Complexity Reduction Techniques for Blind Adaptive Beamforming in OFDM Antenna Arrays

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***Abstract*—In this paper, we propose two complexity reduction techniques for blind adaptive beamforming in orthogonal frequency division multiplexing (OFDM) antenna array systems. For each sub-carrier, a beamformer with generalized sidelobe canceller (GSC) structure is designed according to the constrained constant modulus (CCM) criterion with weight vectors adaptation based on the recursive least squares (RLS) method. The two techniques that we propose for complexity reduction rely on frequency domain interpolation and spatial domain clustering, respectively. The former exploits the coherence bandwidth of the radio channel, so that only the weight vectors at selected frequencies need to be adapted, while the remaining weight vectors are obtained via interpolation. The latter relies on the partitioning of the receiving array into sub-arrays of smaller size. In addition, a combination of these two techniques is proposed to further reduce the complexity. A complexity analysis is presented to quantify the computational savings offered by the proposed techniques. Finally, simulation results are provided to illustrate that these savings can be obtained at the price of only a minor, acceptable loss in performance when compared to the direct application of the conventional CCM-RLS-GSC beamforming algorithm to the wideband OFDM antenna array systems.** [1]

***Index Terms*—Blind adaptive beamforming, OFDM, frequency interpolation technique, spatial clustering technique.**

I. Introduction

To suppress interference and cope with changes in radio environments, an effective approach which consists of using an antenna array along with adaptive beamforming algorithms has been reported in [1]–[3]. The digital receiver is designed to steer a directional beampattern towards the direction of a desired user by computing a properly weighted sum of the individual antenna outputs. Adaptive beamforming techniques can be implemented to drive the iterative weight optimization process and so form optimum beampatterns [4]. For the sake of saving channel bandwidth, there has been much interest in blind beamforming which attempts to restore certain properties of the transmitted signal without the aid of pilots. The CCM-RLS family of algorithm, which aims to restore the constant modulus (CM) property of the source modulation while subject to a constraint on the response to the desired user, is of considerable interest due to its fast convergence and good interference cancelation performance [5], [6].

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Orthogonal frequency division multiplexing (OFDM) has become the most popular technique for high date rate transmission over broadband wireless channels. It has been adopted in several wireless standards such as the 4th generation (4G) of mobile phone mobile communication technology standards and the IEEE 802.11a wireless local area network (WLAN) standard. Undoubtedly OFDM remains a strong air interface candidate for future-generation wireless communication systems [7]. As a multi-carrier modulation method, OFDM converts single high speed data stream into multiple low speed data streams, and modulates them onto different sub-carriers. This allows flat fading channel techniques to be applied to the broadband communication for data processing.

The CCM-RLS-GSC presented in [8] has been proven to offer good performance in the blind adaptive beamforming task over a single narrow-band sub-carrier. However, the direct or complete application of this algorithm for each individual sub-carrier within an OFDM antenna array receiver induces considerable computational complexity. To overcome this limitation, some approaches have been investigated in [9] where the authors proposed two frequency schemes, namely flat-top and linear interpolation, to reduce complexity by exploiting coherence bandwidth. For the transmission of radio signals through highly correlated channels, the number of OFDM sub-carriers is much larger than the channel order. Several contiguous sub-carriers may end up experiencing similar fades. This suggests that the correlation properties between the beamforming weight vectors of adjacent sub-carriers is similar to the sub-channel correlation with one receive antenna.

In this work, we first present an extension of these schemes to a more general form of frequency domain interpolation. Furthermore to make it more practical, the BPSK used in [9] is extended to a more general M-QAM type of modulation where the signal constellation exhibits a CM property. Besides frequency domain interpolation, we propose another clustering technique in the spatial domain which relies on the partitioning of the receiving antenna array into sub-arrays of smaller size. By reducing the dimension of input signal vectors, the computation of correlation matrices can be simplified which will result in a reduction of the system complexity. In addition, a combination of these two techniques, i.e., frequency domain interpolation and spatial domain clustering, is proposed to further reduce the complexity. Simulation results are provided to show that the resulting computational savings can be obtained at the price of only a minor, acceptable loss in performance.

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The rest of the paper is organized as follows. Section II introduces the OFDM system model with beamforming. Section III gives an overview of the CCM-RLS-GSC algorithm and extends it to OFDM system. The two proposed techniques for computational complexity reduction and their combined application are presented in Section IV along with a discussion of computational savings. Simulation results are presented in Section V to demonstrate the system performance after applying the proposed complexity reduction techniques. Finally some conclusions are drawn in Section VI.

II. SYSTEM MODEL

In this work, we consider a wireless communication scenario in which K independent user signals impinge on a uniform linear array (ULA) comprised of M identical omnidirectional antennas as shown in Fig. 1.

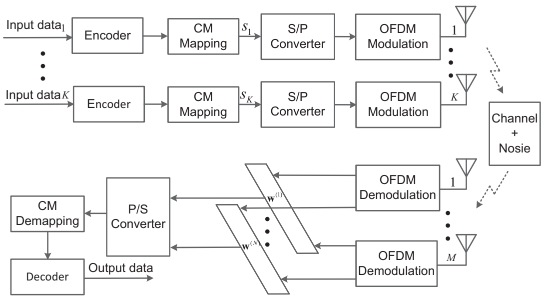

Fig. 1: Baseband OFDM system model

On the TX side, OFDM modulation is employed for each transmitter. The input data from user $k \in \{1, \ldots, K\}$ is first encoded and then mapped to a time sequence of complex valued symbols $s_k(j)$, where j is a discrete-time index.The transmitted symbols are characterized by structural properties that can be exploited for their restoration, which in this work amounts to the use of a constant modulus constellation, that is: $|s_k(j)| = 1$ for all j. The transmitted symbols from user k are assumed to be independent and identically distributed (i.i.d) random variables. Sequences of symbols transmitted by different users are also independent. The input symbols from user k are split into N sub-carriers by means of a serial-to-parallel (S/P) converter, thereby forming a sequence of frequency domain data blocks $\mathbf{s}_k(i) = [s_k^{(1)}(i), \ldots, s_k^{(n)}(i) \ldots, s_k^{(N)}(i)]^T$, where i denotes the symbol epoch at the low sampling rate and the sub-carrier index $n \in \{1, \ldots, N\}$. An inverse discrete Fourier transform (IDFT) operation is then applied to convert the frequency domain data blocks into a vector of N time domain samples and a cyclic prefix is added which aims to eliminate the intersymbol interference.

In going through the wireless channel, the transmitted signals are corrupted by linear channel effects and additive noise. For the nth sub-carrier signal, the channel from the kth user to the mth RX antenna is assumed to contain L discrete paths, which can be modeled as

$$h_{mk}^{(n)} = \sum_{l=0}^{L-1} \alpha_l^{(n)} v_m(\theta_l), \tag{1}$$

where $\alpha_l^{(n)}$ and $v_m(\theta_l)$ respectively denote the complex valued channel gain and steering phasor of the lth path on the nth subcarrier channel. In this work, $\alpha_l^{(n)}$ is normally distributed with zero mean unit variance and is taken to be the same for each antenna. Let λ_c denote the wavelength, $d_s = \lambda_c/2$ be the inter-element spacing of the ULA and θ_l be the direction of arrival (DOA) of the lth path, then we can express the normalized steering phasor as $v_m(\theta_l) = \frac{1}{\sqrt{M}} e^{-j2\pi \frac{d_s}{\lambda_c} \cos\theta_l (m-1)}$.

On the RX side, each antenna signal is fed to an OFDM demodulator where the cyclic prefix is removed and a discrete Fourier transform (DFT) operation is implemented to recover the frequency domain data. Assuming the receiver is under perfect synchronization, the set of received signals on the nth sub-carrier at symbol epoch i yields an M-dimensional vector

$$\mathbf{r}^{(n)}(i) = \mathbf{H}^{(n)} \mathbf{s}^{(n)}(i) + \mathbf{n}(i), \quad i = 1, 2, \ldots \tag{2}$$

where $\mathbf{H}^{(n)} = [\mathbf{h}_1^{(n)}, \mathbf{h}_2^{(n)}, \ldots, \mathbf{h}_K^{(n)}]$ is an $M \times K$ narrowband channel, $\mathbf{h}_k^{(n)} = [h_{1k}^{(n)}, \ldots, h_{Mk}^{(n)}]^T$ is the $M \times 1$ vector of channel responses from user k to the antenna array receiver and $\mathbf{n}(i)$ is the additive noise vector with zero-mean and covariance matrix $\sigma^2 \mathbf{I}$, where σ^2 denotes the variance and $\mathbf{I}$ is an identity matrix of order M. $\mathbf{s}^{(n)}(i) = [s_1(i), \ldots, s_K(i)]^T$ denotes the corresponding user signals transmitted on the nth sub-carrier. Without loss of generality, we let the transmitted signal from user $k = 1$ as the desired signal and assume the corresponding channel vector $\mathbf{h}_1^{(n)}$ is known by the receiver.

By virtue of the multiple antennas on the RX side, narrowband spatial filtering can be applied to the OFDM demodulator outputs to combat the effects of directional interference in each OFDM sub-channel. Adaptive narrow-band linear processors, i.e. beamformers, are applied to the receive signal vectors of different sub-carriers in order to recover an estimate of the transmitted signal $s_1(i)$. We denote by $\mathbf{w}^{(n)}$ the vector of complex beamforming weights applied to the received signal $\mathbf{r}^{(n)}$ on the nth sub-carrier. Our beamforming interest lies in the efficient computation of a set of optimal weight vectors, say $\mathbf{w}_{opt}^{(n)}$ for $n \in \{1, \ldots, N\}$ to recover the original transmitted symbols from desired user 1 in the presence of co-channel interference and noise on each sub-carrier.

III. OVERVIEW OF BLIND ADAPTIVE CCM-RLS-GSC ALGORITHM IN OFDM SYSTEM

A. Blind Adaptive CCM-RLS-GSC Algorithm

For the sake of bandwidth efficiency, we consider the use of a blind adaptive beamforming algorithm that can seek an optimal solution by restoring properties inherent in the transmitted signals. In particular, for each sub-carrier, the CCM-RLS beamformer with the GSC structure can achieve a good learning and tracking performance. The objective of the design is to minimize the expected deviation of the square modulus of the beamformer output from a constant quantity, referred to as the CM cost function and expressed as $J_{CM} = \mathbb{E}\big[\big||\mathbf{w}^{(n)H}\mathbf{r}^{(n)}|^p - 1\big|^2\big]$, while maintaining the contribution from the desired user constant, i.e., $\mathbf{w}^{(n)H}\mathbf{h}_1^{(n)} = c$. Usually, we set $p = 2$ and $c = 1$ for convenience.

By employing a signal blocking matrix $\mathbf{B}$ which is orthogonal to the channel matrix $\mathbf{h}_1^{(n)}$, i.e., $\mathbf{B}^H\mathbf{h}_1^{(n)} = \mathbf{0}$, the practical GSC structure converts this constrained optimization problem into an unconstrained one. We adopt the RLS method to implement our adaptive beamformer, accordingly, a time-averaged CM cost function can be defined as

$$J_{CM}(i) = \sum_{j=1}^{i} \lambda^{i-j} \left(\left| (\mathbf{h}_1^{(n)} - \mathbf{B}\mathbf{w}^{(n)}(i))^H \mathbf{r}^{(n)}(j) \right|^2 - 1 \right)^2, \tag{3}$$

where λ is a forgetting factor which should be chosen as a positive constant close to, but less than 1, $\mathbf{w}^{(n)}(i) = [w_1^{(n)}(i), w_2^{(n)}(i), ..., w_{M-1}^{(n)}(i)]^T$ is the $(M-1)\times 1$ adaptive weight vector which is adjusted on-line to minimize the time-averaged CM cost function. Following the same analysis and derivations steps as in [8], we formulate the CCM-RLS-GSC algorithm for single sub-carrier summarized in Table I.

TABLE I: The CCM-RLS-GSC algorithm for subcarrier n

Initialization: $\mathbf{w}^{(n)}(0) = [1, 0, ..., 0]^T$, $\mathbf{Q}^{(n)-1}(0) = \delta^{-1}\mathbf{I}$, δ=small positive constant.
Update for each symbol epoch i Coefficient updating: $\tilde{\mathbf{w}}^{(n)}(i-1) = \mathbf{h}_1^{(n)} - \mathbf{B}\mathbf{w}^{(n)}(i-1)$, $y^{(n)}(i) = \tilde{\mathbf{w}}^{(n)}(i-1)^H\mathbf{r}^{(n)}(i)$, $\tilde{\mathbf{r}}^{(n)}(i) = y^{(n)}(i)^*\mathbf{r}^{(n)}(i)$, $\mathbf{x}^{(n)}(i) = \mathbf{B}^H\tilde{\mathbf{r}}^{(n)}(i)$, $d^{(n)}(i) = \mathbf{h}_1^{(n)}\tilde{\mathbf{r}}^{(n)}(i) - 1$, Adaptation gain computation: $\mathbf{k}^{(n)}(i) = \frac{\mathbf{Q}^{(n)}(i-1)^{-1}\mathbf{x}^{(n)}(i)}{\lambda+\mathbf{x}^{(n)}(i)^H\mathbf{Q}^{(n)}(i-1)^{-1}\mathbf{x}^{(n)}(i)}$, $\mathbf{Q}^{(n)}(i)^{-1} = \lambda^{-1}\mathbf{Q}^{(n)}(i-1)^{-1} - \lambda^{-1}\mathbf{k}^{(n)}(i)\mathbf{x}^{(n)}(i)^H\mathbf{Q}^{(n)}(i-1)^{-1}$, Weight vector calculation: $e^{(n)}(i) = d^{(n)}(i) - \mathbf{w}^{(n)}(i-1)\mathbf{x}^{(n)}(i)$, $\mathbf{w}^{(n)}(i) = \mathbf{w}^{(n)}(i-1) + \mathbf{k}^{(n)}(i)e^{(n)}(i)^*$.

B. Existing Frequency Clustering Technique in OFDM System

Since the CM property is assumed to hold across all sub-carriers, it is possible to execute the CCM-RLS-GSC algorithm of Table I independently for each sub-carrier. However, practical OFDM systems typically use a large number of sub-carriers and therefore, such a direct application of the algorithm, to which we shall refer as the *complete* solution, induces considerable computational complexity. It is therefore of interest to develop complexity reduction techniques.

In the frequency domain, adjacent OFDM sub-channels are correlated, as the number of sub-carriers is much greater than the length of channel response. Since the optimal weight vectors minimizing (3) depend on the characteristics of the radio channels, it follows that the correlation between these weight vectors is similar to the sub-channel correlation. Motivated by this observation, the authors in [9] proposed flat-top and linear interpolation in order to take advantage of the correlation between neighboring sub-channels and thereby reduce the complexity of the CCM-RLS algorithm in OFDM system.

The flat-top interpolation combines adjacent sub-carriers into a cluster where for each sub-carrier, the beamformer output is computed by using the weight vector corresponding to a selected representative sub-carrier. In this way, only a single carrier per cluster needs to be adapted, which can significantly reduce the computational complexity. In this *frequency clustering* technique, the sub-carrier located in the middle of the cluster is selected for adaptation, which can minimize the spectral distance between the selected and interpolated sub-carriers. Suppose the N sub-carriers are divided into clusters of size P, the receiver evaluates the adaptive weight vectors for the selected sub-carriers $\{\mathbf{w}^{(lP+\lfloor P/2 \rfloor)} : 0 \le l \le N/P-1\}$, and then reconstructs the weight vectors for all the other sub-carriers by copying the nearest $\mathbf{w}^{(lP+\lfloor P/2 \rfloor)}$.

This frequency clustering is an efficient strategy but it suffers from mismatch at the edges of the cluster boundaries because the sub-carriers near the boundary are more likely to experience different fades, especially when the the radio propagation channel changes rapidly. In this case, [9] proposed the use of linear interpolation. In this work, we resort to a general higher-order interpolation technique instead.

IV. COMPLEXITY REDUCTION TECHNIQUES

For highly frequency selective radio propagation channel, the sub-carriers within a cluster will not experience similar fades and the basic techniques proposed in [9], i.e., zero-order and first-order interpolation, may not be adequate to achieve a good system performance In this section, we propose two improved techniques to reduce the system complexity.

A. Proposed Polynomial Interpolation Technique

For the same reason as above but to better exploit the correlation between weight vectors in the frequency domain, we consider the use of polynomial interpolation to improve the accuracy and smoothness of the weight vector across the frequency band of interest. Hence, we propose a general interpolation technique in which the intermediate weight vectors are obtained by connecting the selected weight vectors in each cluster by a polynomial curve in the complex plane. We illustrate this concept with the piecewise polynomial interpolation, which is inspired by OFDM channel interpolation, as presented in [10] for the purpose of channel estimation. It should be noted that under this framework, the linear interpolation technique becomes a special case as will be explained below.

Suppose the cluster size is P and let $\{\mathbf{w}^{(lP+1)} : 0 \le l \le N/P-1\}$ denote the selected sub-carriers, we first update these weight vectors by executing steps of the CCM-RLS-GSC algorithm as shown in Table I. However, instead of copying the nearest weight vector for the other sub-carriers in a cluster as in above frequency clustering technique, we adopt the polynomial interpolation technique [11] to obtain the weight vectors of intermediate sub-carriers. The wight vector on the $(lP+P+k)$th sub-carrier can be computed from a R-basepoint S-order interpolator, which can be expressed as

$$\mathbf{w}^{(lP+P+k)} = \mathbf{W}\mathbf{C}^T\mathbf{U} = \sum_{s=0}^{S-1} \big(\frac{k-1}{P}\big)^s \sum_{r=1}^{R} c_{rs}\mathbf{w}^{((l+R-r)P+1)} \tag{4}$$

where $k = 2, 3, ..., P$, $\mathbf{U} = \big[(\frac{k-1}{P})^0, (\frac{k-1}{P})^1, ..., (\frac{k-1}{P})^{S-1}\big]^T$, $\mathbf{W} = \big[\mathbf{w}^{((l+R-1)P+1)}, ..., \mathbf{w}^{((l+1)P+1)}, \mathbf{w}^{(lP+1)}\big]$, $\mathbf{C}$ denotes the $S \times R$ polynomial interpolator matrix which should be chosen carefully. Fortunately, the authors in [11] suggested a pre-designed four-basepoint third-order piecewise parabolic interpolator which can provide adequate performance in most digital signal processing applications. It is defined as

$$\mathbf{C} = \begin{bmatrix} 0 & 0 & 1 & 0 \\ -\alpha & \alpha+1 & \alpha-1 & -\alpha \\ \alpha & -\alpha & -\alpha & \alpha \end{bmatrix} \tag{5}$$

where $0 \leq \alpha \leq 1$, α denotes the design parameter, through which a trade-off can be made between the steepness of roll-off of the main lobe and the level of its first lobe. Typically $\alpha = 0.5$ is a conservative yet effective choice in most applications, where in this case many coefficients become identical and the multiplications can be replaced by additions which will contribute to reduce the computational complexity in practice. Specially with $\alpha = 0$, this polynomial interpolator reduces to a linear interpolator

$$\mathbf{w}^{(lP+P+k)} = \frac{k-1}{P}\mathbf{w}^{((l+2)P+1)} + (1 - \frac{k-1}{P})\mathbf{w}^{((l+1)P+1)} \tag{6}$$

Like the linear interpolation technique proposed in [9], there exists a phase ambiguity problem when we perform the interpolation operation. Generally, the CCM-RLS-GSC algorithm updates its weight vectors based only on the modulus of the incoming symbols, regardless of the phase rotation in the transmitted data, i.e., it is phase-blind. This may lead to the problem that the interpolated results would not work for the intermediate sub-carriers. To solve this phase ambiguity problem, the weight vectors obtained by the selected sub-carriers should be rotated to minimize the phase difference between them. The rotated phase shift is obtained by minimizing the following formula $||\mathbf{w}^{(lP+1)} - e^{j\phi_r}\mathbf{w}^{((l+r)P+1)}||^2$, in which $\phi_r (r = 1, 2, 3)$ is the phase difference between the weight vectors of $\mathbf{w}^{(lP+1)}$ and the other selected sub-carriers. We can obtain

$$\phi_r = (\mathbf{w}^{((l+r)P+1)H}\mathbf{w}^{((l+r)P+1)})^{-1}\mathbf{w}^{((l+r)P+1)H}\mathbf{w}^{(lP+1)}. \tag{7}$$

Then instead of using the original $\mathbf{w}^{((l+r)P+1)}$, we will employ $e^{j\phi_r}\mathbf{w}^{((l+r)P+1)}$ to compute the weight vectors of unselected sub-carriers. The corresponding equation can be expressed as

$$\mathbf{w}^{(lP+P+k)} = \bar{\mathbf{W}}\mathbf{C}^T\mathbf{U}, \tag{8}$$

where $\bar{\mathbf{W}} = \big[e^{j\phi_3}\mathbf{w}^{((l+3)P+1)}, ..., e^{j\phi_1}\mathbf{w}^{((l+1)P+1)}, \mathbf{w}^{(lP+1)}\big]$.

B. Proposed Spatial Clustering Technique

Besides the use of frequency domain interpolation, system computational complexity can also be reduced by considering processing across the spatial domain. It can be seen from Table I that when the antenna array contains M elements, the CCM-RLS-GSC algorithm requires on the order of M^2 operations per symbol epoch. If we can manage to decrease M, the computational complexity can be reduced. Thus we propose a spatial clustering technique which relies on the partitioning of the receiving array into sub-arrays of smaller size.

To develop the spatial clustering technique, we assume that the original M-element antenna array can be partitioned into Q sub-arrays, each quipped with M/Q antennas. We can see from Table I that vector $\tilde{\mathbf{r}}^{(n)}(i)$, which contains the message of the received signal, is the only input vector for the whole algorithm at a given iteration, other variables such as $\mathbf{x}^{(n)}(i), d^{(n)}(i), \mathbf{k}^{(n)}(i)$ and $\mathbf{Q}^{(n)}(i)^{-1}$ are internal parameters which can be updated independently for each sub-array. Note that $\tilde{\mathbf{r}}^{(n)}(i) = y^{(n)}(i)^*\mathbf{r}^{(n)}(i)$ where $\mathbf{r}^{(n)}(i)$ can be partitioned as

$$\mathbf{r}^{(n)}(i) = [\mathbf{r}_1^{(n)}(i)^T, \ldots, \mathbf{r}_q^{(n)}(i)^T, \ldots, \mathbf{r}_Q^{(n)}(i)^T]^T \tag{9}$$

and $\mathbf{r}_q^{(n)}(i)$ is the received signal vector on the qth sub-array where $q \in \{1, \ldots, Q\}$. We should note that message $\mathbf{r}_q^{(n)}(i)$ associates to the current qth sub-array while $\tilde{\mathbf{r}}^{(n)}(i)$ contains information $y^{(n)}(i)$ from all the sub-arrays. In a corresponding manner, the complete weight vector can be partitioned as

$$\mathbf{w}^{(n)}(i) = [\mathbf{w}_1^{(n)}(i)^T, \ldots, \mathbf{w}_Q^{(n)}(i)^T]^T, \tag{10}$$

and the beamformer output is

$$y^{(n)}(i) = \sum_{q=1}^{Q} y_q^{(n)}(i) = \sum_{q=1}^{Q} \tilde{\mathbf{w}}_q^{(n)}(i)^H\mathbf{r}_q^{(n)}(i). \tag{11}$$

The term $y^{(n)}(i)$ denotes the estimated symbol which contains common information from all the sub-arrays. Now this common information is included in each sub-array through $\tilde{\mathbf{r}}_q^{(n)}(i)$ which can be expressed as

$$\tilde{\mathbf{r}}_q^{(n)}(i) = \mathbf{r}_q^{(n)}(i)\mathbf{r}^{(n)}(i)^H\tilde{\mathbf{w}}^{(n)}(i) = \mathbf{r}_q^{(n)}(i)y^{(n)}(i)^*. \tag{12}$$

Based on the above discussion, a spatial clustering technique with Q sub-arrays can be developed as follows. Once the received signal from qth sub-array $\mathbf{r}_q^{(n)}(i)$ becomes available, the coefficient $y_q^{(n)}(i)$ is computed separately for this sub-array. Then the local outputs from all the sub-arrays, i.e., $y_q^{(n)}$ for $q \in \{1, \ldots, Q\}$, are collected and summed to get the final beamformer output $y^{(n)}(i)$. This common information $y^{(n)}(i)$ is then sent back to each sub-array, where it is used to perform the weight vectors adaptation based on a local realization of the CCM-RLS-GSC algorithm.

Since each sub-array has smaller antenna size, it is possible for the spatial clustering technique to achieve a faster convergence rate compared to the complete solution. Upon further investigation, we note the key difference between this spatial clustering technique and the complete solution lies in the quantity $d^{(n)}(i)$, which takes the form $d_q^{(n)}(i) = \mathbf{h}_{1q}^{(n)}\tilde{\mathbf{r}}_q^{(n)}(i) - 1$ in the former where $\mathbf{h}_{1q}^{(n)}$ is extracted from $\mathbf{h}_1^{(n)}$, while takes the form $d^{(n)}(i) = \mathbf{h}_1^{(n)}\tilde{\mathbf{r}}^{(n)}(i) - 1$ in the latter. This special simplification may result in a loss in system performance.

C. Proposed Combined Technique

As discussed before, we can exploit both the frequency and spatial domain methods to reduce the computational complexity. It is reasonable to combine these two techniques together, which may provide additional flexibility in terms of complexity and system performance.

The combined technique can be developed as follows. Like the spatial clustering technique, we first divide the receiving antenna array into sub-arrays of smaller size. For the weight vectors at the selected sub-carriers in each sub-array, we update their values according to the proposed spatial clustering technique. Then, the remaining weight vectors at the intermediate sub-carriers are obtained via the proposed polynomial interpolation technique. In this case, the system complexity can be further reduced due to both the spatial and frequency domain processing.

D. Computational Complexity

In this section, we discuss the computational complexity of the proposed complexity reduction techniques for the application of the CCM-RLS-GSC algorithm. The computational requirements are described in terms of the number of arithmetic operations, namely multiplications. The basic CCM-RLS-GSC algorithm as presented in [8] needs $5M^2 + M$ complex multiplications per symbol epoch where M is the number of antenna elements at the RX side. Let N denote the number of sub-carriers, P denote the cluster size and Q denote the number of sub-arrays. In Table II below, we list the computational complexity results for different techniques.

TABLE II: Computational Complexity

Technique	Multiplications
complete solution	$5M^2N + MN$
freq clustering	$(5M^2N + MN)/P$
freq interpolation	$(5M^2N + MN)/P + 4M(N-P) + 3MN/P$
spatial clustering	$(5M^2/Q + M)N$
combined	$(5M^2/Q + M)N/P + 4M(N-P) + 3MN/P$

V. SIMULATION RESULTS

In this section, we validate the proposed complexity reduction techniques for the CCM-RLS-GSC algorithm through numerical simulations. These techniques will be applied to the OFDM blind beamforming system, operating over multi-path Rayleigh fading channels.

We consider a coded OFDM system with $N = 64$ sub-carriers and the length of CP is 6. The code used here is a basic convolutional code of rate $1/2$ with the generate matrix $G = [171, 133]$. On the TX side, for each transmitter including the desired user and interferers, 4-QAM modulation is employed to keep the CM property, and the source power is normalized. On the RX side, an ULA containing $M = 16$ antenna elements with half-wavelength inter-element spacing is implemented. The TX symbols propagate through a multi-path channel and are received in the presence of interference and additive white Gaussian noise. The propagation of the desired user's signal is assumed to contain 3 multi-paths. In each simulation, The DOAs are randomly generated with a uniform distribution between 0 and 180 degrees, the exact DOA of the source of interest is assumed to be known by the beamformer. The noise is zero mean spatially and temporally white Gaussian, the forgetting factor λ is set to 0.99 and the design parameter α is set to 0.5.

The performance of the CCM-RLS-GSC algorithm with different techniques are evaluated in terms of their computational complexity and achievable signal plus interference-to-noise ratio (SINR) and bit error rate (BER). The SINR for the nth sub-carrier is given by

$$\mathrm{SINR}^{(n)}(i) = \frac{\tilde{\mathbf{w}}^{(n)H}(i)\mathbf{R}_s(i)\tilde{\mathbf{w}}^{(n)}(i)}{\tilde{\mathbf{w}}^{(n)H}(i)\mathbf{R}_{i+n}(i)\tilde{\mathbf{w}}^{(n)}(i)}, \tag{13}$$

where $\mathbf{R}_s(i)$ is the auto-correlation matrix of the desired signal and $\mathbf{R}_{i+n}(i)$ is the cross-correlation matrix of the interference and noise in the environment. We also define an overall broadband SINR, i.e., $\mathrm{SINR} = \frac{1}{N}\sum_{n=1}^{N}\mathrm{SINR}^{(n)}$.

We first compare the computation complexity of different techniques in terms of multiplications as listed in Table III. To make the complexity of the proposed two techniques close, we choose the following parameter $P = 4, Q = 4$. The data in the Table III show that the complexity ratio for proposed frequency interpolation (30.5%), spatial clustering (25.9%) and combined technique (12.1%) are much smaller when compared to the complete solution.

TABLE III: Computational Complexity Ratio

Technique	Multiplications	Complexity ratio
complete solution	82944	1
freq clustering	$20736 (P = 4)$	0.25
freq interpolation	$25344 (P = 4)$	0.305
spatial clustering	$21504 (Q = 4)$	0.259
combined	$9984 (P = Q = 4)$	0.121

In what follows, we assess the beamformer SINR performance against symbol epoch for these techniques. The number of users is $K = 3$ and the input SNR is fixed at 10dB and these curves in Fig. 2 are plotted by averaging the overall broadband SINR over 1000 independent simulations. For each simulation, the various CCM-RLS-GSC based algorithms, which differ in the type of complexity reduction techniques, are initialized as presented in Table I and run until steady-state convergence. It can be seen that as symbol epoch increases, all output SINR values increase to a steady-state. The graph illustrates that among the complexity reduction techniques, the frequency interpolation can reach the best SINR performance while the spatial clustering can achieve the fastest convergence rate. The combined technique with the lowest computational complexity can result in a higher convergence rate compared with the direct complete solution but smaller steady-state SINR. For these proposed complexity reduction techniques, the SINR loss is no more than 1dB.

In the next experiment, we evaluate the SINR performance of the proposed techniques in a nonstationary scenario. The

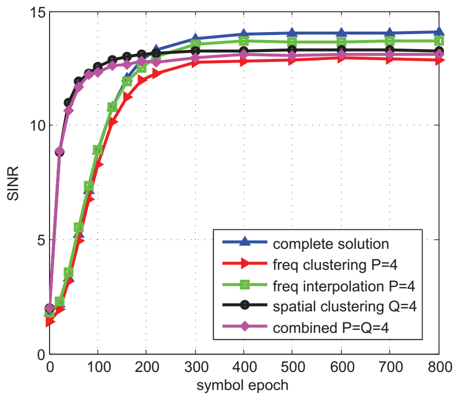

Fig. 2: Average SINR versus symbol epoch

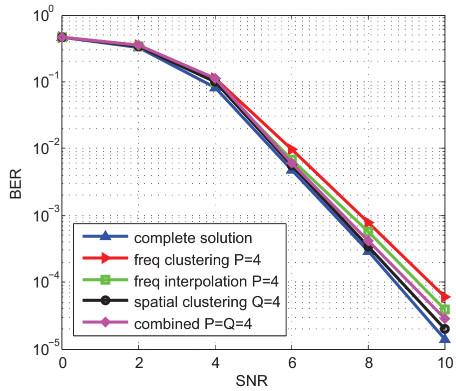

Fig. 4: Average BER versus input SNR

system starts with $K = 3$ users including one desired user and two interferers. After 800 symbol epochs, two more interferers having the same power as the desired user enter the system. The input SNR is 10dB. From the results in Fig. 3, we can see that the abrupt change at 800 symbol epoch reduces the output SINR suddenly and degrades the performance of all algorithms. Although initial convergence may be slow, the adaptive algorithm, including all the complexity reduction techniques, quickly track this change and recover to a new steady-state.

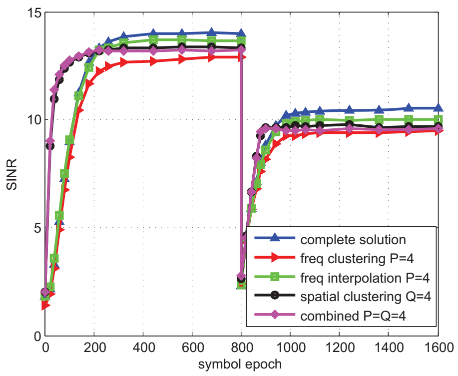

Fig. 3: Average SINR versus symbol epoch

Fig. 4 shows the basic convolutional coded average BER performance for these algorithms. The OFDM system receivers process 800 OFDM symbols, averaged 1000 independent runs for all BER simulations. The experiment is carried out under the same scenario as in Fig. 2, in this case we investigate the average BER performance versus different SNR values. It can be seen that the BER performance of spatial clustering may be better than other complexity reduction techniques over the considered SNR range, especially at high SNR value. For our proposed two techniques and the combined technique, the loss is only around 0.5dB.

VI. CONCLUSION

This paper attempts to make practical the extension of CCM-RLS-GSC blind adaptive beamforming algorithm to OFDM antenna array systems. We proposed two techniques to save the computational complexity. One is the frequency domain interpolation which exploits the coherence bandwidth of the radio channel, only the weight vectors at the selected frequencies are adapted while a general polynomial interpolator is implemented to obtain the weight vectors of intermediate sub-carriers. The other is the spatial domain clustering which relies on the partitioning of the receiving array into sub-arrays of smaller size. Furthermore, we proposed the combination of these two techniques to provide additional reduction. A complexity analysis and the numerical simulation results enabled us to conclude that both complexity reduction techniques can be utilized as good solutions to reduce the system computational complexity in practical OFDM antenna array systems.

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