Compensating frequency response of sensors in blind separation of sources

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1 The problem considered

Blind Source Separation (BSS) is a basic problem in signal processing, which has been considered intensively in the last decade. We have observed the mixture of some independent source signals, and we would like to separate them, without any *a priori* information about the source signals or about the mixing system (hence the term *Blind*). This problem has been first addressed by J. Hérault and C. Jutten [1], and then continued by many other researchers, for example see [2, 3, 4, 5, 6, 7, 8].

In this paper, we study a mixing model which is between the classic instantaneous mixtures and convolutive mixtures. This model, corresponds to the case where the mixture is itself instantaneous, but the sensors are not ideal and their frequency response introduces memory to the system. Hence, for separating this mixture, we must first compensate for the frequency responses of the sensors, and then separate the resulting mixture. We find, the conditions for separability, and then we design an algorithm based on minimization of the output mutual information.

2 The new results

We prove that for this type of mixing, the criterion of separability is the same as instantaneous mixtures, that is, an instantaneous criterion is sufficient for separating the mixture. Hence, we do not need to deal with the stochastic processes, and we can regard the output signals as the different samples of some random variables. In implementation of the algorithm, we propose an estimator for Joint and Marginal score functions of a multi dimensional random variable.

3 Summary

Our mixing-separating model, is shown in the Figure 1. This model consists of a

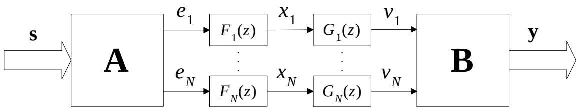

Fig. 1. Mixing-Separating system

linear mixture, following by a Linear Time Invariant (LTI) filter in each output (the filters F_i). The observations are the signals x_i. To separate the sources, we must first compensate the effect of these filters by means of the filters G_i, and then separate the resulting mixture by separating matrix $\mathbf{B}$.

We first show that (under some mild conditions) the signals $y_i(n)$ are independent (for all n), if and only if the filters $H_i(z) = F_i(z)G_i(z)$ satisfy:

$$H_i(z) = c_j H_j(z) \tag{1}$$

and $\mathbf{BA} = \mathbf{DP}$ where $\mathbf{D}$ and $\mathbf{P}$ denote a diagonal and a permutation matrix, respectively.

Note that the independence of $y_i(n)$ is much weaker than the independence of the outputs. For example for case 2 by 2, y_1 and y_2 are independent if and only if $y_1(n)$ and $y_2(n-m)$ are independent for all n and all m. However, our theorem shows that for this type of mixing the independence of $y_1(n)$ and $y_2(n)$ is sufficient for achieving the separation.

At last, we use mutual information of the outputs as the separation criterion, and calculate its derivative with respect to $\mathbf{B}$ and the coefficients of compensating filters, to develop a steepest descent gradient algorithm for separating the mixture.

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