SEMI-BLIND INTERFERENCE CANCELLATION WITH DISTRIBUTED TRAINING

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ABSTRACT

Some of the wireless standards, e.g. IEEE 802.16-2004, allow successive transmission of a number of consecutive slots, where each of them contains a training (pilot) interval. If a number of neighbouring cells asynchronously transmit similar frames, then the resulting interference environment becomes similar to a distributed training scenario. In this paper, a distributed training scenario is addressed by means of semi-blind (SB) processing at the multiple-antenna receiver. A second-order statistics identifiability is analyzed and a SB algorithm is proposed for the situation, where the data and training intervals contain different sets of interference components. Its performance is assessed by means of comparison to the non-asymptotic maximum-likelihood (ML) benchmark initialized by the developed identification algorithm. It is demonstrated that the SB solution significantly outperforms the conventional training-based algorithm and approaches the benchmark in the case of low number of available data symbols. Using all the considered second-order solutions as initializations for the higher-order statistics iterative algorithm is also addressed.

1. INTRODUCTION

In wireless communications systems unsynchronized transmissions in neighbouring cells lead to an asynchronous CCI scenario, where some of the interference components may not overlap with the training data of the desired signal [1] - [3]. Conventional training-based space-time interference cancellation techniques may not be effective in this situation. One example of such a scenario is interference mitigation on the uplink of a cellular WiMAX-compliant system based on the IEEE 802.16-2004 [4] or ETSI HiperMAN [5] standards addressed in [3].

A second-order statistics adaptive semi-blind (SB) algorithm for asynchronous CCI cancellation is proposed and studied in [6] [8]. It is based on regularization of the conventional training-based least squares (LS) solution by means of the weighted covariance matrix estimated over the data interval. It is shown in [6], [7] that its performance in typical asynchronous CCI scenarios is close to the performance of a non-asymptotic ML benchmark jointly estimated over both the training and working intervals. This benchmark is based on the stochastic ML bounds developed in [9]. In [8] the non-asymptotic ML benchmark is expanded to the scenario with the known time-of-arrival information for CCI components.

It is pointed out in [10] that spreading the training symbols over the data slot (distributed training) could significantly simplify cancellation of the asynchronous CCI because it increases probability of overlapping between CCI and the training data. A simple case with one CCI components is addressed in [10] by means of the SB algorithm with projections to the finite alphabet (FA).

Second- and higher-order statistics interference cancellation is addressed in this paper in a more complicated distributed training scenario with a number of interference components.

Some of the wireless standards, such as GSM or WLAN, do not assume distributed training. Some of them, e.g. IEEE 802.16-2004 [4], allow successive transmission of a number of consecutive slots, where each of them contains a training interval. If a number of neighbouring cells asynchronously transmit similar frames, then the resulting interference scenario becomes similar to distributed training as illustrated in Fig. 1.

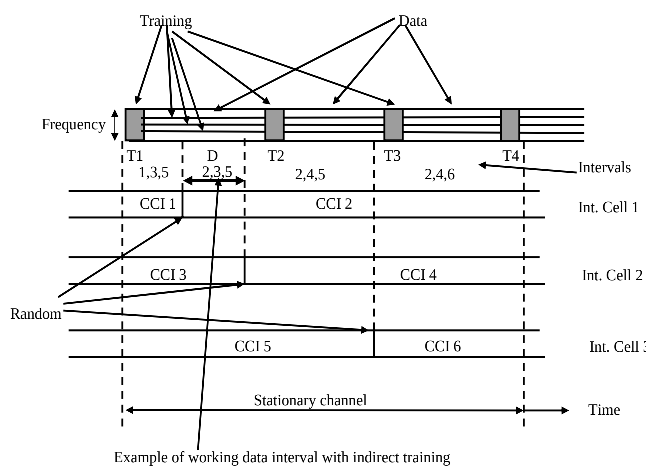

Figure 1: Typical asynchronous scenario with distributed training for three neighbouring cells environment

The main feature of this scenario is that for some data intervals and groups of sub-carriers a set of CCI components may be different compared to the surrounding training intervals leading to significant performance degradation for conventional training-based solutions or initializations for higher-order SB techniques. This type of data intervals will be referred to as intervals with indirect training. For example, training interval T1 overlaps with CCI 1, 3 and 5, T2 overlaps with CCI 2, 4, 5, but the data interval D with indirect training contains different set of CCI 2, 3, 5. All other data intervals in Fig. 1 can be associated with one of the training intervals with the same set of the interference components.

Part of this work has been done in the context of the IST FP6 MEMBRANE project.

Interference cancellation on the data intervals with indirect training is considered in this paper. First of all, a second-order statistics identifiability is demonstrated. A second-order SB solution is proposed, which is based on a two-stage adaptive noise canceller [11], [12] applied over the data and training intervals. Efficiency of the proposed solution is analyzed by means of comparison to the non-asymptotic ML benchmark. Higher-order statistics estimation is also addressed by means of comparison of different second-order initializations including the ML benchmark.

2. DATA MODEL AND PROBLREM FORMULATION

The following narrowband data model of the signal received by an antenna array of K elements is considered:

$$\mathbf{x}(n) = \mathbf{h}s(n) + \sum_{m=1}^{M} \mathbf{g}_m u_m(n) + \mathbf{z}(n), \qquad (1)$$

where $n = 1,\ldots,N$ is the time index; $\mathbf{x}(n) \in \mathscr{C}^{K\times 1}$ is the vector of observed outputs of an antenna array; $s(n)$ is the desired signal, $\mathrm{E}\{|s|^2\} = 1$, $\mathrm{E}\{s(q)s^*(g)\} = 0$, $q \neq g$, $\mathrm{E}\{\cdot\}$ denotes expectation; $u_m(n)$, $m = 1\ldots M$ are the M independent components of CCI:

$$\mathrm{E}\{u_m(q)u_m^*(g)\} = \begin{cases} p_m, & \text{for } q = g \in \mathscr{N}_m \\ 0, & \text{for all other } q \text{ and } g \end{cases}, \qquad (2)$$

$\mathscr{N}_m$ is the appearance interval for the m-th interference component, $\mathbf{z}(n) \in \mathscr{C}^{K\times 1}$ is the vector of noise, $\mathrm{E}\{\mathbf{z}(n)\mathbf{z}^*(n)\} = p_0\mathbf{I}_K$, $\mathrm{E}\{\mathbf{z}(q)\mathbf{z}^*(g)\} = 0$, $q \neq g$ and $\mathbf{h} \in \mathscr{C}^{K\times 1}$ and $\mathbf{g}_m \in \mathscr{C}^{K\times 1}$ are the vectors modelling linear propagation channels for the desired signal and interference. All propagation channels are assumed to be stationary over the whole data slot and independent for different antenna elements and slots.

As illustrated in Fig. 2, two training intervals of $N_\mathrm{t} > K$ samples: $\mathscr{N}_{\mathrm{t}1}$: $n = 1,\ldots,N_\mathrm{t}$ and $\mathscr{N}_{\mathrm{t}2}$: $n = N - N_\mathrm{t} + 1,\ldots,N$ are located in the edges of the data interval $\mathscr{N}_\mathrm{d}$: $n = N_\mathrm{t} + 1,\ldots,N_\mathrm{t} + N_\mathrm{d}$ of $N_\mathrm{d} = N - 2N_\mathrm{t}$ samples. The same training sequence $\mathbf{s}_\mathrm{t} \in \mathscr{C}^{1\times N_\mathrm{t}}$ is assumed for both training intervals.

For simplicity we assume a particular structure of the indirect training interval for $M = 5$ shown in Fig. 2 (three interfering cells or three CCI components at each time instant) leading to the following interference appearance intervals $\mathscr{N}_1 = \mathscr{N}_{\mathrm{t}1}$, $\mathscr{N}_2 = \mathscr{N}_\mathrm{d} \cup \mathscr{N}_{\mathrm{t}2}$, $\mathscr{N}_3 = \mathscr{N}_{\mathrm{t}1} \cup \mathscr{N}_\mathrm{d}$, $\mathscr{N}_4 = \mathscr{N}_{\mathrm{t}2}$, $\mathscr{N}_5 = \mathscr{N}_{\mathrm{t}1} \cup \mathscr{N}_\mathrm{d} \cup \mathscr{N}_{\mathrm{t}2} = 1,\ldots,N$.

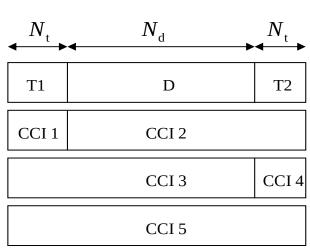

Figure 2: Indirect training data model

One can see that the scenario in Fig. 2 represents D interval shown in Fig. 1 that may contain a group of OFDM sub-carriers, e.g., in the case of WiMAX uplink scenario [3]. Location of this interval is assumed to be known. For example, it can be obtained by using tracking sub-carriers or other abrupt changes techniques. The considered scenario appears when two of three neighbouring cells change their transmitters within one slot of data [1].

A signal estimate can be found as the output of a spatial filter:

$$\hat{s}(n) = \hat{\mathbf{w}}^*\mathbf{x}(n),\, n \in \mathscr{N}_\mathrm{d}, \qquad (3)$$

where $\mathbf{w} \in \mathscr{C}^{K\times 1}$ is a weight vector.

The minimum mean square error (MMSE) weight vector in the scenario shown in Fig. 2 is as follows:

$$\mathbf{w}_{\mathrm{MMSE}} = \mathbf{R}_\mathrm{d}^{-1}\mathbf{h}, \qquad (4)$$

where $\mathbf{R}_\mathrm{d} = \mathbf{h}\mathbf{h}^* + p_2\mathbf{g}_2\mathbf{g}_2^* + p_3\mathbf{g}_3\mathbf{g}_3^* + p_5\mathbf{g}_5\mathbf{g}_5^* + p_0\mathbf{I}_K$ and $\mathbf{I}_K$ is the K-dimension identity matrix.

The problem is to estimate $\mathbf{w}_{\mathrm{MMSE}}$ using second-order statistics over all three available intervals: $\hat{\mathbf{R}}_{\mathrm{t}1(2)} = N_\mathrm{t}^{-1}\sum_{n\in\mathscr{N}_{\mathrm{t}1(2)}}\mathbf{x}(n)\mathbf{x}^*(n)$, $\hat{\mathbf{R}}_\mathrm{d} = N_\mathrm{d}^{-1}\sum_{n\in\mathscr{N}_\mathrm{d}}\mathbf{x}(n)\mathbf{x}^*(n)$, $\hat{\mathbf{r}}_{\mathrm{t}1(2)} = N_\mathrm{t}^{-1}\sum_{n\in\mathscr{N}_{\mathrm{t}1(2)}}s(n)^*\mathbf{x}(n)$, and compare performance to the conventional training-based least squares LS solution

$$\hat{\mathbf{w}}_{\mathrm{LS}} = (\hat{\mathbf{R}}_{\mathrm{t}1} + \hat{\mathbf{R}}_{\mathrm{t}2})^{-1}(\hat{\mathbf{r}}_{\mathrm{t}1} + \hat{\mathbf{r}}_{\mathrm{t}2}), \qquad (5)$$

as well as to the non-asymptotic ML benchmark under Gaussian assumption for all variables.

3. IDENTIFIABILITY

First of all, we develop an identification algorithm and demonstrate that all the parameters of the data model in Fig. 2 can be asymptotically ($N_\mathrm{t} \to \infty$ and $N_\mathrm{d} \to \infty$) identified up to an arbitrary rotation. In Section 7, the identification algorithm based on the estimated covariance matrices will be used for initialization of the non-asymptotic ML benchmark.

At the beginning, we assume the known second-order statistics: $\mathbf{R}_{\mathrm{t}1(2)}$, $\mathbf{R}_\mathrm{d}$ and $\mathbf{r}_{\mathrm{t}1(2)}$ and form two more covariance matrices for the training intervals with the removed training signal: $\mathbf{R}_{\mathrm{t}1(2)}^{(0)} = N_\mathrm{t}^{-1}\sum_{n\in\mathscr{N}_{\mathrm{t}1(2)}}\mathbf{x}(n)\mathbf{B}_s\mathbf{x}^*(n)$, where $\mathbf{B}_s = \mathbf{I}_{N_\mathrm{t}} - \mathbf{s}_\mathrm{t}^*\mathbf{s}_\mathrm{t}/(\mathbf{s}_\mathrm{t}\mathbf{s}_\mathrm{t}^*)$. In terms of interference components, identification means that we find a scalar a_m and a vector $\mathbf{b}_m$ such that a first rank matrix $a_m\mathbf{b}_m\mathbf{b}_m^* = p_m\mathbf{g}_m\mathbf{g}_m^*$. For the desired signal we find a and $\mathbf{b}$ such that $a\mathbf{b}\mathbf{b}^* = \mathbf{h}\mathbf{h}^*$.

For simplicity we assume $K = 5$ in this and following sections because this case represents especially important situation for scenario in Fig. 2, where the total number of signals for the whole interval exceeds the number of antenna elements, i.e., $M + 1 > K$, which makes the conventional solution (5) to be ineffective.

The expressions below are based on the following eigendecompositions of the matrices:

$$\mathbf{R}_{\mathrm{t}1(2)} = \mathbf{U}_{\mathrm{t}1(2)}\mathbf{\Lambda}_{\mathrm{t}1(2)}\mathbf{U}_{\mathrm{t}1(2)}^* + \lambda_{\mathrm{t}1(2),5}\mathbf{u}_{\mathrm{t}1(2),5}\mathbf{u}_{\mathrm{t}1(2),5}^* \qquad (6)$$

$$\mathbf{R}_\mathrm{d} = \mathbf{U}_\mathrm{d}\mathbf{\Lambda}_\mathrm{d}\mathbf{U}_\mathrm{d}^* + \lambda_{\mathrm{d},5}\mathbf{u}_{\mathrm{d},5}\mathbf{u}_{\mathrm{d},5}^* \qquad (7)$$

$$\mathbf{R}_{\mathrm{t}1(2)}^{(0)} = \mathbf{U}_{\mathrm{t}1(2)}^{(0)}\mathbf{\Lambda}_{\mathrm{t}1(2)}^{(0)}\mathbf{U}_{\mathrm{t}1(2)}^{(0)*} +$$

[1] Other intervals shown in Fig. 1 or similar that may appear for different overlapping models can be addressed by similar data models with different appearance intervals.

$$\mathbf{U}^{(0)}_{\mathrm{t1(2),45}}\begin{bmatrix}\lambda^{(0)}_{\mathrm{t1(2),4}} & 0\\ 0 & \lambda^{(0)}_{\mathrm{t1(2),5}}\end{bmatrix}\mathbf{U}^{(0)*}_{\mathrm{t1(2),45}} \tag{8}$$

where eigenvalues are in descending order. For example, notations "t1(2),5" and "d,5" indicate the minimum eigenvalues and corresponding eigenvectors for the training and data intervals, taking into account that $K=5$. The increased by one dimension of the noise sub-space in $\mathbf{R}^{(0)}_{\mathrm{t1(2)}}$ is taken into account in (8).

The identification solution is summarized below without detailed explanations because of space limitation.

- *Identification of* $p_5\mathbf{g}_5\mathbf{g}_5^*$:

$$a_5=\left(\mathbf{e}^*_{\mathrm{d}}\tilde{\mathbf{\Lambda}}^{-1}_{\mathrm{d}}\mathbf{e}_{\mathrm{d}}\right)^{-1},\ \mathbf{b}_5=\mathbf{U}_{\mathrm{d}}\mathbf{e}_{\mathrm{d}}, \tag{9}$$

$$\tilde{\mathbf{\Lambda}}_{\mathrm{d}}=\mathbf{\Lambda}_{\mathrm{d}}-\lambda_{\mathrm{d,5}}\mathbf{I}_4,\ \mathbf{e}_{\mathrm{d}}=\mathbf{u}_{\min}(\mathbf{D}^*_5\mathbf{D}_5),$$

$$\mathbf{D}_5=\begin{bmatrix}\mathbf{U}^*_{\mathrm{t1}}\\ \mathbf{U}^*_{\mathrm{t2}}\\ \mathbf{U}^{(0)*}_{\mathrm{t1,45}}\\ \mathbf{U}^{(0)*}_{\mathrm{t2,45}}\end{bmatrix}\mathbf{U}_{\mathrm{d}}.$$

Now, the fifth CCI component can be removed from all five matrices (6)-(8):

$$\mathbf{R}^{(1)}_{\mathrm{t1(2)}}=\mathbf{U}_{\mathrm{t1(2)}}\left(\tilde{\mathbf{\Lambda}}_{\mathrm{t1(2)}}-\frac{\mathbf{e}_{\mathrm{t1(2)}}\mathbf{e}^*_{\mathrm{t1(2)}}}{\mathbf{e}^*_{\mathrm{t1(2)}}\tilde{\mathbf{\Lambda}}^{-1}_{\mathrm{t1(2)}}\mathbf{e}_{\mathrm{t1(2)}}}\right)\mathbf{U}^*_{\mathrm{t1(2)}} \tag{10}$$

$$\mathbf{R}^{(1)}_{\mathrm{d}}=\mathbf{U}_{\mathrm{d}}\left(\tilde{\mathbf{\Lambda}}_{\mathrm{d}}-\frac{\mathbf{e}_{\mathrm{d}}\mathbf{e}^*_{\mathrm{d}}}{\mathbf{e}^*_{\mathrm{d}}\tilde{\mathbf{\Lambda}}^{-1}_{\mathrm{d}}\mathbf{e}_{\mathrm{d}}}\right)\mathbf{U}^*_{\mathrm{d}} \tag{11}$$

$$\mathbf{R}^{(01)}_{\mathrm{t1(2)}}=\mathbf{U}^{(0)}_{\mathrm{t1(2)}}\left[\tilde{\mathbf{\Lambda}}^{(0)}_{\mathrm{t1(2)}}-\frac{\mathbf{e}^{(0)}_{\mathrm{t1(2)}}\mathbf{e}^{(0)*}_{\mathrm{t1(2)}}}{\mathbf{e}^{(0)*}_{\mathrm{t1(2)}}\left(\tilde{\mathbf{\Lambda}}^{(0)}_{\mathrm{t1(2)}}\right)^{-1}\mathbf{e}_{\mathrm{t1(2)}}}^{(0)}\right]\mathbf{U}^{(0)*}_{\mathrm{t1(2)}}, \tag{12}$$

where $\mathbf{e}_{\mathrm{t1(2)}}=\mathbf{U}_{\mathrm{t1(2)}}\mathbf{b}_5$, $\tilde{\mathbf{\Lambda}}_{\mathrm{t1(2)}}=\mathbf{\Lambda}_{\mathrm{t1(2)}}-\lambda_{\mathrm{t1(2),5}}\mathbf{I}_4$, $\mathbf{e}^{(0)}_{\mathrm{t1(2)}}=\mathbf{U}^{(0)}_{\mathrm{t1(2)}}\mathbf{b}_5$ and $\tilde{\mathbf{\Lambda}}^{(0)}_{\mathrm{t1(2)}}=\mathbf{\Lambda}^{(0)}_{\mathrm{t1(2)}}-0.5(\lambda^{(0)}_{\mathrm{t1(2),4}}+\lambda^{(0)}_{\mathrm{t1(2),5}})\mathbf{I}_3$.

Similarly to (6)-(8), eigendecomposition of matrices (10)-(12) can be obtained taking into account the increased by one dimension of the noise subspace for all of them. Below we keep the eigendecomposition notations from (6)-(8) with the additional upper upper index $(\cdot)^{(1)}$.

- *Identification of* $p_3\mathbf{g}_3\mathbf{g}_3^*$ ($p_2\mathbf{g}_2\mathbf{g}_2^*$):

$$a_{3(2)}=\left[\mathbf{r}^*_{3(2)}\left(\mathbf{\Lambda}^{(1)}_{\mathrm{d}}\right)^{-1}\mathbf{r}_{3(2)}\right]^{-1},\ \mathbf{b}_{3(2)}=\mathbf{U}^{(1)}_{\mathrm{d}}\mathbf{r}_{3(2)}, \tag{13}$$

$$\mathbf{r}_{3(2)}=\mathbf{u}_{\min}(\mathbf{D}^*_{3(2)}\mathbf{D}_{3(2)}),\ \mathbf{D}_{3(2)}=\begin{bmatrix}\mathbf{U}^{(1)*}_{\mathrm{t1(2),45}}\\ \mathbf{U}^{(01)*}_{\mathrm{t1(2),345}}\end{bmatrix}\mathbf{U}^{(1)}_{\mathrm{d}}.$$

- *Identification of* $p_1\mathbf{g}_1\mathbf{g}_1^*$ ($p_4\mathbf{g}_4\mathbf{g}_4^*$):

$$a_{1(4)}=\lambda_{\max}(\mathbf{D}_{1(4)}),\ \mathbf{b}_{1(4)}=\mathbf{u}_{\max}(\mathbf{D}_{1(4)}), \tag{14}$$

$$\mathbf{D}_{1(4)}=\mathbf{U}^{(01)}_{\mathrm{t1(2)}}\left[\tilde{\mathbf{\Lambda}}^{(01)}_{\mathrm{t1(2)}}-\frac{\mathbf{r}_{1(2)}\mathbf{r}^*_{1(2)}}{\mathbf{r}^*_{1(2)}\left(\tilde{\mathbf{\Lambda}}^{(01)}_{\mathrm{t1(2)}}\right)^{-1}\mathbf{r}_{1(2)}}\right]\mathbf{U}^{(01)*}_{\mathrm{t1(2)}},$$

$$\mathbf{r}_{1(2)}=\mathbf{U}^{(01)}_{\mathrm{t1(2)}}\mathbf{b}_{3(2)},$$

where $\lambda_{\max}(\mathbf{A})$ and $\mathbf{u}_{\max}(\mathbf{A})$ are the maximum eigenvalue and the corresponding eigenvector of matrix $\mathbf{A}$.

- *Identification of* $\mathbf{hh}^*$

$$a=\left[\mathbf{r}^*\left(\mathbf{\Lambda}^{(1)}_{\mathrm{d}}\right)^{-1}\mathbf{r}\right]^{-1},\ \mathbf{b}=\mathbf{U}^{(1)}_{\mathrm{d}}\mathbf{r}, \tag{15}$$

$$\mathbf{r}=\mathbf{u}_{\min}(\mathbf{D}^*\mathbf{D}),\ \mathbf{D}=\begin{bmatrix}\mathbf{U}^{(1)*}_{\mathrm{t1,45}}\\ \mathbf{U}^{(1)*}_{\mathrm{t2,45}}\end{bmatrix}\mathbf{U}^{(1)}_{\mathrm{d}}.$$

Thus, all the covariance matrices components for the training and data intervals shown in Fig. 2 can be identified.

The presented solution can be used as an identification algorithm if the known correlation moments are replaced with the second-order statistics estimated over the corresponding intervals.

It is worth emphasizing that we do not propose using such the identified parameters for signal estimation, e.g., as $\hat{\mathbf{w}}=\hat{\alpha}\left(\hat{a}\hat{\mathbf{b}}\hat{\mathbf{b}}^*+\hat{a}_2\hat{\mathbf{b}}_2\hat{\mathbf{b}}_2^*+\hat{a}_3\hat{\mathbf{b}}_3\hat{\mathbf{b}}_3^*+\hat{a}_5\hat{\mathbf{b}}_5\hat{\mathbf{b}}_5^*+\hat{p}\mathbf{I}_K\right)^{-1}\hat{\mathbf{b}}$, where $\hat{\alpha}$ is a rotation coefficient. The reason is that identification solutions that are not obtained from optimization of the signal recovery criterion normally have very slow convergence in terms of the required amount of data for the given quality of signal estimation [13]. In the next Section, the identified parameters will be used for intialization of the no-asymptotic ML benchmark for ad hoc algorithms.

4. NON-ASYMPTOTIC ML BENCHMARK

Similarly to [6], [7], in the considered scenario the ML estimates of the structured covariance matrices could be obtained via maximization of a monotonic function of the product of the likelihood ratios (LR) on the corresponding intervals:

$$\text{Find}\ \max_{\mathbf{c},\mathbf{c}_m,d}\gamma(\bar{\mathbf{A}}_{\mathrm{t1}})\gamma(\bar{\mathbf{A}}_{\mathrm{t2}})\gamma(\mathbf{A}_{\mathrm{d}}))^{N_{\mathrm{d}}/N_{\mathrm{t}}}, \tag{16}$$

$$\gamma(\bar{\mathbf{A}}_{\mathrm{t1(2)}})=\frac{\det(\bar{\mathbf{A}}^{-1}_{\mathrm{t1(2)}}\hat{\bar{\mathbf{R}}}_{\mathrm{t1(2)}})\exp(K+1)}{\exp[\mathrm{tr}(\bar{\mathbf{A}}^{-1}_{\mathrm{t}}\hat{\bar{\mathbf{R}}}_{\mathrm{t1(2)}})]}, \tag{17}$$

$$\gamma(\mathbf{A}_{\mathrm{d}})=\frac{\det(\mathbf{A}^{-1}_{\mathrm{d}}\hat{\mathbf{R}}_{\mathrm{d}})\exp(K)}{\exp[\mathrm{tr}(\mathbf{A}^{-1}_{\mathrm{d}}\hat{\mathbf{R}}_{\mathrm{d}})]}, \tag{18}$$

$$\bar{\mathbf{A}}_{\mathrm{t1}}=\begin{bmatrix}1 & \mathbf{c}^*\\ \mathbf{c} & \mathbf{cc}^*+\mathbf{c}_1\mathbf{c}_1^*+\mathbf{c}_3\mathbf{c}_3^*+\mathbf{c}_5\mathbf{c}_5^*+d\mathbf{I}_K\end{bmatrix}>0, \tag{19}$$

$$\bar{\mathbf{A}}_{\mathrm{t2}}=\begin{bmatrix}1 & \mathbf{c}^*\\ \mathbf{c} & \mathbf{cc}^*+\mathbf{c}_2\mathbf{c}_2^*+\mathbf{c}_4\mathbf{c}_4^*+\mathbf{c}_5\mathbf{c}_5^*+d\mathbf{I}_K\end{bmatrix}>0, \tag{20}$$

$$\mathbf{A}_{\mathrm{d}}=\mathbf{cc}^*+\mathbf{c}_2\mathbf{c}_2^*+\mathbf{c}_3\mathbf{c}_3^*+\mathbf{c}_5\mathbf{c}_5^*+d\mathbf{I}_K>0, \tag{21}$$

where $\hat{\bar{\mathbf{R}}}_{\mathrm{t1(2)}}=\begin{bmatrix}\hat{p}_{\mathrm{t1(2)}} & \hat{\mathbf{r}}^*_{\mathrm{t1(2)}}\\ \hat{\mathbf{r}}_{\mathrm{t1(2)}} & \hat{\mathbf{R}}_{\mathrm{t1(2)}}\end{bmatrix}$ are the sufficient statistics at the training intervals, and $\mathbf{c}$ and $\mathbf{c}_m$, $m=1,\ldots,M$ are $K\times 1$ complex vectors and d is a positive scalar.

The identification algorithm developed in Section 3 applied for the estimated correlation moments can be used for initialization in (16)-(21) as follows: $\hat{\mathbf{c}}^{[0]} = \hat{\alpha}\sqrt{\hat{a}}\hat{\mathbf{b}}$, $\hat{\mathbf{c}}_m^{[0]} = \sqrt{\hat{a}_m}\hat{\mathbf{b}}_m$, $m = 1,\ldots,M$, $\hat{d}^{[0]} = \hat{p}_0$. Noise power $\hat{p}_0$ can be estimated as an average value of all the noise sub-space eigenvalues.

As in [9], [6], [7], the benchmark performance is estimated only over the selected trials, where the LR value exceeds the LR value for the exact parameters. The weight vector for such trials can be calculated as $\hat{\mathbf{w}}_{\mathrm{ML}} = \left(\hat{\mathbf{c}}^{[J]}\hat{\mathbf{c}}^{[J]*} + \hat{\mathbf{c}}_2^{[J]}\hat{\mathbf{c}}_2^{[J]*} + \hat{\mathbf{c}}_3^{[J]}\hat{\mathbf{c}}_3^{[J]*} + \hat{\mathbf{c}}_5^{[J]}\hat{\mathbf{c}}_5^{[J]*} + \hat{d}^{[J]}\mathbf{I}_K\right)^{-1}\hat{\mathbf{c}}^{[J]}$, where J is the number of iterations of the optimization procedure in (16)-(21).

5. SB SOLUTION WITH “CLEANED” TRAINING

The developed non-asymptotic benchmark can be used for assessment of empirical solutions in the considered scenario. One of them is proposed in this section. The idea is to use the data interval for cancellation of the interference components at the training intervals that do not exist at the data interval. This can be done by means of a two-stage adaptive noise canceller (ANC) [11], [12] as illustrated in Fig. 3.

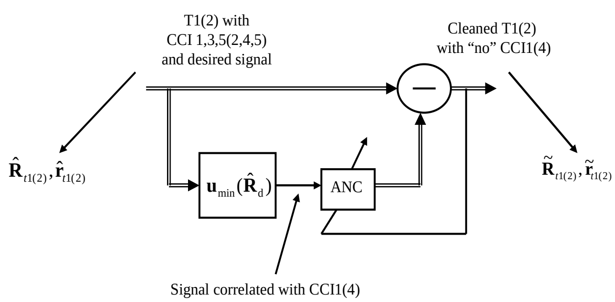

Figure 3: Two-stage “cleaning” ANC

At the first stage the spatial filter estimated over the data interval that cancels all the interference components and the desired signal, is applied over the training intervals to obtain the signals correlated to the interference components not presented on the data interval:

$$y(n) = \hat{\mathbf{v}}_{\mathrm{d}}^* \mathbf{x}(n), n \in \mathscr{N}_{\mathrm{t1(2)}}, \tag{22}$$

where $\hat{\mathbf{v}}_{\mathrm{d}} = \mathbf{u}_{\min}(\hat{\mathbf{R}}_{\mathrm{d}})$ is the eigenvector corresponding to the minimum eigenvalue of matrix $\hat{\mathbf{R}}_{\mathrm{d}}$. Then, “cleaned” training intervals can be obtained:

$$\tilde{x}_k(n) = x_k(n) - \hat{f}_{1(2)k}^* y(n), n \in \mathscr{N}_{\mathrm{t1(2)}}, k = 1,\ldots,K, \tag{23}$$

where $\hat{f}_{1(2)k} = \sum_{n\in\mathscr{N}_{\mathrm{t1(2)}}} x_k^*(n)y(n) / \sum_{n\in\mathscr{N}_{\mathrm{t1(2)}}} |y(n)|^2$.

Eventually, the “cleaned” training intervals $\tilde{\mathbf{x}} = [\tilde{x}_1,\ldots,\tilde{x}_K]^T$ can be used similarly to (5) instead of the original training intervals to get the semi-blind solution:

$$\hat{\mathbf{w}}_{\mathrm{SB}} = (\tilde{\mathbf{R}}_{\mathrm{t1}} + \tilde{\mathbf{R}}_{\mathrm{t2}})^{\#}(\tilde{\mathbf{r}}_{\mathrm{t1}} + \tilde{\mathbf{r}}_{\mathrm{t2}}). \tag{24}$$

One can expect better performance for (24) compared to (5) because of cancellation of the interference components that are not presented on the data interval (CCI 1 and 4 in Fig. 2). Efficiency of such a cancellation depends on the number of antenna elements and duration of all the intervals shown in Fig. 2. It will be evaluated in Section 7 by means of comparison with the non-asymptotic ML benchmark in the considered scenario.

6. SB ALGORITHM WITH FA PROJECTIONS

In communications applications transmitted signals belong to special classes such as FA or constant modulus (CM). Thus, second-order statistics techniques can be used as initializations for iterative higher-order algorithms, for example, as follows

$$\hat{\mathbf{w}}_{\mathrm{SBFA}} = \hat{\mathbf{w}}^{[J]}, \tag{25}$$

$$\hat{\mathbf{w}}^{[j]} = (\mathbf{X}\mathbf{X}^*)^{-1}\mathbf{X}\Theta\left[\mathbf{X}^*\hat{\mathbf{w}}^{[j-1]}\right], j = 1,\ldots,J, \tag{26}$$

where $\mathbf{X} = \left[\mathbf{x}(1),\ldots,\mathbf{x}(N_{\mathrm{d}})\right]$ is the $K \times N_{\mathrm{d}}$ matrix of input signals on the data interval, $\hat{\mathbf{w}}^{[j]}$ is the weight vector at the jth iteration, $\Theta[\cdot]$ is projection to the FA and J is the total number of iterations with stopping rule $\hat{\mathbf{w}}^{[J]} = \hat{\mathbf{w}}^{[J-1]}$.

All the considered above second-order solutions can be used as an initialization $\hat{\mathbf{w}}^{[0]}$ in (25). Comparison of the ML benchmark initialization to the LS and SB initializations for the SBFA algorithm (25), (26) is especially interesting. It can be considered as comparison of the ad-hoc and the best possible second-order initializations.

7. SIMULATION RESULTS

We simulate a five-element antenna array and five-component interference according to the CCI scenario in Fig. 2. The desired signal and interference are generated as independent streams of random symbols $(\pm 1 \pm j)/\sqrt{2}$. All propagation channels are simulated as independent complex Gaussian vectors with unit variance and zero mean. The training sequence of $N_{\mathrm{t}} = 8$ symbols and variable total number of symbols at the data interval N_{d} are considered. The LS and SB algorithms (5) and (24) as well as the ML benchmark developed in Section 4 are compared by means of the MSE and bit error rate (BER) performance estimated over 6000 trials with independent channel and data realizations. Optimization routine “fmincon” from the MATLAB Optimization Toolbox is used for solution of the non-linear constrained optimization problem (16)-(21).

The MSE and BER results for the LS, SB algorithms and the benchmark are presented in Fig. 4 for variable signal-to-noise ratio (SNR) and the fixed signal-to-interference ratio SIR=0 dB (equal power interference components are assumed). The MMSE performance is also shown in Fig. 4 for information. Typical LR distributions of the initialization, exact solution and benchmark are shown in Fig. 5.

First of all, one can see that the benchmark performance is much better compared to the conventional training-based LS case. This means that the considered problem is clearly required an advance semi-blind processing. The proposed SB algorithm significantly outperforms the LS solution, but demonstrates some performance degradation compared to the non-asymptotic ML benchmark. Particularly, one can see 2 dB and 3 dB degradation at 1% BER for $N_{\mathrm{d}} = 16$ and $N_{\mathrm{d}} = 160$ respectively.

The SBFA performance for different initializations is shown in Fig. 6. One can see that for high number of data symbols the difference between the SB and benchmark initializations is reduced to less than 1 dB at 0.1% BER.

Further illustration is presented in Fig. 7 for the fixed SNR=15 dB and variable SIR. Again, one can see significant SB performance improvement, e.g., by more than 7 dB at 1% BER for $N_{\mathrm{d}} = 160$ and by more than 5 dB for SBFA with the SB initialization compared to the LS initialization.

8. CONCLUSION

Second-order statistics identifiability of the considered indirect distributed training scenario has been demonstrated and a semi-blind algorithm has been developed, where the data and training intervals contain different sets of interference components. The SB performance has been assessed by means of the developed non-asymptotic ML benchmark. It has been shown that the SB algorithm significantly outperforms the conventional LS solution. In the case of the large number af data symbols, the SB initialization of the iterative algorithm with FA projections demonstrates the performance close to the benchmark initialization. The proposed approach can be applied for interval-based processing with different interference situations such as shown in the asynchronous scenario in Fig. 1.

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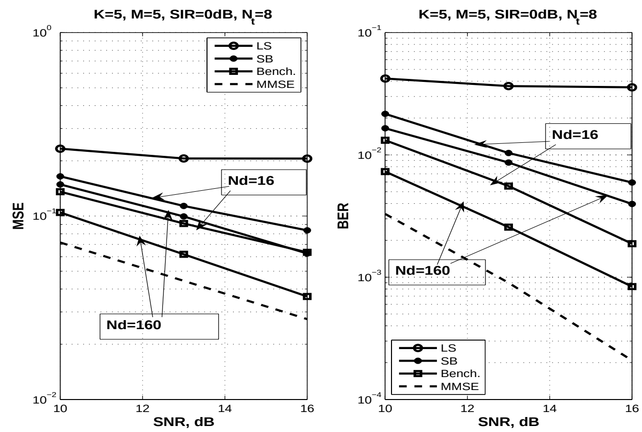

Figure 4: SB and benchmark performance for SIR=0 dB

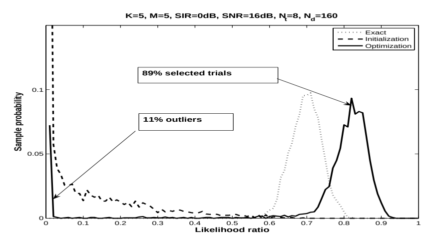

Figure 5: Typical LR distributions

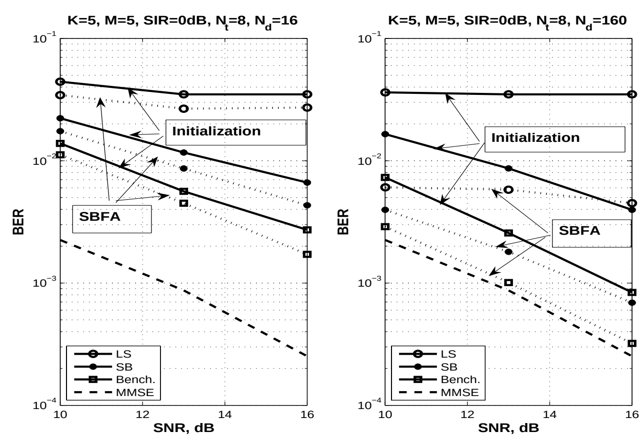

Figure 6: SB, SBFA and benchmark performance for SIR=0 dB

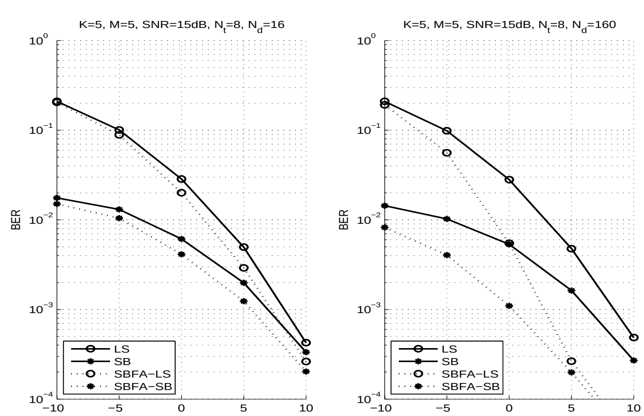

Figure 7: SB and SBFA performance for SNR=15 dB