USING THE PEARSON CORRELATION COEFFICIENT TO DEVELOP AN OPTIMALLY WEIGHTED CROSS RELATION BASED BLIND SIMO IDENTIFICATION ALGORITHM

Yiteng (Arden) Huang[1], *Jacob Benesty*[2], *and Jingdong Chen*[3]

[1] WeVoice, Inc.
Bridgewater, NJ 08807, USA
arden_huang@ieee.org

[2] INRS-EMT, Univ. of Quebec
Montreal, QC H5A 1K6, Canada
benesty@emt.inrs.ca

[3] Bell Labs, Alcatel-Lucent
Murray Hill, NJ 07974, USA
jingdong@research.bell-labs.com

ABSTRACT

Blind SIMO identification is challenging when additive noise is strong and for ill-conditioned/acoustic SIMO systems. A weighted cross relation (CR) algorithm presumably can be robust to noise but there lacks a practical way to define the weights. In this paper, the Pearson correlation coefficient (PCC) is used to develop an optimally weighted CR algorithm, which is validated by simulations.

Index Terms— Weighted cross relations, Pearson correlation coefficient, blind identification, acoustic SIMO system.

1. INTRODUCTION

Blind SIMO (single-input multiple-output) identification can find a variety of speech applications, e.g., time delay estimation for sound source localization [1] and speech dereverberation [2]. In these applications, acoustic impulse responses need to be known while the *a priori* knowledge of the source speech signal is unavailable, making the blind method a necessity.

This paper considers an acoustic SIMO system where the single input is a speech source and the N outputs are microphone observations, as illustrated in Fig. 1. The nth system output $y_n(k)$ at time k is expressed as

$$\begin{aligned} y_n(k) &= g_n * s(k) + v_n(k) \\ &= x_n(k) + v_n(k), \;\; n = 1, 2, \cdots, N, \end{aligned} \quad (1)$$

where g_n is the channel impulse response from the source to the nth microphone, the symbol $*$ denotes the linear convolution operator, $s(k)$ is the source signal, and $v_n(k)$ is the additive noise at the nth microphone. The channel impulse responses are delineated with finite impulse response (FIR) filters. The additive noise signals in different channels are assumed to be uncorrelated with the source signal and uncorrelated with each other.

In a vector/matrix form, the SIMO signal model (1) is written as

$$\begin{aligned} \mathbf{y}_n(k) &= \mathbf{G}_n \cdot \mathbf{s}(k) + \mathbf{v}_n(k) \\ &= \mathbf{x}_n(k) + \mathbf{v}_n(k), \;\; n = 1, 2, \cdots, N, \end{aligned} \quad (2)$$

where

$$\mathbf{y}_n(k) = \left[\, y_n(k) \;\; y_n(k-1) \;\; \cdots \;\; y_n(k-L+1) \, \right]^T,$$

$$\mathbf{G}_n = \begin{bmatrix} g_{n,0} & \cdots & g_{n,L-1} & 0 & \cdots & 0 \\ 0 & g_{n,0} & \cdots & g_{n,L-1} & \cdots & 0 \\ \vdots & \ddots & \ddots & \ddots & \ddots & \vdots \\ 0 & \cdots & 0 & g_{n,0} & \cdots & g_{n,L-1} \end{bmatrix}_{L \times (2L-1)},$$

$$\mathbf{s}(k) = \left[\, s(k) \;\; \cdots \;\; s(k-L+1) \;\; \cdots \;\; s(k-2L+2) \, \right]^T,$$

$$\mathbf{v}_n(k) = \left[\, v_n(k) \;\; v_n(k-1) \;\; \cdots \;\; v_n(k-L+1) \, \right]^T,$$

$$\mathbf{x}_n(k) = \left[\, x_n(k) \;\; x_n(k-1) \;\; \cdots \;\; x_n(k-L+1) \, \right]^T,$$

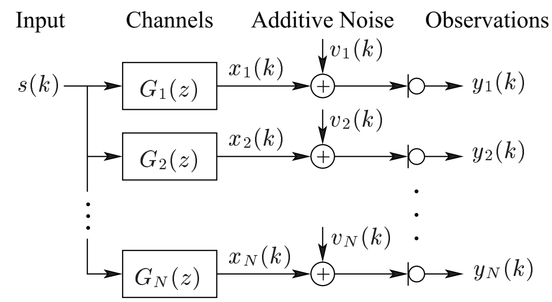

Fig. 1. Illustration of an acoustic SIMO system.

$[\cdot]^T$ denotes a vector/matrix transpose, and L is the length of the longest channel impulse response in such a SIMO system.

Therefore, the blind SIMO identification problem is to estimate

$$\mathbf{g}_n = \left[\, g_{n,0} \;\; g_{n,1} \;\; \cdots \;\; g_{n,L-1} \, \right]^T, \;\; n = 1, 2, \cdots, N \quad (3)$$

from the observations $y_n(k)$ without the knowledge of the source signal $s(k)$.

The innovative idea of blind SIMO identification was first proposed by Sato in [3]. While higher (than second) order statistics (HOS) of the system outputs can be used (see [4] for a tutorial on the HOS-based approaches), second-order statistics (SOS) are sufficient to solve this problem [5]. The focus of the current blind SIMO identification research is primarily on the SOS-based methods. Celebrated work include the cross relation (CR) algorithm [6], [7], among many other variants (see [8] for a comprehensive survey on this subject).

According to [7], two conditions (one on the channel diversity and the other on the input signals) are necessary and sufficient to ensure blind SIMO identifiability, which are shared by all SOS-based methods:

1. The polynomials formed from $\mathbf{g}_n$ ($n = 1, 2, \cdots, N$) are co-prime, i.e., the channel transfer functions $G_n(z) = \sum_{l=0}^{L-1} g_{n,l} z^{-l}$ do not share any common zeros;
2. The autocorrelation matrix of the input signal $\mathbf{R}_{ss} = E\left\{\mathbf{s}(k)\mathbf{s}^T(k)\right\}$ is of full rank, where $E\{\cdot\}$ denotes mathematical expectation, such that the SIMO system can be fully excited.

It is already well known that existing blind SIMO identification algorithms are sensitive to additive noise, particularly for ill-conditioned (in terms of the assumption of no shared common zeros) SIMO systems, hence impairing the usefulness of such a technique in practice. In this paper, we intend to use the Pearson correlation coefficient (PCC) to develop an optimally weighted CR algorithm for use in noisy environments.

978-1-4244-2354-5/09/$25.00 ©2009 IEEE

2. WEIGHTED AND TRADITIONAL CROSS RELATION ALGORITHMS

In the absence of noise (i.e., $y_n = x_n$), a SIMO system has the following cross relations (CRs):

$$y_i * g_j = s * g_i * g_j = y_j * g_i, \;\; i, j = 1, 2, \cdots, N. \qquad (4)$$

At time k, we then have

$$\mathbf{y}_i^T(k)\mathbf{g}_j = \mathbf{y}_j^T(k)\mathbf{g}_i, \;\; i, j = 1, 2, \cdots, N. \qquad (5)$$

Multiplying (5) by $\mathbf{y}_i(k)$ from the left side and taking expectation yields

$$\mathbf{R}_{y_i y_i}\mathbf{g}_j = \mathbf{R}_{y_i y_j}\mathbf{g}_i, \;\; i, j = 1, 2, \cdots, N, \qquad (6)$$

where $\mathbf{R}_{y_i y_j} \triangleq E\left\{\mathbf{y}_i(k)\mathbf{y}_j^T(k)\right\}$.

When noise is present, for N model FIR filters $\mathbf{h}_n$ ($n = 1, 2, \cdots, N$), an error signal can be defined as follows

$$e_{ij}(k) \triangleq \mathbf{y}_i^T(k)\mathbf{h}_j - \mathbf{y}_j^T(k)\mathbf{h}_i. \qquad (7)$$

Accordingly, a weighted cost function can be formulated as

$$J = \sum_{i=1}^{N-1}\sum_{j=i+1}^{N} w_{ij} \cdot E\{e_{ij}^2(k)\}, \qquad (8)$$

where $w_{ij} > 0$ are weighting factors and should be symmetric, i.e., $w_{ij} = w_{ji}$. We can use the expression

$$E\{e_{ij}^2(k)\} = \mathbf{h}_i^T\mathbf{R}_{y_j y_j}\mathbf{h}_i + \mathbf{h}_j^T\mathbf{R}_{y_i y_i}\mathbf{h}_j - 2\mathbf{h}_j^T\mathbf{R}_{y_i y_j}\mathbf{h}_i, \quad (9)$$

and compute the gradient of (8) with respect to $\mathbf{h}_n$:

$$\begin{aligned}\frac{\partial J}{\partial \mathbf{h}_n} &= \sum_{i=1}^{n-1}\frac{\partial E\{e_{in}^2(k)\}}{\partial \mathbf{h}_n}\cdot w_{in} + \sum_{j=n+1}^{N}\frac{\partial E\{e_{nj}^2(k)\}}{\partial \mathbf{h}_n}\cdot w_{nj} \\ &= 2\sum_{i=1, i\neq n}^{N}\left(\mathbf{R}_{y_i y_i}\mathbf{h}_n - \mathbf{R}_{y_i y_n}\mathbf{h}_i\right) w_{in}. \qquad (10)\end{aligned}$$

Equating (10) to zero and putting the N expressions in a matrix form yields

$$\mathbf{R}_{y+}(w_{ij})\mathbf{h} = \mathbf{0}_{NL\times 1}, \qquad (11)$$

where

$$\mathbf{R}_{y+}(w_{ij}) \triangleq \begin{bmatrix} \sum_{n\neq 1} w_{1n}\mathbf{R}_{y_n y_n} & -w_{12}\mathbf{R}_{y_2 y_1} & \cdots & -w_{1N}\mathbf{R}_{y_N y_1} \\ -w_{12}\mathbf{R}_{y_1 y_2} & \sum_{n\neq 2} w_{2n}\mathbf{R}_{y_n y_n} & \cdots & -w_{N2}\mathbf{R}_{y_N y_2} \\ \vdots & \vdots & \ddots & \vdots \\ -w_{1N}\mathbf{R}_{y_1 y_N} & -w_{2N}\mathbf{R}_{y_2 y_N} & \cdots & \sum_{n\neq N} w_{Nn}\mathbf{R}_{y_n y_n} \end{bmatrix},$$

$$\mathbf{h} = \begin{bmatrix} \mathbf{h}_1^T & \mathbf{h}_2^T & \cdots & \mathbf{h}_N^T \end{bmatrix}^T.$$

A weighted CR (WCR) algorithm is then deduced with the solution of (11), i.e., the eigenvector of $\mathbf{R}_{y+}(w_{ij})$ corresponding to its smallest eigenvalue.

The error signal $e_{ij}(k)$ defined in (7) consists of two parts: a modeling error and the error caused by additive noise. The modeling error is what we want to minimize over the model filters. But the additive noise has a negative impact on this minimization procedure. Therefore, intuitively if the additive noise signals in the ith and jth channels are stronger than that in the other channels, then $e_{ij}(k)$ should be de-emphasized in the cost function and w_{ij} should be relatively smaller. From this perspective, the WCR algorithm is a neat idea for its robustness with noise. But there is no straightforward ways to quantify w_{ij} in practice. Therefore, w_{ij} has to be set as 1, leading to the traditional CR method. In the next sections, we will show how the Pearson correlation coefficient can help develop an optimally weighted CR algorithm.

3. BLIND SIMO IDENTIFICATION WITH THE SQUARED PEARSON CORRELATION COEFFICIENT

The Pearson correlation coefficient (PCC) of two zero-mean real-valued random variables y_1 and y_2 is defined as [9]:

$$\rho(y_1, y_2) = \frac{E\{y_1 y_2\}}{\sigma_{y_1}\sigma_{y_2}}, \qquad (12)$$

where $\sigma_{y_1}^2 = E\{y_1^2\}$ and $\sigma_{y_2}^2 = E\{y_2^2\}$ are the variances of the signals y_1 and y_2, respectively. In the context of blind SIMO identification, it will be more convenient to work with the squared Pearson correlation coefficient (SPCC):

$$\rho^2(y_1, y_2) = \frac{E^2\{y_1 y_2\}}{\sigma_{y_1}^2\sigma_{y_2}^2}. \qquad (13)$$

The SPCC gives an indication on the strength of the linear relationship between the two random variables y_1 and y_2. We always have $0 \leq \rho^2(y_1, y_2) \leq 1$. If $\rho^2(y_1, y_2) = 0$, then y_1 and y_2 are said to be uncorrelated. The closer the value of $\rho^2(y_1, y_2)$ is to 1, the stronger the correlation between the two variables.

The concept of SPCC can be generalized to the multichannel case. Let $y_1, y_2, \cdots, y_N$ be N zero-mean real-valued random variables. One possible definition for the multichannel SPCC is

$$\rho^2(y_1, y_2, \cdots, y_N) = \frac{2}{N(N-1)}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\rho^2(y_i, y_j). \qquad (14)$$

This definition considers all possible two-channel SPCCs between y_i and y_j, with $i \neq j$, and counts the $\rho^2(y_i, y_j) = \rho^2(y_j, y_i)$ pair only once. It can be easily checked that $0 \leq \rho^2(y_1, y_2, \cdots, y_N) \leq 1$. If all the signals are completely correlated, then $\rho^2(y_1, y_2, \cdots, y_N) = 1$. If all the signals are completely uncorrelated with each other, then $\rho^2(y_1, y_2, \cdots, y_N) = 0$.

In the problem of blind SIMO identification, instead of using the traditional mean square error (MSE) to define (7), we can measure the difference between the signals $\mathbf{h}_i^T\mathbf{y}_j(k)$ and $\mathbf{h}_j^T\mathbf{y}_i(k)$ with the SPCC:

$$\rho^2\left[\mathbf{h}_i^T\mathbf{y}_j(k), \mathbf{h}_j^T\mathbf{y}_i(k)\right] = \frac{\left(\mathbf{h}_i^T\mathbf{R}_{y_j y_i}\mathbf{h}_j\right)^2}{\left(\mathbf{h}_i^T\mathbf{R}_{y_j y_j}\mathbf{h}_i\right)\left(\mathbf{h}_j^T\mathbf{R}_{y_i y_i}\mathbf{h}_j\right)}. \quad (15)$$

Then the channel impulse responses are determined by searching the model filters that maximize the multichannel SPCC

$$\begin{aligned}\rho^2(\mathbf{h}) &\triangleq \frac{2}{N(N-1)}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\rho^2\left[\mathbf{h}_i^T\mathbf{y}_j(k), \mathbf{h}_j^T\mathbf{y}_i(k)\right] \quad (16) \\ &= \frac{2}{N(N-1)}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\alpha_{ij}(\mathbf{h})\alpha_{ji}(\mathbf{h}) \\ &= \frac{2}{N(N-1)}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\beta_{ij}(\mathbf{h})\left(\mathbf{h}_i^T\mathbf{R}_{y_j y_i}\mathbf{h}_j\right),\end{aligned}$$

where

$$\alpha_{ij}(\mathbf{h}) \triangleq \frac{\mathbf{h}_i^T \mathbf{R}_{y_j y_i} \mathbf{h}_j}{\mathbf{h}_i^T \mathbf{R}_{y_j y_j} \mathbf{h}_i},$$

$$\beta_{ij}(\mathbf{h}) \triangleq \frac{\mathbf{h}_i^T \mathbf{R}_{y_j y_i} \mathbf{h}_j}{\left(\mathbf{h}_i^T \mathbf{R}_{y_j y_j} \mathbf{h}_i\right)\left(\mathbf{h}_j^T \mathbf{R}_{y_i y_i} \mathbf{h}_j\right)} = \frac{\alpha_{ij}(\mathbf{h})}{\left(\mathbf{h}_j^T \mathbf{R}_{y_i y_i} \mathbf{h}_j\right)} = \beta_{ji}(\mathbf{h}).$$

It can be checked that $\rho^2(\mathbf{h}) = 1$ if and only if $\mathbf{h}_n = c_n \mathbf{g}_n$, where $c_n \neq 0$ $(n = 1, 2, \cdots, N)$ are N arbitrary constants.

Taking the gradient of $\rho^2(\mathbf{h})$ in (16) with respect to $\mathbf{h}_n$ produces

$$\frac{\partial \rho(\mathbf{h})}{\partial \mathbf{h}_n} = \frac{4}{N(N-1)} \left[\sum_{i=1, i\neq n}^{N} \beta_{in}(\mathbf{h}) \mathbf{R}_{y_i y_n} \mathbf{h}_i - \sum_{i=1, i\neq n}^{N} \alpha_{ni}(\mathbf{h}) \beta_{in}(\mathbf{h}) \mathbf{R}_{y_i y_i} \mathbf{h}_n \right], \quad (17)$$

$$n = 1, 2, \cdots, N.$$

Equating the gradient (17) to zero and putting the N expressions in a matrix form yields

$$\mathbf{R}_{y+}(\mathbf{h}) \cdot \mathbf{h} = \mathbf{0}_{NL\times 1}, \quad (18)$$

where

$$\mathbf{R}_{y+}(\mathbf{h}) \triangleq \begin{bmatrix} \mathbf{D}_1(\mathbf{h}) & -\beta_{12}(\mathbf{h})\mathbf{R}_{y_2 y_1} & \cdots & -\beta_{1N}(\mathbf{h})\mathbf{R}_{y_N y_1} \\ -\beta_{12}(\mathbf{h})\mathbf{R}_{y_1 y_2} & \mathbf{D}_2(\mathbf{h}) & \cdots & -\beta_{2N}(\mathbf{h})\mathbf{R}_{y_N y_2} \\ \vdots & \vdots & \ddots & \vdots \\ -\beta_{1N}(\mathbf{h})\mathbf{R}_{y_1 y_N} & -\beta_{2N}(\mathbf{h})\mathbf{R}_{y_2 y_N} & \cdots & \mathbf{D}_N(\mathbf{h}) \end{bmatrix},$$

and

$$\mathbf{D}_i(\mathbf{h}) = \sum_{n=1, n\neq i}^{N} \alpha_{in}(\mathbf{h}) \beta_{in}(\mathbf{h}) \mathbf{R}_{y_n y_n}, \quad i = 1, 2, \cdots, N.$$

Equation (18) is highly nonlinear with respect to $\mathbf{h}$, but a simple way to solve it is by iterations. The eigenvector of $\mathbf{R}_{y+}$ corresponding to its smallest eigenvalue, i.e., the solution of the traditional CR algorithm, is taken as the initial estimate $\mathbf{h}(0)$. Then in the tth $(t \geq 1)$ iteration, $\mathbf{h}(t)$ is updated by the eigenvector of $\mathbf{R}_{y+}[\mathbf{h}(t-1)]$ corresponding to its smallest eigenvalue. This procedure proceeds until convergence or a specified maximum number of iterations T has been reached. This iterative procedure is summarized in Table 1.

When noise is weak and $\mathbf{h} \approx \mathbf{g}$ after convergence, we learn from the cross relation (6) that

$$\alpha_{ij}(\mathbf{h}) \approx 1, \quad (19)$$

$$\beta_{ij}(\mathbf{h}) \approx \frac{1}{\mathbf{h}_j^T \mathbf{R}_{y_i y_i} \mathbf{h}_j} = \frac{1}{\mathbf{h}_i^T \mathbf{R}_{y_j y_j} \mathbf{h}_i} \geq 0. \quad (20)$$

In this case, (18) evolves into (11) with $w_{ij} = \beta_{ij}(\mathbf{h})$. So the use of SPCC provides an optimal way to define w_{ij} in the WCR algorithm. From (20), we see that β_{ij} is reverse proportional to the power of the jth and/or the ith channel outputs. This makes sense since a channel output with a higher power implies stronger additive noise in this channel (assuming the same gain over all channels of the SIMO system). Then, per the discussion at the end of last section, w_{ij} should be lower.

Table 1. The iterative SPCC-based algorithm for blind SIMO identification.

Initialization:	$\mathbf{h}(0) = \text{mineig}\left(\mathbf{R}_{y+}\right)$
Iteration:	For $t = 1, 2, \cdots, T$, compute
	$\alpha_{ij}\left[\mathbf{h}(t-1)\right] = \frac{\mathbf{h}_i^T(t-1)\mathbf{R}_{y_j y_i}\mathbf{h}_j(t-1)}{\mathbf{h}_i^T(t-1)\mathbf{R}_{y_j y_j}\mathbf{h}_i(t-1)}$,
	$\beta_{ij}\left[\mathbf{h}(t-1)\right] = \frac{\alpha_{ij}\left[\mathbf{h}(t-1)\right]}{\mathbf{h}_j^T(t-1)\mathbf{R}_{y_i y_i}\mathbf{h}_j(t-1)}$,
	$\mathbf{h}(t) = \text{mineig}\left\{\mathbf{R}_{y+}[\mathbf{h}(t-1)]\right\}$,

where mineig($\mathbf{A}$) stands for the eigenvector of $\mathbf{A}$ corresponding to its smallest eigenvalue.

4. SIMULATIONS

In this section, we will evaluate the performance of the developed SPCC algorithm in comparison with the CR batch method by simulations. Similar to our earlier studies on this subject, we use the normalized projection misalignment (NPM) in dB as the performance measure, which is given by

$$\text{NPM}(\mathbf{h}, \mathbf{g}) \triangleq 20 \log_{10} \frac{1}{N} \sum_{n=1}^{N} \left[\left\| \mathbf{g}_n - \frac{\mathbf{g}_n^T \mathbf{h}_n}{\mathbf{h}_n^T \mathbf{h}_n} \cdot \mathbf{h}_n \right\| / \|\mathbf{g}_n\| \right]. \quad (21)$$

The first experiment is concerned with a simple three-channel SIMO system whose impulse responses are

$$\begin{aligned} \mathbf{g}_1 &= \left[1 \;\; -2\cos(\theta) \;\; 1 \right]^T, \\ \mathbf{g}_2 &= \left[1 \;\; -2\cos(\theta + \vartheta) \;\; 1 \right]^T, \\ \mathbf{g}_3 &= \left[1 \;\; -2\cos(\theta + 2\vartheta) \;\; 1 \right]^T, \end{aligned} \quad (22)$$

where θ and ϑ controls the positions of the zeros of the three channels. For $\theta = \pi/10$ and $\vartheta = 2\pi/3$, the zeros of the three channels are separated far away to each other. The system is definitely blindly identifiable and hence is deemed well-conditioned (WC). For $\theta = \vartheta = \pi/10$, the SIMO system is regarded as ill-conditioned (IC) since the zeros of the two channels are quite close, which is about to invalidate the identifiability assumption of no common zeros. Such a SIMO system was first introduced in [10] (with only the first two channels) and was then widely employed in the studies of blind SIMO identification.

The source is an uncorrelated binary phase-shift-keying (BPSK) sequence and the additive noise is i.i.d. zero-mean Gaussian at a specified signal-to-noise radio (SNR) defined as follows

$$\text{SNR}_n \triangleq 10 \log_{10} \frac{\sigma_s^2 \|\mathbf{g}_n\|^2}{\sigma_{v_n}^2}, \quad n = 1, 2, \cdots, N. \quad (23)$$

We set the SNR of the first two channels always equal but 10 dB higher than that of the third channel in order to study whether the weights in the SPCC algorithm would vary with the channel SNR as expected from our analysis.

For each channel of the SIMO system, 500 output samples were used. The SPCC algorithm took less than $T = 5$ iterations to converge.

For each set of specified SNRs, we averaged the NPMs of 100 Monte-Carlo trials. The results are presented in Fig. 2. We see that the SPCC performs better than the batch CR for low SNRs and their performances are comparable for high SNRs. This advantage of the SPCC is more evident for the ill-conditioned system.

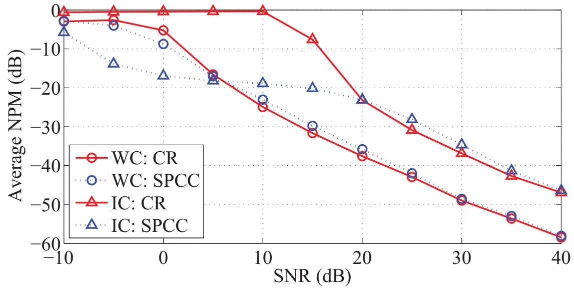

Fig. 2. Comparison of average NPM vs. SNR between the batch CR and the SPCC algorithms for blind identification of the well-conditioned (WC) and ill-conditioned (IC) three-channel SIMO systems in the first experiment. The SNRs are for the first two channels and are 10 dB higher than that of the third channel.

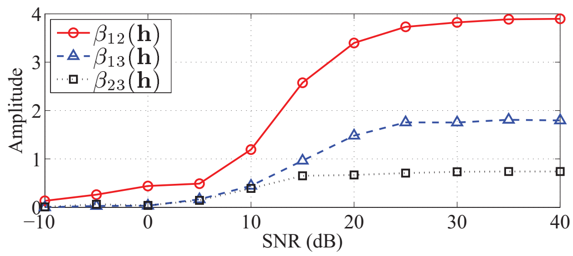

Fig. 3. The amplitude of $\beta_{ij}(\mathbf{h})$ after convergence in one arbitrary Monte-Carlo trial of the first experiment regarding the well-conditioned SIMO system.

Figure 3 plots $\beta_{12}(\mathbf{h})$, $\beta_{13}(\mathbf{h})$, and $\beta_{23}(\mathbf{h})$ in one arbitrary Monte-Carlo trial after convergence for the well-conditioned system. It is consistent with the analysis that $\beta_{12}(\mathbf{h})$ is larger than $\beta_{13}(\mathbf{h})$ and $\beta_{23}(\mathbf{h})$ since the noise in the third channel is stronger.

In the second experiment, we worked on a real acoustic SIMO system. The channel impulse responses were extracted from the measurements made by Härmä [11] in the varechoic chamber at Bell Labs when 89% panels were open and the reverberation time of the chamber was about 240 ms. We set that $N = 3$ and $L = 32$. The three channel impulse responses are shown in Fig. 4 (a). A female speech signal of 5500 samples long (sampled at 8 kHz) was used as the source. It is visualized in Fig. 4 (b). Again the additive noise signals are i.i.d. zero-mean Gaussian. The SNR's of the first two channels are equal but 10 dB higher than that of the third channel. 100 Monte-Carlo trials were conducted. For the SPCC, $T = 10$. The results are presented in Fig. 5. The SPCC outperforms the batch CR for low SNRs.

5. CONCLUSIONS

An optimally weighted cross-relation algorithm for blind SIMO identification algorithm was developed by using the squared Pearson correlation coefficient (SPCC). Simulation results indicated that the new algorithm is more robust than the batch cross-relation method for ill-conditioned or acoustic SIMO systems and when the SNR is low.

6. REFERENCES

[1] J. Benesty, "Adaptive eigenvalue decomposition algorithm for passive acoustic source localization," *J. Acoust. Soc. Am.*, vol. 107, pp. 384–391, Jan. 2000.

[2] Y. Huang, J. Benesty, and J. Chen, "A blind channel identification-based two-stage approach to separation and dereverberation of speech signals in a reverberant environment," *IEEE Trans. Speech Audio Process.*, vol. 13, pp. 882–896, Sept. 2005.

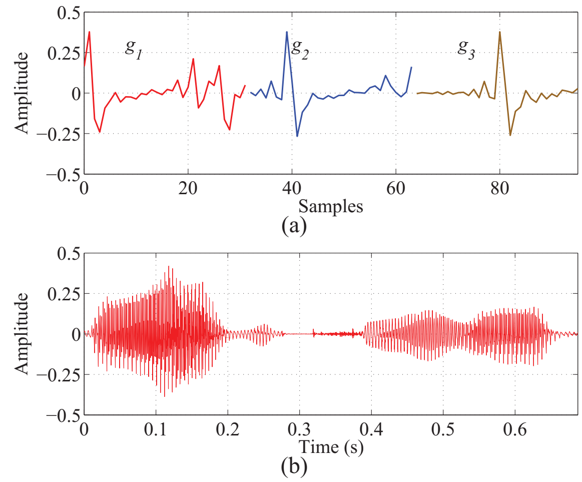

Fig. 4. The three channel impulse responses (a) and the source speech signal (b) used in the second experiment.

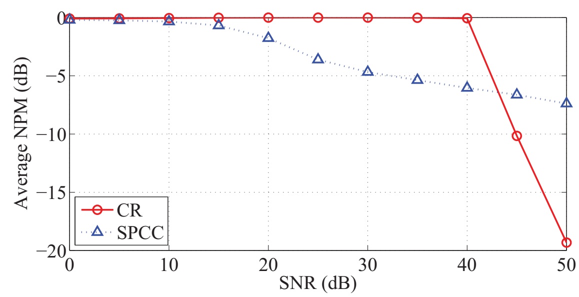

Fig. 5. Comparison of average NPM vs. SNR between the batch CR and the SPCC algorithms for blind identification of the three-channel acoustic SIMO system in the second experiment. The SNRs are for the first two channels and are 10 dB higher than that of the third channel.

[3] Y. Sato, "A method of self-recovering equalization for multilevel amplitude-modulation," *IEEE Trans. Commun.*, vol. COM-23, no. 6, pp. 679–682, June 1975.

[4] J. M. Mendel, "Tutorial on higher-order statistics (spectra) in signal processing and system theory: theoretical results and some applications," *Proc. IEEE*, vol. 79, pp. 278–305, Mar. 1991.

[5] L. Tong, G. Xu, and T. Kailath, "A new approach to blind identification and equalization of multipath channels," in *Proc. 25th Asilomar Conf. on Signals, Systems, and Computers*, 1991, vol. 2, pp. 856–860.

[6] H. Liu, G. Xu, and L. Tong, "A deterministic approach to blind equalization," in *Proc. 27th Asilomar Conf. on Signals, Systems, and Computers*, 1993, vol. 1, pp. 751–755.

[7] G. Xu, H. Liu, L. Tong, and T. Kailath, "A least-squares approach to blind channel identification," *IEEE Trans. Signal Process.*, vol. 43, pp. 2982–2993, Dec. 1995.

[8] L. Tong and S. Perreau, "Multichannel blind identification: from subspace to maximum likelihood methods," *Proc. IEEE*, vol. 86, pp. 1951–1968, Oct. 1998.

[9] K. Pearson, "Mathematical contributions to the theory of evolution.-III. Regression, heredity and panmixia," *Philos. Trans. Royal Soc. London*, Ser. A, vol. 187, pp. 253–318, 1896.

[10] Y. Hua, "Fast maximum likelihood for blind identification of multiple FIR channels," *IEEE Trans. Signal Process.*, vol. 44, pp. 661–672, Mar. 1996.

[11] A. Härmä, "Acoustic measurement data from the varechoic chamber," Technical Memorandum, Agere Systems, Nov. 2001.