Computationally Efficient Approaches for Blind Adaptive Beamforming in SIMO-OFDM Systems *

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Abstract

In orthogonal frequency division multiplexing (OFDM) based transmissions over single-input multiple-output (SIMO) wireless channels, adaptive beamforming can be employed at the receiver side to combat the effect of directional interference. To save channel bandwidth, there is strong incentive to use blind algorithms that attempt to restore properties of the transmitted digital signals. Among these, the recursive least-squares constant modulus algorithm (RLS-CMA) is of considerable interest due to its fast convergence and good interference cancelation properties. However, since a distinct copy of the RLS-CMA must be run on each individual sub-carrier in OFDM applications, this approach may entail considerable computations. In this paper, we investigate frequency interpolation schemes to reduce the computational complexity of the SIMO-OFDM beamforming system based on the RLS-CMA. These approaches, which exploit the coherence bandwidth of the broadband wireless channels, divide the sub-carriers into several contiguous groups and apply the RLS-CMA to a selected sub-carrier in each group; the weight vectors at other frequencies are then obtained by interpolation. We show through simulations that an M-fold reduction in complexity can be achieved where M, the number of sub-carriers in each interpolation group, depends on the characteristics of the radio channel and OFDM system.

1 Introduction

Today's increasing demand for high data rate transmissions continues to spur the search of bandwidth efficient modulation techniques with reduced complexity for broadband wireless communications. System design based on these considerations naturally leads to the use of orthogonal frequency division multiplexing (OFDM) [1]. Furthermore, to mitigate the effects of co-channel interference (CCI) originating from users at different locations, an effective approach consists of using multiple antennas at the base-station along with digital beamforming algorithms. In the case of uplink OFDM transmissions originating from single-antenna terminals, the resulting communication system is referred to as a single-input multiple-output (SIMO) OFDM system. To save channel bandwidth, there is strong incentive to use blind algorithms that attempt to restore certain properties of the transmitted signals. Among these, the recursive least-squares constant modulus algorithm (RLS-CMA) is of considerable interest due to its fast convergence and good interference cancelation properties [2–4].

Nevertheless, the direct use of the RLS-CMA within a SIMO-OFDM receiver structure still induces considerable computational complexity. Indeed, being based on the standard RLS algorithm, the RLS-CMA needs to maintain and update an estimate of the inverse data correlation matrix, which requires on the order of K^2 operations per time iteration, where K is the number of antennas at the receiver side. In SIMO-OFDM applications, this requirement is compounded by the fact that a distinct copy of the RLS-CMA must, in theory, be run on each individual OFDM sub-carrier. In recent years, several authors have considered the use of interpolation methods to reduce the complexity of the channel estimation/equalization in broadband wireless systems [5, 6]. In this paper, we present and study frequency interpolation schemes to reduce the computational complexity of the uplink SIMO-OFDM beamforming system based on the RLS-CMA.

The interpolation techniques that we propose are based on exploiting the coherence bandwidth of the broadband wireless channels. For radio transmission through correlated channels, the number of OFDM sub-carriers can be much larger than the channel order and, as a result, several contiguous sub-carriers may experience similar fading conditions. Therefore, to reduce the overall complexity of the SIMO-OFDM beamformer based on the RLS-CMA, we divide the sub-carriers into several contiguous groups and only apply the RLS-CMA adaptation to a selected sub-carrier in each group; the weight vectors at other frequencies are then obtained by interpolation from adjacent tones. In the paper, we consider two basic forms of interpolation, namely flat-top and linear, but extension to other forms is possible. We show through simulations that an M-fold reduction in complexity can be achieved with a suitable interpolation approach where M, the number of sub-carriers in each group, depends on the SIMO channel's coherence bandwidth and the OFDM system's tone spacing.

The paper is organized as follows. Section 2 introduces the SIMO-OFDM system model and reviews the RLS-CMA. The proposed frequency interpolation schemes for RLS-CMA are presented in Section 3 along with a discussion of computational savings. Simulation results demonstrating the possible advantages of the proposed schemes are presented in Section 4. Some conclusions are drawn in Section 5.

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2 Background

2.1 SIMO-OFDM Beamforming

In recent years, there has been considerable interest in the use of adaptive beamforming techniques in OFDM systems as a way to mitigate the adverse effect of directional co-channel interference [7–10]. In this work, we consider an uplink SIMO-OFDM system model with adaptive narrow-band linear processors, i.e. beamformers, operating across the spatial dimension, as shown in Fig. 1. The system is equipped with K antennas at the receiver side, and the total bandwidth is divided into N sub-carriers. On the TX side, the baseband input symbol stream is split into N sub-streams, forming a frequency-domain data block $\mathbf{s} = [s_0, s_1, \ldots, s_{N-1}]^T$, by means of a serial-to-parallel (S/P) converter. The parallel sub-streams then go through an OFDM modulator, in which the inverse FFT is applied to convert frequency-domain vector **s** into a vector of N time domain samples. To eliminate inter symbol interference, a cyclic prefix is added at the leading edge of each time domain vector. Finally, the resulting time-domain sequence is up-converted to pass-band for transmission over the radio channel.

In going through the SIMO wireless channel, the transmitted signal is corrupted by linear channel effects, interference, and noise. On the RX side, each antenna signal is down-converted to baseband and fed to an OFDM demodulator where the cyclic prefix is removed and an FFT operation is applied to recover the frequency domain data. In this work, to simplify the analysis, we assume that the OFDM demodulators operate under perfect synchronization. Because of the multiple antennas at the receiver side, narrow-band spatial filtering across the antenna dimension can be applied to the OFDM demodulator outputs to combat the effects of directional interference in each OFDM sub-channel. We denote by $\mathbf{w}_j(n)$ the vector of complex beamforming weights applied to the jth subcarrier ($j \in \{0, 1, \ldots, N-1\}$) at the nth symbol epoch ($n \in \{0, 1, 2, \ldots\}$). An adaptive beamforming algorithm is used to compute the optimal weight vector needed to recover the original transmitted symbols from co-channel interference and noise on each sub-carrier.

2.2 The RLS-CMA

The focus of this work is on blind adaptive beamforming algorithms for estimating and tracking the optimal set of weight vectors $\mathbf{w}_j(n)$ to be used in the SIMO-OFDM receiver. Adaptive beamforming algorithms can be generally classified into two broad categories, namely: pilot-aided and blind. Algorithms in the former categories make use of pilot signals or training sequences to drive the adaptation towards an optimal solution. Unfortunately, the transmission of a reference signal consumes precious channel bandwidth which is not always desirable. Accordingly, there has been much interest in blind approaches that can adapt their weights by restoring certain properties of the transmitted digital signals.

Within this class of blind algorithms, the RLS-CMA is of particular interest due to its good overall interference cancelation performance and fast convergence. This algorithms attempts to find an optimal weight vector that restores an underlying constant modulus property of the transmitted signal. For instance, in the present OFDM context, assuming a quadrature phase-shift signal constellation with normalized energy, the transmitted symbol $s_j(n)$ over the jth sub-carrier at time n will have a constant magnitude, i.e. $|s_j(n)| = 1$. An RLS-CMA, applied to that particular sub-carrier, updates its weight vector $\mathbf{w}_j(n)$ so as to restore this property.

Specifically, let $x_j^k(n)$ denote the complex data symbol available at the jth sub-carrier output of the kth antenna's OFDM demodulator at time n. Also let $\mathbf{x}_j(n) = [x_j^1(n), x_j^2(n), \ldots, x_j^K(n)]^T$ denote the complex, K dimensional vector of data symbols induced on all the RX antennas on the jth subcarrier at time n and let $\mathbf{w}_j(n) = [w_j^1(n), w_j^2(n), \ldots, w_j^K(n)]^T$ denote the corresponding adaptive weight vector. The RLS-CMA recursively seeks the optimum weight vector $\mathbf{w}_j^{opt}$ which minimizes the objective function $J(\mathbf{w}_j) = E[|\hat{s}_j(n)|^2 - 1]$, where $\hat{s}_j(n) = \mathbf{w}_j^H \mathbf{x}_j(n)$, the beamformer output, provides an estimate of the transmitted symbol $s_j(n)$. In the RLS-CMA, the optimization step is carried on adaptively, i.e. iteratively over time, in an exponentially weighted least-squares sense. The main equations of the RLS-CMA are summarized below [3]:

$$\mathbf{z}_j(n) = (\mathbf{x}_j^H(n)\mathbf{w}_j(n-1))\,\mathbf{x}_j(n), \quad (1)$$

$$\mathbf{h}_j(n) = \mathbf{P}_j(n-1)\mathbf{z}_j(n), \quad (2)$$

$$\mathbf{g}_j(n) = \mathbf{h}_j(n)/(\lambda + \mathbf{z}_j^H(n)\mathbf{h}_j(n)), \quad (3)$$

$$\mathbf{P}_j(n) = \lambda^{-1}\mathbf{P}_j(n-1) - \lambda^{-1}\mathbf{g}_j(n)\mathbf{z}_j^H(n)\mathbf{P}_j(n-1), \quad (4)$$

$$\xi_j(n) = 1 - \mathbf{w}_j^H(n-1)\mathbf{z}_j(n), \quad (5)$$

$$\mathbf{w}_j(n) = \mathbf{w}_j(n-1) + \mathbf{g}_j(n)\xi_j^*(n), \quad (6)$$

The parameter $\lambda \in (0, 1)$ denotes the forgetting factor. The $K \times K$ matrix $\mathbf{P}_j(n)$ in (4) provides an estimate of the inverse correlation matrix of the observation, i.e. $E[\mathbf{x}_j(n)\mathbf{x}_j^H(n)]^{-1}$. The algorithm can be initialized with the following parameter values: $\mathbf{w}_j(0) = [1, 0, \ldots, 0]^T$, $\mathbf{P}_j(0) = \delta^{-1}\mathbf{I}_K$, where $\mathbf{I}_K$ is the $K \times K$ identity matrix and δ is a small positive constant.

3 Frequency interpolation schemes

The direct use of the RLS-CMA within a SIMO-OFDM receiver structure will induce considerable computational complexity. Indeed, being based on the standard RLS algorithm, the RLS-CMA needs to maintain and update an estimate of the inverse data correlation matrix. This step (see equation (4)) requires $O(K^2)$ operations per time iteration. In SIMO-OFDM applications, this requirement is compounded by the fact that a distinct copy of the RLS-CMA must be run on each of the N individual OFDM sub-carriers, resulting in an overall complexity of $O(NK^2)$.

In the frequency domain, when applying the OFDM scheme over a channel with a relatively large coherence bandwidth, it is possible for adjacent sub-carriers to experience similar fading conditions. This will typically be the case if the number of OFDM sub-carriers is much larger than the order of the channel impulse responses. For instance, when applying the IEEE 802.11a OFDM standard scheme (with subcarrier spacing of 312.5kHz) to a frequency selective channel with coherence bandwidth of say, 1.25MHz, there will be about 4 sub-carriers experiencing similar fading [11]. Hence, the optimal weights generated for a given sub-carrier may remain valid for its neighboring sub-carriers.

Based on such considerations, we propose to divide the set of all sub-carriers into several contiguous groups and only apply the RLS-CMA adaptation to a selected sub-carrier in each group;

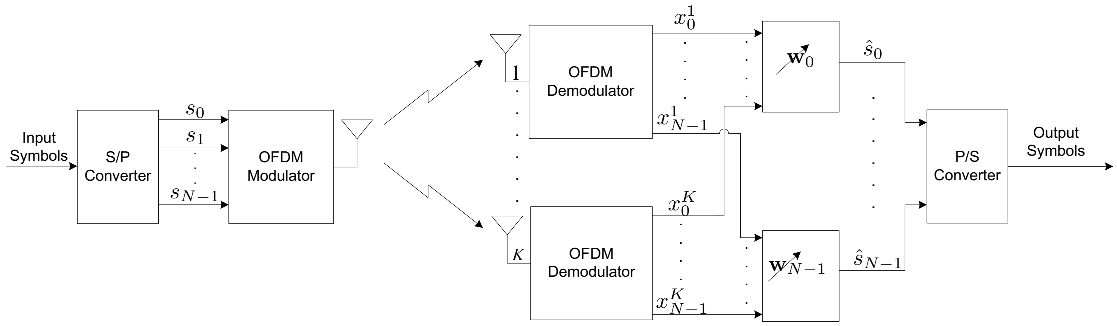

Figure 1. Baseband SIMO-OFDM system model.

the beamforming weights for the remaining sub-carriers can then be obtained by means of interpolation between the selected sub-carriers. Below, we consider both the zero order (flat-top) and first order (linear) form of interpolation as a means to reduce implementation complexity in SIMO-OFDM beamforming systems that employ the RLS-CMA for blind weight adaptation.

3.1 Flat-top interpolation

Flat-top interpolation, also called zero-order hold [12], is the simplest interpolation scheme. By definition, it maintains the level of the function to be interpolated constant between known sample values. To implement flat-top interpolation in the present SIMO-OFDM beamforming framework, we first divide the N OFDM sub-carriers into several contiguous groups and we then apply the RLS-CMA adaptive update to a selected *representative* sub-carrier in each group; the remaining members in a group use this representative weight vector to obtain their corresponding beamformed output. The details of the approach can be formulated as follows.

For simplicity, assume that the number of sub-carriers is a power of 2, i.e. $N = 2^\nu$ and partition the OFDM sub-carrier index set $S = \{0, 1, \ldots, N-1\}$ into a union of $I = 2^a$ contiguous, non-overlapping subsets S_i, each containing an equal number $M = 2^b$ of sub-carriers ($a + b = \nu$). That is, we let $S_i = \{iM + m : m = 0, ..., M-1\}$ for $i \in \{0, \cdots, I-1\}$, so that $S_i \cap S_j = \emptyset$ for $i \neq j$ and $\cup_{i=0}^{I-1} S_i = S$. We shall refer to the tones indexed by subset S_i as the ith group. In our implementation of the flat-top interpolation scheme, we select the middle tone in each group as the representative to which the RLS-CMA is applied. Specifically, define $q_i = iM + 2^{b-1}$ as the index of the representative tone. For each group index $i = 0, \ldots, I-1$, we apply the RLS-CMA to update $\mathbf{w}_{q_i}(n)$:

$$\mathbf{w}_{q_i}(n) = \psi(\mathbf{w}_{q_i}(n-1), \mathbf{x}_{q_i}(n), \lambda) \tag{7}$$

where $\psi(.)$ stands for the RLS-CMA (1)-(6); for the remaining tones in group i, we set $\mathbf{w}_j(n) = \mathbf{w}_{q_i}(n)$ where $j \in S_i$, $j \neq q_i$. Only trivial modifications are needed to accommodate other cases, such as N not a power of 2 or subsets S_i with different sizes.

3.2 Linear interpolation

If the propagation channel is more frequency selective, i.e. the group members are not experiencing similar fades, flat-top interpolation may not be adequate to achieve the desired reduction in complexity while maintaining a good system performance. In this case, one may think of resorting to a higher-order interpolation scheme in which the missing beamforming weight vector coefficients are conceptually obtained by connecting adjacent representative weights by a polynomial curve in the complex plane. However, as we explain below, because of the inherent phase ambiguity in blind constant modulus based algorithms, this approach necessitates certain modifications in order to work properly. We illustrate this concept with the linear interpolations, but extensions to higher-order forms of interpolation are possible.

For $i = 0, \ldots, I-1$, let $r_i = iM$ denotes the lowest tone index in the ith group and, invoking the periodic nature of the FFT operation, also let $r_I = (IM)_{\text{mod } N} = 0$. Thus, the frequency indices r_i and r_{i+1} define the boundary tones of the ith group. In this case, instead of using the same weight vector for all group members, the weight vectors of intermediate sub-carriers (i.e. between boundary tones) are obtained by applying linear interpolation to the weight vectors of boundary tones, which are themselves updated with the RLS-CMA, i.e.: $\mathbf{w}_{r_i}(n) = \psi(\mathbf{w}_{r_i}(n-1), \mathbf{x}_{r_i}(n), \lambda)$ for $i = 0, ..., I-1$. The direct application of linear interpolation for the intermediate tones would lead to the following:

$$\mathbf{w}_j(n) = \frac{r_{i+1} - j}{M}\mathbf{w}_{r_i}(n) + \frac{j - r_i}{M}\mathbf{w}_{r_{i+1}}(n), \tag{8}$$

where $j \in S_i$ and $j \neq r_i$. However, (8) fails to perform properly because of the phase ambiguity in the constant modulus approach.

A simple example is considered below to explain this problem. Assume there is only a single antenna at the RX side, so that instead of a weight vector, each sub-carrier is characterized by a single complex weight. Each copy of the blind RLS-CMA will introduce an ambiguous phase factor in the estimation of $w_{r_i}(n)$. The presence of these phase factors render the direct application of linear interpolation impractical. This is illustrated in Fig. 2, where vector $\vec{OA}$ represents the linearly interpolated weight between w_{r_i} and $w_{r_{i+1}}$ in the complex plane. From the figure, we note that the norm $|\vec{OA}| \neq \frac{1}{2}(|w_{r_i}| + |w_{r_{i+1}}|)$ and, in general, the interpolated weight fails to provide a meaningful solution.

More generally, as a member of the constant modulus family of algorithm, the RLS-CMA updates its weight vector based only on the modulus of the incoming symbols, i.e., it is phase-blind. Therefore, the weight vector convergency is invariant to a phase rotation in the transmitted data. That is, the RLS-CMA can achieve the optimal operating point with an arbitrary phase shift in the incoming data, as long as the correlation between adjacent

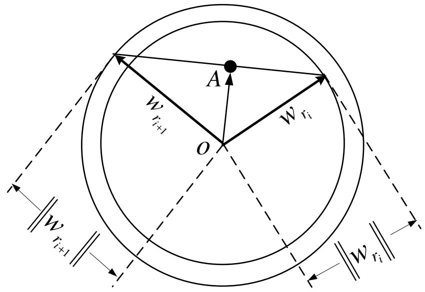

Figure 2. Linear interpolation with phase error in the complex plane.

antenna elements remains the same. Equivalently, if $\mathbf{w}_j(n)$ is optimal for the tone j, so is $\mathbf{w}_j(n)e^{\jmath\phi}$ for any value of the phase factor $\phi \in (-\pi, \pi]$. Because of this phase ambiguity, linear interpolation between $\mathbf{w}_{r_i}(n)$ and $\mathbf{w}_{r_{i+1}}(n)$ may not be suitable for an intermediate tone. To solve this problem, we propose that before applying linear interpolation, the adjacent weight vectors $\mathbf{w}_{r_i}(n)$ and $\mathbf{w}_{r_{i+1}}(n)$, which are obtained by the RLS-CMA, should be phase shifted to remove the effect of the phase ambiguity.

Specifically, we propose a least-square approach in which the required phase shift is obtained by minimizing the cost function:

$$J(\phi) = ||\mathbf{w}_{r_i}(n) - e^{\jmath\phi}\mathbf{w}_{r_{i+1}}(n)||^2, \quad (9)$$

in which ϕ is the phase difference between the weight vectors of adjacent boundary tones. Using standard optimization techniques, the solution to this problem is obtained as follows:

$$\begin{aligned} \phi_0 &= \arg\min_{\phi} ||\mathbf{w}_{r_i}(n) - e^{\jmath\phi}\mathbf{w}_{r_{i+1}}(n)||^2 \\ &= (\mathbf{w}^H_{r_{i+1}}(n)\mathbf{w}_{r_{i+1}}(n))^{-1}\mathbf{w}^H_{r_{i+1}}(n)\mathbf{w}_{r_i}(n). \quad (10) \end{aligned}$$

After obtaining ϕ_0, the linear interpolation is applied between $\mathbf{w}_{r_i}(n)$ and $e^{\jmath\phi_0}\mathbf{w}_{r_{i+1}}(n)$, instead of the original $\mathbf{w}_{r_{i+1}}(n)$. The corresponding equation is shown as ($j \in S_i$ and $j \neq r_i$):

$$\mathbf{w}_j(n) = \frac{r_{i+1} - j}{M}\mathbf{w}_{r_i}(n) + \frac{j - r_i}{M}e^{\jmath\phi_0}\mathbf{w}_{r_{i+1}}(n). \quad (11)$$

3.3 Computational complexity

The computational complexity of the RLS-CMA, as presented in [3], is $3K^2 + 6K$ complex multiplications per iteration, where K is the number of antennas at the RX side. In this expression, the terms $3K^2$ and $6K$ represent the complexity of the weight adaptation and the beamforming steps, respectively. For the direct implementation of the RLS-CMA in a SIMO-OFDM receiver structure, i.e. without complexity reduction, a distinct copy of the RLS-CMA must be run on each individual sub-carrier. Hence, the complexity of the complete system can be expressed as

$$C_{\text{Direct}} = 3NK^2 + 6NK, \quad (12)$$

where N is the number of sub-carriers.

In the flat-top interpolation scheme, only the weight vector of the selected tone in each group, represented by index $q_i \in S_i$, is updated by the RLS-CMA. Therefore, the term associated to the weight adaptation in (12) is reduced by a factor of M, so that the complexity is now

$$C_{\text{Interp}} = \frac{3NK^2}{M} + \gamma KN, \quad (13)$$

where $\gamma = 6$. For linear interpolation, the above formula remains valid, but with $\gamma = 8$ to account for the use of (11). The extra amount of computations needed to obtain the least-squares phase factors in (10) is of order $O(NK/M)$ and can be ignored.

4 Simulation results

Clearly, the use of a larger value of M is advantageous from the viewpoint of reducing system complexity. However, the corresponding reduction will come at the price of a decrease in system performance. Therefore, the size of the interpolation group M should be chosen wisely. In this section, we use numerical simulations to investigate how the choice of M affects the performance of the SIMO-OFDM system with RLS-CMA beamforming under representative radio channel conditions.

4.1 Methodology

We consider an uncoded SIMO-OFDM system with $N = 64$ sub-carriers. At the TX side, we use a quadrature phase shift keying signal constellation with constant normalized power on each sub-carrier, i.e. $E\{|s_l|^2\} = P_S$. Following the IFFT operation, a cyclic prefix of length 8 is added to each time-domain data block. At the RX side, a uniform linear array with $K = 10$ antenna elements is employed. The distance between adjacent antenna elements is set to half the wavelength at the carrier frequency.

The propagation of the desired OFDM signal from the TX to the multiple antenna RX is modeled as a broadband linear dispersive SIMO channel, which is generated by a statistical multi-path vector channel simulator [13]. We assume the presence of 3 resolvable paths with angles of arrival (AOA) of $(-90°, 90°, 150°)$ and corresponding angular spread of $(5°, 10°, 2°)$. The desired signal is received in the presence of directional interference and additive white background noise. The AOA of the interfering signal is set to $-10°$ and its power level is denoted as P_I. The noise samples are complex circular Gaussian random variables with zero-mean and power P_N.

The performance of the SIMO-OFDM systems with adaptive beamforming is evaluated in terms of the signal plus interference-to-noise ratio (SINR) and the bit error rate. For a given realization of the SIMO channel, the SINR for the jth sub-carrier is given by

$$\text{SINR}_\text{j} = \frac{\text{P}_\text{S}\,|\mathbf{w}^\text{H}_\text{j}\mathbf{h}_{\text{S,j}}|^2}{\mathbf{w}^\text{H}_\text{j}(\mathbf{h}_{\text{I,j}}\text{P}_\text{I}\mathbf{h}^\text{H}_{\text{I,j}} + \text{P}_\text{N}\mathbf{I})\mathbf{w}_\text{j}}, \quad (14)$$

where $\mathbf{w}_j$ represents the beamforming weight vector used on the jth sub-carrier and $\mathbf{h}_{S,j}$ and $\mathbf{h}_{I,j}$ denote the $K \times 1$ vectors of complex channel coefficients for the desired source signal and the interference signal, respectively, at that frequency. We also define an overall broadband SINR by averaging SINR_j over all the sub-carriers, i.e. $\text{SINR} = \frac{1}{N}\sum_{j=0}^{N-1}\text{SINR}_j$.

4.2 Performance of Interpolated Schemes

The proposed interpolation schemes across different sub-carriers are evaluated in terms of their complexity and achievable

SINR and BER as a function of the group size M. Since the number of OFDM tones in our system is set to $N = 64$, the following values of the group size are considered $M \in \{4, 8, 16\}$. That is, all the groups have the same bandwidth (i.e. M tones) and the number of groups is $I = N/M$.

According to the analysis above, as M increases, more weight vectors are obtained by interpolation, and consequently the system complexity is reduced. The computational complexity of the direct and interpolated RLS-CMA schemes for different values of M, in unit of complex multiplication per iterations, is shown in Table 1. The value given for $M = 1$ is obtained from (12) and corresponds to a direct application of the RLS-CMA to each sub-carrier (i.e. no interpolation). The values given for $M > 1$ are obtained from (13) for the flat-top interpolation $\gamma = 6$. The right-most column in the table shows the ratio $C_{\text{Interp}}(M)/C_{\text{Direct}}$. These figures are consistent with the observed run times for the MATLAB implementations of the algorithms. We note that even a small values of $M = 4$ results in quite significant computational savings.

Table 1. Complexity of interpolated RLS-CMA

M	Complexity	Complexity ratio
1	23040	1
4	8640	0.38
8	6240	0.27
16	5040	0.22

Fig. 3 and 4 show the time evolution of the SINR for the flat-top and linear interpolation schemes, respectively. The relative signal and interference powers were set to $P_S/P_N = 10$dB, $P_I/P_N = 10$dB. These plots were obtained by averaging the overall broadband SINR over 200 independent realizations of the dispersive SIMO channel. For each realization, the various RLS-CMA-based SIMO-OFDM systems (which differ in the value of M and type of interpolation) were initialized as explained in Section 2.2 and run (with forgetting factor set to $\lambda = 0.99$) until steady-state convergence. That is, the SIMO channel realization remains fixed during the blind adaptation of the weight vectors, which enables us to reach a near optimal steady-state.

Since the RLS-CMA is applied, the system convergence rates are fast for all the different values of M. The main distinction among these plots is the SINR level after convergence, i.e. the steady-state performance of the system. The steady-state SINR level for $M = 16$ is significantly lower than for the other three cases. Indeed, when the interpolation group size M is large, the group bandwidth becomes larger than the channel coherence bandwidth and consequently, the weight vector obtained by interpolation may not be suitable for certain sub-carriers. Hence, from these two figures, $M = 4$ and $M = 8$ yield satisfactory performance for this particular example. Note that the steady-state SINR level for the various SINR plots in Fig. 3 and 4 remain bellow the so-called "optimal limit". This upper bound is obtained from (15) when an optimum weight vector $\mathbf{w}_j^{opt}$ is used in place of $\mathbf{w}_j$ for each sub-carrier index j. The weights $\mathbf{w}_j^{opt}$ is derived as a minimum-variance distortionless response beamformer [14], under perfect knowledge of the channel vectors $\mathbf{h}_{S,j}$ and $\mathbf{h}_{I,j}$.

It is also interesting to look at the SINR performance from a frequency domain perspective. Since our system is working under a frequency selective fading channel, the convergence level of SINR_j for each tone varies greatly. Comparing the results for different frequencies we generally find that the system performance for the linear interpolation scheme is better than for the flat-top interpolation. This advantage is especially apparent when the group size is large, such as $M \geq 8$, and when the sub-carrier is experiencing deep fading. This is because the linear interpolation uses weight vectors at two representative frequencies to carry on the interpolation, instead of only one location in the flat-top scheme, and is therefore more robust to large error in the representative weights that may result from deep fades at the corresponding frequencies.

Fig. 5 and 6 show the uncoded average BER performance for the flat-top and linear interpolation schemes, respectively. It is seen that the BER performance is decreasing with an increase in the group size, M. Compared to $M = 1$, the use of $M = 8$ with flat-top interpolation leads to a 1dB performance loss. For linear interpolation, this loss is only around 0.5dB. Fig. 6 also reveals an interesting feature of the linear interpolation approach. Indeed, when the group size is relatively small, in this case $M = 4$, the weight vectors obtained by interpolation may perform even better than those obtained by individual application of the RLS-CMA on each sub-carrier. It is because for some sub-carriers which are experiencing deep fading, the direct-adaptation of the weight vectors with the RLS-CMA may not properly converge, while the weight vectors obtained by interpolating adjacent sub-carriers, which do not experience deep fades, may form adequate beampatterns.

5 Conclusion

We have investigated frequency-domain interpolation schemes to reduce the computational complexity of a blind SIMO-OFDM beamforming system based on the RLS-CMA. The proposed approaches, which exploit the coherence bandwidth of the broadband wireless channels, divide the sub-carriers into contiguous groups. The RLS-CMA is applied only to a selected sub-carrier in each group while the weight vectors at other frequencies are obtained by interpolation. Both flat-top and linear interpolations were considered in this paper, but other forms of interpolation and variations on this theme are possible. We showed through numerical simulations using representative broadband dispersive channels that a significant reduction in complexity can be achieved (e.g. factor of 4) at the price of a slight loss in SINR and BER performance (e.g. factor of 0.5dB). Better performance were obtained with the linear interpolation. In practice, different choices of the interpolation group size M should be tried, and the one achieving the best trade-off between desired performance and computational complexity should be chosen. Clearly, for given specifications of the OFDM system, this choice depends on the characteristics of the radio channel. For instance, if the channel is less frequency selective, a larger group size M can be used, and vise versa. The optimal choice of M as a function of the parameters defining the radio channel remains a topic for further investigations.

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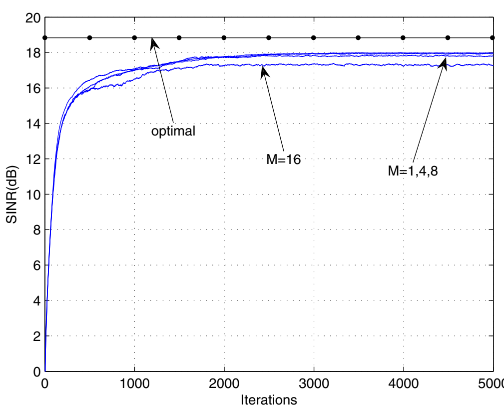

Figure 3. Average SINR versus number of iterations for flat-top interpolation.

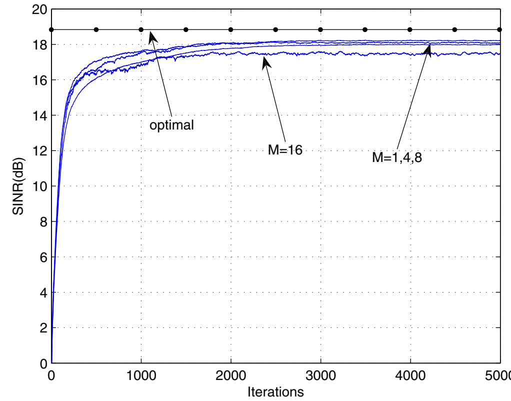

Figure 4. Average SINR versus number of iterations for linear interpolation.

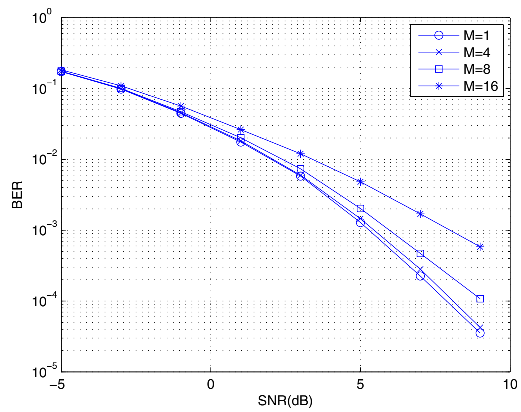

Figure 5. BER for flat-top interpolation.

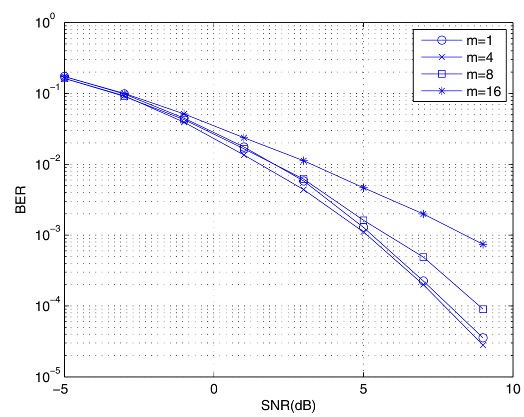

Figure 6. BER for linear interpolation.