A CROSS-RELATION BASED AFFINE PROJECTION ALGORITHM FOR BLIND SIMO SYSTEM IDENTIFICATION

Emanuël A. P. Habets[1], *Jacob Benesty*[2] *and Patrick A. Naylor*[3]

[1] International Audio Laboratories Erlangen
91058 Erlangen, Germany

[2] INRS-EMT, University of Quebec
Montreal, Quebec, Canada

[3] Imperial College London
SW7 2AZ, United Kingdom

ABSTRACT

A new time-domain adaptive algorithm is proposed for blind identification of single-input multiple-output systems that is based on the cross-relation (CR) method. The proposed algorithm novelly exploits the affine projection principle to minimize the CR error. As a result, a cost function is minimized that differs from the one used in existing CR based adaptive algorithms. A major advantage of the proposed multichannel affine projection algorithm (MCAPA) is that the affine projection order can be used to control the tradeoff between the rate of convergence and computational complexity. In an experimental study, MCAPA is compared with two recently developed adaptive algorithms, i.e., the low-cost multichannel least-mean-square (MCLMS) and high-performance multichannel Newton (MCN) algorithms. The results show that MCAPA converges faster than MCLMS with a computational complexity that is significantly lower than MCN, thereby increasing the applicability of the CR method.

1. INTRODUCTION

Blindly identifying single-input multiple-output (SIMO) acoustic systems has become an important research topic with applications in dereverberation, source localization and tracking [1]. Key characteristics of the blind system identification problem is that neither the source nor channels are known in advance. It is a challenging problem as the channels usually exceed thousand finite impulse response coefficients and may be time-varying.

The cross-relation (CR) method [2], was one of the first methods proposed to blindly identify a SIMO system and has served as the foundation for several algorithms. The CR method is based on eliminating the unknown input from the multiple input-output relations and uses only second-order statistics (SOS) of the output signals. The unknown SIMO system is identified by minimizing the CR error. Other SOS methods for blind SIMO system identification are for example subspace methods [3, 4] and the prediction error method [5]. It should be noted that the prediction error method assumes that the source signal consists of an independent and identically distributed random sequence, and is therefore not directly applicable when dealing with speech, which is our signal of interest. In [6, 7] solutions have been presented to relax the assumption on the source signal.

Adaptive time-domain algorithms have been derived based on the CR error, e.g., the multichannel least-mean-square (MCLMS) and multichannel Newton (MCN) algorithms [8]. The main advantage of adaptive algorithms is their ability to track time-varying SIMO systems. In addition, computational efficient frequency-domain algorithms have been developed. Specifically, a frequency domain version of a block-based MCLMS has resulted in the multichannel frequency domain least-mean-square (MCFLMS) algorithm [9]. The normalized MCFLMS (NMCFLMS) derived in [9] is an attempt to combine the low complexity of the MCFLMS approach and the fast convergence of the MCN. It should be noted that various approximations are made throughout the derivation of

This research was supported by the Marie Curie Intra European Fellowship within the 7th European Community Framework Programme under contract number PIEF-GA-2009-237246.

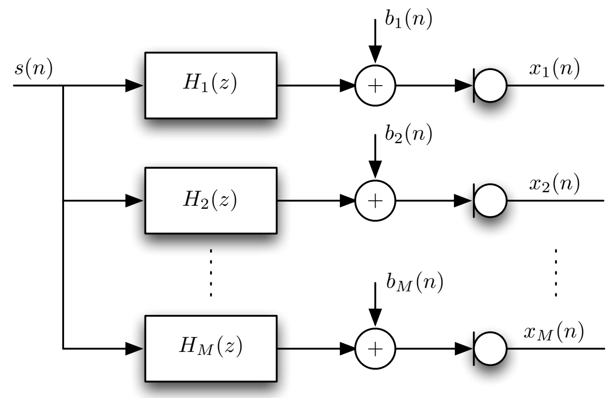


Figure 1: Illustration of an acoustic SIMO system.

the NMCFLMS algorithm and that the convergence speed of the NMCFLMS is generally lower than that of the MCN [9].

In this contribution we focus on time-domain adaptive algorithms for blind SIMO system identification. As shown in Section 4, the rate of convergence of the MCLMS algorithm is highly dependent on the sample correlation coefficient of successive input signal vectors. Affine projection algorithms [10] have been proposed to alleviate this dependency. In this paper, we novelly derive an affine projection algorithm for the blind case of multichannel SIMO system identification. Experimental results demonstrate that the rate of convergence is slower than MCN but faster than MCLMS. It is also shown that the performance of the multichannel affine projection algorithm (MCAPA) is less data dependent than the MCLMS algorithm.

This paper is organized as follows. In Section 2 we define the signal model and briefly outline the MCLMS and MCN algorithms. In Section 3 we derive the MCAPA algorithm and we discuss its computational complexity. Finally, the performance of the MCAPA is compared with the performance of the MCLMS and MCN algorithms in Section 4.

2. SIGNAL MODEL AND EXISTING ADAPTIVE CROSS RELATION METHODS

For an M-channel SIMO system as shown in Fig. 1, the mth channel impulse response with L coefficients can be denoted as

$$\mathbf{h}_m = [h_{m,0}\ h_{m,1}\ \ldots\ h_{m,L-1}]^T, \tag{1}$$

for $m = 1, 2, \ldots, M$, and the mth sensor signal can be expressed as

$$x_m(n) = \sum_{l=0}^{L-1} h_{m,l}\, s(n-l) + b_m(n), \tag{2}$$

where $s(n)$ is the source signal and $b_m(n)$ is the additive noise. The additive noise is assumed to be zero-mean and uncorrelated with the source signal.

The problem of blind SIMO system identification is to find $\mathbf{h} = [\mathbf{h}_1^T\ \mathbf{h}_2^T\ \ldots\ \mathbf{h}_M^T]^T$ using only the received signals $x_m(n)$. Hence, given the received signals, a unique solution to $\mathbf{h}$ should be obtained up to a non-zero scale factor across all channels. This scale factor is irrelevant in most of acoustic signal processing applications.

For the development of adaptive CR algorithm we first define the *a priori* error at discrete time n that is associated with the kth and mth channel impulse responses as

$$e_{mk}(n) = \mathbf{x}_m^T(n)\hat{\mathbf{h}}_k(n-1) - \mathbf{x}_k^T(n)\hat{\mathbf{h}}_m(n-1). \tag{3}$$

Existing adaptive CR algorithms are based on minimizing the total *a priori* squared-error defined as

$$\xi(n) = \sum_{m=1}^{M-1}\sum_{k=m+1}^{M} e_{mk}^2(n), \tag{4}$$

where we excluded the cases where $e_{mm} = 0$ for $m \in \{1, 2, \ldots, M\}$ and count the pairs $e_{mk} = -e_{km}$ only once. With a unit-norm constraint enforced on $\hat{\mathbf{h}}(n-1)$ the normalized *a priori* error is given by

$$\tilde{e}_{mk}(n) = \frac{e_{mk}(n)}{\|\hat{\mathbf{h}}(n-1)\|}, \tag{5}$$

where $\|\cdot\|$ denotes ℓ_2 vector norm. Accordingly, the cost function to be minimized can be defined as

$$J(n) = \sum_{m=1}^{M-1}\sum_{k=m+1}^{M} \tilde{e}_{mk}^2(n) = \frac{\xi(n)}{\|\hat{\mathbf{h}}(n-1)\|^2}, \tag{6}$$

for which the optimal solution $\mathbf{h}_\mathrm{o}$ is given by

$$\mathbf{h}_\mathrm{o} = \arg\min_{\mathbf{h}} E[J(n)] \text{ subject to } \|\mathbf{h}\|^2 = 1, \tag{7}$$

where $E\{\cdot\}$ denotes the mathematical expectation and the unit-norm constraint is used to avoid trivial solutions such as $\mathbf{h} = \mathbf{0}_{ML\times 1}$, where $\mathbf{0}_{ML\times 1}$ is a null vector of length ML. Other constraints can also be used to avoid trivial solutions (see for example [8, 11]).

According to Xu et al. [2], the following two conditions are necessary and sufficient for blindly identifying a SIMO system using the CR method:

1. The channel transfer functions do not share any common zeros, i.e., the polynomials formed by $\mathbf{h}_m$ $(1 \le m \le M)$ are co-prime;
2. The autocorrelation matrix of the input signal $\mathbf{R}_{ss} = E\{\mathbf{s}(n)\mathbf{s}^T(n)\}$ is of full rank, where $\mathbf{s}(n) = [s(n), s(n-1), \ldots, s(n-L+1)]^T$, such that SIMO system can be fully excited.

For the MCLMS algorithm the update equation for $\hat{\mathbf{h}}$ is given by [8]:

$$\begin{aligned}\hat{\mathbf{h}}(n) &= \hat{\mathbf{h}}(n-1) - \mu_{\text{MCLMS}}\nabla J(n)\\ &= \hat{\mathbf{h}}(n-1) - \frac{2\mu_{\text{MCLMS}}}{\|\hat{\mathbf{h}}(n-1)\|^2}\left[\widetilde{\mathbf{R}}(n)\hat{\mathbf{h}}(n-1) - J(n)\hat{\mathbf{h}}(n-1)\right],\end{aligned} \tag{8}$$

where $\nabla J(n)$ is the gradient vector of $J(n)$ with respect to $\hat{\mathbf{h}}(n-1)$ and $\widetilde{\mathbf{R}}(n)$ is the instantaneous estimate of

$$\mathbf{R} = \begin{bmatrix} \sum_{m\neq 1}\mathbf{R}_{x_m x_m} & -\mathbf{R}_{x_2 x_1} & \cdots & -\mathbf{R}_{x_M x_1} \\ -\mathbf{R}_{x_1 x_2} & \sum_{m\neq 2}\mathbf{R}_{x_m x_m} & \cdots & -\mathbf{R}_{x_M x_2} \\ \vdots & \vdots & \ddots & \vdots \\ -\mathbf{R}_{x_1 x_M} & -\mathbf{R}_{x_2 x_M} & \cdots & \sum_{m\neq M}\mathbf{R}_{x_m x_m} \end{bmatrix} \tag{9}$$

of size $ML \times ML$ where $\mathbf{R}_{x_m x_k}$ is the cross-correlation matrix between $\mathbf{x}_m(n-1)$ and $\mathbf{x}_k(n-1)$ given by $\mathbf{R}_{x_m x_k} = \mathrm{E}\{\mathbf{x}_m(n)\mathbf{x}_k^T(n)\}$. If the channel estimate is always normalized after each updating iteration, (8) can be written as [8]

$$\hat{\mathbf{h}}(n) = \frac{\hat{\mathbf{h}}(n-1) - 2\mu_{\text{MCLMS}}[\widetilde{\mathbf{R}}(n)\hat{\mathbf{h}}(n-1) - \xi(n)\hat{\mathbf{h}}(n-1)]}{\left\|\hat{\mathbf{h}}(n-1) - 2\mu_{\text{MCLMS}}[\widetilde{\mathbf{R}}(n)\hat{\mathbf{h}}(n-1) - \xi(n)\hat{\mathbf{h}}(n-1)]\right\|}. \tag{10}$$

Here $\hat{\mathbf{h}}(n-1)$ is initialized as $\hat{\mathbf{h}}_m(0) = [1/\sqrt{M}\ 0\ \ldots\ 0]^T$, $m = 1, 2, \ldots, M$ such that $\|\hat{\mathbf{h}}(0)\|^2 = 1$.

While the MCLMS algorithm with unit-norm constraint can converge in the mean to the desired channel impulse responses the main difficulty is the selection of the step size μ_{MCLMS}. As pointed out in many studies, there is a trade-off between the amount of excess mean-squared error, the rate of convergence, and the ability of the algorithm to track changes in the system. In order to obtain a good balance of these competing design objectives, the unit-norm constrained MCN algorithm with a variable step size during adaptation was derived in [8]. For the MCN algorithm the update of the estimated impulse responses is given by [8]

$$\hat{\mathbf{h}}(n) = \hat{\mathbf{h}}(n-1) - \mathrm{E}^{-1}\{\nabla^2 J(n)\}\,\nabla J(n), \tag{11}$$

where $\nabla^2 J(n)$ is the Hessian matrix of $J(n)$ with respect to $\hat{\mathbf{h}}(n-1)$. With some approximations the unit-norm constrained update equation can be written as [8]

$$\hat{\mathbf{h}}(n) = \frac{\hat{\mathbf{h}}(n-1) - 2\rho\mathbf{V}^{-1}(n)[\widehat{\mathbf{R}}(n)\hat{\mathbf{h}}(n-1) - \xi(n)\hat{\mathbf{h}}(n-1)]}{\left\|\hat{\mathbf{h}}(n-1) - 2\rho\mathbf{V}^{-1}(n)[\widehat{\mathbf{R}}(n)\hat{\mathbf{h}}(n-1) - \xi(n)\hat{\mathbf{h}}(n-1)]\right\|}, \tag{12}$$

where $\mathbf{V}(n) = 2\widehat{\mathbf{R}}(n) - 4\hat{\mathbf{h}}(n-1)\hat{\mathbf{h}}^T(n-1)\widehat{\mathbf{R}}(n) - 4\widehat{\mathbf{R}}(n)\hat{\mathbf{h}}(n-1)\hat{\mathbf{h}}^T(n-1)$ approximates $\mathrm{E}\{\nabla^2 J(n)\}$, ρ $(0 < \rho < 1)$ denotes the step size that is commonly chosen close to 1, and $\widehat{\mathbf{R}}(n)$ is an estimate of (9) computed using $\widehat{\mathbf{R}}(n) = \lambda\widehat{\mathbf{R}}(n-1) + \widetilde{\mathbf{R}}(n)$, where λ $(0 < \lambda < 1)$ is a forgetting factor.

3. AFFINE PROJECTION ALGORITHM FOR MINIMIZATION OF THE CR ERROR

In Section 3.1 the MCAPA is derived for $M = 2$. The algorithm is then generalized for $M \ge 2$ in Section 3.2.

3.1 Two Channel Case ($M = 2$)

Let us denote the estimate of $\mathbf{h}(n-1)$ at time n by $\hat{\mathbf{h}}(n-1)$. We can formulate the criterion for designing an affine projection filter as one of optimization subject to multiple constraints. Specifically, we minimize the squared Euclidean norm of $\hat{\mathbf{h}}(n) - \hat{\mathbf{h}}(n-1)$, subject to a set of $P + 1$ constraints, i.e.,

$$\mathbf{q}^T(n-p)\,\hat{\mathbf{h}}(n) = 0, \text{ for } p = 0, 1 \ldots, P-1, \tag{13}$$

and the unit-norm constraint avoiding the trivial null solution

$$\hat{\mathbf{h}}^T(n)\hat{\mathbf{h}}(n) = 1, \tag{14}$$

where for $M = 2$

$$\begin{aligned}\hat{\mathbf{h}}(n) &= \begin{bmatrix} \hat{\mathbf{h}}_1^T(n) & \hat{\mathbf{h}}_2^T(n) \end{bmatrix}^T,\\ \mathbf{q}(n) &= \begin{bmatrix} \mathbf{x}_2^T(n) & -\mathbf{x}_1^T(n) \end{bmatrix}^T.\end{aligned}$$

In other words, the requirement is to cancel P a posteriori CR errors and to satisfy the unit-norm constraint. Note that the definition of the vector $\mathbf{q}$ and the constraints in (13) are different from those found in the classical APA. In the following, it is assumed that the projection order P is smaller than the channel length L, i.e., $P < L$.

Using Lagrange multipliers, we can write the unconstrained cost function as

$$J(n) = \left\|\hat{\mathbf{h}}(n) - \hat{\mathbf{h}}(n-1)\right\|^2 + \sum_{p=0}^{P-1} \lambda_p \, \mathbf{q}^T(n-p)\, \hat{\mathbf{h}}(n) + \lambda_{\text{n}} \left[\hat{\mathbf{h}}^T(n)\hat{\mathbf{h}}(n) - 1\right], \quad (15)$$

where λ_p with $p \in \{0, 1, \ldots, P-1\}$ and λ_{n} are the Lagrange multipliers.

Taking the gradient of $J(n)$ with respect to $\hat{\mathbf{h}}(n)$ and equating the result to zero, we obtain:

$$2\left[\hat{\mathbf{h}}(n) - \hat{\mathbf{h}}(n-1)\right] + \sum_{p=0}^{P-1} \lambda_p \mathbf{q}(n-p) + 2\lambda_{\text{n}}\hat{\mathbf{h}}(n) = \mathbf{0}, \quad (16)$$

where $\mathbf{0} = [0 \ldots 0]^T$. The latter expression can be rewritten as

$$\hat{\mathbf{h}}(n) = \frac{1}{1+\lambda_{\text{n}}}\left[\hat{\mathbf{h}}(n-1) - \frac{1}{2}\mathbf{Q}^T(n)\boldsymbol{\lambda}\right] \quad (17)$$

where for $M = 2$

$$\mathbf{Q}(n) = \begin{bmatrix} \mathbf{x}_2^T(n) & -\mathbf{x}_1^T(n) \\ \mathbf{x}_2^T(n-1) & -\mathbf{x}_1^T(n-1) \\ \vdots & \vdots \\ \mathbf{x}_2^T(n-P+1) & -\mathbf{x}_1^T(n-P+1) \end{bmatrix},$$

$$\boldsymbol{\lambda} = [\ \lambda_0 \quad \lambda_1 \quad \ldots \quad \lambda_{P-1}\ ]^T.$$

Left multiplying both sides of (17) with $\mathbf{Q}(n)$ of size $P \times 2L$ and using the fact that $\mathbf{Q}(n)\hat{\mathbf{h}}(n) = 0$ we deduce that

$$\frac{1}{2}\boldsymbol{\lambda} = \left[\mathbf{Q}(n)\mathbf{Q}^T(n)\right]^{-1}\mathbf{e}(n), \quad (18)$$

where

$$\mathbf{e}(n) = \mathbf{Q}(n)\hat{\mathbf{h}}(n-1) \quad (19)$$

is the *a priori* CR error vector of length P. By substituting (18) in (17) we obtain

$$\hat{\mathbf{h}}(n) = \frac{1}{1+\lambda_{\text{n}}}\left[\hat{\mathbf{h}}(n-1) - \mathbf{Q}^\dagger(n)\mathbf{e}(n)\right], \quad (20)$$

where $\mathbf{Q}^\dagger(n) = \mathbf{Q}^T(n)\left[\mathbf{Q}(n)\mathbf{Q}^T(n)\right]^{-1}$ is the right inverse of $\mathbf{Q}(n)$.

The first term at the right-hand side of (20) is a scalar, therefore it will not affect the convergence rate or tracking of the algorithm. Rather than computing λ_{n} to satisfy the unit-norm constraint in (17), we update $\hat{\mathbf{h}}(n-1)$ using

$$\hat{\mathbf{h}}(n) = \frac{\hat{\mathbf{h}}(n-1) - \mathbf{Q}^\dagger(n)\,\mathbf{e}(n)}{\left\|\hat{\mathbf{h}}(n-1) - \mathbf{Q}^\dagger(n)\,\mathbf{e}(n)\right\|}. \quad (21)$$

Finally, we control the adaptation in the determined search direction by adding a step size parameter μ_{MCAPA} ($0 \leq \mu_{\text{MCAPA}} \leq 2$) to the update, yielding

$$\hat{\mathbf{h}}(n) = \frac{\hat{\mathbf{h}}(n-1) - \mu_{\text{MCAPA}}\,\mathbf{Q}^\dagger(n)\,\mathbf{e}(n)}{\left\|\hat{\mathbf{h}}(n-1) - \mu_{\text{MCAPA}}\,\mathbf{Q}^\dagger(n)\,\mathbf{e}(n)\right\|}. \quad (22)$$

It should be noted that (22) for $P = 1$ is not equivalent to the MCLMS algorithm that is derived from a different criterion.

3.2 Multichannel Case ($M \geq 2$)

For M channels there are $M(M-1)/2$ independent cross-relations. We can extend the matrix $\mathbf{Q}(n)$ to include all cross-relations in the following way:

$$\mathbf{Q}(n) = \begin{bmatrix} \mathbf{C}_1(n) - \mathbf{D}_1(n) \\ \mathbf{C}_2(n) - \mathbf{D}_2(n) \\ \vdots \\ \mathbf{C}_{M-1}(n) - \mathbf{D}_{M-1}(n) \end{bmatrix}, \quad (23)$$

where

$$\mathbf{C}_m(n) = \begin{bmatrix} \mathbf{0} & \cdots & \mathbf{0} & \mathbf{X}_{m+1}(n) & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \cdots & \mathbf{0} & \mathbf{X}_{m+2}(n) & \mathbf{0} & \cdots & \mathbf{0} \\ \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ \underbrace{\mathbf{0} \ \ldots \ \mathbf{0}}_{(m-1)L} & & & \mathbf{X}_M(n) & \underbrace{\mathbf{0} \ \cdots \ \mathbf{0}}_{(M-m)L} & & \end{bmatrix}, \quad (24)$$

and

$$\mathbf{D}_m(n) = \begin{bmatrix} \mathbf{0} & \cdots & \mathbf{0} & \mathbf{X}_m(n) & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \cdots & \mathbf{0} & \mathbf{0} & \mathbf{X}_m(n) & \cdots & \mathbf{0} \\ \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ \underbrace{\mathbf{0} \ \cdots \ \mathbf{0}}_{mL} & & & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{X}_m(n) \end{bmatrix}, \quad (25)$$

where $\mathbf{X}_m(n) = [\mathbf{x}_m(n)\,\mathbf{x}_m(n-1) \ldots \mathbf{x}_m(n-P+1)]^T$. The matrix $\mathbf{Q}(n)$ is of size $PM(M-1)/2 \times ML$ and the matrices $\mathbf{C}_m(n)$ and $\mathbf{D}_m(n)$ are of size $P(M-m) \times ML$. Because all cross-relations are independent, the rows of $\mathbf{Q}(n)$ are independent and therefore $\mathbf{Q}(n)$ is of full row rank.

3.3 Regularization

When the variance of the additive noise $b_m(n)$ $\forall m$ is small the inversion of the matrix product $\mathbf{Q}(n)\mathbf{Q}^T(n)$ may give rise to numerical difficulties. Therefore, we modify that product by adding to it a regularisation term $\delta\mathbf{I}$, where δ is a small positive constant and $\mathbf{I}$ the identity matrix of size $PM(M-1)/2 \times PM(M-1)/2$. Introducing this modification into $\mathbf{Q}^\dagger(n)$ yields

$$\mathbf{Q}^\dagger(n) = \mathbf{Q}(n)\left[\mathbf{Q}(n)\mathbf{Q}^T(n) + \delta\mathbf{I}\right]^{-1}. \quad (26)$$

3.4 Computational Complexity

The computational complexity of the MCAPA depends on the projection order P, the number of channels M and the channel length L. For $P = 1$ the computational complexity of the MCAPA is approximately equal to that of the MCLMS algorithm. The main computational load of the MCAPA is the computation of the inverse of the matrix $\mathbf{Q}(n)\mathbf{Q}^T(n) + \delta\mathbf{I}$ of size $PM(M-1)/2 \times PM(M-1)/2$, which has a complexity $\mathcal{O}(P^3[M(M-1)/2]^3)$. The main computational load of the MCN algorithm is the computation of the Hessian that includes the inversion of a $ML \times ML$ matrix with a complexity $\mathcal{O}(M^3L^3)$. Hence, the main complexity of the MCAPA is lower than that of the MCN when $P(M-1)/2 < L$. An illustrative example is given in Section 4.2.

4. PERFORMANCE EVALUATION

The performance of MCAPA is now compared to MCLMS and MCN through Monte Carlo simulations in a blind multichannel system experiment. First the performance measures are described in Section 4.1. Secondly, the results of three evaluations are described in Sections 4.2 and 4.3.

The step sizes used for MCLMS and MCAPA were respectively $\mu_{\text{MCLMS}} = 0.025$ and $\mu_{\text{MCAPA}} = 0.5$, while the parameters for MCN were $\rho = 0.5$ and $\lambda = 0.98$. The regularization parameter δ used for the MCAPA and MCN algorithms was set experimentally to 10^{-8}.

4.1 Performance Measures

The normalized root mean square projection misalignment (NRMSPM) in decibels is used as a performance measure of the system estimation accuracy and is given by [8]

$$\mathrm{NRMSPM}(n) = 20\,\log_{10}\left[\frac{1}{\|\mathbf{h}\|}\sqrt{\frac{1}{N_{\mathrm{MC}}}\sum_{i=1}^{N_{\mathrm{MC}}}\|\boldsymbol{\xi}^{(i)}(n)\|^2}\right], \tag{27}$$

where N_{MC} is the number of Monte Carlo runs, the index $(\cdot)^{(i)}$ denotes the value obtained for the ith run, and

$$\boldsymbol{\xi}(n) = \mathbf{h} - \frac{\mathbf{h}^T\hat{\mathbf{h}}(n)}{\hat{\mathbf{h}}^T(n)\hat{\mathbf{h}}(n)}\,\hat{\mathbf{h}}(n) \tag{28}$$

is the projection misalignment vector [12] at time n. By projecting $\mathbf{h}$ onto $\hat{\mathbf{h}}$ and defining a projection error the intrinsic misalignment of the channel estimate is taken into account and therefore disregards an arbitrary gain factor [12]. The results in the subsequent subsections are computed using $N_{\mathrm{MC}} = 100$.

Finally, the rate of convergence is measured by the minimum number of samples required to reach a given NRMSPM, i.e.,

$$Q(\epsilon) = \arg\min_n \{\mathrm{NRMSPM}(n) < \epsilon\}, \tag{29}$$

where ϵ denotes the desired performance level in dB.

The additive noise is i.i.d. zero-mean Gaussian, and the specified SNR is defined as

$$\mathrm{SNR} = \frac{\sigma_s^2\|\mathbf{h}\|^2}{M\sigma_b^2}, \tag{30}$$

where σ_s^2 and σ_b^2 are the signal and background noise powers, respectively.

4.2 System condition

For the first evaluation the source signal consists of a zero-mean Gaussian random sequence of 5 seconds (sampling frequency f_s = 8 kHz) and the SNR $=$ 50 dB. Here two systems ($M = 3$ and $L = 16$) were used that consist of random channels with coefficients drawn from a zero-mean Gaussian distribution. The number of near-common-zeros (NCZ) for both systems were computed using the generalized multichannel clustering algorithm developed in [13] with a tolerance of 10^{-3}. The number of NCZ of the first system is zero while the number of NCZ for the second system is six, indicating that the first system is well-conditioned and the second system is ill-conditioned. The well-conditioned system was changed to the ill-conditioned system at $n/f_s = 2.5$ seconds. The systems were identified using the proposed MCAPA with projections order $P \in \{1, 2, 4\}$ and the MCLMS and MCN algorithms. The NRMSPM is shown in Fig. 2. As expected, it can be seen that the rate of convergence of all three algorithms is affected by the channel conditioning. More importantly, we observe that the MCAPA with $P > 1$ converges faster than MCLMS but slower than MCN, and that the rate of convergence of the MCAPA is increasing for larger projection orders. Following our analysis in Section 3.4, the main complexity of the MCAPA for this example with $M = 3$ is $(1 - P^3/L^3) \times 100\%$, smaller than that of MCN when $P^3 < L^3$. For $P = 4$ and $L \geq 16$ we therefore reduce the computational complexity by more than 99.6%.

4.3 Rate of convergence

We now analyse the rate of convergence by computing the minimum number of iterations required to reach a given NRMSPM. Our objective is to study i) how the sample correlation coefficient of the source affects the rate of convergence and ii) the influence of the projection order P on the rate of convergence. The source

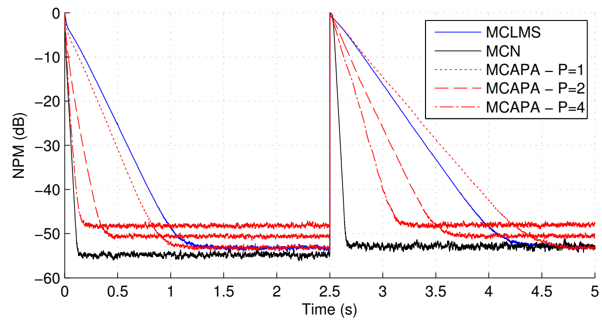
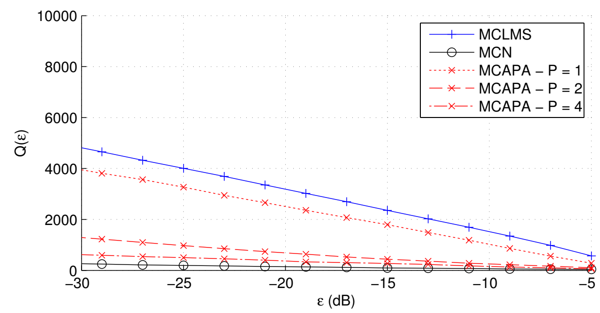
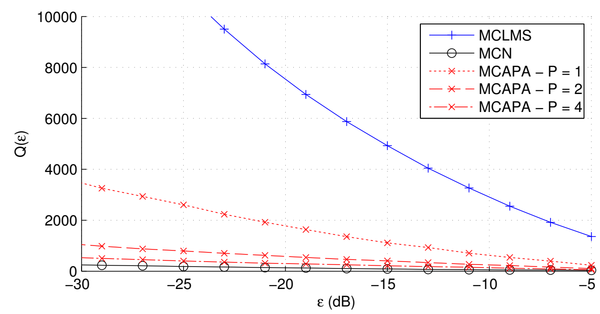


Figure 2: The NRMSPM of the MCLMS, MCAPA, and MCN algorithms (SNR=50 dB).



(a) Uncorrelated source signal.



(b) Correlated source signal.

Figure 3: Minimum number of samples required for the MCLMS, MCAPA, and MCN algorithms to reach a threshold ϵ (SNR=50 dB).

signal consists of a zero-mean Gaussian random sequence and the SNR $= 50$ dB. Here the same well-conditioned system as described in the previous subsection was used. The sample correlation coefficient was increased by passing the source signal through an autoregressive model of order one, i.e., $G(\mathrm{z}) = (1 + 0.95\,\mathrm{z})^{-1}$. The results shown in Fig. 3 are obtained using the well-conditioned system and demonstrate that the rate of convergence for the MCLMS algorithm degrades significantly when the sample correlation coefficient of the source is increased. The rate of convergence of MCAPA and MCN are only moderately affected by the increased correlation.

The influence of the projection order P on the rate of convergence for the aforementioned correlated source signal was studied. In Fig. 4 the number of samples required to reach an NRMSPM of -20 dB when using the well-conditioned system are depicted for the MCLMS, MCAPA, and MCN algorithms. From the results for the MCAPA we conclude that the time it takes to reach an NRMSPM of -20 dB decreases when the projection order P increases. Moreover, we observe that for the considered test scenario the MCAPA with $P = 6$ converges almost as fast as the MCN algorithm to an NRMSPM of -20 dB.

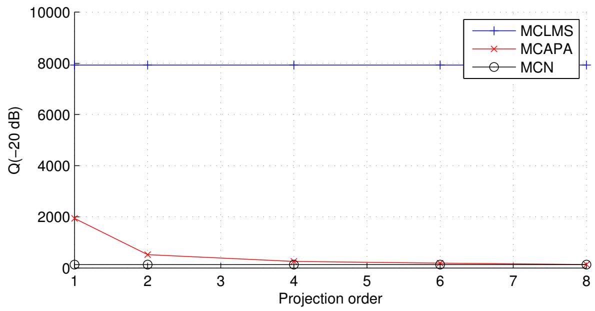


Figure 4: Minimum number of samples required to reach an NRMSPM of -20 dB for the MCLMS, MCAPA (with $P = 1, 2, \ldots, 8$), and the MCN algorithms (SNR=50 dB).

5. CONCLUSIONS

Existing adaptive algorithms for blind SIMO system identification have either a low computational complexity but converge relatively slowly, such as MCLMS, or exhibit extremely high computational complexity but converges rapidly, such as MCN. Furthermore, their complexity scales significantly with increasing number of channels and channel coefficients, making the high performance algorithms usually impractical. Here we have derived a new adaptive algorithm for blind SIMO system identification which novelly exploits the affine projection principle to minimize the CR error. Results demonstrate the advantage of the proposed MCAPA in that it provides a controllable tradeoff between the computational complexity and rate of convergence.

REFERENCES

[1] Y. Huang, J. Benesty, and J. Chen, "Identification of acoustic MIMO systems: Challenges and opportunities," *Signal Processing*, vol. 6, no. 86, pp. 1278–1295, 2006.

[2] G. Xu, H. Liu, L. Tong, and T. Kailath, "A least-squares approach to blind channel identification," *IEEE Trans. Signal Process.*, vol. 43, no. 12, pp. 2982–2993, Dec. 1995.

[3] E. Moulines, P. Duhamel, J.-F. Cardoso, and S. Mayrargue, "Subspace methods for the blind identification of multichannel FIR filters," *IEEE Trans. Signal Process.*, vol. 43, no. 2, pp. 516–525, Feb. 1995.

[4] S. Gannot and M. Moonen, "Subspace methods for multimicrophone speech dereverberation," *EURASIP Journal on Applied Signal Processing*, vol. 2003, no. 11, pp. 1074–1090, 2003.

[5] K. Abed Meraim, P. Duhamel, D. Gesbert, P. Loubaton, S. Mayrargue, E. Moulines, and D. Slock, "Prediction error methods for time-domain blind identification of multichannel fir filters," in *Proc. IEEE Intl. Conf. on Acoustics, Speech and Signal Processing (ICASSP)*, 1995, vol. 3, pp. 1968–1971.

[6] M. Delcroix, T. Hikichi, and M. Miyoshi, "Blind dereverberation algorithm for speech signals based on multi-channel linear prediction," *Acoustical Science and Technology*, vol. 26, no. 5, pp. 432–439, 2005.

[7] M. Triki and D.T.M. Slock, "Blind dereverberation of a single source based on multichannel linear prediction," in *Proc. Intl. Workshop Acoust. Echo Noise Control (IWAENC)*, Sept. 2005.

[8] Y. Huang and J. Benesty, "Adaptive multi-channel least mean square and Newton algorithms for blind channel identification," *Signal Processing*, vol. 82, pp. 1127–1138, Aug. 2002.

[9] Y. Huang and J. Benesty, "A class of frequency-domain adaptive approaches to blind multichannel identification," *IEEE Trans. Signal Process.*, vol. 51, no. 1, pp. 11–24, Jan. 2003.

[10] K. Ozeki and T. Umeda, "An adaptive filtering algorithm using an orthogonal projection to an affine subspace and its properties," *Electronics and Communications in Japan*, vol. 67–A, no. 5, pp. 19–27, May 1984.

[11] C. Avendano, J. Benesty, and D. R. Morgan, "A least squares component normalization approach to blind channel identification," in *Proc. IEEE Intl. Conf. on Acoustics, Speech and Signal Processing (ICASSP)*, Mar. 1999, vol. 4, pp. 1797–1800.

[12] D. R. Morgan, J. Benesty, and M. Sondhi, "On the evaluation of estimated impulse responses," *IEEE Signal Process. Lett.*, vol. 5, no. 7, pp. 174–176, July 1998.

[13] A. W. H. Khong, X. Lin, and P. A. Naylor, "Algorithms for identifying clusters of near-common zeros in multichannel blind system identification and equalization," in *Proc. IEEE Intl. Conf. on Acoustics, Speech and Signal Processing (ICASSP)*, Las Vegas, USA, Apr. 2008, pp. 389–392.