14th European Signal Processing Conference (EUSIPCO 2006), Florence, Italy, September 4-8, 2006, copyright by EURASIP

A CHANNEL DEFLATION APPROACH FOR THE BLIND DECONVOLUTION OF A COMPLEX FIR CHANNEL WITH REAL INPUT

Konstantinos I. Diamantaras[1], *Theophilos Papadimitriou*[2], *and Efthimios Kotsialos*[1]

[1] Department of Informatics
TEI of Thessaloniki
Sindos 57400, Greece
{kdiamant@it.teithe.gr, ekots@uom.gr}

[2] Dept. of Int. Econ. Relat. & Devel.
Democritus University of Thrace
Komotini 69100, Greece
papadimi@ierd.duth.gr

ABSTRACT

In this paper we present a novel second-order statistics method for the blind deconvolution of a real signal propagating through a complex channel. The method is computationally very efficient since it involves only one SVD computation for the time-delayed output covariance matrix. No other optimization is involved. The subspaces corresponding to the left and right singular value matrices can be used to "deflate" the channel: projecting the output signal on either subspace reduces the filter length to 1, thus source reconstruction is simplified. The method is suitable for any channel length and it offers performance improvement compared to well established methods.

1. INTRODUCTION

In a typical digital / wireless broadcast process involving a single transmission and multiple receptions, the encoding - modulation - transmission stage, accompanied by the inverse transformations of demodulation - decoding, requires the removal of the effects of the transmission channel upon the received signal. Communication channels are typically modelled by complex, FIR filters that incorporate signal attenuation and multipath propagation effects. Depending on the coding scheme, the input sequence is either real (e.g. using BPSK modulation) or complex (e.g. using QAM modulation). Deconvolution can be achieved efficiently using predefined training sequences and supervised filter identification techniques. However in many situations we do not have the luxury of training sets to determine the filter's impulse response; hence the need for the so-called blind deconvolution techniques which circumvent this shortcoming, arises naturally.

The blind deconvolution or blind channel equalization problem has attracted the attention of the research community from early on. The problem has been treated under different research angles, yielding a rich bibliography on the topic [1, 2, 4, 5]. Following the taxonomy elucidated in [16], we can classify the schemes used for blind deconvolution, or equalization, as statistical or deterministic, depending on the assumptions made regarding the characteristics of the signals involved. Each of these classes can be further subdivided in two subclasses, namely the Maximum Likelihood (ML) and the Moment Estimation (ME) methods. Blind deconvolution methods can be also grouped according to the mathematical tool used: Second-Order Statistics (SOS) [13, 14], Higher-Order Statistics (HOS) [17, 18], and, lately, Geometric Properties of the observation signal [20, 19]. Recent SOS based techniques [3] showed superior or similar performance, compared to their HOS counterparts. This is mainly due to the fact that standard HOS techniques, cannot efficiently treat limited observation signals [12]. This can overcome certain design restrictions in the implementation of large multipath - channel telecommunication systems, though it does not settle every issue of the problem, as can be demonstrated by the steady and persistent use of HOS techniques.

Obtaining generalized algorithms for the complete channel identification and/or channel equalization, i.e. closed-form solutions, has not yet been successful, although there are some significant case-wise results, e.g. blind channel identification when MSK inputs are used [8], analytical SISO equalization solutions when using D-PSK sources [9], and analytical blind identification of SISO channels in MSK modulations [10].

In what follows, we shall focus on SOS methods only. Our communications model involves a single complex FIR channel and a single user transmitting a sequence of real symbols. This is a realistic scenario, for example, if the transmitter uses a BPSK or a Multilevel PAM modulation scheme. Considering separately the real and imaginary parts of the channel the problem can be easily set into a SIMO formulation with one input and two outputs without the need for oversampling. It is straightforward to extend our method to cover the general complex SIMO case if oversampling is incorporated. The literature contains a large number of SOS methods suitable for the treatment of the SIMO case. The treatment of the corresponding MIMO cases will not be considered in this paper. Blind identification of general FIR MIMO channels poses many interesting challenges of itself, and the subspace methods have been successfully utilized in this area using further ramifications, e.g. sequential subspace methods [6], or group decorrelation methods [7].

In the single complex FIR channel and single user scenario we may distinguish the differences between two classes of algorithms, namely the so-called TXK methods [13] and the Subspace methods [14]. We will select a representative and present its characteristics, as this facilitates comparison and indicates new directions to be investigated for possible improvements.

TXK methods (named after Tong, Xu, and Kailath) provide exact identification of (possibly) non-minimum phase channels, in the absence of noise, or, in a more realistic case, yield asymptotically exact results. They exploit the oversampling technique, as used in fractionally spaced equalization.

This work has been supported by the "EPEAEK Archimides-II" Programme, project "BSP-GRID", funded in part by the European Union (75%) and in part by the Greek Ministry of National Education and Religious Affairs (25%).

This increases the robustness of the algorithm and its resistance to noise degrading. The scheme used is non–iterative, avoiding the usual pitfalls of such methods, typically used in HOS techniques (e.g. convergence to the wrong attractor in the state space, or not converging at all). This class of algorithms performs well when the driven signals exhibit cyclostationary properties, i.e. are periodically correlated.

The subspace method of Moulines *et al.* [14, 15] yields an improvement over TXK methods (at least in their initial setup formulations), as it is computationally more efficient (a single EVD is required, as opposed to two in TXK), and statistically more efficient (in the Monte Carlo sense, i.e. it has lower estimation variance over TXK). It exploits the subspace structure of the system, resulting in the so called signal subspace and the noise subspace, after performing the EVD. A modification of this technique facilitates the estimation of the channel coefficients, i.e. determination of the channel impulse response, even in the case where only few vectors of the noise subspace are computed (this also requires some conditions, not too restrictive, to be met).

It is in the view of the characteristics of the methods just presented, that the new method can be discussed. While numerical simulations [11] show that TXK performs better than the subspace method for the low Signal–to–Noise Ratio (SNR) and again that TXK is more robust in the Normalized Mean Square Error (NMSE) sense, there are trade–offs in the implementations of those methods that can alter this outcome.

A key point is the exploitation of the *structure* of the signal and null (noise) subspaces. By performing a single SVD operation of a specially constructed covariance matrix (see Section 2), we can obtain a specific subspace projector, which annihilates all columns of this matrix except for one. This can be used to deconvolve the signal. Simulations reveal that the presented method compared with the subspace method of Moulines *et al.*, offers significant performance improvement.

The rest of the paper is organized as follows: in Section 2, we present the basic formulation of the problem and the assumptions made. Section 3 presents a novel channel deflation approach which reduces the channel length from L down to 1 thus facilitating the immediate extraction of the source signal. Section 4 discusses numerical simulations and comparisons with the well known subspace method referred above.

2. PROBLEM FORMULATION AND ASSUMPTIONS

Consider the following complex SISO, FIR channel with real input $s(k)$:

$$x(k) = \sum_{l=0}^{L-1} h_l s(k-l) + e(k), \quad k = 1,...,K \tag{1}$$

where h_l, $l = 0,...,L-1$, are unknown complex filter taps and $e(k)$ is additive white noise. We make the following assumptions

A1) The input samples are i.i.d., so

$$E\{s(k)s(k-m)\} = \delta(m) \tag{2}$$

Furthermore, the real and imaginary noise components $e^{(r)}(k)$, $e^{(i)}(k)$, are both white and independent of each other, so, we have

$$E\{e^{(r)}(k)e^{(r)}(k-m)\} = \sigma_e^2\delta(m) \tag{3}$$

$$E\{e^{(i)}(k)e^{(i)}(k-m)\} = \sigma_e^2\delta(m) \tag{4}$$

$$E\{e^{(r)}(k)e^{(i)}(k-m)\} = 0, \text{ any } k,\ m. \tag{5}$$

Call $h_l^{(r)}$ and $h_l^{(i)}$ the real and imaginary parts of h_l respectively, and similarly, let $x^{(r)}(k)$ and $x^{(i)}(k)$ be the real and imaginary parts of $x(k)$. Forming the vector sequence $\bar{\mathbf{x}}(k)$ using time-windows of the real and imaginary parts of the output sequence of length W we obtain

$$\bar{\mathbf{x}}(k) = \mathbf{H}\bar{\mathbf{s}}(k) + \bar{\mathbf{e}}(k) = \begin{bmatrix} \mathbf{H}^{(r)} \\ \mathbf{H}^{(i)} \end{bmatrix} \bar{\mathbf{s}}(k) + \bar{\mathbf{e}}(k) \tag{6}$$

where

$$\begin{aligned} \bar{\mathbf{x}}(k) &= [x^{(r)}(k),\cdots,x^{(r)}(k-W+1), \\ &\qquad x^{(i)}(k),\cdots,x^{(i)}(k-W+1)]^T \end{aligned} \tag{7}$$

$$\bar{\mathbf{s}}(k) = [s(k),\cdots,s(k-W-L+2)]^T \tag{8}$$

$$\begin{aligned} \bar{\mathbf{e}}(k) &= [e^{(r)}(k),\cdots,e^{(r)}(k-W+1), \\ &\qquad e^{(i)}(k),\cdots,e^{(i)}(k-W+1)]^T \end{aligned} \tag{9}$$

The Toeplitz matrices $\mathbf{H}^{(r)}, \mathbf{H}^{(i)} \in \mathbb{R}^{W\times(L+W-1)}$ are composed of the real and imaginary parts of the filter h:

$$\mathbf{H}^{(r)} = \begin{bmatrix} h_0^{(r)} & \cdots & h_{L-1}^{(r)} & & \\ & \ddots & & \ddots & \\ & & h_0^{(r)} & \cdots & h_{L-1}^{(r)} \end{bmatrix} \tag{10}$$

$$\mathbf{H}^{(i)} = \begin{bmatrix} h_0^{(i)} & \cdots & h_{L-1}^{(i)} & & \\ & \ddots & & \ddots & \\ & & h_0^{(i)} & \cdots & h_{L-1}^{(i)} \end{bmatrix} \tag{11}$$

Let the vectors $\mathbf{h}_i$, $i = 1,\cdots,L+W-1$, denote the columns of the total block-Toeplitz matrix $\mathbf{H}$ with size $(2W)\times(L+W-1)$. The following two assumptions relate to $\mathbf{H}$

A2) The window length W is such that $2W \geq L+W-1$, i.e.,

$$W \geq L-1. \tag{12}$$

Consequently, $\mathbf{H}$ is a tall matrix (it has at least as many rows as columns).

A3) The rank of the matrix $\mathbf{H}$ is $L+W-1$, so its columns are linearly independent.

3. CHANNEL DEFLATION TRANSFORMATIONS

Our method will be based on the subspace properties of the output covariance matrix. Define the input covariance matrix function $\mathbf{R}_{\bar{s}}(l) = E\{\bar{\mathbf{s}}(k)\bar{\mathbf{s}}(k-l)^T\}$ which is independent of k due to the stationarity of the source signal. Using Eq. (6) we can compute the output covariance matrix function $\mathbf{R}_{\bar{x}}(l) = E\{\bar{\mathbf{x}}(k)\bar{\mathbf{x}}(k-l)^T\}$ as

$$\mathbf{R}_{\bar{x}}(l) = \mathbf{H}\mathbf{R}_{\bar{s}}(l)\mathbf{H}^T + \mathbf{R}_{\bar{e}}(l) \tag{13}$$

where the noise covariance $\mathbf{R}_{\bar{e}}(l)$ is defined using $\bar{\mathbf{e}}(k)$ in entirely analogous way as $\mathbf{R}_{\bar{s}}(l)$ and $\mathbf{R}_{\bar{x}}(l)$.

Since both the input and the noise are temporally white, the corresponding covariance matrices, for $l = 1$, are

$$\mathbf{R}_{\bar{s}}(1) = \mathbf{J} = \begin{bmatrix} 0 & 0 & \cdots & 0 & 0 \\ 1 & 0 & \cdots & 0 & 0 \\ 0 & 1 & \cdots & 0 & 0 \\ \vdots & & \ddots & & \vdots \\ 0 & 0 & \cdots & 1 & 0 \end{bmatrix}$$

$$\mathbf{R}_{\bar{e}}(1) = \sigma_e^2 \begin{bmatrix} \mathbf{J} & \mathbf{0} \\ \mathbf{0} & \mathbf{J} \end{bmatrix} \tag{14}$$

so,

$$\mathbf{R}_{\bar{x}}(1) = \mathbf{H}_{left}\mathbf{H}_{right}^T + \mathbf{R}_{\bar{e}}(1) \tag{15}$$

where

$$\mathbf{H}_{left} = [\mathbf{h}_2, \cdots, \mathbf{h}_{L+W-1}], \tag{16}$$

$$\mathbf{H}_{right} = [\mathbf{h}_1, \cdots, \mathbf{h}_{L+W-2}]. \tag{17}$$

The noise component $\mathbf{R}_{\bar{e}}(1)$ can be removed from (15) using (14). We need an estimate of the noise power σ_e^2 which can be obtained by the smallest eigenvalue of $\mathbf{R}_{\bar{x}}(0) = \mathbf{H}\mathbf{H}^T + \sigma_e^2\mathbf{I}$. Thus we can obtain the noiseless covariance

$$\bar{\mathbf{R}}_{\bar{x}}(1) = \mathbf{R}_{\bar{x}} - \hat{\mathbf{R}}_{\bar{e}}(1) = \mathbf{H}_{left}\mathbf{H}_{right}^T \tag{18}$$

The matrices $\mathbf{H}_{left}$ and $\mathbf{H}_{right}$ are equal to $\mathbf{H}$ except for lacking the first and the last column, respectively. By assumption (A2) both matrices are "tall". We have

$$\text{rank}\{\bar{\mathbf{R}}_{\bar{x}}(1)\} = \text{rank}\{\mathbf{H}_{left}\} = \text{rank}\{\mathbf{H}_{right}\} = L + W - 2.$$

Therefore, the SVD of $\bar{\mathbf{R}}_{\bar{x}}(1)$

$$\bar{\mathbf{R}}_{\bar{x}}(1) = \mathbf{U}\Sigma\mathbf{V}^T = [\mathbf{U}_1|\mathbf{U}_2] \begin{bmatrix} \Sigma_1 & \\ & \mathbf{0} \end{bmatrix} [\mathbf{V}_1|\mathbf{V}_2]^T \tag{19}$$

has only $L + W - 2$ non-zero singular values, forming the submatrix Σ_1. The sizes of the matrices $\mathbf{U}_1$, $\mathbf{U}_2$, are $(2W) \times (L+W-2)$ and $(2W) \times (W-L+2)$, respectively. It follows that the column span of $\mathbf{U}_1$ is the same as the column span of $\mathbf{H}_{left}$ and consequently, the left null-subspace is orthogonal to $\mathbf{H}_{left}$:

$$\mathbf{U}_2^T\mathbf{H}_{left} = \mathbf{0}. \tag{20}$$

The left multiplication of (6) by the matrix $\mathbf{U}_2^T$ yields

$$\begin{aligned} \mathbf{y}^l(k) &= \mathbf{U}_2^T\bar{\mathbf{x}}(k) \\ &= [\mathbf{U}_2^T\mathbf{h}_1 \,|\, \mathbf{U}_2^T\mathbf{H}_{left}]\bar{\mathbf{s}}(k) + \mathbf{U}_2^T\bar{\mathbf{e}}(k) \\ &= \mathbf{U}_2^T\mathbf{h}_1 s(k) + \mathbf{U}_2^T\bar{\mathbf{e}}(k). \end{aligned} \tag{21}$$

Transformation (21) will be called "left" channel deflation because it involves the left singular vectors of $\bar{\mathbf{R}}_{\bar{x}}(1)$ and it reduces the length of the multi-channel filter from L to 1. By an entirely analogous argument we have

$$\mathbf{V}_2^T\mathbf{H}_{right} = \mathbf{0}, \tag{22}$$

yielding the "right" channel deflation:

$$\begin{aligned} \mathbf{y}^r(k) &= \mathbf{V}_2^T\bar{\mathbf{x}}(k) \\ &= \mathbf{V}_2^T\mathbf{h}_d s(k-d+1) + \mathbf{V}_2^T\bar{\mathbf{e}}(k), \end{aligned} \tag{23}$$

$$\text{with} \qquad d = L + W - 1. \tag{24}$$

3.1 Estimating the source signal

We may use the left (or the right) deflation transformation alone in order to estimate the source signal s. Observe, for example, that the left transformation vector $\mathbf{y}^l(k)$ involves multiple copies of the source in the elements of the vector $\mathbf{U}_2^T\mathbf{h}_1 s(k)$, in addition to the noise component $\mathbf{U}_2^T\bar{\mathbf{e}}(k)$. Then, s can be estimated by an appropriate linear combination of the components y_i^l of $\mathbf{y}^l$.

It is, however, more efficient to combine both left and right deflations into a single estimator. To that end we form the combination vector

$$\mathbf{y}(k) = \begin{bmatrix} \mathbf{y}^l(k-d+1) \\ \mathbf{y}^r(k) \end{bmatrix} \tag{25}$$

which, by Eqs. (21) and (23), becomes

$$\begin{aligned} \mathbf{y}(k) &= \begin{bmatrix} \mathbf{U}_2^T\mathbf{h}_1 \\ \mathbf{V}_2^T\mathbf{h}_d \end{bmatrix} s(k-d+1) + \begin{bmatrix} \mathbf{U}_2^T\bar{\mathbf{e}}(k-d+1) \\ \mathbf{V}_2^T\bar{\mathbf{e}}(k) \end{bmatrix} \\ &= \mathbf{g}s(k-d+1) + \varepsilon(k) \end{aligned} \tag{26}$$

with the obvious definitions of $\mathbf{g}$ and $\varepsilon(k)$. Our source estimator will be a linear combination of the elements y_i of $\mathbf{y}$:

$$\hat{s}(k-d+1) = \mathbf{c}^T\mathbf{y}(k). \tag{27}$$

so that the signal component $\mathbf{c}^T\mathbf{g}s$ is enhanced over the noise component $\mathbf{c}^T\varepsilon$. This is achieved by selecting $\mathbf{c} = \mathbf{g}$ and we estimate this vector by the principal eigenvector of the covariance matrix $\mathbf{R}_y(0) = \mathbf{g}\mathbf{g}^T + \mathbf{R}_\varepsilon(0)$.

4. SIMULATIONS

The proposed method has been tested under two sets of experiments. First, we investigated the impact of the data set length, N, in the estimation accuracy. We let the SNR vary between 10 and 20 dB and for each SNR level we tested various data lengths N = 1000, 2000, 5000 and 10000 samples. For every (SNR, N) pair we created 100 random binary source signals. In each Monte Carlo experiment the source was convolved the following complex 5-tap filter:

$$\begin{aligned} \mathbf{h}^{(5)} = [&-0.0032 - 0.8762i, \; -0.7501 - 1.0260i, \\ &-0.6695 - 0.1583i, \; -2.5327 + 0.1237i, \\ &-0.0791 + 1.4844i]. \end{aligned}$$

In Fig. 1 we present the mean Bit Error Rate (BER) over the data set length. At low SNR's the BER decreases rather slowly as N grows. The impact of N is more pronounced as the SNR becomes higher. This can be explained by the fact that in the high SNR case, the performance error is mostly due to the covariance estimation error due to finite data length. As N increases, the covariance estimation improves leading to a noticeable improvement of the BER.

Secondly, we compared our method against the subspace method of Moulines *et al.* [14]. For the comparison we created 1000 binary source signals which were convolved with the same complex filter $\mathbf{h}^{(5)}$ as above. The two methods were compared for different SNR levels between 10dB and 25dB. The following parameters were used: data set size $N = 2000$ and window size $W = 10$. Figure 2 shows the significant BER improvement of the deflation method over the of the

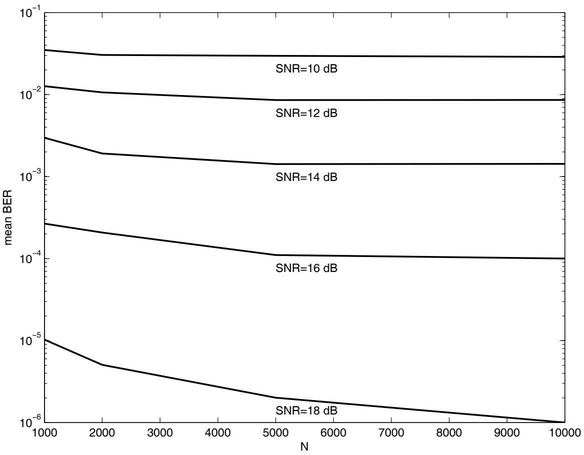

Figure 1: The mean BER as a function of the data length N for different levels of the SNR.

subspace method. For SNR $>$ 15dB the mean BER of the deflation method was zero.

In Fig. 3 we show the results of a similar experiment with $N = 2000$, $W = 20$ and the following 10-tap filter:

$$\begin{aligned}\mathbf{h}^{(10)} = [\,& 1.0179+0.4219i,\ 0.5940+0.4343i,\\ & -0.3784+2.0393i,\ -0.5234-0.1811i,\\ & -1.2114-2.0426i,\ 0.8468+1.9619i,\\ & 0.3974-1.1626i,\ 1.1647+0.2586i,\\ & 0.1033-0.7832i,\ -1.6711+2.0388i].\end{aligned}$$

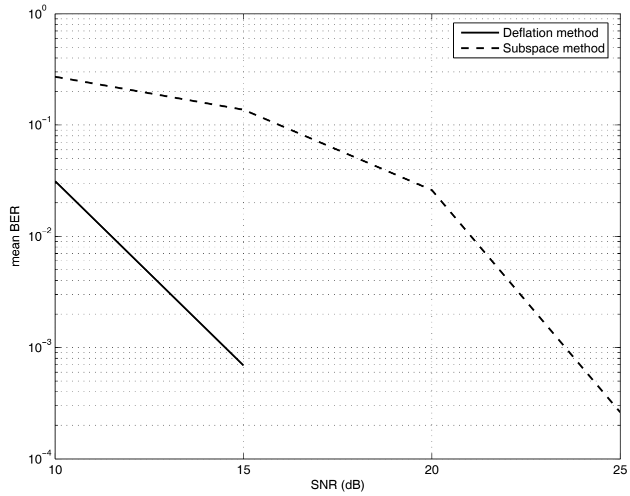

Figure 2: Comparison between the deflation and the subspace methods based on the average BER after 1000 Monte Carlo experiments using filter $\mathbf{h}^{(5)}$.

5. CONCLUSION

In this paper we presented a new method for the blind deconvolution of real signals when convolved with a complex-valued FIR filter. Our batch approach relies exclusively on the second-order statistics of the observation signal. The basic idea is to find the appropriate projection that will annihilate all but one of the columns of the system block-Toeplitz operator. We showed that the left and the right subspaces of a specific delayed covariance matrix SVD can be used to achieve this. This projection on either one of the two subspaces will be called channel deflation transformation since it reduces the filter length to 1. Our method does not use any inverse equalizer filter and it directly estimates the source signal without prior channel identification. The efficiency of our technique was compared against the well known subspace blind deconvolution method. The simulation experiments showed that the deflation method offers significant performance improvement over the subspace method. Furthermore, it is straightforward to see that deflation can be easily extended to treat the general SIMO setup if oversampling is employed.

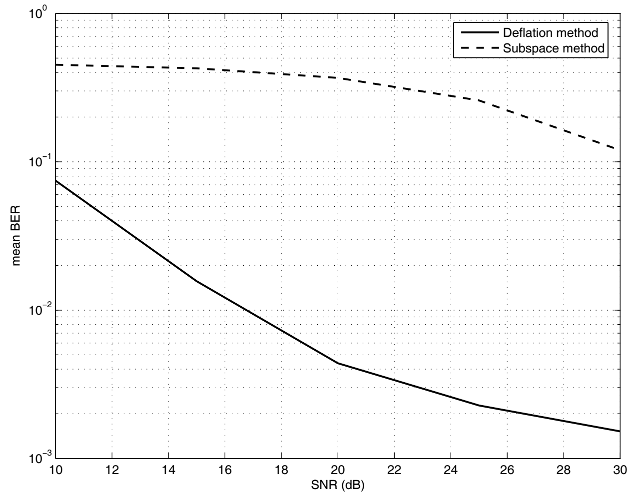

Figure 3: Comparison between the deflation and the subspace methods based on the average BER after 1000 Monte Carlo experiments using filter $\mathbf{h}^{(10)}$.

REFERENCES

[1] P. Comon, "Blind Identification and Source Separation in 2×2 Under-determined Mixtures", *IEEE Trans. Signal Proc.*, Vol. 52, No.1, pp. 11-22, January 2004.

[2] Y. Hua, S. An, and Y. Xiang, "Blind Identification of FIR MIMO Channels by Decorrelating Subchannels", *IEEE Trans. Signal Proc.*, Vol. 51, No. 5, pp. 1143-1155, 2003.

[3] A. Farid, Z.-Q. Luo, and Z. Ding, "Blind Channel Equalization Based on Second Order Statistics", in *Proceedings of IEEE Int. Conf. on Acoustics, Speech, and Signal Processing*, March 18-23, 2005, pp. 433-436, Pennsylvania, USA.

[4] J. F. Cardoso, "Informax and Maximum Likelihood for Blind Source Separation", *IEEE Signal Processing Letters*, vol. 4, no. 4, pp. 112-114, 1997.

[5] A. Belouchrani, K. A. Meraim, J. F. Cardoso, and E. Moulines, "A Blind Source Separation Technique Based on Second Order Statistics", *IEEE Trans. Signal Proc.*, vol. 45, no. 2, pp 434-444, 1997.

[6] S. An, J. H. Manton, and Y. Hua, "A Sequential Subspace Method for Blind Identification of General FIR MIMO Channels", *IEEE Trans. Signal Proc.*, vol. 53, no. 10, pp 3906-3910, 2005.

[7] S. An, Y. Hua, J. H. Manton, and Z. Fang, "Group Decorrelation Enhanced Subspace Method for Identifying FIR MIMO Channels Driven by Unknown Uncorrelated Colored Sources", *IEEE Trans. Signal Proc.*, vol. 53, no. 12, pp 4429-4441, 2005.

[8] P. Comon, O. Grellier, and B. Mourrain, "Closed-Form Blind Channel Identification with MSK Inputs", 32^{th} *Asilomar Conference, California*, Nov 1-4, pp 1569-1573, 1998.

[9] O. Grellier, P. Comon, "Closed-Form Equalization", *IEEE Workshop on Sig. Proc. Adv. in Wireless Com.* (SPAWC), Annapolis, MD, May 9-12, pp 219-222, 1999.

[10] O. Grellier, P. Comon, "Analytical Blind Identification of a SISO Communication Channel", *IEEE Workshop on Stat. Signal and Array Processing*, Pocono Manor, USA, Aug 14-16, pp 206-210, 2000.

[11] E. L. Pinto, C. J. A. Silva, "Performance Evaluation of Blind Channel Identification Methods Based on Oversampling", *Military Communications Conference*, MILCOM 98, 1998.

[12] J.M.F. Xavier, V. A. N. Barroso, and J. M. F. Moura "Closed–Form Blind Channel Identification and Source Separation in SDMA Systems Through Correlative Coding", *IEEE Journal on Selected Areas In Communications*, vol. 16, no. 8, pp. 1506–1517, October 1998.

[13] L. Tong, G. Xu, and Th. Kailath, "Blind Identification and Equalization Based on Second–Order Statistics: A Time Domain Approach", *IEEE Trans. Inf. Theory*, vol.40, no.2, pp.340-349, March 1994.

[14] E. Moulines, P. Duhamel, J. F. Cardoso, and S. Mayrargue, "Subspace Methods for the Blind Identification of Multichannel FIR Filters", *IEEE Trans. Signal Processing*, vol.43, no.2, pp.516-525, February 1995.

[15] J. Fang, R. Leyman, Y. H. Chew, and H. Duan, "Blind SIMO FIR Channel Estimation by Utilizing Property of Companion Matrices", *IEEE Signal Processing Letters*, vol.12, no.5, pp.387-390, May 1995.

[16] L. Tong, S. Perreau, "Multichannel Blind Identification: From Subspace to Maximum Likelihood Methods", *Proceedings of the IEEE*, vol. 86, no. 10, October 1998.

[17] L. Tong, Y. Inouye, and R.-W. Liu, "Waveform-Preserving Blind Estimation of Multiple Independent Sources", *IEEE Transactions on Signal Processing*, vol. 41, pp. 24612470, 1993.

[18] C. B. Papadias, "Globally Convergent Blind Source Separation Based on a Multiuser Kurtosis Maximization Criterion", *IEEE Trans.on Signal Processing*, vol. 48, no. 12, pp. 35083519, December 2000.

[19] K. I. Diamantaras, Th. Papadimitriou, "Blind Deconvolution of Multi-Input Single - Output Systems with Binary Sources", in *Proc. IEEE Int. Conference on Acoustics, Speech, and Signal Processing* (ICASSP-2005), Philadelphia (PA), 2005.

[20] K. I. Diamantaras, Th. Papadimitriou, "Blind Deconvolution of SISO Systems with Binary Sources based on Recursive Channel Shortening", *Lecture Notes in Computer Science*, vol 3195, pp. 548-553, Springer Verlag, 2004.