AUDIO SEPARATION USING RobustICA

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ABSTRACT— **Independent component analysis (ICA) aims at decomposing an observed random vector into statistically independent variables. A novel method for deflationary ICA, referred to as RobustICA. This simple technique consists of performing exact line search optimization of the kurtosis contrast function. RobustICA can avoid prewhitening and deals with real- and complex-valued mixtures of possibly audio sources alike. The absence of prewhitening improves asymptotic performance.**

***KEY-WORDS*— independent component analysis (ICA) RobustICA , kurtosis, performance analysis**

1. Introduction

Independent component analysis (ICA) aims at decomposing an observed random vector into statistically independent variables [1]. Among its numerous applications, ICA is the most natural tool for blind source separation in instantaneous linear mixtures when the source signals are assumed to be independent. The plausibility of the statistical independence assumption in a wide variety of fields, including telecommunications, and biomedical engineering, helps explain the arousing interest in this research area witnessed over the last two decades.

2 Method ROBUSTICA

In the deflation approach to ICA, an extracting vector is sought w so that the estimate

$$y = w^H . x \tag{1}$$

where $(.)^H$ denotes the conjugate-transpose operator and x the observed random vector, maximizes some optimality criterion or contrast function, and is hence expected to be a component independent from the others. A widely used contrast is the kurtosis, which is defined as the normalized fourth-order marginal cumulant:

$$k(w) = \frac{E\{\,|y|^4\} - 2E^2\{\,|y|^2\} - |E\{y^2\}|^2}{E^2\{\,|y|^2\}} \tag{2}$$

where $E\{.\}$ denotes the mathematical expectation. This criterion is easily seen to be insensitive to scale $k(\alpha w) = k(w), \forall\alpha \neq 0$. Since this scale indeterminacy is typically unimportant, we can impose, without loss of generality the normalization $\|w\| = 1$,μ = 1/12 for numerical convenience. The kurtosis maximization (KM) criterion based on contrast (2) is quite general in that it does not require the observations to be prewhitened and can be applied to real- or complex-valued sources without
any modification. RobustICA performs an optimal step-size (OS) based optimization comprising the following steps:

S1) Compute the OS polynomial coefficients.
For the kurtosis contrast, the OS polynomial is given by:

$$p(\mu) = \sum_{k=0}^{4} a_k \mu^k \tag{4}$$

The coefficients $\{a_k\}k_{=0}^{4}$ can easily can be obtained at each iteration from the observed signal

S2) Extract OS polynomial roots

$$\{\mu_k\}k_{=0}^{4} \tag{5}$$

The roots of the 4th-degree polynomial can be found at practically no cost using standard algebraic procedures such as Ferrari's formula, known since the 16th century [2].

S3) Select the root leading to the absolute maximum of the contrast along the search direction:

$$\mu_{opt=argmax_k} |k(w + \mu_k g)| \tag{6}$$

Where g is typically the gradient $g = \nabla_w k(w)$is explain in [3].

S4) Update $w^+ = w + \mu_{optg}$

S5) Normalize $w^+ \leftarrow w^+/\|w\|$. The generality of contrast (2) guarantees that RobustICA is able to separate real and complex (possibly non-circular) sources without any modification. The method described above aims at maximizing the absolute kurtosis, and is thus able to extract sources with positive or negative kurtosis. In many applications, some information may be known in advance about the source(s) of interest.

3 SIMULATION

All the experimental results are implemented in Matlab scripts. this section describe

Simulation 1

In the simulation we use three source signals, are shown as Signal 1 (speech1.wav) and Signal 2 (speech2.wav) And Signal 1 (speech3.wav) in Figure (1) .The observed mixtures of the three source signals are shown in the Figure (2) estimated sources is found by the RobustICA algorithm shown in the Figure (3).

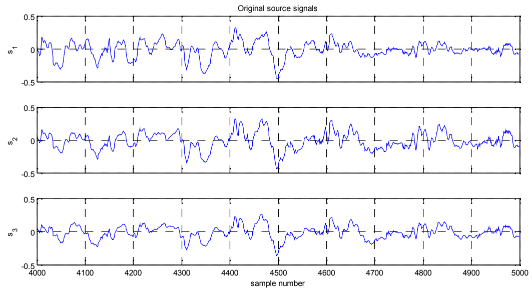

Figure 1. *original sources*

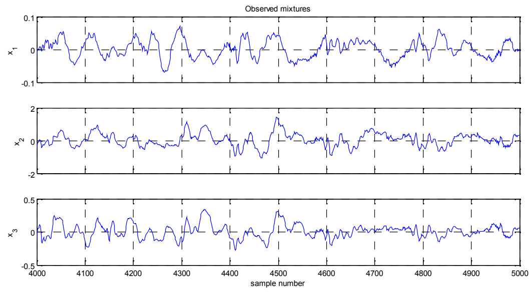

Figure 2. *observed mixture*

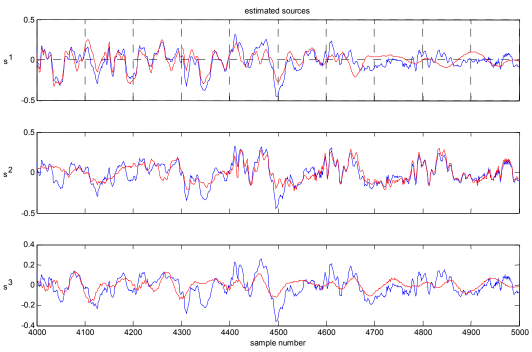

Figure 3. *estimâtes sources*

Simulation 2

In the simulation we use three source signals, are shown as Signal 1 (music1.wav) and Signal 2 (music2.wav) And Signal 1 (music3.wav) in Figure (1) .The observed mixtures of the three source signals are shown in the Figure (2) estimated sources is found by the RobustICA algorithm shown in the Figure (3).

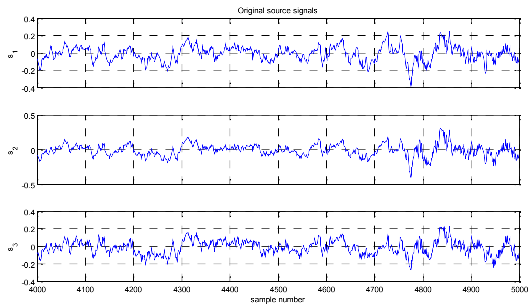

Figure 1. *original sources*

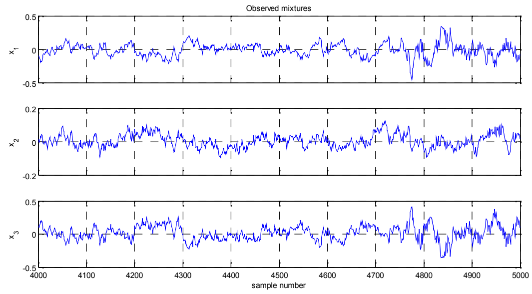

Figure 2. *observed mixture*

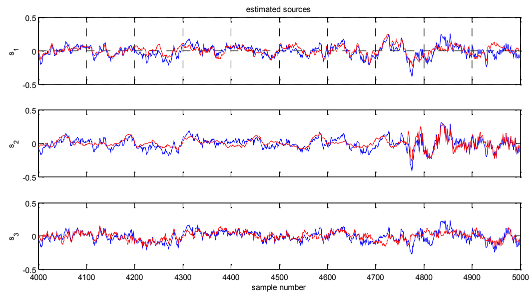

Figure 3. *estimâtes sources*

Simulation 3

In the simulation we use three source signals, are shown as Signal 1 (music1.wav) and Signal 2 (speech1.wav) And Signal 1 (music3.wav) in Figure (1) .The observed mixtures of the three source signals are shown in the Figure (2) estimated sources is found by the RobustICA algorithm shown in the Figure (3).

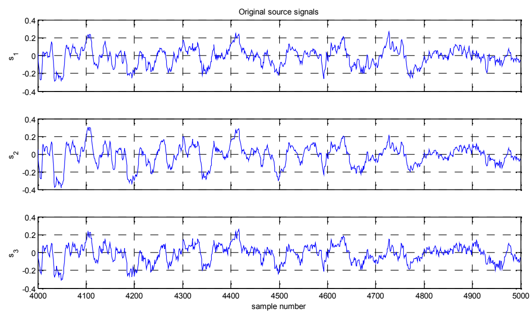

Figure 1. *original sources*

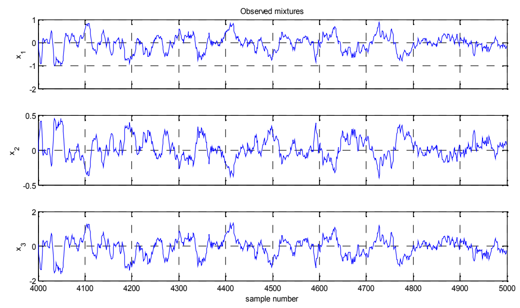

Figure 2. *observed mixture*

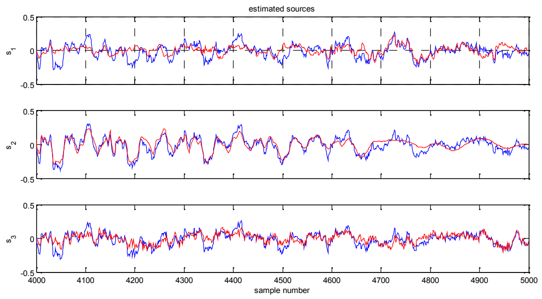

Figure 3. *estimâtes sources*

The following simulations evaluates RobustICA's convergence characteristics, source extraction quality. In the speech source case RobustICA as well of extraction quality extractions are obtained after 9 iterations In the music source case RobustICA a faster more robust performance quality extractions are obtained after 10 iterations. In the music and speech sources RobustICA less performance compared to the preceding cases Performance parameters averaged are summarized in Table I

	iteration	%signal mean square error (SMSE)
Simulation 1	9	0.0054
Simulation 2	10	0.0051
Simulation 3	11	0.0056

4 Conclusion

RobustICA can process audio sources and does not require prewhitening. As a result, the method is more tolerant than whitening-based techniques to residual source correlations likely to appear in short data records. In addition, the optimal step-size approach endows the method with an increased robustness to initialization and saddle points, particularly in small observation windows. The computational complexity required to reach a given source extraction quality and has a very high onvergence speed.

References

[1] D. T. Pham and P. Garat, "Blind separation of mixture of independent sources through aquasi-maximum likelihood" approach," IEEE Transactions on Signal Processing, vol. 45, no. 7, pp. 1712–1725, July 1997.

[2] M. Klemm, J. Haueisen and G. Ivanova, "Independent omponent analysis: comparison of algorithms for the investigation of surface electrical brain activity". *Med Biol Eng Comput*, vol 47, pp. 413–423, 2009.

[3] V. Zarzoso and P. Comon, "Comparative Speed Analysis of FastICA". Proceedings ICA–2007,pp. 293–300, 2007.