Aerospace Science and Technology 53 (2016) 128–135

Contents lists available at ScienceDirect

Aerospace Science and Technology

www.elsevier.com/locate/aescte

# Power allocation and measurement matrix design for block CS-based distributed MIMO radars

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ARTICLE INFO

*Article history:*
Received 26 July 2015
Received in revised form 5 March 2016
Accepted 7 March 2016
Available online 15 March 2016

*Keywords:*
Compressive sensing
Block-sparsity
Multiple-input multiple-output (MIMO) radar
Multiple targets
Measurement matrix design
Power allocation

ABSTRACT

Multiple-input multiple-output (MIMO) radars offer higher resolution, better target detection, and more accurate target parameter estimation. Due to the sparsity of the targets in space-velocity domain, we can exploit Compressive Sensing (CS) to improve the performance of MIMO radars when the sampling rate is much less than the Nyquist rate. In distributed MIMO radars, block CS methods can be used instead of classical CS ones for more performance improvement, because the received signal in this group of MIMO radars is a block sparse signal in a basis. In this paper, two new methods are proposed to improve the performance of the block CS-based distributed MIMO radars. The first one is a new method for optimal energy allocation to the transmitters, and the other one is a new method for optimal design of the measurement matrix. These methods are based on minimizing an upper bound of the sum of the block-coherences of the sensing matrix blocks. Simulation results show an increase in the accuracy of multiple targets parameters estimation for both proposed methods.

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## 1. Introduction

Multiple-input multiple-output (MIMO) radar [1,2] is a radar that uses multiple antennas to simultaneously transmit diverse waveforms and multiple antennas to receive the reflected signal. The received signals are sent to a common processing center that is called fusion center. The difference between a MIMO radar and a phased-array radar is that the MIMO radar can transmit multiple waveforms from its transmitters, while in a phased array radar various shifts of the same signal are transmitted. There are two kinds of MIMO radars: distributed MIMO radars and co-located MIMO radars. In co-located type [3,4], transmitters and receivers are located close to each other relative to their distance to the target; thus, all transmitter-receiver pairs view the target from the same angle. In co-located MIMO radars, the phase differences induced by transmitters and receivers can be used to form a long virtual array with the number of elements equal to the product of the number of transmitters and receivers; therefore, they can achieve superior Direction of Arrival (DOA) resolution [3]. In distributed MIMO radars [5–7], the transmitters are located far apart from each other relative to their distance to the target. In this type of MIMO radars, the target is viewed from different angles. Thus, if the received signal from a particular transmitter and receiver is weak, it can be compensated by the received signals from other transmitter-receiver pairs. This type of MIMO radars is shown to offer superior target detection, more accurate target parameter estimation, and higher resolution [1,5–7].

If the sampling rate in MIMO radars is reduced, the cost of receivers can be reduced, and because of the existence of the multiple receivers, this reduction is very significant. Compressive Sensing (CS) methods make this reduction possible. Using this signal processing method, we can remove the need of the high rate A/D converters and send much less samples to the fusion center. Compressive sensing [8–14] is a new paradigm in signal processing that allows us to accurately reconstruct sparse or compressible signals from a number of samples which is much smaller than that is necessary according to the Shannon–Nyquist sampling theory. A vector $\boldsymbol{x}$ is called $K$-sparse if it is a linear combination of only $K$ basis vectors. In other words, using the basis matrix $\boldsymbol{\Psi}$ with basis vectors as columns, we can express $\boldsymbol{x}$ as

$$\boldsymbol{x} = \boldsymbol{\Psi}\boldsymbol{s} \tag{1}$$

where $\boldsymbol{s}$ is the weighting coefficient vector with length of $N$ in the basis $\boldsymbol{\Psi}$, and if only $K$ elements of $\boldsymbol{s}$ are nonzero, $\boldsymbol{x}$ is called $K$-sparse [8–12]. Compressive sensing is more valuable

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http://dx.doi.org/10.1016/j.ast.2016.03.005
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when $K \ll N$. $\boldsymbol{x}$ is compressible if it has just a few large coefficients and many small coefficients [11].

CS-based MIMO radars can be improved by different methods like: optimal design of measurement matrix [15,16], and optimal design of transmitted waveforms [17–20]. It is shown that these systems can estimate target parameters better than MIMO radars that are using some other estimation methods with higher sampling rates [15–17,21,22].

Let us consider $\boldsymbol{s}$ as a concatenation of blocks with length $d$, i.e.,

$$\boldsymbol{s} = [\underbrace{s_1, \ldots, s_d}_{\boldsymbol{s}[1]}, \underbrace{s_{d+1}, \ldots, s_{2d}}_{\boldsymbol{s}[2]}, \ldots, \underbrace{s_{N-d+1}, \ldots, s_N}_{\boldsymbol{s}[N/d]}]^T \tag{2}$$

where $(.)^T$ denotes transpose of a matrix. If at most $K$ blocks of $\boldsymbol{s}$ have nonzero Euclidean norms, $\boldsymbol{x}$ is called block $K$-sparse in the basis $\boldsymbol{\Psi}$ [23–27]. For block-sparse signals it is better to use block CS methods instead of usual CS methods. References [19, 28], and [29] use block CS methods in distributed MIMO radars and show the advantages of these methods over using the classical CS ones. It should be noted that we can use block CS methods in this type of MIMO radar because the received signal in this system is block-sparse. Reference [19] proposed an adaptive energy allocation method for block CS-based distributed MIMO radars, too. However, so far, no non-adaptive method has been proposed for improving the performance of the block CS-based distributed MIMO radars in particular.

In block CS methods such as BOMP and BMP, a critical parameter named block coherence is required to be small enough for appropriate recovery [25]. This parameter is defined in Section 4. For traditional CS methods, the coherence, the maximum correlation between the sensing matrix columns, is the determinative parameter. However, by reducing the coherence, the block coherence may also decrease. Reference [20] has used this idea to allocate energy to the transmitters in a block CS-based distributed MIMO radar. In this paper, we propose a superior transmitted energy allocation method to minimize an upper bound of the sum of the block-coherences of the sensing matrix blocks. We then, design a proper measurement matrix using the proposed upper bound as the cost function. We show that using these methods, the block CS-based distributed MIMO radar can be more accurate for target parameter estimation when the total transmitted energy is constant. The superiority of our proposed energy allocation method over the proposed method in [20] is also shown in the simulation results section.

The paper is organized as follows. In Section 2, we provide the received signal model of the CS-based distributed MIMO radar system. In Section 3, two important block recovery algorithms are presented. A new method of transmitted-energy allocation based on the sensing matrix block-coherence is introduced in Section 4. In Section 5, we present a new method based on the optimization of the measurement matrix to improve the performance of the CS-based distributed MIMO radars. Section 6 is allocated to simulation results, and finally, we make some concluding remarks in Section 7.

## 2. Received signal model for CS-based distributed MIMO radar

Let us consider a distributed MIMO radar system consisting of $M_t$ transmitters and $N_r$ receivers. The $i$th transmitter and $l$th receiver are located at $\boldsymbol{t}_i = [t_{x_i}, t_{y_i}]$ and $\boldsymbol{r}_l = [r_{x_l}, r_{y_l}]$ on a Cartesian coordinate system, respectively. We transmit orthogonal waveforms of duration $T_P$ from different transmitters, and Pulse Repetition Interval (PRI) is $T$. $x_i(t)$ is a complex baseband waveform with energy equal to 1, and $p_i x_i(t) e^{j2\pi f_c t}$ is the waveform transmitted from the $i$th transmitter where $f_c$ is the carrier frequency. Hence, the transmitted energy from the $i$th transmitter is $(p_i)^2$. Let us assume the total transmitted energy is $M_t$ (i.e. $\sum_{i=1}^{M_t}(p_i)^2 = M_t$). We assume that there are $K$ targets that are moving in a two dimensional plane. However, without loss of generality, this modeling can be extended to the three dimensional case. The $k$th target is located at $\boldsymbol{p}_k = [p_x^k, p_y^k]$ and moves with velocity $\boldsymbol{v}_k = [\tilde{v}_x^k, \tilde{v}_y^k]$. Now, we model the received signal in four stages as follows:

**Stage 1.** Under a narrow band assumption on the waveforms, the baseband signal arriving at the $l$th receiver from the $i$th transmitter can be expressed as

$$\boldsymbol{z}_{il}(t) = \sum_{k=1}^{K} \beta_k^{il} p_i x_i\big(t - \tau_k^{il}\big) e^{j2\pi (f_k^{il} t - f_c \tau_k^{il})} + \bar{n} \tag{3}$$

where $\beta_k^{il}$ denotes the attenuation coefficient corresponding to the $k$th target between the $i$th transmitter and the $l$th receiver, $\bar{n}_{il}(t)$ denotes the corresponding received noise, and $f_k^{il}$ and $\tau_k^{il}$ are respectively the corresponding $k$th target Doppler shift and delay that can be expressed as [19]:

$$f_k^{il} = \frac{f_c}{c}\big(\boldsymbol{v}_k.\boldsymbol{u}_{r_l}^k - \boldsymbol{v}_k.\boldsymbol{u}_{t_i}^k\big) \tag{4}$$

$$\tau_k^{il} = \frac{1}{c}\big(\|\boldsymbol{p}_k - \boldsymbol{t}_i\| + \|\boldsymbol{p}_k - \boldsymbol{r}_l\|\big) \tag{5}$$

where $c$ is the speed of light and $\boldsymbol{u}_{t_i}^k$ and $\boldsymbol{u}_{r_l}^k$ denote the unit vector from the $i$th transmitter to the $k$th target and unit vector from the $k$th target to the $l$th receiver, respectively.

Like [19], we assume that after down converting the received bandpass signal from the radio frequency, it is passed through a bank of $M_t$ matched filters corresponding to $M_t$ transmitters. We assume $\beta_k^{il}$ does not vary within the estimation process duration and the Doppler shift is small (the velocity of targets is much smaller than $c$). Hence, $\beta_k^{il} p_i e^{j2\pi f_k^{il} t}$ can be taken outside of the integral in the matched filter operation. Let us consider $T_s$ as the sampling period time, $T_s \ll T_P$ and $\tau_k^{il} \ll T_P$ for $i = 1, \ldots, M_t$, $l = 1, \ldots, N_r$, and $k = 1, \ldots, K$. The sampled output of the $i$th matched filter at the $l$th receiver in the $m$th pulse of the estimation process from the $k$th target can be expressed as

$$\begin{aligned} z_{il,k}^m(n) = {} & \beta_k^{il} \Psi_{il,k}^m(n) + \bar{n}_{il}(t) * x_i((m-1)T \\ & + T_p - t)|_{t=(m-1)T+T_p+nT_s} \end{aligned} \tag{6}$$

where

$$\Psi_{il,k}^m(n) = p_i e^{j2\pi (f_k^{il}((m-1)T+T_P+nT_s) - f_c \tau_k^{il})} \tag{7}$$

**Stage 2.** In this stage, at first, we consider that there is only the $k$th target. Then, we put the output of the matched filters at the $l$th receiver at a same time in a vector as

$$\begin{aligned} \boldsymbol{z}_{l,k}^m(n) &= \big[z_{1l,k}^m(n), \ldots, z_{M_t l,k}^m(n)\big]^{\boldsymbol{T}} \\ &= \boldsymbol{\Psi}_{l,k}^{\boldsymbol{m}}(n) \boldsymbol{\beta}_{l,k} + \boldsymbol{e}_l^{\boldsymbol{m}}(n) \end{aligned} \tag{8}$$

where

$$\begin{aligned} \boldsymbol{e}_l^{\boldsymbol{m}}(n) = {} & \big[\bar{n}_{1l}(t) * x_1((m-1)T + T_p - t)|_{t=(m-1)T+T_p+nT_s}, \ldots, \\ & \bar{n}_{M_t l}(t) * x_{M_t}((m-1)T + T_p - t)|_{t=(m-1)T+T_p+nT_s}\big]^T, \end{aligned} \tag{9}$$

$$\boldsymbol{\Psi}_{l,k}^{\boldsymbol{m}}(n) = diag\big\{\Psi_{1l,k}^m(n), \ldots, \Psi_{M_t l,k}^m(n)\big\}, \tag{10}$$

$$\boldsymbol{\beta}_{l,k} = \big[\beta_k^{1l}, \ldots, \beta_k^{M_t l}\big]^T \tag{11}$$

Next, we put the output vectors of the receivers that are obtained by (8) in vector $\boldsymbol{z}_k^m(n)$ as

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