On Adaptive LCMV Beamforming for Multiuser Processing in Wireless Systems

Danilo Zanatta Filho, Charles C. Cavalcante, Leonardo S. Resende and João Marcos T. Romano

***Abstract*—Multiuser processing, using an antenna array, has emerged as a suitable solution for capacity increase in wireless systems. The use of an antenna array reduces the multiuser interference, allowing two or more users to share systems resources in an efficient way. The use of a Linearly Constrained Minimum Variance (LCMV) criterion to optimize the antenna array weights has been proved to be a good solution for multiuser processing. This work presents an unified view of LCMV beamforming, including a solution that avoids direction of arrival (DOA) estimation and is able to cope with angular spread. An adaptive versions of the resulting technique is also presented. Moreover, we evaluate the performance of the proposed techniques in non-zero angular spread and non-stationary environments. The results provide an overview of the potential of LCMV techniques in multiuser wireless communication systems.**

Index Terms: Spatial filtering, constraint filtering, beamforming, LCMV, DOA estimation, multiuser processing, wireless systems.

I. Introduction

Wireless communications systems have experienced a great development in the last few years. The improvement on the quality of service, spectrum management and capacity allowed the appearance of the third (3G) and proposal of fourth (4G) generations of wireless systems. A key aspect on the success of the systems is the ability to handle with many different users at the same time. And this is greatly due the advances on signal processing strategies.

The most know strategy is the use of spread spectrum which assigns different and orthogonal spread sequences to each user and use this at the receiver for detection. This is commonly called multiuser detection. If spread spectrum is not used, we denote this process as multiuser processing. *Multiuser processing* is more general than multiuser detection since it does not necessarily takes into account spread spectrum as multiple access technology. This processing, using an antenna array, has emerged as a suitable solution for capacity increase by the inclusion of the spatial dimension, beyond the frontier of the classical dimensions of processing, time, frequency and code. In this work we use the approach of decoupled space-time structure, that means that spatial filter (beamforming) at the base station processes only the multiuser interference (MUI) and leave to the temporal equalizer the task of dealing with intersymbol interference (ISI).

In a previous work [1], two different optimization criteria for beamforming have been investigated: the *Linearly Constrained Minimum Variance* (LCMV) and the *Summed Inverse Carrier to interference Ratio* (SICR). SICR demands an a priori knowledge about the channel covariance matrix (CCM), while LCMV needs a previous estimation of the angle or direction of arrival (DOA) of the desired users. One interesting result of [1] states that when one single eigenvectorial constraint (EV) is used in the LCMV solution, the performance of both criteria (LCMV and SICR) are practically the same. However, LCMV provides adaptive solutions for performing beamforming.

In a further work [2], the application of the LCMV adaptive solutions (namely LMS and RLS) was investigated and compared with the LCMV batch solution. Also, an alternative strategy concerning the implementation of the adaptive LCMV algorithm with EV constraint was proposed. It consists in using the CCM, instead of DOA estimation, for constructing the matrix of constraints to be applied in the adaptation process. Simulations in [2] have been performed for different scenarios in a packet-like environment, in order to evaluate the performance of the proposed method.

This work brings an unified presentation of these previous results. Also, we evaluate the performance of the proposed techniques in the following scenarios:

- Generalized Jakes channel model with non-zero angular spread; and
- Non-stationarity characterized by abrupt change of interferers' DOA.

The set of simulation results provide an overview of the potential of LCMV techniques in multiuser wireless communication systems.

The rest of the work is organized is follows. In Section II the system model is described. Section III is devoted to the derivation of the optimum combining solution and shows that it can be seen as a constrained filtering problem. Linearly constrained minimum variance (LCMV) filtering is discussed in Section IV. The novel algorithm that does not requires DOA estimation is described in Section V and their adaptive versions are derived in Section VI. Simulation results are shown in Section VII and, finally, conclusions are stated in Section VIII.

II. System Model

Let us consider the uplink of a wireless system where U users share the same resources in a same cell reuse (SCR) scheme. Each user u transmits over a space-time channel, represented by its uplink channel correlation matrix (UCCM) $\mathbf{R}_u$ given by

$$\mathbf{R}_u = \sum_{l=1}^{L_T} g\left(\theta_l^u\right) \cdot \mathbf{d}^H\left(\theta_l^u\right) \cdot \mathbf{d}\left(\theta_l^u\right), \tag{1}$$

where $g\left(\theta_l^u\right)$ is the mean power of the received signal in direction θ_l^u and L_T is the total number of multipaths linking the mobile u to the base station. The received signal at time

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instant n is denoted by $\mathbf{x}(n)$ and is processed by a spatial filter denoted by $\mathbf{w}_k$.

The mean power corresponding to the u-th user after array processing is then given by

$$\overline{E}_{bu} = \mathbf{w}_u^H \mathbf{R}_u \mathbf{w}_u, \tag{2}$$

and the mean power of the interference provided by the other users is

$$\overline{I}_u = \sum_{\substack{i=1 \\ i \neq u}}^{U} \mathbf{w}_u^H \mathbf{R}_i \mathbf{w}_u. \tag{3}$$

If we consider the spatial noise from the neighbor cells and also the thermic noise over each element of the array as spatially white, we can group both components in a single noise term with power σ^2. Thus, we can write the signal-to-noise plus interference ratio (SNIR) for each user as

$$\text{SNIR}_u = \left(\frac{\overline{E}_b}{\overline{I} + \sigma^2} \right)_u = \frac{\mathbf{w}_u^H \mathbf{R}_u \mathbf{w}_u}{\mathbf{w}_u^H \left(\sum\limits_{\substack{i=1 \\ i \neq u}}^{U} \mathbf{R}_i + \sigma^2 \right) \mathbf{w}_u} \tag{4}$$

Then, our problem consists in obtaining the spatial filters $\mathbf{w}_u$ that maximize the SNIR each user. The next section poses the analytical solution of the problem, based on constrained optimization.

III. Optimum Combining (OC)

Equation (4) represents the so-called carrier-to-interference ratio (CIR) that relates the useful signal power with interference plus noise. In order to simplify the manipulations, we can redefine the carrier-to-interference plus carrier ratio (CICR) as:

$$\text{CICR}_u = \frac{\mathbf{w}_u^H \mathbf{R}_u \mathbf{w}_u}{\mathbf{w}_u^H \left(\sum\limits_{i=1}^{U} \mathbf{R}_i + \sigma^2 \right) \mathbf{w}_u} = \frac{\mathbf{w}_u^H \mathbf{R}_u \mathbf{w}_u}{\mathbf{w}_u^H \mathbf{R}_{\mathbf{xx}} \mathbf{w}_u} \tag{5}$$

where $\mathbf{R}_{\mathbf{xx}}$ is the covariance matrix of the received signal $\mathbf{x}(n)$.

Then, one can easily note that maximize the CIR corresponds to maximize the CICR, which has a maximum value equals 1. Such optimization can be written in a minimization with constraints form, given by:

$$\begin{aligned} &\min_{\mathbf{w}_u} \quad \mathbf{w}_u^H \mathbf{R}_{\mathbf{xx}} \mathbf{w}_u \\ &\text{subject to } \mathbf{w}_u^H \mathbf{R}_u \mathbf{w}_u = c \end{aligned} \tag{6}$$

where c is an arbitrary constant.

Using the Lagrange multipliers to insert the constraints into the cost function, it can be written as the following:

$$J_{\text{CICR}}(\mathbf{w}_u, \lambda) = \mathbf{w}_u^H R_{\mathbf{xx}} \mathbf{w}_u + \lambda \left(c - \mathbf{w}_u^H \mathbf{R}_u \mathbf{w}_u \right) \tag{7}$$

where λ is the Lagrange multipliers.

If we derive (7) w.r.t. $\mathbf{w}_u^H$ and set the resulting expression to zero, we obtain

$$\mathbf{R}_{\mathbf{xx}} \mathbf{w}_u - \lambda \mathbf{R}_u \mathbf{w}_u = 0 \tag{8}$$

Equation (8) states that $\mathbf{w}_u$ is an eigenvector of the generalized decomposition of $(\mathbf{R}_{\mathbf{xx}}, \mathbf{R}_u)$ with λ as the corresponding eigenvalue. It is worth emphasizing the relationship between the Lagrange multiplier and the criterion to be maximized, it means, the CICR. In fact, from (8) we easily obtain:

$$\lambda = \frac{\mathbf{R}_{\mathbf{xx}} \mathbf{w}_u}{\mathbf{R}_u \mathbf{w}_u} = \frac{\mathbf{w}_u^H \mathbf{R}_{\mathbf{xx}} \mathbf{w}_u}{\mathbf{w}_u^H \mathbf{R}_u \mathbf{w}_u} = \frac{1}{\text{CICR}_u} \tag{9}$$

that shows that maximize the CICR corresponds to minimize the Lagrange multiplier. Moreover, λ must be an eigenvalue of the decomposition of (8). So, the optimum filter $\mathbf{w}_u^{opt}$ is given by the eigenvector corresponding to the minimal eigenvalue of the generalized decomposition of $(\mathbf{R}_{\mathbf{xx}}, \mathbf{R}_u)$. One can easily note that the value of constant c does not influence the determination of the optimum filter.

The carried optimization also consists in maximize the power of the desired signal under the constraint that the total received power be constant. In [3] the same development is carried out in the direct link and called *Summed Inverse Carrier-to-interference Ratio* (SICR).

The optimal solution $\mathbf{w}_u^{\text{opt}}$ is to be compared with our approach based on LCMV filtering, described in the sequel.

IV. Constrained Filtering (LCMV)

The principle of the Linearly Constrained Minimum Variance (LCMV) beamformer was proposed by Frost in [4] and consists in establishing a constant array response for a given user while minimizing noise and interference arriving from other directions.

Such procedure can be mathematically expressed as the constraint minimization of the received power, where the constraints on $\mathbf{w}_u$ assures the reception of the desired directions. It can be written as:

$$\underset{\mathbf{w}_u}{\text{minimize}} \qquad \mathbf{w}_u^H \mathbf{R}_{\mathbf{xx}} \mathbf{w}_u \tag{10a}$$

$$\text{subject to} \qquad \mathbf{C}_u^H \mathbf{w}_u = \mathbf{f}_u \ , \tag{10b}$$

where $\mathbf{C}_u$ is the constraint matrix and $\mathbf{f}_u$ is the response vector, given by

$$\mathbf{C}_u = \begin{bmatrix} \mathbf{d}(\theta_1^u) & \mathbf{d}(\theta_2^u) & \cdots & \mathbf{d}(\theta_{K_u}^u) \end{bmatrix} \tag{11a}$$

$$\mathbf{f}_u = \begin{bmatrix} f_1^u & f_2^u & \cdots & f_{K_u}^u \end{bmatrix}^T \ , \tag{11b}$$

where θ_k^u is the direction of the k-th path of the u-th user and K_u is the number of constraints.

The solution of (10) is given by [5]

$$\mathbf{w}_u^{opt} = -\mathbf{R}_{\mathbf{xx}}^{-1} \mathbf{C}_u \alpha \ . \tag{12a}$$

$$\alpha = -\left(\mathbf{C}_u^H R_{\mathbf{xx}}^{-1} \mathbf{C}_u \right)^{-1} \cdot \mathbf{f}_u \tag{12b}$$

A. Angular Spread and the Degrees of Freedom

Up to now we have not considered angular spread in the system model, which means that DOAs should be precisely determined. From that, the introduction of the so-called point constraints are made, which force the array response to certain values in some specific DOAs. For all other directions, the response tends to be nulled, provided that the degrees of freedom in the array are sufficient. The total number of degrees of freedom is the number of antennas in the array. Each point constraint requires one degree of freedom. The remaining degrees of freedom are involved in the minimization procedure. Hence, for a given array, the bigger the number of constraints, the smaller the number of degrees of freedom remaining to reduce interference and noise.

For non-null angular spread, the array response must be controlled over ranges of DOAs, and a set of equally spaced point constraints could be used to cover each range. However, as previously stated, the ability of the array to cancel interference and noise is related to the number of remaining degrees of freedom of the array. Therefore, there is a trade-off between better represent the range of DOAs, using more point constraints in each set, and better cancel the interference and noise, which requires a larger number of remaining degrees of freedom. Moreover, increasing the number of point constraints in each set can lead to numerical problems as the columns of the constraint matrix $\mathbf{C}_u$ tends to loose the condition of linear independence. This is due to its representation in finite precision and will pose problems in the inversion of the term $\mathbf{C}_u^H \mathbf{R}_{\mathbf{xx}}^{-1} \mathbf{C}_u$.

B. Eigenvectorial Constraints

The use of the so-called Eigenvectorial (EV) constraints is a solution to cover a range of DOAs which allows a control of the number of degrees of freedom used by the constraints. Moreover, the use of EV constraints also avoids the problem of ill condition of the matrix $\mathbf{C}_u$. The use of EV constraints on LCMV beamforming was proposed in [5] and proceeds from a lower rank orthonormal representation of the signal space, based on the Karhunen-Loève discrete expansion [5]. Such representation is obtained using the set of singular vectors corresponding to the most significant singular values of the singular value decomposition (SVD) of the constraint matrix $\mathbf{C}_u$.

In practice, the SVD is directly applied to the point constraints matrix and a more simple representation of $\mathbf{C}_u^H$ is given as follows

$$\mathbf{C}_u^H = \mathbf{U}_u \begin{bmatrix} \boldsymbol{\Sigma}_u & \mathbf{0}_{N_u \times (M-N_u)} \\ \mathbf{0}_{(K_u-N_u)\times P} & \mathbf{0}_{(K_u-N_u)\times(M-N_u)} \end{bmatrix} \mathbf{V}_u^H \ , \tag{13}$$

with

$$\mathbf{U}_u = \begin{bmatrix} \mathbf{u}_1^u & \mathbf{u}_2^u & \cdots & \mathbf{u}_{K_u}^u \end{bmatrix}_{K_u \times K_u} \tag{14a}$$

$$\mathbf{V}_u = \begin{bmatrix} \mathbf{v}_1^u & \mathbf{v}_2^u & \cdots & \mathbf{v}_{M}^u \end{bmatrix}_{M \times M} \tag{14b}$$

$$\boldsymbol{\Sigma}_u = \text{diag}\left(\sigma_1^u, \sigma_2^u, \ldots, \sigma_{N_u}^u\right)_{N_u \times N_u} \ , \tag{14c}$$

where $\mathbf{U}_u$ and $\mathbf{V}_u$ are unitary matrices, containing the left and right singular vectors, respectively; and $\boldsymbol{\Sigma}_u$ is a diagonal matrix composed by the N_u non-zero singular values of $\mathbf{C}_u^H$ sorted as $\sigma_1^u \geq \sigma_2^u \geq \ldots \geq \sigma_{N_u}^u > 0$.

For a reduced number $\widetilde{K}_u < K_u$ of constraints, the matrices $\mathbf{U}_u$, $\mathbf{V}_u$ and $\boldsymbol{\Sigma}_u$ are reduced to

$$\widetilde{\mathbf{U}}_u = \begin{bmatrix} \mathbf{u}_1^u & \mathbf{u}_2^u & \cdots & \mathbf{u}_{\widetilde{K}_u}^u \end{bmatrix}_{K_u \times \widetilde{K}_u} \tag{15a}$$

$$\widetilde{\mathbf{V}}_u = \begin{bmatrix} \mathbf{v}_1^u & \mathbf{v}_2^u & \cdots & \mathbf{v}_{\widetilde{K}_u}^u \end{bmatrix}_{M \times \widetilde{K}_u} \tag{15b}$$

$$\widetilde{\boldsymbol{\Sigma}}_u = \text{diag}\left(\sigma_1^u, \sigma_2^u, \ldots, \sigma_{\widetilde{K}_u}^u\right)_{\widetilde{K}_u \times \widetilde{K}_u} \ . \tag{15c}$$

Thus the EV constraints are implemented by the following reduced matrix of constraints and reduced response vector

$$\widetilde{\mathbf{C}}_u = \widetilde{\mathbf{V}}_u \tag{16a}$$

$$\widetilde{\mathbf{f}}_u = \widetilde{\boldsymbol{\Sigma}}_u^{-1} \widetilde{\mathbf{U}}_u^H \mathbf{f}_u \ . \tag{16b}$$

The choose of $\widetilde{K}_u$ is directly related to the quality of the representation of the reduced matrix of constraints $\widetilde{\mathbf{C}}_u$ and to the number of degrees of freedom remaining to cancel interference and noise. One can choose $\widetilde{K}_u$ to include all the non-zeros singular values in order to obtain the best representation of the desired range of DOAs but with a lower number of constraints.

In previous works [1], [2] we have concluded that the better performance is achieved by the use of only one EV constraint. This simplifies significantly the problem and allows the use of an approach, discussed in the sequel, for LCMV solutions, that does not requires DOA estimation.

V. LCMV BEAMFORMING AVOIDING DOA ESTIMATION

Despite the similarities of the LCMV and OC solutions, the main difference between these techniques relies in the fact that the LCMV requires the DOAs estimation of desired user and the OC uses the UCCM estimation of the desired user. Therefore, the main drawback of the LCMV solution is that the DOA estimation methods existent in the scientific literature have a high computational complexity and are able to estimate a number of DOAs limited by the number of antennas in the array. Hence, the utilization of such technique in practical systems depends on the particular characteristics of the system and on the environment geometry. More specifically, it depends on the number of users and the number of multipaths by user, which is related to the total number of DOAs to be estimated. On the other hand, the OC solution is directly derived from the UCCM.

Thus, the OC solution is more suited to the mobile environments and systems in general. However, from what is possible to known, there is no adaptive version of such technique in the scientific literature but it is easy to derive adaptive version of the LCMV. In [4] an LMS version of the LCMV is presented while an RLS version is proposed in [6].

Keeping in mind the main features of both solutions we propose, in the present work, to derive an LCMV solution that does not require DOA information in an explicit manner, but implicitly through the use of the desired user UCCM.

The equation (16a) shows that the reduced matrix of constraints $\widetilde{\mathbf{C}}_u$ is formed by the right singular vectors of the *original* matrix of constraints $\mathbf{C}_u$. The definition of the SVD states that these vectors are also eigenvectors of the matrix $\mathbf{C}_u \mathbf{C}_u^H$ [7]. This matrix can be written as follows

$$\mathbf{C}_u \mathbf{C}_u^H = \sum_{k=1}^{K_u} \mathbf{d}\left(\theta_k^u\right) \mathbf{d}^H\left(\theta_k^u\right) \ . \tag{17}$$

It is worth to note that the matrix above and the desired user UCCM, given by (1), are formed in a similar manner. The structure of both matrices are the same, except for the powers $g\left(\theta_{u,l}\right)$. Moreover, in order to maximize the desired signal power received by the array, one needs to incorporate the greater number possible of DOAs of the desired user into the matrix of constraints $\mathbf{C}_u$. The greater the number of constraints, better represented will be the ranges of DOAs and closer to the matrix $\mathbf{R}_u$ will be the matrix $\mathbf{C}_u \mathbf{C}_u^H$.

Therefore, we propose to take the UCCM matrix in (1) as the best representation of $\mathbf{C}_u \mathbf{C}_k^H$. So, the EV constraint $\widetilde{\mathbf{C}}_u$ in (1) is now formed by the eigenvectors associated with the $\widetilde{K}_u$ most significant eigenvalues of the matrix $\mathbf{R}_u$. This

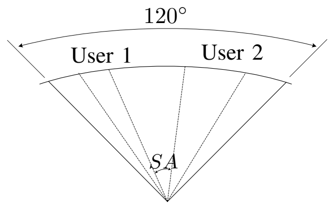


Figure 1. Simulation scenario.

procedure replaces the DOA estimation of the desired user by the estimation of its UCCM. We also propose the use of only one EV constraint for it leads to the best performance in presence of angular spread as shown in [1]. In this case, the response vector is reduced to a scalar that does not influence the solution as it corresponds to a scale factor. So, without loss of generality, it can be taken as 1.

Hence, the LCMV without DOA estimation solution, so-called LCMV_{CM} (LCMV Covariance Matrix), consists of the following steps for each user u:

1) Estimation of $\mathbf{R}_u$.
2) Computation of $\widetilde{\mathbf{C}}_u$, as the eigenvector associated with the maximum eigenvalue of $\mathbf{R}_u$.
3) Computation of the beamforming weight: $\mathbf{w}_u = {\mathbf{R}_{\mathbf{xx}}}^{-1}\widetilde{\mathbf{C}}_u\left(\widetilde{\mathbf{C}}_u^H{\mathbf{R}_{\mathbf{xx}}}^{-1}\widetilde{\mathbf{C}}_u\right)^{-1}$.

VI. Adaptive LCMV

The LMS adaptive version of the LCMV criterion was firstly proposed by Frost uses an instantaneous estimation of the total covariance matrix $\mathbf{R}_{\mathbf{xx}}$. This algorithm is can be found in [4]. The RLS version was proposed by Resende *et al.* in [6]. For more details on the algorithms, see [2].

Hence, the final adaptive procedure for LCMV solutions avoiding DOA estimation is:

1) Estimation of $\mathbf{R}_u$.
2) Computation of $\widetilde{\mathbf{C}}_u$

3a) Use CLMS with $\mathbf{C}_u = \widetilde{\mathbf{C}}_u$ and $\mathbf{f}_u = 1$ (CLMS_{CM})
or
3b) Use CFLS with $\mathbf{C}_u = \widetilde{\mathbf{C}}_u$, $\mathbf{f}_u = 1$ and the corresponding recursive estimation of $\mathbf{R}_{\mathbf{xx}}^{-1}$ (CFLS_{CM})

VII. Simulation Results

We consider a macrocellular environment equipped with an antenna array with 4 elements for reception of signals in a sector of $120°$, as depicted in Figure 1. The separation of the elements of the array is equals $\frac{\lambda_c}{2}$, where λ_c is the carrier wavelength.

In the simulations we have considered the transmission of 10^4 symbols by two mobile units in a SCR context with the reception in an AWGN environment with Signal-to-Noise Ratio (SNR) equals 20 dB. We have also considered both users with two distinct multipath and the same angular spread. In order to allow the separation only in the spatial domain, a minimal angular separation (SA) between the users is assured, as depicted in Figure 1. Table I summarizes the space-time channel parameters in terms of the relative powers, DOA and delays of the multipaths from both users.

In order to evaluate the performance of the proposed LCMV_{CM}, we have compared it with the optimal combining

Table I
Space-time channel parameters used in the simulations.

User	Multipath	DOA	Angular Spread	Delay	Power
#1	#1	θ_1^1	σ_θ	0	0.6
	#2	θ_2^1	σ_θ	T	0.4
#2	#1	θ_1^2	σ_θ	$0.5T$	0.6
	#2	θ_2^2	σ_θ	$1.2T$	0.4

(OC) and with LCMV using point constraints and eigenvectorial constraints (LCMV_{EV}). The matrix $\mathbf{R}_{\mathbf{xx}}$ was estimated by means of a temporal mean of its instantaneous value $\mathbf{x}^H(n)\mathbf{x}(n)$ using all 10^4 symbols. The UCCM of the users, $\mathbf{R}_1$ and $\mathbf{R}_2$, were estimated using 10^4 symbols and the training sequence of the u-th user. When necessary, the perfect knowledge of the multipath DOAs for both users was assumed. The channel is modeled using the Generalized Jakes Model that is an extension of the Jakes model for all values of angular spread comprised in the range from $0°$ to $360°$ [8].

The results were evaluated by the statistical distribution of the mean SNIR, for each method, in 10^3 different trials. For each trial, the DOAs for each user and multipath are chosen randomly. The cumulative distribution function of the mean SNIR is then computed and denoted by $F(\text{SNIR})$. We define as a performance measure the SNIR at 10% due to the fact that the spatial filter is used to assure a minimal SNIR to allow more than one user to share the resources. Several methods are able to provide that SNIR, but we can differentiate one method from another by its behavior in the 10% worst cases.

Initially, to evaluate the performance w.r.t. the angular spread, we have set the angular separation to $30°$ and angular spread varying from $0°$ to $30°$. Figure 2 shows the variation of the SNIR at 10% with the variation of the angular spread.

As expected, the performance of all methods degrades with the increasing of the angular spread. The LCMV has a degradation more accentuated due to the fact it is a point constraint-based method, what presupposes no angular spread. The LCMV_{EV} deals a little better with the angular spread, but it still suffers with the determination of the angle bandwidth that is desired to be received, what can be seen by its higher performance than the LCMV, but still poorer than the OC and LCMV_{CM}. Concerning those two methods, we can note an equivalence of the performance for angular spreads up to $15°$. To higher values the LCMV_{CM} degrades in a more intense way. However, both of them achieve an SNIR high enough to justify their use in all the analyzed angle bandwidth.

To evaluate the performance in function of the angular separation, we have carried out simulations with the angular spread set to $2.5°$ and the angular separation varying in a range from $0°$ to $40°$. Figure 3 shows the SNIR variation at 10% for each method. We can verify that the performance of all methods is bad for no angular separation, where the multipaths can have the same DOA. When the angular separation increases, all methods present an improvement up to the value of $25°$, when there is no more improvement on the performance when the angular separation increases.

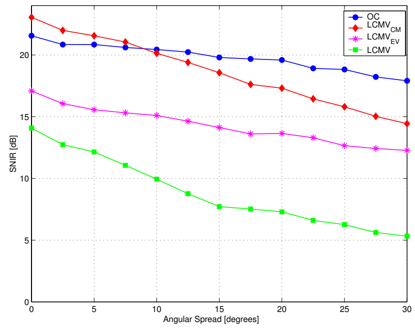


Figure 2. SNIR at 10% as a function of the angular spread for an angular separation of $30°$.

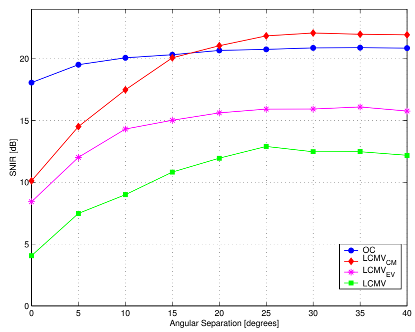


Figure 3. SNIR at 10% as a function of the angular spread for an angular separation of $2.5°$

Non-stationary Environment

Aiming to verify the behavior of the adaptive versions of the solution LCMV_{CM}, we have simulated a non-stationary scenario. The non-stationarity is characterized by an abrupt change of the interferers' DOAs, what, in practice, can occur when a user is turned off and another one is inserted into the system. This situation is also characteristic in a packet-like network, when different packets, from different users, are interfering on the desired user.

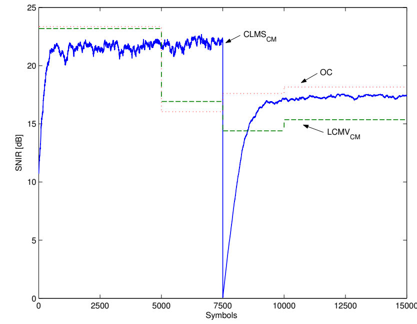
Figure 4 shows the capability of the adaptive algorithms to track the variations of the channel and interferers in a packet-like environment. We can see that the CLMS-CM and CFLS-CM follows the behavior of the channel and interferers. This shows the ability of the methods to be applied in a large number of non-stationary environments.

VIII. Conclusion

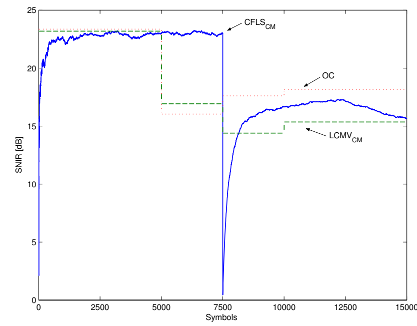
We have presented the use of LCMV beamforming, in both batch and adaptive versions, for multiuser processing in wireless systems, including a solution that avoids DOA estimation and is able to cope with angular spread. We have evaluated the performance of the proposed techniques in non-zero angular spread and non-stationary environments. The results provide an overview of the potential of LCMV techniques in multiuser wireless communication systems.

This approach has the advantage to avoid the high complexity of the DOA estimation-based algorithms, such as MUSIC and ESPRIT, and also allows to deal with non-zero angle spread since the covariance matrix brings more information about the spatial channel than DOA estimation.

The good performance in packet-like systems indicates that the new method is suitable to be applied in the upcoming mobile systems, such as 3G and beyond, where packet networks will be used.



(a) CLMS-CM Algortihm



(b) CFLS-CM Algorithm

Figure 4. Evolution of the SNIR in function of the number of symbols for the algorithms CLMS-CM and CFLS-CM (mean of 10 trials).

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