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Robust AOA based acoustic source localization method with unreliable measurements

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ABSTRACT

The performance degradation problem of the angle of arrival (AOA)-based acoustic localization methods in the presence of unreliable bearing measurements (outliers) is addressed in this paper. Two typical M-estimators based on Tukey and Huber functions are applied to tackle the problem. Both functions are solved by the iterative reweighted nonlinear least squares (IRNLS) method. Considering the Huber function is convex in nature, it is specifically utilized to mitigate the influence of large residuals on pseudolinear estimator (PLE) by convex optimization. To make the IRNLS method more feasible to use, an approximate relationship between the outlier probability and the bound parameter is provided. The robustness and effectiveness of the proposed methods are clearly demonstrated through a series of simulation results in the presence of various unreliable measurements.

1. Introduction

The angle of arrival (AOA), also named bearing, based acoustic source localization technique has been successfully applied in many promising applications, such as security, telecommunication and environmental monitoring [1–3]. As a hot research topic, many effective approaches have been proposed, such as maximum likelihood estimator (MLE) [4], pseudolinear estimator (PLE) [5], reduced-bias PLE [6], approximate maximum likelihood (AML) [7], extended Kalman filtering [8,9] and total least squares (TLS) [10]. Among these methods, MLE and PLE are most commonly used methods. MLE is an asymptotically unbiased and efficient estimator, but it does not have a closed-form solution and has to be implemented in an iterative search way [4]. PLE which does not require a Gaussian noise assumption is simple to implement with lower complexity. Though PLE suffers from bias, it can be overcome by the bias compensation methods [6].

With the progresses in sensor technology, people start to uses a large amount of low cost sensor nodes for sound source localization in unknown fields [11,12]. Theoretically speaking, if the background noise in the field follows the Gaussian distribution, both PLE and MLE perform well, even though Gaussian noise is not always strictly required by PLE. However, the distributed sensors often encounter unexpected interferences [13], such as external attacks, natural causes (wind or storm for example), or sensor failures, etc. On the other hand, the low cost sensor nodes are usually made with stringent resource in transmission power, AD sampling resolution, or computational capacity, etc. These interferences and limitations may result in many unreliable measurements or called outliers. As a result, the above-mentioned traditional AOA-based methods fail to provide reasonable estimates when outliers are present.

One way to solve outlier problem is to identify them, then remove them. A least squares estimator that leverages the hybrid estimate method of AOA and TOA has been used to detect the NLOS signal [14]. By assuming that the reliable sensors are expected to behave similarly, the Bayesian method is proposed to identify unreliable sensors from a given set of sensors [15]. A distributed localization approach based on expectation maximization (EM) method is developed when sensor failure happens [16]. The EM based method is also introduced to attain the accurate localization results for AOA based localization method by identifying the unreliable measurements from NLOS propagation environment [17]. The unreliable bearing measurements method is presented by detecting the outliers from a set of estimated positions obtained by different sensor combinations [18].

Another typical way is incorporating all the measurements into a robust estimator against outliers. A well-known robust estimator is the M-estimator, which has been widely used to process outlier problems for robust registration of point sets [19], linear regression [20] and robust estimation of diffusion magnetic resonance parameters [21]. For acoustic source localization problems, a bi-square M-estimation has been proposed to estimate the acoustic source

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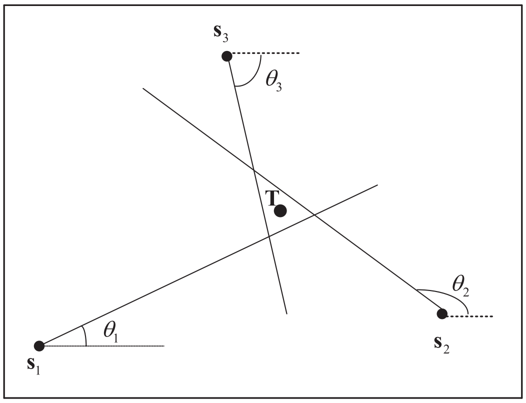

Fig. 1. I Illustration of an AOA localization system using three sensors.

location with outlier-corrupted sensor observations in an energy-based localization method [22]. The M-estimator has been introduced into the extended Kalman filter based on the time difference of arrival (TDOA) method to solve the NLOS mitigation problem [23]. Chen describes a robust least-mean-M-estimate algorithm to estimate the time delay in case of multichannel propagation [24]. Note that specific methods to estimate the accurate AOAs for non-Gaussian channel before localization are outside the scope of this paper; interested readers are referred to [25–29].

The motivation of this paper is to propose a robust localization method to reduce the influence of unreliable AOA measurements caused by uncertain environments. The main contributions can be summarized as follows:

- The performances of the traditional localization methods using the Non-Linear Estimator (NLE) and the Pseudo Linear Estimator (PLE) are analyzed when these estimators are subject to the AOA outliers.
- Two estimators based on Tukey and Huber function, respectively, are proposed to decrease the influence of the AOA outliers for NLE, and Huber function is addressed for HPLE.
- To make the new estimators easy to use, a threshold determination method based on the outlier probability is designed and verified through a series of simulations.

This paper is organized as follows. In Section 2, the traditional AOA based localization methods are reviewed, with an emphasis on the influence of unreliable bearings on the localization performance. Section 3 provides the uncertain model for AOA measurements. Both the Tukey and Huber estimators are proposed to solve the outlier problem for NLE, the Huber function is also applied to solve the outlier problem for PLE. Section 4 presents the proper bound parameter determination method for the proposed methods; the localization performances of our proposed methods and several traditional methods are compared using numerical experiments. The conclusions are discussed in Section 5.

2. AOA based localization methods and problem formulation

2.1. Angle of arrival model with gaussian noise

As shown in Fig. 1, in this paper, we consider an acoustic localization system with a single stationary acoustic source located at $\mathbf{T} = [x, y]^{\mathrm{T}}$ and multiple sensors, located at $\mathbf{s}_k = [x_k, y_k]^{\mathrm{T}}$, $k = 1, 2, \ldots, N$. Ideally, the true bearing θ_k can be expressed as:

$$\theta_k = \arctan\left(\frac{y - y_k}{x - x_k}\right), k = 1, \ldots, N. \tag{1}$$

The observations are usually subject to measurement noise:

$$\hat{\theta}_k = \theta_k + \varepsilon_k, k = 1, \ldots, N, \tag{2}$$

where ε_k are assumed to be independent zero-mean Gaussian noise with variance σ_k^2. The set of measurements from N sensors can be written in vector form as

$$\hat{\boldsymbol{\theta}} = \boldsymbol{\theta} + \boldsymbol{\varepsilon}, \tag{3}$$

where $\hat{\boldsymbol{\theta}} = [\hat{\theta}_1 \quad \hat{\theta}_2 \quad \ldots \quad \hat{\theta}_N]^{\mathrm{T}}$, $\boldsymbol{\theta} = [\theta_1 \quad \theta_2 \quad \ldots \quad \theta_N]^{\mathrm{T}}$, and $\boldsymbol{\varepsilon} = [\varepsilon_1 \quad \varepsilon_2 \quad \ldots \quad \varepsilon_N]^{\mathrm{T}}$.

2.2. Maximum likelihood estimator and its outlier effect

Under the Gaussian noise assumption, the likelihood function of the bearing observations can be given by

$$f(\hat{\boldsymbol{\theta}} \,|\, \mathbf{T}) = \frac{1}{(2\pi)^{N/2} |\mathbf{Q}|^{1/2}} \exp\left\{ -\frac{1}{2} (\hat{\boldsymbol{\theta}} - \boldsymbol{\theta}(\mathbf{T}))^{\mathrm{T}} \mathbf{Q}^{-1} (\hat{\boldsymbol{\theta}} - \boldsymbol{\theta}(\mathbf{T})) \right\}, \tag{4}$$

where $\mathbf{Q}$ is the $N \times N$ covariance matrix of bearing observation errors

$$\mathbf{Q} = \mathrm{diag}(\sigma_1^2, \sigma_2^2, \ldots, \sigma_N^2). \tag{5}$$

The target position, $\hat{\mathbf{T}}_{ML}$, can be obtained by maximizing the likelihood function (4). Typically, the log- function of (4) is used to simplify the maximization problem:

$$\ln f(\hat{\boldsymbol{\theta}} \,|\, \mathbf{T}) = -\frac{1}{2} \ln\left((2\pi)^N |\mathbf{T}|\right) - \frac{1}{2} (\hat{\boldsymbol{\theta}} - \boldsymbol{\theta}(\mathbf{T}))^{\mathrm{T}} \mathbf{Q}^{-1} (\hat{\boldsymbol{\theta}} - \boldsymbol{\theta}(\mathbf{T})). \tag{6}$$

The maximization of (6) can be obtained by minimizing the second term of (6) [4]

$$\hat{\mathbf{T}}_{ML} = \arg\min L_{ML}(\mathbf{T}), \tag{7}$$

where

$$L_{ML}(\mathbf{T}) = (\hat{\boldsymbol{\theta}} - \boldsymbol{\theta}(\mathbf{T}))^{\mathrm{T}} \mathbf{Q}^{-1} (\hat{\boldsymbol{\theta}} - \boldsymbol{\theta}(\mathbf{T})). \tag{8}$$

A simple gradient-descent approach can be used to solve (8) recursively:

$$\mathbf{T}(k+1) = \mathbf{T}(k) - \mu \left.\frac{\partial L_{ML}(\mathbf{T})}{\partial \mathbf{T}}\right|_{\mathbf{x}=\mathbf{x}(k)}, k = 0, 1, \ldots, \tag{9}$$

where $\mu > 0$ denotes a small step size, $\mathbf{T}(0)$ is the initial position of the sound source. The iterations are stopped when the gradient term is sufficiently close to zero.

The Cramér-Rao lower bound (CRLB), which is equal to the inverse of the Fisher information matrix (FIM), provides a performance lower bound for the asymptotically unbiased estimator [30,31]. The FIM for MLE can be given by [30]

$$\mathbf{F} = \begin{bmatrix} \sum_{k=1}^{N} \frac{\cos^2\theta_k}{r_k^2\sigma_k^2} & -\frac{1}{2}\sum_{k=1}^{N} \frac{\sin 2\theta_k}{r_k^2\sigma_k^2} \\ -\frac{1}{2}\sum_{k=1}^{N} \frac{\sin 2\theta_k}{r_k^2\sigma_k^2} & \sum_{k=1}^{N} \frac{\sin^2\theta_k}{r_k^2\sigma_k^2} \end{bmatrix}. \tag{10}$$

The determinant of FIM can be obtained by

$$\det(\mathbf{F}) = \frac{1}{4}\left\{ \left(\sum_{k=1}^{N} \frac{1}{r_k^2\sigma_k^2}\right)^2 - \left(\sum_{k=1}^{N} \frac{\cos 2\theta_k}{r_k^2\sigma_k^2}\right)^2 - \left(\sum_{k=1}^{N} \frac{\sin 2\theta_k}{r_k^2\sigma_k^2}\right)^2 \right\}, \tag{11}$$

$$\det(\mathbf{F}) = \sum_{S} \frac{\sin^2(\theta_i - \theta_j)}{r_i^2 r_j^2 \sigma_k^2 \sigma_k^2}, j > i. \tag{12}$$

$S = \{(i, j)\}$ is the set of all combinations of i and j, with $i, j \in \{1, 2, \ldots, N\}$ and $j > i$. From (12), we can see that the FIM determinant is approximately inversely proportional to the variance of the