# DOA and polarization estimation via signal reconstruction with linear polarization-sensitive arrays 

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Array signal processing; DOA estimation; Polarization estimation; Polarization sensitive array; Sparse Bayesian reconstruction


#### Abstract

This paper addresses the problem of direction-of-arrival (DOA) and polarization estimation with polarization sensitive arrays (PSA), which has been a hot topic in the area of array signal processing during the past two or three decades. The sparse Bayesian learning (SBL) technique is introduced to exploit the sparsity of the incident signals in space to solve this problem and a new method is proposed by reconstructing the signals from the array outputs first and then exploiting the reconstructed signals to realize parameter estimation. Only 1-D searching and numerical calculations are contained in the proposed method, which makes the proposed method computationally much efficient. Based on a linear array consisting of identically structured sensors, the proposed method can be used with slight modifications in PSA with different polarization structures. It also performs well in the presence of coherent signals or signals with different degrees of polarization. Simulation results are given to demonstrate the parameter estimation precision of the proposed method. © 2015 The Author. Production and hosting by Elsevier Ltd. on behalf of CSAA \& BUAA. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).


## 1. Introduction

The polarization sensitive arrays (PSA) are able to collect the signal energy in different polarization directions and they have been widely used to improve the performance of direction-of-arrival (DOA) estimation (see Refs. ${ }^{1-6}$ and the references

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therein). Many PSA with different polarization structures are now available in practical systems, such as the co-centered crossed-dipole pair (CCD) array, the co-centered orthogonal loop and dipole (COLD) array and the electromagnetic vector array (EVA) of super-resolution compact array radiolocation technology (SuperCART). However, the research on DOA estimation with PSA has lagged behind as many shortcomings still remain in the existing methods.

When 2-D DOA estimation and joint polarization estimation are required, the existing methods generally turn to the multi-dimensional searching techniques as the parameters can hardly be separated in the objective functions. ${ }^{7-9}$ Such a computationally prohibitive searching procedure greatly blocks the theoretical study and practical application of those
methods. Therefore, some of the researches focus on the simpler 1-D estimation problems. ${ }^{10,11}$ In addition, as more than one parameter is usually concerned for each signal with the PSA, a possibly confusion-inducing procedure of variablepairing is required for successful parameter estimation of multiple signals. ${ }^{7,10}$ Spatial and polarization smoothing techniques have also been combined with the ordinary subspace-based DOA estimation methods, so as to separate coherent signals. ${ }^{11,12}$ However, these techniques can be realized only with particularly designed PSA, thus they have been blocked from widespread applications. Similar constraints lie in the method proposed for DOA estimation when completely and incompletely polarized signals coexist, ${ }^{13}$ as it can be used only on PSA with particular triangular geometries.

The sparsity of the incident signals in space is a comprehensive property in various array applications. Previous research based on the exploitation of such a property in scalar sensor arrays has witnessed significant performance improvements, especially in scenarios with low signal-to-noise ratio (SNR) and much limited snapshots. ${ }^{14-19}$ Among the existing sparsitybased DOA estimation methods, the ones based on the sparse Bayesian learning (SBL) technique ${ }^{20,21}$ exceed their counterparts in DOA estimation precision in adequate scenarios. ${ }^{17-19}$ In this paper, the SBL technique is introduced to solve the direction and polarization estimation problem with PSA. By exploiting the sparsity of the incident signals, the signal components contained in the differently polarized array measurements are reconstructed first, and then combined with respect to the sources to estimate the parameters of interest. In order for notational facilitation, the proposed method is named reconstruction and combination of polarized signal components and ReCoP for short. It avoids the computationally prohibitive multi-dimensional searching procedure and the confusioninducing variable-pairing procedure. With very slight modifications, it can be used in various linear PSA consisting of identically structured sensors, such as CCD arrays, COLD arrays and SuperCART, and it is also able to process coherent signals and signals with different degrees of polarization.

The rest of the paper consists of six parts. Section 2 reviews the observation model of the PSA, the SBL technique is introduced in Section 3 to reconstruct the polarized signal components, and those reconstructed signals are combined in Section 4 to estimate the direction and polarization parameters. Based on the differences during method implementation between the proposed method and its counterparts, Section 5 highlights some special properties of the proposed method. Section 6 demonstrates the performance of the proposed method via simulations and Section 7 concludes the whole paper.

## 2. Model formulation

Suppose that $K$ transverse electromagnetic waves impinge onto an $M$-element PSA, the azimuths of the signals are $\vartheta_{1}, \vartheta_{2}, \ldots, \vartheta_{K} \in[0, \pi]$, which are defined as the projections of the incident signal directions on the $x-y$ plane to the $x$ axis, and their elevations, defined as the signal directions to the $z$ axis, are $\varphi_{1}, \varphi_{2}, \ldots, \varphi_{K} \in[0, \pi / 2]$. The sketch of a linear COLD array is shown in Fig. 1, where $s(t)$ indicates the incident signal. When only 1-D DOA estimation is concerned, one should set $\varphi_{1}=\varphi_{2}=\cdots=\varphi_{K}=\pi / 2$.


Fig. 1 Sketch of a linear COLD array.

The output of the PSA at time $t$ is
$\tilde{\boldsymbol{x}}(t)=\tilde{\boldsymbol{A}} \tilde{\boldsymbol{u}}(t)+\tilde{\boldsymbol{v}}(t)$
where $\quad \tilde{\boldsymbol{A}}=\left[\tilde{\boldsymbol{a}}_{1, \mathrm{~h}}, \tilde{\boldsymbol{a}}_{1, \mathrm{v}}, \tilde{\tilde{\boldsymbol{a}}}_{2, \mathrm{~h}} \tilde{\tilde{\boldsymbol{a}}}_{2, \mathrm{v}}, \cdots, \tilde{\boldsymbol{a}}_{K, \mathrm{~h}}, \tilde{\boldsymbol{a}}_{K, \mathrm{v}}\right], \quad \tilde{\boldsymbol{a}}_{k, \mathrm{~h}}=\boldsymbol{a}_{k} \otimes \boldsymbol{\psi}_{k, \mathrm{~h}}$, $\tilde{\boldsymbol{a}}_{k, v}=\boldsymbol{a}_{k} \otimes \boldsymbol{\psi}_{k, v}, \otimes$ represents the Kronecker product, the subscripts $(\bullet)_{\mathrm{h}}$ and $(\bullet)_{\mathrm{v}}$ are used to indicate the horizontal and vertical components, respectively, $\boldsymbol{a}_{k}=\left[\mathrm{e}^{\mathrm{j} 2 \pi d_{1} \cos \vartheta_{k} \sin \varphi_{k} / \lambda}\right.$, $\left.\mathrm{e}^{\mathrm{j} 2 \pi d_{2} \cos \vartheta_{k} \sin \varphi_{k} / \lambda}, \cdots, \mathrm{e}^{\mathrm{j} 2 \pi d_{M} \cos \vartheta_{k} \sin \varphi_{k} / \lambda}\right]^{\mathrm{T}}$ stands for the phaseshift vector depending on the array geometry, $\lambda$ is the signal wavelength, $d_{m}$ denotes the distance between the $m$ th sensor and the reference point on the array axis, $\boldsymbol{\psi}_{k, \mathrm{~h}}=\boldsymbol{\Xi} \tilde{\boldsymbol{\psi}}_{k, \mathrm{~h}}$, $\tilde{\boldsymbol{\psi}}_{k, \mathrm{~h}}=\left[-\sin \vartheta_{k}, \cos \vartheta_{k}, 0, \cos \varphi_{k} \cos \vartheta_{k}, \cos \varphi_{k} \sin \vartheta_{k},-\sin \varphi_{k}\right]^{\mathrm{T}}$, $\boldsymbol{\psi}_{k, \mathrm{v}}=\boldsymbol{\Xi} \tilde{\boldsymbol{\psi}}_{k, \mathrm{v}}, \tilde{\boldsymbol{\psi}}_{k, \mathrm{v}}=\left[\cos \varphi_{k} \cos \vartheta_{k}, \cos \varphi_{k} \sin \vartheta_{k},-\sin \varphi_{k}, \sin \vartheta_{k}\right.$, $\left.-\cos \vartheta_{k}, 0\right]^{\mathrm{T}}, \boldsymbol{\Xi}$ indicates the polarization dimensions that the array selects from the EVA, e.g., $\boldsymbol{\Xi}=\left[\begin{array}{llllll}1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0\end{array}\right]$ for COLD arrays; $\tilde{\boldsymbol{u}}(t)=\left[\boldsymbol{u}_{1}^{\mathrm{T}}(t), \boldsymbol{u}_{2}^{\mathrm{T}}(t), \cdots, \boldsymbol{u}_{K}^{\mathrm{T}}(t)\right]^{\mathrm{T}}, \quad \boldsymbol{u}_{k}(t)=$ $\left[s_{k, \mathrm{~h}}(t), s_{k, \mathrm{v}}(t)\right]^{\mathrm{T}}, s_{k, \mathrm{~h}}(t)$ and $s_{k, \mathrm{v}}(t)$ represent the polarized components of the $k$ th signal in two orthogonal polarization directions; $\tilde{\boldsymbol{v}}(t)$ is the additive white Gaussian noise independent of the signals with variance $\sigma^{2}$. For completely polarized signals, $s_{k, \mathrm{~h}}(t)$ and $s_{k, v}(t)$ are linearly dependent as $\boldsymbol{u}_{k}(t)=\left[\cos \phi_{k}, \sin \phi_{k} e^{\mathrm{j} \eta_{k}}\right]^{\mathrm{T}} s_{k}(t)$, with $\phi_{k}$ and $\eta_{k}$ representing the polarization angle and phase of the $k$ th signal and $s_{k}(t)$ being the signal waveform.

By separating the outputs of the array elements with identical polarization directions from $\tilde{\boldsymbol{x}}(t), P$ measurement vectors of $\boldsymbol{x}_{1}(t), \boldsymbol{x}_{2}(t), \cdots, \boldsymbol{x}_{P}(t) \in \mathbf{C}^{M \times 1}$ can be obtained as follows:
$\boldsymbol{x}_{p}(t)=\sum_{k=1}^{K} \boldsymbol{a}_{k}\left(\boldsymbol{g}_{k, p}^{\mathrm{T}} \boldsymbol{u}_{k}(t)\right)+\boldsymbol{v}_{p}(t)=\boldsymbol{A} \boldsymbol{w}_{p}(t)+\boldsymbol{v}_{p}(t)$
$p=1,2, \ldots, P$
where $P$ represents the number of polarization directions of each array sensor, $\boldsymbol{x}_{p}(t)=\boldsymbol{G}_{p} \tilde{\boldsymbol{x}}(t), \boldsymbol{G}_{p}=\boldsymbol{I}_{M} \otimes \boldsymbol{e}_{p}^{\mathrm{T}}, \boldsymbol{I}_{M}$ denotes the identity matrix with dimension $M \times M, \boldsymbol{e}_{p} \in \mathbf{C}^{P \times 1}$ stands for a vector with its $p$ th element being the only non-zero one of $1, \quad \boldsymbol{g}_{k, p}=\left[\boldsymbol{\psi}_{k, \mathrm{~h}}, \boldsymbol{\psi}_{k, \mathrm{v}}\right]^{\mathrm{T}} \boldsymbol{e}_{p}, \quad w_{k, p}(t)=\boldsymbol{g}_{k, p}^{\mathrm{T}} \boldsymbol{u}_{k}(t), \quad \boldsymbol{w}_{p}(t)=$ $\left[w_{1, p}(t), w_{2, p}(t), \cdots, w_{K, p}(t)\right]^{\mathrm{T}}, \quad \boldsymbol{A}=\left[\boldsymbol{a}_{1}, \boldsymbol{a}_{2}, \cdots, \boldsymbol{a}_{K}\right], \quad \boldsymbol{v}_{p}(t)=$ $\boldsymbol{G}_{p} \tilde{\boldsymbol{v}}(t)$. Eq. (2) indicates that the $P$ measurement vectors consist of signals impinging from the same $K$ directions and

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