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Robust MIMO radar target localization via nonconvex optimization

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ABSTRACT

This paper addresses the problem of robust target localization in distributed multiple-input multiple-output (MIMO) radar using possibly outlier range measurements. To achieve robustness against outliers, we construct an objective function for MIMO target localization via the maximum correntropy criterion. To deal with such a nonconvex and nonlinear function, we apply a half-quadratic optimization technique to determine the target position and auxiliary variables alternately. Especially, we derive a semidefinite relaxation formulation for the aforementioned position determination step. The robust performance of the developed approach is demonstrated by comparing with several conventional localization methods via computer simulation.

1. Introduction

Multiple-input multiple-output (MIMO) radar [1–3] has received considerable attention because it can achieve significantly enhanced target detection and parameter estimation performance through utilizing the waveform or spatial diversity. In this paper, we address the target localization problem in distributed MIMO radar.

Distributed MIMO radar localization methods can be classified into two categories, namely, direct and indirect. The former, including the maximum likelihood (ML) [4,5] and sparse recovery [6] methods, requires two-dimensional search. Whereas the latter approach first estimates the ranges, which correspond to the sum of transmitter-to-target and target-to-receiver distances, referred to range-sum, from the received signals. The target position is then determined using a set of elliptic equations constructed from the range estimates. Especially, among the indirect methods, the ML technique has also been exploited to find the location in an iterative manner with an initial position estimate [4,7]. Note that the nonconvex ML formulation can be approximated as a convex program [8]. In addition, the elliptic measurements can be converted to linear equations [9,10] from which global solution is obtained via the linear least squares (LLS) technique. It is worth pointing out that our addressed problem belongs to multilateration based target localization which employs multiple transmitters and/or multiple receivers to obtain the range, range-difference or range-sum estimates determined from the time-of-arrival [11,12], received signal strength [13,14], time-difference-

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of-arrival (TDOA) [15,17] or time-sum-of-arrival (TSOA) [7–10] measurements.

In the MIMO radar systems, there are multiple transmit waveforms, which interfere with each other apart from the interferences. In particular, in the low signal-to-interference-plus-noise ratio (SINR) environment, the obtained range measurements in distributed MIMO radar systems via the matched filter may not be accurate. In addition, the presence of non-line-of-sight (NLOS) [18,19] propagation is common in practical applications. Either low SINR or NLOS observations can result in extreme values corresponding to outlier measurements, making the MIMO radar localization problem more complicated.

Motivated by the robustness of correntropy for outlier rejection [20], we develop a distributed MIMO radar target localization method using the maximum correntropy criterion (MCC), which can handle outlier range measurements. First, we introduce MCC [20] based on the conventional ML formulation and construct a new objective function for target localization. Furthermore, the half-quadratic optimization technique [21,22] is applied to cope with the corresponding nonconvex and nonlinear function, which results in determining the target position and auxiliary variables alternately. Finally, the semidefinite relaxation (SDR) [23] formulation for position estimation is devised. Note that our work is different from [4–17] which assume the absence of NLOS propagation. In particular, although [8] and we consider range-sum based localization, the former employs convex optimization and only one receiver is allowed, while the latter utilizes the nonconvex half-quadratic optimization technique with multiple transmitters and receivers. On the other hand, TDOA based positioning is addressed in [16,17] but our focus is to exploit TSOA measurements.

The rest of this paper is organized as follows. The problem of target localization using distributed MIMO radar is formulated in Section 2. The proposed localization method is developed in Section 3. Numerical examples are included in Section 4. Finally, conclusions are drawn in Section 5.

Notation: Vectors and matrices are denoted by boldface lowercase and uppercase letters, respectively. The $E[.]$, $\|\cdot\|_2$, $(\cdot)^T$, trace[.], and rank[.] stand for the expectation, Frobenius norm, transpose, trace, and rank operators, respectively. A $n \times n$ diagonal matrix with diagonal entries $a_1, \ldots, a_n$, is denoted by $\text{diag}(a_1, \ldots, a_n)$. The $\mathbf{0}_{m\times n}$, $\mathbf{1}_n$, and $\mathbf{I}_n$ represent the $m \times n$ zero matrix, $n \times 1$ vector of 1 and $n \times n$ identity matrix, respectively. We use $\mathbf{A} \succcurlyeq \mathbf{0}_{m\times n}$ to indicate that $\mathbf{A} \in \mathbb{R}^{m\times n}$ is positive semidefinite.

2. Background

2.1. Problem formulation

Consider a two-dimensional MIMO radar system equipped with M transmitters and N receivers and a target that is in the region of interest. Denote $\mathbf{t}_m = [x_m^t \ y_m^t]^T$, $\mathbf{r}_n = [x_n^r \ y_n^r]^T$, and $\boldsymbol{\theta} = [x^\theta \ y^\theta]^T$ as the positions of the mth transmitter, the nth receiver, and the target, respectively. In this study, we assume that the TSOAs have been estimated by a preprocessing step. Multiplying them by the propagation speed yields the range-sum estimates. Let $r_{m,n}$ be the estimate corresponding to the sum of the distance between the mth transmitter and the target and the distance between the target and the nth receiver, it is modeled as:

$$r_{m,n} = \|\boldsymbol{\theta} - \mathbf{t}_m\| + \|\boldsymbol{\theta} - \mathbf{r}_n\| + q_{m,n}, \tag{1}$$

where $q_{m,n} = v_{m,n} + o_{m,n}$ consists of two components, namely, $v_{m,n}$ is the zero-mean additive white Gaussian noise and $o_{m,n}$ is the possible outlier. That is, $\{o_{m,n} = 0\}_{m=1,n=1}^{M,N}$ corresponds to the case with no outliers. The task is to estimate $\boldsymbol{\theta}$ from $r_{m,n}$, $m = 1, 2, \ldots, M$, $n = 1, 2, \ldots, N$.

2.2. Maximum correntropy criterion

The concept of correntropy [20] in information theoretic learning is related to Renyi's quadratic entropy using Parzen windowing, and is used for assessing similarity of two random variables in a local manner and by the kernel function. Especially, the cross correntropy of two arbitrary scalar random variables X and Y is defined as [20]:

$$V_\sigma(X, Y) = E[k_\sigma(X - Y)], \tag{2}$$

where

$$k_\sigma(X - Y) = \exp\left(-\frac{(X - Y)^2}{2\sigma^2}\right), \tag{3}$$

Here, σ is called the kernel bandwidth, which is a user-defined parameter.

In practice, the joint probability density function of (X, Y) may be unknown and only a finite number of samples $\{X_i, Y_i\}_{i=1}^N$ are available. Thus, the sample estimator of cross correntropy [20] is given by:

$$\hat{V}_{N,\sigma}(X, Y) = \frac{1}{N}\sum_{i=1}^{N} k_\sigma(X_i - Y_i). \tag{4}$$

According to [20], the cross correntropy of the error between X_i and Y_i corresponding to the MCC, which in a general framework, bears a close relationship with the well-known M-estimation, that is, a generalized ML methodology. It is also shown in [24] that the MCC results in a smoothed maximum *a posteriori* estimator. Note that MCC has been successfully applied in nonlinear and non-Gaussian signal processing, especially in the impulsive noise environment. Especially, the adjustable window or kernel bandwidth provides an effective mechanism to eliminate the adverse effect of outliers.

3. Proposed algorithm

When there is no outlier in (1), the ML solution [4] is obtained from minimizing the following least squares cost function:

$$\sum_{m=1}^{M}\sum_{n=1}^{N}\left(r_{m,n} - \|\boldsymbol{\theta} - \mathbf{t}_m\| - \|\boldsymbol{\theta} - \mathbf{r}_n\|\right)^2. \tag{5}$$

However, when there are outlier range measurements, the quadratic function in (5) will amplify the contributions of the outliers which are far away from the mean value of the