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Design of measurement matrix in CS-MIMO radar for extended target estimation

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ABSTRACT

In this paper, we propose a measurement matrix design that improves the parameter estimation of an extended target in a compressive sensing multiple-input multiple-output (CS-MIMO) radar system. In our signal model, we consider the target impulse response (TIR) as an unknown vector that should be estimated in a compressive sensing scenario. Our proposed measurement matrix optimization method is based on minimizing the trace of the Cramer–Rao lower bound (CRLB) matrix in the presence of signal-dependent interference and receiver noise, which leads to a nonlinear and non-convex optimization problem. To tackle design problem, we propose a three-stage optimization procedure in which a low rank matrix constraint is enforced. For comparison purpose, we also obtain the measurement matrix based on minimizing the block-coherence of the sensing matrix blocks. Numerical results demonstrate the effectiveness of our proposed method in parameter estimation of extended targets for CS-MIMO radar.

1. Introduction

Multiple-input multiple-output radars are the state-of-the-art radars inspired by the idea of MIMO communications in which multiple antennas are used at the transmitter and the receiver. Generally speaking, MIMO radars can be classified according to antennas placement. In MIMO radar with widely separated antennas, the transmit and receive antennas are set apart leading to independent target observations from different directions, and thus, target detection, identification and tracking performance of targets will be improved [1–3]. In collocated type of MIMO radar, which is considered in this paper, the antennas are closely spaced leading to high angular resolution, more flexible design in transmit/receive beampattern, and enhanced target localization [4–7]. However, the fundamental problem in MIMO radars is high computational complexity due to the large amount of received data from all receive antennas. A solution for reducing the amount of data is to exploit compressive sensing (CS) [8–12].

CS, which is rooted on the mathematical and statistical theory underlying sparse representations, has recently received considerable attention in many different applications such as image reconstruction [13,14], remote sensing [15,16], and radar systems [17,18]. The concept of CS theory can be summarized as follows: if our interested signal $\mathbf{x} \in \mathcal{C}^{N_1 \times 1}$ is sparse in a certain domain, it can be described as $\mathbf{x} = \mathbf{A}\mathbf{s}$, where $\mathbf{A} \in \mathcal{C}^{N1 \times N2}$ is the basis matrix describing sparse domain and $\mathbf{s} \in \mathcal{C}^{N2 \times 1}$ is a sparse signal, i.e. most of its components are zero. Then, it is possible to compress signal $\mathbf{x}$ by using a measurement matrix $\mathbf{T} \in \mathcal{C}^{M_1 \times N_1}$ as $\mathbf{y} = \mathbf{T}\mathbf{x}$, where $(M_1 < N_1)$ and $\mathbf{y} \in \mathcal{C}^{M_1 \times 1}$ is the measurement vector. To recover the sparse signal from measurement vector, various one and two dimensional sparse recovery algorithms such as ℓ_1-ls [19] and 2D-IAA [20] have been developed.

Owing to the fact that the number of actual targets in radar surveillance area is much smaller than the whole number of radar bins, the received signal can be expressed by a sparse model [22]. In traditional CS radar, the problem of signal recovery for pointed targets has been investigated in many articles such as [5–12]. Recently, sparse reconstruction and waveform design have been addressed for extended targets in CS radar [23] using mutual coherence criterion. In extended target model, the target is characterized by several scattering centers described as target impulse response (TIR) [24,25]. Therefore, many optimization problems in radar systems such as waveform optimization [26], and target tracking [27] are developed accordingly. Also, different TIR models such as known, unknown deterministic, or random parameters have been considered in these applications.

In MIMO radar system, CS can be exploited to reduce the traditional sampling rate below the Nyquist rate by using a measure-

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ment matrix [8–11]. Therefore, measurement matrix can play a key role in the performance of target detection and estimation. In conventional approaches, random matrices such as Gaussian random measurement matrix (GRMM), and Bernoulli are used in CS recovery because such matrices are incoherent with any basis matrix with high probability [8], and thus, they satisfy the restricted isometry property (RIP) that guarantees the stability of sparse reconstruction algorithms [28]. However, these random measurement matrices are not necessarily the best matrices for CS and may cause wasting of accurately sampled signals. In [29], two different measurement matrices for CS-MIMO radar are designed to improve detection performance based on two main criteria. The first one is minimization of linear combination of the inverse signal-to-interference ratio (SIR) and the sum of the mutual coherence of all the cross columns of sensing matrix $\boldsymbol{\Psi} = \mathbf{TA}$. The second criterion is maximization of SIR by enforcing a special structure on the measurement matrix. As shown in this paper, if the proper waveforms (i.e. waveforms with very low auto- and cross-correlation sidelobes are very low) are selected, the mutual coherence criterion can be ignored due to heavy computational load and low performance in poor SIR. Also, this paper has considered the problem for point-like target model. Furthermore, a measurement matrix design and power allocation for block CS-based distributed MIMO radars are conducted in [30] by considering point-like target model.

One of the best optimization criterion for parameter estimation is the Cramer–Rao lower bound (CRLB) which is the lowest possible root-mean-square error (RMSE) of deterministic parameters estimation for any unbiased estimator. If an unbiased estimator exist, the CRLB can be achieved in high SNR. The analysis of CRLB for parameter estimation has been considered for CS in [31–34]. In the presence of normal Gaussian noise, an adaptive CS method is proposed in [34] by minimizing the CRLB of only amplitude of nonzero elements in the sparse vector $\mathbf{s}$. Furthermore, the waveform design for MIMO radar based on the CRLB is conducted in [35] and [36], showing the effectiveness of the CRLB criterion for radar optimization. Therefore, we hope that by pushing the CRLB down to zero, the RMSE of estimator will be reduced, which is confirmed by our simulation results.

In this paper, we optimize the measurement matrix of a CS-MIMO radar system by minimizing the CRLB of the extended target parameters (including target angle and TIR coefficients) in the presence of signal-dependent interference (i.e. clutter) and receiver noise. In signal model derivation, we assume that the TIR of the extended target is unknown and should be estimated. As shown later, we are faced with a nonlinear and non-convex optimization problem. To tackle this problem, we propose a three-stage optimization procedure to cope with nonlinearity and low rank matrix constraint.

To the best of our knowledge, no study of measurement matrix design for extended targets based on CRLB has been conducted prior to this work. Also, for comparison purpose, we obtain the measurement matrix based on minimizing the coherence of the sensing matrix. Since the CS model of extended target is block sparse, we minimize an upper bound of the summation of block-coherence of the sensing matrix blocks.

This paper includes the following sections: Section 2 describes the signal model for extended targets in CS-MIMO radar. In section 3, we derive the CRLB matrix of unknown parameters and optimize the measurement matrix based on minimizing the trace of the CRLB matrix. Simulation results are given in section 4 and Section 5 concludes the paper.

Notations. Lower case and capital letters in bold denote vectors and matrices, respectively. Superscripts $(.)^T$, $(.)^*$ and $(.)^H$ denote the transpose, conjugate and Hermitian transpose of a matrix/vector, respectively. The operator $\otimes$, $tr(.)$, and $ln(.)$ are the Kronecker product, trace of a matrix, and natural logarithm respectively, and $\mathbb{E}\{x\}$ denotes the expected value over x. $Re(.)$ and $Im(.)$, are real and imaginary part of a complex-valued matrix (vector). $\mathbf{I}_M$ is an $M \times M$ identity matrix.

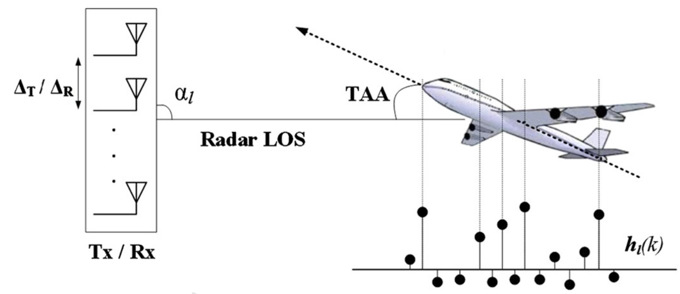

Fig. 1. Returns from the extended target can be represented by several scattering centers projected on the LOS of MIMO radar.

2. Problem formulation

Considering a high range resolution radar in which the size of range cell is far smaller than the physical shape of the target, we can describe the target by a set of dominant scattering centers [37], [38] (see Fig. 1). In this case, the target can be represented by a finite impulse response corresponding to the projection of the scattering centers on the radar line-of-sight (LOS) [39]. As a matter of fact, the TIR is a function of the radar carrier frequency, physical shape of the target, and the target aspect angle (TAA), which is the angle between the radar LOS and the major axis of the target (heading direction) [40]. Let us consider a collocated MIMO radar having uniform linear array (ULA) with M_t transmit and M_r receive antennas. The spatial steering vector of the transmit and receive antenna arrays for the azimuth angle α_l are shown respectively as,

$$\mathbf{a}_{\alpha_l} = \begin{bmatrix} 1 & e^{-jp_2(\alpha_l)} & \cdots & e^{-jp_{M_t}(\alpha_l)} \end{bmatrix}^T \in \mathcal{C}^{M_t \times 1}, \tag{1}$$

and

$$\mathbf{b}_{\alpha_l} = \begin{bmatrix} 1 & e^{-jq_2(\alpha_l)} & \cdots & e^{-jq_{M_r}(\alpha_l)} \end{bmatrix}^T \in \mathcal{C}^{M_r \times 1}, \tag{2}$$

where $p_t(\alpha_l) = 2\pi(t-1)\Delta_T \sin(\alpha_l)/\lambda_0$, and $q_r(\alpha_l) = 2\pi(r-1)\Delta_R \sin(\alpha_l)/\lambda_0$, with $(t = 1, ..., M_t)$, $(r = 1, ..., M_r)$. Also, Δ_T, and Δ_R are the distance between elements of the transmit and the receive antennas and λ_0 is the transmitted signal wavelength. We show the TIR vector in the radar interest area by

$$\mathbf{h}_l = [h_l(0) \quad \cdots \quad h_l(L_h - 1)]^T \in \mathcal{C}^{L_h \times 1}. \tag{3}$$

The transmitted code sequence of tth transmit antenna with length L_t is denoted by $\mathbf{c}_t \in \mathcal{C}^{L_t \times 1}$ $(t = 1, \cdots, M_t)$, whose ith component is $c_t(i) = 0$ unless $i \in \{1, 2, \cdots, L_t\}$. For extended target model, the echoed signal is the convolution of the transmitted signal and the TIR. Considering an extended target located at particular L_h range-bins of interest, the nth sample of the received signal by the rth receive antenna corresponding to the tth transmit antenna is given by

$$v_{rt}(n) = \sum_{l=1}^{N_t} e^{-j(q_r(\alpha_l)+p_t(\alpha_l))} (\mathbf{h}_l * \mathbf{c}_t)(n), \tag{4}$$

where α_l is the target angle and $*$ denotes the convolving operation. The convolution of transmitted signal and target TIR could be calculated as,

$$(\mathbf{h}_l * \mathbf{c}_t)(n) = \sum_{k=0}^{L_h-1} h_l(k)\, c_t(n-k), \tag{5}$$

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