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EFFECTIVE INTERFERENCE SUPPRESSION VIA SPATIO-TEMPORAL BLOCK DECORRELATION

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ABSTRACT

In this paper, we present an effective method for suppressing spatially and temporally correlated interference. The method treats adjacent temporal samples of the received signal as signal branches coming from additional antennas and uses conventional methods for cancelling spatially correlated interference to decorrelate blocks of spatio-temporal signal samples. Based on a maximum-likelihood formulation, two algorithms for jointly estimating the channel response, the synchronization position, and the spatio-temporal block decorrelation matrix are derived. A multiple-input-single-output prefilter is used to combine the multiple signal branches generated by the proposed method into a single branch so that conventional single-branch equalizers can be employed. In the case of single-antenna interference cancellation (SAIC) in GSM terminals, the proposed technique achieves substantial performance gains over conventional interference-rejection techniques in various interference scenarios.

I. INTRODUCTION

Numerous interference cancellation techniques, cf. [1]-[7] [9]-[17], have been proposed over the past decade. In particular, the class of interference cancellation techniques that exploit the correlation of interference in the spatial dimension introduced by attenna arrays has long been recognized and proven as one of the most effective means of mitigating interference [1][2][3]. For systems with time-dispersive channels, it has also been shown, cf. [4]-[7], that additional performance gains can be obtained by taking into acount the temporal correlation of the interference along with the spatial correlation.

In this paper, we present an effective method for exploiting the spatio-temporal correlation of interference by treating adjacent temporal samples of the received signal as signal branches coming from additional antennas so that conventional techniques for cancelling spatially correlated interference can be applied to the spatio-temporal signal branches. Conceptually, the proposed method consists of two stages, a block-decorrelation stage and a combining stage, as depicted in Fig. 1 in the following page. In the first stage, temporal samples of a multi-branch received signal are first stacked to form a sequence of sample blocks with increased number of branches in each block. A spatio-temporal block-decorrelation (STBD) matrix is then used to operate on each of these blocks in order to suppress interference. The STBD matrix is computed based on the spatio-temporal covariance matrix of noise/interference, which is jointly estimated with the channel response and the synchronization position over a sequence of known training or pilot symbols. Unlike most of the interference rejection methods proposed in the literature, the block-decorrelation operation proposed here treats the spatial and temporal correlation of the interference in the same manner. In the second stage, an anti-causal, multiple-input single-output (MISO) prefilter is used to combine the multiple output branches of the STBD matrix (or the MIMO whitening filter) into a single-branch signal for subsequent equalization. This MISO prefilter not only preserves the whiteness of the underlying noise component in the combined signal but also guarantees a minimum-phase equivalent channel response for the combined signal, which is well suited for use with decision-feedback-type, reduced-complexity equalizers. In practice, the two stages of filtering can be efficiently combined to form a single filter.

The performance of the proposed interference-suppression method is evaluated in the context of single-antenna interference cancellation (SAIC) for GSM terminals [8], which has received much attention in recent years, cf. [9]-[17]. For SAIC, the in-phase (I) and quadrature-phase (Q) components of the complex-valued baseband received signal are treated as two separate spatial branches. We compare the STBD-based method with other previously proposed methods of exploiting spatio-temporal correlation of interference derived based on a vector-valued autoregressive (VAR) model of the interference [5][6][9][10], which have comparable computational complexity. The STBD-based method consistently outperforms the conventional VAR-based methods in suppressing interference, especially when there are multiple interferers.

II. SYSTEM MODEL AND NOTATIONS

Let $\mathbf{r}[n] = [r_1[n], r_2[n], \cdots, r_{n_r}[n]]^T$ denote a discrete-time, symbol-spaced, vector received signal with n_r branches. The multiple signal branches may be obtained from multiple receive antennas, the I and Q components of a complex-valued signal, different down-sampling versions of an over-sampled signal, or combinations of these. Consider the following model of $\mathbf{r}[n]$:

$$\mathbf{r}[n+n_0] = \sum_{k=0}^{L} \mathbf{c}[k]s[n-k] + \mathbf{v}[n] \tag{1}$$

for $n = L, L+1, \cdots, N-1$, where $\{\mathbf{c}[k]\}_{k=0}^{L}$ denotes the $(L+1)$-tap baseband channel response, n_0 denotes the ideal synchronization position which lies within a finite set of possible positions Π, $\{s[n]\}_{n=0}^{N-1}$ denotes a training sequence of length N, $\{\mathbf{v}[n]\}$ denotes the total noise process that includes both thermal noise and interference from other users.

A. Spatio-Temporally Stacked Signal Model

By vertically stacking $(M+1)$ temporally adjacent received vectors, where M indicates the extent that the temporal noise

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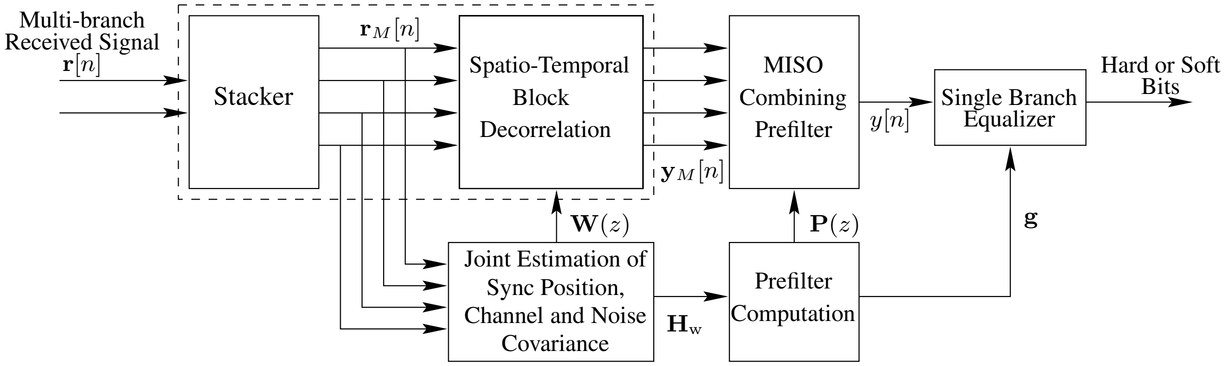

Figure 1: Receiver Structure for Interference Suppression via Spatio-Temporal Block Decorrelation

correlation is being accounted for, the signal model in (1) can be expressed as

$$\begin{aligned}\mathbf{r}_M[n+n_0] &\triangleq \text{vec}\left([\mathbf{r}[n],\mathbf{r}[n-1],\cdots \mathbf{r}[n-M]]\right)\\ &= \mathcal{T}(\mathbf{c})\mathbf{s}_{L+M}[n]+\mathbf{v}_M[n] \end{aligned}\tag{2}$$

for $n = L+M, L+M+1, \cdots, N-1$, where vec$(\cdot)$ denotes vectorization or stacking of columns of the argument,

$$\begin{aligned}\mathbf{s}_{L+M}[n] &= \left(s[n], s[n-1], \cdots, s[n-(L+M)]\right)^T,\\ \mathbf{v}_M[n] &= \text{vec}\left(\mathbf{v}[n],\mathbf{v}[n-1],\cdots,\mathbf{v}[n-M]\right),\\ \mathbf{c} &= \left(\mathbf{c}[0],\mathbf{c}[1],\cdots,\mathbf{c}[L]\right),\end{aligned}$$

and $\mathcal{T}(\mathbf{c})$ denotes a block Toeplitz matrix of size $(M+1)n_r \times (L+M+1)$ with $[\mathbf{c}, \mathbf{0}]$ as the first n_r rows. In matrix form, (2) can be expressed as

$$\mathbf{R}_M(n_0) = \mathcal{T}(\mathbf{c})\mathbf{S}_{L+M} + \mathbf{V}_M \tag{3}$$

where

$$\begin{aligned}\mathbf{R}_M(n_0) &= \left(\mathbf{r}_M[L+M+n_0],\cdots,\mathbf{r}_M[N+n_0-1]\right),\\ \mathbf{S}_{L+M} &= \left(\mathbf{s}_{L+M}[L+M],\cdots,\mathbf{s}_{L+M}[N-1]\right),\\ \mathbf{V}_M &= \left(\mathbf{v}_M[L+M],\cdots,\mathbf{v}_M[N-1]\right).\end{aligned}$$

III. Spatio-Temporal Decorrelation

In this section, we consider different methods of exploiting the spatio-temporal correlation of the noise process $\{\mathbf{v}[n]\}$ to suppress interference.

A. Decorrelation based on VAR Noise Model

As proposed in [5], one approach to exploit the spatio-temporal correlation of $\{\mathbf{v}[n]\}$ is to model it as a VAR Gaussian process:

$$\mathbf{v}[n] = \sum_{m=1}^{M}\mathbf{A}[m]\mathbf{v}[n-m] + \mathbf{e}[n] = \mathbf{A}\mathbf{v}_M[n] + \mathbf{e}[n], \tag{4}$$

where $\mathbf{A} \triangleq [\mathbf{A}[1], \mathbf{A}[2], \cdots, \mathbf{A}[M]]$ denotes the VAR coefficients, and $\{\mathbf{e}[n]\}$ denotes a zero-mean, temporally white, stationary Gaussian vector process with a spatial covariance matrix $\mathbf{Q} \triangleq E[\mathbf{e}[n]\mathbf{e}[n]^H]$. Based on (4), interference cancellation can be achieved by filtering the received signal $\mathbf{r}[n+n_0]$ using an $(M+1)$-tap whitening filter, denoted by $\mathbf{W}_\text{A} \triangleq (\mathbf{W}_\text{A}[0], \mathbf{W}_\text{A}[1], \cdots, \mathbf{W}_\text{A}[M])$, to obtain a whitened received signal given by

$$\mathbf{y}_\text{A}[n] \triangleq \sum_{m=0}^{M}\mathbf{W}_\text{A}[m]\mathbf{r}[n+n_0] = \mathbf{W}_\text{A}\mathbf{r}_M[n+n_0]$$

which contains a smaller contribution from the noise/interference component than $\mathbf{r}[n]$. The whitening filter taps $\mathbf{W}_\text{A}$ are related to $\mathbf{A}$ and $\mathbf{Q}$ by

$$\mathbf{W}_\text{A} = \mathbf{Q}^{-1/2}[\mathbf{I}_{n_r}, -\mathbf{A}], \tag{5}$$

where $\mathbf{Q}^{-1/2}$ denotes a square root of $\mathbf{Q}^{-1}$ such that $\mathbf{Q}^{-1} = \mathbf{Q}^{-H/2}\mathbf{Q}^{-1/2}$. Estimates of $\mathbf{A}$ and $\mathbf{Q}$ can be obtained by solving the corresponding Yule-Walker equations of the VAR process, as suggested in [6], using the efficient Whittle-Wiggins-Robinson (WWR) algorithm, or, alternatively, by solving a generalized least-squares problem, as described in [5][9][10]. In any case, each whitening filter tap $\mathbf{W}_\text{A}[m]$ is an $n_r \times n_r$ matrix, and the number of branches in $\mathbf{y}_\text{A}[n]$ is n_r, independent of the model order M.

B. Sliding Block Decorrelation

In this paper, an alternative approach is taken where we treat the individual branches of the stacked received signal $\mathbf{r}_M[n+n_0]$ as if they were received from different antennas and apply conventional technqiues of spatial decorrelation, cf. [3], to decorrelate the spatio-temporally stacked noise vector $\mathbf{v}_M[n]$. Specifically, based on the covariance matrix $\mathbf{\Lambda}_M \triangleq E\left[\mathbf{v}_M[n]\mathbf{v}_M[n]^H\right]$ of $\mathbf{v}_M[n]$, we compute a block decorrelation matrix $\mathbf{W}$ that satisfies $\mathbf{W}^H\mathbf{W} = \mathbf{\Lambda}_M^{-1}$, using any matrix decomposition method (e.g. the Cholesky decomposition), and apply it to the stacked received signal $\mathbf{r}_M[n+n_0]$ to suppress the underlying noise component $\mathbf{v}_M[n]$. This sliding block decorrelation operation can also be implemented as a whitening filtering operation on the original received signal $\mathbf{r}[n+n_0]$. The resulting signal $\mathbf{y}_M[n]$ is given by

$$\mathbf{y}_M[n] \triangleq \mathbf{W}\,\mathbf{r}_M[n+n_0] = \sum_{m=0}^{M}\mathbf{W}[m]\mathbf{r}[n+n_0-m], \tag{6}$$

where $\{\mathbf{W}[m]\}_{m=1}^{M}$ denotes the whitening filter taps that satisfy $\mathbf{W} = (\mathbf{W}[0], \mathbf{W}[1], \cdots, \mathbf{W}[M])$. We refer to the matrix $\mathbf{W}$ as the spatio-temporal block decorrelation (STBD) matrix and the corresponding whitening filter as the STBD filter, whose z-transform is given by $\mathbf{W}(z) = \sum_{m=0}^{M}\mathbf{W}[m]z^{-m}$. Unlike $\mathbf{W}_\text{A}[m]$, the matrix tap $\mathbf{W}[m]$ has a dimension of $Mn_r \times n_r$ instead of $n_r \times n_r$. Therefore, the number of branches in the whitened received signal $\mathbf{y}_M[n]$ varies with the model order M.

If both $\mathbf{c}$ and n_0 are known, $\mathbf{\Lambda}_M$ can be estimated as

$$\hat{\mathbf{\Lambda}}_M(\mathbf{c}, n_0) = (\mathbf{R}_M(n_0) - \mathcal{T}(\mathbf{c})\mathbf{S}_{L+M})(\mathbf{R}_M(n_0) - \mathcal{T}(\mathbf{c})\mathbf{S}_{L+M})^H. \quad (7)$$

The STBD matrix can then be derived from $\hat{\mathbf{\Lambda}}_M(\mathbf{c}, n_0)$. In practice, however, both $\mathbf{c}$ and n_0 are unknown and need to be estimated along with $\mathbf{\Lambda}_M$.

IV. Joint Synchronization and Estimation

In this section, we consider joint synchronization and estimation of the channel and the noise covariance matrix. Specifically, based on the stacked signal model (3), we want to compute, for a fixed M, a joint estimate of n_0, $\mathbf{c}$ and Λ_M that minimizes the negative log-likelihood function given by

$$L(\mathbf{c}, \Lambda_M, n_0) \triangleq \mathrm{tr}\{(\mathbf{R}_M(n_0) - \mathcal{T}(\mathbf{c})\mathbf{S}_{L+M})^H \mathbf{\Lambda}_M^{-1}(\mathbf{R}_M(n_0) - \mathcal{T}(\mathbf{c})\mathbf{S}_{L+M})\} + (N - L - M)\log\det\mathbf{\Lambda}_M. \quad (8)$$

where $\mathrm{tr}\{\}$ and $\det\{\}$ denote the trace and the determinant of a matrix, respectively. In other words, we like to compute

$$\left(\hat{\mathbf{c}}, \hat{\mathbf{\Lambda}}_M, \hat{n}_0\right) = \arg\max_{(\mathbf{c},\mathbf{\Lambda},n_0)} L(\mathbf{c}, \Lambda_M, n_0). \quad (9)$$

Note that an implicit assumption behind the use of the log-likelihood function given in (8) is that the stacked noise vectors $\{\mathbf{v}_M[n]\}$ are temporally uncorrelated, which is not completely valid since $\mathbf{v}_M[n]$ and $\mathbf{v}_M[n-1]$ share M common noise samples. Nevertheless, one can view (8) as an approximation to the true likelihood function, and, as shown later, the joint estimates derived based on this approximate likelihood function perform quite well in practice.

Owing to the block Toeplitz structure of the matrix $\mathcal{T}(\mathbf{c})$, closed-form expressions for the solution of (9) are difficult, if not impossible, to obtained. In the following, we consider two methods of computing approximate solutions of (9).

A. Iterative Method

Approximate solutions of (9) can be obtained by iteratively optimizing one of the three quantities in $(\mathbf{c}, \Lambda_M, n_0)$ while holding the others fixed. Two different iterative algorithms that correspond to two possible cyclic orders of iterations, namely $n_0 \to \mathbf{\Lambda}_M \to \mathbf{c}$ and $n_0 \to \mathbf{c} \to \mathbf{\Lambda}_M$, can be derived. Due to space limitation, we will describe only the first algorithm, which gives better performance in our simulations.

Let $(\hat{\mathbf{c}}^{(i)}, \hat{\mathbf{\Lambda}}_M^{(i)}, \hat{n}_0^{(i)})$ denote the joint estimate at the i-th iteration. The main steps of the algorithm are outlined below.

Iterative Algorithm for Joint Sync. and Estimation

1. Initialize $\hat{\mathbf{c}}^{(0)}$, and set iteration index $i = 0$
2. Update estimate of synchronization position as
$$\hat{n}_0^{(i+1)} = \arg\min_{n_0\in\Pi} \det\hat{\mathbf{\Lambda}}_M(\hat{\mathbf{c}}^{(i)}, n_0) \quad (10)$$
where $\hat{\mathbf{\Lambda}}_M(\hat{\mathbf{c}}^{(i)}, n_0)$ is given in (7).
3. Update estimate of noise covariance matrix as
$$\hat{\mathbf{\Lambda}}_M^{(i+1)} = \hat{\mathbf{\Lambda}}_M(\hat{\mathbf{c}}^{(i)}, \hat{n}_0^{(i+1)}) \quad (11)$$
4. Compute STBD matrix $\mathbf{W}^{(i)}$ such that $(\mathbf{W}^{(i)})^H\mathbf{W}^{(i)} = (\hat{\mathbf{\Lambda}}_M^{(i+1)})^{-1}$.
5. Generate whitened received samples $\mathbf{y}_M[n]$ and whitened training symbols $\mathbf{t}[n]$ as
$$\begin{aligned} \mathbf{y}_M[n] &= \mathbf{W}^{(i)}\mathbf{r}_M[n + \hat{n}_0^{(i+1)}] \\ \mathbf{t}[n] &= \mathbf{W}^{(i)}\left(\mathbf{S}_{L,M}[n]^T \otimes \mathbf{I}_{n_r}\right) \end{aligned}$$
where $\mathbf{S}_{L,M}[n] \triangleq (\mathbf{s}_L[n], \mathbf{s}_L[n-1], \cdots, \mathbf{s}_L[n-M])$ for $n = L+M, \cdots, N-1$, and $\otimes$ denotes the Kronecker product.
6. Update channel estimate as
$$\mathrm{vec}(\hat{\mathbf{c}}^{(i+1)}) = \left(\sum_{n=L+M}^{N-1} \mathbf{t}[n]^H\mathbf{t}[n]\right)^{-1}\left(\sum_{n=L+M}^{N-1} \mathbf{t}[n]^H\mathbf{y}_M[n]\right)$$
7. Increment i and return to Step 2 until certain stopping criteria is satisfied.

The initial channel estimate $\hat{\mathbf{c}}^{(0)}$ may be computed over the training sequence using conventional least-squares estimation techniques. If an initial estimate of the noise covariance matrix $\hat{\mathbf{\Lambda}}_M^{(0)}$ is available instead of $\hat{\mathbf{c}}^{(0)}$, the algorithm can begin with Step 4 and proceed to Step 6 to update $\hat{\mathbf{c}}^{(i+1)}$ before updating $\hat{n_0}^{(i+1)}$ and $\hat{\mathbf{\Lambda}}_M^{(i+1)}$ in subsequent iterations.

B. Direct Method

Another approach we considered is to neglect the block Toeplitz structure of $\mathcal{T}(\mathbf{c})$ and directly estimate the unstructured channel $\mathbf{H} \triangleq \mathcal{T}(\mathbf{c})$, instead of $\mathbf{c}$. Considering the following modified form of (8):

$$\tilde{L}(\mathbf{H}, \Lambda_M, n_0) \triangleq \mathrm{tr}\left\{(\mathbf{R}_M(n_0) - \mathbf{H}\mathbf{S}_{L+M})^H\mathbf{\Lambda}_M^{-1}(\mathbf{R}_M(n_0) - \mathbf{H}\mathbf{S}_{L+M})\right\} + (N - L - M)\log\det\mathbf{\Lambda}_M. \quad (12)$$

The joint estimate of $(\mathbf{H}, \mathbf{\Lambda}, n_0)$ that minimizes $\tilde{L}(\mathbf{H}, \Lambda_M, n_0)$ can be expressed in closed form as

$$\hat{\mathbf{H}} = \mathbf{R}_M(\hat{n}_0)\mathbf{S}_{L+M}^H\mathbf{\Sigma}, \quad (13)$$

$$\hat{\mathbf{\Lambda}}_M = \hat{\mathbf{\Lambda}}_M(\hat{n_0}), \quad \text{and} \quad \hat{n}_0 = \arg\min_{n_0\in\Pi}\det\hat{\mathbf{\Lambda}}_M(n_0)$$

where $\mathbf{\Sigma} \triangleq \left(\mathbf{S}_{L+M}\mathbf{S}_{L+M}^H\right)^{-1}$ and

$$\hat{\mathbf{\Lambda}}_M(n_0) \triangleq \mathbf{R}_M(n_0)\mathbf{R}_M(n_0)^H - \mathbf{R}_M(n_0)\mathbf{S}_{L+M}^H\mathbf{\Sigma}\,\mathbf{S}_{L+M}\mathbf{R}_M(n_0)^H. \quad (14)$$

The block correlation marix $\mathbf{W}$ can be obtained as a Cholesky factor of the inverse of $\hat{\mathbf{\Lambda}}_M$.

A few noteworthy remarks can be made regarding the computation of this joint estimate. Since the matrix $\mathbf{\Sigma}$ depends only on the training sequence but not on the received signal, it can be pre-computed and stored in the receiver's memory. Moreover, when Π consists of consecutive synchronization positions, the two key quantities, namely $\mathbf{R}_M(n_0)\mathbf{S}_M^H$ and

$\mathbf{R}_M(n_0)\mathbf{R}_M(n_0)^H$, involved in the computation of $\mathbf{\Lambda}_M(n_0)$ as described in (14) can be computed efficiently for all $n_0 \in \Pi$.

Since this direct method does not exploit the Toeplitz structure within $\mathbf{H}$, the number of parameters being estimated is larger than needed, which can lead to a higher error variance in each of estimated parameters. However, the resulting estimation algorithm has relatively low complexity, and, as shown later, the interference cancellation performance is comparable to that of the iterative approach.

V. MISO Combining Prefilter

As mentioned above, the output signal $\mathbf{y}_M[n]$ of the STBD filter may have more branches than the original received signal $\mathbf{r}[n]$. To detect the transmitted symbol sequence based on $\mathbf{y}_M[n]$, a multi-branch Viterbi (or vector-Viterbi [23]) equalizer with a Euclidean metric given by

$$M_1(\{s[n]\}) \triangleq \sum_n \left\| \mathbf{y}_M[n] - \hat{\mathbf{H}}_{\mathrm{w}} \mathbf{s}_{L+M}[n] \right\|^2, \tag{15}$$

where $\hat{\mathbf{H}}_{\mathrm{w}} = \mathbf{W}\hat{\mathbf{H}}$, can be used. However, the computational complexity of this equalizer increases with the model order M. Alternatively, to minimize complexity, we combine all branches of $\mathbf{y}_M[n]$ into a single branch using a combining prefilter and then perform symbol sequence detection based on the output of the prefilter, denoted by $y[n]$, using a single-branch (or scalar) Viterbi equalizer with a Euclidean metric given by

$$M_2(\{s[n]\}) \triangleq \sum_n \left| y[n] - \mathbf{g}\, \mathbf{s}_{L+M}[n] \right|^2, \tag{16}$$

where $\mathbf{g} \triangleq (g[0], g[1], \cdots, g[L+M])$ denotes a causal, minimum-phase equivalent channel response with $L+M+1$ taps. The z-transform of the combining prefilter is given by

$$\mathbf{P}(z) = \frac{\hat{\mathbf{H}}^{\dagger}_{\mathrm{w}}(z^{-1})}{G^{\dagger}(z^{-1})} \tag{17}$$

where † denotes the conjugation of coefficients without affecting the variable z or z^{-1}, $\hat{\mathbf{H}}_{\mathrm{w}}(z) \triangleq \hat{\mathbf{H}}_{\mathrm{w}}\mathbf{z}$ denotes the z-transform of the whitened channel, $\mathbf{z} = (1, z^{-1}, \cdots, z^{-(L+M)})^T$, and $G(z)$ denotes the z-transform of $g[n]$, which satisfies

$$G^{\dagger}(z^{-1})G(z) = \hat{\mathbf{H}}^{\dagger}_{\mathrm{w}}(z^{-1})\hat{\mathbf{H}}_{\mathrm{w}}(z). \tag{18}$$

The prefilter $\mathbf{P}(z)$ can be viewed as a concatenation of a multi-dimensional matched filter [21][23][24] $\hat{\mathbf{H}}^{\dagger}_{\mathrm{w}}(z^{-1})$, and a "phase-minimizing" filter $1/G^*(z^{-1})$. It is similar to the multiple whitened matched filter described in [21] except that the resulting equivalent channel response $g[n]$ is minimum phase instead of maximum phase, and is particularly suited for use with a reduced-complexity, decision-feefback-type, single-branch equalizer, cf. [19][20]. The prefilter $\mathbf{P}(z)$ preserves the "whiteness" of the noise in the sense that if the underlying noise component of its multi-branch input signal is uncorrelated both spatially and temporally, then the noise component at its single-branch output is also uncorrelated (temporally). Since $G(z)$ is minimum phase, $1/G^*(z^{-1})$ and hence $\mathbf{P}(z)$ can only be implemented stably with an anti-causal impulse response.

Note that when the symbol sequence is infinitely long, the difference between the two equalizer metrics shown in (15) and (16) is independent of the symbol sequence $\{s[n]\}$. More precisely, in this case, it can be shown that

$$M_1(\{s[n]\}) = M_2(\{s[n]\}) + \sum_n \left[\|\mathbf{y}_M\|^2 - |y[n]|^2 \right]. \tag{19}$$

Hence, they are equivalent in the sense that the same hypothesized symbol sequence will be detected, regardless of the underlying noise/interference statistics, if either one of the two metrics is used with an optimal full-search equalizer [18].

VI. Simulation Results

In this section we compare different methods of exploiting spatio-temporal correlation for single-antenna interference cancellation (SAIC) in GSM mobile terminals [8]. For SAIC, we split the I and Q components of a two-times oversampled received signal into four symbol-rate, real-valued spatial branches (i.e. $n_r = 4$). The adopted interference models are based on those of DTS-1 and DTS-2 interference scenarios, as described in [8], except that actual (randomly selected) GSM training sequences are used for the interferers. The DTS-1 interference model has only one co-channel interferer, while the DTS-2 model consists of two co-channel interferers and an adjacent-channel inteferer, with relative power levels of 0 dB, -10 dB, and 3 dB, respectively, along with some white Gaussian background noise. The typical urban (TU) channel model at 3 km/hr with ideal frequency hopping is assumed.

Figure 2 shows the simulated performance of STBD-based methods with order $M = 1$ in terms of modem bit error rate (BER) in the presence of a single dominant interferer. For comparison, we also show the performance of two VAR-based methods with the same order $M = 1$, one derived from the solution of the Yule-Waler equations, as described in [6] while the other dervied from the solution of a generalized least-squares problem, as described in [5][9][10]. The VAR-based methods preserves the orginal number of (i.e. four) signal branches after spatio-temporal decorrelation, while the STBD-methods produce twice as many (i.e. eight) branches. In either case, all

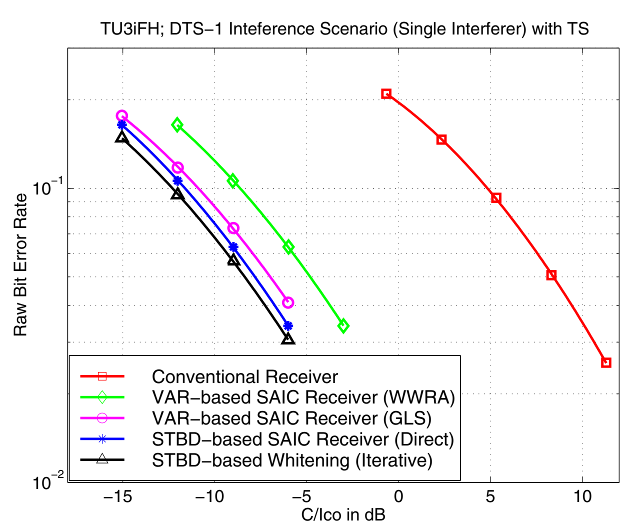

Figure 2: Receiver Performance in DTS-1 Scenario

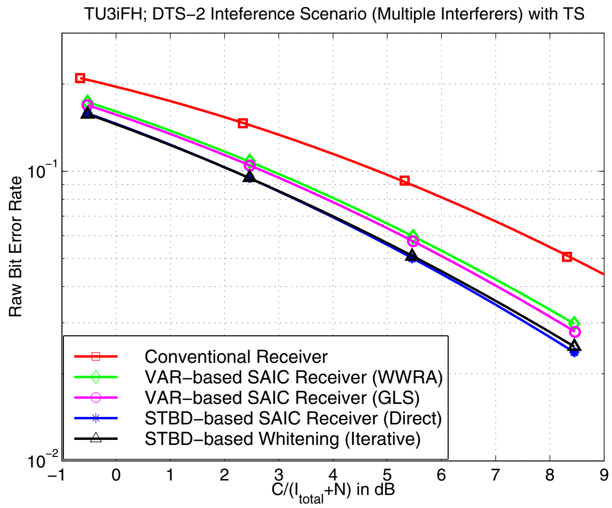

Figure 3: Receiver Performance in DTS-2 Scenario

branches are combined into a single branch using the MISO prefilter before equalization. As shown in the figure, the direct STBD-based method provides a gain of about 17 dB over a conventional non-SAIC receiver and outperforms the two VAR-based methods by about 1 dB and 3 dB, respectively, at 10% BER. Morever, additional gain of about 1 dB can be obtained by the iterative STBD-based method with an initial estimate of the STBD matrix generated by the direct method. With such an initial estiamte, only one iteration suffices to attain most of the performance gain, and further iterations (not shown) do not seem to enhance performance.

Figure 3 shows the performance of STBD-based methods in the presence of multiple (two co-channel and one adjacent-channel) interferers and some background noise as in the DTS-2 test scenarios [8]. As shown, STBD-based methods outperform VAR-based methods by about 0.7 dB at 10% BER, which is significant for such a test scenario. The iterative STBD-based method does not provide noticable performance gain over the direct STBD-based method in this case. Thus, the direct method is preferable in practice, since it has lower implementation complexity than the iterative method.

VII. Conclusions

An effective method of suppressing interference based on block decorrelation of spatially and temporally stacked signal vectors has been proposed. Two algorithms for jointly estimating the block decorrelation matrix, the channel response and the synchronization position were presented. A multi-input-single-output prefilter that enables the proposed interference-suppression method to work with conventional single-branch equalizers was also presented. Simulation results have shown that the proposed method consistently outperforms those interference cancellation methods based on VAR modeling of the interference in various test scenarios.

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