Available online at www.sciencedirect.com

SCIENCE DIRECT®

Engineering Applications of Artificial Intelligence 19 (2006) 305–311

Engineering Applications of
ARTIFICIAL INTELLIGENCE

www.elsevier.com/locate/engappai

Blind source separation based on self-organizing neural network

Anke Meyer-Bäse[a], Peter Gruber[a,b], Fabian Theis[a,b], Simon Foo[a,*]

[a]Department of Electrical Engineering, Florida State University, Tallahassee, FL 32310-6046, USA
[b]Institute of Biophysics, University of Regensburg, Regensburg 93040, Germany

Received 6 December 2004; received in revised form 26 May 2005; accepted 15 September 2005
Available online 11 November 2005

Abstract

This contribution describes a neural network that self-organizes to recover the underlying original sources from typical sensor signals. No particular information is required about the statistical properties of the sources and the coefficients of the linear transformation, except the fact that the source signals are statistically independent and nonstationary. This is often true for real life applications. We propose an online learning solution using a neural network and use the nonstationarity of the sources to achieve the separation. The learning rule for the network's parameters is derived from the steepest descent minimization of a time-dependent cost function that takes the minimum only when the network outputs are uncorrelated with each other. In this process divide the problem into two learning problems one of which is solved by an anti-Hebbian learning and the other by an Hebbian learning process. We also compare the performance of our algorithm with other solutions to this task.

Keywords: Self-organization; Independent component analysis; Hebbian and anti-Hebbian learning

1. Introduction

Blind separation of sources, also known as independent component analysis (ICA), is an extension of the widely used statistical technique principal component analysis (PCA). ICA has been developed in the context with blind separation of independent sources from their linear mixtures and it occurs in many application areas such as speech, radar, medical instrumentation, mobile telephone communication and hearing aid devices. The problem is defined as the recovery of original source signals from a sensor output when the sensor receives an unknown mixture of the source signals. An interesting form of blind source separation is sometimes known as the "cocktail party problem", where a person can single out a specific speaker from a group speaking simultaneously (Girolami and Fyfe, 1997a).

General blind source separation is an underdetermined problem since the source signal statistics, the mixing, and the transfer channels are all unknown. Therefore closed form solutions are impossible. But for many problems there exists solutions if some assumptions on the data can be made. (For example here independent and nonstationary sources.) To achieve the separation with neural networks, higher order statistics are necessary. Hence often it's required that some suitable nonlinearities must be used in the learning phase, even though the final input–output mapping is still linear.

Jutten and Herault (1991) were the first to develop a neural architecture and learning algorithm for blind separation; since then a number of variants on this architecture have appeared in the literature. Bell and Sejnowski (1995a) have developed a feedforward network and learning rule which minimizes the mutual information at the output nodes. Karhunen and Joutsensalo (1994) have developed a number of nonlinear variants of principal component analysis learning and show their utility in sinusoidal frequency estimation. Oja (Karhunen et al., 1997) and Girolami and Fyfe (1997b) have given theoretic justification for the use of the nonlinear PCA algorithm in blind separation of source signals. In general, source separation is obtained by minimizing an appropriate contrast function, i.e., a function of the distribution of

*Corresponding author. Tel.: +1 850 410 6474; fax: +1 850 410 6479.
E-mail address: foo@eng.fsu.edu (S. Foo).

0952-1976/$ - see front matter © 2005 Elsevier Ltd. All rights reserved.
doi:10.1016/j.engappai.2005.09.006

the estimated sources, and the most common contrast functions are based on maximum likelihood (Attias, 1999; Cardoso, 1998; Pham and Garat, 1997), the infomax principle (Bell and Sejnowski, 1995b; Roth and Baram, 1996; Lee et al., 1999), and mutual information (Comon, 1994; Amari et al., 1996; Hyvarinen, 1999). Although each model derives from different considerations, they can all be unified under the maximum likelihood principle leading to simple and efficient algorithms (Cardoso, 1998; Pearlmutter and Parra, 1996).

Matsuoka et al. (1995) extend the Jutten and Herault network, utilizing only second-order statistics and report on separation of nonstationary artificial signals. We will extend Matsuoka's network by combining an anti-Hebbian and Hebbian learning algorithm. By that we are able to show that Matsuoka's network is only a special case of our proposed method. Based on the proposed architectural changes, we increase the convergence speed and decrease the error between the desired and computed function compared to Matsuoka's network.

We propose a new adaptive linear network that acquires the function of blind separation, using the nonstationarity of the signals. It utilizes only the second-order moments of the signals, as opposed to many conventional methods online learning algorithms. The network's parameters are iteratively modified to minimize a time-dependent cost function until the network outputs are uncorrelated with each other.

In neural terminology, two kinds of learning rules are used for adaptation of the connection weights between constituent units: regular Hebbian rules and anti-Hebbian rules. The characteristic point of the self-organizing neural nets mentioned above is that an anti-Hebbian rule is also used for the modification of the strengths of feedback connections between output units whereas a normal Hebbian rule is used for the weights of feedforward connections from input units to output units. Namely, the connection weights between output units are decreased proportionally to the product of the activation values of the two units involved.

The proposed neural network can be considered as a generalization of a type of network model proposed by Matsuoka et al. (1995). In both the models the network is self–organized such that the outputs of the network are uncorrelated with each other. Matsuoka's network is considering only anti-Hebbian learning and fixed feedforward weights. We are able to show that the equilibrium solution of the Hebbian-type learning dynamics is equal to his chosen fixed values for the feedforward learning.

The paper is organized as follows. In Section 2, we describe the blind source separation problem. Section 3 describes the proposed separation neural network combining both Hebbian and anti-Hebbian learning and in Section 4 the learning algorithms for achieving blind source separation are derived. The advantages in terms of performance of the new method are shown in Section 5.

2. Signal sources

Suppose that the sensor signals $s_i(t)$, $i = 1, \ldots, N$, $t = 1, \ldots$ are generated by a linearly weighting of a set of N statistically independent random sources $x_j(t)$ with time-independent coefficients a_{ij}:

$$s_i(t) = \sum_{j=1}^{N} a_{ij} x_j(t). \tag{1}$$

This equation can be expressed in vector notation as

$$\boldsymbol{s}(t) = \boldsymbol{A}\boldsymbol{x}(t), \tag{2}$$

where $\boldsymbol{s}(t) = [s_1(t), \ldots, s_N(t)]^{\mathrm{T}}$, $\boldsymbol{x}(t) = [x_1(t), \ldots, x_N(t)]^{\mathrm{T}}$, and $\boldsymbol{A} = [a_{ij}]$.

As usual the sensor signals can only be possibly recalled up to reordering and scaling. Thus they might be in a different order and rescaled from the resulting vector $\bar{\boldsymbol{x}}(t)$ and we obtain

$$\bar{\boldsymbol{x}}(t) = \boldsymbol{D}\boldsymbol{P}\boldsymbol{x}(t). \tag{3}$$

$\boldsymbol{P}$ is a permutation matrix and $\boldsymbol{D}$ is a diagonal matrix with nonzero elements.

The following assumptions (Matsuoka et al., 1995) are necessary for the blind separation process:

1. Matrix $\boldsymbol{A}$ is nonsingular.
2. $x_j(t)$, $j = 1, \ldots, N$ are statistically independent signals with zero mean.

These conditions imply that the covariance matrix $\boldsymbol{R}$ of $\boldsymbol{x}(t)$ is a diagonal matrix this is also true for every subcovariance matrix:

$$\begin{aligned}\boldsymbol{R}(t) &= \mathrm{diag}\{r_1(t), \ldots, r_N(t)\} \\ &= \mathrm{diag}\{\langle x_1^2 \rangle_t, \ldots, \langle x_N^2 \rangle_t\}\end{aligned} \tag{4}$$

here $\langle y \rangle_t$ denotes the ensemble average of y for the samples $1, \ldots, t$, i.e.

$$\langle x_j^2 \rangle_i = \frac{1}{t} \sum_{i=1}^{t} x_j^2(t).$$

In a generic setting, i.e. truly nonstationary sources, this also implies separation. That means it suffices to find a separation matrix such that the sources have these properties to solve the blind source separation problem. This can easily be proved using at least two covariance matrices at different time steps and using a similar reasoning as for the SOBI algorithms in Parra and Sajda (2003) and Cardoso and Souloumiac (1996). Variants of SOBI which diagonalize other collections of second-order matrices, including a collection of correlation matrices acquired across various intervals, have also been proposed (Parra and Spence, 2001; Ferreol and Chevalier, 2000).