A fast semi-blind source separation algorithm

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Abstract

Many algorithms have been invented to perform blind source separation. There, it is assumed that the sources are completely unknown. However, in many cases of time series separation there exists some a priori knowledge on the behaviour of the sources. This is the case especially, when the data is collected in a controlled experiment. In this paper we introduce a fast semi-blind source separation algorithm (SBSS) when either the power spectrum of the sources is partly known or in case of on/off -non-stationary sources, the onsets and offsets of the sources are known at least partially or the sources are quasi-periodic. We also suggest a method how this algorithm can be generalised to blind source separation with certain conditions. The algorithm is tested on simulated data.

1 Introduction

Recently many algorithms have been proposed to solve the problem of blind source separation (BSS) [2], where n sources ($\mathbf{s}(t)$) are observed ($\mathbf{x}(t)$) through a constant, instantaneous linear process ($\mathbf{A}$), possibly including process noise ($\mathbf{n}(t)$):

$$\mathbf{x}(t) = \mathbf{A}\mathbf{s}(t) + \mathbf{n}(t), \tag{1}$$

where $\mathbf{A}$ is usually referred to as the mixing matrix. This separation is to be carried out with minimal knowledge on the sources $\mathbf{s}(t)$ and the mixing matrix $\mathbf{A}$. In independent component analysis (ICA) [1] it is assumed that the sources are independent of each others and that they have non-Gaussian distributions. Mixing matrix is assumed to have $rank(\mathbf{A}) = n$, *i.e.* there exist at least as many mixtures as sources.

In many practical cases, however, we do not actually have to perform *blind* source separation, but some prior knowledge is available. This is the case especially in data sets gathered in designed experiments typical for psychophysical and biomedical research.

In this paper we interpret the algorithmic scheme for ICA introduced in [3] in a beamformic way that enables the incorporation of the prior knowledge of the sources in various forms resulting in a fast algorithm. Some suggestions are also made towards blind source separation using the same algorithm.

2 Fast algorithm for SBSS by denoising / re-estimation

Assume the data white or prewhitened. Then the semi-blind source separation algorithm proceeds as follows:

1. Start from a random projection vector $\mathbf{w}$.
2. Orthogonalize $\mathbf{w}$ with respect to the other already estimated projections $\mathbf{W}$ by $\mathbf{w} \leftarrow \mathbf{w} - \mathbf{W}^T\mathbf{W}\mathbf{w}$.
3. Normalize: $\mathbf{w} \leftarrow \frac{\mathbf{w}}{||\mathbf{w}||}$.
4. Find the estimate for the source by $\hat{s}_i = \mathbf{w}^T\mathbf{x}$.
5. Denoise the source estimate using ith mask.
6. Re-estimate $\mathbf{w}$ to the MLS fit of the denoised source estimate.
7. Repeat orthogonalization (step 2) and normalization (step 3) of $\mathbf{w}$ and estimation (step 4) for $\hat{s}_i$.
8. If $\Delta\mathbf{w} > \epsilon$, reiterate from step 5.
9. Add $\mathbf{w}$ to already estimated projections $\mathbf{W}$ and $\hat{s}_i$ to $\hat{\mathbf{s}}$. Increment i and go back to step one, if not done.

The orthogonalisation step 2 is needed to keep the source estimate from converging to an already found source. The crucial part of the algorithm is the denoising step 5. Different types of denoising are suitable for different kinds of prior information. It is usual to control a psychophysical or biomedical experiment by having periods of activity and non-activity. In such experiments the denoising can be done simply by multiplying the source estimate $\hat{s}_i$ by a binary mask, where ones represent the active parts and zeroes the non-active parts. If we are interested in signals having certain frequency components, we can Fourier transform the source estimate, mask the spectrum and inverse transform to get the denoised signal. A third kind of denoising can be used in analysis of experiments having repetitive stimuli. The source estimate can be averaged around the stimuli onset and that averaged signal can be used as the denoised signal around the onsets. It is not hard to imagine other kinds of denoising procedures in experiments having different kinds of prior knowledge. Furthermore, the three denoising strategies can be combined as needed.

3 Experiments

3.1 Artificial signals

To test the performance of the SBSS we mixed artificial signals having either a specific frequency content, a clear on/off nonstationarity in time domain or a quasi-periodic behaviour. There was no process noise. The original sources and the mixtures are shown in Fig. 1 (a) and (b) respectively. A priori it was assumed to be known that the first two signals had a strong sinusoidal

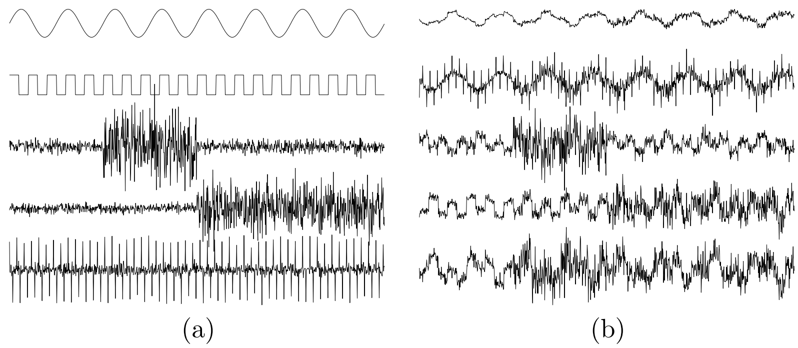

Figure 1: (a) Five artificial signals with simple frequency content (signals #1 and #2), simple on/off non-stationarity in time domain (signals #3 and #4) or quasi-periodicity (signal #5). (b) Five mixtures of the signals in (a).

components on their mode frequency, *i.e.* the frequency content of the first signal was completely known, while only the main frequency of the second was known. Respectively the on-off nonstationarity of the third signal was assumed to be known. Of the fourth it was known only that it is active in the last fourth of the time course. The last signal was assumed to have a known quasi-periodic repetition rate.

After few iterations the SBSS converged to almost perfect result, which can be seen from the estimates of the sources (Fig. 2) and from the table (Table 1) showing the product of the estimated unmixing matrix $\widehat{\mathbf{W}}^T$ and the true mixing matrix $\mathbf{A}$.

-1.0000	-0.0000	-0.0000	0.0000	0.0000
0.0004	-1.0001	-0.0128	0.0047	-0.0002
0.0229	-0.0037	-1.0000	0.0053	0.0181
0.0239	0.0029	0.0199	0.9880	0.1241
-0.0025	-0.0067	0.0216	-0.1608	0.9928

Table 1: $\widehat{\mathbf{W}}^T\mathbf{A}$

4 Discussion

In this paper a fast algorithm for source separation called semi-blind source separation (SBSS) using partial prior knowledge of the source behaviour was introduced. It was shown using artificial mixtures that SBSS easily and quickly finds the components having the prior structure even when the knowledge is only partial.

Often it is the case that we want to use BSS for exploratory data analysis. We would like to keep all the components having meaningful characteristics and discard the rest. We suggest that in that case, each mask is used to produce a candidate estimate of a component. Then the user can study the properties of

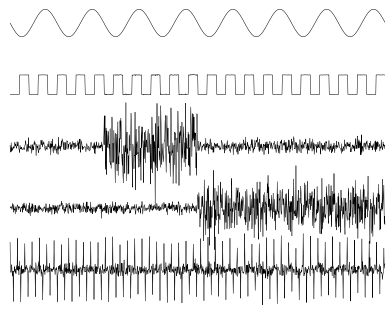

Figure 2: Estimated sources.

the estimates and tune the masks to reflect the interesting aspects of the signal even better.

The denoising principle can be extended to full blind source separation by adaptively creating suitable masks by inspecting *e.g.* the spectrogram of the data.

References

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