

## Chapter XII

# Flexible Blind Signal Separation in the Complex Domain

**Michele Scarpiniti**

*University of Rome “La Sapienza”, Italy*

**Daniele Vigliano**

*University of Rome “La Sapienza”, Italy*

**Raffaele Parisi**

*University of Rome “La Sapienza”, Italy*

**Aurelio Uncini**

*University of Rome “La Sapienza”, Italy*

### ABSTRACT

*This chapter aims at introducing an Independent Component Analysis (ICA) approach to the separation of linear and nonlinear mixtures in complex domain. Source separation is performed by an extension of the INFOMAX approach to the complex environment. The neural network approach is based on an adaptive activation function, whose shape is properly modified during learning. Different models have been used to realize complex nonlinear functions for the linear and the nonlinear environment. In nonlinear environment the nonlinear functions involved during the learning are implemented by the so-called “splitting functions”, working on the real and the imaginary part of the signal. In linear environment instead, the “generalized splitting function” which performs a more complete representation of complex function is used. Moreover a simple adaptation algorithm is derived and several experimental results are shown to demonstrate the effectiveness of the proposed method.*

### INTRODUCTION

In the last years *Blind Source Separation (BSS)* realized through *Independent Component Analysis (ICA)* have raised great interest in the signal processing community (Cichocki & Amari, 2002; Haykin, 2000; Roberts & Everson, 2001). In this context the neural network approach (Haykin, 1999) (usually based on a single layer

perceptron (SLP) or a multilayer perceptron (MLP)) seems to be one of the preferred methodologies (Jutten & Herault, 1991; Bell & Sejnowski, 1995); this interest is justified by the large number of different approaches and applications. As a matter of fact, in several fields, from multimedia to telecommunication and to biomedicine, ICA is currently employed to effectively recover the original sources from their mixtures or to remove interfering signals from the signal of interest. Initial studies on ICA aimed at solving the well-known *cocktail party problem*, in a instantaneous or slightly reverberant environment. Pioneering works in ICA appeared at the beginning of the 90's, when Jutten and Herault (1991) presented their "*neurometric architecture*" and Comon (1994) published his often referenced work.

Recently the problem of source separation has been extended to the complex domain (Cardoso & Laheld, 1996; Fiori, Uncini & Piazza, 1999; Bingham & Hyvärinen, 2000), due to the need of frequency domain signal processing which is quite common in telecommunication (Benvenuto, Marchesi, Piazza & Uncini, 1991) and biomedical applications (Calhoun, Adali, Pearlson & Pekar, 2002b; Calhoun, Adali, Pearlson, Van Zijl & Pekar, 2002c). One of the most critical issues in ICA is the matching between the *probability density function (or pdf)* of sources (usually unknown) and the algorithm's parameters (Yang & Amari, 1997). In this way one of the most important issues in designing complex neural networks consists in the definition of the complex activation function (Clarke, 1990; Benvenuto & Piazza, 1992; Kim & Adali, 2001a). In order to improve the pdf matching for the learning algorithm, the so called *Flexible ICA* was recently introduced in (Choi, Cichocki & Amari, 2000; Fiori, 2000; Solazzi, Piazza & Uncini, 2000a; Vigliano & Uncini, 2003; Vigliano, Parisi & Uncini, 2005). Flexible ICA is the approach in which the *activation function (AF)* of the neural network is adaptively modified during the learning. This approach provides faster and more accurate learning by estimating the parameters related to the pdf of signals. In literature it is possible to find several methods based on polynomials (Amari, Cichocki & Yang, 1996) and on parametric function approaches (Pham, Garrat & Jutten, 1992; Solazzi, Piazza & Uncini, 2001).

Moreover the main properties that the complex activation function should satisfy (Kim & Adali, 2002a; Vitaliano, Parisi & Uncini, 2003) are that it should be non linear and bounded and its partial derivatives should exist and be bounded. Unfortunately the analytic and boundedness characteristics are in contrast with the Liouville theorem (Clarke, 1990; Kim & Adali, 2001a). In other words, according to this theorem, an activation function should be bounded almost everywhere in the complex domain (Clarke, 1990; Leung & Haykin, 1991; Georgiou & Koutsougeras, 1992; Kim & Adali, 2000, 2001a, 2002b; Adali, Kim & Calhoun, 2004).

In this context, spline-based nonlinear functions seem to be particularly appealing as activation functions. In fact splines can model a very large number of nonlinear functions and can be easily adapted by suitably varying their control points, with low computational burden.

Unfortunately linear instantaneous mixing models are too unrealistic and unsatisfactory in many applications. Recent studies on ICA in the real domain showed that source separation can be effectively performed also in the case of convolutive nonlinear mixing environments, (Jutten & Karhunen, 2003; Vigliano et al., 2005). In the case of the complex domain only linear instantaneous mixtures have been considered so far (Uncini, Vecchi, Campolucci & Piazza, 1999; Bingham & Hyvärinen, 2000; Calhoun et al., 2002b, 2002c; Adali et al., 2004).

A more realistic mixing system inevitably introduces a nonlinear distortion in the signals. In this way the possibility of taking into account these distortions can give better results in signal separation. The problem is that in the nonlinear case the uniqueness of the solution is not guaranteed.

The solution becomes easier in a particular case, called *Post Nonlinear (PNL) mixture*, well-known in literature in the case of the real domain (Taleb & Jutten, 1999; Taleb, 2002). In this context the solution is unique too.

The work here exploited extends the linear and PNL mixture to the complex domain (complex-PNL). This extension requires proper modelling of the nonlinear distorting functions and of the activation functions of a feed-forward network. In this work this modelling has been performed by use of the *splitting functions* described in (Uncini & Piazza, 2003). Another important issue is the definition of the theoretical conditions that grant the uniqueness of the solution.

The chapter is organized as follows: the "Background" describes the most important issues on ICA both in linear and nonlinear case. Next section ("The complex environment") defines the problem of separation in the complex domain. "The flexible activation function" section introduces the solution to the problem of flexibility used in this chapter, while "The de-mixing algorithm and separation architecture" defines in detail the networks used to solve the ICA problems introduced in previous sections. Finally the section "Results" describes experimental tests that demonstrate the effectiveness of the proposed approach.

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