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A MATRIX-PENCIL APPROACH TO BLIND SEPARATION OF MULTI-CHANNEL BIO-SIGNALS*

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ABSTRACT

Many biological and physiological processes can be modeled as a linear Multi-Input Multi-Output (MIMO) system. Blind deconvolution is ideal for retrieving the input signals and/or system parameters, given only the outputs and some input statistical information, but not the inputs themselves. In general biomedical signals sources have distinct, non-stationary, colored power spectral density, so, we use our algorithm developed before which works well for such kinds of signals [1]. Simulation results are presented.

key words: Blind source separation, matrix pencil.

1. INTRODUCTION

A memoryless mixture of multiple signals is often modeled as $\vec{x}(n) = A\vec{s}(n) + \vec{w}(n)$, where $\vec{s}(n)$ is a vector of source signals of dimension N, $\vec{x}(n)$ is the received signal vector of dimension M, A is an $M \times N$ memoryless mixing matrix, and $\vec{w}(n)$ is the additive white noise vector. We impose the following conditions: **1)** $M \geq N$; **2)** the various components of $\vec{s}(n)$ are mutually uncorrelated but not temporally white, and **3)** $\vec{w}(n)$ is stationary, temporally white, zero mean and uncorrelated to the sources. Our objective is to find a signal extracting matrix B such that $B^H\vec{x}(n) = B^H A\vec{s}(n) + B^H\vec{w}(n) = P\vec{s}(n) + B^H\vec{w}(n)$, where $P = B^H A$ is a permutation matrix having only one nonzero element in each row and column.

2. MATRIX PENCIL ALGORITHM

We choose the matrix pencil to be $\{R_1, R_2\} = \{R_x(k_1), R_x(k_2)\}$, where $R_x(k_i) = E\{\vec{x}(n)\vec{x}(n-k_i)^H\} = AR_s(k_i)A^H$, and $R_s(k_i) = E\{\vec{s}(n)\vec{s}(n-k_i)^H\} = diag\{r_1(k_i), r_2(k_i), \cdots, r_N(k_i)\} = \Lambda_i, k_i \neq 0, i = 1, 2$. To solve the generalized eigenvalue problem $R_1\vec{v} = \lambda R_2\vec{v}$, we rewrite it as $A(\Lambda_1 - \lambda\Lambda_2)A^H\vec{v} = 0$. Assume that there are l generalised eigen values, λ_j and l corresponding generalised non-trivial eigen vectors, $v_j, j = 1, 2, \ldots, l$. Let V be the generalized eigen-vector matrix. If $l = N$, $V^H A$ becomes purely diagnal and all source signals are completely separated by V. Otherwise V separates source signals into disjoint groups which can be further separated by using additional matrix pencil formed by correlation matrices at different lags. For a thorough treatment of the algorithm, the reader can reffer to our previous work [1].

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3. SIMULATION RESULT

We used 5 sinusoids with different frequencies to simulate the signals of AF wavelets, i.e. $s_i = \cos(2\pi f_i t + \phi_i)$, $i = 1, 2, \ldots, 5$, where ϕ_i are randomly chosen among $[0, 2\pi)$. The additive noises w_i are five stationary, temporally white, zero mean Gaussion processes. After getting the generalized eigen-vector matrix V, the sources were extracted by

$$\hat{\vec{s}}(n) = V^H\vec{x}(n) = (V^H A)\vec{s}(n) + V^H\vec{w}(n).$$

We denote $\hat{s}_{i_0}(n)$ as the estimation of $s_i(n)$ if it has the largest signal to interference ratio (SIR) among all the estimated sources $\vec{s_i}(n)$. Let $C = V^H A$, the SIR of $s_i(n)$ can be computed as $SIR_i = |C_{i_0 i}|^2 / \sum_{j \neq i} |C_{i_0 j}|^2$. The system performance was measured by the averaged value of SIR for all the sources, that is, $ASIR = 10\log_{10}(\frac{1}{N}\Sigma_{i=1}^{N} SIR_i)$ dB. Table I shows the ASIRs against the input SNRs from -10 dB to 30 dB at 10 dB intervals.

TABLE I. PERFORMANCE OF THE ALGORITHM

SNR (dB)	-10	0	10	20	30
ASIR (dB)	5.0	4.9	5.3	8.6	9.1

4. CONCLUTION

The matrix pencil approach to blind source separation based on second order statistics enjoys the following attractive features: 1) good performance in short data case, 2) ability to separate colored Gaussian sources in contrast to the higher order statistical methods, and 3) effectiveness to non-stationary source separation. These features make it suitable for multi-channel biomedical signal separation applications.

References

[1] C. Chang, Z. Ding, S. Yau, and F. Chan, "A matrix-pencil approach to blind separation of non-white signals in white noise", *Proc. ICASSP98*, vol. IV, pp.2485-2488.

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