International Journal of Rough Sets and Data Analysis
Volume 6 • Issue 1 • January-March 2019

A Comparative Study of Infomax, Extended Infomax and Multi-User Kurtosis Algorithms for Blind Source Separation

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ABSTRACT

In this article for the separation of Super Gaussian and Sub-Gaussian signals, we have considered the Multi-User Kurtosis(MUK), Infomax (Information Maximization) and Extended Infomax algorithms. For Extended Infomax we have taken two different non-linear functions and new coefficients and for Infomax we have taken a single non-linear function. We have derived MUK algorithm with stochastic gradient update iteratively using MUK cost function abided by a Gram-Schmidt orthogonalization to project on to the criterion constraint. Amongst the various standards available for measuring blind source separation, Cross-correlation coefficient and Kurtosis are considered to analyze the performance of the algorithms. An important finding of this study, as is evident from the performance table, is that the Kurtosis and Correlation coefficient values are the most favorable for the Extended Infomax algorithm, when compared with the others.

KEYWORDS

Blind Source Separation, Correlation Coefficient, Extended Infomax, Information Maximization (Infomax), Kurtosis, Multi-User Kurtosis

1. INTRODUCTION

Over the past few decades, the Blind Source Separation (BSS) problem has found wide attention in the area of speech and signal processing, communication and neuroscience. The Blind source separation problem recovers the original sources from their mixtures without any prior information about the input sources (Amari, 1998). In BSS there are different approaches are considered, one approach is instantaneous BSS and the other one is convolutive BSS. In both cases the nature of mixing process are different. Here we have considered the number of outputs similar to the number of input sources and the mixing process is instantaneous. Different researchers have studied the BSS problem in different areas such as neural network and statistical signal processing. It is necessary for a blind source separation algorithm to separate the signal sources of different distributions, but due to some significantly fluctuating parameter values most of the algorithms failed to separate the sources. The Information maximization approach which was developed by Bell and T. Sejnowski based on entropy maximization approach can separate the signals those have super Gaussian distributions and fails to

DOI: 10.4018/IJRSDA.2019010101

separate the negative kurtosis values of a signal. It motivated the researchers to develop the extended Information maximization approach which is able to separate the signals those have super-Gaussian and sub Gaussian distributions (Lee, Girolami, & Sejnowski, 1999). Here the performance of the source separation is evaluated by different quality measures: such as k, co-relation coefficient and SIR which are one of the essential parameter measurement of quality of separation. Researchers Soloumiac and Cardoso (1993), Comon (1994) and Garrat and Pham (1997) proposed some of the algorithms which also separate mixtures of Supergaussian and Sub Gaussian sources. Also, C. B Papadias (2000) suggested another algorithm based on higher order statistics i.e multiuser kurtosis algorithm; this can separate the signals of Gaussian and super-Gaussian signals. Here we have compared Information maximization algorithm, Extended Infomax and Multi-User Kurtosis maximization algorithms, based on source separation. Also, we have obtained the results for blind deconvolution of one speech signal, for both Infomax and Extended Infomax algorithms.

The paper is orchestrated as follows; Section 2 describes problem formulation. In section 3, the information maximization approach is discussed. In sections 4 and 5, we describe the different algorithms used for blind source separation. In section 6 all the experimental procedures and the corresponding results are described in detail. Section 7 concludes the study.

2. METHODOLOGY

We have passed signal S to the model which is statistically independent, then the signal mixed with matrix A to get result vector Y. After that matrix W is calculated using de-mixing (Routray & Kishore, 2007).

The BSS model as in equation (1) below

$$X\left(r\right) = AS\left(r\right) + v\left(r\right) \tag{1}$$

Where

$S\left(r\right) = \left[s_1\left(r\right), s_2\left(r\right), \ldots, s_p\left(r\right)\right]^T$ transmitted Source Signals vector

A : is Mixing Matrix.

$X\left(r\right)$: is a vector (acquired signal)

$v\left(r\right)$: Vector with add-on noise samples at time instant r

T is Matrix / Transpose Vector

Figure 1 shows schematic overview of BSS model. We have considered six audio sources of different distributions, primarily sub-Gaussian and super-Gaussian using Multiuser kurtosis, Information maximization and Extended Information maximization algorithms (Comon & Rota, 2003) for the BSS. Here we have considered the number of source signals equal to the number of sensors. In earlier studies there were various algorithms already developed for BSS. In our model, we have taken the extended Infomax, one of the successful neural network based approaches in separating super-Gaussian signals, in addition to Infomax and multiuser kurtosis algorithm. Subsequently the cross-correlation coefficient and kurtosis were computed for performance measurement in-between the input data and output data.

The six sources $s_1\left(r\right), s_2\left(r\right), s_3\left(r\right), s_4\left(r\right), s_5\left(r\right), s_6\left(r\right)$ are mixed through a mixing matrix A, gives observed mixed signals $X_1\left(r\right), X_2\left(r\right), X_3\left(r\right), X_4\left(r\right), X_5\left(r\right), X_6\left(r\right)$ (Lee, Girolami, &