Blind Deconvolution of Sources in Fourier Space Based on Generalized Laplace Distribution

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ABSTRACT
An approach to multi-channel blind de-convolution is developed, which uses an adaptive filter that performs blind source separation in the Fourier space. The approach keeps (during the learning process) the same permutation and provides appropriate scaling of components for all frequency bins in the frequency space. Experiments indicate that Generalized Laplace Distribution can be used effectively to blind de-convolution of convolution mixtures of sources in Fourier space compared to the conventional Laplacian and Gaussian function.

Keywords: Adaptive Filter, Blind Deconvolution, Blind Source Separation, Fourier Space, Generalized Laplace Distribution, Laplacian and Gaussian Function

1. INTRODUCTION
Source signals, like in speech, seismology or medicines get mixed and distorted if they are transmitted over disperse environment. The simplest case of a mixing model is an instantaneous (linear) mixing of source signals (Amari, Douglas, Cichocki, & Yang, 1997; Cichocki & Amari, 2002; Kasprzak, Cichocki, & Amari, 1997), but this is a practically no feasible model. In general, the nature of the transmission environment is dynamic and nonlinear. The goal of blind source deconvolution is to reconstruct from many distorted signals the estimates of original sources (Cichocki & Amari, 2002). Some ambiguity is inherent, i.e. The permutation order, the scaling and delay factors cannot be reliably predicted. 1-D signals are the main application field of blind
signal processing techniques. But there appear some possible applications in image processing as well (Cichocki & Amari, 2002; Kasprzak & Cichocki, 1997): (1) the extraction of sparse binary images (e.g. documents), (2) contrast strengthening of “smoothed” images in selected regions, (3) encryption of transmitted images. In this paper we solve the source deconvolution problem by repetitive use of blind source separation method in the frequency space. The sensor signals are converted first into the Fourier domain. In such a case the convolutive mixture given in time space corresponds to a set of instantaneous mixtures, one mixture for each frequency bin. Although, the simplified problem of blind source separation (BSS) can be quite robustly solved for each subband (Tong, Xu, Hassibi, & Kailath, 1995; Smaragdis, 1998), it is still far from a real solution to the deconvolution problem. As the BSS process is conducted independently for each bin, the ordering and scaling of obtained outputs and weights are arbitrary (Araki, Makino, Mukai, Nishikawa, & Saruwarai, 2001). At least some solutions for the permutation problem have recently been proposed by Murata et al (computing the output correlations) (Murata, Ikeda, & Ziehe, 2001) and Kurita and Saruwatari (to use “directivity patterns” of weights matrices) (Saruwatari, Kurita, & Takeda, 2001). In this paper we propose another approach to both problems – the permutation and scaling indeterminancy - by making an integration of the (up to now) independent learning processes for all frequency bins into one learning process. This allows us to avoid non-compatible output permutations and different component scales for different frequencies.

2. THE BSS/MBD PROBLEMS

The blind source separation task. Assume that there exist \( n \) zero-mean source signals, \( s_1(t), s_2(t), \ldots, s_n(t) \), that are scalar valued and mutually (spatially) statistically independent (or as independent as possible) at each time instant or index value \( t \) number \( n \) of sources (Amari, Douglas, Cichocki, & Yang, 1997; Cichocki & Amari, 2002). Denote \( [x_1(t), x_2(t), \ldots, x_m(t)]^T \) the \( m \)-dimensional \( t \)-th mixture data vector, at discrete index value (time) \( t \). The blind source separation (BSS) mixing model is equal to:

\[
x(t) = A s(t) + N(t) = \sum_{i=1}^{n} s_i(t)a_i + N(t)
\]

where \( N \) is noise signal. A well-known iterative optimization method is the stochastic gradient (or gradient descent) search (Zeckhauser & Thompson, 1970). In this method the basic task is to define a criterion \( J(W(k)) \), which obtains its minimum for some \( W_{\text{opt}} \) if this \( W_{\text{opt}} \) is the expected optimum solution. Applying the natural gradient descent approach (Amari, Douglas, Cichocki, & Yang, 1997; Cichocki & Amari, 2002) with the cost function, based on Kullback-Leibler divergence, we may derive the learning rule for BSS:

\[
\Delta W(t) = \eta(t) \left[ I - \left\langle f(y(t)), y^T(t) \right\rangle \right] W(t)
\]
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