Chapter 7
Applications to Signal Processing - Blind Source Separation

Abstract. In this chapter an alternative method to make independent component analysis and source separation is introduced. It is based upon Fuzzy Adaptive Simulated Annealing and uses mainly mutual information measures to achieve its final goals. After presenting the central arguments of the method, some experimental results are shown and comparison to previous work is done.

7.1 Introduction

In many applications of Medicine (EEG, ECG), Acoustics (noise filtering), Econometrics, Defense (radar and sonar systems) etc. [7], several signals are received by sensors that process and transmit them to posterior stages in order to be further conditioned. By their own physical structure, such sensors distort original signals and, commonly, such a distortion should be reversed. Otherwise the whole acquisition apparatus may be compromised and not achieve its aim, that is to identify the proper signals under investigation. In some cases, it is possible to model such a phenomenon as being the result of a linear mixture, that is, original signals would have been processed by a linear and time invariant system, represented by an invertible matrix. Such a premise resumes the problem to the search for another matrix that, composed to the first one, takes back the actual readings. Assuming that original signals are statistically independent, such a problem was solved by many researchers, using diverse methods [2]. It occurs that not always the assumption of linearity is compliant with physical device structure and has thus to be discarded if we want to implement certain functional characteristics - from that comes the need of creation of nonlinear mixture separation methods, that keep straight relationship to independent component analysis.

Although there are several and conclusive results concerning independent component analysis of linear mixtures (obtained through linear combinations of two or more signals), the case of nonlinear mixtures is yet in its infancy, taking into account the relatively few conclusive results in the literature concerning separation of...
mixtures resulting from nonlinear operations. Among the most relevant methods we find MISEP [2], that extends INFOMAX [3], the latter having its scope restricted to linear mixtures of statistically independent signals. The MISEP approach enlarges the reach of the INFOMAX model in two directions, that is, it is able to separate nonlinear mixtures and uses adaptive nonlinearities at their outputs. Taking into account that such features are related to the probability distributions of vectors resulting from the final analysis, the extra flexibility allows us to handle a larger number of cases. In what follows, it will be presented a brief description of the problem under investigation and the proposed contribution to tackle the problem of blind separation of nonlinear mixtures and related independent component analysis. At last, the advantages of the proposed algorithm will be shown through specific experiments.

The problem under investigation consists of, given observed vectors \( \mathbf{o} = [o_1, o_2] \), obtained from nonlinear sensor readings (mixers) and whose original signals \( \mathbf{s} = [s_1, s_2] \) were generated according to unknown distributions, obtaining the transformation \( \mathbf{y} = F(\mathbf{o}) = [y_1, y_2] \) that estimates original vectors \( \mathbf{s} \) without previous knowledge of specific characteristics, admitting only the hypothesis that original signals are mutually statistically independent and the nonlinearity inserted in the acquisition device is an invertible function, at least when restricted to the operational domain of the physical apparatus. Fig. 7.1 shows schematically the described setting.

![Fig. 7.1 General diagram of the separation problem](image)

Both INFOMAX and MISEP approaches aim to minimize the mutual information of components of random variable \( \mathbf{y} \), defined by the formula

\[
I(\mathbf{y}) = \sum_i H(y_i) - H(\mathbf{y}) \tag{7.1}
\]

where \( H(\mathbf{y}) \), the Shannon differential entropy [2], is defined by

\[
H(\mathbf{y}) = - \int p(\mathbf{y}) \log p(\mathbf{y}) d\mathbf{y} \tag{7.2}
\]