Blind Source Separation
–
Literature Search Protocol

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Abstract

Blabla..

Contents

1 Introduction

The blind source separation problem refers to the process of recovering one or more signals that have been mixed in some unknown manner and possibly also contamined by noise. Without any assumptions on the mixing process, this problem is ill-poised. In practice therefore, all BSS methods rely on some stylized fact about the nature of the signals and/or the mixing process. It is therefore useful to dichotomize BSS methods by these assumptions.

Arguably, two of the most important facts characterizing a mixing process, are its temporal dynamics and the number of degrees of freedom. The first point refers to whether the nature of the mixing process changes over time, that is if the mixing matrix at time $t+k$ is different from that at time t for $k > 0$. The number of degrees of freedom is the same concept as in linear algebra - the connection is apparent by seeing the mixing process as a system of linear equations. If m is the number of observed signals and n the number of sources, the system is said to be *underdetermined* if $m < n$ and conversely *overdetermined* if $m > n$.

We can also differentiate between method based on the nature of input data. Early BSS research often considered the case of $n = m$, which allows one to work with data in the time domain. For undetermined systems, it is commonplace to work with some transformation of the data, which in the case of audio data a time-frequency representation. Common methods include the *short-term Fourier transform* and the *wavelet transform*.

2 Literature Review Process

3 Literature Overview

3.1 Independent Component Analysis

Among the most common approaches to blind source separation is independent component analysis (ICA). Common definitions of ICA use either the maximization of independence or minimization of mutual information between the source signals[1]. Formally, we can state the ICA problem in terms of a generative model of the observed signals $\mathbf{x}$, and the unknown a mixing matrix $\mathbf{W}$ and source signals $\mathbf{s}$:

$$\mathbf{x} = \mathbf{W}\mathbf{s} \tag{1}$$

The AIM of the ICA process is to estimate the inverse mixing process along with the original signals.

The classical reference on ICA is [1], where the method of minimization of mutual information between sources is presented. [1] also presents an analysis of the ambiguities and limitations of ICA, hereunder the permutation of sources, scaling and non-gaussianity.

Computationally, ICA can be stated in many different forms, hereunder neural networks ([2]), maximum likelihood ([3]) and maximization of non-gausianity as measured by excess kurtosis, which is used in the popular FastICA algorithm ([**?**]). For a much more thorough survey on the classical literature on ICA, see [4].

[1] It should be noted that while this text presents ICA in terms of blind source separation, the method is applicable to a wide array of machine learning problems including dimension reduction, classification, and de-noising.

Study	Method	Data	Description
Comon (94)	ICA	Time domain	Blabla..
Bell and Sejnowski (95)	ICA	Time domain	Joint entropy maximization by gradient descent.

Table 1: This table shows some data

3.2 ICA in Underdetermined Systems

The classic studies on ICA focus to a large extent on developing the formal framework for ICA, and examples are largely centered on time domain analysis in systems of an equal number of sensors and sources. ICA has however been extended to underdetermined systems and the extreme case of single sensor systems. This involves transforming the observed signals from the time domain to some other basis, the most common of which are the frequency domain (Fourier transform), the time-frequency domain (short-term Fourier transform) and the wavelet domain.

3.3 Factoral Hidden Markov Models

3.4 Wavelets

Ichir Hidden markov models

4 Conclusion

A Protocol

References

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