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Single-step localization using multiple moving arrays in the presence of observer location errors

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ABSTRACT

Direct position determination (DPD) is a promising technique that offers superior performance compared with conventional two-step localization methods. Existing DPD methods presume that the observer locations are known exactly, whereas in practical environments, a small error in the observer locations will lead to an erroneous localization. This study considers the localization of a stationary transmitter by separated moving arrays from passive measurements taken at different points along the trajectory. The precise locations and velocities of the observers are not available, but their errors are assumed to be Gaussian distributed. Using this probability distribution, we propose maximum likelihood-based DPD approaches in the presence of observer location errors for both unknown and known signals. The proposed DPDs rely on alternating iteration schemes, which reduce the multidimensional nonlinear optimization problem to optimizations of dimensions that are much smaller than the number of unknowns. As opposed to the conventional two-step methods that extract measurement parameters and then estimate the positions from them, the proposed DPDs achieve the localization in a single step by exploiting the information of angles, time delays, and Doppler frequency shifts, but without computing them. Additionally, we derive the Cramér–Rao bound (CRB) formula for this DPD problem in the presence of observer location errors. The simulation results prove that the performance of our methods attains the associated CRB. Moreover, they are more robust than the conventional two-step approaches with respect to observer location errors. We demonstrate our methods for the scenario of multiple moving arrays, but these methods can easily be extended to DPD problems accounting for observer location errors in different scenarios.

1. Introduction

The passive localization of stationary transmitters is a classic problem in various fields such as signal processing, wireless communication, radar, sonar, and radio astronomy. Traditional localization methods employ two-step processing [1–3], where the measurement parameters (e.g., direction of arrival (DOA), time of arrival, and Doppler frequency shift) are first extracted and then the source positions are estimated. Because they estimate parameters at each observer separately and independently without the constraint that the measurements correspond to the same transmitter location, the performance of two-step localization techniques are suboptimal and they cannot guarantee high localization accuracy. Recently, there has been an upsurge in interest in the direct position determination (DPD) technique [4–7] because of its performance, which is superior to that of the two-step methods. Compared with the two-step methods, DPD directly localizes the transmitter from sensor outputs under the constraint that the measurements correspond to the same transmitter location, which enables the estimation of locations in a single step without estimating intermediate parameters.

A number of maximum likelihood (ML)-based DPD algorithms can be found in the literature. For the scenario of widely separated arrays, Weiss proposed ML-based DPD algorithms in [8] for a single source with either a known or unknown signal. An ML-based DPD for multiple sources with known waveforms was advocated in [9]. ML-based algorithms can approach the corresponding Cramér–Rao bounds (CRBs). However, when solving ML estimators in the presence of multiple sources with unknown waveforms, numerous parameters require considerable computational effort. As one solution, an iterative DPD method for multiple unknown sources was developed in [10], where a lower dimensional grid search is required during each iteration. The preceding DPD algorithms, which use widely separated arrays, involve a centralized processing of the frequency-domain observations of all the arrays, and implicitly use the location information embedded in angles and time delays. If

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there is relative motion between the observer and transmitter, the Doppler shift of the transmitter frequency can also be exploited for localization [11]. In a localization system consisting of multiple moving sensors, [12] proposed a direct geolocation algorithm for a narrowband radio transmitter based on the location information in the Doppler shift. For the scenario where the source emits a relatively wideband signal (i.e., the bandwidth is considerable compared to the inverse of the propagation time delays) and is observed by moving receivers, two kinds of ML-based DPD approaches for a stationary target were developed based on the time delay and Doppler frequency shift [13–15]. One method models the transmitted signal as a random Gaussian signal, whereas the other assumes the signal to be deterministic and considers the cases of known and unknown signal waveforms. To achieve higher accuracy, an ML DPD was developed in [16] using coherent summation that takes into account the coherency among the short-time signals received at the same receiver. Note that the studies in [12–16] are unable to exploit angle information, because they are designed for moving observers, each of which is equipped with a single sensor. The localization accuracy of these ML-based DPDs has shown to be significantly better than those of the conventional two-step methods, especially under low signal-to-noise ratio (SNR) conditions.

In spite of the above advances of the DPD technique, to the best of our knowledge, most existing DPDs presume that the accurate locations or velocities of the observers are known in advance, and few efforts have been devoted to solving the DPD problem accounting for observer location uncertainties. In practice, the receiver locations may not be known exactly [17]. For instance, in underwater acoustic localization applications, sensor nodes are deployed randomly and their exact positions are often not available. In airborne localization systems, the positions and velocities of airplanes or unmanned aerial vehicles (UAVs) may not be precisely known. A slight error in observer location will lead to a big error in the location result, and therefore the source location accuracy can be very sensitive to the accuracy of the observer positions and velocities in practical environments. It has been known that observer location uncertainty can have a dramatic effect on the performance of the two-step localization [17–19]. As a result, it is important to take the inaccuracy in observer locations into account for the DPD problem.

This study investigates the DPD algorithm for a stationary transmitter observed by several arrays mounted on fast-moving platforms. The observers intercept the transmitted signal during their movements and collect batches of data at different points along the trajectory. Typical examples include a communication or radar transmitter, where the observer platforms are airborne, e.g. on aircraft, helicopters, or UAVs [20–21]. Because the moving observers frequently have errors in their positions and velocities, we deal with a practical environment in our study, where the positions and velocities of the observers are not known exactly but their errors are assumed to obey Gaussian distributions with known covariance matrices. Given that the signal waveform may be known in some cases where the transmitter emits a synchronization sequence or a known message [22], the DPD problems for both unknown and known signals are considered. We show that the DPD methods proposed here can improve the location accuracy compared with the two-step approaches in the presence of observer location errors.

The main contributions are summarized as follows:

- We establish a signal model in which the angles, time delays and Doppler shifts are incorporated. This signal model is complex and can be regarded as a general version of those in [8,13–15]. By combining the established signal model and the probability distribution of the observer location uncertainties, two ML-based functions are formulated for an unknown signal and a known signal with unknown transmission time. The proposed DPDs can exploit the location information contained in the angles, time delays and Doppler shifts, and minimize the effect of observer location errors.
- To solve the prescribed ML-based functions, which are nonlinearly related to a variety of unknown parameters, we develop two alternating iteration schemes, one for a known signal and one for an unknown signal. In the alternating iteration procedures, two sets of parameters, namely, the positions and velocities of the observers, and other parameters including the source position, are updated alternately. A by-product of the alternating iteration is that we can decouple the updating of all observer locations and velocities into the updating of the location and velocity for each observer. Additionally, iterative methods are designed and employed to update each set of parameters instead of the commonly used grid search, which makes our method practically more attractive.
- We provide a detailed derivation of the compressed CRB of the source position estimation based on the received signal model in the presence of observer location errors. The position-related block of the CRB with observer location errors is proved to be lower bounded by the associated CRB without observer location errors.

The paper is organized as follows. Section 2 presents the notations used throughout this paper. Section 3 describes the signal model and formulates the problem. In Section 4, the DPD methods are proposed for the unknown and known signal waveforms. Section 5 derives the CRB expression. In Section 6, we present two series of simulation results and analyze them. Finally, the conclusion is drawn in Section 7.

2. Notations

In this paper, boldface italic upper-case letter denotes matrix and boldface italic lower-case letter signifies vector. In addition, $\{\cdot\}^*$, $\{\cdot\}^{\mathrm{T}}$, and $\{\cdot\}^{\mathrm{H}}$ stand for the conjugate, transpose, and conjugate transpose, respectively. Operators blkdiag$\{\cdot\}$ and diag$\{\cdot\}$ indicate the compositions of a block diagonal matrix and diagonal matrix. Operator vec$\{\cdot\}$ is the "vectorization" operator that turns a matrix into a vector by stacking the columns of a matrix one below the other. Furthermore, $\otimes$ is the Kronecker matrix product, tr$\{\cdot\}$ and $\mathbb{E}[\cdot]$ are the trace and expectation, respectively, Re$\{\cdot\}$ and Im$\{\cdot\}$ signify the real and imaginary parts, respectively, $\|\cdot\|_2$ and $\|\cdot\|_{\mathrm{F}}$ represent the Euclidean norm and Frobenius norm, respectively, $[\cdot]_n$ and $[\cdot]_{n,m}$ are the nth element of a vector and the n,mth entry of a matrix, respectively, and $\dot{\boldsymbol{X}}$ and $\ddot{\boldsymbol{X}}$ indicate the first-order and second-order partial derivatives of $\boldsymbol{X}$, respectively. Finally, $\boldsymbol{x}^{(a)}$ denotes the updated $\boldsymbol{x}$ in the last update, and $\boldsymbol{x}^{(b)}$ denotes the estimation of $\boldsymbol{x}$ in the on-going update.

For convenience, we provide the main notations used throughout this paper in Table 1.

3. Signal model and problem formulation

3.1. Signal model over multiple moving arrays

Let us consider the scenario in which a stationary transmitter is intercepted by L observer arrays mounted on fast-moving platforms and each moving array is composed of M sensors. The transmitter is assumed to radiate a signal in the far field of the moving arrays with a frequency centered at f_c, which is the nominal transmitted frequency and thus is known to the observers. We denote the transmitter position by a $D \times 1$ vector of coordinates $\boldsymbol{p} \in \mathbb{R}^{D\times 1}$. The observers intercept the transmitted signal during their movements and collect batches of data in K short intervals. Considering