ADAPTIVE FILTERING IN WIRELESS COMMUNICATIONS

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ABSTRACT

This paper reviews the current investigations and the established results on the applications of adaptive systems to wireless communications. The recently proposed blind channel estimation methods based on subspace decomposition of the received signal matrix or of the received signal correlation matrix are briefly discussed. These methods are compared with the prediction-based blind methods which are less computationally complex. In both cases, there is a great interest in obtaining efficient adaptive implementations in order to allow their use in real time telecommunications application, specially at mobile receivers that should be small in size and should have low consumption of power.

1. INTRODUCTION

Adaptive signal processing is a mature subject nowadays, and is employed in a number of practical applications, such as speech processing, active noise cancellation, and communications [1]. In wireless communication systems one of the main factors limiting the system capacity are interferences such as: i) intersymbol interference due to multipath fading in frequency selective channels, which is the main impairment in single user communications and can be corrected through the use of an adaptive equalizer; ii) in CDMA systems the dominant sources of impairment are cochannel (or multiple access) and adjacent channel interferences.

In recent years, there is an extensive literature dealing with multiple access (or multiuser) interference suppression in batch and in adaptive modes. The adaptive mode is very attractive due to its reduced computational complexity which allows its implementation in situations where there are tight complexity and processing delay constraints, as in the case of a mobile handset.

In this paper, we aim to provide a brief review of some of the adaptive solutions to interference suppression in CDMA wireless systems. We start with an introduction to most widely considered methods of multiuser detection schemes, a subject found in Verdu's book [2], and comment on their potential to adaptive implementation. Then we discuss recently proposed blind channel estimation methods based on subspace decomposition of the received signal matrix and compare them with the prediction-based blind methods which are less computationally complex. For synchronous system, channel equalization can provide performance gains, for example, if users are separated with orthogonal codes, like in IS-95 and WCDMA downlink. Channel equalization on chip-level approximately restore user orthogonality leading to simpler symbol detection methods.

We finally discuss the potential use of a recently proposed family of set-membership adaptive algorithms in these interference suppression methods.

2. OPTIMUM RECEIVER

Is there a demodulation scheme that is optimum in the presence of white Gaussian background noise and multiple access interference?

For coherent reception, the optimum solutions exist, each specialized for the chosen optimality criterion. However, the computation of the optimum solution requires dynamic programming and is very computationally complex. The solution generated by an optimum demodulator does not have the performance disadvantages of the single user conventional demodulator, and for high signal-to-noise ratio (SNR), the performance of the optimum demodulator approaches that of single user system.

The main drawbacks of the optimum receiver are: much higher complexity; coupled processing (not a major problem at the base station); the amplitudes of the individual users signal are required.

If one chooses maximum-likelihood for detection, the objective is to maximize

$$P\{[r(t), t \in \mathcal{R}]|\mathbf{b}\} = Be^{\left(\frac{\Gamma(\mathbf{b})}{2\sigma_n^2}\right)} \tag{1}$$

where $P[\cdot]$ denotes probability of $[\cdot]$, B is a constant, $\mathcal{R}$ represents the set of real numbers, $\mathbf{b}$ is a vector including the bits sent by all L users.

The function $\Gamma(\cdot)$ is defined as

$$\Gamma(\mathbf{b}) = 2\int_{-\infty}^{\infty} S(t,\mathbf{b})r(t)dt - \int_{-\infty}^{\infty} S^2(t,\mathbf{b})dt \quad (2)$$

where

$$S(t,\mathbf{b}) = \sum_{n=-\infty}^{\infty}\sum_{m=0}^{L}\sqrt{2E_m}\; b_m(nT_b)c_m(t-nT_b-\tau_l) \quad (3)$$

where $b_m(nT_b)$ represents the symbols sent by the mth user, and $c_m(t-nT_b-\tau_l)$ its spreading code waveform, and τ_l represents a delay. The optimum solution clearly requires the knowledge of all the information sent by all users all the time, along with their signature waveform. The asynchronous mode of operation allows each bit to overlap with two adjacent bits from each interfering user.

3. CLASS OF RECEIVERS

There are a number of CDMA receivers ranging from the optimum (the most complex) to the single user matched filter (the least complex). Below we list other multiuser detection receivers which were proposed to provide a tradeoff between performance and complexity. The corresponding information requirements for each receiver can be found in Table 1.

1. Conventional receiver with matched filter.
2. Optimum receiver with coupled decision (also known as optimum multiuser detector, exponentially complex with the number of users).
3. Optimum linear receiver (with coupled decision).
4. Minimum MSE adaptive receiver.
5. Decorrelating receiver.
6. PIC, SIC and multistage receiver.
7. Blind receivers based on second- and higher-order statistics.

4. DECORRELATING RECEIVER

The decision in the decorrelating receiver is made after multiplying the received signal by an estimate of the inverse of the matrix of correlations between signature sequences.

$$\mathbf{R}^{-1}\mathbf{r} = \mathbf{A}\mathbf{b} + \mathbf{R}^{-1}\mathbf{v}$$

where $\mathbf{A}$ is a diagonal matrix containing the amplitudes of each user, $\mathbf{v}$ is the additional noise filtered by the spreading sequence matrix. If asynchronous case, the decorrelating receiver generalizes to an IIR filter. As can be observed on the table: The inverse of $\mathbf{R}$ must be computed or estimated; timing of all the users must be acquired; receiver is coupled or centralized, all users are received; the users signatures must be known.

Table 1: Requirements of each approach

	Interf. codes	User code	Relative power	Timing user	Timing interf.	Train. seq.
1		×	×	×		
2	×	×	×	×	×	
3	×	×	×	×	×	
4				×		×
5	×	×		×	×	
6	×	×	×	×	×	
7		×		×		

It has worse performance, in terms of BER, than the matched filter receiver for low SNR due to noise enhancement.

5. MMSE RECEIVER

The optimum linear minimum MSE receiver is designed as follows

$$\min_{\mathbf{W}\in\mathbf{R}^{K\times K}} \mathrm{E}[\|\mathbf{b}-\mathbf{W}\mathbf{r}\|^2] \quad (4)$$

where the expectation is taken with respect to $\mathbf{b}$ and the filtered noise vector $\mathbf{n}$.

Assuming $\mathbf{n}$ Gaussian, the solution for the MMSE actually replaces $\mathbf{R}^{-1}$ of the decorrelating receiver by $[\mathbf{R}+\sigma_n^2\mathbf{A}^{-2}]^{-1}$.

It has the features of the decorrelating receiver but requires the received amplitudes of the users. If additional noise or the interferers are weak, the MMSE receiver approaches the single user matched filter detector. As $\sigma_n^2 \to 0$ the MMSE receiver tends to the decorrelating receiver.

6. MMSE ADAPTIVE RECEIVER

The MMSE receiver can easily be made adaptive. The signature waveform of the user of interest does not need to be known, although it helps in the algorithm initialization. The MMSE receiver can be made adaptive and can be used in asynchronous channel, then the desired user timing must be acquired.

7. SIC AND PIC RECEIVERS

The detection strategy for the SIC is to first detect stronger a user with conventional matched filter detector, then subtract the signal due to that user from the received waveform. Repeat the process to the resulting signal by removing the second strongest user. Note that the previous stronger user is not there if it was properly demodulated. It requires accurate user relative power estimation, otherwise the decorrelating detector will be better.

The PIC receiver estimates all the user signals and thereafter subtracts the estimates from the received waveform in parallel. The PIC receiver has a better performance than SIC when the power differences of the users are small. To further improve the PIC performance a decorrelator can be used as a first stage.

8. BLIND RECEIVERS

Inspired by array processing techniques a blind multiuser detector based on constrained adaptive filtering was proposed in [3]. This algorithm is briefly described here.

Estimate the desired user data as follows:

$$\hat{b}_1 = \mathrm{sgn}(< \mathbf{r}, \mathbf{w}_1 >)$$

with

$$\mathbf{w}_1 = \mathbf{c}_1 + \tilde{\mathbf{w}}_1$$

where $< \mathbf{c}_1, \tilde{\mathbf{w}}_1 >= 0$.

The solution vector $\mathbf{w}_1$ cannot be represented in this form either if $< \mathbf{w}_1, \mathbf{c}_1 >\neq 0$ and the decisions are scale variant, or if $< \mathbf{w}_1, \mathbf{c}_1 >= 0$.

We must choose $\tilde{\mathbf{w}}_1$ such that

$$\begin{aligned} \min_{\tilde{\mathbf{w}}_1}\{\mathrm{E}[(< \mathbf{r}, \mathbf{w}_1 >)^2]\} &= \min_{\tilde{\mathbf{w}}_1}\{\mathrm{E}[(< \mathbf{r}, \mathbf{c}_1 + \tilde{\mathbf{w}}_1 >)^2]\} \\ &= \min_{\tilde{\mathbf{w}}_1}\{\mathrm{E}[(A_1 b_1 - < \mathbf{r}, \mathbf{c}_1 + \tilde{\mathbf{w}}_1 >)^2] - A_1^2\} \end{aligned} \tag{5}$$

The gradient updating algorithm will be described by

$$\begin{aligned} \tilde{\mathbf{w}}_1(k) &= \tilde{\mathbf{w}}_1(k-1) \\ &\quad - \mu < \mathbf{r}, \mathbf{c}_1 >< \mathbf{r}, \mathbf{c}_1 + \tilde{\mathbf{w}}_1(k-1) > \end{aligned} \tag{6}$$

The algorithm above does not explore any diversity provided by multiple antenna and/or oversampling leading to poor performance in multipath environments.

9. ADAPTIVE BLIND CHANNEL EQUALIZATION

The blind receiver method described in previous section requires cyclostationay interference on symbol level. As mentioned previously, channel equalization can successfully be applied in systems employing long codes. Furthermore, in case of synchronous system with orthogonal user separation, the equalizer can be followed by a conventional matched filter used for symbol detection.

Several blind methods for channel equalization have been proposed in the literature. Many of the early methods relied on high-order (greater than second-order) statistics which leads to multiple minima, slow convergence, and are more sensitive to noise than those using second-order statistics.

Blind channel equalization using second-order statistics is possible by exploring diversity of antennas or by oversampling. The channel inverse filter can be constructed from the observed data using subspace methods or prediction methods. The subspace methods are in general computationally complex. Furthermore they are sensitive to channel modeling errors causing dimension errors in the constructed signal and noise subspaces [4]. Prediction error methods (PEM) [5] are robust to overmodeling and lend themselves to adaptive implementations. A brief description of this method is given here.

Assuming a single input L-output linear system, the received signal can be described by

$$\mathbf{x}(k) = \sum_{n=0}^{M} r(k-n)\mathbf{h}(n) + \mathbf{n}(k) \tag{7}$$

$$\bar{\mathbf{x}}(k) = \mathcal{H}\bar{\mathbf{r}}(k) + \bar{\mathbf{n}}(k) \tag{8}$$

This can be solved by a constrained adaptive algorithm as described in [5].

The PEM's rely on the following assumptions

AS1) $\mathrm{rank}(\mathcal{H}) = M + N$

AS2) $NL > N + M$, i.e., $\mathcal{H}$ is "tall."

AS3) $\mathrm{E}[r(k)r(k-n)] = \delta_n$, i.e., input signal is white.

In a noise-free environment, the prediction coefficients leading to an acceptable FIR channel inverse can be obtained by solving the Yule-Walker equations

$$\mathbf{R}_p \mathbf{p} = \mathbf{a} \tag{9}$$

In noisy environment the solution above is biased and will not correspond to the FIR channel inverse. In a noise-free environment the correlation matrix $\mathbf{R}_p$ is rank-deficient. The idea proposed in [5] is to restore this property and consequently the estimated prediction coefficients would be unbiased.

Another method related to the predictor method is based on least squares smoothing [6] that allows joint channel order estimation. This method, as well as most blind methods using second-order statistics, requires that the zeros of the subchannels (obtained by the oversampling or by the antenna array) be distinct. The smoothing approach is very sensitive to this condition.

10. SET-MEMBERSHIP ADAPTIVE ALGORITHMS WITH DATA-REUSE

Most adaptive algorithms applied in communications use gradient type search algorithms. However, it appears that the algorithms briefly revised here have a great potential to be used in this type of applications. In set-membership filtering (SMF) a deterministic upper bound γ is specified on the output estimation error $e = d - \mathbf{w}^{\mathrm{T}}\mathbf{r}$. This bound γ is a design parameter and can vary depending on the application. For example, in a simple channel equalization setup, a natural choice would be to choose $\gamma = d_{min}/2$ where d_{min} is the minimum distance between the signal constellations [7]. As a result of the bound constraint γ, the adaptive filtering algorithms derived within the framework of SMF will not perform filter update for all incoming signals, in other words they are data selective.

In [8] a set-membership version of the NLMS algorithm was derived. The set-membership NLMS (SM-NLMS) algorithm was shown to have the following update

$$\mathbf{w}(k+1) = \mathbf{w}(k) + \alpha(k)\frac{e(k)\mathbf{r}(k)}{\|\mathbf{r}(k)\|^2} \tag{10}$$

where

$$\alpha(k) = \begin{cases} 1 - \frac{\gamma}{|e(k)|} & \text{if } |e(k)| > \gamma \\ 0 & \text{otherwise} \end{cases} \tag{11}$$

The main drawback with the SM-NLMS algorithm is that the convergence speed slows down considerably for correlated inputs. To overcome this problem at a low additional complexity, data from two consecutive time instants can be utilized as is done in the set-membership binormalized data-reusing LMS (SM-BNDRLMS) algorithms presented in [9]. A generalization of the ideas given in [8] and [9] to an algorithm utilizing data from P consecutive time instants is possible, and the updating algorithm is given by

$$\mathbf{w}(k+1) = \mathbf{w}(k) + \mathbf{X}(k)\mathbf{t}(k) \tag{12}$$

$$\mathbf{t}(k) = \left[\mathbf{X}^{\mathrm{T}}(k)\mathbf{X}(k) + \delta\mathbf{I}\right]^{-1}\alpha(k)e(k)\mathbf{u}_1 \tag{13}$$

$$\mathbf{X}(k) = \left[\mathbf{x}(k)\ \mathbf{x}(k-1)\ \cdots\ \mathbf{x}(k-P+1)\right] \tag{14}$$

where $\mathbf{u}_1 = [1, 0, \ldots, 0]^{\mathrm{T}}$ is a unity vector with 1 in the first position, and $\alpha(k)$ is the same as given in (10), and δ is a small constant.

11. SUMMARY AND CONCLUSIONS

We reviewed the current investigations on the applications of adaptive systems to wireless communications. In particular the recently proposed blind channel estimation methods based on subspace decomposition of the received signal matrix or of the received signal correlation matrix were addressed. These algorithms have high computational complexity and are very sensitive to estimation errors in the order of the channel [10]. It is also an open problem which are the best adaptive algorithms for subspace decomposition methods in order to allow their online implementation. We also discussed the prediction-based blind methods which are less computationally complex but are highly sensitive to channel noise. As can be verified there is plenty of room for further investigations.

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