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Wideband tensor array processing

Francesca Raimondi, Rodrigo Cabral Farias, Olivier Michel, Pierre Comon

Abstract—This paper establishes the general tensor model for wideband array processing including multiple physical diversities. A separable coherent focusing operation is proposed as a preprocessing step in order to ensure the multi-linearity of the interpolated data. We propose an ALS algorithm to process tensor data, dealing with the noise correlation structure introduced by the focusing operation. We show through computer simulations that the estimation of DoA and polarization parameters improves existing narrowband tensor processing and wideband MUSIC. Performance is also compared to Cramér-Rao bounds of the wideband tensor model.

Index Terms—localization, DoA estimation, interpolation, wideband, antenna array processing, tensor, MUSIC, High Resolution, polarization, CP decomposition

I. INTRODUCTION

Direction of Arrival (DoA) estimation is a central problem in array signal processing, and in particular in telecommunications, seismology, speech, biomedical engineering, and astronomy. We are interested in acquisition systems composed of multiple sensors that receive source signals from different directions [1], [2]. In order to estimate DoA, existent techniques such as beamforming, MUSIC (Multiple Signal Classification) [3], root-MUSIC [4] and ESPRIT (Estimation of Signal Parameters via Rotational Invariance Techniques) [5], take advantage of the space diversity embedded in the acquisition system. In particular, the time delay of a narrowband wave received at a given sensor can be expressed by a simple multiplication by a complex exponential carrying the information on the DoA. In addition to the space diversity, ESPRIT assumes the presence of two identical subarrays, displaced from each other by a space shift.

The space shift diversity was extended to more than one displacement through tensor decomposition of narrow-band waves, through a deterministic approach that allows to separate and estimate more sources than sensors in each subarray [6]. Tensor analysis requires at least three diversities to allow a multilinear decomposition¹ [7], that guarantees uniqueness under mild conditions.

Another element of diversity is given by wave polarization, whenever each sensor has multiple components [8], [9], [10], [11]. The above mentioned tensor approach was extended to include polarization diversity in [12], [13], [14], and propagation speed diversity of seismic waves in [15].

MUSIC, ESPRIT and tensor decomposition for array processing originally addressed the narrow-band case. In fact, in

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¹This decomposition is often referred to as *Canonical Polyadic* (CP), and sometimes as CanDecomp or PARAFAC.

wideband, signal subspace and steering matrices vary with frequency, thus requiring a focusing operation onto the same reference subspace. This approach, named *Coherent Signal Subspace* (CSS), may require an approximate prior estimate of DoA to form focusing matrices [16], [17], [18], or virtual arrays obtained by spatial interpolation [19], [20]. The latter extend MUSIC algorithm to wideband processing for Uniform Linear Arrays (ULA). To our knowledge, only recently tensor analysis was extended to process wideband waves for ULAs in [21], where a spatial interpolation technique was adopted. For sake of clarity, Table I illustrates the state of the art and our contributions: rows refer to theoretical approaches, and columns to physical diversities taken into account.

This paper aims at establishing the general model for high resolution wideband tensor array processing with multiple antenna diversities (space, space shift, polarization and spatial gain patterns), under the assumption of plane waves in the far field. The multilinear coherent subspace preprocessing, required in the wideband case, introduces a correlation in the noise structure. An algorithm for tensor decomposition taking into account the noise covariance is proposed, and performance are evaluated via Cramér-Rao Bounds (CRB).

This paper is organized as follows: Section II introduces the physical model and main issues of wideband array processing; Section III illustrates the main antenna diversities that can be exploited in tensor processing; tensor notations and multilinear decompositions are introduced in Section IV; Section V illustrates the effect of wideband coherent processing on tensor formulation; CRB are computed in Section VI; Section VII addresses algorithmic issues; Section VIII reports computer results for the particular case of space shift and polarization diversities, in comparison with wideband MUSIC and with the multilinear CRB.

II. FROM NARROW-BAND TO WIDE-BAND

A. Observation model

We consider R radiating sources in the far-field², s_r , $1 \leq r \leq R$, arriving from directions defined by unit vectors $\mathbf{d}(\theta_r)$, θ_r being a pair of angles in 3D, or a single angle in 2D. These sources impinge on an arbitrary array of L sensors located at positions \mathbf{p}_ℓ in space, $1 \leq \ell \leq L$. The signal received at the ℓ -th sensor at time t can be modeled as:

$$x_\ell[t] = \sum_{r=1}^R g_\ell(\theta_r) s_r[t - \tau_\ell(\theta_r)] + n_\ell[t] \quad (1)$$

where $s_r[t]$ is the signal transmitted by the r -th source, $t \in \{1, 2, \dots, T\}$, $g_\ell(\theta_r)$ is the sensor gain of the ℓ -th sensor,

²This means that the wavefront curvature and dissipation are neglected.

	Time	Space	Freq.	Space Shift	Gain Pattern	Polar
Vector Sensor MUSIC [3], [22]	s, \times	\times				
Vector Sensor MUSIC [3], [9], [10]	s, \times	\times				\times
WB MUSIC [23], [17], [24], [19], [20], [25]	s	\times	\times			
WB Vector Sensor MUSIC [26]	s	\times	\times			\times
ESPRIT ($M = 2$) [5]	s, \times	\times		\times		
WB ESPRIT [18], [27]	s	\times	\times	\times		
Tensor ESPRIT [6], [28], [29]	\times	\times		\times		
Vector Sensor CP [12], [13], [14]	\times	\times				\times
WB Tensor CP [21]		\otimes	\otimes	\otimes		
Gain Pattern CP	\otimes	\otimes	\otimes		\otimes	
WB Vector Sensor CP		\otimes	\otimes			\otimes

TABLE I

MULTIPLE DIVERSITY IN ARRAY PROCESSING: s = AVERAGE OF THE COVARIANCE MATRIX THROUGH MULTIPLE SNAPSHOTS; WB = WIDEBAND; \times = WHAT EXISTS IN LITERATURE, \otimes = OUR CONTRIBUTION

\mathbf{v}	vector: in bold lower case
v_i	i -th element of \mathbf{v}
\mathbf{A}	matrix: in bold upper case
\mathbf{I}_L	identity matrix of size $L \times L$
\mathbf{a}_i	i -th column of \mathbf{A}
$\bar{\mathbf{g}}$	vector \mathbf{g} without its first entry
A_{ij}	$\{i, j\}$ element of \mathbf{A}
\mathbf{A}^\top	transpose of \mathbf{A}
\mathbf{A}^*	complex conjugate of \mathbf{A}
\mathbf{A}^H	conjugate transpose of \mathbf{A}
\mathbf{A}^\dagger	Moore-Penrose pseudoinverse of \mathbf{A}
$\mathbf{v}^\top \mathbf{u}$	scalar product between real vectors \mathbf{v} and \mathbf{u}
$\mathbf{v} \otimes \mathbf{u}$	outer (tensor) product between two vectors
$\mathbf{A} \boxtimes \mathbf{B}$	Kronecker product between \mathbf{A} and \mathbf{B}
$\mathbf{A} \square \mathbf{B}$	Hadamard (element-wise) product
$\ \cdot\ _F$	Frobenius norm
\mathcal{T}	tensor: in bold calligraphic font
\mathcal{T}_{ijk}	$\{i, j, k\}$ element of \mathcal{T}
$\text{vec}\{\mathcal{T}\}$	vectorization of \mathcal{T}
$\dot{\mathbf{f}}(\theta)$	derivative $\partial \mathbf{f} / \partial \theta$

TABLE II
NOTATIONS

assumed to be independent of frequency, and $n_\ell[t]$ is an additive noise. The delay of arrival $\tau_\ell(\theta)$ is directly related to sensor locations and DoA's via the expression

$$\tau_\ell(\theta) = \mathbf{p}_\ell^\top \mathbf{d}(\theta) / c \quad (2)$$

c being the wave propagation speed and (\top) transposition.

At this stage, it is important to fix a scaling indeterminacy, present in all blind approaches. Observe that changing the pair $(g_\ell(\theta_r), s_r)$ into $(\rho g_\ell(\theta_r), s_r / \rho)$, $\forall \rho \neq 0$, leads to the same model. So we may fix $g_1(\theta) = 1, \forall \theta$, without restricting the generality, which means that the first sensor is treated as omnidirectional.

Denote by ω the radial frequency, and by $x(\omega)$ the Fourier Transform (FT) of $x[t]$. In this framework, model (1) can be

equivalently rewritten in the frequency domain:

$$x_\ell(\omega) = \sum_{r=1}^R g_\ell(\theta_r) e^{-j\omega\tau_\ell(\theta_r)} s_r(\omega) + n_\ell(\omega) \quad (3)$$

where $j = \sqrt{-1}$ and g_ℓ are *a priori* unknown real functions unless otherwise specified, and $n_\ell(\omega)$ refers to a circular Gaussian white noise process at the ℓ -th sensor. The noise processes at different sensors are considered to be identically distributed and uncorrelated from one another. Alternatively, in vector form, (3) becomes

$$\mathbf{x}(\omega) = \mathbf{A}(\omega, \boldsymbol{\theta}) \mathbf{s}(\omega) + \mathbf{n}(\omega) \quad (4)$$

where the $L \times R$ matrix $\mathbf{A}(\omega, \boldsymbol{\theta})$ depends on the vector³ of directions of arrival (DoA's), $\boldsymbol{\theta} = [\theta_1, \dots, \theta_R]^\top$. The r -th column of $\mathbf{A}(\omega, \boldsymbol{\theta})$, denoted $\mathbf{a}(\omega, \theta_r)$ in the remainder, is the value of the *array manifold* taken at $\theta = \theta_r$.

To summarize, we assume the following hypotheses:

- the first sensor ($\ell = 1$) is taken as origin, so that $\mathbf{p}_1 = \mathbf{0}$, and has a unit gain in all directions, *i.e.* $g_1(\theta) = 1, \forall \theta$;
- the sensor gains $g_\ell(\theta)$ are real (which is actually equivalent to assuming that their phase is known) and frequency-flat;
- sources $s_r[t]$ are deterministic;
- the wave propagation speed c does not depend on frequency (*i.e.* the medium is not dispersive)⁴.

B. Virtual arrays

High Resolution (HR) methods are based on a partition of the observation space into signal and noise subspaces, usually via low-rank approximations. The advantage of transforming the dynamical model (1) into model (3) is that the latter is formally static for every fixed radial frequency ω , which makes it easier to define and compute the above-mentioned subspaces. The drawback is that these subspaces change with frequency, which raises difficulties in the frame of a wideband coherent processing. As a consequence, in order to estimate

³In 3D, $\boldsymbol{\theta}$ is a $R \times 2$ matrix of angles; it is a $R \times 1$ vector in 2D.

⁴The principles would actually remain valid for dispersive media provided the function $c(\omega)$ is known.

coherently the DoA's, it is necessary to first steer them towards a subspace defined at a reference radial frequency ω_0 [17], [19], [20], [30].

For this purpose, the complex exponential in (3) needs to become constant, in order to constitute a coherent contribution. Since sensor gains do not depend on frequency, this steering operation leads to defining a virtual array for each radial frequency ω defined by sensor positions $\tilde{\mathbf{p}}_\ell(\omega)$, related to actual sensor positions \mathbf{p}_ℓ by:

$$[\omega\tilde{\mathbf{p}}_\ell(\omega) - \omega_0\mathbf{p}_\ell]^\top \mathbf{d}(\theta) \equiv 0, \text{ mod } 2\pi. \quad (5)$$

where ω_0 is fixed. This equation is satisfied if the term within brackets is orthogonal to $\mathbf{d}(\theta_r)$ for every DoA, $1 \leq r \leq R$; but this requires a prior knowledge of DoA's [17]. On the other hand, a sufficient condition is clearly that $\tilde{\mathbf{p}}_\ell(\omega) = \frac{\omega_0}{\omega}\mathbf{p}_\ell$, which this time does not depend on θ ; this corresponds to the stretched arrays proposed in [19], [20], [30].

Remark: More generally, if gains depended on frequency, equation (5) would become

$$\exp\{j[\omega\tilde{\mathbf{p}}_\ell(\omega) - \omega_0\mathbf{p}_\ell]^\top \mathbf{d}(\theta)\} = \frac{g_\ell(\omega, \theta)}{g_\ell(\omega_0, \theta)}. \quad (6)$$

Satisfying this equation would then require prior knowledge of DoAs. As pointed out in Section II, this case is beyond the scope of the present paper.

C. Interpolation

Equation (5) defines virtual arrays with identical array manifolds, but do not provide the signals that would be measured by the latter. It is hence necessary to devise an interpolator to compute synthetic measurements. However, to preserve the separation between noise and signal subspaces, it is suitable to map $\mathbf{a}(\omega, \theta)$ to the same manifold $\mathbf{a}(\omega_0, \theta)$ via a multiplication by some $L \times L$ matrix $\mathbf{U}(\omega, \omega_0, \theta)$, which we call focusing matrix. It turns out that this is possible exactly only for at most L distinct values of θ . There are thus two possibilities.

- Either the DoA's are unknown, and a focusing matrix $\mathbf{U}(\omega, \omega_0, \theta)$ can be computed so as to satisfy the following relationship only approximately [30]:

$$\mathbf{U}(\omega, \omega_0, \Theta_k) \mathbf{a}(\omega, \theta) \approx \mathbf{a}(\omega_0, \theta) \quad (7)$$

in an angular sector $\theta \in \Theta_k$ of limited extent, where ω_0 is a fixed reference frequency. They can be obtained by solving in the Least Squares (LS) sense the linear system $\mathbf{U}(\omega, \omega_0, \Theta_k)\mathbb{A}(\omega, \Theta_k) \approx \mathbb{A}(\omega_0, \Theta_k)$, where Θ_k contains I discrete angular values θ_i , $1 \leq i \leq I$, and matrix $\mathbb{A}(\omega, \Theta_k)$ is built with the corresponding columns $\mathbf{a}(\omega, \theta_i)$; see [31] for more details.

- Or the R DoA's are approximately known in advance, $R \leq L$, and it is possible to satisfy (7) exactly for these approximate DoA's; see [17] for more details.

D. Example: the covariance matrix approach

For the sake of completeness, we shall now describe the model described in [30], [17], even if it is not used in subsequent sections. In the state of the art [30], [17], the previously

explained interpolation method is used as a preprocessing for subspace methods (such as MUSIC), in order to solve the problem of coherent averaging the estimated covariance matrices. In fact, this model is based on second order moments whereas a deterministic approach will be described along with a multi-linear interpolation procedure in Section IV. This is illustrated below, as the covariance matrix $\mathbf{R} = \mathbb{E}[\mathbf{x} \mathbf{x}^H]$ depends on the frequency:

$$\mathbf{R}(\omega) = \mathbf{A}(\omega, \boldsymbol{\theta})\mathbf{R}_s(\omega)\mathbf{A}(\omega, \boldsymbol{\theta})^H + \mathbf{R}_n(\omega) \quad (8)$$

As a consequence, in order to estimate the DoA's by a coherent average over different values of ω , it is necessary to first steer all estimated $\hat{\mathbf{R}}(\omega)$ towards a subspace defined at a reference radial frequency ω_0 [17], [19], [20], [30]. By doing so, in every angular sector Θ_k we can use contributions of all frequencies to build an averaged estimate of the covariance matrix:

$$\bar{\mathbf{R}}(\Theta_k) = \sum_{\omega} \mathbf{U}(\omega, \omega_0, \Theta_k) \mathbf{x}(\omega)\mathbf{x}(\omega)^H \mathbf{U}(\omega, \omega_0, \Theta_k)^H \quad (9)$$

From (4) and (7) we obtain

$$\bar{\mathbf{R}}(\Theta_k) \approx \sum_{\omega} \mathbf{A}(\omega_0, \boldsymbol{\theta})\mathbf{R}_s(\omega)\mathbf{A}(\omega_0, \boldsymbol{\theta})^H + \bar{\mathbf{R}}_n(\omega)$$

where $\mathbf{R}_s(\omega)$ denotes the covariance of the sources about radial frequency ω and $\bar{\mathbf{R}}_n(\omega)$ the noise covariance transformed by matrix $\mathbf{U}(\omega, \omega_0, \Theta_k)$ in the considered sector, *i.e.* $\theta \in \Theta_k$. This summation corresponds to averaging observations received on virtual arrays, each being a stretched or shrunk version of a reference array at radial frequency ω_0 .

III. MULTIPLE DIVERSITIES

Direction of arrival estimation can be significantly improved if other modalities are taken into account into the model. In array processing, space shift and polarization are the most widely studied diversities (in addition to time, frequency and space). In this section we establish all relevant relations for these diversities in a narrowband around a radial frequency ω .

A. Space shift and gain pattern diversity

Space shift diversity was initially exploited by ESPRIT algorithm for two subarrays deduced from each other by a translation [5]. It has been extended to more than two subarrays in [6] giving rise to a third order tensor decomposition for array processing. The diversities involved are space, time, and space shift. It is also possible to consider diversities induced by polarized sensors, and by anisotropic sensor gains. We refer to the latter as *gain pattern diversity*.

Denote $\boldsymbol{\delta}_m$ the location of the m -th subarray. We may take the first subarray as origin, so that $\boldsymbol{\delta}_1 = \mathbf{0}$. In addition, the gain of sensor ℓ is assumed to be the same for any subarray m , and is given by $g_\ell(\theta)$.

Let $\zeta_m(\theta) = \boldsymbol{\delta}_m^\top \mathbf{d}(\theta)/c$ be the delay of arrival on subarray m , and denote by $\mathcal{F}\{\cdot\}$ the Fourier Transform operator applied

to received signals in the time window $t \in [0, T]$. Then, in presence of additive noise \mathcal{N} :

$$\mathcal{X}_{\ell m}(\omega) = \sum_{r=1}^R A_{\ell r}(\omega) B_{mr}(\omega) S_r(\omega) + \mathcal{N}_{\ell m}(\omega)$$

$$\text{with} \quad \begin{cases} \mathcal{X}_{\ell m}(\omega) &= \mathcal{F}\{x_{\ell m}[t]\} \\ A_{\ell r}(\omega) &= g_{\ell}(\theta_r) e^{-j\omega\tau_{\ell}(\theta_r)} \\ B_{mr}(\omega) &= e^{-j\omega\zeta_m(\theta_r)} \\ S_r(\omega) &= \mathcal{F}\{s_r[t]\} \end{cases} \quad (10)$$

In the remainder, since received signals are assumed real, we consider only positive frequencies (without any loss of information), in an interval \mathcal{Q} of interest:

$$\mathcal{X}_{\ell m}(\omega_q) = \sum_{r=1}^R A_{\ell r}(\omega_q) B_{mr}(\omega_q) S_r(\omega_q) + \mathcal{N}_{\ell m}(\omega_q) \quad (11)$$

where frequency $0 < \omega_{min} \leq \omega_q \leq \omega_{max} < \pi$, and $q \in \mathcal{Q}$.

Let's look at two relevant particular cases.

1) *Diversity of space shift only*: In that case, $g_{\ell}(\theta) = 1 \forall \theta$, and we end up with the model described in [6].

2) *Diversity of gain pattern only*: This is the particular case where sensors in each sub-array are located at the same place, and differ only through their gain pattern, *i.e.* $\tau_{\ell}(\theta) = 0$ and $A_{\ell r}(\omega) = g_{\ell}(\theta_r)$. In Appendix A-C, we shall briefly go back to this rarely addressed case.

B. Polarization diversity

If we have at our disposal a single antenna ($m = 1$) array of polarized elements, each capable to record 3 orthogonal components, the observation model is similar to (10), if we omit measurement noise:

$$\mathcal{M}_{\ell p}(\omega_q) = \sum_{r=1}^R A_{\ell r}(\omega_q) K_{pr} S_r(\omega_q), \quad 1 \leq p \leq P = 3 \quad (12)$$

where the R columns of the $3 \times R$ factor matrix \mathbf{K} are detailed in [32], [7]:

$$\mathbf{k}_r = \mathbf{H}(\theta_r) \mathbf{W}(\alpha_r) \mathbf{w}(\beta_r)$$

where the two angles $\alpha_r \in (-\pi/2, \pi/2]$ and $\beta_r \in [-\pi/4, \pi/4]$ characterize the polarization of the r -th source transverse wave, and

$$\mathbf{H}(\theta_r) = \begin{bmatrix} -\sin \phi_r & -\cos \phi_r \sin \psi_r \\ \cos \phi_r & -\sin \phi_r \sin \psi_r \\ 0 & \cos \psi_r \end{bmatrix}$$

$$\mathbf{W}(\alpha_r) = \begin{bmatrix} \cos \alpha_r & \sin \alpha_r \\ -\sin \alpha_r & \cos \alpha_r \end{bmatrix} \quad (13)$$

$$\mathbf{w}(\beta_r) = \begin{bmatrix} \cos \beta_r \\ j \sin \beta_r \end{bmatrix}$$

where it is reminded that $\theta_r = (\phi_r, \psi_r)$. Without restricting too much the generality, we assume that polarization does not depend on ω over the bandwidth of interest. Furthermore, for the sake of clarity, only transverse waves are considered. The main difference between (11) and (12) is that the second factor matrix, \mathbf{K} , now depends on extraneous unknown angular parameters (α_r, β_r) , instead of the subarray space shifts δ_m .

C. All together

It is clear that all diversities can be modeled all together, at the price of an increased notational complexity. If frequency, space, space shift and pattern, and polarization diversities are simultaneously considered, the data measurements depend on 4 variables, the data array is of size $L \times M \times P \times Q$, with $P = 3$, and involves 4 unknown matrices to identify. Therefore, discretizing and merging models (11) and (12) yield

$$\mathcal{X}_{\ell mpq} = \sum_{r=1}^R A_{\ell r}(\omega_q) B_{mr}(\omega_q) K_{pr} S_{qr} + \mathcal{N}_{\ell mpq} \quad (14)$$

Traditional subspace processing usually breaks the multi-dimensionality of the multiple diversity model through a vectorization of the entire array manifold (including space, polarization and/or space shift) [3].

The tensor approach through CP decomposition fully takes advantage of the multilinearity of a model with at least three diversities [7]. However, in order to have a totally multilinear model in (14), we need to remove the dependency on ω_q from factor matrices \mathbf{A} and \mathbf{B} , *e.g.* through a bilinear interpolation. This matter will be addressed in Section V, while tensor model and notations will be discussed in Section IV.

IV. TENSOR DECOMPOSITION

A. Canonical Polyadic decomposition

The tensor model allows to express a structured phenomenon, through a multidimensional array of order D , by finite sums and products of simpler constituents [7]. A *decomposable* D -way tensor \mathcal{D} can be defined as the outer product of D vectors: $\mathcal{D} = \mathbf{a} \otimes \mathbf{b} \otimes \dots \otimes \mathbf{s}$, where $\mathbf{a} \in \mathbb{C}^L, \mathbf{b} \in \mathbb{C}^M, \dots, \mathbf{s} \in \mathbb{C}^Q$. Any order- D tensor admits a decomposition into a sum of decomposable tensors

$$\mathcal{M} = \sum_{r=1}^R \lambda_r \mathcal{D}_r \quad (15)$$

where coefficients λ_r can always be chosen to be real positive, and decomposable tensors \mathcal{D}_r to have unit norm, *i.e.* the product $\|\mathbf{a}\| \|\mathbf{b}\| \dots \|\mathbf{s}\| = 1$, but other choices are possible (cf. Section IV-B). The minimal value of R such that this decomposition holds is called the tensor rank. When R is the rank, decomposition (15) is called Canonical-Polyadic (CP); if R is not too large, this decomposition is unique; see [33], [34] and references therein. This is the main motivation in resorting to tensors.

In practice, we admit that observations \mathcal{X} , related to the model \mathcal{M} , are corrupted by an additive noise \mathcal{N} . In other words, the observation model becomes $\mathcal{X} = \mathcal{M} + \mathcal{N}$, and the goal is to fit (15) with the data. The fact that the set of rank- R tensors is not closed when $R > 1$ may raise difficulties, which are out of the scope of the present paper; we refer to [7], [29] for further details.

B. CP factors, normalisation and scaling

Consider the case of a tensor of order $D = 4$ to fix the ideas, which is sufficient for our purposes. Once the bases of

the linear spaces involved are fixed, a fourth order tensor \mathcal{M} is defined by its coordinates, denoted $\mathcal{M}_{\ell mpq}$. If its dimensions are $L \times M \times P \times Q$, then the CP decomposition (15) becomes

$$\mathcal{M} = \sum_{r=1}^R \lambda_r \mathbf{a}_r \otimes \mathbf{b}_r \otimes \mathbf{k}_r \otimes \mathbf{s}_r \quad (16)$$

and can be rewritten in terms of array of coordinates:

$$\mathcal{M}_{\ell mpq} = \sum_{r=1}^R \lambda_r A_{\ell r} B_{mr} K_{pr} S_{qr}$$

where matrices \mathbf{A} , \mathbf{B} , \mathbf{K} and \mathbf{S} , are of dimension $L \times R$, $M \times R$, $P \times R$ and $Q \times R$, respectively. For practical purposes and without restricting the generality, we have preferred to impose the first row of matrices \mathbf{A} and \mathbf{B} to be formed of ones (in fact, as justified in sections II-A and III-A, $\mathbf{p}_1 = \mathbf{0}$, $\delta_1 = \mathbf{0}$ and $g_1(\theta) = 1$), unit norm columns in matrix \mathbf{K} , and to pull the remaining $R \times R$ scaling matrix, $\text{Diag}\{\lambda_r A_{1r} B_{1r}\}$, into matrix \mathbf{S} . This choice permits to compute performance bounds on the retrieval of CP factors more easily. To conclude, in the rest of the paper, we shall use a CP decomposition model of the form:

$$\mathcal{X}_{\ell mpq} = \sum_{r=1}^R A_{\ell r} B_{mr} K_{pr} S_{qr} + \mathcal{N}_{\ell mpq} \quad (17)$$

with the normalizations mentioned above.

V. TENSOR WIDEBAND PROCESSING

In this section, we aim at exploiting model (11) for several angular frequencies. As mentioned in Section III-C, the difficulty comes from the fact that model (11) is obviously not multi-linear w.r.t. ω_q , because exponentials in $\mathbf{A}(\omega_q)$ and $\mathbf{B}(\omega_q)$ are a function of frequency.

A. Virtual arrays

To face this problem, the idea is to build virtual arrays, as described in (7); but we have now a second condition to satisfy, in addition to (5):

$$[\omega_q \tilde{\delta}_m(\omega_q) - \omega_0 \delta_m]^\top \mathbf{d}(\theta) \equiv 0, \text{ mod } 2\pi \quad (18)$$

It is clear that it is sufficient to define the location of virtual sensors by:

$$\tilde{\mathbf{p}}_\ell(\omega_q) = \frac{\omega_0}{\omega_q} \mathbf{p}_\ell, \quad \tilde{\delta}_m(\omega_q) = \frac{\omega_0}{\omega_q} \delta_m \quad (19)$$

to satisfy both (5) and (18). With these virtual arrays, one can associate time delays $\tilde{\tau}_\ell(\theta) = \tilde{\mathbf{p}}_\ell^\top \mathbf{d}(\theta)$ and $\tilde{\zeta}_m(\theta) = \tilde{\delta}_m^\top \mathbf{d}(\theta)$, and corresponding steering vectors $\tilde{\mathbf{a}}(\omega_q, \theta) = \exp\{-j\omega_q \tilde{\tau}(\theta)\}$ and $\tilde{\mathbf{b}}(\omega_q, \theta) = \exp\{-j\omega_q \tilde{\zeta}(\theta)\}$. Once virtual arrays are defined, it is necessary to compute the virtual data these array would receive, and this is done by interpolation as explained in the two next sections.

B. Bilinear transform

The space is first partitioned in K angular sectors of limited extent, Θ_k , $1 \leq k \leq K$. Then each sector is discretized in I angular values: $\Theta_k = \{\theta_{k1}, \dots, \theta_{kI}\}$. In each sector Θ_k and for every discretized frequency ω_q , we define matrices \mathbb{A} and \mathbb{B} of size $L \times I$ and $M \times I$, respectively:

$$\begin{aligned} \mathbb{A}(\omega_q, \Theta_k) &= [\mathbf{a}(\omega_q, \theta_{k1}), \dots, \mathbf{a}(\omega_q, \theta_{kI})] \\ \mathbb{B}(\omega_q, \Theta_k) &= [\mathbf{b}(\omega_q, \theta_{k1}), \dots, \mathbf{b}(\omega_q, \theta_{kI})] \end{aligned}$$

We also build $\tilde{\mathbb{A}}$ and $\tilde{\mathbb{B}}$ in the same manner with vectors $\tilde{\mathbf{a}}(\omega_q, \theta_{ki})$ and $\tilde{\mathbf{b}}(\omega_q, \theta_{ki})$ respectively. For a fixed reference frequency ω_0 (generally chosen to be inside of the band [20]), two focusing matrix families can then be defined by solving for square matrices \mathbf{U} and \mathbf{V} the linear systems below in the Least Squares (LS) sense:

$$\mathbf{U}(\omega_q, \omega_0, \Theta_k) \mathbb{A}(\omega_q, \Theta_k) \approx \tilde{\mathbb{A}}(\omega_0, \Theta_k) \quad (20)$$

$$\mathbf{V}(\omega_q, \omega_0, \Theta_k) \mathbb{B}(\omega_q, \Theta_k) \approx \tilde{\mathbb{B}}(\omega_0, \Theta_k) \quad (21)$$

for every angular sector Θ_k and every frequency ω_q . In what follows we only consider one angular sector Θ , and we refer to $\mathbf{U}(\omega_q, \omega_0, \Theta)$ and $\mathbf{V}(\omega_q, \omega_0, \Theta)$ with \mathbf{U}_q and \mathbf{V}_q respectively.

C. Bilinear interpolation

Measurements recorded on actual arrays with sensors located at $\mathbf{p}_\ell + \delta_m$ at frequency ω_q are interpolated to yield virtual measurements recorded by sensors located at $\tilde{\mathbf{p}}_\ell + \tilde{\delta}_m$, at frequency ω_0 . More precisely, applying the bilinear interpolation (20-21) to model (11) leads to

$$\tilde{\mathcal{M}}_{\ell mq} \approx \sum_{r=1}^R \tilde{A}_{\ell r}(\omega_0) \tilde{B}_{mr}(\omega_0) S_{qr} \quad (22)$$

where the slice $\tilde{\mathcal{M}}_q$ of tensor $\tilde{\mathcal{M}}$ is obtained through the bilinear transformation of slice \mathcal{M}_q : $\tilde{\mathcal{M}}_q = \mathbf{U}_q \mathcal{M}_q \mathbf{V}_q^\top$. Now, $\tilde{\mathcal{M}}$ may be seen as a tensor of order 3, since frequency ω_q affects only the third mode, and Equation (22) is actually a CP decomposition model.

In the remainder of this Section, only space, space-shift and polarization will be addressed (this means that sensors are assumed omnidirectional: $g_l(\theta) = 1, \forall l, \forall \theta$).

However, a new difficulty appears, due to the fact that the bilinear transformation affects the color of the noise. This must be taken into account into the CP identification algorithm (cf. Section VII) and the computation of the performance bounds (cf. Section VI).

D. Noise correlation induced by interpolation

The observation model (22) can be expressed through Q tensor slices, $1 \leq q \leq Q$:

$$\tilde{\mathbf{X}}_q = \tilde{\mathcal{M}}_q + \tilde{\mathbf{N}}_q$$

where $\tilde{\mathbf{N}}_q$ is colored by the transform:

$$\tilde{\mathbf{N}}_q = \mathbf{U}_q \mathbf{N}_q \mathbf{V}_q^\top \quad (23)$$

Yet from [35], we have $\text{vec}\{UNV^T\} = (\mathbf{V} \boxtimes \mathbf{U}) \text{vec } \mathbf{N}$. This leads to the following noise vectorization:

$$\tilde{\mathbf{n}}_q = (\mathbf{V}_q \boxtimes \mathbf{U}_q) \mathbf{n}_q$$

Hence, for every frequency ω_q , the noise vector $\tilde{\mathbf{n}}_q$ is complex Gaussian circular with covariance $\Sigma_q = \sigma^2 \mathbf{V}_q \mathbf{V}_q^H \boxtimes \mathbf{U}_q \mathbf{U}_q^H$. If we stack all vectors $\tilde{\mathbf{n}}_q$ in a single vector $\tilde{\mathbf{n}}$, then the latter has a covariance $\Sigma_{(1)}$ that is block-diagonal, with diagonal blocks Σ_q . Notice that $\Sigma_{(1)}$ also corresponds to the covariance matrix of the vectorization of the 1-mode tensor unfolding of \mathcal{N} , $\text{vec}\{\mathbf{N}_{(1)}\}$. This change in covariance structure will be taken into account for calculating the FIM in Section VI, and into the CP identification algorithm in Section VII.

E. Interpolation in the presence of polarization

If we consider as second diversity the polarization \mathbf{K} , since it does not depend on frequency anymore, the bilinear transformation becomes $\tilde{\mathbf{M}}_q = \mathbf{U}_q \mathbf{M}_q \mathbf{I}_P^T$, yielding

$$\tilde{\mathcal{M}}_{\ell pq} \approx \sum_{r=1}^R \tilde{A}_{\ell r}(\omega_0) K_{pr} S_{qr} \quad (24)$$

Moreover, the diagonal blocks of vectorized noise covariance are simplified to $\Sigma_q = \sigma^2 \mathbf{I}_P \boxtimes \mathbf{U}_q \mathbf{U}_q^H$.

If we include all the diversities as in model (14), then interpolation is given by the following multi-linear transformation:

$$\tilde{\mathcal{M}}_q = (\mathbf{U}_q \otimes \mathbf{V}_q \otimes \mathbf{I}_P) \mathcal{M}_q$$

where index q may be seen as denoting the q -th slice of the fourth order tensor:

$$\tilde{\mathcal{M}}_{\ell mpq} \approx \sum_{r=1}^R \tilde{A}_{\ell r}(\omega_0) \tilde{B}_{mr}(\omega_0) K_{pr} S_{qr} \quad (25)$$

Thus, the noise covariance of the q -th vectorized slice becomes $\Sigma_q = \sigma^2 \mathbf{I}_P \boxtimes \mathbf{V}_q \mathbf{V}_q^H \boxtimes \mathbf{U}_q \mathbf{U}_q^H$.

VI. IDENTIFIABILITY AND CRAMÉR-RAO BOUNDS

In order to assess the performance of the proposed approach, we can compare obtained parameter errors with the CRB, *e.g.* for DoA and polarization parameters. The CRB, which is the lower bound on the covariance \mathbf{R} of any unbiased estimator, is given by the inverse of the Fisher Information Matrix (FIM); in other words⁵, $\mathbf{R} \succeq \mathbf{CRB} = \mathbf{F}^{-1}$. The evaluation of the FIM requires the partial derivatives of the log-likelihood. In what follows we derive the log-likelihood of the tensor model, the parameters of interest, and the general expression of the FIM.

For simplicity, we assume from now on that sources and antennas are coplanar, which permits to parameterize Directions of Arrival (DoA's) by a single angle, $\theta_r = \phi_r$. Vectors \mathbf{p}_ℓ and $\mathbf{d}(\theta)$ are thus in \mathbb{R}^2 , and we shall use the notation $\mathbf{p}_\ell = [p_{\ell 1}, p_{\ell 2}]^T$ and $\mathbf{d}(\theta) = [\sin \theta, \cos \theta]^T$. The reasoning would be the same in 3D but with an increased notation complexity.

⁵This inequality means that matrix $\mathbf{R} - \mathbf{F}^{-1}$ is semi-definite positive.

A. Likelihood

It is wished to first store the multi-dimensional $L \times M \times P \times Q$ array \mathcal{X} in a vector \mathbf{x} of dimension $LMPQ$, following a bijective map: $\mathbf{x} = \text{vec } \mathcal{X}$. We adopt the usual definition [35] where the vec operation takes indices in lexicographical order. Then we have the identity [35], [36]: $\text{vec}\{\mathbf{a}\mathbf{b}^T\} = \mathbf{b} \boxtimes \mathbf{a}$, for any pair of vectors (\mathbf{a}, \mathbf{b}) . More generally:

$$\text{vec}\{\mathbf{a} \otimes \mathbf{b} \otimes \mathbf{c}\} = \mathbf{c} \boxtimes \mathbf{b} \boxtimes \mathbf{a}. \quad (26)$$

Thus, applying the vec operator to equation (16) leads to:

$$\mathbf{x} = \sum_{r=1}^R \mathbf{s}_r \boxtimes \mathbf{k}_r \boxtimes \mathbf{b}_r \boxtimes \mathbf{a}_r + \mathbf{n} \quad (27)$$

Now since the noise vector \mathbf{n} is circular Gaussian, with zero mean and covariance Σ , the log-likelihood then takes the form, up to a constant additive term:

$$\Upsilon(\boldsymbol{\theta}, \boldsymbol{\alpha}, \boldsymbol{\beta}, \mathbf{s}) = -(\mathbf{x} - \boldsymbol{\mu})^H \Sigma^{-1} (\mathbf{x} - \boldsymbol{\mu}) \quad (28)$$

where $\boldsymbol{\mu} = \sum_{r=1}^R \mathbf{s}_r \boxtimes \mathbf{k}_r \boxtimes \mathbf{b}_r \boxtimes \mathbf{a}_r$. We shall assume an isotropic *measurement* noise, *i.e.* $\Sigma = \sigma^2 \mathbf{I}$, but as we explained in Section V, this covariance will be affected by wideband interpolation.

B. Fisher Information matrix (FIM)

When computing the Fisher information matrix (FIM) with respect to complex parameters, it is also necessary to include the complex conjugate parameter, in order to avoid a loss in information [37]. This means just appending $\partial \mathbf{f} / \partial \mathbf{z}^*$, which is nothing else but $(\partial \mathbf{f} / \partial \mathbf{z})^*$. Consequently, for each source, there are three real parameters, θ_r , α_r and β_r , and two complex parameters, \mathbf{s}_r and \mathbf{s}_r^* . In addition to these, the $(L-1)R$ entries $g_{\ell r}$, $2 \leq \ell \leq L$ are real nuisance parameters requiring to be estimated. For every r , we store them in a vector $\bar{\mathbf{g}}_r$ of size $L-1$ (obtained by just deleting the first entry of \mathbf{g}_r). In turn, we stack all these vectors $\bar{\mathbf{g}}_r$ in a $(L-1)R$ -dimensional vector denoted by $\boldsymbol{\gamma}$.

Now real and complex parameters must be treated differently [37]. With this goal, define $\mathbf{v} = [\boldsymbol{\theta}^T, \boldsymbol{\alpha}^T, \boldsymbol{\beta}^T, \boldsymbol{\gamma}^T]^T$, a real parameter vector of dimension $(L+2)R$, and $\boldsymbol{\xi} = [\mathbf{s}_1^T, \dots, \mathbf{s}_R^T]^T$, a complex parameter vector of size RT . Then, from (28), the FIM contains nine blocks [38]:

$$\mathbf{F} = \frac{1}{\sigma^2} \begin{bmatrix} 2\Re\{\mathbf{G}_{11}\} & \mathbf{G}_{12} & \mathbf{G}_{12}^* \\ \mathbf{G}_{12}^H & \mathbf{G}_{22} & \mathbf{0} \\ \mathbf{G}_{12}^T & \mathbf{0} & \mathbf{G}_{22}^* \end{bmatrix} \quad (29)$$

where \mathbf{G}_{11} is related to real parameters, and \mathbf{G}_{22} is related to complex ones. More precisely, blocks \mathbf{G}_{ij} are defined by:

$$\begin{aligned} \mathbf{G}_{11} &= \left(\frac{\partial \boldsymbol{\mu}}{\partial \mathbf{v}} \right)^H \Sigma^{-1} \left(\frac{\partial \boldsymbol{\mu}}{\partial \mathbf{v}} \right) \\ \mathbf{G}_{22} &= \left(\frac{\partial \boldsymbol{\mu}}{\partial \boldsymbol{\xi}} \right)^H \Sigma^{-1} \left(\frac{\partial \boldsymbol{\mu}}{\partial \boldsymbol{\xi}} \right) \\ \mathbf{G}_{12} &= \left(\frac{\partial \boldsymbol{\mu}}{\partial \mathbf{v}} \right)^H \Sigma^{-1} \left(\frac{\partial \boldsymbol{\mu}}{\partial \boldsymbol{\xi}} \right) \end{aligned}$$

where Σ is the covariance of noise \mathbf{n} . The total dimension of the FIM \mathbf{F} is hence $R(L+2+2T)$ if all diversities are

present. With these definitions, the covariance matrix \mathbf{R} of any unbiased estimator of $[\mathbf{v}^\top, \boldsymbol{\xi}^\top, \boldsymbol{\xi}^\text{H}]$ satisfies $\mathbf{R} \succeq \mathbf{F}^{-1}$.

Note that in \mathbf{G}_{11} , we obtain the derivative w.r.t. DoA using the chain rule below:

$$\frac{\partial \boldsymbol{\mu}}{\partial \theta_r} = \frac{\partial \boldsymbol{\mu}}{\partial \bar{\mathbf{a}}_r} \frac{\partial \bar{\mathbf{a}}_r}{\partial \theta_r} + \frac{\partial \boldsymbol{\mu}}{\partial \bar{\mathbf{b}}_r} \frac{\partial \bar{\mathbf{b}}_r}{\partial \theta_r} + \frac{\partial \boldsymbol{\mu}}{\partial \mathbf{k}_r} \frac{\partial \mathbf{k}_r}{\partial \theta_r}. \quad (30)$$

Scalar factor 2 in (29) is justified by (39), because chain rules used to calculate \mathbf{G}_{11} involve complex variables when computing real derivatives. The derivatives required to evaluate (29) and (30) are given in Appendix A.

VII. ALGORITHMS

Tensor wideband processing will be executed in two stages: we first recover factor matrices through CP model fitting, and then estimate DoA's, pattern diversities or polarization parameters from estimated factor matrices. A refinement could also be executed as a post-processing, *e.g.* by a local descent, but it generally brings negligible improvement. Hence it will not be reported in this paper. We first describe both steps of this procedure, in their respective orders: retrieval of the CP factors taking into account the noise correlation structure, and the estimation of DoA's and polarization parameters.

A. CP approximation: ALS for correlated noise

CP fitting corresponds to minimizing the tensor approximation error for model (22). Notice that similar considerations can be made for models (24) and (25). Supposing that the interpolation error is negligible compared to the error introduced by measurement noise, we are interested in minimizing the following cost function with respect to $\bar{\mathbf{a}}_r$, $\bar{\mathbf{b}}_r$ and \mathbf{s}_r :

$$\begin{aligned} \Upsilon &= \frac{1}{\sigma^2} \left\| \text{vec}\{\tilde{\mathbf{X}}_{(1)}\} - \sum_{r=1}^R \mathbf{s}_r \boxtimes \bar{\mathbf{b}}_r \boxtimes \bar{\mathbf{a}}_r \right\|_{\Sigma_{(1)}}^2 = \\ &= \frac{1}{\sigma^2} \left\| \text{vec}\{\tilde{\mathbf{X}}_{(2)}\} - \sum_{r=1}^R \mathbf{s}_r \boxtimes \bar{\mathbf{a}}_r \boxtimes \bar{\mathbf{b}}_r \right\|_{\mathbf{P}_{12}\Sigma_{(1)}\mathbf{P}_{12}^T}^2 = \\ &= \frac{1}{\sigma^2} \left\| \text{vec}\{\tilde{\mathbf{X}}_{(3)}\} - \sum_{r=1}^R \bar{\mathbf{b}}_r \boxtimes \bar{\mathbf{a}}_r \boxtimes \mathbf{s}_r \right\|_{\mathbf{P}_{13}\Sigma_{(1)}\mathbf{P}_{13}^T}^2 \end{aligned} \quad (31)$$

where we define the weighted matrix norm $\|\mathbf{X}\|_{\Sigma} = \sqrt{\text{trace}\{\mathbf{X}^H \Sigma^{-1} \mathbf{X}\}}$. Expression $\mathbf{X}_{(i)}$ refers to the i -mode unfolding of tensor \mathcal{X} . Notice that $\Sigma_{(1)}$ is the covariance matrix of the vectorization of the first unfolding $\tilde{\mathbf{X}}_{(1)}$, and permutation matrix \mathbf{P}_{ij} denotes the transfer matrix from the covariance of unfolding i to that of unfolding j .

The above mentioned minimization corresponds to maximum likelihood estimation and can be performed in several ways: gradient descent, conjugate gradient, Newton methods and coordinate descent methods [39]. For ease of implementation, we choose to minimize (31) using block coordinate descent, with blocks corresponding to factor matrices themselves. This is commonly known as Alternating Least Squares (ALS) [39], since each block coordinate update corresponds to the solution of a least squares problem. The proposed algorithm is detailed in Alg. 1, that we name *ALS COLOR*.

Algorithm 1. **ALS COLOR** : ALS for correlated noise

1: Inputs:

- $\hat{\mathbf{A}}^0, \hat{\mathbf{B}}^0, \hat{\mathbf{S}}^0$
- Covariance matrix of the vectorized tensor $\Sigma_{(1)}$
- Interpolated data tensor $\tilde{\mathbf{X}}$

2: Initialize with $\hat{\mathbf{A}}^0, \hat{\mathbf{B}}^0, \hat{\mathbf{S}}^0$

3: While convergence criterion not met, do $k = k+1$

$$\begin{cases} \mathbf{M}_{SB}^k = (\hat{\mathbf{S}}^k \odot \hat{\mathbf{B}}^k) \boxtimes \mathbf{I}_L \\ \hat{\mathbf{a}}^k = \left(\mathbf{M}_{SB}^{k,H} \Sigma_{(1)} \mathbf{M}_{SB}^k \right)^{-1} \mathbf{M}_{SB}^{k,H} \Sigma_{(1)} \tilde{\mathbf{X}}_{(1)} \end{cases}$$

Similar for $\hat{\mathbf{b}}^k$ and $\hat{\mathbf{s}}^k$, with $\Sigma_{(2)} = \mathbf{P}_{12}\Sigma_{(1)}\mathbf{P}_{12}^T$ and $\Sigma_{(3)} = \mathbf{P}_{13}\Sigma_{(1)}\mathbf{P}_{13}^T$.

Notice that

$$\begin{cases} \hat{\mathbf{a}}^k = \text{vec}\{\hat{\mathbf{A}}^k\} \\ \hat{\mathbf{b}}^k = \text{vec}\{\hat{\mathbf{B}}^k\} \\ \hat{\mathbf{s}}^k = \text{vec}\{\hat{\mathbf{S}}^k\} \end{cases}$$

4: Unvectorize estimates: $\hat{\mathbf{A}} = \text{unvec}\{\hat{\mathbf{a}}^k\}$, $\hat{\mathbf{B}} = \text{unvec}\{\hat{\mathbf{b}}^k\}$ and $\hat{\mathbf{S}} = \text{unvec}\{\hat{\mathbf{s}}^k\}$; normalize columns of $\hat{\mathbf{A}}$ and $\hat{\mathbf{B}}$ by first elements:

$$\begin{cases} \hat{\mathbf{A}} = \hat{\mathbf{A}} / \hat{\mathbf{A}}(1, :) \\ \hat{\mathbf{B}} = \hat{\mathbf{B}} / \hat{\mathbf{B}}(1, :) \end{cases}$$

5: End

B. DoA and polarization estimation

Once directional vectors $\hat{\mathbf{a}}_r$ and/or $\hat{\mathbf{b}}_r$ are recovered from the tensor approximation algorithm, we can estimate DoA θ_r through an exhaustive search within the considered angular sector Θ and/or polarization parameters β_r and/or α_r .

1) *Space shift diversity*: if there are only space, space shift and frequency diversities (cf VIII-A), DoA's are estimated as follows:

$$\begin{aligned} \hat{\theta}_r &= \arg \min_{\theta \in \Theta_i} \left[(\hat{\mathbf{a}}_r - \tilde{\mathbf{a}}_r(\theta))^H (\hat{\mathbf{a}}_r - \tilde{\mathbf{a}}_r(\theta)) \right] \\ &\quad + \left[(\hat{\mathbf{b}}_r - \tilde{\mathbf{b}}_r(\theta))^H (\hat{\mathbf{b}}_r - \tilde{\mathbf{b}}_r(\theta)) \right] \end{aligned} \quad (32)$$

Furthermore, we can integrate the approximate knowledge on the covariance of estimators $\hat{\mathbf{a}}_r$ and $\hat{\mathbf{b}}_r$ into the cost function. This knowledge can be provided, at least asymptotically at high Signal to Noise Ratio (SNR), by the CRB, thus giving the following estimators for the DoA:

$$\begin{aligned} \hat{\theta}_r^{CRB} &= \arg \min_{\theta \in \Theta_i} \left[(\hat{\mathbf{a}}_r - \tilde{\mathbf{a}}_r(\theta))^H \Sigma_{\hat{\mathbf{a}}_r}^{-1} (\hat{\mathbf{a}}_r - \tilde{\mathbf{a}}_r(\theta)) \right] \\ &\quad + \left[(\hat{\mathbf{b}}_r - \tilde{\mathbf{b}}_r(\theta))^H \Sigma_{\hat{\mathbf{b}}_r}^{-1} (\hat{\mathbf{b}}_r - \tilde{\mathbf{b}}_r(\theta)) \right] \end{aligned} \quad (33)$$

where $\Sigma_{\hat{\mathbf{a}}_r} = \text{CRB}(\hat{\mathbf{a}}_r)$ and $\Sigma_{\hat{\mathbf{b}}_r} = \text{CRB}(\hat{\mathbf{b}}_r)$. See [29], [28] for further details on the computation of CRB for factor matrices.

2) *Polarization diversity*: If there are only space, polarization and frequency diversities (cf VIII-A), we can also estimate polarization parameters. For one single polarization parameter β_r , we perform an exhaustive search over a 2D grid of DoA $\theta \in \Theta$ and polarization angles $\beta \in [-\pi/4, \pi/4]$:

$$(\hat{\theta}_r, \hat{\beta}_r) = \arg \min_{\theta \in \Theta, \beta \in [-\pi/4, \pi/4]} \left[(\hat{\mathbf{a}}_r - \tilde{\mathbf{a}}_r(\theta))^H (\hat{\mathbf{a}}_r - \tilde{\mathbf{a}}_r(\theta)) \right] + \left[\left(\hat{\mathbf{k}}_r - \tilde{\mathbf{k}}_r(\theta, \beta) \right)^H \left(\hat{\mathbf{k}}_r - \tilde{\mathbf{k}}_r(\theta, \beta) \right) \right] \quad (34)$$

Analogously, we can also integrate weighting matrices into the cost function:

$$\begin{aligned} & (\hat{\theta}_r^{CRB}, \hat{\beta}_r^{CRB}) = \\ & = \arg \min_{\theta \in \Theta, \beta \in [-\pi/4, \pi/4]} \left[(\hat{\mathbf{a}}_r - \tilde{\mathbf{a}}_r(\theta))^H \Sigma_{\hat{\mathbf{a}}_r}^{-1} (\hat{\mathbf{a}}_r - \tilde{\mathbf{a}}_r(\theta)) \right] \\ & + \left[\left(\hat{\mathbf{k}}_r - \tilde{\mathbf{k}}_r(\theta, \beta) \right)^H \Sigma_{\hat{\mathbf{k}}_r}^{-1} \left(\hat{\mathbf{k}}_r - \tilde{\mathbf{k}}_r(\theta, \beta) \right) \right] \end{aligned} \quad (35)$$

where $\Sigma_{\hat{\mathbf{a}}_r} = \text{CRB}(\hat{\mathbf{a}}_r)$ and $\Sigma_{\hat{\mathbf{k}}_r} = \text{CRB}(\hat{\mathbf{k}}_r)$.

Remark: the above mentioned minimization procedures are performed in a limited domain: $\theta \in \Theta, \beta \in [-\pi/4, \pi/4]$. In order to prevent this search from becoming too costly, we apply an iterative progressive refinement of the grid, where each iteration is a zoomed version of the previous one.

VIII. COMPUTER RESULTS

This Section is meant to illustrate the advantage of wideband tensor processing for the problem of DoA and/or polarization estimation.

Monte Carlo simulations make use of multiple diversities, throughout the Section (in addition to space and frequency):

- 1) VIII-A: space shifts of the same subarray described in Subsection III-A.
- 2) VIII-B: polarization diversity described in subsection III-B.

Impinging sources are coplanar with respect to the array: only azimuth is to be estimated, and not elevation, without any loss of generality. We simulated $R = 2$ white Gaussian unit-variance sources, at sampling frequency $f_s = 1\text{kHz}$, for an observation time of 64ms and propagating at $c = 1800\text{m/s}$, which is the propagation speed of seismic S-waves through ice [15]. Hence, $N = 64$ time samples are available. The number of working frequency bins is $Q = 14$ (within the selected frequency range from $f_{min} = 0.25f_s$ to $f_{max} = 0.45f_s$). Spatial Nyquist criterion is ensured through a condition on the distance d_{ij} between two close by sensors ($\ell = i$ and $\ell = j$) of the same subarray, *i.e.* by $d_{ij} \leq \lambda_0/2$ where $\lambda_0 = c/f_0$. The reference frequency is chosen to be the central bin $f_0 = (f_{min} + f_{max})/2 = 0.35f_s$. Correlation between sources, when present, is $\rho = 0.9$. Wideband processing is performed in a single sector Θ , assuming interesting sectors (*i.e.* sectors containing most of the signal power) have been previously detected through a former low resolution beamforming technique. Former detection of relevant sectors is beyond the scope of this paper and can be found in the

literature [1], [2]. Interpolation is then performed within the angular sector $\Theta = [0, 25^\circ]$, with a discretization of 0.1° .

In order to understand the relevance of tensor wideband processing, we also present a narrowband alternative for comparison (referred to as *NB Tensor CP*): received signals are filtered around central frequency $f_0 = \omega_0/2\pi$ with narrowband filter bandwidth $BW = 0.015f_s$, and then directly processed through tensor CP approximation [6], [29]. Estimation efficiency is also evaluated in comparison to the wideband MUSIC approach [17], and to wideband multilinear CRB. The performance criterion is the relative total *Mean Square Error* (MSE) on the DoA's and, whenever present, polarization ellipticity angles:

$$\begin{cases} \text{MSE}(\boldsymbol{\theta}) = \frac{1}{\theta_{max}^2} \frac{1}{NR} \sum_{n=1}^N \sum_{r=1}^R (\hat{\theta}_{rn} - \theta_r)^2 \\ \text{MSE}(\boldsymbol{\beta}) = \frac{1}{\beta_{max}^2} \frac{1}{NR} \sum_{n=1}^N \sum_{r=1}^R (\hat{\beta}_{rn} - \beta_r)^2 \end{cases} \quad (36)$$

where $\hat{\theta}_{rn}$ and $\hat{\beta}_{rn}$ are the estimated DoA and ellipticity angle respectively of source r in the n -th Monte-Carlo trial, $N = 1000$ being the number of trials, $\theta_{max} = \pi = 180^\circ$ and $\beta_{max} = \pi/4 = 45^\circ$. As in [29], [28], the SNR definition below is assumed:

$$SNR = 10 \log_{10} \frac{\mathbb{E}[\mathbf{x}^H \mathbf{x}]}{\mathbb{E}[\mathbf{u}^H \mathbf{u}]} = 10 \log_{10} \frac{\|\mathbf{x}\|_2^2}{KLM\sigma_n^2} \quad (37)$$

Estimation algorithms evaluated herein are the following:

- 1) *NB Tensor CP*: standard narrowband ALS in time domain as in [6], [29], after narrowband filtering around f_0 .
- 2) Standard *ALS* not taking into account the correlation structure of noise.
- 3) *ALS COLOR*: WB preprocessing and ALS Alg. 1 for correlated noise and simple parameter estimation, in that parameters are estimated through (32) and (34).
- 4) *ALS COLOR CRB*: WB preprocessing and ALS Alg. 1 for correlated noise and weighed DoA estimation, in that parameters are estimated through (33) and (35).
- 5) *WB MUSIC* with covariance matrix expressed in (9) and, for polarized sensors, *WB vector MUSIC*, where the array manifold takes into account wave polarization parameters.

A. Wideband and space shift

As described in Section III-A, the same sub-array is repeated in space through M translations (cf. Fig. 1):

- 1) $M = 5$ sub-arrays.
- 2) Each sub-array is a square 2D array of $L = 4$ sensors.
- 3) Distance between two consecutive sensors is $\lambda/2$.
- 4) Distance between two consecutive sub-arrays is $\approx 4*\lambda/2$.

Interpolation of the data tensor is bilinear, which means it is performed for matrices \mathbf{A} and \mathbf{B} separately, as described in subsection V-B. Therefore, both sensor positions \mathbf{p}_l and space shifts $\boldsymbol{\delta}_m$ need to be known, and DoA can be estimated both from \mathbf{A} and \mathbf{B} .

The quality of the linear interpolation for \mathbf{A} is proportional to the number of sensors L and the quality of the linear interpolation for \mathbf{B} is proportional to the number of subarrays M . The interpolation of wideband MUSIC, on the other hand, is performed on the global matrix \mathbf{P}_{tot} of the whole acquisition system (cf. Fig. 1), without taking into account

the bilinearity of the tensor model. The quality of the linear interpolation for \mathbf{A}_{tot} is proportional to the total number of sensors within the acquisition system, $L \times M$. In order for both interpolations to be comparable, the number of sub-arrays cannot be too low, and/or the sub-arrays too distant from one another. Interpolation quality is also dependent on the distance between two sensors within a sub-array, and the distance of two consecutive sub-arrays: a distance between sub-arrays $\gg \lambda/2$ might worsen interpolation quality of matrix \mathbf{B} .

Fig. 2 shows the dependence of the narrowband tensor CP method on the number of available time samples N : the MSE drastically drops for increasing data samples, because a larger data window allows a narrowband filtering of higher quality. In what follows, we fix the number of time sample to $N = 64$: we expect then that narrowband tensor CP will show a saturation starting from a certain SNR.

Fig. 3a shows the MSE on DoA estimation with respect to the SNR when $R = 2$ uncorrelated sources arrive from angles $\theta_1 = 5^\circ$ and $\theta_1 = 20^\circ$ respectively; Fig. 3b refers to $\rho = 0.9$ correlation between sources. ALS COLOR (*i.e.* Alg. 1) significantly improves the standard ALS, since it takes into account the noise correlation structure introduced by interpolation. The reliability information contained in the CRB on factor vectors also helps the estimation performance. In the present experimental conditions, tensor methods outperform both MUSIC and narrowband CP. If the sources are correlated, the performance of all the algorithms slightly deteriorates correspondingly, and the gap w.r.t. the CRB increases (cf. Fig. 3b).

B. Wideband and polarization

Impinging signals are then supposed to be elliptically polarized seismic sources, recorded by one three-component (3C) sensor array, or *vector-sensor array* as defined in [9] (cf. Fig. 4):

- 1) An array of $L = 5$ sensors.
- 2) Distance between two sensors: $< \approx \lambda/2$.
- 3) Seismic wave: $P = 3$ components for a given sensor (3C sensors).
- 4) Rayleigh wave (coplanar with the array), $\alpha = 0$, $\beta \neq 0$.
In particular, $\beta_1 = -20^\circ$, $\beta_2 = 10^\circ$.

Interpolation is linear, only for matrix \mathbf{A} , since polarization factor matrix \mathbf{K} is independent from frequency. We compare tensor methods with wideband *scalar MUSIC* (an incoherent average of $P = 3$ covariances), and wideband *vector MUSIC*, through a coherently averaged covariance matrix of size $3L \times 3L$. The overall performance of the compared algorithms are similar to the space-shift case of Section VIII-A (cf. Fig. 5a for DoA and Fig. 5b for polarization estimation). However, the gain granted by CRB information is less significant, especially for β .

IX. CONCLUSION

The crucial difficulty of the tensor wideband approach stems from the need to focus every frequency contribution onto the same subspace. We show that multi-linear interpolation can

solve this issue: it allows to have a multi-linear model and thus to apply tensor decomposition techniques to wideband data. In simulations, both with space shift diversity and polarization diversity, the proposed approach improves narrowband tensor processing and outperforms traditional subspace methods such as wideband MUSIC. We also show that, in addition to space and frequency, gain pattern or polarization can be used instead of space shift diversity.

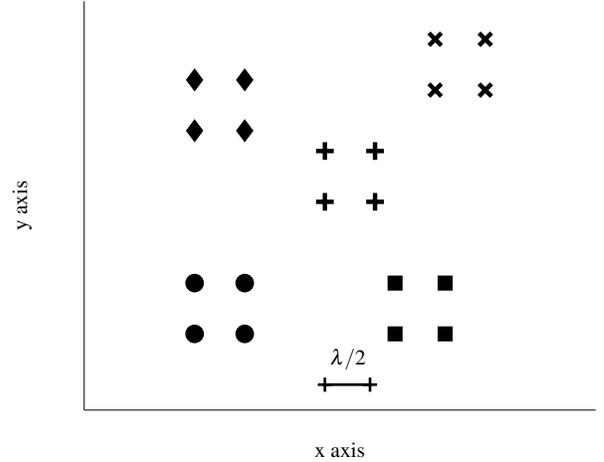


Fig. 1. Sensor position matrix

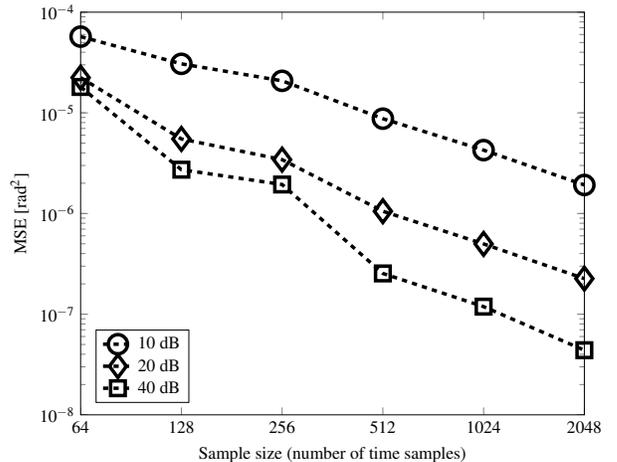
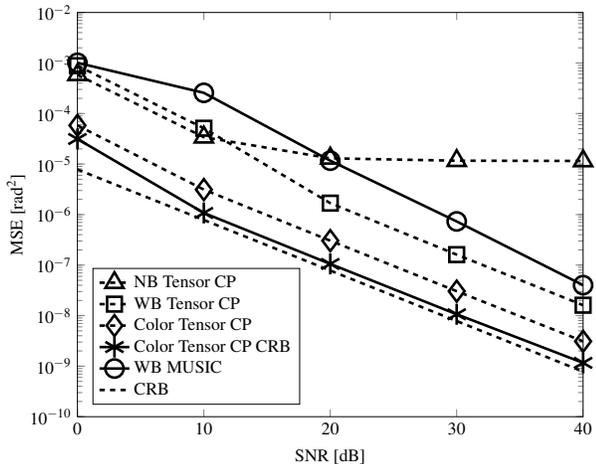
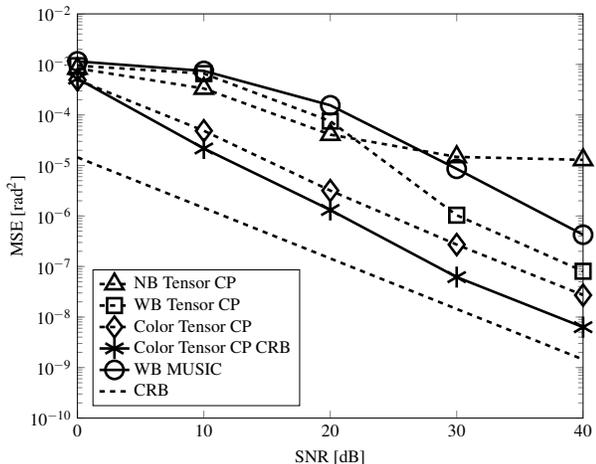


Fig. 2. MSE vs N - Narrowband tensor ESPRIT



(a) Uncorrelated sources



(b) Correlated sources: $\rho = 0.9$

Fig. 3. MSE vs SNR - space shift diversity

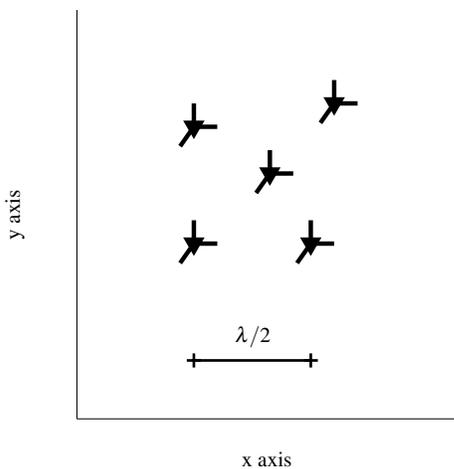
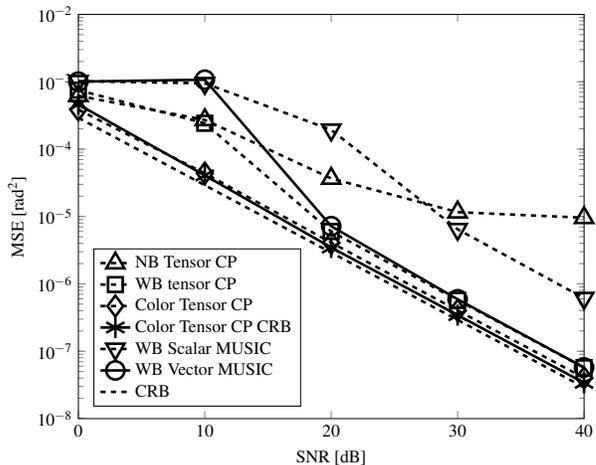
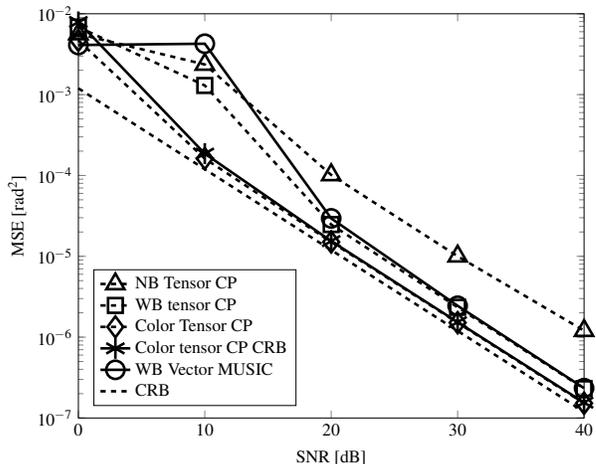


Fig. 4. 3C sensor position matrix (polarization diversity)



(a) DoA estimation



(b) Polarization estimation

Fig. 5. MSE vs SNR - polarization diversity - seismic Rayleigh waves

APPENDIX A
DERIVATIVES REQUIRED FOR THE FIM

In order to evaluate the derivatives required for the computation of the FIM, and consequently for the CRB, we have to introduce the concept of complex derivatives.

A. Complex derivatives

A real function of a complex variable is never holomorphic, unless it is constant [40]. It is hence necessary to precise which convention is assumed. Even if a convention has been proposed much earlier in [40], we assume the definition proposed in [37] since it is now more widely used. Let $f(z)$ be a real function from \mathbb{C}^P to \mathbb{R}^N . Its complex derivative with respect to $z \in \mathbb{C}^P$ is defined by:

$$\frac{\partial f}{\partial z} = \frac{1}{2} \frac{\partial f}{\partial x} - \frac{j}{2} \frac{\partial f}{\partial y} \quad (38)$$

where x and y denote the real and imaginary parts of z , respectively. This definition is consistent with [37], [29], [28]. This derivative is stored in a complex $N \times P$ matrix, *regardless* of the fact that f and z are row or column vectors, which allows easy-writing chain rules of the form: $\frac{\partial f}{\partial z} = \frac{\partial f}{\partial \mathbf{a}} \frac{\partial \mathbf{a}}{\partial z}$ with compatible matrix sizes.

Next, it is often convenient to compute some derivatives by the chain rule, which means that derivatives of a complex quantity w.r.t. a complex variable are needed. It turns out that quantities involved are holomorphic, so that this differential is meant in the usual sense of complex analysis.

If a real function f is to be derived w.r.t. a real variable θ , but using a chain rule involving a complex variable z , then for consistency with (38) the following relation must apply [37], [29], [14]:

$$\frac{\partial f}{\partial \theta} = 2\Re \left\{ \frac{\partial f}{\partial z} \frac{\partial z}{\partial \theta} \right\} \quad (39)$$

In what follows, we calculate the derivatives required for the evaluation of the FIM in (29).

B. Derivative w.r.t. S

Matrices \mathbf{A} and \mathbf{B} depend on angles of arrival θ_r , whereas \mathbf{K} depends on angles⁶ $(\theta_r, \alpha_r, \beta_r)$, $1 \leq r \leq R$. Let's start with matrix \mathbf{S} , which is unconstrained. The source signals are indeed treated as deterministic parameters, which allows to extract them. The derivative w.r.t s_r is [29]:

$$\frac{\partial \boldsymbol{\mu}}{\partial s_r} = \mathbf{I}_Q \boxtimes \mathbf{k}_r \boxtimes \mathbf{b}_r \boxtimes \mathbf{a}_r \in \mathbb{C}^{LMKQ \times Q} \quad (40)$$

C. Derivative w.r.t. A and B, and their parameters

Since the first row of \mathbf{A} and \mathbf{B} contains only ones, only the remaining rows need to be estimated. The submatrices formed of remaining rows are denoted by $\bar{\mathbf{A}}$ and $\bar{\mathbf{B}}$, and their columns by $\bar{\mathbf{a}}_r$ and $\bar{\mathbf{b}}_r$, respectively. In other words, $\bar{\mathbf{A}} = \mathbf{J}_L \mathbf{A}$ where \mathbf{J}_L is the $L-1 \times L$ line-selection matrix $\mathbf{J}_L = [\mathbf{0}, \mathbf{I}_{L-1}]$. This

⁶In a 3D space, $\theta_r = (\phi_r, \psi_r)$ since two angles are necessary. In a 2D space, we shall just use notation θ_r .

is necessary to reduce the size of the FIM (otherwise it would be always rank deficient). We have:

$$\frac{\partial \boldsymbol{\mu}}{\partial \bar{\mathbf{a}}_r} = s_r \boxtimes \mathbf{k}_r \boxtimes \mathbf{b}_r \boxtimes \mathbf{J}_L^\top \in \mathbb{C}^{LMKQ \times L-1}$$

Now, since functions $g_\ell(\theta)$ are unknown, $g_{\ell r} = g_\ell(\theta_r)$ are extraneous nuisance (unknown) parameters, and must be treated as such. For convenience, we denote by \mathbf{g}_r the L -dimensional vector with entries $g_\ell(\theta_r)$, $1 \leq \ell \leq L$, and $\bar{\mathbf{g}}_r$ the vector obtained by removing the first entry of \mathbf{g}_r (which is equal to 1 by definition). The following derivatives can be readily obtained:

$$\begin{aligned} \frac{\partial \bar{\mathbf{a}}_r}{\partial \theta_r} &= -\frac{j\omega}{c} \mathbf{J}_L \left(\mathbf{g}_r \boxtimes \mathbf{P} \dot{\mathbf{d}}(\theta_r) \boxtimes \exp\{-j\omega\boldsymbol{\tau}(\theta_r)\} \right) \\ \frac{\partial \bar{\mathbf{a}}_r}{\partial \bar{\mathbf{g}}_r} &= \mathbf{J}_L \exp\{-j\omega\boldsymbol{\tau}(\theta_r)\} \mathbf{J}_L^\top \in \mathbb{C}^{L-1 \times L-1} \end{aligned}$$

Similarly, we have:

$$\frac{\partial \boldsymbol{\mu}}{\partial \bar{\mathbf{b}}_r} = s_r \boxtimes \mathbf{k}_r \boxtimes \mathbf{J}_M^\top \boxtimes \mathbf{a}_r \in \mathbb{C}^{LMKQ \times M-1}$$

Denote by $\boldsymbol{\Delta}$ the matrix with M rows defined by $\boldsymbol{\Delta} = [\boldsymbol{\delta}_1, \dots, \boldsymbol{\delta}_M]^\top$. The following derivative is a column vector with $M-1$ entries:

$$\frac{\partial \bar{\mathbf{b}}_r}{\partial \theta_r} = -\frac{j\omega}{c} \mathbf{J}_M \left(\boldsymbol{\Delta} \dot{\mathbf{d}}(\theta_r) \boxtimes \exp\{-j\omega\boldsymbol{\zeta}(\theta_r)\} \right)$$

where the exponential is taken entry-wise.

The case of pattern diversity: if time, space shift and gain pattern diversities are available, but not space and polarization, then expressions are simpler. It is worth detailing this scenario because it has not been reported in the literature. In this case, matrix \mathbf{A} contains only gains g_{mr} and matrix \mathbf{B} only delays, and one can prove that:

$$\left(\frac{\partial \boldsymbol{\mu}}{\partial s_r} \right)^H \left(\frac{\partial \boldsymbol{\mu}}{\partial s_k} \right) = (\mathbf{b}_r^H \mathbf{b}_k) (\mathbf{a}_r^H \mathbf{a}_k) \quad (41)$$

$$\left(\frac{\partial \boldsymbol{\mu}}{\partial g_r} \right)^H \left(\frac{\partial \boldsymbol{\mu}}{\partial g_k} \right) = (s_r^H s_k) (\mathbf{b}_r^H \mathbf{b}_k) \quad (42)$$

$$\left(\frac{\partial \boldsymbol{\mu}}{\partial \theta_r} \right)^H \left(\frac{\partial \boldsymbol{\mu}}{\partial \theta_k} \right) = \omega^2 \dot{\boldsymbol{\zeta}}(\theta_r)^\top \dot{\boldsymbol{\zeta}}(\theta_k) \quad (43)$$

D. Derivative w.r.t. K and its parameters

From (27) and (13), we have [14]:

$$\begin{aligned} \frac{\partial \boldsymbol{\mu}}{\partial \mathbf{k}_r} &= s_r \boxtimes \mathbf{I}_3 \boxtimes \mathbf{b}_r \boxtimes \mathbf{a}_r \\ \frac{\partial \boldsymbol{\mu}}{\partial \alpha_r} &= s_r \boxtimes \frac{\partial \mathbf{k}_r}{\partial \alpha_r} \boxtimes \mathbf{b}_r \boxtimes \mathbf{a}_r \\ \frac{\partial \boldsymbol{\mu}}{\partial \beta_r} &= s_r \boxtimes \frac{\partial \mathbf{k}_r}{\partial \beta_r} \boxtimes \mathbf{b}_r \boxtimes \mathbf{a}_r \end{aligned} \quad (44)$$

with

$$\begin{aligned} \frac{\partial \mathbf{k}_r}{\partial \theta_r} &= \begin{bmatrix} -\cos \theta_r & \sin \theta_r \\ -\sin \theta_r & -\cos \theta_r \end{bmatrix} \mathbf{W}(\alpha_r) \mathbf{w}(\beta_r) \\ \frac{\partial \mathbf{k}_r}{\partial \alpha_r} &= \mathbf{H}(\theta_r) \begin{bmatrix} -\sin \alpha_r & \cos \alpha_r \\ -\cos \alpha_r & -\sin \alpha_r \end{bmatrix} \mathbf{w}(\beta_r) \\ \frac{\partial \mathbf{k}_r}{\partial \beta_r} &= \mathbf{H}(\theta_r) \mathbf{W}(\alpha_r) \begin{bmatrix} -\sin \beta_r \\ j \cos \beta_r \end{bmatrix} \end{aligned}$$

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