BLIND ADAPTIVE REDUCED-RANK ESTIMATION BASED ON THE CONSTANT MODULUS CRITERION AND DIVERSITY-COMBINED DECIMATION AND INTERPOLATION

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ABSTRACT

This work proposes a low-complexity blind adaptive reduced-rank method (BARC) for symbol estimation using an adaptive decimation and interpolation scheme based on diversity-combining and the constant modulus criterion for interference suppression. The proposed approach employs an iterative procedure to jointly optimize the interpolation, decimation and estimation tasks for blind reduced-rank parameter estimation. We describe joint iterative estimators based on the constrained constant modulus (CCM) criterion, introduce alternative decimation structures, including the optimal decimation scheme, and develop low-complexity stochastic gradient adaptive algorithms for the proposed structure. Simulations for a CDMA interference suppression application show an excellent performance and substantial gains over prior art.

Index Terms— Blind adaptive estimation, reduced-rank techniques, iterative methods.

1. INTRODUCTION

Blind estimation algorithms based on constrained optimization techniques are important in several areas of signal processing and communications such as beamforming and interference suppression [1]. The constrained optimization required in these applications usually deals with linear constraints that correspond to prior knowledge of certain parameters such as direction of arrival (DoA) of user signals in antenna array processing [2] and the signature sequence of the desired signal in CDMA interference suppression [3].

Reduced-rank estimation is a strategic technique in low-sample support situations and large optimization problems that has gained considerable attention in the last few years [4]-[8]. The origins of reduced-rank parameter estimation lie in the problem of feature selection encountered in statistical signal processing, which refers to a process whereby a data space is transformed into a feature space, that theoretically has the same dimension of the original data space. It is, however, desirable to devise a transformation in such a way that the data vector can be represented by a reduced number of effective features and yet retain most of the intrinsic information content of the input data [4]. In this context, there is relatively little work in blind reduced-rank estimation.

Prior work on blind reduced-rank parameter estimation is limited and relies on the constrained minimum variance (CMV) design approach and is based on the multi-stage Wiener filter (MWF) [6] and the auxiliary vector filtering (AVF) scheme [7, 8]. However, in the literature, the design of algorithms based on the constant modulus criterion (CCM) [9, 10] has shown an increased robustness against signature mismatch and improved performance over the CMV approach. Recently, a reduced-rank version of the CCM based on the MWF and the Krylov subspace was shown [11] to outperform the previous blind methods and to achieve a performance close to the supervised MWF and AVF techniques. A drawback of MWF- and AVF-based schemes is their relatively high complexity.

In this work, we propose a low-complexity blind reduced-rank symbol estimator (BARC) based on the CCM criterion and diversity-combined interpolation and decimation. The proposed scheme is simple, flexible, and provides a substantial performance advantage over existing techniques. The BARC approach consists of an iterative procedure where the interpolation, decimation and estimation tasks are jointly optimized using the CCM design criterion. In the BARC system, the number of elements for estimation is substantially reduced, resulting in considerable computational savings and very fast convergence performance for tracking dynamic signals. A unique feature of the BARC method is that, unlike existing schemes, it does not rely on the full-rank covariance matrix $\mathbf{R}$ (that may require a large amount of data to be estimated) before projecting the received data onto a reduced-rank subspace. The BARC approach skips the processing stage with $\mathbf{R}$ and directly obtains the subspace of interest through a set of simple interpolation and decimation operations, which leads to faster convergence. In order to design the estimators and the decimation unit of the proposed scheme, we describe a joint iterative CCM design for both the interpolator and reduced-rank estimators, propose alternative decimation structures and develop low-complexity stochastic gradient (SG) algorithms.

This paper is organized as follows. The blind reduced-rank problem is formulated in Section 2. Section 3 is dedicated to the proposed blind reduced-rank estimation (BARC) scheme and CCM reduced-rank estimators. Section 4 is devoted to the blind adaptive SG algorithms. Section 5 presents and discusses the simulation results and Section 6 gives the concluding remarks.

2. BLIND REDUCED-RANK PROBLEM STATEMENT

Let us consider a blind estimation problem which corresponds to the design of a parameter vector $\mathbf{w}[i] = [w_1^{[i]}\ w_2^{[i]}\ \ldots\ w_M^{[i]}]^T$ according to an appropriate cost function (eg. mean square error (MSE), MV and CM) to process a received data vector $\mathbf{r}[i] = [r_0^{[i]}\ \ldots\ r_{M-1}^{[i]}]^T$ and estimate a desired signal $d[i]$ at time instant i. The symbols $(\cdot)^T$ and $(\cdot)^H$ denote transpose and Hermitian transpose, respectively. Since the literature of blind estimation algorithms for communications indicates that the CCM criterion is superior to the CMV approach, we focus here on the CCM criterion.

The set of parameters $\mathbf{w}[i]$ can be estimated via standard SG or least-squares estimation techniques [1]. However, the laws that govern the convergence behavior of these estimators imply that the convergence speed of these algorithms is proportional to M, the number of elements in the estimator. Thus, a large M implies slow convergence. A reduced-rank algorithm strives to circumvent this limitation in terms of speed of convergence by reducing the number of adaptive coefficients and extracting the most important features of the processed data. This dimensionality reduction is accomplished by projecting the received vectors onto a lower dimensional subspace. Consider an $M \times D$ projection matrix $\mathbf{S}_D[i]$ which carries

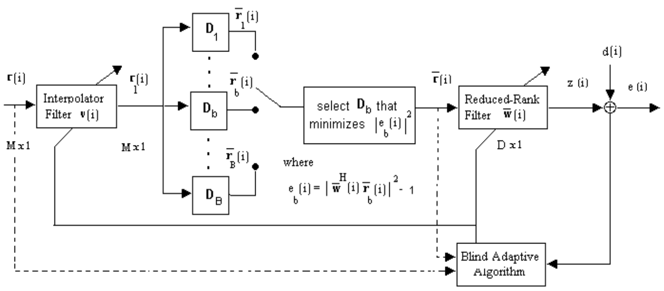

Fig. 1. Proposed blind adaptive reduced-rank estimation structure.

out a dimensionality reduction on the received data as given by

$$\bar{\mathbf{r}}[i] = \mathbf{S}_D^H \mathbf{r}[i] \tag{1}$$

where, in what follows, all D-dimensional quantities are denoted with a "bar". The resulting projected received vector $\bar{\mathbf{r}}[i]$ is the input to a tapped-delay line represented by the $D \times 1$ vector $\bar{\mathbf{w}}[i] = [\bar{w}_1^{[i]} \ \bar{w}_2^{[i]} \ \ldots \bar{w}_D^{[i]}]^T$ for time interval i. The estimator output corresponding to the ith time instant is

$$z[i] = \bar{\mathbf{w}}_k^H[i]\mathbf{S}_D^H[i]\mathbf{r}[i] = \bar{\mathbf{w}}^H[i]\bar{\mathbf{r}}[i] \tag{2}$$

If we consider the constant modulus (CM) cost function

$$J_{CM}(\bar{\mathbf{w}}_k[i]) = E\big[(\big|\bar{\mathbf{w}}_k^H[i]\mathbf{S}_D^H[i]\mathbf{r}[i]\big|^2 - 1)^2\big] \tag{3}$$

subject to the constraint $\bar{\mathbf{w}}_k^H[i]\mathbf{S}_D^H[i]\mathbf{p}[i] = \nu$, where $E[\cdot]$ stands for expectation, ν is a convexity enforcing parameter [10] and $\mathbf{p}[i]$ is a quantity that corresponds to the effective signature of the desired user in a CDMA system or to the array response of the signal of interest in beamforming. The expression that solves (3) is given by

$$\begin{aligned}\bar{\mathbf{w}}[i+1] = \bar{\mathbf{R}}_z^{-1}[i]\big[\bar{\mathbf{d}}_z[i] - (\bar{\mathbf{p}}^H[i]\bar{\mathbf{R}}_z^{-1}[i]\bar{\mathbf{p}}[i])^{-1} \\ \cdot \bar{\mathbf{p}}[i]\big(\bar{\mathbf{p}}^H[i]\bar{\mathbf{R}}_z^{-1}[i]\bar{\mathbf{d}}_z[i] - \nu\big)\big]\end{aligned} \tag{4}$$

where $\bar{\mathbf{R}}_z[i] = E[|z[i]|^2\bar{\mathbf{r}}[i]\bar{\mathbf{r}}^H[i]] = \mathbf{S}_D^H[i]\mathbf{R}_z[i]\mathbf{S}_D[i]$, $\mathbf{R}_z[i] = E[|z[i]|^2\mathbf{r}[i]\mathbf{r}^H[i]]$, $\bar{\mathbf{d}}_z[i] = E[z^*[i]\bar{\mathbf{r}}[i]] = \mathbf{S}_D^H[i]E[z^*[i]\mathbf{r}[i]]$ and, $\bar{\mathbf{p}} = \mathbf{S}_D^H[i]\mathbf{p}$. The basic problem of the design in (4) is how to efficiently (or optimally) design the $M \times D$ matrix $\mathbf{S}_D[i]$ that projects the observed data vector $\mathbf{r}[i]$ with dimensions $M \times 1$ onto a reduced-rank data vector $\bar{\mathbf{r}}(i)$ with dimensions $D \times 1$. In the next section we present the proposed blind reduced-rank approach.

3. PROPOSED BLIND REDUCED-RANK SCHEME

The framework of the proposed BARC scheme is detailed in this section. Fig. 1 shows the structure of the system, where an interpolator, a decimator unit with several decimation branches and a reduced-rank estimator which are time-varying are employed. The $M \times 1$ received vector $\mathbf{r}[i]$ is filtered by the interpolator filter $\mathbf{v}[i] = [v_0^{[i]} \ldots v_{N_\mathrm{I}-1}^{[i]}]^T$, yielding the interpolated received vector $\mathbf{r}_\mathrm{I}[i]$. The $M \times 1$ vector $\mathbf{r}_\mathrm{I}[i]$ is then decimated by B decimation patterns in parallel, leading to B different $D \times 1$ vectors $\bar{\mathbf{r}}_b[i]$, where L is the decimation factor and $D = M/L$ is the rank. The proposed architecture, that employs several decimation branches in parallel to improve symbol estimation, is inspired by the use of receive diversity to improve the reliability of wireless communications links [12]. The proposed decimation procedure corresponds to discarding $M - D$ samples of $\mathbf{r}_\mathrm{I}[i]$ of each set of M received samples with different patterns, resulting in B different $D \times 1$ decimated vectors $\bar{\mathbf{r}}_b[i]$. Then, we compute the inner product of $\bar{\mathbf{r}}_b[i]$ with the $D \times 1$ vector of the reduced-rank filter coefficients $\bar{\mathbf{w}}[i]$ that minimizes the squared norm of the error signal.

3.1. Adaptive Interpolation, Decimation and Estimation Scheme

The front-end adaptive filtering is carried out by the interpolator filter $\mathbf{v}[i]$ on the received vector $\mathbf{r}[i]$ and yields the interpolated received vector $\mathbf{r}_\mathrm{I}[i] = \mathbf{V}^H[i]\mathbf{r}[i]$, where the $M \times M$ convolution matrix $\mathbf{V}^H[i]$ with the coefficients of the interpolator is given by

$$\mathbf{V}^H[i] = \begin{bmatrix} v_0^{*[i]} & \ldots & v_{N_\mathrm{I}-1}^{*[i]} & \ldots & 0 & 0 & 0 \\ 0 & v_0^{*[i]} & \ldots & v_{N_\mathrm{I}-1}^{*[i]} & \ldots & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \ldots & 0 & \ldots & v_0^{*[i]} \end{bmatrix}. \tag{5}$$

Let us express the $M \times 1$ vector $\mathbf{r}_\mathrm{I}[i]$ in an equivalent way which will be useful when dealing with the different decimation patterns:

$$\mathbf{r}_\mathrm{I}[i] = \mathbf{V}^H[i]\mathbf{r}[i] = \boldsymbol{\Re}_\mathrm{o}[i]\mathbf{v}^*[i], \tag{6}$$

where the $M \times N_I$ matrix with the received samples of $\mathbf{r}[i]$ and that implements convolution is described by

$$\boldsymbol{\Re}_\mathrm{o}[i] = \begin{bmatrix} r_0^{[i]} & r_1^{[i]} & \ldots & r_{N_\mathrm{I}-1}^{[i]} \\ \vdots & \vdots & \ddots & \vdots \\ r_{M-1}^{[i]} & r_M^{[i]} & \ldots & r_{M+N_\mathrm{I}-2}^{[i]} \end{bmatrix}. \tag{7}$$

The $D \times 1$ decimated interpolated received vector for branch b is

$$\bar{\mathbf{r}}_b[i] = \mathbf{D}_b[i]\mathbf{r}_\mathrm{I}[i], \tag{8}$$

where the $D \times M$ decimation matrix $\mathbf{D}_b[i]$ that adaptively minimizes the squared norm of the error at time instant i. The matrix $\mathbf{D}_b[i]$ is mathematically equivalent to signal decimation with a chosen pattern on the $M \times 1$ vector $\mathbf{r}_\mathrm{I}[i]$, which corresponds to the removal of $M - D$ samples of $\mathbf{r}_\mathrm{I}[i]$ of each set of M observed samples.

In order to express the proposed reduced-rank estimator output, we resort to a strategy, which will allows us to devise solutions for both interpolator and receiver. Specifically, we express the estimated symbol $z[i]$ as a function of $\bar{\mathbf{w}}[i]$ and $\mathbf{v}[i]$:

$$\begin{aligned} z[i] &= \bar{\mathbf{w}}^H[i]\mathbf{S}_D^H[i]\mathbf{r}[i] = \bar{\mathbf{w}}^H[i]\big(\mathbf{D}_b[i]\mathbf{V}^H[i]\mathbf{r}[i]\big) \\ &= \bar{\mathbf{w}}^H[i]\big(\mathbf{D}_b[i]\boldsymbol{\Re}_\mathrm{o}[i]\big)\mathbf{v}^*[i] = \bar{\mathbf{w}}^H[i]\boldsymbol{\Re}_b[i]\mathbf{v}^*[i] \\ &= \mathbf{v}^H[i]\big(\boldsymbol{\Re}_b^T[i]\bar{\mathbf{w}}^*[i]\big) = \mathbf{v}^H[i]\mathbf{u}[i], \end{aligned} \tag{9}$$

where $\mathbf{u}[i] = \boldsymbol{\Re}_b^T[i]\bar{\mathbf{w}}^*[i]$ is an $N_\mathrm{I} \times 1$ vector, the D coefficients of $\bar{\mathbf{w}}[i]$ and the N_I elements of $\mathbf{v}[i]$ are assumed complex and the $D \times N_\mathrm{I}$ matrix $\boldsymbol{\Re}_b[i]$ is $\boldsymbol{\Re}_b[i] = \mathbf{D}_b[i]\boldsymbol{\Re}_\mathrm{o}[i]$.

3.2. Reduced-Rank Joint Iterative CCM Estimators Design

Let us describe the CCM estimators design of the proposed reduced-rank structure. The CCM expressions for $\bar{\mathbf{w}}[i]$ and $\mathbf{v}[i]$ can be computed through the minimization of

$$J_\mathrm{CM}(\mathbf{v}[i], \bar{\mathbf{w}}[i]) = E\Big[\big(|\bar{\mathbf{w}}^H[i]\boldsymbol{\Re}[i]\mathbf{v}^*[i]|^2 - 1\big)\Big], \tag{10}$$

subject to $\bar{\mathbf{w}}_k^H[i]\mathbf{S}_D^H[i]\mathbf{p}[i] = \nu$. By using the method of Lagrange multipliers, fixing $\bar{\mathbf{w}}[i]$ and minimizing the Lagrangian with respect to $\mathbf{v}[i]$, the expression for the interpolator becomes

$$\begin{aligned}\mathbf{v}[i+1] = \bar{\mathbf{R}}_u^{-1}[i]\big[\bar{\mathbf{d}}_u[i] - (\bar{\mathbf{p}}_w^H[i]\bar{\mathbf{R}}_u^{-1}[i]\bar{\mathbf{p}}_w[i])^{-1} \\ \cdot \bar{\mathbf{p}}_w[i]\big(\bar{\mathbf{p}}_w^H[i]\bar{\mathbf{R}}_u^{-1}[i]\bar{\mathbf{d}}_u[i] - \nu\big)\big]\end{aligned} \tag{11}$$

where $\bar{\mathbf{R}}_u[i] = E[|z[i]|^2\mathbf{u}[i]\mathbf{u}^H[i]]$, $\bar{\mathbf{d}}_u[i] = E[z^*[i]\mathbf{u}[i]]$, $\mathbf{u}[i] = \boldsymbol{\Re}^T[i]\bar{\mathbf{w}}^*[i]$ and $\bar{\mathbf{p}}_w = \boldsymbol{P}_o^T[i]\bar{\mathbf{w}}[i]$. The $D \times N_{\mathrm{I}}$ matrix $\boldsymbol{P}_o[i]$ is a function of $\mathbf{D}_b[i]$ and $\mathbf{p}[i]$ taken from the constraint and the equivalence $\bar{\mathbf{w}}_k^H[i]\mathbf{S}_D^H[i]\mathbf{p}[i] = \bar{\mathbf{w}}_k^H[i]\boldsymbol{P}_o^T[i]\mathbf{v}^*[i] = \mathbf{v}_k^H[i]\mathbf{p}_w[i] = \nu$. By fixing the interpolator $\mathbf{v}[i]$ and minimizing the Lagrangian with respect to $\bar{\mathbf{w}}[i]$ the expression for the reduced-rank estimator is

$$\bar{\mathbf{w}}[i+1] = \bar{\mathbf{R}}_z^{-1}[i]\big[\bar{\mathbf{d}}_z[i] - (\bar{\mathbf{p}}^H[i]\bar{\mathbf{R}}_z^{-1}[i]\bar{\mathbf{p}}[i])^{-1} \cdot \bar{\mathbf{p}}[i]\big(\bar{\mathbf{p}}^H[i]\bar{\mathbf{R}}_z^{-1}[i]\bar{\mathbf{d}}_z[i] - \nu\big)\big] \quad (12)$$

where $\bar{\mathbf{R}}_z[i] = E[|z[i]|^2\bar{\mathbf{r}}[i]\bar{\mathbf{r}}^H[i]] = \mathbf{S}_D^H[i]\mathbf{R}_z[i]\mathbf{S}_D[i]$, $\mathbf{R}_z[i] = E[|z[i]|^2\mathbf{r}[i]\mathbf{r}^H[i]]$, $\bar{\mathbf{d}}_z[i] = E[z^*[i]\bar{\mathbf{r}}[i]] = \mathbf{S}_D^H[i]E[z^*[i]\mathbf{r}[i]$, $\bar{\mathbf{p}} = \mathbf{S}_D^H[i]\mathbf{p}$ and $\mathbf{S}_D[i] = \mathbf{D}_b[i]\mathbf{V}^H[i]$. We remark that (11) and (12) are not closed-form solutions for $\bar{\mathbf{w}}[i]$ and $\mathbf{v}[i]$ since they depend on each other and their previous values. Thus it is necessary to iterate (11) and (12) with an initial value to obtain a solution.

3.3. Adaptive Decimation Schemes

We present an optimal approach and three sub-optimal procedures for designing the decimation unit of the novel reduced-rank scheme, where the common framework is the use of parallel branches with decimation patterns that yield B decimated vectors $\bar{\mathbf{r}}_b[i]$ as candidates. Mathematically, the scheme chooses the decimation pattern $\mathbf{D}_b$ and consequently the decimated interpolated observation vector $\bar{\mathbf{r}}_b[i]$ that minimizes $|e_b[i]|^2$, where $e_b[i] = |\bar{\mathbf{w}}^H[i]\bar{\mathbf{r}}_b[i]|^2 - 1$ is the error signal at branch b. Once the decimation pattern is selected for the time instant i, the decimated interpolated vector is computed as $\bar{\mathbf{r}}[i] = \mathbf{D}[i]\mathbf{r}_{\mathrm{I}}[i]$. The decimation pattern $\mathbf{D}[i]$ is selected on the basis of the following criterion:

$$\mathbf{D}[i] = \mathbf{D}_b[i] \ \text{ when } \ b = \arg\min_{1 \le b \le B} |e_b[i]|^2, \quad (13)$$

where the optimal decimation pattern $\mathbf{D}_{\mathrm{opt}}$ for the BARC scheme with decimation factor L is derived through the counting principle. We consider a procedure that has M samples as possible candidates for the first row of $\mathbf{D}_{\mathrm{opt}}$ and $M - m + 1$ samples as candidates for the following $D-1$ rows of $\mathbf{D}_{\mathrm{opt}}$, where m denotes the mth row of the matrix $\mathbf{D}_{\mathrm{opt}}$, resulting in a number of candidates equal to

$$B = \underbrace{M \cdot (M-1) \dots (M-D+1)}_{D \ \text{terms}} = \frac{M!}{(M-D)!}. \quad (14)$$

The optimal decimation scheme described in (13)-(14) is, however, very complex for practical use as it requires D permutations of M samples for each symbol interval and carries out an extensive search over all possible patterns. Thus, a decimation scheme that renders itself to practical and low-complexity implementations is of great interest. In order to consider a general framework for sub-optimal decimation schemes with decimation factor L and a finite number of B parallel branches, let us describe the following structure:

$$\mathbf{D}_b[i] = \begin{bmatrix} \underbrace{0 \ \dots \ 0}_{r_1 \ zeros} & 1 & 0 & 0 & 0 & 0 & \dots & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \underbrace{0 \ 0 \ \dots \ 0}_{r_m \ zeros} & 1 & 0 & 0 & 0 & \dots & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \underbrace{0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \dots 0}_{r_D \ zeros} & 1 & \underbrace{0 \ \dots \ 0}_{(M - r_D - 1) \ zeros} \end{bmatrix}, \quad (15)$$

where m ($m = 1, 2, \dots, M/L$) denotes the m-th row and r_m is the number of zeros chosen according to the following proposed alternative decimation patterns:

A. Uniform (U) Decimation with $B = 1$. We make $r_m = (m-1)L$ and this corresponds to the use of a single branch on the decimation unit.

B. Pre-Stored (PS) Decimation. We select $r_m = (m-1)L + (b-1)$ which corresponds to the utilization of uniform decimation for each branch b out of B branches and the different patterns are obtained by selecting adjacent samples with respect to the previous and succeeding decimation patterns.

C. Random (R) Decimation. We choose r_m as a discrete uniform random variable, which is independent for each row m out of B branches and whose values range between 0 and $M-1$.

4. BLIND ADAPTIVE ESTIMATION ALGORITHMS

In this section we present SG algorithms [1] to estimate the parameters of the filter $\bar{\mathbf{w}}[i]$, the decimation unit $\mathbf{D}[i]$ and the interpolator $\mathbf{v}[i]$. Consider the adaptive processing shown in Fig. 1. To design the estimators $\mathbf{v}[i]$ and $\bar{\mathbf{w}}[i]$, we consider the Lagrangian

$$\mathcal{L}_{\mathrm{CM}}(\mathbf{v}[i], \bar{\mathbf{w}}[i]) = E\Big[\big(|\bar{\mathbf{w}}^H[i]\boldsymbol{\Re}[i]\mathbf{v}^*[i]|^2 - 1\big)\Big] - \Re\Big[\big(\bar{\mathbf{w}}_k^H[i]\mathbf{S}_D^H[i]\mathbf{p}[i] - \nu\big)\lambda\Big], \quad (16)$$

where λ is a Lagrange multiplier. By minimizing (16) and using the constraint $\mathbf{v}_k^H[i]\mathbf{p}_w[i] = \nu$, we get the update recursion

$$\mathbf{v}[i+1] = \mathbf{v}[i] - \mu_v e[i] z^*[i]\big(\mathbf{I} - (\mathbf{p}_w^H[i]\mathbf{p}_w[i])^{-1}\mathbf{p}_w[i]\mathbf{p}_w^H[i]\big)\mathbf{u}[i], \quad (17)$$

where μ_v is the step size. We subsequently form $\mathbf{V}^H[i]$ as in (5), compute $\mathbf{r}_{\mathrm{I}}[i]$ and compute the decimated interpolated vectors $\mathbf{r}_b[i]$ for the B branches with the aid of the decimation patterns $\mathbf{D}_b[i]$, where $1 \le b \le B$. Once the B candidate vectors $\bar{\mathbf{r}}_b[i]$ are computed, we select the vector $\bar{\mathbf{r}}_b[i]$ that minimizes the squared norm of

$$e_b[i] = |\bar{\mathbf{w}}^H[i]\bar{\mathbf{r}}_b[i]|^2 - 1. \quad (18)$$

Based on the selection of $\mathbf{D}_b[i]$ that minimizes $|e_b[i]|^2$, we choose the corresponding reduced-rank vector $\bar{\mathbf{r}}[i]$ and select the error of the proposed SG algorithm $e[i]$ as the error $e_b[i]$ with the smallest squared magnitude of the B branches

$$\mathbf{r}[i] = \mathbf{r}_b[i] \text{ and } e[i] = e_b[i] \text{ when } b = \arg\min_{1 \le b \le B} |e_b[i]|^2. \quad (19)$$

At last, by minimizing (16) and using the constraint $\bar{\mathbf{w}}_k^H[i]\mathbf{S}_D^H[i]\mathbf{p}[i] = \nu$, we obtain the update recursion for $\bar{\mathbf{w}}[i]$

$$\bar{\mathbf{w}}[i+1] = \bar{\mathbf{w}}[i] - \mu_w e[i] z^*[i]\big(\mathbf{I} - \mathbf{S}_D^H[i]\mathbf{p}[i]\mathbf{p}^H[i]\mathbf{S}_D^H[i]\big)\bar{\mathbf{r}}[i], \quad (20)$$

where μ_w is the step size. The SG algorithms for the proposed structure presented here have a computational complexity $O(D + N_I)$. In fact, the proposed structure trades off one SG algorithm with complexity $O(M)$ against two LMS algorithms with complexity $O(D)$ and $O(N_I)$, operating simultaneously and exchanging information.

5. SIMULATIONS

In this section we assess the BARC scheme and algorithms in a CDMA interference suppression application. We consider the uplink of a symbol synchronous QPSK DS-CDMA system with K users, N chips per symbol and L propagation paths. Assuming that the channel is constant during each symbol interval and the random spreading codes are repeated from symbol to symbol, the received signal after filtering by a chip-pulse matched filter and sampled at chip rate yields the M-dimensional received vector

$$\mathbf{r}[i] = \sum_{k=1}^{K} \mathbf{H}_k[i] A_k \mathbf{C}_k \mathbf{d}_k[i] + \mathbf{n}[i], \quad (21)$$

where $M = N + L - 1$, $\mathbf{n}[i] = [n_1[i] \ \ldots \ n_M[i]]^T$ is the complex Gaussian noise vector with zero mean and $E[\mathbf{n}[i]\mathbf{n}^H(i)] = \sigma^2\mathbf{I}$, the symbol vector is $\mathbf{d}_k[i] = [d_k[i + L_s - 1] \ \ldots \ d_k[i] \ \ldots \ d_k[i - L_s + 1]]^T$, the amplitude of user k is A_k, L_s is the intersymbol interference span and the $((2L_s - 1) \cdot N) \times (2L_s - 1)$ block diagonal matrix $\mathbf{C}_k$ is formed with N-chips shifted versions of the signature $\mathbf{s}_k = [s_k(1) \ldots s_k(N)]^T$ of user k. The $M \times (2 \cdot L_s - 1) \cdot N$ convolution matrix $\mathbf{H}_k(i)$ is constructed with shifted versions of the $L \times 1$ channel vector $\mathbf{h}_k(i) = [h_{k,0}(i) \ \ldots \ h_{k,L_p-1}(i)]^T$ on each column and zeros elsewhere, which are generated with Clarke's model [12]. All simulations assume $L = 9$ as an upper bound, 3-path channels with relative powers given by 0, -3 and -6 dB, where in each run the spacing between paths is obtained from a discrete uniform random variable between 1 and 2 chips and average the curves over 200 runs. The system has a power distribution among the users for each run that follows a log-normal distribution with standard deviation equal to 1.5 dB. All adaptive algorithms employ the CCM criterion, linear receivers and SG estimators and we measure the BER of user 1. We compare the BARC scheme with the full-rank [9], reduced-rank schemes with the MWF method [11] and the SVD-based approach that selects the D largest eigenvectors [5] to compute the projection matrix $\mathbf{S}_D[i]$ and the MMSE, which assumes the knowledge of the channels and the noise variance. All algorithms have their step size and rank D optimized with respect to the BER for each scenario and employ the blind channel estimator of [9] to compute the effective signature $\mathbf{p}[i]$.

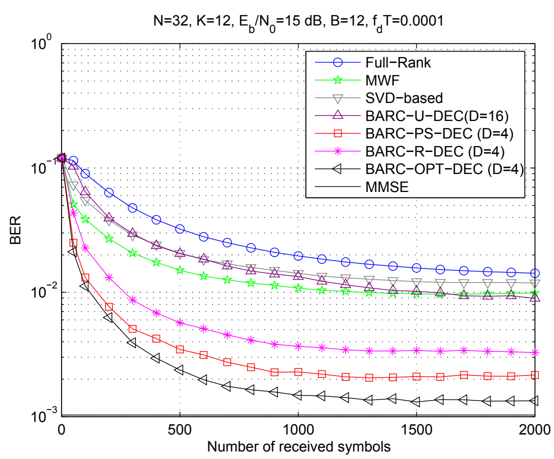

Fig. 2. BER performance versus number of decimation branches.

In order to assess the proposed decimation methods, we compute the BER performance of the algorithms for the uniform (U-DEC), the random (R-DEC), the pre-stored (PS-DEC) and the optimal (OPT-DEC) schemes. The results, shown in Fig.2, indicate that the BARC scheme with the optimal decimation (OPT-DEC) achieves the best performance, followed by the proposed method with pre-stored decimation (PS-DEC), the random decimation system (R-DEC), the uniform decimation (U-DEC), the MWF, the SVD and the full-rank approach. Due to its exponential complexity, the optimal decimation algorithm is not practical and the PS-DEC is the one with the best trade-off between performance and complexity.

In the next experiment, we evaluate the effect of the number of decimation branches B on the performance for various ranks D with a data support of 1500 symbols and the PS-DEC decimation approach. The results, depicted in Fig.3, indicate that the performance of the BARC scheme is improved and approaches the optimal MMSE estimator, which assumes that the channels and the noise variance are known, as B is increased.

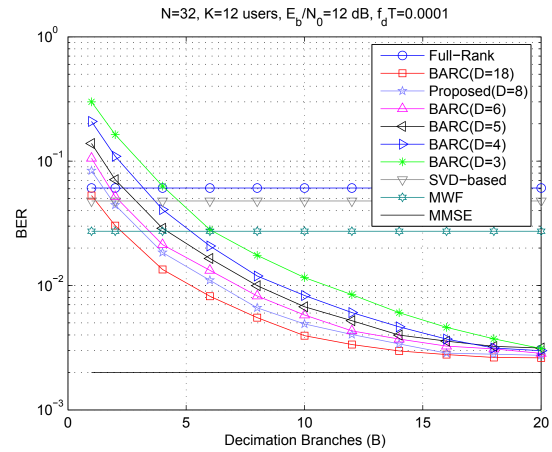

Fig. 3. BER performance versus number of decimation branches.

6. CONCLUSIONS

We propose a low-complexity reduced-rank method for blind parameter estimation with an adaptive decimation and interpolation scheme based on diversity-combining. The proposed approach is applied to CDMA interference suppression, outperforms the best known methods and approaches the optimal MMSE estimator.

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