Blind Adaptive Multiuser Detection for the MC-CDMA Systems Using Orthogonalized Subspace Tracking

Imran Ali, Doug Nyun Kim, and Jong Soo Lim

In this paper, we study the performance of subspace-based multiuser detection techniques for multicarrier code-division multiple access (MC-CDMA) systems. We propose an improvement in the PASTd algorithm by cascading it with the classical Gram-Schmidt procedure to orthonormalize the eigenvectors after their sequential extraction. The tracking of signal subspace using this algorithm, which we call OPASTd, has a faster convergence as the eigenvectors are orthonormalized at each discrete time sample. This improved PASTd algorithm is then used to implement the subspace blind adaptive multiuser detection for MC-CDMA. We also show that, for multiuser detection, the complexity of the proposed scheme is lower than that of many other orthogonalization schemes found in the literature. Extensive simulation results are presented and discussed to demonstrate the performance of the proposed scheme.

Keywords: Subspace, multiuser detection, MC-CDMA, Gram-Schmidt procedure.

Manuscript received May 14, 2008; revised Feb. 06, 2009; accepted Feb. 18, 2009.

Imran Ali (phone: +92 334 6872276 email: imran_ali@comsats.edu.pk) was with the Department of Communication Engineering, Myongji University, Yongin, Gyeonggido, Rep. of Korea, and is now with Center for Advanced Studies in Telecommunications (CAST), COMSATS Institute of Information Technology, Islamabad, Pakistan.

Doug Nyun Kim (email: dnkim@mju.ac.kr) is with the Department of Communication Engineering, Myongji University, Yongin, Gyeonggido, Rep. of Korea.

Jong Soo Lim (email: ljten@etri.re.kr) is with Broadcasting & Telecommunications Convergence Research Laboratory, ETRI, Daejeon, Rep. of Korea.

I. Introduction

The ever-growing demand for higher data rates and greater mobility has attracted a huge interest from both industry and academia towards the design of more sophisticated networks. Multicarrier code-division multiple access (MC-CDMA) is a particularly promising technique for higher data-rate wireless communication systems [1] and is a potential candidate for future 4G cellular networks [2]. Like direct sequence (DS)-CDMA, however, MC-CDMA systems are inherently vulnerable to multiple access interference (MAI). Multiuser detection techniques are well known as effective measures against MAI. In this regard, blind adaptive detection methods are very attractive because they require minimal information processing for the detection of signal in nonstationary environments [3]-[5]. Wang and Poor [4] derived linear multiuser detectors based on signal subspace parameters and showed that, if computed from precisely known eigen components of signal subspace, the subspace MMSE detector converges to the ideal multiuser detector. However, since traditional techniques for computing eigencomponents such as singular value decomposition (SVD) and eigenvalue decomposition (EVD) incur huge computational costs, the subspace detector in [4] is implemented via projection approximation subspace tracking deflation (PASTd) [6] by exploiting complexity-performance tradeoff.

Although the PAST and PASTd algorithms are acknowledged to be efficient in tracking the principle subspace with computational requirements of only $O(NK)$ (where N is spreading gain of CDMA, and K is the number of users in the cell), the algorithms suffer from a major shortcoming of being relatively slow in converging to signal subspace. This is because PAST approximates the projection of current input vector on the columns of the weight matrix in the current iteration with projection of the current input vector on the weight matrix in the previous iteration. Even though this approximately modified cost function helps in using the recursive least-square (RLS) algorithm for the iterative minimization of cost function, the orthonormality of the weight matrix columns cannot be guaranteed if the input vector changes quickly. Hence, the iterative minimization of this approximated cost function using the method of least-squares estimate cannot always lead to convergence of the weight matrix into the signal subspace. In non-stationary environments, this approximation may trigger an oscillation rather than converging at all [7]. Several efforts have been reported in the literature to orthogonalize eigenvectors. As proposed in [6], any orthonormalization procedure can be recursively applied to the updated correlation matrix of the input vector, with a complexity of $O(NK^2)$. The author reports that this scheme leads to poor numerical properties due to bad conditioning of the correlation matrix, especially at low SNRs. In [8], the so-called improved-PASTd (I-PASTd) is proposed with orthonormalization carried out using a technique similar to Gram-Schmidt procedure, but the complexity of this algorithm, $O(N^2K)$, is relatively high. OPAST [7] and exponential window FAPI [9] (we will refer to it as FAPI, for the remainder of this paper) are proposed as efficient algorithms with very small orthonormality error and low linear complexity, $O(NK)$. However, these algorithms cannot track the eigenvalues of the correlation matrix and therefore cannot be used to implement the subspace multiuser detection directly. Estimation of eigenvalues from eigenvectors increases the computational complexity up to $O(N^2K)$.

In this paper, we propose the recursive application of the Gram-Schmidt orthonormalization procedure to the PASTd algorithm after each eigenvector is extracted. This results in orthonormalized tracking, which yields faster convergence to the signal subspace. The complexity of our technique is of the order of $O(NK^2)$.

Throughout this paper, the symbols $(\cdot)^T$ and $(\cdot)^H$ represent the matrix transpose and Hermitian transpose respectively; $\mathbb{E}\{\}$ denotes the expectation operator; and sign($\cdot$) represents the signum function. The remaining of this paper is organized as follows. Section II develops the signal model for MC-CDMA system and reviews subspace-based blind linear multiuser detectors. Section III presents the PASTd algorithm. In section VI, we develop our OPASTd algorithm to track orthogonalized signal subspace and compare its complexity with the other orthonormalization schemes. Simulation results are presented and discussed in section V, and section VI concludes this paper.

II. Signal Model

Consider a K-user synchronous multicarrier CDMA system, where the k-th user's transmitter is shown in Fig. 1. The data is first serial-to-parallel converted into P-substreams. The k-th user's data bit in the p-th substream is denoted as $b_p^k(t)$. The spreading code of the k-th user, $c_k=[c_0^k, c_1^k, \cdots, c_{N-1}^k]^T$, is multiplied with each bit in each substream, which yields the total number of M=PN symbols, so that the transmitted spread data vector at time t is given as $\boldsymbol{u}_k(t)=[c_0^k b_0^k(t), \cdots, c_{N-1}^k b_0^k(t), \cdots, c_0^k b_{P-1}^k(t), \cdots, c_{N-1}^k b_{P-1}^k(t)]$. The modulation of this $M\times1$ spread data vector on subcarriers is carried out by multiplying it with an $M\times M$ IFFT matrix, $\mathbf{F}$, whose (u, v)th entry is given as $\mathbf{F}(u,v)= 1/N \exp(j2\pi uv/m)$, $0\leq u, v\leq M-1$. After the addition of a cyclic prefix with the duration of N_{CP} spreading chips, the modulated signal, $\boldsymbol{s}_k(t)=\mathbf{F}\boldsymbol{u}_k(t)$, becomes a transmitted signal corresponding to one OFDM symbol. The received signal, which is the superposition of K users' signals, each passing through the L_p path channel, is given as

$$r(t)=\sum_{k=1}^{K}\sqrt{A_k}\sum_{l=1}^{L_p} g_{k,l} s_k(t-\tau_{k,l})+\eta(t), \qquad (1)$$

where A_k is the chip energy of the k-th user; $g_{k,l}$ and $\tau_{k,l}$ are the complex channel gain and the propagation delay of the k-th user along the l-th path, respectively; and $\eta(t)$ is the zero-mean complex additive white Gaussian noise process with variance δ^2.

Next, this signal is sampled at a rate of M+N_{CP} samples per symbol time and the cyclic prefix is removed. If the timing of the desired user is known, then it is also known for all the active users in the cell under the assumption of synchronism. In such a case, if the length of the cyclic prefix is greater than the channel delay spread, then no ISI exists. However, since the cyclic prefix is removed with respect to the first arrived copy, the delayed copies of spreading waveforms still contain some portion of the cyclic prefix as shown in Fig. 2. Specifically, at the i-th sampling interval, the delayed spreading waveform of the k-th user from l-th channel path is $c_k^l(i)=[c_{N-\tau_{k,l}+1}^k, \cdots, c_N^k, c_1^k, \cdots, c_{N-\tau_{k,l}}^k]^T$, where the length of channel delay $\tau_{k,l}$ is an integer multiple of a spreading chip.

After removal of the cyclic prefix, FFT is performed on the $M\times1$ sampled vector by multiplying it with the $M\times M$ FFT matrix $\mathbf{F}_1$, whose (u, v)th entry is given as $\mathbf{F}_1(u,v)=\exp(-j2\pi uv/M)$, $0\leq u, v\leq M-1$. Then, the baseband signal corresponding to the p-th stream is given as

$$\mathbf{r}_p(i)\sum_{k=1}^{K} A_k \mathbf{d}_{k,p}(i) b_{k,p}(i)+\mathbf{n}(i), \qquad (2)$$

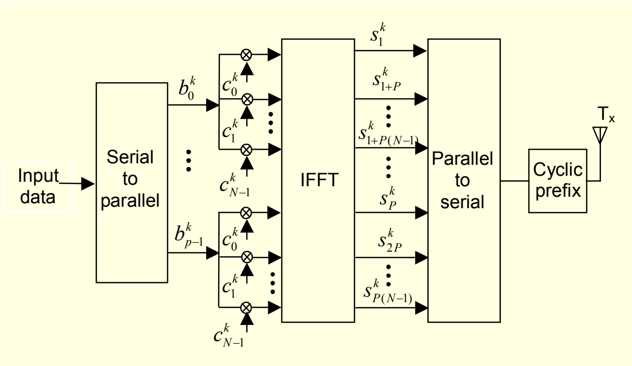


Fig. 1. The k-th MC-CDMA transmitter.

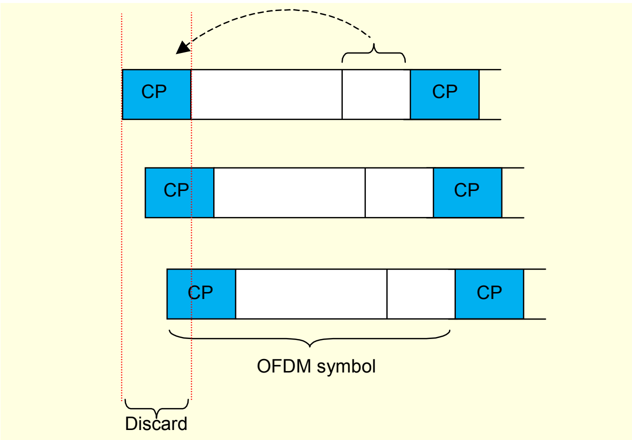


Fig. 2. Three path channel showing signature mismatch due to multipath delay.

where $\mathbf{d}_{k,p}(i)$ is the $N\times 1$ vector, called the effective signature vector of the k-th user, whose n-th entry is given as $\sum_{l=0}^{L_p-1} g_{k,l} c_{k,n}^{l} \exp(-j2\pi \frac{(n+p)l}{N})$, $0\le n\le N-1$, $0\le p\le P-1$, such that $c_{k,n}^{l}$ corresponds to n-th chip of the delayed waveform from the l-th path, and $\mathbf{n}(t)$ is the FFT of AWGN noise samples corresponding to the i-th sampling interval. The channel state information can be estimated using a variety of subspace channel estimation techniques, such as those presented in [10] to [12]. In this paper, unless stated otherwise, we assume that the channel state information is known at the receiver.

The autocorrelation matrix for the received input vector is given as

$$\mathbf{R} = \mathbb{E}\{\mathbf{r}\mathbf{r}^H\} = \sum_{k=1}^{K} A_k \mathbf{d}_k \mathbf{d}_K^H + \delta^2 \mathbf{I}_N, \tag{3}$$

where we have dropped the subscript p to consider any substream in general. Define diagonal matrix $\mathbf{A}$, such that $\mathbf{A} = diag(A_1, A_2, \cdots, A_K)$ and $N\times K$ matrix $\mathbf{D}$, whose K columns are the effective signatures of K users. The correlation matrix can be written as

$$\mathbf{R} = \mathbf{D}\mathbf{A}\mathbf{D}^H + \delta^2 \mathbf{I}_N. \tag{4}$$

The eigenvalue decomposition of the $M\times N$ autocorrelation matrix, $\mathbf{R}$, can be written as

$$\mathbf{R} = \mathbf{U}_s \Lambda_s \mathbf{U}_s^H + \mathbf{U}_n \Lambda_n \mathbf{U}_n^H, \tag{5}$$

where $\Lambda_s = diag(\lambda_1, \lambda_2, \cdots, \lambda_K)$ contains the K largest eigenvalues. Their corresponding eigenvectors are the columns of $\mathbf{U}_s$, and the remaining N–K eigenvalues are all equal to δ^2 and are diagonal entries of Λ_n. Their corresponding eigenvectors are columns of $\mathbf{U}_n$. The linear multiuser detector for the k-th user is any weight vector, $\boldsymbol{m}_k$, such that

$$b_k(i) = sign[\mathrm{Re}(\mathbf{m}_k^H \mathbf{r}(i))]. \tag{6}$$

Subspace-based linear multiuser detectors, namely MMSE and a decorrelating detector, were proposed in [4]. They are given respectively as

$$\mathbf{m}_D^k = \frac{\mathbf{U}_s(\Lambda_s - \delta^2 I_N)\mathbf{U}_s^H \mathbf{d}_k}{[\mathbf{d}_k^H \mathbf{U}_s(\Lambda_s - \delta^2 I_N)\mathbf{U}_s^H \mathbf{d}_k]}, \tag{7}$$

$$\mathbf{m}_M^k = \frac{\mathbf{U}_s \Lambda_s^{-1} \mathbf{U}_s^H \mathbf{d}_k}{[\mathbf{d}_k^H \mathbf{U}_s \Lambda_s^{-1} \mathbf{U}_s^H \mathbf{d}_k]}. \tag{8}$$

Both the decorrelating and MMSE detectors need only the effective signature and the timing of the desired user besides the signal subspace parameters. Thus, the detectors are completely blind.

III. Subspace Tracking Using PASTD Algorithm

An unconstrained cost function [6]

$$\begin{aligned} J(\mathbf{W}) &= \mathbb{E}\{\|\mathbf{r}\text{-}\mathbf{W}\mathbf{W}^H \mathbf{r}\|\}^2 \\ &= \mathrm{tr}(\mathbf{R}) - 2\mathrm{tr}(\mathbf{W}^H\mathbf{R}\mathbf{W}) + \mathrm{tr}(\mathbf{W}^H\mathbf{R}\mathbf{W}.\mathbf{W}^H\mathbf{W}), \end{aligned} \tag{9}$$

will have a stationary point $\mathbf{W}$, such that $\mathbf{W}=\mathbf{U}_s\mathbf{Q}$, where $\mathbf{W} \in \mathbb{C}^{N\times K}, \mathbf{Q} \in \mathbb{C}^{K\times K}$, and $\mathbf{U}_s \in \mathbb{C}^{N\times K}$ contain K dominant eigenvectors of correlation matrix of received vector $\mathbf{r}$. Furthermore, by iterative minimization of $J(\mathbf{W})$ its global minimum, $\mathbf{W}_{min}$, contains K distinct dominant eigenvectors of correlation matrix, $\mathbf{R}$. Replacing the expectation in cost function with an exponentially weighted sum modifies the cost function as

$$J(\mathbf{W}(i)) = \sum_{j=1}^{i} \beta^{i-j} \|\mathbf{r}(i) - \mathbf{W}(i)\mathbf{W}^H(i)\mathbf{r}(i)\|^2, \tag{10}$$

where β is the forgetting factor, defined as $0 < \beta \le 1$. Here, the authors of [6] make an approximation that $\mathbf{y}(i) \stackrel{\text{def}}{=} \mathbf{W}^H(i)\mathbf{r}(i) \cong \mathbf{W}^H(i-1)\mathbf{r}(i)$, such that (10) becomes

$$J(\mathbf{W}(i)) = \sum_{j=1}^{i} \beta^{i-j} \left\| \mathbf{r}(i)\mathbf{W}(i)\mathbf{y}(i) \right\|^2 . \tag{11}$$

This approximated exponentially weighted modified cost function can be solved for **W**(i) using the RLS algorithm, which results in the PAST and PASTd algorithms [6].

The approximation of **W**(i) with **W**(i–1) works well for stationary or slowly varying signals; however, for rapidly changing cellular CDMA environments, the weight vector **W**(i) cannot maintain the orthonormality of its columns, and convergence to signal subspace cannot always be guaranteed. To make convergence faster, some additional orthonormalization process is needed.

IV. Orthonormalized Subspace Tracking Using the OPASTd Algorithm

Consider the eigenvector update step of the PASTd algorithm (step III in Fig. 3), where each eigenvector is extracted under the iterations of k. After the first eigenvector is extracted, the extraction of the second eigenvector may be followed by some orthonormalization step, which confirms that it is orthonormal to first eigenvector and so on. Here we propose the use of the Gram-Schmidt orthonormalization procedure given as

$$\mathbf{u}_k^*(i) = \mathbf{u}_k(i) - \sum_{j=1}^{k-1} (\mathbf{u}_j^H(i)\mathbf{u}_k(i))\mathbf{u}_j(i), \tag{12}$$

and then

$$\mathbf{u}_k^o(i) = \frac{\mathbf{u}_j^*(i)}{\left\| \mathbf{u}_j^*(i) \right\|}, \tag{13}$$

where $\mathbf{u}_k^o(i)$ is orthonormalized $\mathbf{u}_k(i)$ for k=1,2,⋯,K. Thus, after the addition of these steps, the OPASTd algorithm can be written as given in Fig. 3.

A. Computational Complexity

The complexity of the OPASTd algorithm is of the order of $O(NK^2)$. Table 1 gives a detailed account of the complexity of OPASTd for all the K iterations. We compare this complexity with other techniques for orthogonalized subspace tracking published in the literature. The OPAST algorithm [7], which is also a modification of PAST, guarantees the orthonormality of eigenvectors with complexity of the order of $O(NK)$, but it cannot track the eigenvalues because the diagonal matrix that contains eigenvalues in PASTd is replaced by a matrix $(\mathbf{U}(i-1)\mathbf{R}(i)\mathbf{U}(i-1))^{-1}$. Subspace multiuser detection also needs K largest distinct eigenvalues. Therefore, to compute the eigenvalues from eigenvectors, if we use the Rayleigh quotient given in [13],

$\mathbf{x}_1(i)=\mathbf{r}(i)$
for k=1:K

$y_k(i) = \mathbf{u}_k^H(i-1)\mathbf{x}_k(i)$ (I)

$\lambda_k(i) = \beta\lambda_k^H(i-1) + |y_k(i)|^2$ (II)

$\mathbf{u}_k(i) = \mathbf{u}_k(i-1) + (\mathbf{x}_k(i) - \mathbf{u}_k(1-i)y_k(i))\left(\frac{y_k^H(i)}{\lambda_k(i)}\right)$ (III)

sum = 0
if $k \geq 2$
for j=1:k-1
sum = sum+ $(\mathbf{u}_j^H(i)\mathbf{u}_k(i))\mathbf{u}_j(i)$ (IV)
end for
end if

$\mathbf{u}_k^*(i) = \mathbf{u}_k(i) - \text{sum}$ (V)

$\mathbf{u}_k^o(i) = \frac{\mathbf{u}_k^*(i)}{\left\|\mathbf{u}_k^*(i)\right\|}$ (VI)

$\mathbf{u}_k(i) = \mathbf{u}_k^o(i)$

$\mathbf{x}_{k+1}(i) = \mathbf{x}_k(i) - \mathbf{u}_k(i)y_k(i)$ (VII)

end for

Fig 3. OPASTd algorithm.

Table 1. Stepwise complexity of OPASTd.

Step (in Fig. 3)	Multiplications	Additions
I	NK	$(N-1)K$
II	$2K$	K
III	$K(N+1)$	$2KN$
IV (for all k)	NK^2-NK	$NK^2 - NK - \frac{K(K-1)}{2}$
V	0	NK
VI	$(N+1)K$	$(N-1)K$
VII	K	K
Total	$NK^2+2NK-6K$	$NK^2 + 4NK - \frac{K(K-1)}{2}$

Table 2. Comparison of complexity for subspace multiuser detection.

Detector	Multiplications	Additions
OPASTd	$NK^2+2NK-6K$	$NK^2 + 4NK - \frac{K(K-1)}{2}$
Kalman	$4N^2-3N$	$4N^2-3N$
OPAST	$N^2K+6NK+4N+4K^2+5K+11$	$N^2K+6NK+2K-11$
FAPI	$N^2K+5NK+2N+6K^2+11K+14$	$N^2K+5NK+N+4K^2+4K$

$$\lambda_k(i) = \frac{\mathbf{u}_k^H(i)\mathbf{R}(i)\mathbf{u}_k(i)}{\mathbf{u}_k^H(i)\mathbf{u}_k(i)}, \quad (14)$$

we also need to keep an updated correlation matrix of the received vector by

$$\mathbf{R}(i) = \beta\mathbf{R}(i-1) + \mathbf{r}(i)\mathbf{r}^H(i). \quad (15)$$

The exact same situation occurs for the FAPI algorithm [9] when it is used for subspace multiuser detection. This additional labor to compute eigenvalues from the eigenvectors has a cost of N^2K+2NK multiplications and N^2K+2NK additions. Thus, the total complexity of the OPAST and FAPI algorithms for subspace multiuser detection becomes of the order of $O(N^2K)$. Moreover, the well known Kalman-filter-based blind adaptive multiuser detection [5] has a complexity of $4N^2-3N$ additions and $4N^2-3N$ multiplications. Table 2 summarizes the computational complexity comparison of the algorithms. For all practical values of N and K, the OPASTd algorithm is the least complex. The complexity of OPASTd is lower than that of OPAST and FAPI in general, and in some cases, such as low cell loading (K<10), it is lower than that of a full rank Kalman filter.

V. Simulation Results

In all simulation examples, unless stated otherwise, the following system parameters are used. We consider a synchronous MC-CDMA cell with K=10 active users, each of which uses a random spreading code with a spreading gain of N=31. There are P=6 parallel substreams, the cyclic prefix of N_{CP}=8 is used by each user, and the data of each user is BPSK modulated. A near-far situation with five 10 dB interferers, three 20 dB interferers, and one 30 dB interferer is considered. That is, $A_1^2=1$, $A_2^2=A_3^2=\cdots=A_6^2=10$, $A_7^2=A_8^2=A_9^2=100$, and $A_{10}^2=1000$. The first user, k=1, is the desired user. The signal-to-noise ratio (SNR) of 20 dB is used. A single-path flat-fading Rayleigh channel is considered. The Doppler frequency shift of the desired user is 120 Hz, and that for interfering users is generated from the uniform distribution in the interval [50 150] Hz. For the initialization of eigen-components, SVD is applied on the first 50 data vectors, as in [4]. For the OPAST and FAPI algorithms, the eigenvalues are computed by a Rayleigh quotient. A total of 1,000 data vectors are applied to all algorithms. The forgetting factor of $\beta=0.998$ is used. Finally, the simulation results plotted in this paper do not include the results of the PASTd algorithm since it cannot converge at all for the MC-CMDA system considered here.

Example 1: Orthogonality error. Orthogonality error [7] is defined as $20\log_{10}(\|\mathbf{U}_s^H(i)\mathbf{U}_s(i)-\boldsymbol{I}\|)$, where $\|\cdot\|$ denotes the Frobenius norm. Figure 4 plots the orthogonality error comparison of OPASTd, PAST, and FAPI subspace tracking schemes in decibel units. As seen in Fig. 4, OPASTd achieves its steady state orthonormality error in around 20 iterations. This is because of sequential application of Gram-Schmidt procedure ensures the orthonormality of eigenvectors at each discrete time instant.

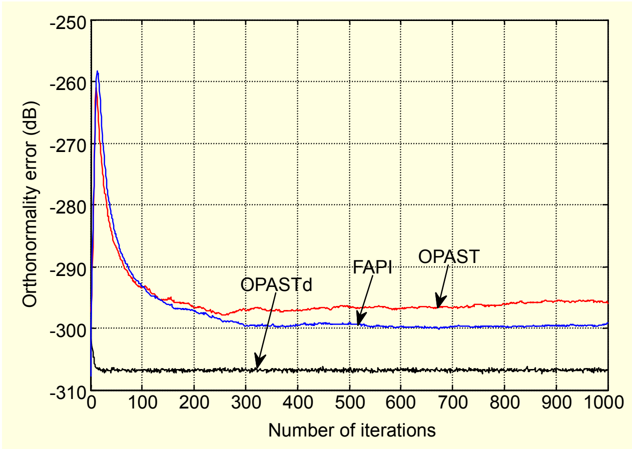


Fig. 4. Comparison of orthogonality error of the eigenvectors tracked by OPASTd, FAPI, and OPAST, averaged over 100 simulation runs.

Example 2: Similarity. The practical best result of a subspace blind adaptive detector would be obtained when the eigen-components are precisely known, such as those obtained by EVD of the correlation matrix of the received vector updated at each time sample. We refer to this detector as the ideal subspace detector. Since the subspace multiuser detector is indeed a unique weight vector for a certain received vector, we can compare the similarity of the subspace detector computed by tracking the subspace components (by OPASTd, OPAST, and FAPI) with the ideal detector. The similarity of any vector (subspace detector, $\mathbf{m}_s(i)$), with some other vector (ideal detector, $\mathbf{m}(i)$), can be defined as given in [14] as

$$Similarity(i) = \frac{|\mathbf{m}_S^H(i)\mathbf{m}(i)|}{\sqrt{|\mathbf{m}^H(i)\mathbf{m}(i)||\mathbf{m}_S^H(i)\mathbf{m}_S(i)|}}. \quad (16)$$

Figure 5 shows the similarity comparison of three detectors for 1,000 iterations plotted as the average of 100 Monte Carlo simulation runs. As seen in Fig. 5, the OPASTd-based subspace detector tends toward the ideal detector faster than detectors with the OPAST and FAPI algorithms.

Example 3: SNIR comparison. In this example, we analyze the interference suppression capability by comparing the output SINR of the OPASTd-based subspace multiuser detector with the Kalman filter blind adaptive multiuser detector [5] and the subspace Kalman filter [15] as shown in Fig. 6. The results

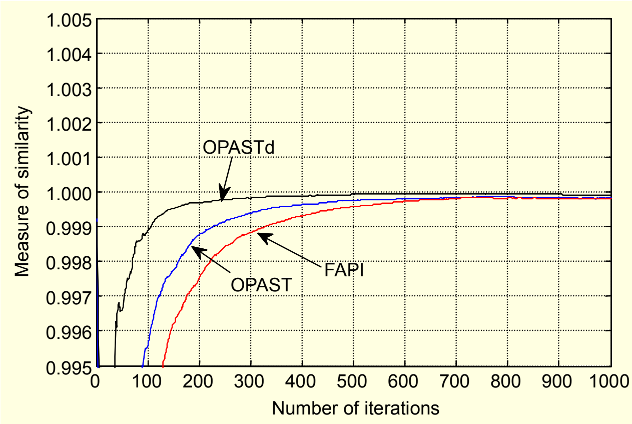


Fig. 5. Comparison of rate of convergence of OPASTd, OPAST, and FAPI towards the ideal detector.

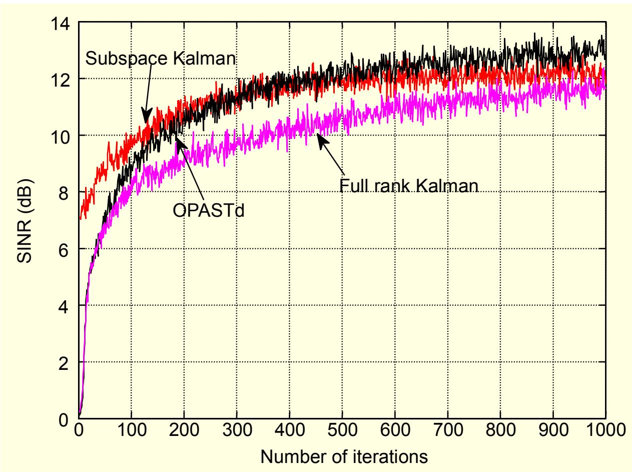


Fig. 6. Comparison of SINR for OPAST, subspace Kalman filter, and full rank Kalman filter.

plotted in the Fig. 6 are averages of over 500 simulation runs. In the mature state, the SINR of OPASTd is slightly better than tht of both Kalman algorithms, while the subspace Kalman algorithm converges more quickly at the beginning of iterations.

Example 4: BER performance. Figure 7 shows the bit error rate against the SNR of the subspace Kalman filter and full rank Kalman filter as well as the OPASTd-, OPAST-, and FAPI-based detectors.

The SNR is varied from 0 dB to 20 dB, and the plotted results are averages of over 100 simulation runs. A total of 100,000 bits are applied to all algorithms at each SNR value. In general, the performance of the subspace and full rank Kalman detectors is better than any other subspace detector at low SNRs. However, as the SNR values increase, the other subspace methods outperform the Kalman filter methods.

Example 5: BER versus number of iterations. This simulation example is designed to give an insight into the BER performance of the detectors at all individual iterations towards

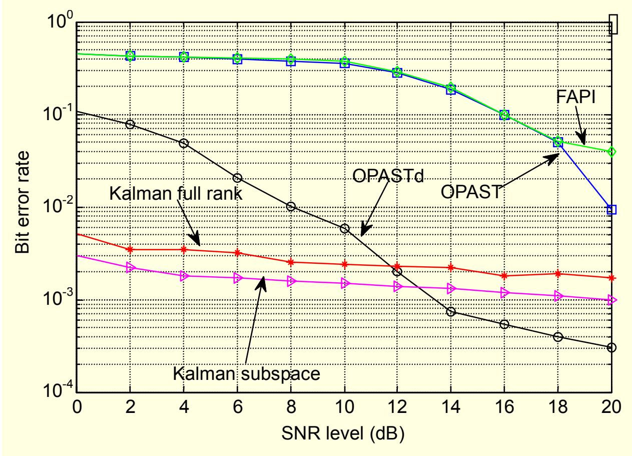


Fig. 7. Bit error rate comparison for various SNR values.

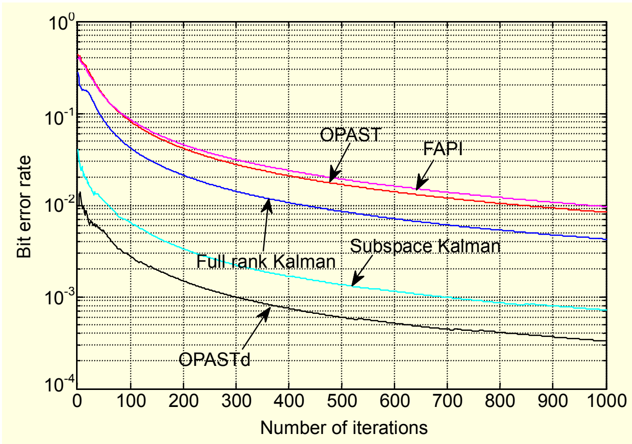


Fig. 8. Instantaneous BER performance of various multiuser detectors.

its convergence which is not revealed by example 5. The signal to noise ratio of 20 dB was used. The curves plotted in Fig. 9 are averages of over 500 simulation runs. Figure 8 can be interpreted to indicate that the steeper the decay rate of the curve of a detector, the lower the chance is of errors occurring towards the convergence. A relatively straight horizontal curve would mean that occurrence of error is equally probable at all iterations.

Example 6: Sensitivity to channel estimation errors. In this simulation example, perfect channel state information is not available at the receiver; rather, it is estimated with certain channel estimation error (CEE), given by $CEE = \|g - \hat{g}\|^2 / \|g\|^2$, where g is the actual channel gain, and $\hat{g}$ is its estimated value. At each value of CEE, a total of 100,000 bits are transmitted. The performance criterion is BER versus CEE. Figure 9 shows the robustness of different multi-user detection (MUD) techniques against channel estimation errors. Both Kalman methods are more robust against channel estimation errors than

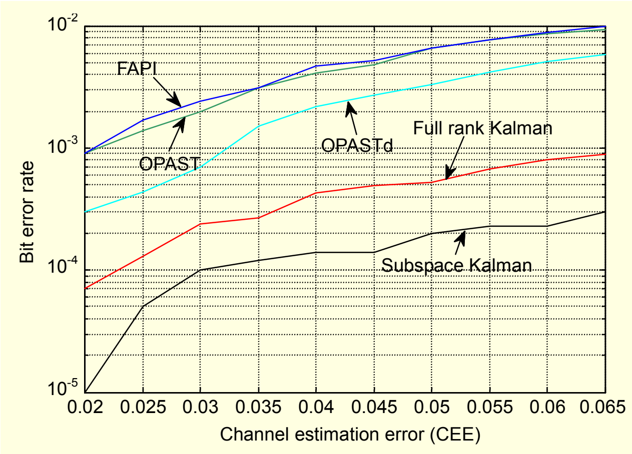


Fig. 9. BER performance of various MUD techniques with respect to applied channel estimation errors.

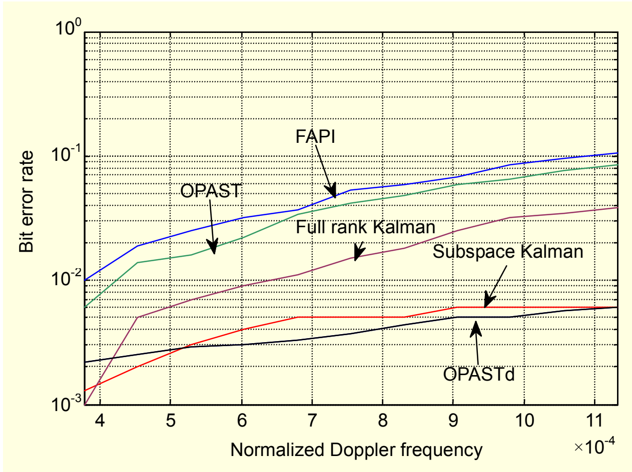


Fig. 10. BER performance of various MUD techniques with respect to applied maximum normalized Doppler frequency.

other methods.

Example 7: Sensitivity to nonstationarity of channel. In this simulation example, the MUD algorithms are tested in non-stationary channels. The amount of channel variation is measured in maximum normalized Doppler frequency, defined as the product of (OFDM) symbol time and Doppler frequency shift [16]. Using P=6 parallel MC-CDMA substreams, a spreading gain of N=31, and the number of cyclic prefix chips of N_{CP}=8, each OFDM symbol contains 6×(31+8)=234 chips. Considering a data rate of 1 Mbps, we get a chip rate of 31 Mcps. Then the duration of one OFDM symbol becomes 234 chips/31 Mcps=7.55 µs. The carrier frequency of 1,800 MHz is used, and the Doppler frequency of the desired user is varied from 50 Hz to 150 Hz (approximate ground speed of 8 to 25 m/s). At each value of the maximum normalized Doppler frequency, a total of 100,000 bits are transmitted. Figure 10 shows the results of this simulation.

VI. Conclusion

In this paper, we studied the performance of subspace multiuser detection using subspace tracking. We proposed a new subspace tracking scheme based on cascading the PASTd algorithm with the classical Gram-Schmidt procedure. We demonstrated that for multiuser detection applications, the Gram-Schmidt procedure OPASTd has less computational complexity, contrary to common belief. We demonstrated through the simulation results that Gram-Schmidt orthonormalization practically leaves no space for orthonormality error and leads to faster convergence towards the ideal subspace detector. Through various simulation results for MC-CDMA, we have shown that the performance of the OPASTd detector is superior to other subspace tracking schemes and the well known Kalman filter algorithm. We also found that the OPASTd subspace detector has lower performance than the Kalman filter at low SNRs; however, for more common SNR values around 15 dB, the OPASTd detector outperforms the Kalman filter, too.

References

[1] N. Yee, J.P. Linnartz, and G. Fettweis, “Multicarrier CDMA in Indoor Wireless Radio Networks,” *Proc. of IEEE PIMRC*, Sept. 1993, pp. 468-472.

[2] S. Chatterjee, W.A.C. Fernando, and M.K. Wasantha, **“**Adaptive Modulation Based MC-CDMA Systems for 4G Wireless Consumer Applications,” *IEEE Trans. on Consumer Electronics*, vol. 49, no. 4, Nov. 2003, pp. 995-1003.

[3] M. Honig, U. Madhow, and S. Verdu, “Blind Adaptive Multiuser Detection,” *IEEE Trans. on Information Theory*, vol. 41, no. 4, July 1995, pp. 944-960.

[4] X. Wang and H.V. Poor, “Blind Multiuser Detection: A Subspace Approach,” *IEEE Trans. on Information Theory*, vol. 44, no. 2, Mar. 1998, pp. 677-690.

[5] X. Zhang and W. Wei, “Blind Adaptive Multiuser Detection Based on Kalman Filtering,” *IEEE Trans. on Signal Processing*, vol. 50, no. 1, Jan. 2002, pp. 87-95.

[6] B. Yang, “Projection Approximation Subspace Tracking,” *IEEE Trans. on Signal Processing*, vol. 43, no. 1, Jan. 1995, pp. 95-107.

[7] K. Abed-Meraim, A. Chkeif, and Y. Hua, “Fast Orthonormal PAST Algorithm,” *IEEE Signal Processing Letters*, vol. 7, no. 3, Mar. 2000, pp. 60-62.

[8] Y. Meng et al., “A Semi-blind Multiuser Detection Based on Chebyshev Approximation and Subspace Tracking for MC-CDMA Uplink,” *IEEE TENCON*, Nov. 2006, pp. 1-4.

[9] R. Badeau, B. David, and G. Richard, “Fast Approximated Power Iteration Subspace Tracking,” *IEEE Trans. on Signal Proc.*, vol. 53, no. 8, Aug. 2005, pp. 2931-2941.

[10] S.E. Bensley and B. Aazhang, "Subspace-Based Channel Estimation for Code-Division Multiple Access Communication System," *IEEE Trans. on Communication*, vol. 44, no. 8, Aug. 1996, pp. 1009-1020.

[11] H. Liu and G. Xu, "A Subspace Method for Signature Waveform Estimation for in Synchronous CDMA Systems," *IEEE Trans. on Communication*, vol. 44, no. 10, Oct. 1996, pp. 1346-1354.

[12] C.J. Escudero et al., "Analysis of Subspace Channel Estimation Technique for Multicarrier CDMA Systems," *Proc. IEEE Workshop on Statistical Signal and Array Processing*, Aug. 2000, pp. 10-14.

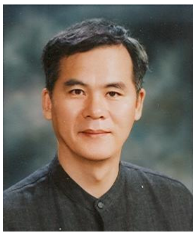
[13] G.H. Gloub and C.F. Van Loan, *Matrix Computation*, 3rd ed., John Hopkins Univ. Press, Baltimore, 1996.

[14] G. Zhang, G. Bi, and L. Zhang, "Blind Multiuser Detection for Asynchronous MC-CDMA Systems without Channel Estimation," *IEEE Trans. on Vehicular Technology*, vol. 53, no. 4, July 2005, pp. 1001-1013.

[15] H. Zhou, W.L. Woo, and B. Sharif, "A Subspace Blind Adaptive Multiuser Detection Scheme over Multipath Channel Using Kalman Filter," *VTC-2004*, Fall, vol. 7, pp. 3807-3811.

[16] N. Rahimian and A. Falahati, "A New Analytical Method to Investigate the Effect of Normalized Doppler Rate on the Capacity of MIMO Channels Using Karhunen-Loeve Expansion," *2nd Aus. Wireless Conference*, Sydney, Australia, 2007.

Imran Ali received his Bachelor's degree from Mehran University, Jamshoro, Pakistan, and his Master's degree from Myongji University, South Korea, in communication engineering, in 2005 and 2008, respectively. Currently, he is with the Center for Advanced Studies in Telecommunication (CAST), COMSATS Institute of Information Technology, Islamabad, Pakistan. His research interests include signal processing for wireless communication, with emphasis on CDMA and MIMO-OFDM systems.



Doug Nyun Kim received the MS degree from SUNY at Stony Brook in 1983 and the PhD degree from Auburn University, USA, in 1988. He joined Electronics and Telecommunications Research Institute, Daejeon, Korea in 1988, where he served as a leader of the group for developing VSAT systems under the Koreasat project. He is currently a professor with the Communication Engineering Department of Myongji University. He is also working with Broadcasting System Research Group as an invited senior researcher. His research interests include multimedia broadcasting protocols, digital modulation techniques and networking.

Jong Soo Lim received the MS degree in electronics engineering from Kyungpook National University, Daegu, Korea, in 1990. In 1999, he joined Electronics and Telecommunications Research Institute, Daejeon, Korea, where he has been working on broadcasting system technologies. Currently, he serves as the team leader for the Terrestrial Transmission Technology Research Team. His research interests include terrestrial DTV and DMB systems.