ORTHOGONALLY-ANCHORED ADAPTIVE CDMA INTERFERENCE REJECTION IN SPACE-TIME RAKE PROCESSING

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ABSTRACT

The paper presents an orthogonally-anchored adaptive linear interference rejection technique in space-time rake processing. With the use of a super short training sequence, the initial space-time adaptive filtering vector composed of two mutually orthogonal components is calculated by using a projection-based filter optimization technique. The adaptive filter optimization based on the pre-optimized initial weight vector is implemented to efficiently suppress the multiuser access interference in the filtering procedure. In contrast to the blind space-time rake processing, the computation efficiency exhibited in the suggested approach is achieved by implementing the linear optimization for the filtering vector in reduced-dimensional (or full-dimensional) space-time complex vector spaces instead of using eigenvector-based processing, in which the optimization of the filtering vector in full-dimensional data vector space is required.

Key words : Space-time filtering, Adaptive interference rejection, DS/CDMA

1. INTRODUCTION

In DS/CDMA space-time (ST) rake processing, the existing blind techniques are often based on two operations, the MMSE (MVDR) optimization and eigenvector estimation [1]-[3]. Aside from the heavy computational requirements, a large number of samples are required in the blind adaptive algorithms to approach the performances of their ideal counterparts [4]. To develop computationally efficient ST rake processing approaches, therefore, will be of great significance for DS/CDMA mobile communication systems.

Recently, several linearly constrained adaptive algorithms [5] [6] are suggested for blind linear interference suppression in DS/CDMA communications. In these time-only processing, an unconstrained optimization structure, the generalized interference canceller (GIC) structure [7], is commonly used to solve the constrained problems. In the GIC structure as shown in Figure 1, the upper path filtering vector $\boldsymbol{w}_q$ is designated as the code sequence of the desired user, while the lower path adaptive portion is designed to include a blocking matrix $\boldsymbol{G}$ and an adaptive vector $\boldsymbol{w}_a$. With linear constraints, $\boldsymbol{G}$ is chosen to make the adaptive component $\boldsymbol{G}\boldsymbol{w}_a$ orthogonal to the quiescent vector $\boldsymbol{w}_q$, so that the desired signal can be extracted without distortion regardless of how the algorithm updates the weight vector [7]. When one attempts to extend these blind time-only detection schemes directly to the antenna array based filtering, it seems that the eigenvector techniques should be employed to obtain the quiescent vector $\boldsymbol{w}_q$ as well as the blocking matrix $\boldsymbol{G}$. Therefore, the computational complexity is increased.

In contrast to the blind processing, the auxiliary vector (AV) based ST rake filtering approach was recently proposed in [8] to exploit the computational efficiency by using the training sequence and reduced-dimensional filter optimization technique. Unfortunately, the filter vector in [8] is based on the ST data vector of dimension $M(L + L_c - 1)$, where M, L and L_c denote the number of antennas, the spreading factor and the maximum delay of all the dominant multipaths, respectively. The filter optimization is conducted with respect to q bit-level ST samples obtaining from the received training sequence of length q. In order to get a statistical efficient filtering vector, the value of q must be several times the value of $M(L + L_c - 1)$. This is absolutely impossible in DS/CDMA communications, where super short training sequences are expected.

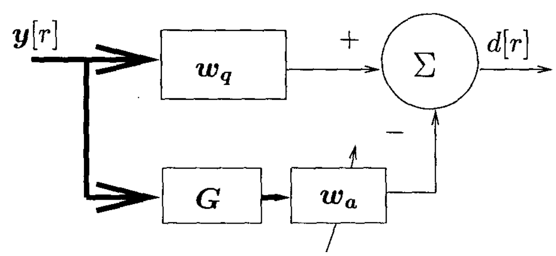

Figure 1: The generalized interference canceller

Borrowing the idea of reduced-dimension optimization from [8], we present a training sequence based adaptive linear interference cancellation scheme in this paper. We suggest a different ST data vector structure in contrast to that used in [8] for ST rake processing. The structure exploits the large value of DS/CDMA processing gain and facilitates the use of super short training sequences in DS/CDMA systems. In the scheme, the projection based linear optimization in reduced-dimensional (or full- dimensional) ST complex vector subspaces is employed to get an initial adaptation weight, and the adaptive optimization for the filter with the GIC structure is conducted to efficiently suppress MAI in adaptive ST filtering.

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2. SIGNAL MODEL

Consider an asynchronous DS/CDMA system with K users. After periodic spreading and BPSK modulation, the resulting signals are simultaneously transmitted over additive white Gaussian noise (AWGN) multipath channels. We assume that each user has N dominant multipaths and the receiver is chip-synchronized to the desired user. With the narrow-band signal model, the output of the antenna array after carrier demodulation can be written as

$$\boldsymbol{x}(t) = \sum_{k=0}^{K-1}\sum_{n=0}^{N-1}\sum_{r} d_k(r)\boldsymbol{h}_{k,n}(t - rT_c) + \boldsymbol{n}(t) \quad (1)$$

where

$$d_k(r) = b_k(j)c_k(r - jL), \quad j = \lfloor \frac{r}{L} \rfloor, \quad (2)$$

$$\boldsymbol{h}_{k,n}(t) = \rho_{k,n}\boldsymbol{a}_{k,n}\psi(t - \tau_{k,n}),\ \boldsymbol{h}_{k,n}(t) \in \mathbb{C}^{M}, \quad (3)$$

with

- $d_k(r)$: the chip sequence of the kth user after spreading each data symbol $b_k(j) \in \{1, -1\}$ by using a periodic PN sequence $c_k(l) \in \{1, -1\}, l = 0, \cdots, L-1$;
- $\boldsymbol{h}_{k,n}$: the impulse response of the nth multipath channel from the kth user to the antenna array;
- $\boldsymbol{a}_{k,n}$: the array response vector corresponding to the nth multipath of the kth user;
- $\psi(t)$ and T_c: the pulse shaping function and the chip interval ;
- $\rho_{k,n}$ and $\tau_{k,n}$: the complex amplitude and delay for the nth multipath of the kth user.

For an antenna array with M sensors, qL array data vector $\boldsymbol{x}(r)$, $r = 0, \cdots, qL-1$, of dimension M can be obtained by directly sampling q data bits at chip rate (or by applying chip-matched filtering followed chip-rate sampling to q data bits).

For ST rake processing, the ST data vector structure is formed by extending the space-only data vector from dimension M to an ML_c-dimensional ST data vector $\boldsymbol{y}$(r), where L_c denotes the maximum delay (in chip duration) of all the dominant multipaths, to capture the diversities offered by the multipath channels, *i.e.*,

$$\begin{aligned}\boldsymbol{y}(r) &= [\boldsymbol{x}^H(r)\, \boldsymbol{x}^H(r+1) \cdots \boldsymbol{x}^H(r + L_c - 1)]^H, \\ &\quad r = 0, \cdots, qL-1. \quad (4)\end{aligned}$$

The corresponding ST covariance matrix $\boldsymbol{R} \in \mathbb{C}^{ML_c \times ML_c}$ can be estimated by

$$\hat{\boldsymbol{R}} = \frac{1}{qL}\sum_{r=0}^{qL-1} \boldsymbol{y}(r)\boldsymbol{y}^H(r). \quad (5)$$

3. PROJECTION-BASED INITIAL WEIGHT OPTIMIZATION

For training sequence based ST processing, we apply the Maximal Ratio Combining (MRC) approach to obtain a basic filtering vector corresponding to the kth user.

$$\boldsymbol{w}_q = \frac{1}{qL}\sum_{r=0}^{qL-1} \boldsymbol{y}(r)d_k(r), \quad \boldsymbol{w}_q \in \mathbb{C}^{ML_c}. \quad (6)$$

For the (qL) ST inputs $\{\boldsymbol{y}(r), r = 0, \cdots, qL-1\}$ corresponding to q training bits, the outputs of the filter $\bar{\boldsymbol{w}}_q$ can be written as

$$\hat{d}(r) = \bar{\boldsymbol{w}}_q^H \boldsymbol{y}(r),\ \ r = 0, \cdots, qL-1. \quad (7)$$

where $^-$ denotes the normalization operation. Let us denote by $d(j,l)$ the output of $\bar{\boldsymbol{w}}_q$ corresponding to the lth chip of the jth bit. After despreading $d(j,l)$ to $d_b(j,l)$, the bit decision can be made by

$$\hat{b}(j) = sgn(Re\{\sum_{l=1}^{L} d_b(j,l)\}). \quad (8)$$

Using the filter outputs $\hat{d}(r)$, the reconstruction of the filtering vector $\boldsymbol{w}_q$ can be implemented by

$$\hat{\boldsymbol{w}}_q = \frac{1}{qL}\sum_{r=0}^{qL-1} \boldsymbol{y}(r)\hat{d}^*(r). \quad (9)$$

In order to examine the quality of the filtering vector $\bar{\boldsymbol{w}}_q$, let us consider the projection $\boldsymbol{g}_1$ of vector $\hat{\boldsymbol{w}}_q$ onto the ST subspace orthogonal to the basic filtering vector $\boldsymbol{w}_q$, *i.e.*,

$$\boldsymbol{g}_1 = (\boldsymbol{I} - \bar{\boldsymbol{w}}_q\bar{\boldsymbol{w}}_q^H)\hat{\boldsymbol{w}}_q, \quad (10)$$

where $\boldsymbol{I}$ is the identity matrix of size $ML_c \times ML_c$. If the length of the orthogonal projection $\boldsymbol{g}_1$ is zero, the vector $\bar{\boldsymbol{w}}_q$ will be a perfect or desired filtering vector for filtering the training data. It means that all the MAI vectors are orthogonal to $\boldsymbol{w}_q$, and the filter can completely eliminate the ST MAIs in training data. When $||\boldsymbol{g}_1||_2 > 0$, the filtering vector $\bar{\boldsymbol{w}}_q$ can not reject all the ST MAIs. In this case, a new ST filtering vector can be formed by linearly combining $\bar{\boldsymbol{w}}_q$ and $\bar{\boldsymbol{g}}_1$ as

$$\boldsymbol{w}_1 = \bar{\boldsymbol{w}}_q - \mu_1\bar{\boldsymbol{g}}_1. \quad (11)$$

The scalar μ_1 is chosen to minimize the mean output energy (Maximize the mean output SINR)

$$MOE = E\{(< \boldsymbol{y}(r), \boldsymbol{w}_1 >)^2\},\ \ r = 0, \cdots, qL-1. \quad (12)$$

It is easy to obtain $\mu_1 = \frac{\bar{\boldsymbol{g}}_1^H\hat{\boldsymbol{R}}\bar{\boldsymbol{w}}_q}{\bar{\boldsymbol{g}}_1^H\hat{\boldsymbol{R}}\bar{\boldsymbol{g}}_1}$. The choice of μ_1 will try to make the $\boldsymbol{w}_1$ as close as possible to the perfect filtering vector in the ST subspace spanned by $\bar{\boldsymbol{w}}_q$ and $\bar{\boldsymbol{g}}_1$.

Applying $\boldsymbol{w}_1$ to filtering the training data again, we can use the outputs $\hat{d}_1(r)$ of the filter $\boldsymbol{w}_1$ to reconstruct the MRC filtering vector as

$$\hat{\boldsymbol{w}}_1 = \frac{1}{qL}\sum_{r=0}^{qL-1} \boldsymbol{y}(r)\hat{d}_1^*(r). \quad (13)$$

where

$$\hat{d}_1(r) = \boldsymbol{w}_1^H\boldsymbol{y}(r),\ \ r = 0, \cdots, qL-1. \quad (14)$$

Let us examine the orthogonal projection of $\hat{\boldsymbol{w}}_1$ onto the ST subspace $Span\{\bar{\boldsymbol{w}}_q, \bar{\boldsymbol{g}}_1\}$,

$$\boldsymbol{g}_2 = (\boldsymbol{I} - [\bar{\boldsymbol{w}}_q, \bar{\boldsymbol{g}}_1][\bar{\boldsymbol{w}}_q, \bar{\boldsymbol{g}}_1]^H)\hat{\boldsymbol{w}}_1. \quad (15)$$

Again, if $||\boldsymbol{g}_2||_2 = 0$, the filter $\boldsymbol{w}_1$ can completely eliminate the MAIs in the training data. For nonzero $||\boldsymbol{g}_2||_2$, a new filtering vector lying in $Span\{\bar{\boldsymbol{w}}_q, \bar{\boldsymbol{g}}_1, \bar{\boldsymbol{g}}_2\}$ can be constructed as

$$\boldsymbol{w}_2 = \boldsymbol{w}_1 - \mu_2\bar{\boldsymbol{g}}_2. \quad (16)$$

The scalar $\mu_2 = \frac{\bar{g}_2^H R w_1}{\bar{g}_2^H R \bar{g}_2}$ is chosen to minimize the mean output energy $E\{(< y(r), w_2 >)^2\}$ of w_2.

We can form at most $ML_c - 1$ projection vector $g_i, i = 1, \cdots, ML_c - 1$, by repeating the above procedure to get an *optimum* filtering vector in the full-dimensional ST space $Span\{\bar{w}_q, \bar{g}_1, \cdots, \bar{g}_{ML_c-1}\}$, *i.e.*,

$$w_o = \bar{w}_q - G\mu, \tag{17}$$

where

$$\begin{aligned} G &= [\bar{g}_1, \cdots, \bar{g}_{ML_c-1}], \\ \mu &= [\mu_1 \ \cdots \ \mu_{ML_c-1}]^T. \end{aligned} \tag{18}$$

In order to lower the computational complexity in full-dimension optimization, the optimization can be conducted in a reduced- dimensional space by constructing the matrix G (as well as the corresponding vector μ) as $G = [\bar{g}_1, \cdots, \bar{g}_i]$ for any $0 < i < ML_c - 1$.

4. ADAPTIVE ST INTERFERENCE CANCELLATION

For a filter w with the *canonical representation* (The filtering vector is composed of two components each orthogonal to another) [9], the fact that minimizing the mean output energy of the filter is equivalent to minimizing the mean square error [9] motivates us to consider the following filter optimization in the sense of minimizing MOE

$$\min_{w} w^H R w, \tag{19}$$

with

$$w = \bar{w}_q - G w_a, \tag{20}$$

where w is an $ML_c \times 1$ filtering vector, R denotes the covariance matrix of the input data vector of the filter. The vector w_q and matrix G are obtained by using approaches shown in last section.

For the adaptive vector w_a, the stochastic gradient optimization technique can be used to yield the adaptation equation as

$$w_a(r+1) = w_a(r) + \eta d^*(r) G^H y(r), \tag{21}$$

where $y(r)$ and $d(r)(d(r) = w^H(r)y(r))$ represent the input and output of the filter w at time 'r', respectively, and η is a small step size. Obviously, the filtering vector w_o will be the initial weight vector $w(0)$ of w in Eqn. (20) by choosing $w_a(0) = \mu$.

Taking the resulting filtering vector w_o from the training-based optimization as the initial adaptive filtering vector will result in the following advantages in adaptive filtering:

- The orthogonality between $\bar{w}_q$ and $G\mu$ is directly introduced into the relation between the nonadaptive component and the adaptive component in the complete adaptive filtering vector w. Thereby, the signal cancellation phenomenon in the adaptive interference suppression procedure can be avoided.
- The initial adaptive weight from the training sequence based optimization will be of high quality, so that fast convergence in the adaptive filter optimization can be obtained and low bit error ratios (BER) already in the starting phase can be achieved.
- Without eigendecomposition, the linear optimization of the filtering vector in reduced-dimensional subspace can be commonly applied to the two optimization stages.

5. SIMULATION EXAMPLES

In the simulation examples, a linear array with $M = 5$ antennas uniformly spaced by half-wavelength is used to receive the DS/CDMA signals from $K = 6$ independent users. We assume that each user signal experiences $N = 4$ multipaths. All the multipaths for 6 users are uniformly distributed in $(-\frac{\pi}{2}, \frac{\pi}{2})$. The delay-line model is used to generate multipath for each user. The delay of the desired direct-signal is set to be 0, and the delays of the other 23 multipaths are uniformly distributed in $(0, 4T_c)$, hence $Lc = 4$. The INRs (in dB) of the 5 direct interference signals each corresponding to the shortest delay for an interference user are fixed at 0, 1, 3, 4.5, 7, respectively. The INRs of the 3 indirect multipaths for each interferer are uniformly distributed in $(0, 5)dB$ lower than the INR of the direct interferer. In each example, independent 200 AWGN channels are used for statistics.

In Figure 2, we examine the BER performances of filter w_q and w_1 for the ST data vector structure suggested in the paper (DS1 in figure) in comparison with that of the corresponding filters for the ST data vector structure (DS2 in figure) used in [8]. In this example, both the training sequence of length $q = 16$ and the $L = 32$ periodic spreading sequence for each user are randomly generated.

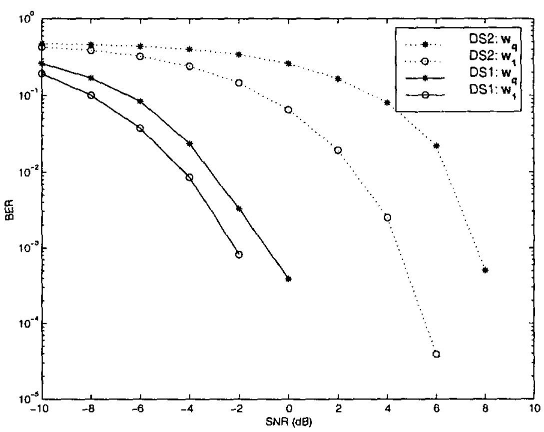

Figure 2: BER performances of different filters versus SNR.

The second example is given to show the advantages of the adaptive interference cancellation following the basic projection-based optimization of the filtering vector over the basic projection-based optimization. We first form the filter w_5 by using the training sequence. The weight vector w_5 is then used as the initial adaptive weight (nonadaptive component plus adaptive component) of the adaptive filter w. A small step size $\eta = 0.0001$ is used in adaptation. The BER performances of w_5 and w are given in Figure 3. For comparison, the performances of w_q, w_1 and the training-based MMSE filter are also given. In this example and next example, the 2-bit training sequence $[1, -1]$ and $L = 64$ periodic code sequence randomly generated for each user are used.

In Figure 4, the BER performances of different filters versus the near-far coefficient (NFC) are investigated. In this example, the SNR of the desired direct-signal is fixed at 10dB The INRs (dB) of the 5 direct interferers are set to be $[0, 1, 3, 4.5, 7] \times NFC$ with NFC changing from 0.5 to 5 with step 0.5. The SNRs(INRs)

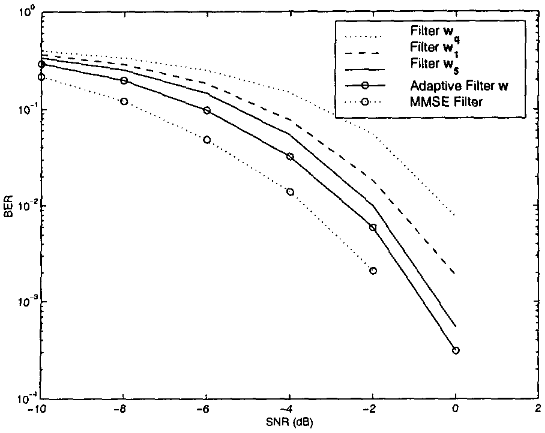

Figure 3: BER performances of different filters versus SNR.

of the 3 indirect multipaths for each user are uniformly distributed in $(0, 5)dB$ lower than the SNR(INR) of the direct signal. $\eta = 0.00001$ is used.

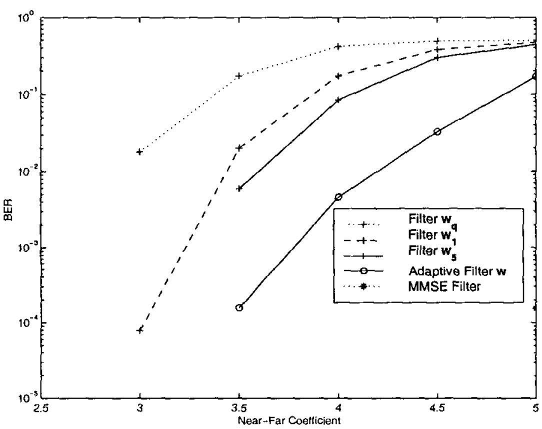

Figure 4: BER performances of different filters versus NFC.

6. CONCLUSIONS

The proposed linear interference suppression scheme exploits the use of super short training sequences with large spreading factors. In the scheme, the filtering vector optimization is implemented through first the projection based optimization then the adaptive optimization, so that more efficient MAI suppression in contrast to the basic AV technique can be achieved. Since the suggested filter optimization technique can be conducted in reduced-dimensional ST complex vector subspaces without any matrix inversion and eigendecomposition operation, the low computational costs are required in contrast to the general blind filtering technique. The suggested approach can be directly extended to other adaptive algorithms of the GIC structure.

7. REFERENCES

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