Blind Source Separation with Image De-Noising Using SVD Regularization

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HARMANDEEP SINGH SODHI

Roll No: 801563006

Under Supervision of

Dr. Amit Mishra

Assistant Professor, ECED

ELECTRONICS AND COMMUNICATION ENGINEERING DEPARTMENT

THAPAR UNIVERSITY

PATIALA-147004 (PUNJAB)

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DECLARATION

I, Harmandeep Singh Sodhi hereby declare that the work presented in this dissertation, entitled " **Blind Source Separation with Image De-Noising Using SVD Regularization,** " in partial fulfillment of the requirement for the award of degree of Master of Engineering in Wireless Communication Engineering, submitted at Electronics and Communication Department (ECED), Thapar University, Patiala, is an authentic record of work carried out under the supervision of **Dr. Amit Mishra** (Assistant Professor, ECED, Thapar University, Patiala) from July 2015 to July 2017 . The matter presented in this has not been submitted either in part or full to any other university or institute for the award of any other degree.

Harmandeep Singh Sodhi

Date: 17-07-2017

Harmandeep Singh Sodhi

801563006

It is certified that the above statement made by the student is correct to the best of my knowledge and belief.

Date: 17-07-2017

Dr. Amit Mishra

Assistant Professor
ECED
Thapar University, Patiala

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We cannot achieve anything in the field of technical education until or unless the theoretical education acquired in the classroom is effectively joined to its practical approach that is taking place in the research. Although an engineer can only be successful through hard work, but the contribution of his teachers and all those who have been helpful cannot get unnoticed.

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Harmandeep Singh Sodhi

801563006

ABSTRACT

The aim of this report is to provide a comprehensive overview of neural networks for blind source separation scheme along with mathematical foundation. Blind source separation (BSS) is scheme of separating source signals from a set of mixed signals without having any information or with very little information about the source signals or the mixing process. So BSS usually assumed that source signals count is known as priori. Typically it should be equivalent to the number of sensors and mixtures.

The analysis of BSS using neural networks which are separation rule with prewhitening, Global rule, Local Rule for detecting and extract the presence of the useful source signal from mixed signal, along with the different Kurtosis conditions are also explained. The method is proposed for separating the images from mixtures. The principle of proposed method includes BSS scheme followed by a SVD regularization procedure. The SVD has potential to smooth the source image through regularizations. The proposed scheme not only reduces the noise but enhance the quality of source images also.

The problem of less sensor count then sources are try to be address out in the simulated process, in which compression of data is done first in prewhitening stage then in separation stage where there are more mixtures then original images $t > r$, but the results are good in prewhitening than separation stage since compression in separation stage enhanced the noise. Also the redundancy elimination is describe for both noise free and noisy environment where sources are fever then mixtures then single layer global rule is applied. The performance of proposed scheme is compared with existing BSS schemes based on parameters such as PSNR, MSE, SSIM and EI.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

BSS	Blind Source Separation
DSP	Digital Signal Processing
ECG	Electrocardiography
EEG	Electroencephalography
EI	Error Index
HOS	Higher-Order Statistics
ICA	Independent Component Analysis
iid	Independent Identical Sources
MEG	Magnetoencephalography
MSE	Mean Square Error
NN	NEURAL NETWORK
PCA	Principle Component Analysis
PSNR	Peak Signal to Noise Ratio
SOS	Second-Order Statistics
SS	Source Separation
SSIM	Structural Similarity
SVD	Singular Value Decomposition

Chapter 1

Introduction

1.1 Preamble

Image processing is a type of method in which some operations has been performed on image in such as way that required useful information or quality of image has been enhanced as the resultant of the operations performed. This type of work comes under signal processing where an image is provided as an input, therefore after operations there might be image or the characteristics/features related with that image at the output [1]. Moreover, image processing is one of the rapidly flourishing technologies in the last few decades in many of the industries and develops as a vital research field in engineering and others area which include the biomedical, astronomy, agriculture, weather forecasting and imaging, telescopic images, military purposes and many more [2].

The image processing are mainly differentiated on two vast categories depending on their nature, first one is analogue and second one is digital image processing which is used by DSP. The first class of image processing, that is, Analogue mostly utilize in the field of hard copies, for example printouts and photographs. Many experts used most of the techniques which are related to image interpretation for improving the visual effects. The other technique is digital image processing, in which digital images are manipulated on computer. All type of digital images has to experience three familiar stages during digital processing and these are pre-processing of the image, enhancement and display, and required information extraction for different purposes [1].

In most of the situation while performing image processing such as in weather forecasting or medical imaging [3], the signal which is received is completed intermixed with noise, therefore the separation of these received signal required a whole new type of research which started a new area of blind separation, moreover the technique which is used for these kind of separation of different signals are called as blind source separation. Blind source separations is the approach which is used to separate out the signal which does not contain any priori information about all the source images, these images are mixed together and form a single signal [2]. So BSS developed the different means to separate out these mix signals. So the discussion on blind source separation is carried out in this and the subsequent chapters.

1.2 History

In the initial years of the 1980s new era of research and development has been initiated in the domain of BSS by Bernard A, Jeanny Hérault and Christian Jutten by modelling of the decoding movement in vertebrate's problem [4]. The influential progress in the domain of blind source separation has been achieved by Jutten, Herault and Guerin in the year 1988 [5] where they all suggested a new adaptive algorithm which is in the form of simple feedback architecture. The learning rule was established on a new approach, that is, neuromimetic approach and this is capable of separating unknown independent sources. The similar approach has been further explained and carried out by many researchers. For example: in 1991 both Jutten and Herault [6] and Comon [7] with their independent component analysis, Cichocki and Moszczynski in 1992 [8] with their synaptic weights learning algorithm and Karhunen and Joutsensalo in 1993 and so on.

Moreover, in the year 1994 Comon suggested the improved technique of independent component analysis in which the mutual information that was present between the sensors was reduced with the help of cost function. Afterwards, BSS also emerge into an unsupervised neural learning as a highly popular research topic. The different analysts who work on neural network, each one take the different path for solving the BSS problem, likewise information theory, negentropy maximization approach, maximum likelihood estimation [9], nonlinear generalizations of Hebbian/anti-Hebbian learning rules and many more [10]. Although many latest achievements in the area of neural BSS, however there was many open questions still present such as primary mixing model with their possible extensions only getting the narrow consideration so far [10]. Since, many BSS algorithms have been developed based on neural networks for blind separation over the period. In this section, some methods for blind source separation such as second-Order Blind Identification [11], Singular value decomposition [12], Joint Approximate Diagonalization [11] of Eigen-matrices, Fast Independent Component Analysis [11] has been explained below.

1.2.1 Methods used for BSS

The number of methods that are used for blind signal separation that are listed below:

i. Principle component analysis (PCA)

ii. Independent component analysis (ICA)

iii. Dependent component analysis (DCA)
iv. Second-Order Blind Identification (SOBI)
v. Joint Approximate Diagonalization of Eigen-matrices (JADE)
vi. Fast Independent Component Analysis (FastICA)

- **Principle component analysis (PCA)**

  PCA is also known as Karhunen-Loeve transformation. This technique is mostly used in signal processing for reducing data for statistical pattern recognition. It analyzes the data pattern and expresses the data in such a way that it highlights the similarities and differences [13].

- **Singular value decomposition (SVD)**

  SVD is used in linear algebra which factorizes the real or complex rectangular matrix into three unique matrices. SVD finds its application in digital image processing. Let M is an image matrix having size L_{XP} [12], Therefore, SVD will divide it into three unique matrices namely:

$$M = VDU^T \tag{1.1}$$

  Here, V and U denote orthogonal matrices [14].

- **Independent component analysis (ICA)**

  ICA is a technique used to recognize the independent component of a multivariate random variable. The components are directed in the direction in which the elements of the random variable are independent. A simple application of the ICA where multivariate random variable are suppose to be linear mixtures of unknown sources, and unknown mixing system where variable are mutually independent [2]. Independent component analysis is more capable than principal component analysis.

- **Dependent component analysis (DCA)**

  It is an extension of independent component analysis which is used in Blind source separation. In ICA, signal is separated from the mixed signal without knowing the source signal. Whereas, in dependent component analysis (DCA) signal is separated from the mixture into specific sets of signals which are dependent on other signals within own signal set without any information and knowing about the source signal. In particular situation where DCA acts as ICA when single same signal is present in all the sets [15].

- **SOBI (Second-Order Blind Identification**, Belouchrani and al. 1997) utilizes not one but many covariance matrices of the observations. After whitening the data, a joint diagonalization method criterion was used to estimate or approximate the mixing matrix [11].
- **JADE (Joint Approximate Diagonalization of Eigen-matrices**, Cardoso and Souloumiac 1993) presents the algebraic solution for maximizing the contrast, based on the fourth order cumulants [16].
- **FastICA (Fast Independent Component Analysis**, Hyvärinen and Oja 1997) it utilizes the principle of neguentropy by approximated the absolute value of kurtosis of the estimated source signal [11].

1.3 Introduction to BSS

Blind signal separation techniques are promising because it does not require any prior information on the geometry and array response of the signals in order to equalize the channels. Further they are more than capable under severe multi-path fading environmental conditions.

Blind source separation (BSS) is a technique where number of individual source signals is unknown to us, that is, why it is called blind. BSS is the technique use to separate the set of original signals from a set of mixed received signals, without having any information or with very little information about the original source signals or the mixing process. It is called blind because number of individual source images and signals, mixing process is not known to user at the receiver end.

Blind source separation can be utilize in various fields such as communication, speech and signal processing and many medical signal processing problems like EEG data, Magnetoencephalography (MEG) data [10].

Even with times different types of neural learning rules have been recommended for determining the BSS problem, moreover complementary architectures, networks and models are generally suppose that the information about the source signal count is known as priori [2].

Usually source signal count should be equivalent to the output signals or the number of sensors. Anyhow, in real situations, these theorizing assumptions are not always hold. The elementary objective of studying all the corresponding models and networks so to analyses the working of different network models for BSS, where usually the source signal count is not same from the output number count, however the number of sources is typically not known in the earlier stage. Moreover, in later chapters many distinct alternative solutions have been used for solving these problems.

A mathematical BSS model is shown in figure 1.

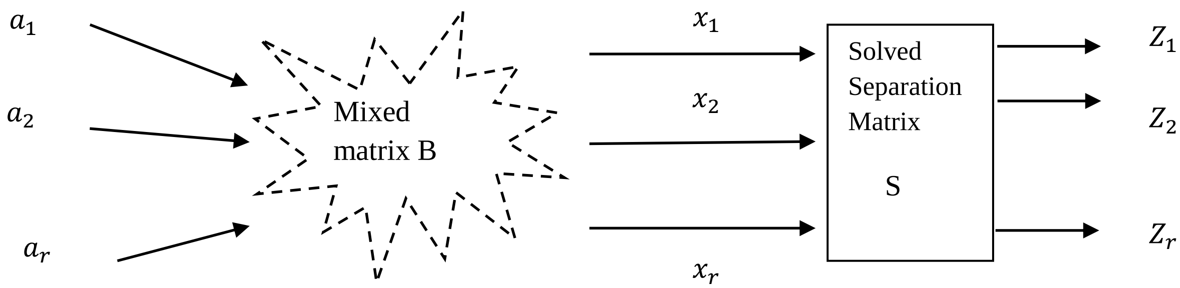

Figure 1.1 Blind Signal Separation model

Usually two different types of mixtures are described

- Instantaneous mixtures
- Convolutive mixtures

Instantaneous mixtures:- The mixing of the signals is instantaneous, related to the architecture model $Z = B.S$. The model where Z is a matrix which includes the recorded signals. The mixing matrix is represented by B and the independent signal sources are shown by the matrix S. Essentially this model is based on the condition that each recorded signal is a linear combination signal of the same sources. With the mixing matrix B, one should effortlessly capable of explaining the above model for S matrix which has the independent source signals by standard means. Although, in regular practical cases B and S are not known in general and there are countless number of feasible decompositions that are available for Z. However the general problem of BSS could be solved by taking a few mild assumptions regarding B and S.

Convolutive mixtures:-The mixtures in which the mixing is in the form of convolutive nature [2], i.e representation by the model is shown below

$$z_i(t) = \sum_j^m \sum_\tau^{M_{ij}-1} a_{ij}(\tau) s_j(t-\tau) + N_i(t) \qquad for\ i = 1 \ldots .r \qquad (1.2)$$

where $z_i(t)$ is the i^{th} source signal of the t^{th} sample, the number of sources is represented by r, the filter $a_{ij}(\tau)$ is linear which has the source impulse response that can handle the multi-input multi-output signals which illustrate the propagation of the signal. A noise source is described by N_i. The model of this nature is more difficult to explain than the above instantaneous one because of the $a_{ij}(\tau)$ filter term includes the thousands of coefficients [17].

Solving the instantaneous mixtures for blind source separation

- Various methods are available for tackling the problem of blind source separation for the mixtures of instantaneous type. Most admirable and famous one is second order statistics in which the method is simultaneously try to diagonalize a large amount of components of the cross-correlation matrices. Other approaches are independent component analysis that tries to find out the independent components, which are the source signals by using the higher order statistics [17].
- The particular decomposition problem $Z = B.S$ are given, the solution for this can be figure out only in the form of scaling and permutation of the components. Therefore this type of BSS is known as indeterminancy problem. This can be explain by considering the given permutation matrix P_1, described as a matrix that includes only zeros apart from one in each row and column, and other D is a diagonal scaling matrix, whichever scaling and permutation is performed on the independent components $S_n = (D.P_1).S$, then these operations can be counter by reversing scaling operation on the mixing matrix $B_n = B.(D.P)^{-1}$ for that reason $B.(D.P_1)^{-1}.(D.P_1).S = B.S = Z$ [17].

Solving the convolutive mixtures for blind source separation

- The resultant for the problem of convolutive mixtures is a lot harder to accomplish. The one will normally originate to solve the problem by firstly transforming it into the frequency domain, so that the convolution will change into the multiplication. Therefore, in the frequency domain, problem then divided into the different instantaneous mixing problem for each individual frequency. Afterwards, the indeterminacy problem again came up because initially it is not clear, how the system can evaluate the independent components for each distinct frequency [2].
- When neural models are utilized, then the learning algorithms are chosen in such a way that they provide the desirable result with sufficient performance but overall system will

remain simple as possible. Different types of neural algorithms are developed which performs the separation function. The performance of these algorithms usually counts on the stochastic properties of the original source signals. Moreover, one can measure these properties of the sources from the higher order statistics. However, the fourth-order cumulant [18] is the most useful one [17].

1.3.1 Application of BSS

1) One of the most promising and acknowledging utilization of blind signal processing involves the biomedical signal processing like evoked potentials, Electrocardiography (ECG) [19] for heart, electromyography (EMG), EEG and magnetoencephalography (MEG) are both for brain activity. But also include
    - ECG also be used for fetal extraction, which means that the electrocardiogram signal and noise signal from maternal are removed and filter out from fetal electrocardiogram signals.
    - Used to distinguish the original heart signals residue from the transplanted heart signal.
    - Reduction and removal of noise from the recording of electroencephalographic and magnetoencephalographic signals [20].
    - ECG components which are of the low-level should be improved by BSS.
2) BSS is used for analyzing and information extraction from the multispectral astronomical images that are gathered by the telescope.
3) Also utilize in the field of speech processing where main task is to detect single signal from the bunch of mixed signals like in cocktail party problems [2].
4) In the field of radio and wireless communication many systems depends upon the BSS signal separation like digital radio which utilizes the diversity, radio link where both channels are polarized, high speed digital subscriber lines, multi-track magnetic recording on digital format, sonar and radar systems with multiple sensors array.
5) In radio and wireless communications the observed signals are taken from the antenna array at the output, thus the different elements experiences the effects of mutual couplings which are generated as a response as signal is transmitted by many antennas, therefore BSS is used.
6) The polarized multiplexing are used in microwave links which suffers from the difficulty of preserving the orthogonality among polarized multiplexing which is the most challenging part, but to separate the incoming transmissions still required the BSS.

7) The radar technology experiences the overlapping of signals that are coming from different targets that are present at the same place thus the observation of modulated signals required special algorithms and receivers those are responsive to different polarizations.
8) Blind deconvolution of multiple channels is come into existence where the lungs sound is removed from the heart beat sound.
9) Improvement in the evoked potentials (EP) by sorting out brain signals. The stimulation of the sensory like the visual and somatosensory or acoustic are predominantly evoked the brain potential are known as evoked potentials [3].
10) Sleep-spindles are firstly detected and then evaluated for possible solutions. They are defining as the particular phenomena of electroencephalograms (ECG) that occurs during sleep, these spindles are identifies from the batch of oscillation which are in the frequency range of 11.5-15 Hz.
11) Disintegration of images that are collected from brain source imaging as the independent components, then localizing and representing these images in time and space [20].

1.4 Modelling of blind source separation

The blind source separation has a key responsibility of finding the waveforms, that is, source signals $a_i(t)$ which are initially assume as r sources, only the information about the mixture signal $z_j(t)$ is pre-known and the number of sources r is assumed and generally equal to the sensors count and the process of BSS is explain in the figure 1.2.

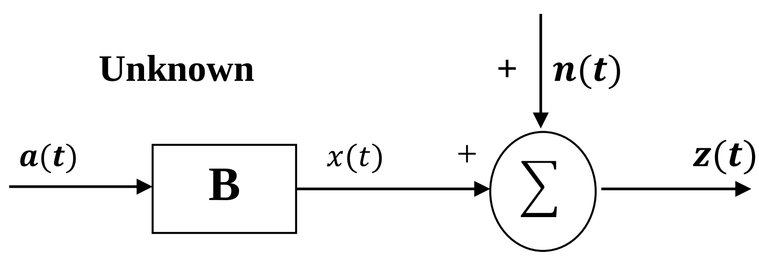

Figure 1.2 Block diagram of BSS [10]

- The Blind signal separation can be represented though the mixing model where data is mixed and it can be shown in the form of vector. General equation for BSS is shown below [19].

$$z(t) = Ba(t) + n(t) = \sum_{i=1}^{r} a_i(t) b_i + n(t) \tag{1.3}$$

- Here, the $z(t) = [z_1(t) \dots \dots z_t(t)]^T$, is formed from the mixture, typically $(q > r)$ where q is for sensor count and r is for source count has the n-dimensional t^{th} data vector that has discrete index value at unique time t.

- A full-rank $q \times r$ constant mixing matrix $B = [b_i \dots .. b_m]$, where the elements of this matrix are coefficients of the mixtures which are unknown.

- This model supposes that there are r zero mean source signals which represented as $a_1(t) \dots \dots . a_m(t)$ and has a scalar value and these are mutually statistically independent on every time instant.

- Additive noise is shown by $n(t)$.

In BSS, different situation are there for finding the output images as follows:

i. When number of sources = sensors mixtures $(r = t)$

   When this condition occur the complexity of finding the output images is less.

ii. When sources ≠ sensors then the complexity is more.

   a) If $t > r$ means that over determination, when mixtures are greater than sources, the quality of output image is worse when it is compared with the case when sources and sensors are equal $(r = t)$.

   b) If $t < r$ means under determination where sources are higher than mixture count number, does not enclosed sufficient information for source separation, therefore source determination is most tricky in this case then $t > r$.

The different type of source separation algorithms are exists, but the principle of all the algorithms can be compile into the four approaches that are illustrate below (see figure.1.3):

- In first approach, the more universally used approach is accomplished via the cost function and non-Gaussianity by describing the independence of signals from each other or sparseness. The original sources or images are hypothesized that they are statistically independent without using the temporal structure, the crucial part of solving the BSS is the HOS for the implicitly or explicitly problem. Therefore, in these cases, only one Gaussian source is allowed by the scheme.

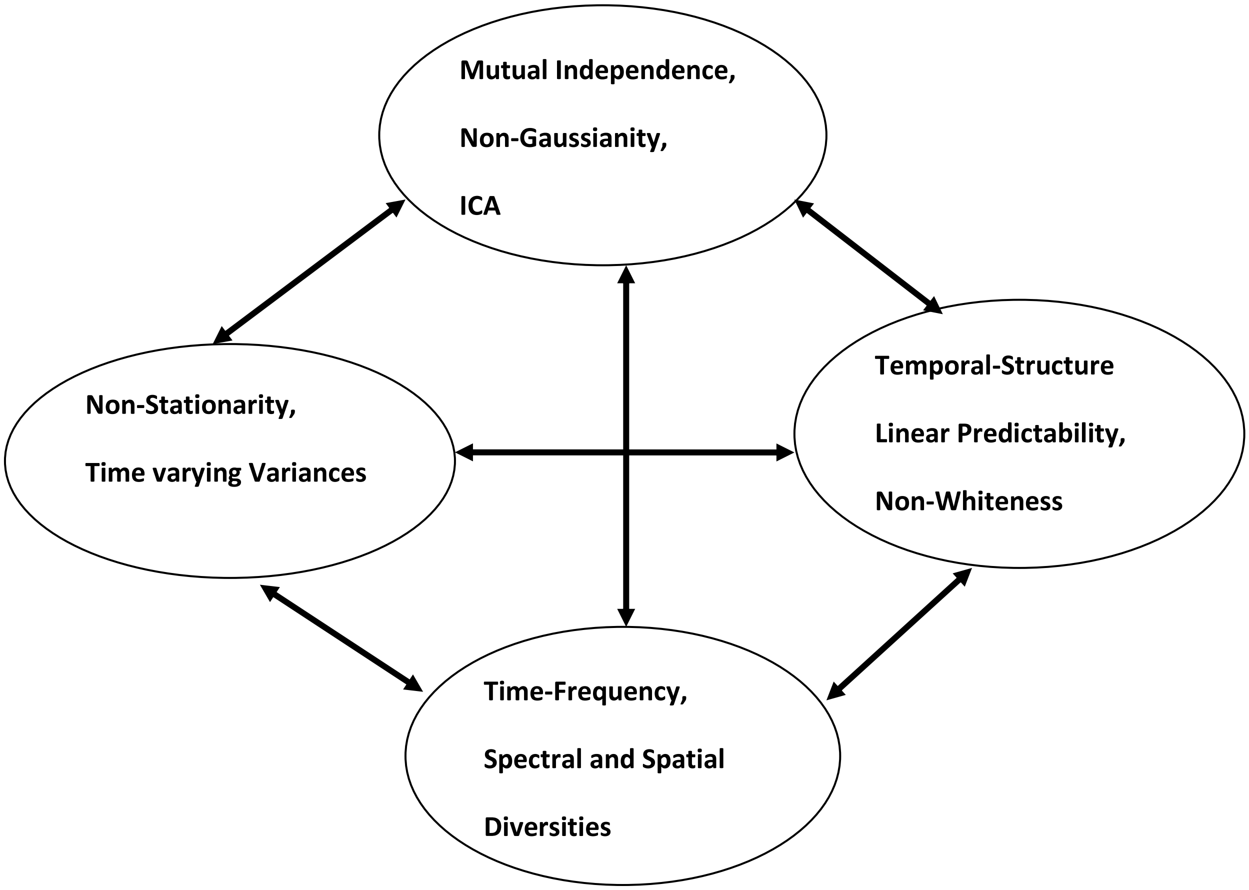

Figure 1.3 The flow diagram explains the basic blind source separation approaches along with priori information [20].

- In second approach, if the temporal structures are present in the sources, then circumstances are raised where temporal correlation are non-vanishing for every source, thereby, instead of using statistical independence less restrictive conditions are taken into consideration, specifically, for estimating the source signals with their mixing matrix then the second-order statistics (SOS) is enough. By the side of above, many different schemes are developed because the existing SOS scheme is unable to perform the separation of different sources which has the identical power spectra or have the independent and identical distributed sources, that is, i.i.d.
- In the third approach, second order statistics and nonstationarity properties are taken into the account. Primarily, the main objective of this is to acknowledge the second-order nonstationarity in such sense where the variances of sources vary in time. Matsuoka was the first who establish the nonstationarity and consider it into a BSS and it further explain

that the nonstationarity and plain decorrelation technique is suited for the blind separation task. The nonstationarity methods can also be employs on colored Gaussian sources and it can exact information even with the identical power spectra shapes, in contrast these are not available in other approaches.

Moreover, the source separation is not employs if the sources have identical nonstationarity properties. Therefore, some works is currently undergone on nonstationary source separation.

- In fourth approach, illustrates the several types of signals diversities, mostly in contrast with time diversity, frequency diversity or time-frequency diversities or finally more important is joint space-time-frequency diversity [20].

1.4.1 Extraction of sources from the mixture

- Pre-whitening and separation

Firstly, for the source extraction different algorithms are present. So initially the prewhitening and separation method is used. In whitening equation, essential condition is covariance matrix $E\{y(t)y(t)^T\} = 1$ and in separation $\tilde{S}\tilde{S}^T = I_m$ needs to be satisfied. Then the resultant is in the form of separated sources that are orthogonal in nature but original sources must have the non-zero mean. Sometimes this is also known as two layer rule.

- Global rule and multi layer local rule

This rule does not utilize the two layer approach which means pre whitening layer is missing. Here the mixture is directly undergone for separation where learning rule decides the weight of the separating matrix and provides the separated sources. But the global rule is single layer rule and local rule also be used as a single layer. The necessary condition for them is $E[f[z(t)]g[z^T(t)] = I$ and the kurtosis is used for the selection of activation function.

All these rule can be explain in detail in the chapter 3 where the application of prewhitening and separation is compression of data and global rule is for redundancy reduction with post processing layer are also illustrated and SVD is also discussed, which has many applications in digital image like image compression and noise reduction, but in this SVD is used for noise reduction which is applied to any real matrix.

1.4.2 Performance Evaluation

The performance of the separation techniques is determined based on parameters such as the PSNR (peak signal to noise ratio), mean square error (MSE) and SSIM (structural similarity). But the PSNR is less useful to the human eye perception therefore SSIM is also used. Finally error index (EI) is calculated as performance measure. Each neural learning rule provides different values of performance parameters and these results are compared with the proposed neural Singular value decomposition (SVD) method.

1.5 Organization of the Dissertation

The dissertation is sorted out in chapter formation as discussed below:

Chapter 2: Literature Review, A comprehensive study on different schemes and techniques available in literature are discussed. The historical background of blind source separation and contribution of eminent researchers in this blind field is also mentioned. The research gaps are identified and objectives of this dissertation are also included.

Chapter 3: Blind Source Separation based on Neural Networks, The various neural learning rules are explained along with methodology and various performance parameters are discussed. The proposed BSS scheme is also explained in detailed for comparative study.

Chapter 4: Results and Discussions, The simulation results of proposed scheme along with various neural methods are compared based on performance parameters such as MSE, PSNR, SSIM and EI.

Chapter 5: Conclusion and Future scope, the work done is summarized in this chapter, based upon the observations received, future scope is also discussed.

CHAPTER 2

Literature Survey

2.1 Introduction

In this chapter, different architecture, schemes and methods are discussed that had been developed by various researchers over the period of time. These several methods bring the interior knowledge for easy understanding of blind signal separation with learning neural networks and the assumption made for solving the BSS with neural. This survey provides ample emphasis on BSS problem thus provides the objective for the dissertation and gaps are analyzed from literature.

2.2 Literature Review

Cao *et al.* [21] in 1996 identifies and analyze the two major effects that are present in the blind signal separation problem are separability and separation principles. This paper describes that the inherent property of the calculated sources is separability and that could be portray by the approach of m-row decomposability. The discussion was made on building the separating principles by employing the structure characterization explained by theory of random variables. The especially, above principles should be carried out ostensibly and concisely by exercising the Darmois Skitovich theorem that is well taught theory in statistical inference and psychology. The few new progresses are also made for designing and making the BSS filters.

Puntonet *et al.* [22] in 1996 in this paper new approach had been presented for blind separation having mixed signals depending upon the source is digital or analog, that lies on the geometrical consideration in the observation space. By taking p mixed source signals, where p should be larger, or equivalent to two, the presented method suggest that the p- dimensional hyperparallelepiped is created in the observation space, and by the use of a neural network, with weights w, that helps in confronting the p vectors by considering its coordinates correlated to the image in the source space that contains a orthogonal inputs. The position of the coordinates grants the information of unknown mixture matrix, with the a_{ij} elements then neural network regressively used to separate out sources which that are unknown. So these geometrical process do not required the computational need for all order of statistics, instead primitives method can be used because that may effectively implemented by equipment hardware and the polynomial complication completely relies upon the quantity of sources *(p).*

Karhunen *et al.* [19] in 1997 in this blind source separation, main attempt is to separate out the unknown sources with statistically independence, without the information and knowledge about the mixing coefficients. These techniques were firmly studied out in both the areas like in unsupervised neural algorithms and statistical signal processing. This paper uses the neural learning as a blind separation technique which is refined in the laboratory to distinguish out the features from the images that are natural in type and also to separate the signals from medical EEG. This new evaluated method provides the features that interpret the hidden data better than principal component analysis which is a classical method. This paper also briefly discusses the challenges related to the real-life applications of blind source processing.

Cichocki *et al.* [10] in 1999 Blind source separation issue gets a lot of concentration for using unsupervised neural rules. In the usual scenario, the count of sources is supposed that they are known in advance, but in practical situations this is generally not hold. This paper illustrate, many neural network algorithms and their architectures coupled with adaptive learning techniques are described for leading the situations where the signals counts are not known. So these techniques constitute to predict the number of sources, elimination of redundancy from the output signals, and to extract only single source at every interval of time. Validity of the narrated approach in this paper is established by the computer results which are taken from simulations of natural image and magneto-encephalographic (MEG) images.

Woo *et al.* [23] in 2002 a latest method is unearthed in which the blind separation for instantaneous signals by utilizing the general neural network based demixer scheme from nonlinear mixtures. The nonlinear demixer model directly drives from general mixer model. In the first portion of the paper describe a general mixer model which constitutes linear mixtures as a unique case. In the next portion, the outline for the demixer model based upon the feed forward multilayer perceptron (FMLP) which work as a continuous differentiable nonlinear function. As in depth explanation for the learning algorithm with adaptive demixer parameters are shown in this paper. The cost functions which are employed entirely constitute from two things, one is minimum mutual information (MMI) and other one is maximum entropy (ME). The efficiency of the new method was studied using different experiments carried out using real-time data on general mixer model. This study explains the generality and the superiority of the new method than the existing old methods.

.**Chevalier** *et al.* [11] in 2004 after decades of research various blind separation methods based on Second Order (SO) and Fourth Order (FO) are developed to separate out different Narrow- band (NB) sources which are statistically independent. Further, there are some problems in these methods so new Sixth Order methods have been cultivated, despite of these great methods. The performance parameter is still unidentified for these arbitrary electromagnetic sources that limit their operational use. The main objective of this paper is to quietly cover the gap that are discussed by giving the relative performance comparison for the eight Blind Source Separation (BSS) technique for the arbitrary source mixtures signals which are lent from the radio communications context, and by showing off the advantages and disadvantages of these different methods.

Hirayama *et al.* [24] in 2007 ICA was a most accepted and used technique for blind source separation (BSS). In BSS the actual issue is that the mixing processes is not known but have to recover the unknown signal sources from the mixtures of signals. Various ICA methods consider a fixed number of sources persistently present in mixtures throughout the operation for which the original signal has to be examined. Moreover, in actual-world scenario signals occurs where a single source signal rapidly shows then disappears, so such nonstationarity difficulty are present. Thus the group of active source signals are dynamically shifted with time period. This paper recommended the switching ICA algorithm, which emphasis the attention on this situational cluster. The approach which is proposed is dependent on the noisy ICA, thus this formulate a generative model. This paper applies a unique kind of hidden Markov model (HMM) to symbolize and solve the prior knowledge problem where the sources might be appear then disappear suddenly with time. This special HMM model thus provides a special selection technique in which variables are selected in a dynamic way. For this model, the variational Bayes (VB) method is employs to derive and approximately calculated the effective Bayesian inference for this method. The artificial and realistic source signals are employed in the experiments during simulation, the existing methods comes out to be less superior then the proposed method, particularly when the noise exists. The natural-gradient ICA along the nonholonomic constraint are consider for the comparison, with the existing ICA method associate with an HMM source model then nonstationarities in source signals may exist which is the main aim to deal with them. In extensions to the proposed method, even the true total number of source signals was over evaluated or was taken more than mixtures then the source signals are effectively decoded. This paper also suggests the improvements in the original Markov model into a semi-Markov model, and draw that the semi-Markov model is extra impressive effective estimation method.

Vrins *et al.* [25] in 2007 even there are various techniques that exist for determining the problem of the independent component analysis (ICA), but there is still a scope of introducing new approach, along with other reasons, especially when a priori knowledge is utilized to increase the separation performances. This paper lies on investigating the blind extraction of sources which are bounded with the minimum-range approach. The relation has been established with other well-known criteria that are existed. It presents the proof that this new minimum-range technique is a contrast, and this norm is discriminant in such a way that it does not depend on spurious maxima. The real challenges are also explained, and new estimation method on the basis of order statistics is designed which is range measure estimation. The technique has a particular aims of maximizing the contrast over the orthogonal group of matrices. The simulated results demonstrate the efficiency of the technique which utilizes the proposed range estimation criterion over existing techniques.

Suna *et al.* [26] in 2008 this paper deals with the complicated BSS problem of having unknown and dynamic number of sources. In the past most of the BSS techniques and algorithms habituate the condition when the count of source signals are believe to be given in prior, because dimensions of the algorithm are hypothesize around this critical information. Furthermore, these hypothesize information will not held in several advanced applications. Therefore, this paper suggests an adaptive neural algorithm (ANA) which is operates and design in a manner in which mechanism is adjustable to counter the different BSS problems. The first part is on-line estimator uses the cross-validation technique for recovering the source numbers. The other part is neural network with adaptive structure which joins the feed-forward model with the self-coordinated criterion. The last work is to alter the rate of learning for maximizing the performance efficiency of the learning rate. The validity of proposed model with its performance quality is illustrated by simulations on the computers and compared with others high end models. The computer results established that the proposed ANA is better and more viable for dynamic BSS than static BSS.

Ying Sun *et al.* [27] in 2008 this paper targeted the problem of unknown number of sources from blind source separation, which is the case typically hypothesized in several practical scenarios. Various over-driven neural models where less sources n then sensors m would be suggested to solve the problems related to this scenario however to avoid the divergence the separation efficiency is habitually neglected. The natural gradient for estimating the sources is generally applied for $m = n$ descent only. Moreover, for getting better in this problem the proposed neural network with the feed-forward algorithm utilizes the auto-trimming model. The network starts the process of learning by utilizing the two step mechanism for each of the iteration. Initially, stability discriminant function is vital for predicting the number of sources. Further, the redundant nodes are slowly trimmed by the neural network by using an instant estimation. In proposed approach the quality and performance validation are determined by the signals that are artificially synthesized from computer simulations.

Hui *et al.* [28] in 2010 the numerous blind source separation (BSS) algorithms compromise to the fact that the source count is known, that is the assumption. This paper proposes the algorithm with online robust technique for dynamic and unknown source numbers. Until this time architecture depend upon over-determined of larger sensor count than sources. SVD estimator is used for assessing the source count number, after that new momentum term is introduce into the conventional Cichocki-Unbenauen algorithm for the improvement such that independence is maintain at the output however it also keeps the separation results for falling towards the local minimization. In addition to this a learning step which is changeable and moving, boost the separation performance. After comparison with classical method, proposed new ANA method, having more efficiency with lower steady-state error on computer simulations with higher convergence speed.

Li *et al.* [29] in 2011 progress is made in quality assessment (QA) method with no-reference image by setting up the GRNN a general regression neural network. The new assessment technique is lucratively valuating the quality of image with precision to human subjection. The parallel features that are required for QA are calculated by the distorted image gradient, phase congruency image entropy and mean value, and distorted image's entropy. The functional association is established between the above reference features and mean opinion based scores that are achieved through a GRNN algorithm for image estimation. The experimental outcome for this method is very much allied to human subjective judgment.

Oda *et al.* [30] in 2014 This paper illustrating the restoring challenge in duplex scanned documents for protecting the inside printed or handwritten content of documents which cause the back side intrusive show-through effect. So this is a separating problem of nonlinear type. The previous solution for this effect is a linear-quadratic mixing model. A show-through for gray scale printing cancellation model is proposed. The proposed approach works as a bidirectional two-layer neural network act as stochastic network which changes the gray scale image into binary before simulating the procedure of linear-quadratic mixing. However the suppression of blurring phenomena is the additional advantage of neural network by just tweaking the probability density function. Therefore duplex images reveal minimum show-through effects due to the bidirectional two-layer neural network. Further in some other experiments it is helpful as linear-quadratic mixing model. Thus, the validity of the proposed approach for reducing the show-through effect and blurring phenomenon is confirmed by experimental results.

Kulchandani *et al.* [2] in 2014, typical problem of blind source separation is that where assumptions about prior and mixing methodology are made for retrieving the sources from mixture of signals that are practically unknown to us. The extensively used technique for BSS is independent component analysis (ICA) in which signal or sources are allow to separate from complex mixture of signals by taking few statistical assumptions. The author of this paper presents the ICA by explaining its basic concepts. Further provides the survey for different ICA methods. After that, it outlines the merits and demerits for various ICA techniques. At last, a short portrayal about ICA latest application is explained.

Berg *et al.* [13] in 2005 this paper for blind source separation (BSS) inspect and explore the combining effect of both principle component analysis (PCA) and independent component analysis (ICA). For competing in the real-time scenarios recursive PCA method is applied, furthermore, adapted on-line version of information maximization principle is also utilized. The first problem of dimensions is reduced by combined PCA-ICA algorithm followed by the separation of sources. The assessment of the new combined algorithm displays finer noise suppression proficiency then the individual PCA or ICA. The insignificant distortion is carried out by the proposed algorithm.

Zarzoso *et al.* [31] in 1998 this paper urged that a simple distribution of the random variable from the Bernoulli is manipulated in such a way that the probability of the two events illustrates all feasible normalised kurtosis values. This distribution is answerable for all the outcomes from normalised kurtosis, therefore such a frame work is significant for blind source separation which is lies on fourth-order cumulants, that is, normalised kurtosis.

Takore *et al.* [14] in 2016 a watermarking method is proposed for blind imaging which merges the discrete wavelet transform (DWT), singular value decomposition (SVD) and discrete cosine transform (DCT). The number one, host source image is engaged with DWT technique using a Haar wavelet then the approximation is used for selecting the sub band of LL which divide the image into two sub images. The 8×8 block size for DCT and SVD are required to operate on both sub images. The watermark image which is in binary is rated by the pixel values and sub image of singular value is rectifying by taking another sub image as reference. Genetic algorithm (GA) method is used because to optimize superiority of image in form of vision by the means of PSNR, robustness and imperceptibility by Normalized Cross correlation (NCC) of watermarked image. Experimented simulation outcome authenticate that this method is more prone to different degrading parameters, such as noise and compression in JPEG, gamma correction, bit plane removal, image enhancement and cropping effect.

Cao *et al*. [12] in 2006 this paper presented the work on image processing in digital form by applying linear algebra equation on SVD. The digital image and its processing are generally processed by considering two areas for testing that are compression of the digital image and recognition of faces. The functioning of SVD that convert the only matrix of digital image into three different USV matrixes. Therefore, this set of representation provides the opportunity to showcase the images into smaller matrixes which obligate less memory space by protect the deterioration of different image features, so lesser space helps to achieve compression. The simulation is performed with different singular values for evaluating the compression and quality measurement. Moreover, faces that are known are serving as database for face detection approach using SVD. After retrieving the faces, images are evaluated with original base images for comparison.

Zhang *et al.* [32] in 2015 this paper illustrates the BSS with its problem. This also evaluates the different condition by considering different mathematic models and algorithms. Also demonstrate the uncertainties that encounter while solving the BSS. However EFFICA is more effective than ICA so it is validated to use it for data processing. The major utilization of EFFICA is in the area of data processing where both gravity and magnetic handling is done, which is verified by experimental results. Further ICA is used for denoising and weak signal extraction than traditional methods.

Caiafa *et al.* [15] in 2006 in this work, hyperspectral image for remote sensing is presented for assessing the material per image pixel. The orthodox method of unmixing that is spectral unmixing techniques is only work if existing material information is available with their spectra. The difficulty rises when no prior knowledge then independent component analysis is not worthy because it depend on material information in real data. For this reason maxNG technique is proposed for highly dependent signal to be separated. Then minimum-mean-squared-error was exploiting the constraint on sources for predicting the unknown scale factors. The synthetic image that is generated in which noise is mixed with real image or real data which is taken from image spectrometer. Then results shows that proposed technique is successful in end member separation only if variation in spectral condition and noise is low then linear mixing model for separation is valid.

Amari *et al.* [33] in 1996 the main shortcoming of the ordinary gradient is that it was unable to describe its steepest direction when function is evaluated but natural gradient does and this is measured by information theory by utilizing the parameter space of perceptron for determining the blind source separation and deconvolution. The behavior is investigated and is confirmed by Fisher efficiency for presenting the equivalent performance. Therefore plateau phenomenon for backpropagation learning algorithm would be vanishes or become less serious in the presence of natural gradient.

Cichocki *et al.* [34] in 1996 in this paper multi layer method with neural learning techniques is developed for BSS which is robust, fast and suitable for real-time implementations. The initial source signals or images acquired any non-Gaussian distribution such as sub-Gaussian or super-Gaussian. Also used for separating the weak sources from ill-conditioned mixing matrixes. The computer experiment verifies the performance of the suggested technique.

Abbadi *et al.* [35] in 2015 this paper discusses the concept of denoising the image by using singular value decomposition filtering which work well on gray images. The noise is completely a random variation in image so SVD filtering is used somehow unable to remove noise in colored image. The new method is proposed by combining with total least square value with SVD. This gives better results on comparing with other methods and it uses Salt and pepper and Speckle as noise.

2.3 Gaps, Presumption and Observation in BSS

Blind source separation is different and noteworthy from different countless source separation (SS) techniques where BSS demands lesser assumption like on sources and process of mixing.

- The major constraint in many neural networks for BSS algorithms and their architecture is that the number of source signals count is available in advance. In general, it must be equivalent to the number of sensors and output signals.

- The sources are deliberately considered thought out to be statistically independent or close to independent.
- The matrix which are form by mixing must be invertible

Moreover, in practice these assumptions are not frequently embrace. However the number of sources more or less is not match with the number of outputs and in general the number of source count is typically unknown [36].

- In addition the typical assumption that further taken in BSS is the noise signal has been represented by a Gaussian distribution but in general no source signal is of Gaussian nature. The source signals $a_i(t)$ are assume to have a Gaussian distribution for the simplification of the problem. But these assumptions fail in real life where it is unfeasible to distinguish different Gaussian sources from one another [10].
- The neural gradient rules which estimates and separate one source at single time interval and sources are drawn out in the order of somewhat arbitrary manner depending sorely on their initial values. Therefore, the sources which are separated usually in the initial or first stage are typically the most powerful ones and bound them for applying these rules to high-dimensional problems.
- The system becomes noise model if they are having less sensors count than source signals [36].

2.4 Objectives

The primary aspiration of using a neural realization for the sake it is advisable to prefer the algorithms on neural learning since these are most simple ones but yet capable of providing effective performance. When the neural networks are used to solve the problem of blind separation as the complexity of neural methods is less, thus reduces the works.

- It is likely chosen that sources are not Gaussian as it is link to the signal independence and complexity rises as practically the Gaussian sources are hard to separate as sum of these random variable signals are also Gaussian signal but this can be undermine assumption as common sources of interest are not the Gaussian ones.
- If source signals $a_i(t)$ are Gaussian, then kurtosis the fourth order cumulant is calculated. The cumulant is comes as negative then source signals are generally known as sub-Gaussian. The probability distribution of sub-Gaussian signals is flatter in comparison to the typical Gaussian distribution.

The subsequently, the positive cumulant which are positive kurtosis are represented as super-Gaussian sources, with probability distribution has sharper peak with longer tail then the Gaussian distribution.

- The system model works on by assuming more sensors than sources thus extend algorithm to discuss this problem
- The SVD regularization is used for denoising the images.

The statistical independence presumption is utilized to extract the independent source components $z_i(t)$ from the observations $y(t)$. Then the invertible assumption is straightforward if mixing matrix is not an invertible matrix then the unmixing matrix is unable to exist.

2.5 Chapter Summary

In this chapter, various blind source separation techniques have been review and studied. The blind source separation is carried out with different methods like maximum likelihood, PCA, ICA, DCA, SVD and neural learning algorithms. The different mixtures used in BSS are instantaneous and convolutive mixtures. The feedback architecture is proposed in different papers which are applied by learning algorithms. In BSS none of the information is available about the source signal count or mixing process in practical scenario. The different challenges in BSS are illustrated along with the presumption in BSS problem. The estimation of the sources from mixture is possible by taking some trivial ambiguities. Thus in this problem of blind source separation assumption are not restrictive in nature as a result even the minute information of the sources and mixing process are adequate for finding the output images and sources. The neural techniques like pre whitening, global and local rule, and there implementation that are discuss in subsequent chapters.

CHAPTER 3

Blind Source Separation based on Neural Networks

3.1 Methods to solve BSS

The French scholars Herault and Jutten, in April 1984 developed the method of recurrent neural network with learning algorithms which is based on Hebbian learning rule by implement the blind source separation of two sources [10]. Due to greater application potential this immediately induced the attention of other researchers, thereby opening the new era of research has been started in the area of signal processing, specifically in blind source separation.

After numerous years of research and development, significant progress has been made in blind source separation, both in theoretical basic and actual practical applications. Instantly, in blind source separation algorithm, a theory system was developed based on information entropy or likelihood estimation as the basic building block, the core root is the independent component analysis, and non-negative matrix decomposition, sparse components analysis and other emerging algorithms [20]. Moreover, blind source separation has been successfully deployed in many areas of research applications such as in signal, image, and voice processing [36].

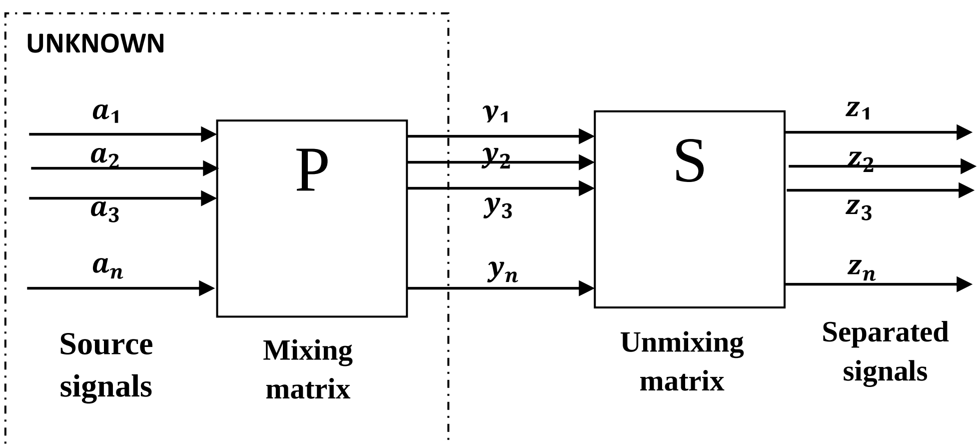

Figure 3.1 Block diagram of BSS source signals a_i, estimated signals z_i, P mixing matrix and S un-mixing matrix.

3.1.1 Types of Approaches for Blind Source Separation

1. Information-theoretic Approach [20]
2. Maximum Likelihood Approach [9]
3. Neural Network approach [20]

3.1.2 Popular schemes for Blind Source Separation

- ICA (Independent Component Analysis): Mostly used to separate BSS sources [2].
- Principle component analyses (PCA) analyzes the data pattern that express the data to a point which highlights the similarities and differences [13].
- Dependent component analysis (DCA): It is an extension of independent component analysis which is used in Blind source separation [14].
- SOBI (Second-Order Blind Identification, Belouchrani and al. 1997) utilizes not one but many covariance matrices for the observations. After whitening the data, a joint diagonalization method criterion was used to estimate or approximate the mixing matrix [11].
- JADE (Joint Approximate Diagonalization of Eigen-matrices, Cardoso and Souloumiac 1993) presents the algebraic solution for maximizing the contrast, based on the fourth order cumulants [16].
- FastICA (Fast Independent Component Analysis, Hyvärinen and Oja 1997) it utilizes the principle of neguentropy by approximated the absolute value of kurtosis of the estimated source signal [11].

3.2 Methodology

A primary advantage of novel learning methods is that it can be accomplished in a straightforward manner. The sources are of zero mean signals which are scaled to -1 to 1, are mixed by using neural learning rules to form a mixture which can be separated out using separation rule with prewhitening, global rule separation with single layer or local rule of separation with multi layer structure [10]. In prewhitening, separation mixture is separated out using prewhitening learning rule with condition that the covariance matrix is convergence into a unitary matrix, and then separation rule is applied. It is a simple straightforward one-layer modification in standard symmetric PCA network that grant us comparatively simple (elementary) neural implementation. The mathematical analyzes of the separation properties have been explain in paper [10]. The Nonlinear PCA rule which is used for separation is relevant to various other ICA and BSS schemes along with their contrast functions. Therefore faster convergence has been provided by this method than the stochastic gradient method at the price of considerably higher computational complexity and load.

The aim to find out the initial signals using neural algorithm known as unmixing which provides the signals that are statistically independent signals. The second method is global rule which perform unmixing of sources without prewhitening because prewhitening suffers fewer limitations that are explain in later section. This rule has single layer unmixing mechanism which implies learning rule by the mean of activation function which depends on the fourth order cumulant that is kurtosis. This counters the higher order statistics so that separation quality improves which approximately leads towards statically independence. Then local rule performs the unmixing of sources with its learning rule that are discus in subsequent section. These are the three unmixing methods that separate the images then SVD regularization is applied for noise reduction. SVD noise reduction is applied for each of the method for improving the image quality, as SVD has the property of suppressing the lower singular values [35]. But these rules are first applied when sensor count is equivalent to source count number $r = t$. Further for compression of data and elimination of redundancy signals count is less for mixtures $t > r$, these all are shown in the result section.

3.2.1 Performance Parameters

- **Kurtosis**

The performance matrix is dependent on the stochastic properties of the source signals. The higher order statistics (cumulants) can be used to determine stochastic properties of the source signal [10]. Exclusively, useful in higher order that is a fourth-order cumulant commonly known as the kurtosis [20].

The normalized kurtosis $(\widehat{k_4})$ is denoted by the following equation, for the i^{th} source signal $(a_i(t))$ is

$$\widehat{k_4}[a_i(t)] = \frac{E\{a_i(t)^4\}}{E^2\{a_i(t)^2\}} - 3 \tag{3.1}$$

The sign value of the normalized kurtosis is used for the selection of the nonlinearity as activation function of source signals. If $a_i(t)$ is assume as Gaussian, then sign value of the kurtosis is zero ($\widehat{k_4}[a_i(t)]$ =0) [20].

The source signals whose kurtosis has a negative value are known as sub-Gaussian ones and has a flatter probability distribution with respect to Gaussian distribution. Moreover, the super-Gaussian source has a positive kurtosis value and having a probability distribution with a longer tail and steeper peak in comparison with the Gaussian distribution [10].

If kurtosis is expected to have a negative value for the source signals then, signals are sub-Gaussian and the activation functions $f(z_i)$ or $g(z_i)$ are chosen from below equation for algorithm which is used in separation, global and local rule.

$$f(z_i) = z_j^3 \text{ and } g(z_i) = z_j \tag{3.2}$$

or

$$f(z_i) = z_j^3 \text{ and } g(z_i) = \tanh(\alpha z_j) \tag{3.3}$$

Subsequently, sources has positive kurtosis value then they are super-Gaussian signals, the activation functions ($f(z_i)$ or $g(z_i)$) is chosen from

$$f(z_i) = \tanh(\alpha z_j) \text{ and } g(z_i) = z_j \tag{3.4}$$

or

$$f(z_i) = \tanh(\alpha z_j) \text{ and } g(z_i) = z_j^3 \tag{3.5}$$

For getting successful separation, activation function $g_i(z_i) = \tanh(\alpha z_j)$ for sub-Gaussian sources and $g_i(z_i) = z_j^3$ for super Gaussian sources [10].

- **Error Index (EI)**

For the separated sources, average error index EI should be calculated, and this parameter is defined by the following equation

$$EI = \frac{1}{r}\left[\sum_{m=1}^{t}\left(\sum_{n=1}^{r}\frac{|p_{mn}|^2}{\max_{\mathrm{m}}|p_{mn}|^2} - 1\right)\right] + \frac{1}{t}\left[\sum_{n=1}^{r}\left(\sum_{m=1}^{t}\frac{|p_{mn}|^2}{\max_{\mathrm{n}}|p_{mn}|^2} - 1\right)\right] \tag{3.6}$$

The error index equation has two parts and denoted by EI. The first part of equation provides the information about the output signal errors which is averaged over the number of sources [10].

The additional penalty will be added by those sources which appear couple of times in the output set by the second part of the equation.

This additional penalty is averaged over all the outputs. The necessary condition for calculating the additional penalty is estimated by using the row-like normalization of the $\widehat{P}_i$ matrix. The normalized matrix $P_i(t)$ and its entries are p_{rt}, where $\widehat{P}_i = \hat{S}S^k \ldots \ldots S^1 PB$ by normalizing non zero row $m = 1 \ldots . t$ in a way that $max_m|p_{mn}| = 1$.

When the matrix P_i converted into a permutation matrix then it is a case of perfect separation. Then in each row and column, one of the elements becomes equals to unity, then rest of the all elements becomes zero. Then EI achieve its minimum possible ideal value which is zero. In practical case it is not possible [10].

- **PSNR**

For peak signal to noise ratio which is often represented by PSNR, it is define as the ratio between power of a output signal with its noise and the corresponding source signal that alter the fidelity and accuracy of its representation.

PSNR generally calculated in form of logarithmic decibel scale value. To measure the quality of reconstructed image, PSNR is commonly used. PSNR of the reconstructed image and its quality is depending approximately on human perception.

$$PSNR(in\,dB) = 10log_{10}\left(\frac{{A_i}^2}{MSE}\right) \tag{3.7}$$

The mean square error which is denoted by MSE of the separated output signal is

$$MSE = \frac{1}{n}\sum_{k=1}^{n}\left(\widehat{a_{jk}} - a_{jk}\right)^2 \tag{3.8}$$

where $A_i = a_{max} - a_{min}$ is the value of the peak amplitude of the source signal and $n = r \times t$,

- **SSIM**

The structural similarity index is represented by SSIM. It is method for calculating the similarities among two images. The SSIM is a reference metric index. In other words, image quality is measured based on an initial distortion-less uncompressed image as reference image. SSIM is designed because it is less inconsistent according to human eye perception then the peak signal-to-noise ratio and mean squared error.

3.3 Neural Network Based Blind Source Separation Techniques

3.3.1 Pre-whitening and Separation Rule

For separating matrix, pre-whitening is one of the approaches to separate signals from different sources. The main use is that by modifying one of the layers takes subsequent direct neural implementation. The separation is a two layer approach. The first is pre-whitening and second is source separation. The following diagram explains the feed forward structure with elaborated inside view of neural network.

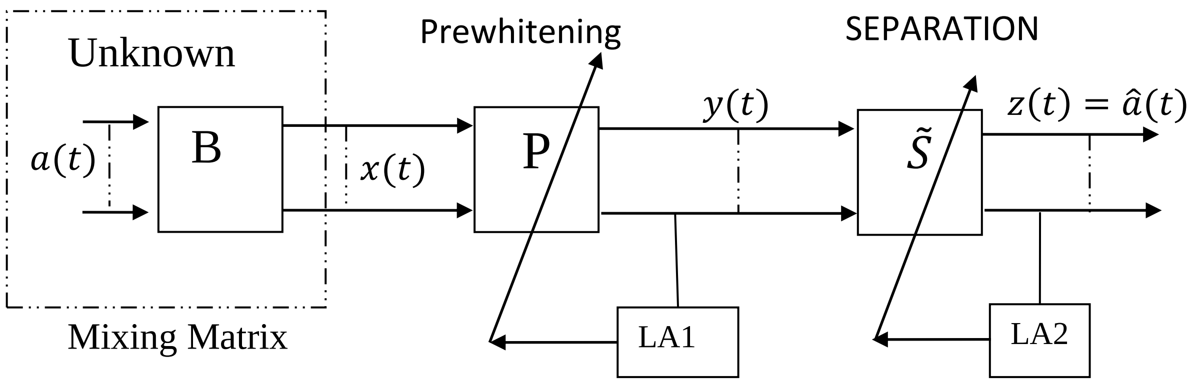

Figure 3.2 The block diagram of two-level feed-forward network for pre-whitening and blind sources separation [10].

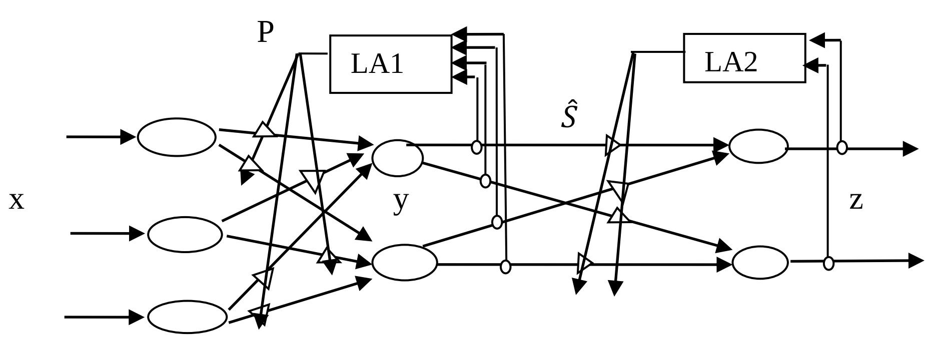

Figure 3.3 The two-layer feed-forward detailed neural network with signal reduction for pre-whitening and blind separation [10].

The respective weight matrices P and $\tilde{S}$ are represented by the below equation along with working operation of the network.

$$z(t) = \tilde{S}(t)y(t) = \tilde{S}Px(t) = S(t)x(t) \tag{3.9}$$

where $S \equiv \tilde{S}P$ is the complete separating matrix. In whitening, whitening transformation is used for pre-processed the data vectors $z(t)$ and whitening transformation is $y(t) = P(t)z(t)$. In this equation the whitened vector symbolizes by $y(t)$, and $r \times t$ whitening matrix is symbolizes by $P(t)$. In case $t > r$, where r is known in advance.

In whitening, the $P(t)$ matrix is selected in such a way that the covariance matrix $E\{y(t)y(t)^T\}$ emerges into the unitary matrix I_m.

Hence, the whitened vectors $y(t)$ and there components are mutually uncorrelated with unit variance. The necessary condition is uncorrelatedness between signals for stronger source to source independence. Eventually the separation task is easily done after pre-whitening, because the following separating matrix $\tilde{S}$ could be orthogonal as its parent constrained [10].

$$\tilde{S}\tilde{S}^T = I_m \tag{3.10}$$

where I_m is the $r \times r$ unit matrix. Whitening appears to be friendly exclusively in large-sizeable problems, occasionally the separation of different sources become difficult in practice, therefore resorting was required [10].

The following update rule for the pre-whitening matrix

$$P(t+1) = P(t) + \vartheta(t)[I - y(t)y^T(t)]P(t) \tag{3.11}$$

The combining both mixing and de-correlation process is sorely independent from the mixing matrix B.

The following is nonlinear PCA subspace rule [20] as separation rule for orthogonal separating matrix

$$\hat{S}(t+1) = \hat{S}(t) + \varphi(t)g[z(t)][y(t) - \hat{S}^T(t)g[z(t)]]^T \tag{3.12}$$

where $y(t) = P(t)x(t), x(t) = Ba(t)$ and $z(t) = \hat{S}(t)y(t)$. Therefore, $g[z(t)]$ represents the column vector where i^{th} component is $g_i[z_i(t)]$, where $g_i(t)$ is an odd and monotonically increasing non linear activation function [10]. For stability reasons the learning rate $\varphi(t)$ should be positive.

The activation function is selected by viewing the sign of the kurtosis so that choice is made whether the signal is sub Gaussian or super Gaussian by considering the negative or positive sign of the kurtosis which is explain in the above section and the value of kurtosis is find out by using equation (3.1) and for activation function equations (3.2- 3.5) are used. But whitening also suffers from some disadvantages, the most dominant one was when weak sources were separated by ill conditioned mixing matrices then results were not up to the mark [10].

3.3.2 Global Rule

In whitening rule there are some problems. Therefore further developments were made so that separating matrix can be directly learn from the single layer linear transformation. So this single layer global rule [10] is shown below,

$$z(t) = Sx(t) \tag{3.13}$$

where S is $r \times r$ nonsingular square matrix in which weights are updated by the learning rule. These models and learning rule does not require any pre processing. General form of this rule is shown below [10, 20]

$$S(t+1) = S(t) + \psi(t)\{I - f[z(t)]g[z^T(t)]\}S(t) \tag{3.14}$$

where $\psi(t) > 0$ for the adaptive learning rate and I is a square identity matrix $(r \times r)$, $S(t)$ is the separating matrix, $f[z]\ and\ g[z^T]$ are activation functions which are chosen from there kurtosis value as explained in above section and these functions are nonlinear in nature.

This rule can be derived by minimizing the Kullback-Leibler divergence and natural gradient concept by Amari [33], only for the independent outputs this minimum is achieved. The output images which received after applying global rule are in fact more independent than the actual correlated images or sources. This exact derivation for sources is valid irrespective of there true independent components present or not.

The one on one outputs with their product distribution are match to the situation where truly independent output images are present and this is the target distribution where the distance is minimizing between true joint distributions. The Kullback-Leibler divergence is achieved by measuring the distance or difference in these two different distributions, that is, product distribution and target distribution. The elementary achievement for global rule in the ICA problem is that it gave the more accurate approximate solution for the problem by reducing the Kullback-Leibler divergence [10, 20].

On the flip side, the following equation will be satisfied by the global rule after convergence

$$E[f[z(t)]g[z^T(t)] = I \tag{3.15}$$

This condition can be derived from Eq. (3.12) and Eq. (3.14) by taking both side expectations and substituting $S(t+1) = S(t) = S$.

By substituting $f[z(t)] = \tanh(t)$ and $g[z^T(t)] = z^T(t)$, then Taylor series expansion of $\tanh(t)$ can be inserted in Eq. (3.15) that leads to the condition in which the higher-order moment matrices $z(t)$ and sum of the correlation matrix $E[z(t)z^T(t)]$ tries to become the unit matrix I [10].

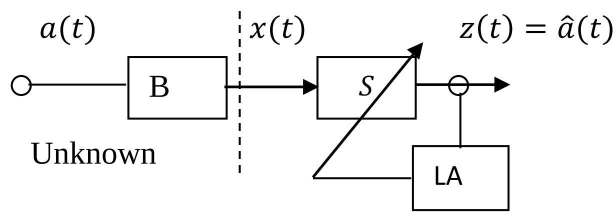

Figure 3.4 The architecture of a feed forward neural network without using pre whitening for blind source separation.

This rule can also be utilize in redundancy reduction in noise free and noisy condition by using post processing layer for eliminating the redundancy. This post processing is applied after the global rule separation. The output images are passed thought this layer for final processing and this is explain in detail in redundancy reduction section.

Therefore it eradicates the weak source problem which is separated by the ill conditioned mixing matrices which ultimately improves quality of the output images.

3.3.3 Local Rule

There are some disadvantages are present in whitening that are explain in global rule. Moreover, single layer implementation is developed in later algorithm. Therefore the local learning rule can be drive by using another generalized gradient form. The self normalized simple local learning rule is [10, 37]

$$S(t+1) = S(t) \pm \psi(t)\{I - f[z(t)]z^T(t)\} \tag{3.16}$$

The local rule is stable under zero initial condition for both + and – signs. Due to ill conditioned problem single layer adaptive network was not able to separate the images properly, then multi layer neural network with a feed forward ability is used to perform separation on ill conditioned matrices so multilayer local rule [20] called as local rule was used.

As explain in figure 3.5 on each individual layer simple local rule was proceed and each time different nonlinear function was used so that different higher order statistics was introduced which ultimately enhances the separation condition and quality of the separated sources.

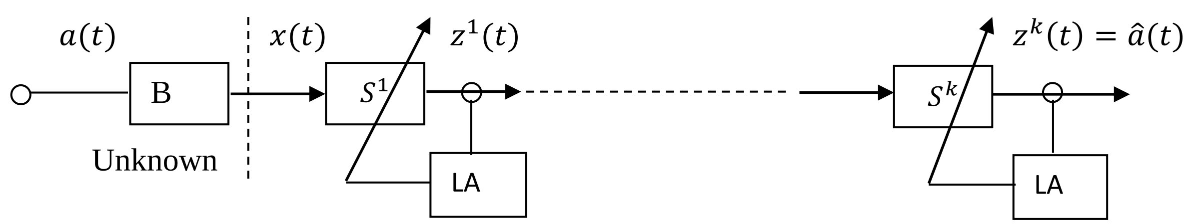

Figure 3.5 Multi layer bock diagram of feed forward neural network for BSS without using prewhitening.

This learning algorithm is used for source separation where number of sources is same as sensors $(r = t)$ but it can also be applied when sources are not known and must be less than sensors. The same exact condition that shown in Eq. (3.15) is valid for local learning rule with $g\left(z^T(t)\right) = z^T(t)$ such that moderately correlated sources are also separated out [37].

3.4 Data Compression in Blind Source Separation Schemes

3.4.1 Compression of the data in pre-whitening level

The pre whitening layer has the natural ability of compression which is utilize to determine the number of sources. When the standard form of principal component analysis is taken for pre whitening operations then optimal compression will taken place in mean square error sense and the noise will also filter out simultaneously [10].

In situation where mixtures are more than sources, that is, $t > r$, then PCA will be possible technique for source determination [10]. Moreover, if estimated sources are guessed rightly then data vectors at the input side are converge to vectors $y(t)$. This will done in whitening stage using network structure in figure 3.3 thereafter in separation level no clear cut issue will appear. The source power is higher than noise power, and then the assessment of sources is easy. Anyhow, if power of noise is larger, then it is difficult to assess the true number of sources [10].

For assessing the source number in BSS by employing the NN with two layers as showing in figure 3.3, three sub-Gaussian sources are used with negative kurtosis. Then the five mixture images are developed from these three sources.

Again, pre whitening will take place that explain in Eq. (3.11) which give three images, thus the compression is done in this stage followed by separation which used orthogonal separation matrix S by using nonlinear PCA subspace explain in Eq. (3.12), figure 3.3 show all these steps. However, in noise free condition, this estimates the true source number by taking by-product of PCA based whitening [10] and data in covariance matrix is used for source determination which is equal to non zero eigen values of covariance matrix.

3.4.2 Compression of the data at separation stage

In separation stage, feasible data compression will take place by employing modified network structure instead of pre whitening stage. The learning separation matrix $\hat{S}$ can be developed from Eq. (3.12) which is nonlinear PCA subspace rule which is primarily designed where data compression and learning weight matrix S simultaneously take place [10].

When the mixture number t is equal to the source number r, then the exaction of some sources is the basic aim, therefore output number $l < r,\ l$ is the number of the prewhitening signals, this alternative structure sounds too has better performance.

On the flip side, if mixtures count is higher that source count $(t > r)$ and $l = r,$ then data compression and separation quality is better in whitening stage than the separation stage. Normally, compression of data in separation stage is not suitable, either noise power level is not less or count number for sources is less than number of mixtures because in whitening level compression has not taken place so it enhances the noise [10] by formulating the whitened vectors components equal to unity.

The situation where mixture signals are smaller than sources, where nonlinear separation rule that show in Eq. (3.12) was exercised. In case when two outputs were shown which would reasonably close to initial sources and one was disappeared [10] because of less mixtures, thus some sources were lost forever.

In conclusion data compression which is provided by pre whitening layer harvest the good results than the separation layer where mixtures are more than sources and $l = r$ are separated sources.

3.5 Redundancy Reduction in Noisy and Noise Free Signals

The post processing layer is applied after the separation network for eliminating the redundant signals. Therefore, two or more layer neural network as shown in figure 3.10, in which first component that has a single or multilayer network used for source separation and last component of a network is post processing layer which is applied for redundancy elimination [10]. Also this layer provides the number of sources, in case where mixtures are larger than the elementary sources. However this layer is represented as a linear transformation shown below

$$r(t) = \tilde{S}(t)z(t) \tag{3.17}$$

where the weights are revised by adaptive local learning rule explain as

$$\widetilde{s_{ii}}(t) = 1, \qquad \forall\ t\ \forall\ i,$$

$$\nabla\widetilde{s_{ij}}(t) = -\varphi(t)f[r_i(t)]g\big[z_j(t)\big],\ i \neq j \tag{3.18}$$

where odd activation function $g(r)$ taken as $\tanh(\alpha r)$ and $f(r)$ used as linear or randomly nonlinear odd function [10].

The global and local separating algorithm can also be used in more difficult case where source count is not known but sensors are always higher than the sources $t > r$. Then matrix dimension for separation is suppose as $t \times t$. Therefore redundancy is arrived in the separation level where more than one signal is withdrawn from one channel. In case where additive noise is also present then it came out at the output in the form of redundancy [10]. By applying post processing in noise free case then it removes the redundant sources.

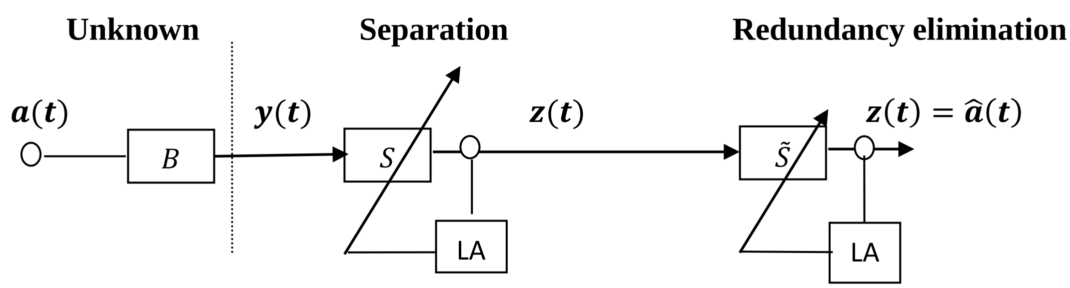

Figure 3.6 The two layer block diagram of neural network for blind separation and redundancy reduction [10].

In another class of structure which does not required pre whitening. In this architecture whether global rule is used or multi layer local rule is used to separate out the images at the output. Although in noise free environment extra post processing layer show in Eq. (3.18) is used for redundancy elimination.

3.6 The Proposed Work

In this, a method is proposed where neural network is combined with SVD regularization procedure, in which neural network techniques are used for separating the images from mixed images that is, BSS.

In this proposed scheme additional SVD regularization layer is added with the traditional three neural algorithms for separation which are separation with prewhitening, global rule and local rule that are explain in [20]. The significance of SVD in proposed scheme is that it can be used for any real matrix [12]. The singular values have provided the good stability and has the rotationally invariant values. These properties of SVD operation enclose enormous application on digital image recognition, quality improvement and image compression [35]. In this work SVD is used for noise reduction.

Moreover, the small modifications in singular values do not cause significant degradation of image quality. The result of the extracted images contain high level of ensemble recognized objects in the image from the original image and has performance associated with human vision. Then comparison is done between the images extracted from neural method along with images that are collected from the proposed neural SVD method as shown in figure 3.7.

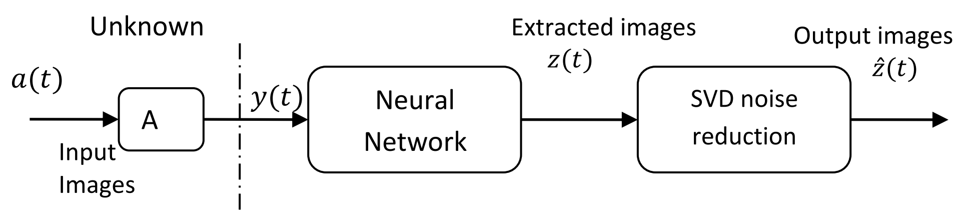

Figure 3.7 The proposed method for extraction of source images in BSS.

Overall, SVD approach is one of the robust, simple and easy to implement. Its working in the constrained environment is better than other schemes. It just creates the small set of the given image and created sets are compared with the given image for recognition purpose which results in the enhancement of our image. SVD tends to remove the lower singular values. Since the noise also has low singular values so it results in the noise reduction process.

Let us assume that SVD consist a rectangular matrix 'M' having $m < q$ matrix. Where, m represents the rows and q column, along with rank r and $r \leq q \leq m$ [20]. Then the matrix B can be factorized into three matrices: Where U and V are orthogonal unitary matrices and D is a diagonal matrix

$$M = VDU^T \tag{3.19}$$

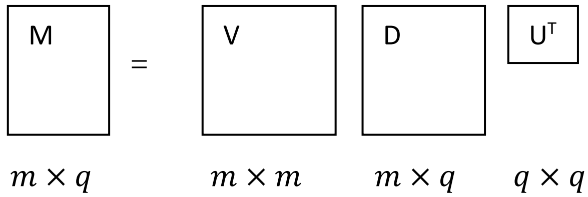

Figure 3.8 SVD Factorization

SVD decomposition is realized by unitary matrix V. SVD is stable for any minute perturbation in M which directly link to minute perturbation in D and conversely. The diagonality of the matrix D makes it easier to determine D when M is near to rank degenerate matrix. Therefore, decomposition gave the optimal low-rank approximation to M.

3.7 Chapter Summary

In this chapter methodology has been discussed which includes different learning rules for Blind Source Separation such as separation rule with prewhitening, global rule and local rule. The separation rule with prewhitening is a two level method for BSS implementation. The global rule is single layer method whereas the local rule is multi level method without applying prewhitening for unmixing the signal. The different performance parameters like SSIM, PSNR, MSE and error index are discussed. The kurtosis is calculated for choosing the activation function which depends upon the sign value of the kurtosis. The scheme is proposed where neural network used for blind separation is combined with SVD which is used for noise damping thus enhancing the quality of image for human perception.

CHAPTER 4

Results and Discussion

4.1 Introduction

In this chapter, the simulation results for BSS problem for unmixing of images are calculated with neural techniques like prewhitening and nonlinear PCA subspace separation rule, global rule and local rule are combine with SVD. In this work different cases are considered and these are, sources count is equal to mixtures count $(r = t)$, and $t > r$ that is mixture count is greater than sources for retrieving the original images at the output. The results of proposed method are compared with the standard neural network. In the research work gray scale images are used having size equal to 256×256 of gray scale levels. Before starting the work, the image signal has to be converted into zero- mean signals and for similarity between the learning rate and initial weights they are scaled between the interval ranges from [-1, +1] [20]. For the simulation three images are considered in which two images are natural images and one image is synthetic image.

For the case when mixture and source count are different, the prewhitening and separation layer are used for data compression and global rule for redundancy elimination. The parameters as SSIM, PSNR and MSE, error index, kurtosis are used for performance comparison.

4.2 Simulation Results

4.2.1 Standard Neural Methods

The three images are taken and the size of the each image is 256×256 of grey scale level. Firstly all three images are mixed together then pre-whitening in Eq. (3.11) which is the first step for unmixing the sources and images obtained is displayed as (g, h, i), further prewhitening also improves the convergence property in the BSS algorithm. To improve the quality of the images, separation rule in Eq. (3.12) has been applied on the pre-processed prewhitened images and the results are shown below in (j, k, l).

In global method pre-whitening is not applied. The global rule in Eq. (3.14) and local rule Eq. (3.16) in which the separating matrix $S(t)$ is utilized to recover the sources from mixed matrix as shown in figure 4.1 (m, n, o) and (p, q, r). Local rule is used in scalar form under zero initial condition. To separate the images using global rule and local rule, selection of the activation function is lies upon the sign of the kurtosis as explained in Eq. (3.1).

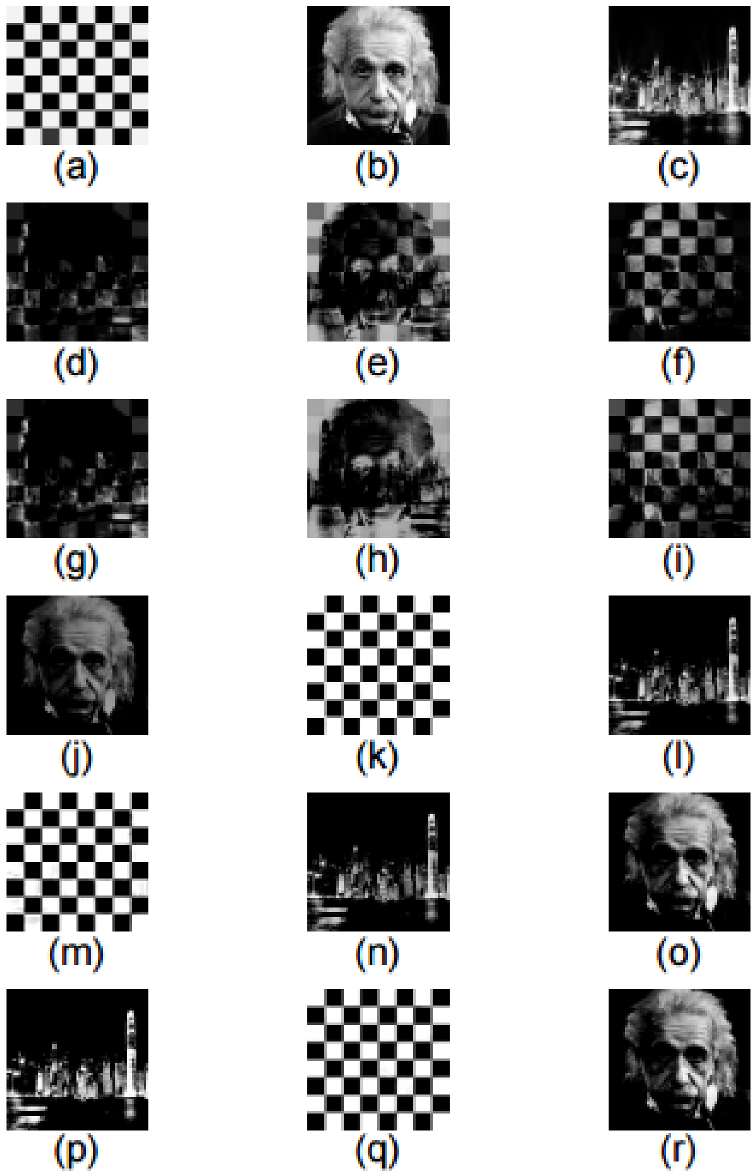

Figure 4.1 Simulation results (Neural Networks): $(a),(b),(c)$ are the original images in grey scale of size (256×256), $(d),(e),(f)$ are the mixed images, $(g),(h),(i)$ images after pre-whitening, $(j),(k),(l)$ images after separation, $(m),(n),(o)$ images after global rule separation, $(p),(q),(r)$ images after local rule separation.

4.2.2 Proposed Method

In proposed method, SVD is applied on the images which are obtained from the neural methods. Thus SVD regularization is used for denoising the images and the results are shown in figure 4.2 for separation rule $(S1, S2, S3)$, global rule $(S4, S5, S6)$ and local rule $(S7, S8, S9)$ with the original images as (a, b, c) and the mixed images as (d, e, f).

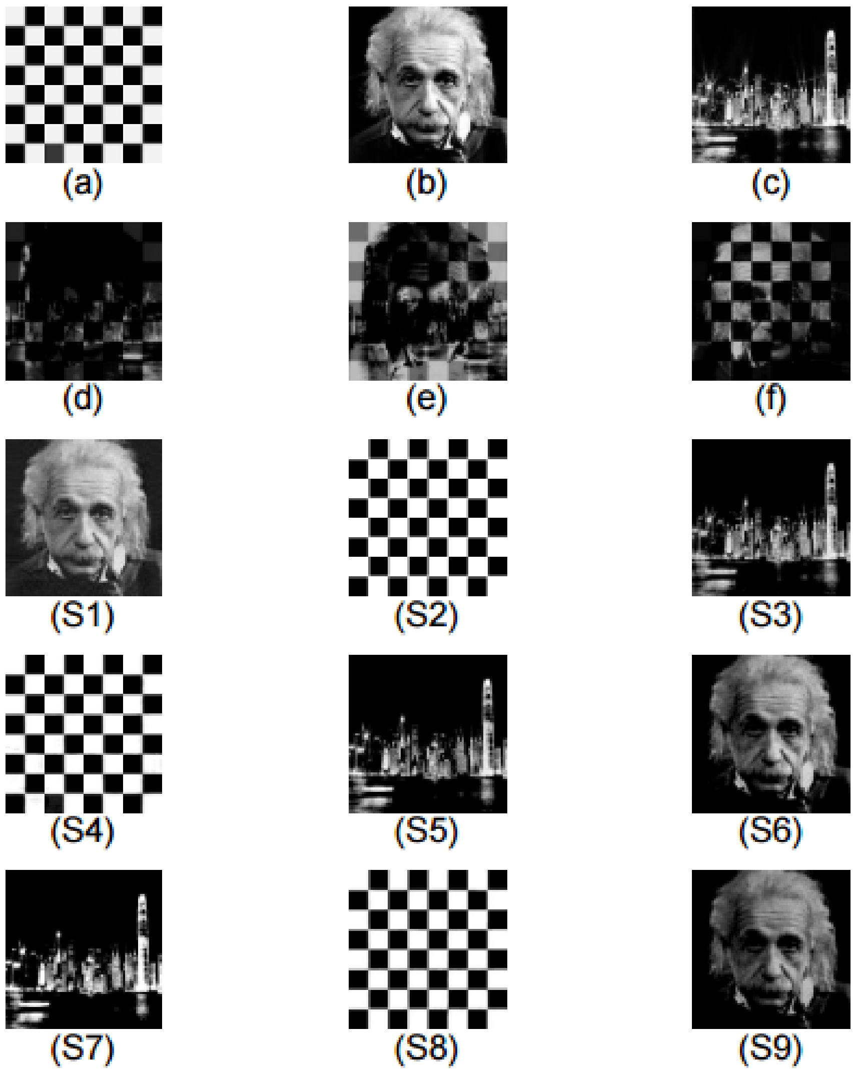

Figure 2 Simulation Results (Proposed scheme): $(a), (b), (c)$ are the original images in grey scale of size (256×256). $(d), (e), (f)$ are the mixed images, (S1),(S2),(S3) images after applying proposed method with pre-whitening and separation rule, (S4),(S5),(S6) images after proposed method with global rule separation and (S7),(S8),(S9) images after proposed method with local rule separation.

The comparison between different parameters is shown below in table 4.1 after separation of images.

Table 4.1: The performance comparison between proposed method and existing schemes

Neural Methods	Images	PSNR		MSE		SSIM		EI	
		Standard Neural network based Scheme	Proposed Scheme	Standard Neural network based Scheme	Proposed Scheme	Standard Neural network based Scheme	Proposed Scheme	Standard Neural network based Scheme	Proposed Scheme
Separation rule	Person	30.5544	**30.8310**	56.7843	**53.2800**	0.9808	**0.9992**	0.7569	**0.4195**
	Boxes	29.2334	**29.4198**	77.5777	**74.3190**	0.8297	**0.8371**		
	City	33.9364	**34.0638**	26.2691	**25.5092**	0.9769	**0.9974**		
Global Rule	Person	30.5674	**30.6361**	57.0617	**56.1650**	0.9798	**0.9905**	0.0922	**0.0722**
	Boxes	28.1806	**28.2050**	98.0856	**97.5375**	0.9753	**0.9912**		
	City	33.9055	**33.9564**	26.4566	**26.1483**	0.9709	**0.9905**		
Local Rule	Person	30.5937	**30.5940**	56.7172	**56.7127**	0.9803	**0.9875**	0.0991	**0.0987**
	Boxes	28.1481	**28.2767**	98.8225	**95.9403**	0.9708	**0.9739**		
	City	34.0018	**34.0250**	25.8764	**25.7386**	0.9545	**0.9663**		

Table 4.2: Value of normalised Kurtosis of the source images

Images	Kurtosis ($\widehat{k_4}$)	Signal
Person	-1.3318	Sub-Gaussian
Boxes	-1.9339	Sub-Gaussian
City	0.4217	Super-Gaussian

4.3 Results for Data Compression at different stages

The compression of data can be take place in either prewhitening stage or in separation stage.

4.3.1 Pre-whitening Stage

The pre whitening layer has the natural ability of compression. In this case are considered where mixtures are higher in count than sources, that is $t > r$. The optimal compression will taken place in mean square error sense and the noise will also filter out simultaneously [10]. And all this happen in whitening stage thereafter in separation level no clear cut issue will appear. The source power is higher than noise power, and then the assessment of sources is easy otherwise it is difficult to assess the true number of sources [13].

In data compression three images are taken, each of the size is 256×256 in grey scale level. Primarily, five mixed images are formed from the mixing matrix as shown in figure 4.3 from $(d\ to\ h)$ images. The compression is done in pre whitening stage followed by separation rule as explain in Eq. (3.12). After pre-whitening, two images are compressed and got only three images which are shown in $(i - k)$ and separated images $(l\ to\ n)$. Further images are enhanced by SVD regularization as represented in figure 4.3 (o, p, q). The performance parameters are shown in table 4.3.

4.3.2 Separation Stage

The feasible data compression will take place in separation stage by employing modified network structure as shown in figure 3.3 instead of pre whitening stage. The separation matrix $\hat{S}$ is explained in Eq. (3.12) simultaneously used for data compression and separation when the mixtures count is higher that source count $(t > r)$.

The three sources each of the size is 256×256 in grey level shown as (a, b, c) where separation provides the compression of data rather than pre whitening stage. The images with various reduction ratios that is 3, 2 & 1 at the output is shown in figure 4.4 as $(j, k, l), (m, n), (o)$. Further, the images from the proposed method are shown in figure 4.5 as $(p, q, r), (s, t), (u)$. The performance parameters are shown in table 4.4.

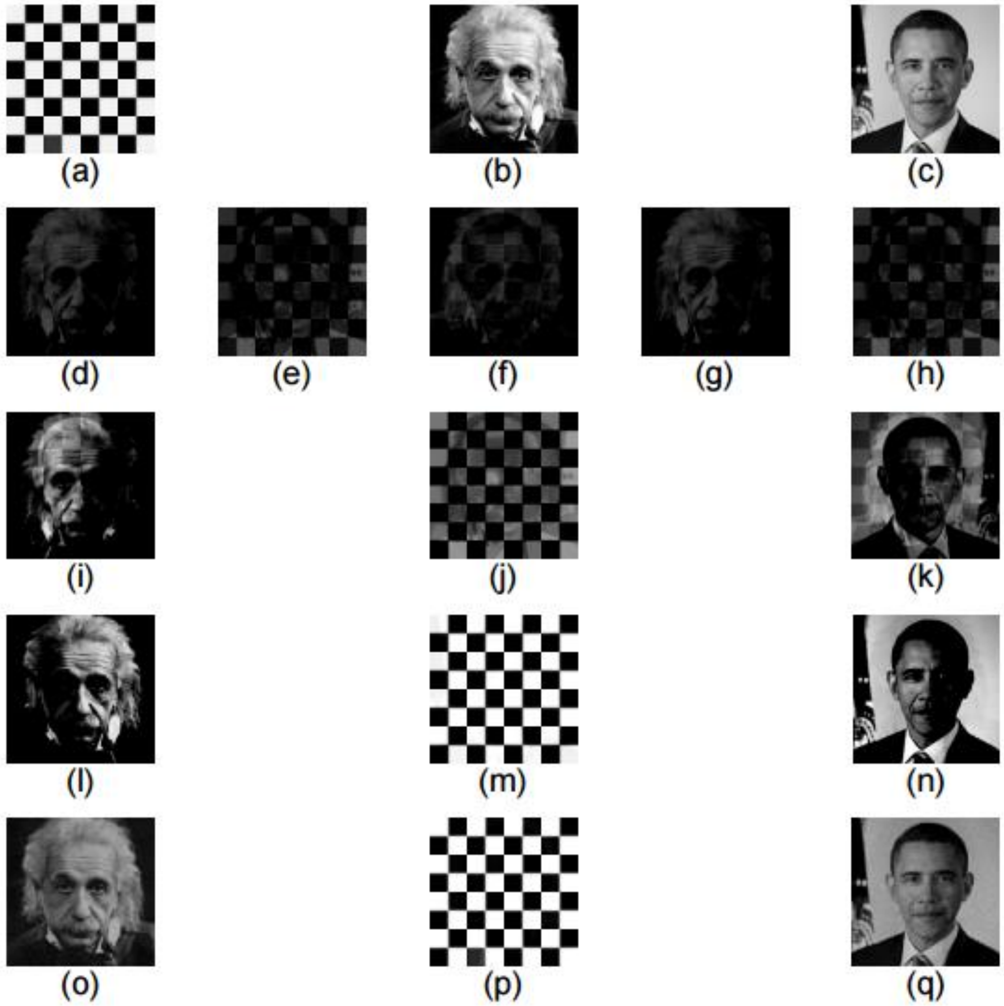

Figure 4.3: Simulation results for compression of data (prewhitening layer): $(a),(b),(c)$ are the original images in grey scale of size (256×256), (d,e,f,g,h) are the mixed images for $(t > r)$, $(i),(j),(k)$ images after pre-whitening, $(l),(m),(n)$ images after separation. $(o),(p),(q)$ are the improved images after proposed method.

Table 4.3: Comparison between separation rule and proposed method for compression of data

Images	$\widehat{k_4}$	Separation Rule				Proposed Method			
		PSNR	MSE	SSIM	EI	PSNR	MSE	SSIM	EI
Person 1	-1.331	30.3509	59.5079	0.8656		30.7240	54.6094	0.9969	
Boxes	-1.933	27.4069	118.1375	0.8884	1.2581	28.0445	102.0063	0.9997	0.8634
Person 2	-1.360	29.0453	77.8662	0.9622		29.0675	77.4699	0.9977	

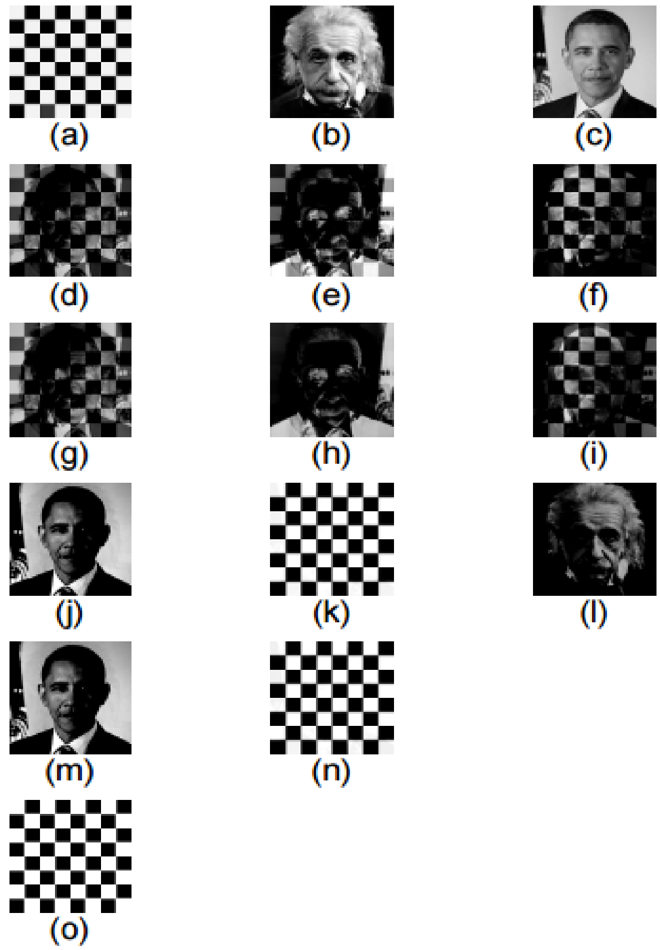

Figure 4.4 Results for compression of data (separation layer) $(a - c)$ are the original images in grey scale of size (256×256), $(d - f)$ the mixed images, $(g - i)$ are the images after pre-whitening. Compression of data take place at separation layer where $(j - l)$, (m, n) and (o) images with various reduction ratios that is 3,2 & 1 at the output.

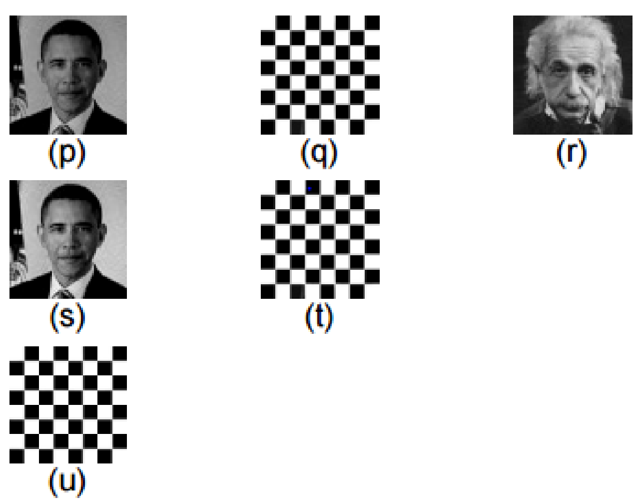

Figure 4.5 Simulation results: (p, q, r), (s, t) and (u) are the images that are processed with proposed method.

Table 4.4: Comparative summary of the separation rule and the proposed method for compression of data with reduction ratio as 3, 2 & 1.

	Methods	Performance Parameters	Images		
			Boxes	Person 1	Person 2
Compression Ratio 3	Separation Rule	MSE	77.8613	77.8613	77.8613
		PSNR	29.0456	29.0456	29.0456
		SSIM	0.9622	0.9622	0.9622
	Proposed Scheme	MSE	**77.8613**	**77.8613**	**77.8613**
		PSNR	**29.0456**	**29.0456**	**29.0456**
		SSIM	**0.9965**	**0.9965**	**0.9965**
Compression Ratio 2	Separation Rule	MSE	77.9111	77.9111	
		PSNR	29.0428	29.0428	
		SSIM	0.9620	0.9620	
	Proposed Scheme	MSE	**76.0243**	**76.0243**	
		PSNR	**29.1493**	**29.1493**	
		SSIM	**0.9989**	**0.9989**	
Compression Ratio 1	Separation Rule	MSE	76.1074		
		PSNR	29.2824		
		SSIM	0.4685		
	Proposed Scheme	MSE	**75.3807**		
		PSNR	**29.3241**		
		SSIM	**0.5618**		

4.4 Redundancy Reduction in Noisy and Noise free Signals

The redundancy of the images that is present when mixtures and sources are uneven. Therefore global learning rule was employed for this for both the cases for noise free and noisy condition follow by SVD regularization for quality improvement.

4.4.1 Noise Free Signals

In this redundancy reduction three images are taken of size 256×256 in grey scale level. This is a case of blind separation with noise free condition which contains five mixtures having redundancies when count of source images is less than the mixture images. Firstly, global rule is applied as in Eq. (3.14) for separation. After using post processing layer explain in Eq. (3.18) two unwanted images are suppressed as shown in figure 4.6. Further SVD processing is applied then quality of the separated images at the end side is better than the global rule using post processing method [20]. The blank images (q, r) indicate that these are the noise signals that are separated from the original signal. The performance parameters are shown in table 4.5.

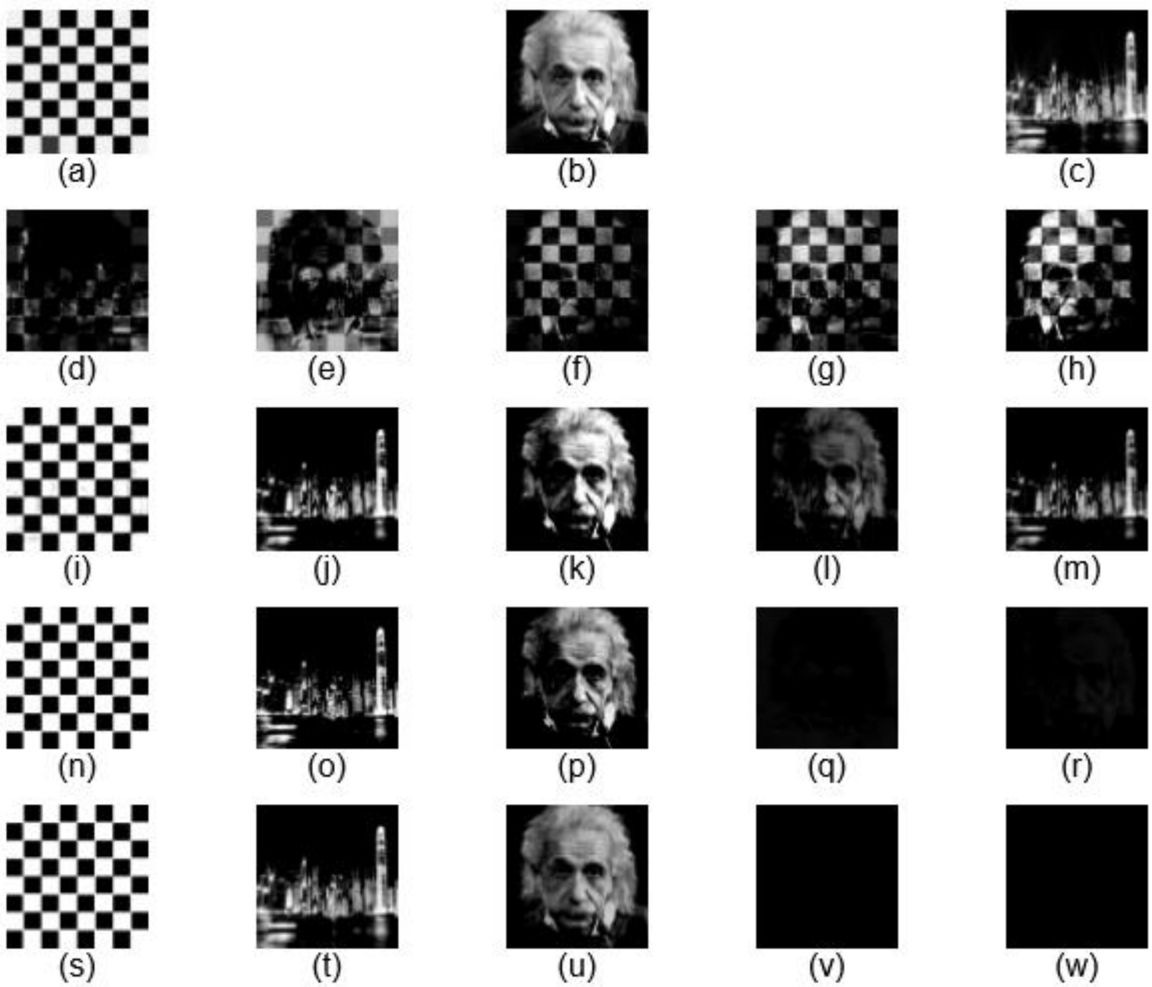

Figure 4.6 Simulated results: $(a), (b), (c)$ are the original images in grey scale of size (256×256), $(d), (e), (f), (g), (h)$, are the mixed images, $(i - m)$ are the images after global rule. Two redundant images are suppressed after applying post processing layer which are shown in $(n), (o), (p), (q), (r)$ images. $(s), (t), (u), (v), (w)$ are images after the proposed scheme with NN based separation.

Table 4.5: Redundancy Reduction in noise free condition using Global rule with Post Processing Layer and Proposed Method

<table>
<tr><th>Images</th><th colspan="4">Global Method</th><th colspan="4">Proposed Method</th></tr>
<tr><th></th><th>PSNR</th><th>MSE</th><th>SSIM</th><th>EI</th><th>PSNR</th><th>MSE</th><th>SSIM</th><th>EI</th></tr>
<tr><td>Boxes</td><td>30.5164</td><td>57.2826</td><td>0.5573</td><td rowspan="3">0.0475</td><td>30.5164</td><td>57.2826</td><td>0.6715</td><td rowspan="3">0.0416</td></tr>
<tr><td>City</td><td>33.9662</td><td>26.0893</td><td>0.9606</td><td>36.3099</td><td>15.2088</td><td>0.9965</td></tr>
<tr><td>Person 1</td><td>30.6991</td><td>55.3571</td><td>0.9774</td><td>30.7629</td><td>54.5494</td><td>0.9965</td></tr>
</table>

4.4.2 Noisy Signals

In noisy case for $t > r$, supplementary additive noise was added to each one of the sensor mixture which is in the form of image. If no redundancy will appear in noisy case for different sources, after separation only noise image was shown at the output along with source images. Therefore on the use of redundancy reduction, the quality of output images may decrease to some extent. In this section, we are adding extra noise along with the random signal. Thus in noisy condition, if redundancy of different sources is not present in global rule then noise signal or redundancy is shown only at the endside. To some extent the quality of endside signal is less when mixtures are more than original signals [10].

The random matrix A is mixed with three source signals which gave the output of five mixtures (d, e, f, g, h) as shown in figure 4.7. Now, 0.1 % of the noise image has been added to each one of the mixture image then the resultant images were displayed in figure 4.7 as (i, j, k, l, m). After applying global rule with SVD processing, two noise image and three source images has been appeared in the output as (s, t, u, v, w) in figure 4.7.

In the noisy environment the post processing layer or the redundancy layer does not need to be applied, as redundancy is appeared itself followed by global rule. The performance parameters for the same are shown in table 4.6.

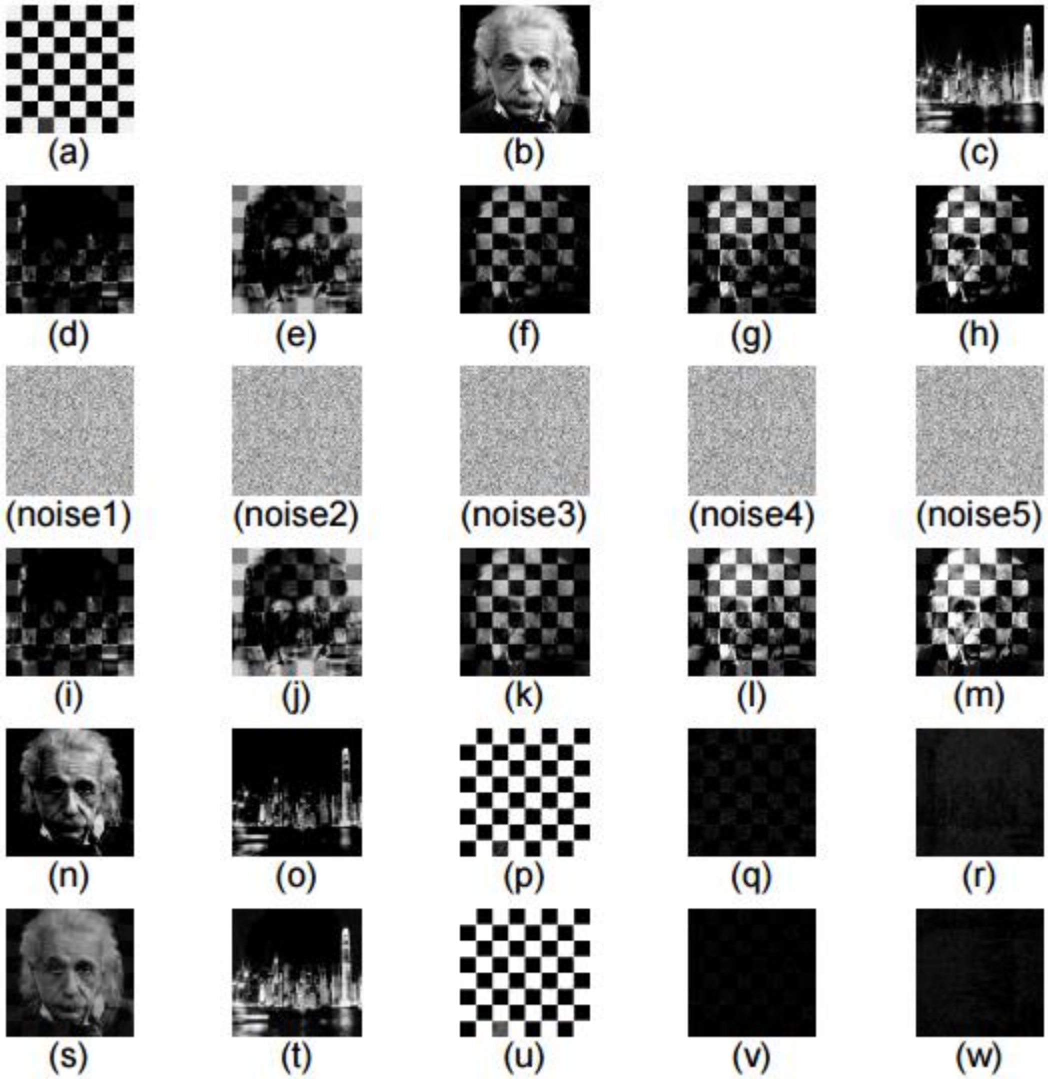

Figure 4.7 Simulated results: $(a), (b), (c)$ are the original images in grey scale of size (256×256), $(d-h)$ are the mixed images for $t > r$ and $(i), (j), (k), (l), (m)$ are the images after global rule. Two redundant images are suppressed as shown in $(n), (o), (p), (q), (r)$ images. $(s), (t), (u), (v), (w)$ images after the proposed scheme .

Table 4.6: Comparison between Global Rule and Proposed Method for redundancy reduction in noisy condition.

Images	Global Rule				Proposed Method			
	PSNR	MSE	SSIM	EI	PSNR	MSE	SSIM	EI
Person1	27.5882	113.3086	0.9885	0.1045	27.5882	113.3086	0.9959	0.1035
City	33.9165	26.3892	0.9756		34.1683	24.9032	0.9993	
Boxes	30.5179	57.2630	0.8521		30.7182	54.6822	0.9559	

4.5 Chapter Summary:

The three neural algorithms are compared with the proposed method. Thus, the performance comparison of proposed method gives better results than the existing schemes. Moreover, the SSIM,PSNR and EI has higher values in proposed method with neural network based global rule and local rule which reflect the fine separation of sources than the proposed method with neural network based prewhitening and separation rule. In this, the problem of more mixture count then sources ($t > r$) are try to be address out in the simulated process that are shown in section 4.3 and 4.4, in which compression of data is done first in prewhitening stage then in separation stage respectively along with SVD regularization for noise suppression but the result of compression in prewhitening stage are better than separation stage since compression in separation stage enhanced the noise. Also the redundancy elimination is describe in both noise free and noisy environment where sources are fever then mixtures then proposed method is compare with single layer global rule to eliminate the redundancy of sources.

CHAPTER 5

Conclusions and Future Scope

5.1 Conclusions

In this report, the blind source separation scheme along with mathematical foundation of neural networks is explained. Blind separation techniques find its numerous applications structuring from medical imaging, speech processing, signal processing, pattern analysis, astronomical imaging and for military purposes [2]. The discussion on BSS about mixing models, the underlying assumptions and limitations were examined. BSS usually assumes that each source is statistical independent among other sources and the number of source count is known to us which is equal to the number of mixtures that is, $r = t$.

There is a general advantage of favoring the neural realization as learning algorithms because it is simple and also gives considerable performance for solving the blind source separation problem. Major edge in neural methods is that change in single layer leads to direct neural implementation and adaption. The various techniques that have been discussed such as separation rule with prewhitening [10], global rule and local rule [10].

In this SVD regularization with neural network based method is proposed for blind source separation. Further, the compression of data in various stage and redundancy reduction for both noise and noisy condition is also discussed when $r \neq t$ [38]. The existing schemes such as separation rule with prewhitening, global rule and local rule are simulated along with SVD regularization process. During this pre-whitening is performed by first layer and source separation is done by second layer [20], at last SVD is used for the improvement in image quality. But in SVD regularization based single layer global and local rule do not utilize the prewhitening concept. As these rules interestingly retrieve the images even whether original signals are not solely independent and correlation among them is present. Therefore, the output is not essentially de-correlated for the correlated sources. But the output images are retrieve in the random order after separated from these algorithms.

The primarily used of post processing, where mixture count is greater than source counts $t > r$, is used in redundancy elimination in the noise free environment. The superior compression results were obtained in prewhitening compression rather than separation stage. Noise is enhanced in prewhitening stage if compression is not done there.

5.2 Future Scope

An appealing issue that requires to be dressed out in the future is the behavior in which the different separating layers behave when the combination of additive and/or multiplicative noises in the neural networks, so that noises can be removed internally.

Hence, a challenging task is to improve adaptive algorithm and make it generalized for the multichannel blind deconvolution and equalization, furthermore, the separation of various sources which are convolved and delayed and their delays are unknown. Further development in adaptive neural techniques should be done for improving the learning methods.

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