduces the impact of faulty nodes in the source localization by decreasing their trust index. And the TISNAP algorithm assumes that the distance between any two sources is far enough, i.e., the node is influenced by only one source initially. So the localization process is similar to the single source localization process. To the best of our knowledge, fewer papers investigate the multiple sources localization when the sources are close to each other in BSN.

In this paper, we propose an algorithm to estimate the locations of multiple acoustic sources in BSN under the assumption that the sensor nodes can be influenced by multiple sources simultaneously. We firstly employ the Fuzzy C-Mean (FCM) algorithm to compute the membership degrees of the alarmed nodes associated with different sources. Then we propose a likelihood matrix to estimate the location of sources. The main contribution of this paper is the development of a low computational complexity method for estimating the location of multiples sources. When the sources are close to each other, our proposed method could distinguish them by the fuzzy c-mean algorithm. Furthermore, this method is fault tolerant when the sensor node produces false positives and negatives.

The paper is organized as follows. In Section 2, we present the background. In Section 3, we introduce our proposed method to the problem of estimating the location of sources. Section 4 provides some representative simulation results and we conclude with Section 5.

2. Background

2.1. System model

Suppose there are N sensor nodes and K static acoustic sources in the sensor field Ω. Each sensor node is equipped with an acoustic energy measuring sensor. The received signal strength at i-th sensor node can be expressed as [9]:

$$z_i(t) = \begin{cases} s_i(t) + \gamma_i(t), & H_1 \\ \gamma_i(t), & H_0 \end{cases} \tag{1}$$

where H_1 represents the acoustic sources emitted signal, H_0 represents that there is no source in the field, s_i is the acoustic intensity measured at the i-th sensor node due to all K acoustic sources, γ_i is the background noise and is modeled as zero-mean additive white Gaussian noise random variable with variance ε_i^2.

During the time interval $T = M/f_s$, where M is the number of sample points used for estimating the acoustic energy received by the sensor during this time interval, f_s is the sampling frequency. And the average energy measurements over the time window $[t - T/2, t + T/2]$ as $y_i(t)$ leads to

$$\begin{aligned} y_i(t) &= \frac{1}{fT_s} \sum_{j=(t-T/2)f_s}^{(t+T/2)f_s} z_i^2(t) \\ &= \underbrace{\frac{1}{fT_s} \sum_{j=(t-T/2)f_s}^{(t+T/2)f_s} s_i^2(t)}_{\text{received energy } y_{si}(t)} + \underbrace{\frac{1}{fT_s} \sum_{j=(t-T/2)f_s}^{(t+T/2)f_s} \gamma_i^2(t)}_{\text{noise}, n_i(t)} \end{aligned} \tag{2}$$

In this paper, we assume that the acoustic intensity and energy emitted from each source does not vary too much over a short time delay and thus we neglect the propagation delay for the energy decay function. A concise acoustic energy decay model is as follows:

$$y_i(t) = \begin{cases} y_{si}(t) + n_i(t), & H_1 \\ n_i(t), & H_0 \end{cases} = \begin{cases} g_i \sum_{k=1}^{K} \dfrac{S_k(t)}{d_{ik}^2(t)} + n_i(t), & H_1 \\ n_i(t), & H_0 \end{cases} \tag{3}$$

where g_i represents the gain factor of the i-th sensor. We assume that $g_i = 1$, S_k is the signal energy at 1 m away from the k-th source, d_{ik} is the Euclidean distance between the i-th sensor and the k-th source. In addition n_i is the measurement noise modeled as zero mean white Gaussian with variance σ_i^2, namely, $n_i \sim N(0, \sigma_i^2)$.

Although the energy decay model in Eq. (3) appears quite simplistic, it is the one commonly used in literature. The main limitations it poses are its inability to take sound reverberations into account due to obstacles. However, the sound sources may not be isotropic and that it assumes point sources [11].

All sensor nodes have been programmed with a common threshold T. If $y_i \geq T$, the sensor node alarms (sends its ID to fusion center), otherwise it remains silent. The fusion center knows the locations of sensors. The fusion center computes the locations of the sources according to the binary information and the locations of the sensor nodes.

2.2. Maximum likelihood location estimation

The maximum likelihood method is one of the most popular methods to estimate the location. The maximum likelihood estimation of the location is optimal in accuracy under the condition that the measurement errors are identical and independently distributed with a zero mean normal distribution. Based on the acoustic signal energy attenuation model, we formulate the multiple sources localization problem as an optimization problem via the maximum likelihood method. The threshold can be expressed as:

$$I_i = \begin{cases} 0, & y_i < T \\ 1, & y_i \geq T \end{cases} \tag{4}$$

After obtaining the data $\mathbf{I} = \{I_1, \ldots, I_N\}$, the fusion center will estimate the parameter $\theta = [S_1, \ldots, S_K, x_1, y_1, \ldots, x_K, y_K]$. S_i is signal energy at 1 m away from the i-th source. (x_i, y_i) is the location of