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Blind Multiuser Detection with Array Observations

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Abstract. Cochannel interference is usually a major limitation to the performance of mobile wireless systems. Examples of different forms of cochannel interference include multiple-access interference in CDMA systems and cochannel interference resulting from frequency reuse in TDMA systems. In order to mitigate the interference from other users we present a blind multiuser receiver which utilizes array observations and performs both spatial and temporal processing of the received signal. The presented technique is completely blind in the sense that no signature sequences, channel state or spatial location needs to be known a priori, nor use of a training sequence is required for the adaptation. The diversity introduced by the array observations can be efficiently combined with the use of CDMA signature sequences. After initial convergence, a reliable estimate of the combined temporal and spatial signature for each user is provided that can be employed by a multiuser receiver of lower complexity.

Key words: multiuser communications, blind identification, array signal processing, CDMA, adaptive receivers.

1. Introduction

The capacity of modern wireless systems is primarily determined by the impact of the interference. The interference can result from different types of radiating devices, from propagation effects such as multipath fading or from other non-coordinated systems. Besides this unintentional interference, a system design which targets high spectral efficiency can result in additional interference sources. In code division multiple-access (CDMA) systems multiple-access interference (MAI) is a result of low cross-correlations among the users' spreading codes, whereas in time division multiple-access (TDMA) systems cochannel interference is a result of frequency reuse. In both cases the goal is to increase the capacity of the wireless system in the interference-limited scenarios, expressed as a number of users in a given bandwidth.

Recent advances in wireless communications are based on the use of antenna arrays to exploit the spatial distribution of the users' signals for source separation. Regardless of the CDMA or TDMA choice, independent signal observations from the antenna array can be used to suppress the interference and to improve the performance in the presence of multipath fading by utilizing the diversity concept [1, 2]. The resulting receiver structures are based on the different combinations of spatial and temporal processing of the signals.

In the case of CDMA systems, advances in multiuser detection theory show that the shortcomings of CDMA systems are not inherent to the system itself, but are rather a consequence of suboptimal detection [3]. Since multiple-access interference is a highly structured interference and the signature waveforms of all users are available at the central receiver, this additional knowledge may be exploited in the decision process. The multiuser detection concept has been primarily applied to receiver design in a temporal domain. Two different approaches to multiuser detection with array observations have been addressed as well. Integrated multiuser receivers with antenna arrays using the beamforming approach have been considered in [4, 5], assuming a narrowband propagation model. The structure of the multiuser receiver in that case consists of a beamforming network which perform spatial processing, followed by a bank of matched filters and a multiuser detection algorithm which performs temporal processing [4]. The second approach does not rely on a specific plane-wave propagation assumption and utilizes pure diversity schemes, provided that the antennas are separated far enough so the received signals can be regarded as independent [6, 7].

Multiuser detection in CDMA systems usually requires either knowledge of the transmitted signature sequences and channel state information or use of a known training sequence for adaptation. Blind adaptive multiuser receivers have been increasingly considered to overcome these limitations [8, 9]. We have recently proposed a near far resistant joint multiuser deconvolution scheme [10] in which no knowledge of the timing, channel state information or signature sequences nor use of training sequences is required for any user. Additionally, the estimate of the signature sequence of each user convolved with its physical channel impulse response is provided after the initial convergence.

In this paper we further investigate an integrated blind multiuser receiver which utilizes array observations of the received signal. Array processing is efficiently used to suppress the multiple-access interference and to increase the robustness of the signal detection in the presence of fading. As illustrated in the paper the proposed technique is not restricted to CDMA systems only and can be efficiently exploited in a general cochannel interference suppression scenario. The complexity of the proposed algorithm is unaffected by the size of the array compared to the complexity in the single-sensor case.

The paper is organized as follows. In Section II the system model is presented, which takes into account general cochannel interference as well as the delays and the channel impulse responses of all users. The number of users is assumed to be known together with a bound of the channel impulse response length. In Section III, the blind detection algorithm is derived based on an array observation in which the combined spatial and temporal signatures are recursively updated. Performance of the algorithm strongly depends on the convergence to the actual system model. Possible convergence to local minima, resulting from severe intersymbol interference and the near-far effect, is considered in Section IV. The solution to this problem is proposed for the moderate ISI and dominant near-far case. Simulation results are given in Section V illustrating the effectiveness of the proposed algorithm in various system configurations. Concluding remarks are given in Section VI.

2. System Model

We consider the general asynchronous multiple-access channel model which can be applied both to CDMA and TDMA scenarios with cochannel interference. The multichannel receiver employs a P sensor array in which the signal received by sensor $p, p = 1, \ldots, P$ is given, regardless of the array structure by,

$$r_p(t) = \sum_n \sum_{k=1}^{K} b_k[n] h_{kp}(t - nT, t) + \sigma w_p(t) \tag{1}$$

where $h_{kp}(t - nT, t)$ is the overall complex channel impulse response of user k at sensor p, given by the convolution of its signature sequence (in CDMA system), physical channel and the receiving filter impulse responses. It incorporates the amplitude and the delay for user k at sensor p, and its duration is assumed to be smaller or equal to L symbol periods, i.e.

$$h_{kp}(\tau, t) = 0, \quad \tau < 0, \quad \tau > LT, \quad \forall t, p, k. \tag{2}$$

Note that in a TDMA case there are no distinct signature sequences among the users, and for a particular user of interest, only the physical channel and the angle of arrival could make distinction from other active users. The total number of active users is K and their transmitted data sequences are binary independent symbols $b_k[n] \in \{1, -1\}$. The symbol rate is $1/T$ and $w_p(t)$ is normalized temporal and spatially white Gaussian noise. The multi sensor multiple-access channel is sampled at a rate $f_s = 1/T_s = M/T$ to derive the discrete vector sequence $\mathbf{r}[n]$

$$\mathbf{r}[n] = [\mathbf{r}_1[n]^T, \ldots, \mathbf{r}_P[n]^T]^T \tag{3}$$

where M length vector corresponding to a p^{th} sensor is given by

$$\mathbf{r}_p[n] = [r_p(nT), \ldots, r_p(nT + (M-1)T_s)]^T. \tag{4}$$

The observation $\mathbf{r}[n]$ is modeled as a probabilistic MP length vector sequence of a state vector $\mathbf{s}[n]$,

$$\mathbf{r}[n] = \mathcal{H}[n]\mathbf{s}[n] + \mathbf{w}[n]. \tag{5}$$

Since, at any give time, a maximum of L symbols for each user affect the observation, there are $N = 2^{LK}$ possible state vectors corresponding to all combinations of L binary symbols of the K active users. Note that the number of state vectors is independent of the array size and therefore the number of sensors does not increase the complexity of the algorithm. We denote each of the possible states as the KL length vectors $\mathbf{s}_i$,

$$\mathbf{s}_i \in \mathcal{S} = \{\mathbf{s}_1, \mathbf{s}_2, \ldots, \mathbf{s}_N\} \tag{6}$$

such that,

$$\mathbf{s}_i = [A_i(0,1), \ldots, A_i(0,K), \ldots, A_i(L-1,1), \ldots, A_i(L-1,K)]^T, A_i(l,k) \in \{1, -1\}. \tag{7}$$

The actual state at time instant nT is denoted by $\mathbf{s}[n], \mathbf{s}[n] \in \mathcal{S}$.

The $(MP \times KL)$ matrix $\mathcal{H}[n]$ depends of the overall discrete impulse response for each user, denoted by the matrix $\mathbf{H}_k[n]$,

$$\mathcal{H}[n] = [\mathbf{H}_1[n], \ldots, \mathbf{H}_K[n]]. \tag{8}$$

Each of these matrices incorporates a vector response for each of the L symbols that may be present in the observation due to the ISI,

$$\mathbf{H}_k[n] = [\mathbf{h}_{k0}[n], \ldots, \mathbf{h}_{k(L-1)}[n]] \tag{9}$$

which again includes the vector response for each of the P sensors,

$$\mathbf{h}_{kl} = [\mathbf{h}_{kl1}[n]^T, \ldots, \mathbf{h}_{klP}[n]^T]^T \tag{10}$$

and finally the resulting signature for each user, symbol and sensor

$$\mathbf{h}_{klp}[n] = \begin{bmatrix} h_{kp}((n+l)T, nT) \\ \vdots \\ h_{kp}((n+l)T + (M-1)T_s, nT) \end{bmatrix}. \tag{11}$$

The noise is modeled as the MP length vector

$$\mathbf{w}[n] = [\mathbf{w}_1[n]^T, \ldots, \mathbf{w}_P[n]^T]^T \tag{12}$$

that includes the observed noise for each sensor at the sample rate,

$$\mathbf{w}_p[n] = \sigma[w_p(nT), \ldots, w_p(nT + (M-1)T_s)]^T. \tag{13}$$

The probability density function of the observation vector conditioned on a given channel state $\mathbf{s}_j$ is given by:

$$p(\mathbf{r}[n]|\mathbf{s}_j) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(\mathbf{r}[n] - \mathbf{m}_j[n])^H(\mathbf{r}[n] - \mathbf{m}_j[n])}{2\sigma^2}\right) \tag{14}$$

where

$$\mathbf{m}_j[n] = \mathcal{H}[n]\mathbf{s}_j, \quad 1 \leqslant j \leqslant N. \tag{15}$$

The channel model presented is depicted in Fig. 1, illustrating how all symbols present in the observation at a given time for all users are incorporated in the state vector, whereas the signature, channel and possible delay for each user and sensor appear in the global impulse response matrix $\mathcal{H}[n]$.

3. Blind Identification and Detection Algorithm

The optimal multiuser receiver for the multiple-access system presented is the multiuser maximum-likelihood (ML) sequence detector, provided that the overall impulse response for each user at each sensor was known, that is, the signature sequence, physical channel impulse response, amplitude and delay corresponding to each user at each sensor were available. Using this information, the Viterbi algorithm could be employed to efficiently determine the most likely transmitted sequence [6]. In the method we present, however, the Viterbi algorithm is applied with current estimates of the overall impulse responses which are updated recursively after arbitrary initialization. The number of users (K) is assumed known together with a bound on the impulse response duration (L).

The detection part of the algorithm iterates at the symbol rate as in a conventional Viterbi scheme. In this case however, metrics along the trellis are computed using for each state its own current estimate of the overall impulse response, $\hat{\mathcal{H}}_j[n], j = 1, \ldots, N$. At each iteration,

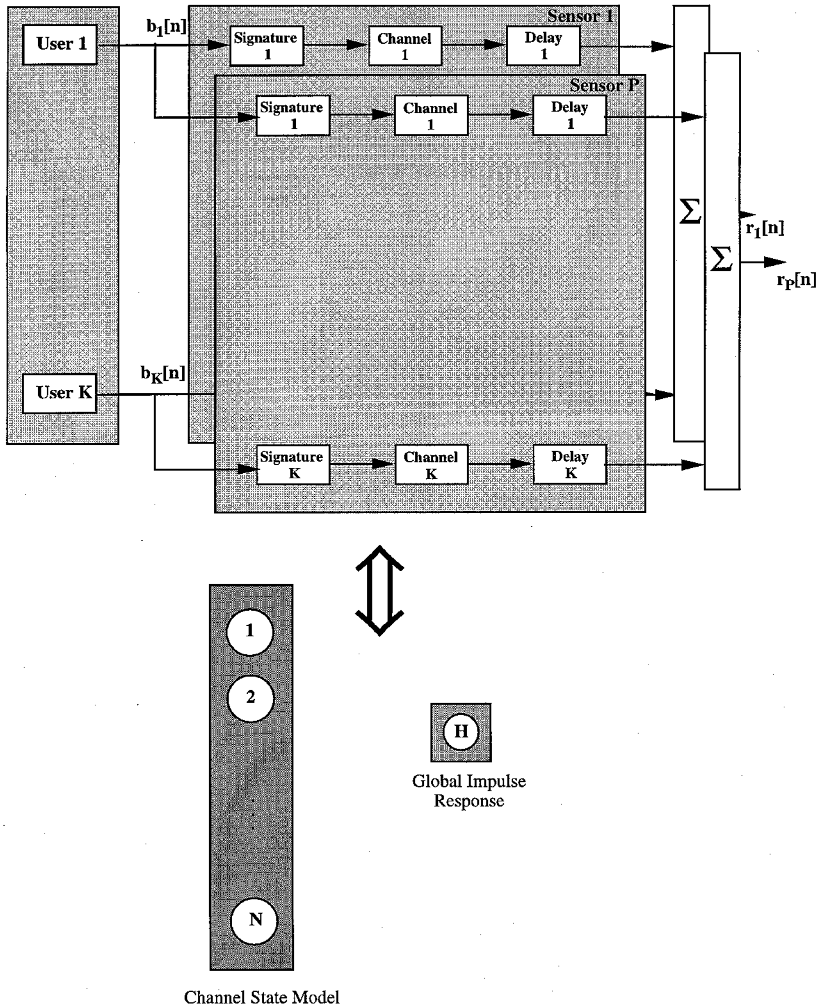

Figure 1. System model of multiple-access channel with array observation.

a ML path is continued for each state selecting the most likely possible predecessor and updating the accumulated metric using (14). Each state has $L-1$ symbols in common for each user with all possible predecessors and thus there are only 2^K predecessors per state.

The channel estimate matrix $\hat{\mathcal{H}}_j[n], j=1,\ldots,N$ is updated for each state modifying the one associated to its most likely predecessor using a standard system identification stochastic gradient (LMS) scheme,

$$\hat{\mathcal{H}}_j[n] = \hat{\mathcal{H}}_i[n-1] + \mu \mathbf{e}_{ij}^*[n]\mathbf{s}_j^T, \tag{16}$$

where state $\mathbf{s}_i$ precedes state $\mathbf{s}_j, \mu$ is the adaptation constant and the error vector $\mathbf{e}_{ij}[n]$ is defined as

$$\mathbf{e}_{ij}[n] = \mathbf{r}[n] - \hat{\mathcal{H}}_i[n-1]\mathbf{s}_j. \tag{17}$$

The algorithm adaptation is illustrated in Fig. 2 in which the system model is updated with every iteration of the Viterbi algorithm corresponding to a new observation. The detection and

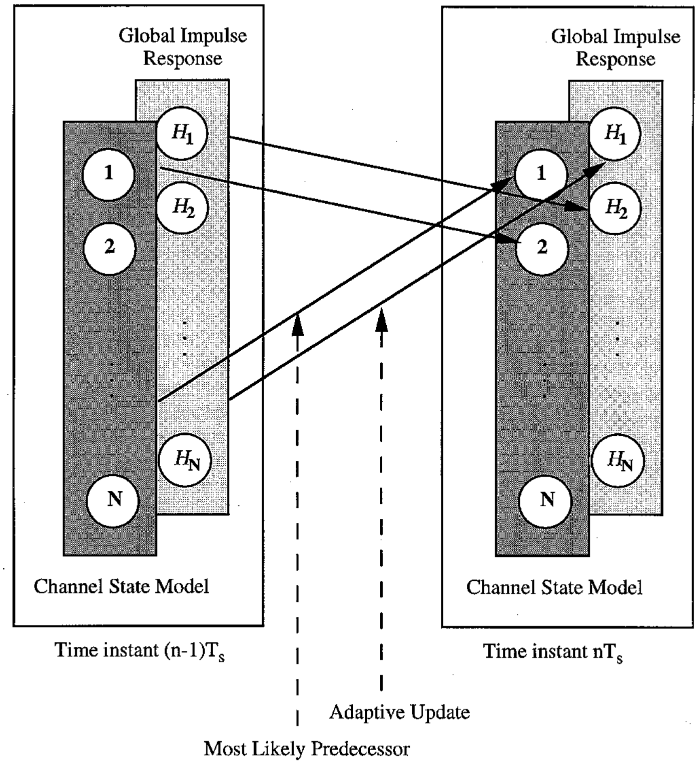

Figure 2. Blind algorithm operation principle.

estimation algorithms progress somehow independently. The detection is carried out in the multiuser Viterbi scheme like in [11] assuming perfect knowledge of the joint temporal/spatial signature of users which are in turn estimated blindly for each path assuming correct detection.

It is worth mentioning that, since the overall impulse response is estimated blindly, and in most practical cases the employed symbol constellation is rotation invariant, the estimation suffers from a phase ambiguity. In real constellations like BPSK this implies a sign ambiguity which can be easily circumvented using differential modulation.

In stationary environments, adaptation should not proceed after convergence and the impulse response that corresponds to the most likely final state can be employed to yield the ML transmitted sequence for each user as in the conventional multiuser optimal receiver [11]. A more practical strategy, suitable for slow varying channels, consists in switching after convergence to a simple MMSE algorithm [12] which can be adapted using standard adaptive filtering algorithms in a decision directed mode. The MMSE algorithm working in a decision directed mode for array observation requires initial knowledge of the equivalent impulse response for each users and sensor which is contained in matrix $\hat{\mathcal{H}}_i$, where $\mathbf{s}_i$ is the most likely final state after convergence.

The blind deconvolution of multiuser signals with single-sensor observation has been addressed in [10]. Also, a similar technique was previously proposed for the blind equilization of single user channels using the Viterbi algorithm [13] and the Baum-Welch algorithm [14].

4. Near-Far Effect

4.1. EXISTENCE OF LOCAL MINIMA

In practice, this algorithm can only be employed without further refinement if an approximate knowledge of the overall impulse response is used for initialization and all users are received with similar power. In this case, the stochastic gradient adaptive scheme updates the estimate of $\mathcal{H}$ for each estate until convergence is attained within few hundred symbols [10]. In the array observation case this approximate knowledge requires a priori angle of arrival information for each user which might be impractical in most of the applications.

If the algorithm is initiated with no knowledge of the global impulse response $\mathcal{H}$ the adaptation scheme can be easily trapped in local minima as consequence of two fairly independent phenomena:

- Severe intersymbol interference which leads to local minima as in Godard-type blind equalizers in the single user single sensor case. Solutions to this problem was proposed for the single user and the multiuser cases employing the idea of anchored equalizers [15, 8]. The extension of the multiuser blind equalizer of [8] to an array observation is straightforward but implies approximate knowledge the desired user angle of arrival which is not usually available.
- Local minima due to the multiuser structure of the signal resulting from the near-far effect.

The first circumstance rarely occurs in most practical radio-communication channels in which ISI spans very few symbols and therefore we concentrate on analyzing and overcoming the near-far effect in the proposed algorithm.

The effect can be easily understood in the two users case. When one of the users is characterized by an impulse response of much greater magnitude than the other, the stochastic gradient scheme tends to split the greater impulse response among both users (since this locally maximizes the probability function (14)) and the signal received from the *weak* user is just taken as part of the noise. The algorithm converges to a good approximation of the *strong* impulse response and neglects the *weak* one. The same effect can happen after random initialization of $\hat{\mathcal{H}}_i$. This phenomenon, however, can be easily detected since the corresponding estimated ML sequences for both users are exactly the same (except for a possible sign change). In the more general case of K users, any of their actual impulse responses, $\mathbf{H}_k[n]$ could in principle appear partitioned into an arbitrary number of users, i.e.

$$\mathbf{H}_k[n] \simeq \hat{\mathbf{H}}_k[n] + \sum_j \pm \hat{\mathbf{H}}_{k_j}[n], \tag{18}$$

but still this effect will be reflected in identical estimated ML sequences for these users (k and k_j) again except for a possible sign difference.

4.2. AVOIDING LOCAL MINIMA

We propose a simple procedure to overcome convergence to local minima due to the multiuser structure of the observation. Consider the two synchronous users case with $L = 1$. A near-far effect robust implementation of the algorithm checks every N_c symbols for total coherence of the corresponding ML sequences for each user. The probability of random coincidence of two independent binary sources, except for a possible sign change, is $1/2^{N_c-1}$, and can be made arbitrarily small increasing N_c. In case this absolute coherence is detected, it is assumed that the algorithm has converged to a local minimum and the impulse responses of each user are added (or subtracted if the sequences were of opposite sign) and assigned arbitrarily to one of them. The other user impulse response is just reset to zero, i.e.,

$$\begin{aligned}\hat{\mathbf{h}}_1[n] &\leftarrow \hat{\mathbf{h}}_1[n] \pm \hat{\mathbf{h}}_2[n]\\ \hat{\mathbf{h}}_2[n] &\leftarrow \mathbf{0}.\end{aligned}$$

This compensation may be necessary until a good estimate of the *strong* impulse response is obtained which cancels the local minimum. In practice, we observed that one such compensation is necessary for approximately each $10dB$ in power difference.

In general, for an arbitrary number of users and value of L, a total of $\binom{K}{2} = K(K-1)/2$ symbol cross-correlation functions need to be computed, and each of them for $2L-1$ lags. This cross-correlation functions are defined as

$$\rho_{kk'}[l] = \left\lfloor \frac{1}{N_c - |l|} \sum_{p=0}^{N_c-1} \hat{b}_k[p+l]\hat{b}_{k'}[p] \right\rfloor; \quad k' > k \tag{19}$$

where $\hat{b}_k[p]$ is the estimated ML sequence associated with user k for the previous N_c symbols. The global impulse response is compensated iterating for each user in ascending order, i.e., $k = 1, \ldots, K$, the following impulse response update

$$\hat{\mathbf{h}}_{kl}[n] \leftarrow \hat{\mathbf{h}}_{kl}[n] + \sum_{k'=k+1}^{K} \sum_{l'=0}^{L-1} \rho_{kk'}[l-l']\hat{h}_{k'l'}[n] \tag{20}$$

and possible re-initialization,

$$\begin{aligned}&\hat{\mathbf{h}}_{k'l'}[n] \leftarrow (1 - |\rho_{kk'}[l-l']|)\hat{\mathbf{h}}_{k'l'}[n]\\ &k' = k+1, \ldots, K; l' = 0, \ldots, L-1.\end{aligned} \tag{21}$$

Let us note also that, like in most blind multiuser schemes, there is an implicit data association ambiguity. This ambiguity is reflected in the fact that coherently estimated impulse responses are arbitrarily assigned to the estimate with the smallest index in the impulse response update (20). Consequently, in high near-far scenarios, users tend to be sorted with descending power.

5. Simulation Results

In this section numerical results are presented which illustrate the effectiveness of the proposed algorithm. Depending on the system design, the algorithm can be applied at different stages of the detection and/or estimation process:

- The algorithm can be used to estimate the combined temporal and spatial signature without the use of training sequences. After initial convergence this type of estimate can be used as a side information by lower complexity spatial/temporal multiuser receivers, either in TDMA or CDMA systems.

- In a scenario where the complexity of a blind scheme is not an obstacle (e.g. small numbers of cochannel interferers in a channel with moderate ISI) the blind receiver can be used as an optimal multiuser MLSE detector with spatial diversity. In TDMA systems, the algorithm can be used as a complement to a single-user receiver to provide a reliable detection when cochannel interference is present. In a CDMA system, it can be used to increase the capacity of the system by exploring the spatial distribution of the users.

Both the computational complexity and the memory requirements are proportional to the number of states which are exponential in the number of users times (N) the impulse response bound in symbols (L). This result is equivalent in order of magnitude to the complexity associated with the optimal detector [11] although the blind operation of the proposed scheme requires additional resources for the estimation algorithm. A detailed computational analysis study is included in [16] where the proposed algorithm is compared to a similar approach that employs the Baum-Welch algorithm for detection.

A. Separation of BPSK signals

The first example illustrates the convergence of the algorithm considering two BPSK signals impinging into a $\lambda/2$ linearly spaced array of four sensors. This presents the case of a one dominant cochannel interferer in a TDMA system where no temporal signatures are used. The sources are assumed to radiate from broadside and 5 degrees apart, and to be received with 0 and $20dB$ SNR respectively by each sensor. A total of 100 Monte Carlo runs were observed to assess the performance of the technique. In all simulations the angle of arrival of the signals is unknown to the receiver and the adaptation constant μ was set to 0.02.

Convergence is the basic measure of the performance of this blind algorithm since a simpler decision-directed receiver could be employed after the initial convergence. Fig. 3 shows the evolution of the magnitude of each of the elements of the global impulse response estimate for both users $\hat{\mathcal{H}}_{ML} = \hat{\mathcal{H}}_i$, where $\mathbf{s}_i$ is the most likely final state. The mean value appears in solid line whereas the mean $\pm$ the standard deviation along the 100 runs is indicated by the dotted lines. The mean square error (MSE) of the estimate of $\mathcal{H}$ is illustrated in Fig. 4. Convergence is attained within approximately 200 symbols for all realizations.

The same simulation was repeated with a single channel observation to quantify the improvement in performance due to the spatial diversity. The results in terms of learning curves for the estimated global impulse response and its corresponding MSE are given in Figs. 5 and 6 respectively. In the single channel observation case, the algorithm can still separate both sources based on the different received amplitudes. Nevertheless, the convergence period is increased with respect to the case when spatial diversity is employed. Note that in both cases two coherence compensations are required, after 30 and 60 symbols, to cope with the near far effect (the parameter N_c was set to 30). coherence compensations result is a distinctive step characteristic of the MSE learning curve. After 60 symbols the algorithm converges to the actual global impulse response.

B. SDMA Operation

The blind multiuser detector permits capacity increase exploiting the different spatial signature of users impinging from different angles. Again, no temporal signature is used to distinguish the different users. This mode of operations is known as spatial division multiple-access (SDMA) [17]. As an example we illustrate the separation of 4 BPSK signals that are received

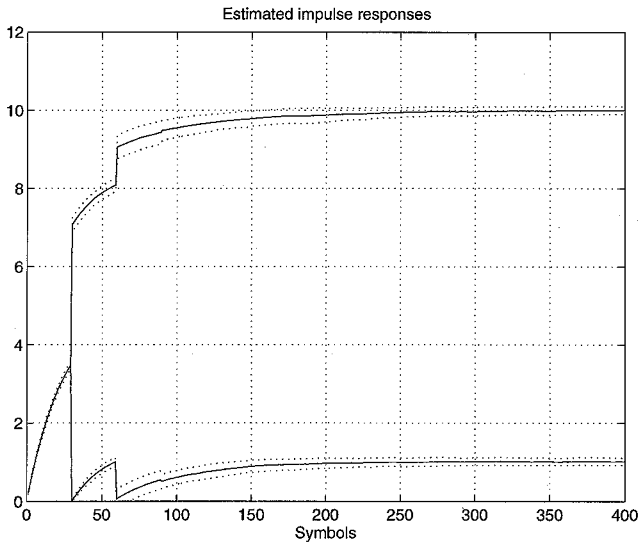

Figure 3. Array: Learning curve for $\hat{\mathcal{H}}_{ML}$ of two BPSK signals.

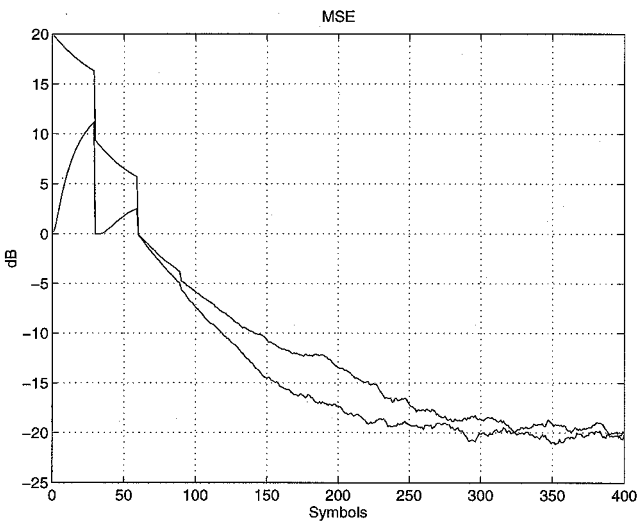

Figure 4. Array: Learning curve for the MSE of $\hat{\mathcal{H}}_{ML}$ of two BPSK signals.

by an array of four $\lambda/2$ linearly spaced sensors. Their angle of arrival is arbitrarily chosen to be 0, 5, 10 and 15 degrees from broadside whereas their respective SNR are 0, 10, 20 and 30 dB at each sensor. In Fig. 7 the evolution of the magnitude of each of the coefficients of the global impulse response $\mathcal{H}$ is illustrated for a total of 100 Monte Carlo runs. It can be observed how the amplitudes converge to the values corresponding to the amplitudes of the four incoming signals. The evolution of the MSE of the estimate of $\mathcal{H}$ can be visualized in Fig. 8 in which several coherence compensations are apparent until final convergence is attained $(N_c = 30)$. Signal separation has been achieved relying only on the spatial distribution of the incoming signals and with no previous knowledge. This suggest that this mode of operation

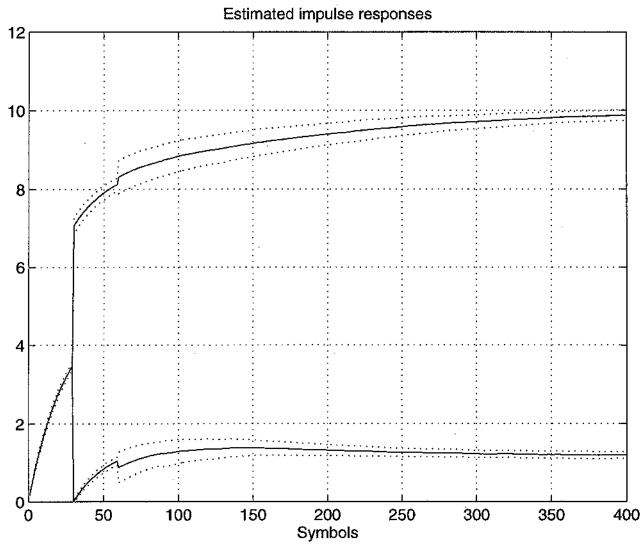

Figure 5. Single Sensor: Learning curve for $\hat{\mathcal{H}}_{ML}$ of two BPSK signals.

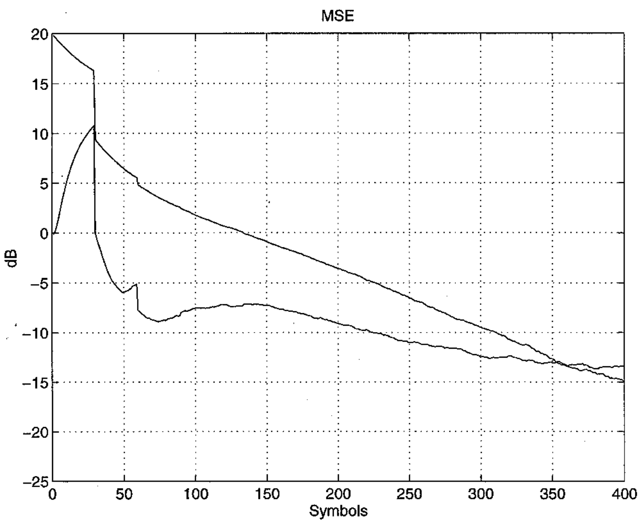

Figure 6. Single Sensor: Learning curve for the MSE of $\hat{\mathcal{H}}_{ML}$ of two BPSK signals.

can be successfully combined with basic access techniques such as TDMA or CDMA. In this case the estimation algorithm provides an estimate of the spatial signature of the users.

C. Capacity gain in DS-CDMA Systems

We also illustrate the convergence of the algorithm in a scenario of 8 DS-CDMA users employing the 8 different Gold sequences of length 7 as temporal signatures. The multiuser signal is received by an array of two $\lambda/2$ separated sensors. Users' signals are synchronous and their angle of arrival is -30, -20, -10, 0, 10, 20, 30 and 40 degrees from broadside respectively. All users are received with different powers such that their SNR at each sensor are

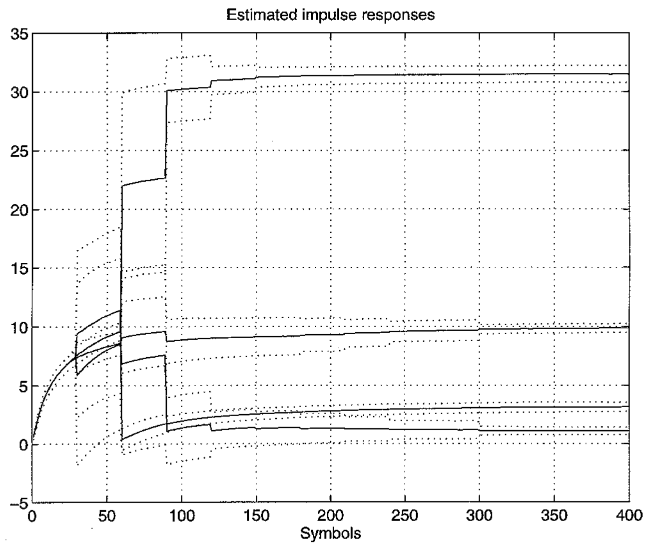

Figure 7. SDMA: Learning curve for $\hat{\mathcal{H}}_{ML}$.

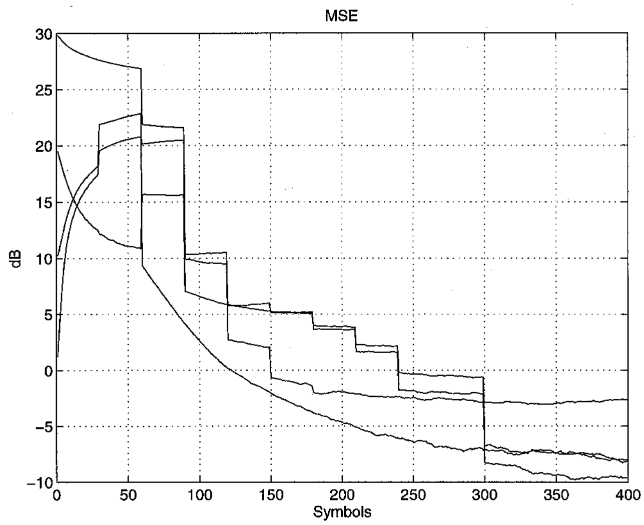

Figure 8. SDMA: Learning curve for the MSE of $\hat{\mathcal{H}}_{ML}$.

10, 13, 16, 19, 22, 25, 28 and 31dB respectively. Fig. 9 shows the evolution of the magnitude of the coefficients of $\hat{\mathcal{H}}_{ML}$ in which convergence is observed after few hundred symbols. After initial convergence the estimate of $\mathcal{H}$ provided by this algorithm can be used by a lower complexity multiuser receiver. Capacity gain in DS-CDMA can be achieved by exploiting both the spatial and temporal signatures of the users for joint signal detection.

D. Application to GSM Frequency Selective Fading channels

In mobile communications, channel characteristics undergo time variations mainly caused by the combined effect of multipath propagation and Doppler effects. The multiuser detection

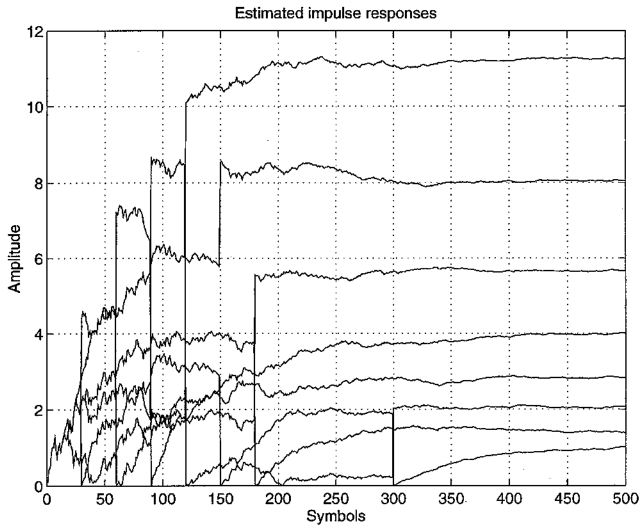

Figure 9. DS-CDMA: Learning curve for $\hat{\mathcal{H}}_{ML}$ of 8 DS-CDMA users.

algorithm presented in this paper relies on a (blind) channel identification procedure and therefore requires tracking of temporal channel variations. An important benchmark of adaptive algorithms for mobile systems is provided by the frequency selective fading channels standardized in GSM. They include among others the TUx and RAx channels that represent the mobile radio channel model for typical urban and rural areas respectively. They are modeled by the equation:

$$h(\tau, t) = \sum_{m=1}^{6} c_m(t)\delta(\tau - T_m) \tag{22}$$

where $c_m(t)$ are 6 independent Rayleigh distributed $(c_1(t)$ has Rician distribution in RAx with 6.47dB of Rician factor) fading coefficients which mean power is $-3, 0, -2, -6, -8$ and -10 dB and $0, -4, -8, -12, -16$ and -20 dB for TUx and RAx respectively. The parameters T_m are their corresponding tab delays of 0, 0.2, 0.5, 1.6, 2.3 and 5μs and 0, 0.1, 0.2, 0.3, 0.4 and 0.5μs respectively. In both cases, x is the speed of the mobile in km/h.

We first consider the case of two users using signatures [1, 1, 1] and [1, -1, 1] propagated using independent TU60 channels and received by a two sensor array ($\lambda/2$ spaced). In addition to the receiver characteristics outlined in the previous examples, the multisensor reception provides diversity benefit in fading channels. The system is asynchronous and the direct path of the second user arrives with a delay of $2T_s$ with respect to the first one. The mobile's speed is 60 km/h and the carrier frequency 915MHz generates a Doppler frequency of 50.8Hz. The bit rate is 270.833Kbs and thus the dispersion caused by the channel spans 1.35 symbols. The blind deconvolution algorithm was initialized assuming no knowledge of the users' signature, angle of arrival and physical channel impulse response. The dispersion of the channel was upper bounded by one symbol and thus the parameter L was set to 2. The received SNR was 13 dB for both users.

The experiment was repeated using independent RA100 channels and a four sensor array ($\lambda/2$ spaced). In this case the higher speed of the mobiles and corresponding fading rate

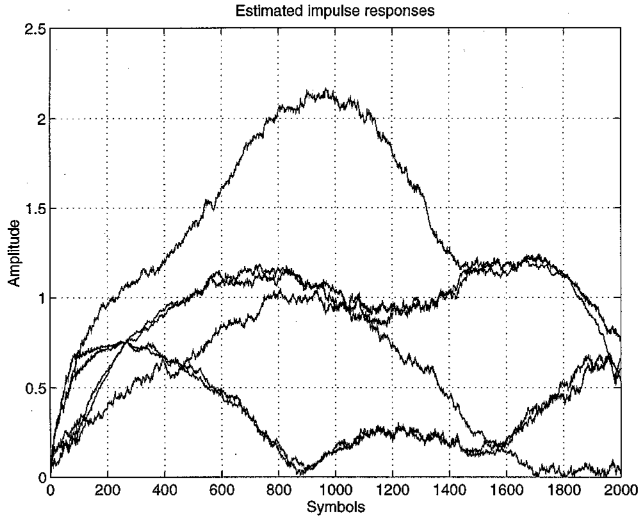

Figure 10. TU60: Learning curve for $\hat{\mathcal{H}}_{ML}$.

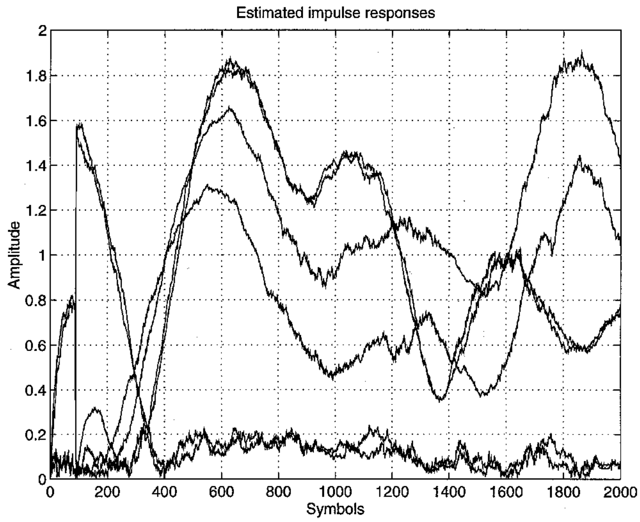

Figure 11. RA100: Learning curve for $\hat{\mathcal{H}}_{ML}$.

(Doppler frequency equals $84.7Hz$) is compensated with an almost negligible ISI of the RAx channel at this bit rate (0.135 symbols). The received SNR was 13 dB for both users. In both cases, convergence was attained again within approximately a hundred symbols to the dispersive fading channel. After convergence, channel variations were accurately tracked by the adaptive estimation scheme. Figs. 10 and 11 illustrate the evolution of the magnitude of the estimate of the global channel impulse responses during 2000 symbols. In the $TU60$ case the observed errors, including the adaptation period, were 0 and 23 whereas 41 and 161 errors were observed when using the $RA100$ channels.

6. Conclusions

The new generation of mobile wireless systems targets high spectral efficiency providing, at the same time, a wide range of new services with high quality and reliability. One of the most important requirements for high performance receivers is the operation in the interference limited scenarios. To achieve this goal the advances in spatial and temporal signal processing should be combined in the implementation of the receiver.

We have proposed a multiuser receiver based on array observation which efficiently combines spatial diversity and optimal multiuser MLSE. Moreover, the receiver can be adapted blindly, i.e. without the use of training sequences. The drawback is the receiver's high complexity coming from the optimal detection stage, which is exponential in number of active users times the length of the ISI. However, the complexity does not increase compared to a single-sensor case. The estimation algorithm of the receiver employs a simple stochastic gradient technique, of linear complexity in the number of sensors, for combined spatial and temporal signature acquisition and tracking. Possible occurrence of local minima during the blind mode of operation due to near-far effect has been eliminated by means of coherence tests.

The blind scheme presented in this paper was shown to be effective in separating cochannel signals in near-far situations without relying on signature sequences, thus enabling improved performance in TDMA systems with cochannel interference. It can also increase CDMA capacity by exploiting spatial information of active users and provide SDMA operation. Further benefits of array reception in fading channels are due to spatial diversity. Different modes of the proposed receiver operation could range from combined spatial/temporal signature estimation to full adaptive MLSE receiver operation, depending on the performance/complexity tradeoff. This algorithm can be a viable solution in situations with moderate ISI and small number of active users. Undergoing research focuses on reduced complexity schemes with comparable performance.

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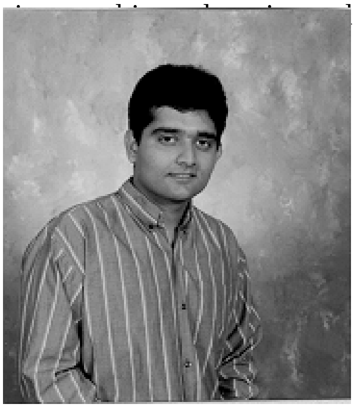

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