Digital Image Separation Based on Joint PDF of Mixed Images

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Under the supervision of

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by

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Declaration

I, Mayank Sharma hereby declare that this project work entitled “Digital image separation based on joint pdf of mixed images “submitted at Jaypee university of information Technology, Solan is record of original work done by me under the supervision and guidance of Mohammad Wajid, Department of Electronics and Communication Engineering, Jaypee University of Information Technology, Waknaghat, Solan. The information submitted here in is true and original to the best of my knowledge. I will not publish this work unlit I will get the permission from the supervisor and review of the paper from the Supervisor.

Signed:……………..

Date:………………

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Certificate

This is to certify that project report entitled "Digital image separation based on joint pdf of mixed images", submitted by Mr. Mayank Sharma in partial fulfillment for the award of degree of Master of Technology in Electronics and communication Engineering to Jaypee University of Information Technology, Waknaghat, Solan has been carried out under my supervision, as per my knowledge this work has not been submitted partially or fully to any other university or institute for the award of this or any other degree or diploma.

Mohammad Wajid

Assistant Professor

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ABBREVIATIONS

BSS	**B**lind **S**ource **S**eparation
PCA	**P**rincipal **C**omponent **A**nalysis
SVD	**S**ingular **V**alue **D**ecomposition
ICA	**I**ndependent **C**omponent **A**nalysis
AMMCA	**M**orphology **C**omponent **A**nalysis
SCA	**S**parse **C**omponent **A**nalysis
SIR	Signal interference ratio
EEG	Electroencephalography
FMRI	Fundamental Magnetic Resonance-Imaging
1M2	Fused image Ima1 and Ima2
2M3	Fused image Ima2 and Ima3
3M4	Fused image Ima3 and Ima4
4M5	Fused image Ima4 and Ima5
5M6	Fused image Ima5 and Ima6
6M7	Fused image Ima6 and Ima7
7M8	Fused image Ima7 and Ima8
8M9	Fused image Ima8 and Ima9
9M10	Fused image Ima9 and Ima10
10M11	Fused image Ima10 and Ima11
PSNR	Peak signal to noise ratio

NOMENCLATURE

$\leq$	Less than Equal
$\geq$	Greater than Equal
$\boldsymbol{\theta}$	Rotation angle
$\boldsymbol{\sigma_1}$	Variance along the first principal component
$\boldsymbol{\sigma_2}$	Variance along the second principal component
K	Mixing matrix
X	Fused image
S	Original images
U	Unitary matrix
$\sum$	Diagonal matrix
V	Rotation matrix

ABSTRACT

In a real environment, Image separation is very difficult task from observed fused and merged image some fingerprint application and cloud detection and measurement .It is frequently arising problem in image processing field .Image separation is more typical case of image de-noising where more than one image are to be reconstruct from a single observation. The whole problem resembles, the task a human can solve fused image separation problem where using two images (two finger print). We can separate the overlapped finger print with different technique. In this thesis we examine the image separation problem basis that two fused image are independent to each other. The technique of image separation aims to estimate the original image and mixing matrix using only the fused image .we are using two technique for estimate the mixing matrix (*1*) Estimate the mixing matrix ,given an estimate fused image .(*2*) Estimate the original image given an estimate mixing matrix. In this thesis we have some prior information about the image on the basis of information of image we can estimate the mixing matrix with help of different graphical scatter plot of two fused image we are trying to estimate mixing coefficient Image separation is based blind source separation . BSS has been applied image separation .biomedical image processing, remote sensing, communication field, data mining, neural network, exploration seismology. Source separation problem can be formulated using ICA technique

CHAPTER 1

INTRODUCTION

1.1 Image separation and its application

Separation of mixed and overlapped images is a frequently arising problem in image processing, for example separation of overlapped images obtained from many applications. In which we get a mixture which consists of two or more than two images and for identification we need to separate them. In this thesis, it is assumed that original images are identifiable and mutually statistically independent at the time of mixing, and the problem is solved by applying Scatter method, SVD based Ica method in frequency domain [49]. To apply ICA in frequency domain EASI algorithm was extended to separate complex valued signals when photographing objects placed behind a glass window or windscreen, since most varieties of glass have semi reflecting properties [50]. The need to separate the contributions of the original and the virtual images to the combined, superimposed, images is important in applications where reflections may create ambiguity in scene analysis. In which we get a mixture which consists of two or more than two images and for identification we need to separate them [50]. Mathematically, image mixture can be seen as

$$X = KS \tag{1}$$

$$K = \begin{bmatrix} k_{11} & k_{12} \\ k_{21} & k_{22} \end{bmatrix} \tag{2}$$

Where, $X = [x_1,\ x_2]^T$ are mixed images, $S = [s_1,\ s_2]^T$ are the original images and K is a mixing matrix. The mixed image separation is a blind source separation (BSS) problem, because neither source signal, nor mixing coefficients are known. The observed images are a weighted linear combination of source signals and mixing weights are also not known [3]. If we can estimate mixing matrix, the original unmixed images can also be estimated as

$$S = k^{-1}X \tag{3}$$

There are many other applications of image separation namely, image denoising [4, 5], medical signal processing like FMRI, ECG, EEG [6, 7, 8] feature extraction in Content-Based Image Retrieval (CBIR**)** [9, 10, 11], face recognition [10, 5], compression redundancy reduction [12], watermarking [13,14], remote sensing in cloud detection [15] ,where cloud detection of the atmospheric remote sensing image of a VHRR (very high resolution radiometer) is tested using separation technique, scientific data mining [16], finger print extraction (in crime branch) [18].

There are few technologies and systems which permit separates the specific speaker from fused image data which is consist at some noisy circumstances. The related application studies are conducted, in particular, for TV meeting area, image recognition systems, and digital hearing aid system etc. In particular, the microphone array system as well as Independent Component Analysis (ICA) base approach [27] is focused. Microphone array permit enhance a target image from the mixed images remove noises and taking into account the phase difference among the image sources which corresponds to the distance between the microphone and the location of the image sources. There is a delay sum [27] and an adaptation [27] types array microphone systems. These types of array microphone permit direct the beam to the authentic direction of the target of interest. There are many approaches for digital mixed image separation namely scatter technique, principal component analysis (PCA), SVD based ICA technique, and etc. There are many approaches for digital mixed image separation namely (*1*) scatter technique (*2*) SVD based ICA technique *3*) convolutive mixture separation .These technique are based on BSS (Blind source separation. Blind source separation, that became an active-analysis topic in signal processing within the last decade, consisting of separating a group of unknown signals from a set of mixture of linear combination of signals, once no information is out there about the blending coefficient [3]. Blind source separation (BSS) is a fundamental problem that is encountered in many sensible applications like Telecommunications, image/speech processing, and medical signal analysis .where multiple sensors square measure concerned. In its simplest type, the dimensional observation vector is assumed to be generated, many algorithm have been used for image separation such as scatter method, Independent component analysis (ICA), convolutive mixture [31]. AMMCA process [48], Principal component analysis (PCA), in scatter plot based technique, the geometrical shape of joint probability density function is used [19 20]. For two histogram equalize images its shape will be parallelogram [22, 50], and orientation of its sides depends on mixing coefficients [22]. The robustness of this technique is more if image sizes are large. Scatter technique is an efficient technique for image separation. ICA technique is a Second efficient technique for image separation .PCA thought –about a BSS technique further however distrusted to the second order statics of the observation. PCA cannot apply fourth order Moment. Principal component analysis (PCA) is a linear Transformation that is derived from the second order signal statically (covariance structure). PCA have been used first and second order moments of the measure Data, It is fail for fourth order moment and depends on orthogonal data than we can prefer ICA for image separation. The main concept of ICA statistics provided that the observed data is non-gaussian and independent. In this thesis, it has been assumed that original images are histogram equalized and statistically independent and image separation procedure based on scatter data of the observed images is established. The results are compared with SVD based ICA algorithms. of Bind source separation is introduce on image's Result of experiment show the scatter approach can separate images and show proposed approach can separate every independent component effectively. Experimental result show that image –residual error [19]

1.2 Image separation problem

In signal and image processing, there are more case where a set of observed signal is available and our aim to recover the original image from fused image. Image separation problem can be mathematically expressed as follows. N set of observation $s(t) = [S_1(t)S_2(t) \dots\dots]^T$ an number of images .which are random process is generated as a mixture of underlying N two dimensional signal $x(t) = [x_1(t)x_2(t) \dots\dots]^T$ [19 20] is given below

$$\begin{bmatrix} X_1 \\ X_2 \\ X_N \end{bmatrix} = \begin{bmatrix} k_{11} & k_{12} & k_n \\ k_{21} & k_{22} & k_{2n} \\ k_N & k_{2N} & k_{2N} \end{bmatrix} \begin{bmatrix} s_1 \\ S_2 \\ S_N \end{bmatrix} \tag{4}$$

The Difficulty of separating mixtures is complicated task when the component layers have both unknown spatial shifts and changing mixing coefficients. Furthermore, if the number of Source image is large, even larger than the number of mixtures, the problem will be particularly complicated. A number of approached have been proposed to separate the method describe here to separate two image relies on reversing the action of the SVD the two statiscally different image .Again the matrix K in is not known , so a direct implementation of the SVD cannot be performed However, each of the individual matrices can be similar to by considering is net effect on the assumed uniformly distributed images.

Three specific computations must be considered:

(i) The rotation of parallelogram must be approximated

(ii) The scaling of parallelogram according variance must be computed.

(iii) The final rotation back to a separable probability distribution must be obtained.

We deal with a problem of separating the effect of reflection from images taken behind glass.

1.3 Motivation

In crime scene investigation under the event of a. homicide. The law enforcers' main duty is to bring the culprit to justice. as ofenly the occurrence of crime goes untwitness' in such an events the key to any investigation lies in the realm of the vari instrument use to commit the crime. The offender leaves behind his mark upon the murder weapons, unknowingly this is the most important impression which hold the key of his Involvement. Then how can be separate the mark from murder weapon?. Second motivation is when one takes some picture from a window, we have often has a problem caused by the glass the picture are mixtures of two layer picture, one of which is the transmitted scene behind the window and the second is the scene reflected by the window. Then it is Difficult to separate the scene of interest. Consider a situation where there are a number of signals emitted by some physical objects or sources. These physical sources could be, for example, different brain areas emitting electric signals; people speaking in the same room, thus emitting speech signals; how can be separate out these signal ?

1.4 Classification Of BSS

In signal and image processing ,there are many instances where a set of observation is present and we wish to recover the sources generating these observation [51].This problem is called a BSS Blind source separation is well studied ,old problem in electrical engineering too BSS was discover from J.H Herault and Jutten in 1986.Stated Piere common[51].Blind source separation, that became an active-analysis topic in signal processing within the last decade, consisting of separating a group of unknown signals from a set of mixture of linear combination of signals ,once no information is out there about the blending coefficient[3].Blind source separation problem is concentrated on retrieving the original sources given the observation [19].The mixed image separation is a blind source separation (BSS) problem, because neither source signal, nor mixing coefficients are known. In the instantaneous mixture case, we only have to estimate the non-mixing matrix .We can easily see that $w = K^{-1}$, we can separate the 2d signal (image) directly. This is a problem in 1D and 2D signal and processing. Historical background of ICA showed this problem. Suppose many of the people speaking simultaneously , each of the microphone located different places then each of the microphone recorded weighted sum of the speech signal, separation of signal with help ICA, this is called a blind source separation. Blind source separation (BSS) is a fundamental problem that is encountered in many sensible application like telecommunication image/speech process, and medical Typical blind source separation way's request separation once the mixing process is unknown .Blind source separation (BSS) is that methodology of separating different source signal from a group of ascertained Signal –mixture with very little or no information on the character of those source signal (ICA) is used for locating Part from variable statistical information and is one-amongst The various solution to the BSS

$$X_1(t) = K_{11}S_1(t) + k_{12}S_2(t) \tag{5}$$

$$X_2(t) = K_{21}S_1(t) + k_{22}S_2(t) \tag{6}$$

Where $X_1(t)$ and $X_1(t)$ are observed data

$$k = \begin{bmatrix} k_{11} & k_{12} \\ k_{21} & k_{22} \end{bmatrix} \tag{7}$$

k =Mixing matrix, S=source signal

1.5 Application of BSS (Blind Source separation)

Image separation application .There have been proposed several Bayesian approaches [31]. Due to the diverse promising and exciting applications .Many application of the Blind source separation in image processing field, main application of BSS finger print Separation cloud detection and fused image separations problem, Blind separation method which is proposed here is based on the MRA based separability improvement.[15,27].Brain imaging ,we often have different source in the brain emit signal that are mixed up in sensor outside of the head ,just like basic blind source separation[28]Image feature extraction ,where we want to find feature that are independent as possible[28].Different application is in image feature extraction [18,19],Image denoising [19 20], Medical signal processing – fMRI, ECG, EEG [6],Feature extraction, face recognition [19].Finger print separation[18] Remote sensing [15] Topic extraction [19].Scientific Data Mining[18]

CHAPTER 2

TECHNIQUES FOR DIGITAL IMAGE SEPARATION FROM ITS FUSED IMAGES

2.1 Introduction

Image separation is a frequently arising problem [49].image separation goal is estimate both the original image and mixing matrix using fused image. Image separation is a more typical case of image denoising where more than one image are to be reconstruct from a fused image[48].In signal and image processing there are more instance we can reconstruct the image generating these observation. This problem is called BSS. In this section we only review system or technique that are suitable For image separation from fused image .Separation of finger print from overlapped finger in frequency domain is very typical task. Many algorithm have been developed, a few of them utilize source – specific prior knowledge for separation [19, 20]. The common Graphical approach created sparse component analysis in BSS[22].This method is depend on projecting the mixture in to space[22]where two dimensional image signal are assume sparse. We have to introduce a new technique of the geometrical approach to mixing matrix estimation that does not require Sparsification and is therefore-robust in regard to source dependencies technique[22] .ISA is another technique for image separation Independent subspace analysis (ISA) also called a multidimensional Independent component analysis[39]. For example, there is some method which use of gaussian scaled mixture to capture all possible variation of image separation. Since most of the image separation method try to avoid the use of source specific prior knowledge. Image separation becomes estimating these parameter for two dimensional source signals. Many algorithm have been proposed for image separation (*1*) convolutive mixture separation *2*) AMMCA Process *3*) scatter graphical approach 4) SVD based independent component analysis .At present an ICA is devloped in signaling field .Principal component analysis is a based on second order statistics of the covariance matrix [15].when the ICA based on the higher level amount not only consider the irrelevant characteristics of the PCA.ICA give the better result compare to PCA [15]

2.2 Convolutive separation Method

Convolutive mixtures of images are common in photography of semi-reflections. They additionally occur in research and pictorial representation [31]. Their formations Method involves focusing that specialize in an object layer, over that defocused layers are superimposed. Blind source separation (BSS) of convolutive image mixtures by direct optimization of mutual information is incredibly complex and suffers from local minima [31] Thus, we have a tendency to devise an economical approach to solve these issues. Our technique is quick, while achieving high quality image separation. The convolutive BSS problem is converted into a set of instantaneous (point wise) problems [31], employing a short time Fourier transform (STFT). Standard BSS solutions for instantaneous issue suffer, however, from scale and permutation ambiguities. We have to tendency these ambiguities by exploiting a parametric model of the defocus point spread function. Moreover, we have a tendency to enhance the potency of the approach by exploiting the exiguity of the STFT illustration as a previous blind separation of convolution mixture.

2.3 Ammca Algorithm

Ammca algorithm is a morphological component analysis .it is a popular for image separation field, we can extract degrading pattern or texture from image with help of in this method and we can simultaneously perform in painting. The morphological component Analysis is a new method for image separation which is allows to separate feature in image and these feature are present in different morphological aspect. To extend MCA to a multichannel (MMCA) for analyzing multispectral data and present a range of example which illustrate the result Image separation in signal and image processing .there are many instance where a set of observation is available and we wish to recover the source generating these observations. This problem, which is known as

Blind source separation (BSS). Blind source separation by independent component analysis (ICA) has received attention because of its potential application in signal processing such as in speech recognition system, telecommunication and medical signal processing .The goal of independent component analysis is to recover independent source given

2.4 Scatter-geometrical based method

Scatter graphical method is an efficient technique for separation. In this thesis we will use scatter graphical technique for image separation.

The two-dimensional BSS problem considers the input signals (i.e. mixtures) to be the linear combination of two source signals [22]. Scatter graphical approach is applicable for non-sparse signal. The mixtures are accordingly represented by equations (8) and (9):

$$X_1(x,y) = k_{11}s_1(x,y) + k_{12}s_2(x,y) \tag{8}$$

$$X_2(x,y) = k_{12}s_2(x,y) + k_{21}s_2(x,y) \tag{9}$$

Where s_i and X_i are the sources and mixtures signals, respectively. The signals s_i, are assumed to be normalized and nonnegative, i.e. $0 \leq S \leq 1$. The dynamic range and the gain of the signals are integrated into the mixing matrix. Dependencies are presented. The Problem of Blind Source Separation (BSS) when the hidden images are Nonnegative (N-BSS). In this case, the scatter plot of the mixed data is contained within the simplified parallelogram generated by the columns of the mixing matrix. Shrinking Algorithm for not mixing Non-negative Sources, aims at estimating the mixing matrix and the sources by parallelogram

$$X_a = \max(w_1) \tag{10}$$

$$y_a = \max(w_2) \tag{11}$$

Where w_1 *and* w_2 *are* one dimensional image vector

Further analysis is based on the assumption that Q1 < Q2, where Q1 and Q2 are defined by:

$$Q_1 = \frac{K_{21}}{K_{22}} \tag{12}$$

$$Q_2 = \frac{K_{22}}{K_{12}} \tag{13}$$

The boundaries of the fused data distribution in (12) and (13) can be established. From (13) one can write:

$$S_1 = \frac{X_1 - k_{12} s_2}{k_{11}} \tag{14}$$

$$S_2 = \frac{X_1 - k_{11} s_2}{k_{12}} \tag{15}$$

Substituting (14) and (15) into (12) yields:

$$x_2 \ = \frac{k_{21}}{k_{11}} x_1 + \left((k_{22} - \frac{k_{12} k_{21}}{k_{11}} \right) s_2 \tag{16}$$

$$x_2 = \frac{k_{22}}{k_{12}} x_1 + \left((k_{22} - \frac{k_{22} k_{11}}{a_{12}} \right) s_1 \tag{17}$$

Equations (16) and (17) separate the data point distribution into a linear part (left expression) and a source correlated part (right expression). Substitution of the general assumption (12) into equations (16) and (17) yields the following relations:

$$\left(k_{22} - \frac{k_{21} k_{12}}{k_{11}} \right) \geq 0 \tag{18}$$

$$\left(k_{21} - \frac{k_{22} k_{11}}{k_{12}} \right) \geq 0$$

The combination of relation (18) with equations (16) and (17) constitutes the basic linear boundaries of the data distribution represented in as follows:

$$\boldsymbol{x_2} \geq \frac{k_{21}}{K_{11}} \boldsymbol{x_1} + \left((k_{22} - \frac{k_{12} k_{21}}{k_{11}} \right) s_{2min} \tag{19}$$

$$x_2 \leq \ \frac{k_{22}}{k_{12}} x_1 + \left((k_{22} - \frac{k_{22} k_{11}}{a_{12}} \right) s_{1min}$$

Another mathematical concept of scatter approach [21]

$$A = [(k_{11} + k_{12})k, [(k_{21} + k_{22})]k \quad (20)$$

$$B = [(k_{12} - k_{11})k, [-(k_{21} - k_{22})]k \quad (21)$$

$$C = [-(k_{11} + k_{12})k, [-(k_{21} + k_{22})]k \quad (22)$$

$$D = [-(k_{12} + k_{11})k, [(k_{21} - k_{22})]k \quad (23)$$

Where ABCD is a parallelogram edges

$$[(K_{11} + K_{12})]K = x_a \; , \qquad [(K_{21} + K_{22})]k = y_b \quad (24)$$

$$[(K_{12} - K_{11})]K = x_b \; , \qquad [-(k_{21} - k_{22})]K = y_b \quad (25)$$

$$[-(K_{11} + K_{12})]K = x_c \; , \; [-(k_{21} + A_{22})]K = y_c \quad (26)$$

$$[(K_{12} - K_{11})]K = x_d \; , \qquad [(K_{21} - K_{22})]K = y_d \quad (27)$$

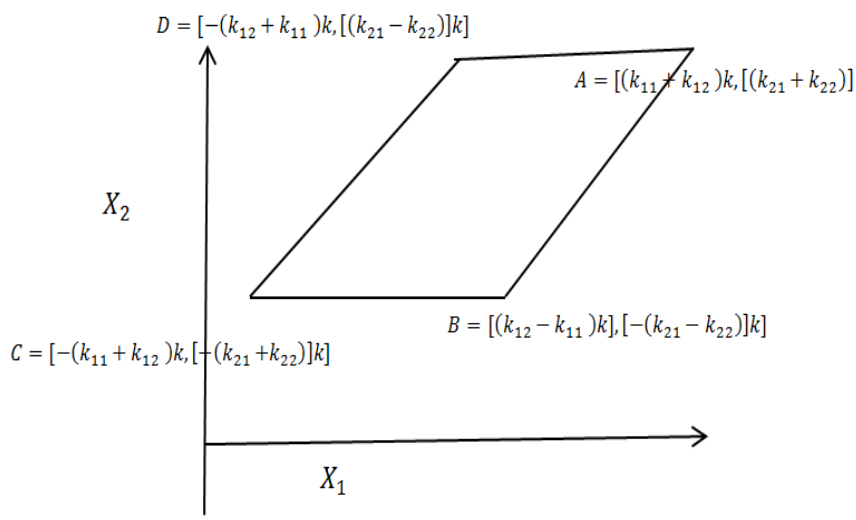


FIGURE 1: SCATTER PLOT OF FUSED IMAGE

We will estimate the mixing coefficient with some algebraic equation .These equation are given below

$$k_{11}k = \frac{x_a + x_d}{2} \qquad k_{11}k = \frac{x_a - x_b}{2} \quad (28)$$

$$k_{12}\, k = \frac{x_a + x_b}{2} \qquad k_{12} k = \frac{x_a - x_d}{2} \tag{29}$$

$$k_{22} k = \frac{y_a - y_d}{2} \qquad k_{22} k = \frac{y_a + y_b}{2} \tag{30}$$

$$k_{21} k = \frac{y_a - y_b}{2} \qquad k_{21} k = \frac{y_a + y_d}{2} \tag{31}$$

2.5 SVD based independent component analysis

SVD based independent component analysis is the good technique for image separation .In this thesis we will compare own result with SVD based ICA Method. We will briefly understand SVD based ICA. Firstly we will understand, this technique and SVD apply for image separation

2.5.1 SVD concept for image separation

To make explicit the algebraic concept to be pursued here, an important example of image separation will be used .Although there a many of mathematical alternative for separation will be used although there are many of algebraic alternative for the independent component [44].the aim consider here will be based upon PCA and SVD. To illustrate the phenomena of ICA .consider the example data represented in fig(2-a).The three panels are given to understanding the concept of ICA . In the left panel (a), measurement is consider of a given system and are shown to Project nicely on to a dominant direction. Leading principal component indicate by the red vector. The red vector would be the principal component length is σ_1 calculated by the larger singular value. Singular value σ_2 corresponding to the orthonormal direction of the second principal component should be small. In the middle panel (b). the measurement denoted that There are two principal direction in the data fluctuation [23]. When SVD is applied to the data, then dominant singular direction is denoted green vector. Green vector is not represent the data .important concept is consider SVD of the two independent component would generate two principal component. And last third panel (c) , Gaussian distribution data is clearly seen where no principal component can be measured .There are infinite number of orthogonal projection ,two arbitrary direction have been clearly seen in figure(2) .

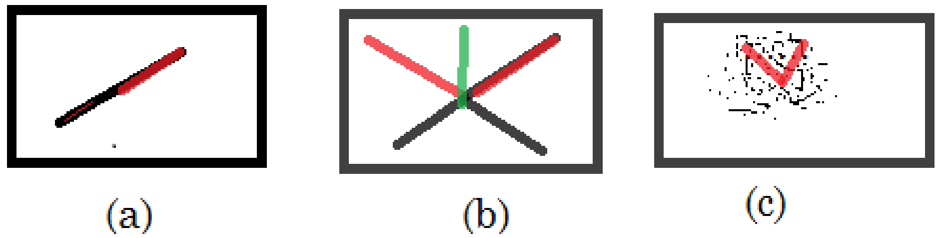


FIGURE 2: IILLUSTRATION OF THE PRINCIPAL OF PCA (A)ICA (B) AND THE FAILURE OF GAUSSIAN DISTRIBUTION

To distinguish principal component (c) .The red vector show the principal direction, While the green vector in the middle panel show that would be the principal direction if the direct SVD where applied rather than an ICA. The principal direction in (c) are arbitrary chosen since no principal direction can be distinguished.

2.5.2 Independent component analysis

ICA method is closely related to the Blind source separation ,Method [19 20].Source denoted the original signal or independent component and blind denoted the fact the mixing matrix coefficient k_{ij} are unknown .Ica method is a generative method ,which means that it define how the observed data are developed by a method of mixing the component S_i

$$x_j(t) = k_{j1}S_1 + k_{j2}s_2 \ldots\ldots k_{jn}s_n \qquad 1 \leq j \leq N \tag{32}$$

SVD based independent component analysis is well developed method [44]. The aim of this method separate independent component from estimate mixing matrix it is applicable for non-Gaussian data.

2.5.3 Concept behind ICA

We can Assume that we tends to observe n linear mixtures x_1, ...,x_n of n independent components

$$x_j = k_{j1}s1 + k_{j2}s_2 \ldots\ldots\ldots\ldots + k_{jn}\, s_n \text{ for all j.} \tag{33}$$

We have now dropped the time index t; in the ICA model, we tends to assume that every mixture x_j furthermore as every independent part s_k could be variant is a random, instead of a proper time signal. The observed values$x_j(t)$, the microphone signals in the cocktail party problem are then a sample of this random variable. Without loss of generality[19], we will assume that each the mixture variables and the independent components have zero mean: If this is often not true, then the observable variables x_i can always be centered by subtracting the sample mean, which makes the model zero-mean.

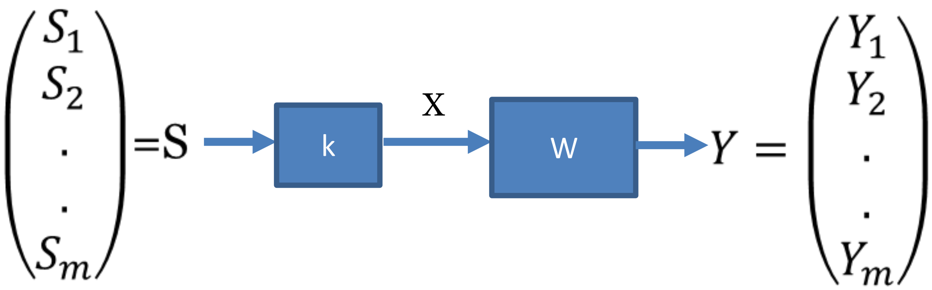


FIGURE 3: ICA ALGORITHM BLOCK DIAGRAM

The independent component analysis is (ICA) of a random vector consist of searching for a linear transformation that minimizes the statistical dependence between its component[19].Independent components are the maximally non-Gaussian component .Another, very intuitive and important principal of ICA estimation is maximum non Gaussianity . Independent component analysis based on blind source separation .The idea is that according to the central limit theorem sums of non-Gaussian random variable are closer to Gaussian that the original one. The independent component analysis is strong tool that extends the concept of PCA , POD and SVD. A simple way to creative thinking about ICA is by considering the cocktail party problem .thus consider many conversion in a room that are happening simultaneously .How is it that two different acoustic signals of conversion are and two can be separated out?[19]

Specific example for signal separation when two group are conversing .Two microphone are placed in room at different spatial location and from the two signals s_1(t) and $s_2(t)$ a algebric attempt is made to separate the signal that have been mixed at each of the microphone locations.

Provided that the noise level is not too more or that the conversion volume are sufficiently more, human can perform this work with significant ease. In our case, the two microphones are considered for different places.

This scenario and its algebraically foundation are foundation to the concept of eavesdropping a conversion. From a mathematically standpoint, this problem can be formulated with the following mixing equations.

$$x_1(t) = a_{11}s_1 + a_{12}s_2 \qquad (34)$$

$$x_2(t) = a_{21}s_2 + a_{22}s_2 \qquad (35)$$

Where $x_1(t)$ and $x_2(t)$ are the combined ,recorded signals at microphone one and two ,respectively the coefficient a_{ij} are the mixing parameter that are determined by a variety of factor consider the placement of the microphone in a room .the distance to the conversation ,and the overall room acoustics . Note that we are omitting time – delay signals that may reflect off the walls of the room .This difficulty also resemble quite nearly what may happen in a large number of application .For instance consider the following.

(1) Radar detection

If there are numerous target that are being tracked , ,then there is significant mixing in the scattered signal from all of the target .without a process for clear separation of the target ,the detector become impractical for recognizing location .

(2) Electroencephalogram(EEG)

EEG reading are electrical recording of brain activities typically these EEG reading are from multiple location of the scalp .However, at each EEG readings position, all the brain activity signals are merged, thus stopping a clear understanding of how many underlying signal are contained within, with a large number of EEG probe ICA permit for the separation of the brain activity reading and a better assessment of the overall neural activity [23]

(3) Terminator salvation

If you remember in the movie, John Connor and the resistance found a unseen signal (ICA) embedded on the ordinary signal in the communication sent between the terminator and sky net vehicles and ship, Although not mentioned in the movie, this was clearly somebody in the future who is reading this book now ,somehow that bit of sweet math only made it to the cutting room floor .regardless one shouldn't underestimate how awesome data analysis skills are in the real world of the future.

2.5.4 SVD Method for Ica

$$S = K^{-1}X \tag{36}$$

How is the physical drawback, how is SVD used then to separate the two images consider the action of the SVD on the image mixing matrix K of Eq (36). In this situation, we take two different images IMA1 and IMA. It gives us six unknown (IMA1, IMA2,$K_{11}, K_{12,} k_{21,} k_{22}$)With only the two constraints. Thus system cannot be algebraically solved without assumption being made. "The first condition" will be that the two images are statistically independent. When the pixel intensities are indicate by p_1 and p_2 condition of statiscally independent.

$$\mathrm{p}(\mathrm{p}_1, \mathrm{p}_2) = \mathrm{p}(\mathrm{p}_1)\mathrm{p}(\mathrm{p}_2) \tag{37}$$

Second vital condition mixing matrix (K) is full rank.

SVD process to the mixing Matrix $K = U\sum V^*$.Where U and V are unitary matrices that simply denoted to rotation and $\sum$ scales an image as prescribed by the singular value.A graphical illustration of this process is shown .The mixing matrix K can via the diagonal matrix $\sum$ and then rotate the parallelogram by the unitary matrix U .This is now fused image X($X_{1,} X_2$).The estimation, or ICA of the independent image thus reduces to finding how to transform the rotated parallelogram back in to square, or mathematically ,transforming the fused image back in to separable product of one-dimensional probability distributions. This is defining the mathematically aim of ICA image analysis problem, or any general ICA reduction technique [44]

2.5.5 Image separation

The common task of image separation can be specified as follows: given M distinct linear combinations of M images determine the original M images. For our job we can restrict ourselves to the case of just two images. Row vector of two images are denoted byX_1 and X_2, the linear mixing of these images can be denoted in matrix form as follows:

$$\begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = \begin{bmatrix} k_{11} & k_{12} \\ k_{21} & k_{22} \end{bmatrix} \begin{pmatrix} s_1 \\ s_2 \end{pmatrix} \tag{38}$$

$$X = K * S \tag{39}$$

Where the matrix K the linear mixing .Note that with this model .It is assumed that linear mixing in uniform over the entire image. The mixed image in X each contain a linear combination of the source image in S our job is to reconstruct the source –image from the fused images of course given the full rank matrix$K$.

$$S = K^{-1}Y \tag{40}$$

But we don't, typically known the mixing matrix so our aim will be to estimate it form the mixed. We will follow three step for image separation (*1*) Rotation of parallelogram *(2*) scaling of the parallelogram (*3*) again rotation of parallelogram minimize kurtosis.

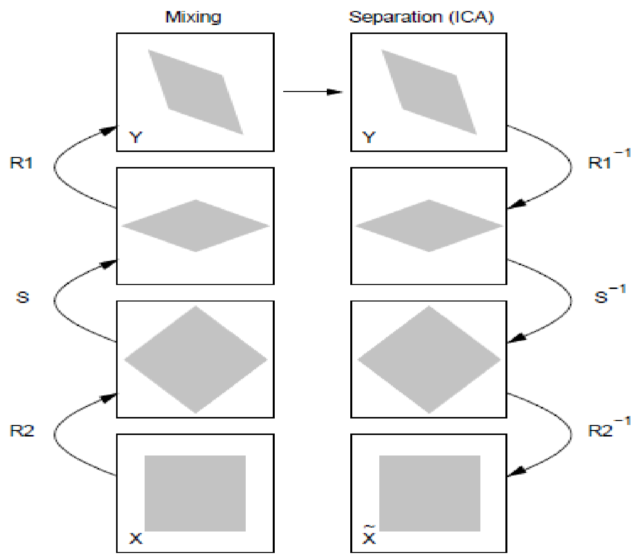


FIGURE 4: [44] GRAPHICAL DEPICTION OF THE SVD PROCESS OF MIXING OF TWO IMAGE .THERE CONSTRUCTION OF THE IMAGE IS ACCOMPLISHED BY APPROXIMATING OF THE SVD MATRICES SO AS TO ACHIEVE A SEPARABLE (STATISCALLY INDEPENDENT) PROBABILITY DISTRIBUTION OF THE TWO IMAGES

2.5.6 Rotation of parallelogram:

The –first important step in separating the image is to consider a rotation that aligns the long side and short side of the parallelogram with the primary axis [44]. To begin, consider once again figure (4) our first aim is to undo the rotation of the unitary matrix U. Thus we will ultimately want to estimate the inverse of the matrix which is simply U*.In a geometrical way of thinking, our aim is to align the long and short axes of the parallelogram with the primary axis as depicted in the two top right shaded boxes of fig.(4).The angle of parallelogram relative to the first axes will be denoted by θ and the long and short axes corresponds to the axes of the maximal and minimal variance respectively ,from the image data itself, then the maximal and minimal variance direction will be separated, Let zero mean measurement[44] .the variance at an arbitrary angle of orientation is given by

$$var(\theta) = \sum_{j=1}^{N}[x_1\,(J)x_2(j)]\begin{bmatrix}cos\theta\\ sin\theta\end{bmatrix}\sum_{j=1}^{N}[x_1\,(J)x_2(j)]\begin{bmatrix}cos\theta\\ sin\theta\end{bmatrix} \qquad (41)$$

Maximal variances is determined by calculating the angle θ that maximizes this function .it will be assumed that the corresponding angle of minimal variance will be perpendicular to this at $\theta - \pi/2$ These axes are fundamentally the principal component direction that would be estimate .if we actually knowledge about matrix K The maximum of with respect to θ can be found by differentiating $var(\theta)$ and setting it equal to 0.and get angle of detection

2.5.7 Maximal /minimal variance angle detection

The recovering the image the subsequent algebraic operation is performance Note that the coefficient of mixing matrix k can have intense effect on our ability to separate one image from another so change the parameter β from 1/5 to 3/5 can show .the impact a little change to the mixing matrix[44] .it is these image that we have a tendency to would like to reconstruct by numerically computing an approximation to the SVD the highest row fig demonstrate the mixing that occur with the .two ideal image given below when the mixing matrix with β=1/5 and 3/5.

$$S = k^{-1}X \tag{42}$$

$$var(\theta) = \sum_{j=1}^{N}[x_1\,(J)x_2(j)]\begin{bmatrix}cos\theta\\ sin\theta\end{bmatrix}\sum_{j=1}^{N}[x_1\,(J)x_2(j)]\begin{bmatrix}cos\theta\\ sin\theta\end{bmatrix} \tag{43}$$

$$\frac{1}{2}atan[-2\sum_{j=1}^{N}\frac{x_1\,(j)x_2(j)}{r^2(j)cos(2\varphi j)} \tag{44}$$

In polar coordinate x_1(j) = $r_1(j)cos(2\varphi)$ and x_2(j) = $r_1(j)sin(2\varphi)$ Then, the first rotation matrix in the separation

$$\mathrm{U} = \begin{bmatrix}\cos\theta & \sin\theta\\ -\sin\theta & \cos\theta\end{bmatrix} \tag{45}$$

With the angle θ computed directly from the experimental data.

2.5.8 Scaling parallelogram

The second important concept The principal component parallelogram achieved by the singular value of the SVD decomposition This process is proceed as the second step in the right column[23].The now aligned parallelogram need to be transformed in to diamond (fig4).more precisely the axes need to be independently scaled so that variance is rotationally invariant[23].The task however is rendered straight forwarded now that the principal axes have been determined from step 1 in particular the assumption was that along the direction θ the maximal variance is achieved when along $\theta - \pi/2$ the minimal –variance is achieved. Thus the component or singular value, thus the component or singular value of the orthogonal matrix $\sum -1$ and be computed with two difference weight to product two mixed image our object will be at given outline

$$\sigma_1 = \sum_{j=1}^{N}[x_1\,(J)x_2(j)]\begin{bmatrix} cos\theta \\ sin\theta \end{bmatrix}\sum_{j=1}^{N}[x_1\,(J)x_2(j)]\begin{bmatrix} cos\theta \\ sin\theta \end{bmatrix} \tag{46}$$

$$\sigma_2 = \sum_{j=1}^{N}[x_1\,(J)x_2(j)]\begin{bmatrix} \cos(\theta - pi/2 \\ \sin(\theta - pi/2 \end{bmatrix}\sum_{j=1}^{N}[x_1\,(J)x_2(j)]\begin{bmatrix} \cos(\theta - pi/2 \\ \sin(\theta - pi/2 \end{bmatrix}^2 \tag{47}$$

$$\begin{bmatrix} \sqrt{1/\sigma_1} & 0 \\ 0 & \sqrt{1/\sigma_2} \end{bmatrix} \tag{48}$$

2.5.9 Rotation To Separability

A final rotation is required to transform this diamond in to square .yielding the independent component One approach to the determination of this –final rotation is to find the orientation $\emptyset$ that maximizes the fourth statiscally moment (fig4) the fourth moment ,arbitrary orientation is given by The final rotation is aimed towards producing as best as possible a separable probability-distribution the analytically form and associated method used to do this is to minimize both the variance and kurtosis of the remaining distribution .The angle that accomplish this task is computed analytically form and the associated rotation matrix v is given by before computing. The rotation matrix or unitary transformation associated then with the rotation of the parallelogram back to its aligned position is then with the angle φ computed direction from the experiment data. The two images are quite different with one overlooking other.

2.5.10 Separation

The final rotation the likelihood distribution could be a lot of delight and refined ,but crucial to producing nearly separable probability distribution[23] .This separation method depend on the higher moment of the probability distribution .Since the mean has been assumed to be zero[23] and there is no reason to believe that there is an asymmetry in the probability distribution i.e higher order odd moment (such as skewness) are negligible [23] , the next dominant Statically moment to consider is the fourth moment or the kurtosis of the probability distribution .The goal will be to minimize this fourth order moment , and by doing so we will determine the appropriate rotation angle .Note that the second moment has already been handled through step1 and step 2 .said in a different mathematical way minimizing the kurtosis will be another step in trying to approximate the probability distribution of the image as separable function so that

$$\mathrm{p}(s_1)p(s_2) = p(s_1)p(s_2) \tag{49}$$

Appropriate rotation is sought by maximizing the non-Gaussianity

$$k(\varphi) = \sum_{j=1}^{n} x_1\,(j)x_2(j)\begin{bmatrix} cos\varphi \\ sin\varphi \end{bmatrix}^4 \tag{50}$$

$$k(\emptyset) = \sum_{j=1}^{N} \frac{1}{{x_1}^2(j)+{x_2}^2}\, x_1(j)x_2(j)\begin{bmatrix} cos\varphi \\ sin\varphi \end{bmatrix}^4 \tag{51}$$

$$\emptyset = \frac{1}{4}\, tan^{-1}\left[\frac{\sum_{j=1}^{N}[2{x_1}^3(j)x_2(j)-2x_1(j){x_2}^3(j)]/{x_1}^2(j)+{x_2}^2(j)]}{\sum_{j=1}^{N}[\;\;3\;x_1(j)\;\;{x_2}^2(j)-\left(\frac{1}{2}\right){x_1}^4(j)-(\frac{1}{2}){x_2}^4(j)]/[{x_1}^2(j)+{x_2}^2(j)]}\right] \tag{52}$$

Kurtosis: Kurt(y)=E[y4]-3(E[y2])2 (53)

Where $\emptyset$ is image of rotation associated with the unitary matrix U and variable $x_1(j)\; andx_2(j)$ represent the image that has undergone the two step of transformed as outlined previously for analysis. We based on the additive property of kurtosis we have

$$kurt(y) = kurt(q_1 s_1) + kurt(q_2 s_2) \tag{54}$$

kurtosis and its properties to use non-Gaussianity in ICA estimation .we must have a quantities measure of non-Gaussianity of a random variable say image separation method relies on the statistically properties of the image for reconstructing an approximation to the SVD decomposition

2.5.11 Complete the analysis

Our finally aim is estimate the mixing matrix from given fused image We will follow three step for estimating mixing matrix .To recovering the image , the following mathematical is performed .

$$S = K^{-1}X = V\sum^{-1}U^{*}X \tag{55}$$

$$S = \begin{bmatrix} cos\emptyset & sin\emptyset \\ -sin\emptyset & cos\emptyset \end{bmatrix} \begin{bmatrix} \sqrt{1/\sigma_1} & 0 \\ 0 & \sqrt{1/\sigma_2} \end{bmatrix} \begin{bmatrix} cos\theta & sin\theta \\ -sin\theta & cos\theta \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \tag{56}$$

Some inherent uncertainties in the reconstruct of the two images, the two matrices are indistinguishable

$$\begin{bmatrix} k_{11} & k_{12} \\ k_{21} & k_{22} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} k_{21} & k_{22} \\ k_{21} & k_{22} \end{bmatrix} \begin{bmatrix} x_2 \\ x_1 \end{bmatrix} \tag{57}$$

$$\text{k}=\begin{bmatrix} k_{11} & k_{12} \\ k_{21} & k_{22} \end{bmatrix} \tag{58}$$

Thus image’s one and two are arbitrary and two are arbitrary to some extent in practice, this does not matter. Thus image’s and two are arbitrary to extent no matter ,since the aim, was simple to separate ,not label the theta measurement there is also an uncertainty the Scaling since. Second is a scale ambiguity that is the independent components can only the determined within a scaling factor. Scaling matrix is given below

$$\begin{bmatrix} k_{11} & k_{12} \\ k_{21} & k_{22} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} k_{11}/_{\alpha} & k_{12}/_{\delta} \\ \\ k_{21}/_{\alpha} & k_{22}/_{\delta} \end{bmatrix} \tag{59}$$

Again .This is no matter since two separated image can be rescaled to

2.5.12 Uncertainties of ICA

(1) We cannot calculate the variance of the ICA.

The reason is that both mixing matrix and observation matrix are not known, any scalar multiplies in one of the source x_m could always be cancelled by dividing the corresponding column K_M of k by the same scalar see (62) As a method to leaves the ambiguity of the sign we could multiply the an independent component by -1 without affecting the model .this ambiguity is, fortunately, insignificant in most application

$$x(t) = [x_1(t)\ x_2(\text{t})\ldots\ldots\ldots\ldots\ldots x_m] \tag{60}$$

$$Y(t) = kx\ (t) \tag{61}$$

$$x = \sum \left(\frac{1}{\alpha_i} a_i\right)(s_i) \tag{62}$$

(2) We cannot determine the order of independent component

The reason is that again both x and k being are not known we can freely change the order of the term in sum and call any of independent component the first and formally a permutation matrix p and it’s inverse can be substitute in the mode to give y= k inv (p)x Consequent we may quite as well fix the magnitude of the independent component as they are random variables. The most natural way to do this is to assume that each has unit variance. Then the matrix k will be adapted in the ICA solution.

CHAPTER 3

DIGITAL IMAGE SEPARATION ALGORITHM BASED ON JOINT PDF OF MIXED IMAGES

3.1 Automatic Image Separation

A number of Algorithms have been proposed to separate two-fused image containing transparency and reflections. When only one fused image is present, automatic separation is quite Typical because it is extremely ill-posed (although Levin etal. attempted it on simple mixtures [41] and then Levin and Weiss [42] developed a two-image separation system with user's assistances, the system is not automatic). However, when two or more mixtures are present, each slightly different, automatic separation can be achieved "by accurate exploitation of the diversity in different fused image" [41]. Some The image separation method relies on the statically properties of the image for reconstructing an approximation to the SVD decomposition ..Separation of mixed and overlapped images is a frequently arising problem in image processing for example separation of overlapped fingerprint obtain from any crime scene in which we get a mixture which consist of two or more The apply ICA in frequency domain . three step have been outlined ,three step in the last that must be followed ,first the rotation of the parallelogram must be computed by finding the maximal and minimal direction of the variance of the data. EASI algorithm was extended to separate complex valued signal Scaling of the principal component direction is evaluated by calculating the variance, Third the final rotation is computed by minimize both the variance and kurtosis of the data this yield an approximately separable probability distribution the three step are each handled in term .To make explicit the mathematical mythology to be pursued here a specific example of image separation. There are a variety of mathematical alternative for separating the independent component the approach consider here will be based upon PCA and SVD illustrate the concept of ICA.

The general problem of image separation can be stated as follows given N distinct linear combination of N image determine .The Original N image's for our application we can restrict ourselves. To the case of just two images denoting these image in row vector from x_1 and x_2 the linear mixing of these image can be expressed

$$\begin{pmatrix} X_1 \\ X_2 \end{pmatrix} = \begin{pmatrix} k_{11} & k_{12} \\ k_{21} & k_{22} \end{pmatrix} \begin{pmatrix} s_1 \\ s_2 \end{pmatrix} \tag{63}$$

$$X = KS \tag{64}$$

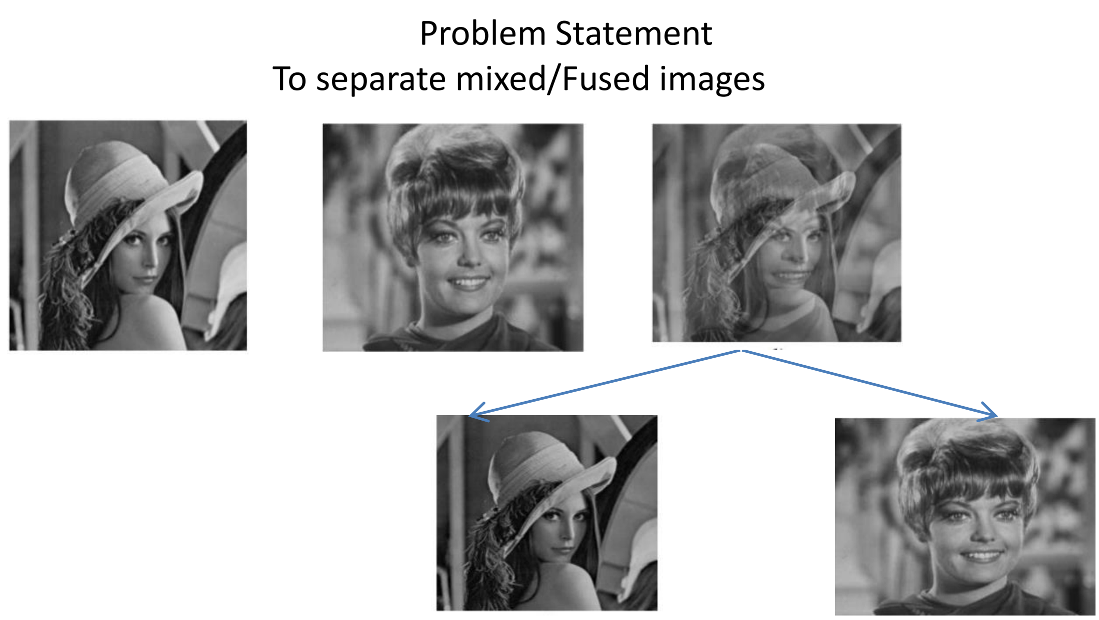


FIGURE 5: IMAGE FUSION AND IT'S SEPARATION

$$(X, Y) = k_{i1} s_2(x, y) + k_{i2} s_2(x, y) \tag{65}$$

We have proposed many algorithms for image separation but scatter graphical approach is very efficient technique for separation.

3.2 Work done

We will take 11 different images. We will fused these images with help Scatter and ICA technique and make 55 combinations of these images according to $c^n{}_2$ where n=number of images. we will separate these image with help of Scatter method and SVD based ICA method, then calculate the PSNR and Signal interference ratio (SIR) of difference between the original image and separated image .In this Thesis a scatter method and SVD based ICA algorithms of bind source separation is introduce on image's Result of experiment show the scatter approach can separate images. And show proposed approach can separate every image.

3.2.1 Estimation of mixing matrix

Image separation aims to estimate both original image and mixing matrix using fused image. Since there are two way for the estimation of both the original image and mixing matrix. Estimate the mixing matrix, given a separate of image. Separation with SVD based ICA method given below. Estimate the mixing matrix ,given an estimate of source signal .2) Estimate the source signal, given an estimate of mixing matrix .Here we prefer the first method that is estimate the mixing matrix, given an estimate of source signals. Two method of find out mixing matrix (1) scatter graphical approach (2) SVD based ICA method.

3.2.2 Scatter method

It has been Consist that original images are histogram equalized and statistically independent; the automatic image separation procedure based on scatter data [20] of the observed images is established for the mixture of two images. where it has been assumed that maximum variance orientation is orthogonal to the minimum variance orientation [23].The scatter plot of two image mixtures ,generated by mixing two positive source is enclosed by a parallelogram[22], the orientation of that area unit presented by the two ratios of the four mixing coefficients[22]. The existence of inter-source dependencies create a distribution enclosed by a different parallelogram (rectilinear) shape [22], enclosed by the original parallelogram. Based on this observation a geometrical graphical method for Blind Source Separation (BSS) is presented with reference to the scatter plot of the merged image. The two-dimensional BSS problem considers the input signals (i.e. mixtures) to be the linear combination of two source signals [22]. The mixtures are accordingly represented by equations (66) and (67):

$$x_1(x,y) = k_{11}s_1(x,y) + k_{12}s_2(x,y) \tag{66}$$

$$x_2(x,y) = k_{12}s_2(x,y) + k_{21}s_2(x,y) \tag{67}$$

Where s_i and x_i are the original image and fused image, respectively. The signals s_i, are assumed to be normalized and nonnegative, i.e. $0 \leq S_i \leq 1$. The dynamic range and the gain of the signals are integrated into the mixing matrix. Scatter plots of the mixture data points, observed in satisfy the following equation:

$$x_2 = \left(\frac{k_{21}s_1 + k_{22}s_2}{k_{11}s_1 + k_{12}s_2}\right) x_1 \tag{68}$$

Two mixed variable $x_1$and x_2 .it is easily computed that the mixed data has uniform distribution on a parallelogram. The random variable x_1 and x_2 are not random independent anymore. The drawback of estimating the information model of scatter graphical methodology is currently estimate the mixing matrix k using only information contained within the mixture x_1 and x_2. The edge of the parallelogram the direction of the column this mean that we tends to may in principal estimate the scatter model by initial estimating the joint density of x_1 and x_2 and then locating the edge The problem of Blind Source Separation (BSS) when the hidden images are Nonnegative (N-BSS)[22]. During this case, the scatter plot of the merged information is contained among the simplified parallelogram generated by the columns of the mixing matrix. Shrinking Algorithm for not mixing Non-negative Sources, aims at estimating the mixing matrix and the sources by parallelogram [22].

To analyze (66), and to outline the approach to the BSS problem in the Scenario where two dimensional image signals are not sparse, the boundary values of the input signals are defined:

$$x_a = \max(w_1) \tag{69}$$

$$y_a = \max(w_2) \tag{70}$$

Where w_1 and w_2 is an image Dimensional vector

Further analysis is based on the assumption that Q1 < Q2, where Q1 and Q2 are defined by:

$$Q_1 = \frac{K_{21}}{K_{22}} \tag{71}$$

$$Q_2 = \frac{K_{22}}{K_{12}} \tag{72}$$

3.3 Image Separation with scatter geometrical method

We will take 11 different gray images size 512*512 bmp images.SO our aim is to estimate the mixing matrix from original image .let us take two images IM(1) and IM(2) in figure 6.

Figure 6: ORIGINAL IMAGE

FIGURE 7 FUSED IMAGES OF IM1 AND IM2

When two histogram equalized images are linearly mixed (3.3.1) and (3.3.2) then the observed images will no longer have uniform distributions.

$$x_1 = k_{11}IM1 + K_{12}IM2 \quad (3.3.1)$$

$$x_2 = k_{21}IM1 + K_{22}IM2 \quad (3.3.2)$$

In vector matrix form the above equation can be written

$$1M2 = KIM \quad (3.3.3)$$

Where, mixing coefficient is given by

$$K = \begin{bmatrix} K_{11} & K_{12} \\ K_{21} & K_{22} \end{bmatrix} \quad (3.3.4)$$

IM1 and IM2 are independent to each other. Then we will take histeqlization (uniform distribution) of given image

$$\mathrm{fIM}(\mathrm{IM_i}) = \begin{Bmatrix} \frac{1}{2\mathrm{k}}, \text{if} & \mathrm{IM_i} \in [-\mathrm{k}\ \ \mathrm{k}] \\ 0 & \text{elsewhere} \end{Bmatrix} \quad (3.3.5)$$

Graphical, both the source im1 and im2 and fuse image x_1, x_2 are independent with each other and having the uniform distribution within range $[-k\ k]$ is shown below

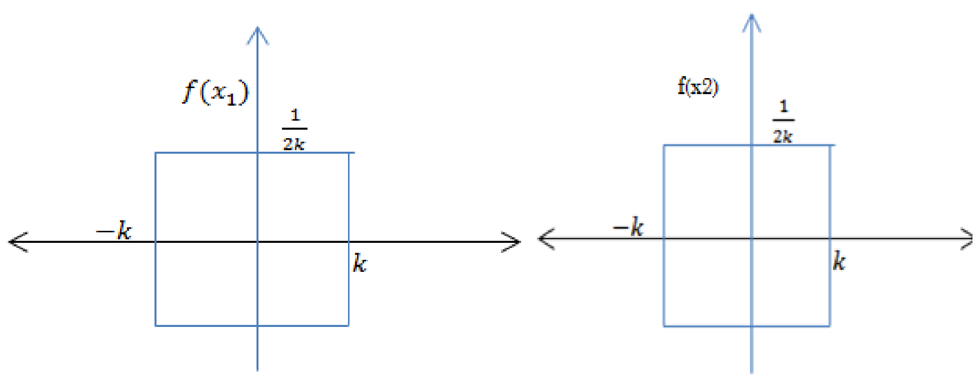


Figure 8 probability density function (PDF) of independent component x_1 and x_2

Uniform distribution of independent component x_1 and x_2 having uniform distribution within the range of –k to k and magnitude of uniform distribution is $\frac{1}{2k}$

$$\mathrm{F}\ (x_1) = \frac{1}{k_{11}} f x_1(\frac{X_1}{k_{11}}) * \frac{1}{k_{12}} f x_2(\frac{X_1}{k_{12}}) \quad (3.3.6)$$

$$\mathrm{F}\,(x_2) = \frac{1}{k_{11}} f x_2(\frac{X_2}{k_{21}}) * \frac{1}{k_{12}} f x_2(\frac{X_2}{k_{22}}) \tag{3.3.7}$$

Where ‘*’ operator the convolution let us assume that

Scaling of the fused data

$$\frac{1}{k_{11}} f x_1 \left(\frac{X_1}{k_{11}}\right) = f_{g1}(g_1) \tag{3.3.8}$$

$$\frac{1}{k_{12}} f x_1 \left(\frac{x_2}{k_{12}}\right) = f_{g1}(g_2) \tag{3.3.9}$$

$$f x_1(x_1) = f g_1(g_1) * f g_2(g_2) \tag{3.3.10}$$

Mathematical, we get the expression for the probability density function of the mixture x_1 and likewise for mixture x_2 graphical probability density function (pdf) of mixture x_1 and mixture x_2 [21]

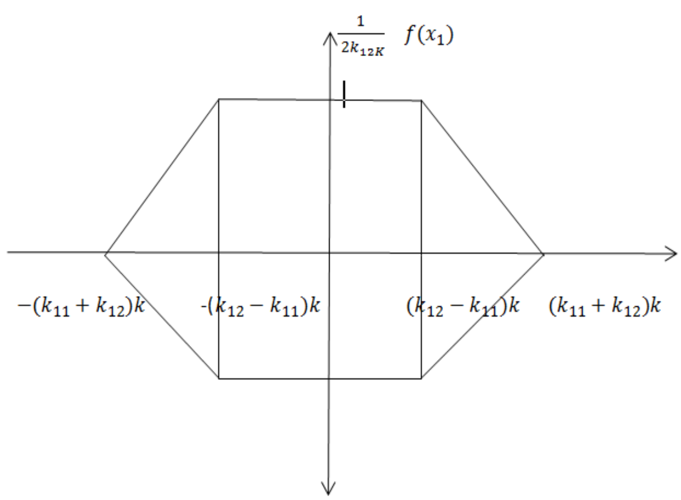


Figure 9: Probability distribution function of fused image $\boldsymbol{x_1}$

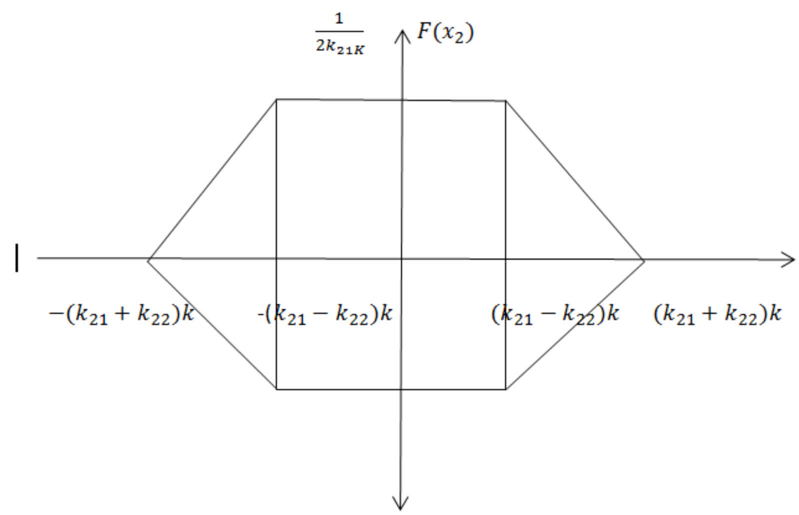


Figure 10 Joint PDf of fused image $\boldsymbol{X_2}$

Then the resultant distribution of the observed images for k12 > k11 and k22 > k21 is given in (3.3.11) and (3.3.12). Where, w1

$$F(w_1) = \left[\begin{array}{lll} & \frac{1}{4k_{11}k_{12}k^2}(k_{11}k+k_{12}k+w_1) & -(k_{11}+k_{12})k \le w_1 \le -(k_{12}-k_1)k \\ \frac{1}{2k_{12}k} & & -\ (k_{12}-k_{11})k \le w_1 \le (k_{12}-k_{11}) \\ & \frac{1}{4k_{11}k_{12}k^2}(k_{11}k+k_{12}k+w_1) & -(k_{11}+k_{12})k \le w_1 \le (k_{11}+k_{12})k \\ & otherwise & 0 \end{array}\right]$$

(3.3.11)

$$f(w_2) = \left[\begin{array}{ll} \frac{1}{4k_{21}k_{22}k^2}(k_{21}k+k_{22}k+w_2) & -(k_{21}+k_{22})k \le w_2 \le -(k_{22}-k_{21})k \\ \frac{1}{2k_{22}k} & -\ (k_{22}-k_{21})k \le w_2 \le (k_{22}-k_{21}) \\ \frac{1}{4k_{11}k_{12}k^2}(k_{11}k+k+y_1) & (k_{22}+k_{21})k \le w_2 \le (k_{21}+k_{22})k \\ otherwise & 0 \end{array}\right]$$

(3.3.12)

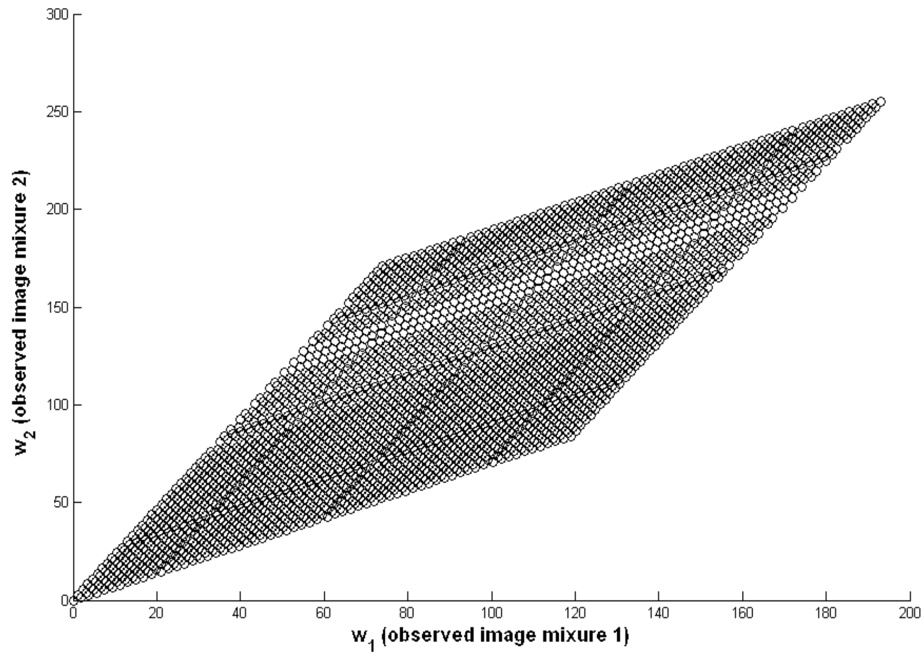


Figure 11 SCATTER PLOT FOR THE TWO MIXED IMAGES

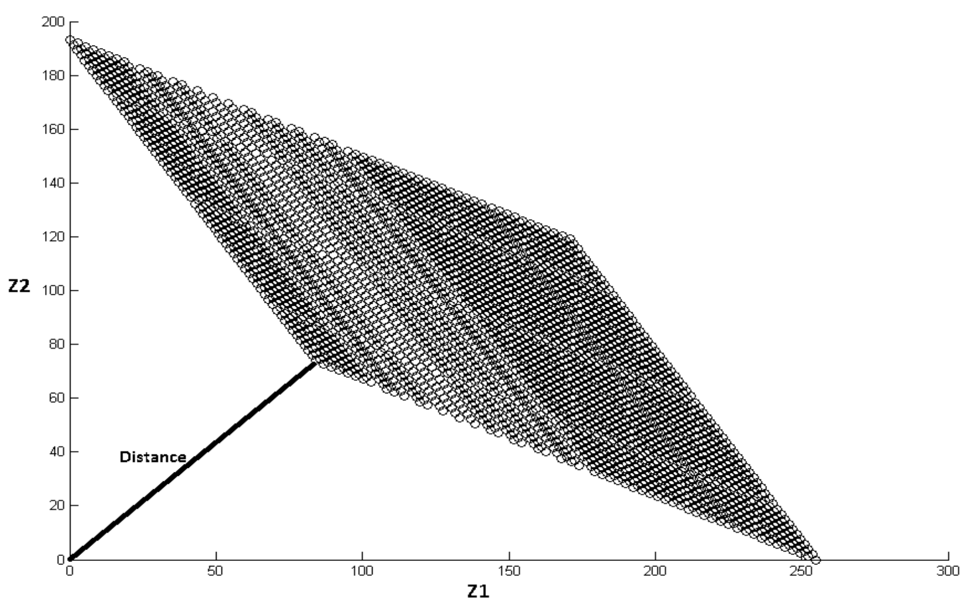


Figure 12. ROTATED (ANTI-CLOCK WISE) SCATTER PLOT FOR THE MIXED IMAGES

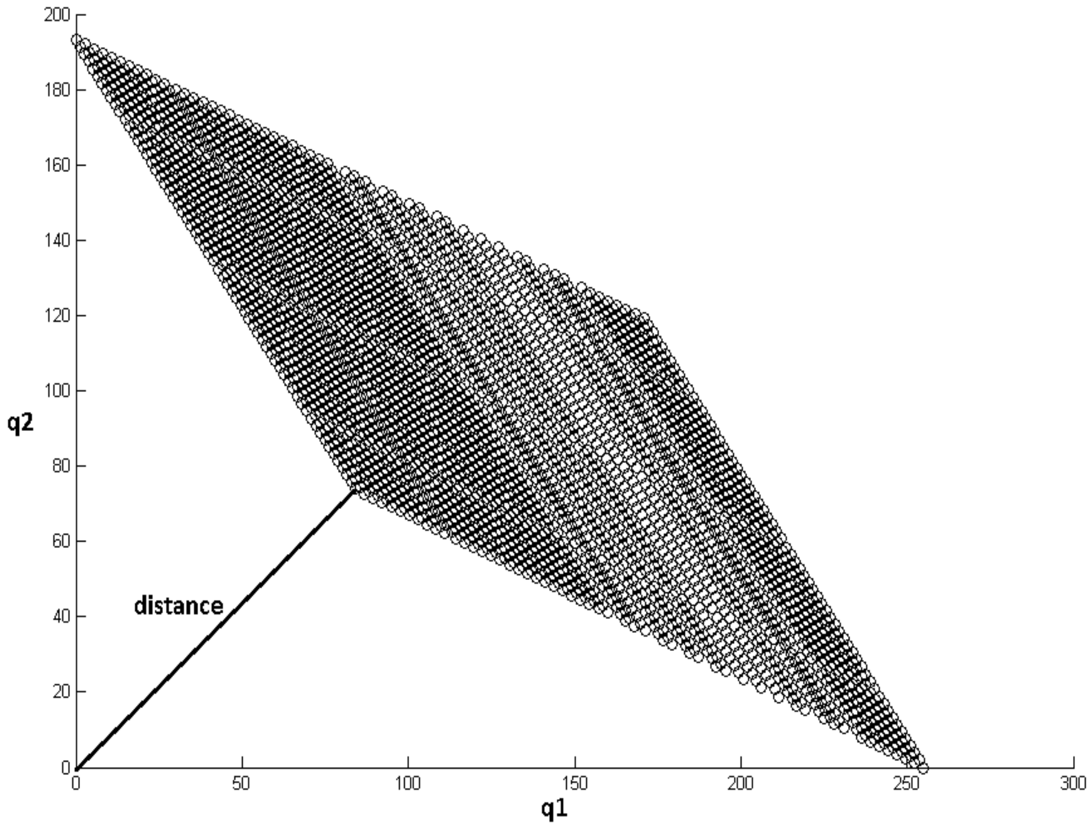


FIGURE 13 ROTATED (CLOCK WISE) SCATTER PLOT FOR THE MIXED IMAGES

Parallelogram edge is given as $A = (X_{a,}Y_a)$, $B = (X_b, Y_b)$, $C = (X_{c,}Y_C)$, $D = (X_d, Y_d)$ We will find out Maximum value of parallelogram edges which is denoted $A = (X_{a,}Y_a)$ And find out minimum value of parallelogram edges which is denoted $C = (X_{c,}Y_C)$ Image vector size is $512 * 512$ .we will convert 2 dimensional vector to the one dimensional vector. Size of one dimensional vector become 1 by N^2

1. Draw scatter plot of two mixed image (w1(image IM1) and w2(image ima2)
2. we will rotate scatter plot anti clock wise Direction(rotate(anticlockwise) direction scatter plot is denote Z
3. Third condition is again scatter plot is rotate clockwise direction.
4. Finally we can estimate mixing matrix with help of scatter plot and we can separate image from fused image

3.4 Scatter data based algorithm

Algorithm: Algorithm for image separation based of scatter plot

(1) Find maximum and minimum value x_1 and x_2

(a) $x_a = \max(x_1)$ and $y_a = \max(x_2)$

(b) $x_c = \min(x_1)$ and $y_c = Max(x_1)$

(2) convert x_1 and x_2 in to row vector w_1 and $w_2$of order 1 by N^2

a) $w_1(1,(x-1)*N+y) = x_1(X,Y)$

b) $w_2(1,(x-1)*N+y) = x_2(X,Y)$

(3) $z = \begin{bmatrix} -w_2 \\ w_1 \end{bmatrix} - \begin{bmatrix} \min(-w_2) \\ \min(w_1) \end{bmatrix}$

(4)find vector V.V=[$||z_1|| \quad ||z_2|| \ldots\ldots\ldots |z_{N^2}|$

Where $||z_p|| \quad = \sqrt{z^2(1,p) + z^2(2,p)}$

(5)Search for the smallest component in the row vector V and store its index in j

(6) $\begin{bmatrix} x_d \\ y_d \end{bmatrix} = \begin{bmatrix} \mathrm{Z}(2,\mathrm{j}) + \min(w_1) \\ -Z(1,j) - \min(w_2) \end{bmatrix}$

(7)) $Q = \begin{bmatrix} w_2 \\ -w_1 \end{bmatrix} - \begin{bmatrix} \min(w_2) \\ \min(-w_1) \end{bmatrix}$

(8) find vector T,T=$||q_1|| \quad ||q_2|| \ldots\ldots\ldots |q_{N^2}||]$

where$||q_p|| \quad = \sqrt{Q^2(1,p) + Q^2(2,p)}$

(9)Search for the smallest component in the row vector T and store its index in i

(10) $\begin{bmatrix} x_b \\ y_b \end{bmatrix} = \begin{bmatrix} -\mathrm{Q}(2,\mathrm{j}) - \min(-w_1) \\ -Q(1,i) + \min(w_2) \end{bmatrix}$

(11)$K = \frac{1}{2L} \begin{bmatrix} x_a + x_d & x_a - x_d \\ y_a - y_{b,} & y_a + y_{b,} \end{bmatrix}$,Where L is the number of intensity levels in an image

(12)$X = K^{-1}Y$

(13) If mod(y,N)≠0 then q=mod(y,N); else q=N

(14)$x_1{}^{Seprated}\left(\left\lfloor \frac{y}{N} \right\rfloor, q\right) = X(1,y), x_2{}^{separated}\left(\left\lfloor \frac{y}{N} \right\rfloor, q\right) = X(2,y)$

w_1 And w_2 are the row vector of order 1 by N^2 of the observed images x_1 and x_2. So the joint probability density functions or scatter plot of the two observed images will be parallelogram in shape. The scatter data based separation algorithm for the two mixed images x_1 and x_2 (order of N by N) is given in Algorithm 1. The scatter plot of the two mixed images and their variants are given in fig. 11 to 13. Since, and w_2 are the row vector of order 1 by N^2 of the observed image x_1 and x_2 .So the joint pdf or scatter plot of the two four vertices of the scatter plot contains the information of the mixing matrix, these variants of the scatter plot is used to estimate the four vertices. In fig 12 and 13, the smallest distance between the origin and a point in the scatter plot is calculated. The point in a scatter plot corresponding to smallest distance has maximum probability to be a vertex point of a parallelogram.

CHAPTER 4

RESULT, CONCLUSION AND FUTURE WORK

4.1 Different Fused image

$2M3\_1$ $2M3\_2$

Figure 14: Fused image of 2M3

$$2M3\_1 = k_{11}IM1 + K_{12}IM2$$
$$2M3\_2 = k_{21}IM1 + K_{22}IM2 \quad (4.1.1)$$

3M4_1 **3M4_2**

Figure 15: Fused image of 3M4

$$3M4\_1 = k_{11}IM3 + K_{12}IM4$$
$$3M4\_2 = k_{21}IM3 + K_{22}IM4 \quad (4.1.2)$$

4M5_1 **4M5_2**

Figure 16: fused image of 4M5

$$4M5\_1 = k_{11}IM4 + K_{12}IM5$$
$$4M5\_2 = k_{21}IM4 + K_{22}IM5 \quad (4.1.3)$$

5M6_1 **5M6_2**

Figure 17: fused image of 5M6

$$5M6\_1 = k_{11}IM5 + K_{12}IM6$$
$$5M6\_2 = k_{21}IM5 + K_{22}IM6 \quad (4.1.4)$$

6M7_1 6M7_2

Figure 18: fused image of IM6 and IM7

$$6M7_1 = k_{11}IM6 + K_{12}IM7 \quad (4.1.5)$$

$$6M7\_2 = k_{21}IM6 + K_{22}IM7$$

7M8_1 7M8_2

Figure 19: fused image of 7M8

$$7M8\_1 = k_{11}IM7 + K_{12}IM8$$

$$7M8\_2 = k_{21}IM7 + K_{22}IM8$$

(4.1.6)

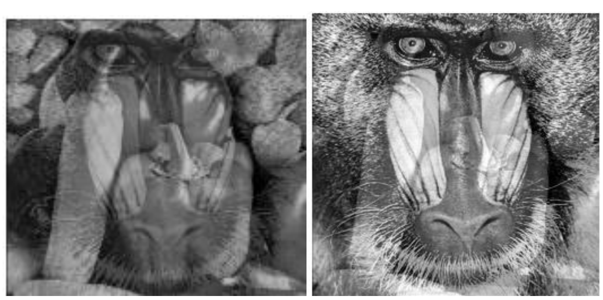
8*M*9_1 8M9_2

Figure 20: fused image of 8M9

$$8M9\_1 = k_{11}IM8 + K_{12}IM9$$

$$8M9\_2 = k_{21}IM8 + K_{22}IM8$$

(4.1.7)



9M10_1 9M10_2

Figure 21: fused image of 9M10

$$9M10\_1 = k_{11}IM9 + K_{12}IM10$$
$$9M10\_2 = k_{21}IM9 + K_{22}IM10 \tag{4.1.8}$$

10M11_1

10M11_2

Figure 22: fused image of 10M11

$$10M11\_1 = k_{11}IM10 + K_{12}IM11$$
$$10M11_2 = k_{21}IM10 + K_{22}IM1 \tag{4.1.8}$$

4.2 Scatter plot of mixed image

Show uncorrelated mixture of those independent component, when the mixture are uncorrelated that the distribution is not same .The independent component are mixed using orthogonal mixing matrix, which corresponds rotation of plane .The edge of the square, we are estimate the rotation that gives the original component nonlinear correlation that gives the original component Using two independent component with uniform distribution

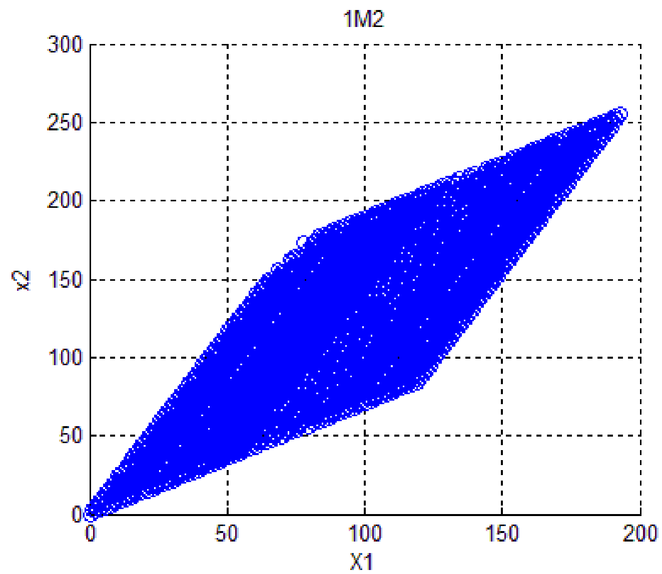


Figure 23 Scatter plot of mixture $\boldsymbol{X_1 and\ X_2(1M2)}$ ($\boldsymbol{K_{11} = 0.467\ K_{12} = 0.23\ K_{21} = 0.33\ K_{22} = 0.667}$) Horizontal axis is labeled as $\boldsymbol{X_1}$ and vertical axis $\boldsymbol{X_2}$ Fig

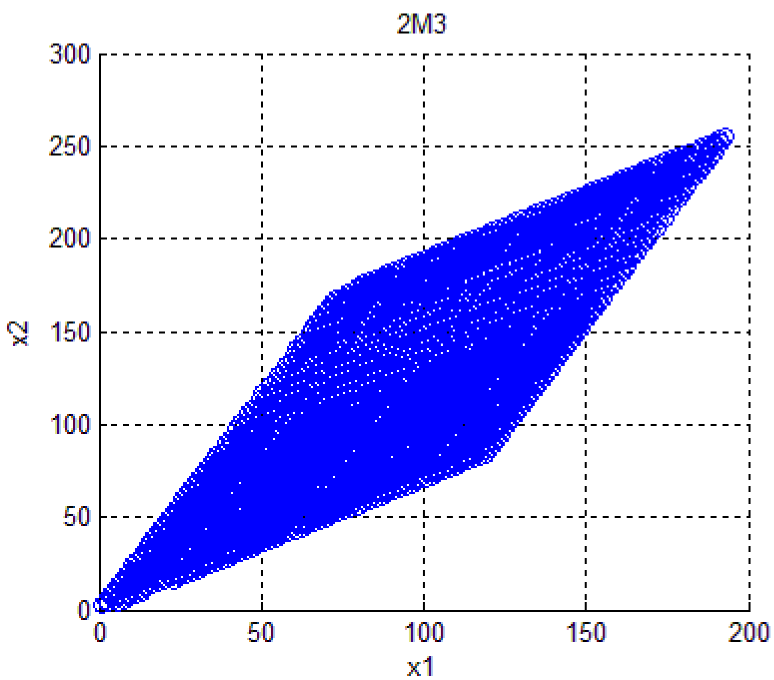


Figure 24 Scatter plot of mixture $\boldsymbol{X_1 and\ X_2(2M3)}$ ($\boldsymbol{K_{11} = 0.467\ K_{12} = 0.23\ K_{21} = 0.33\ K_{22} = 0.667}$) Horizontal axis is labeled as $\boldsymbol{X_1}$ and vertical axis $\boldsymbol{X_2}$

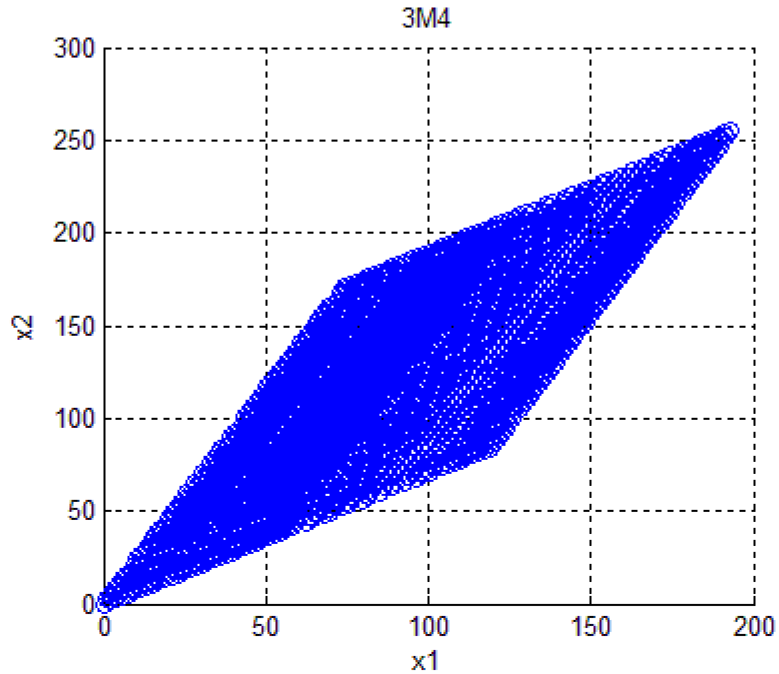


Figure 25 Scatter plot of mixture $\boldsymbol{X_1 and\ X_2}$(**3**$\boldsymbol{M4_1}$ **, 3M4_2**) ($\boldsymbol{K_{11} = 0.467\ K_{12} = 0.23\ K_{21} = 0.33\ K_{22} = 0.667}$) Horizontal axis is labeled as $\boldsymbol{X_1}$ and vertical axis $\boldsymbol{X_2}$

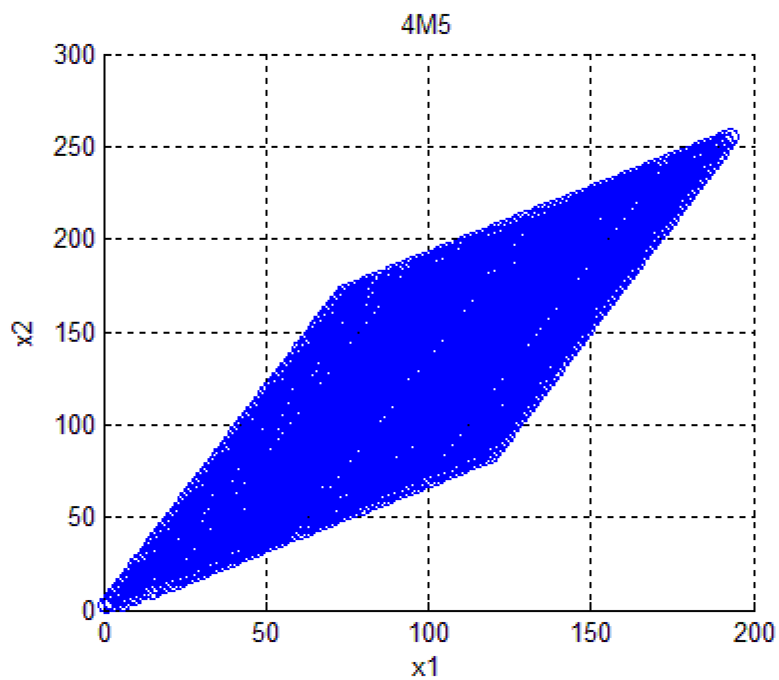


Figure 26 Scatter plot of mixture $\boldsymbol{X_1 and\ X_2(4M5)}$ ($\boldsymbol{K_{11} = 0.467\ K_{12} = 0.23\ K_{21} = 0.33\ K_{22} = 0.667}$) Horizontal axis is labeled as $\boldsymbol{X_1}$ and vertical axis $\boldsymbol{X_2}$

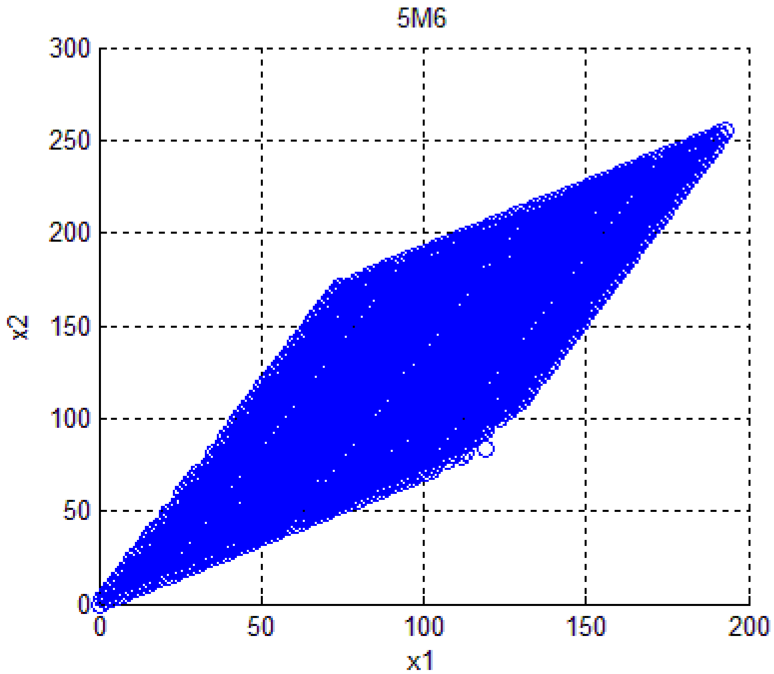


Figure 27 Scatter plot of mixture $\boldsymbol{X_1 and\ X_2 (5M6)}$ ($\boldsymbol{K_{11} = 0.467\ K_{12} = 0.23\ K_{21} = 0.33\ K_{22} = 0.667}$) Horizontal axis is labeled as $\boldsymbol{X_1}$ and vertical axis $\boldsymbol{X_2}$

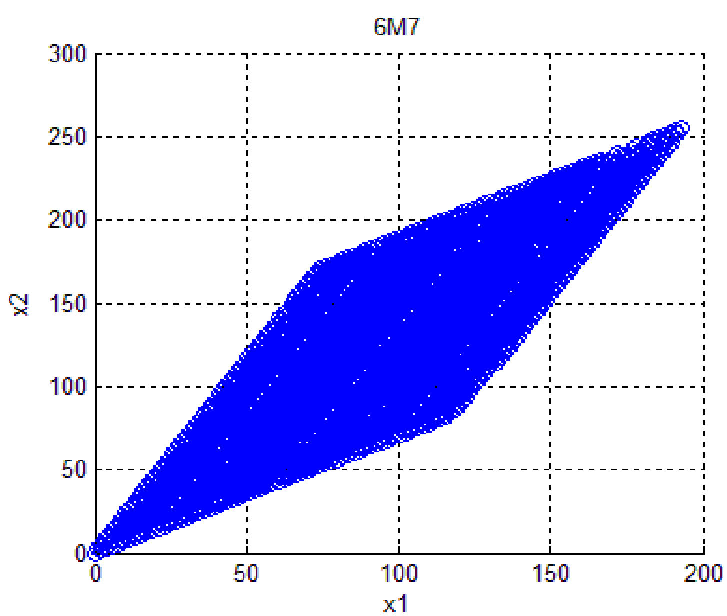


Figure 28 Scatter plot of mixture $\boldsymbol{X_1 and\ X_2 (6M7)}$ ($\boldsymbol{K_{11} = 0.467\ K_{12} = 0.23\ K_{21} = 0.33\ K_{22} = 0.667}$) Horizontal axis is labeled as $\boldsymbol{X_1}$ and vertical axis $\boldsymbol{X_2}$

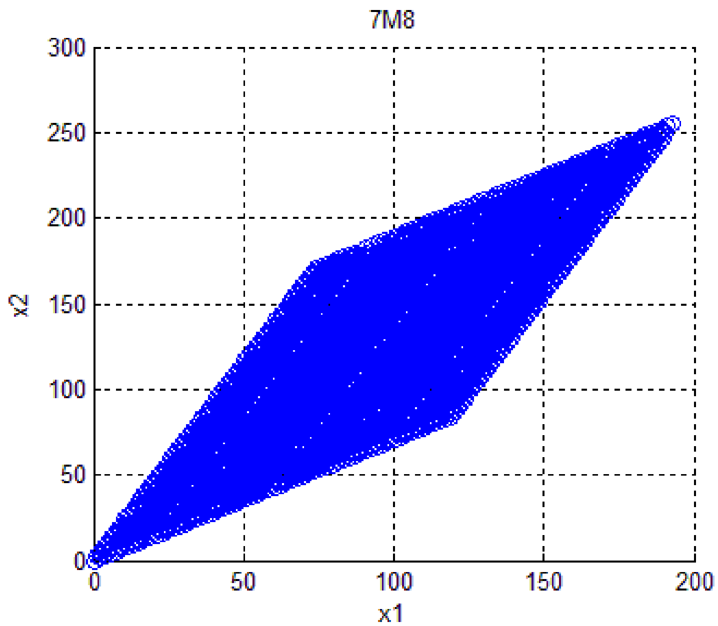


Figure 29 Scatter plot of mixture $\boldsymbol{X_1 and\ X_2 (7M8)}$ $(\boldsymbol{K_{11} = 0.467\ K_{12} = 0.23\ K_{21} = 0.33\ K_{22} = 0.667})$ Horizontal axis is labeled as $\boldsymbol{X_1}$ and vertical axis $\boldsymbol{X_2}$

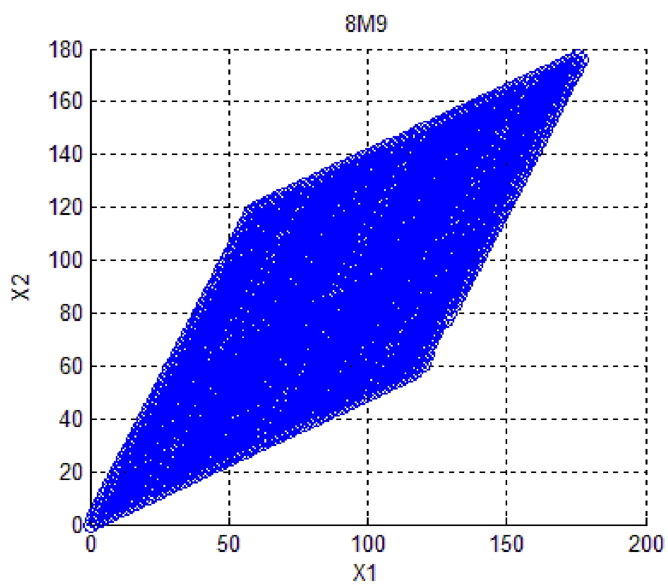


Figure 30Scatter plot of mixture $\boldsymbol{X_1 and\ X_2 (8M9)}$ $(\boldsymbol{K_{11} = 0.467\ K_{12} = 0.23\ K_{21} = 0.33\ K_{22} = 0.667})$ Horizontal axis is labeled as $\boldsymbol{X_1}$ and vertical axis $\boldsymbol{X_2}$

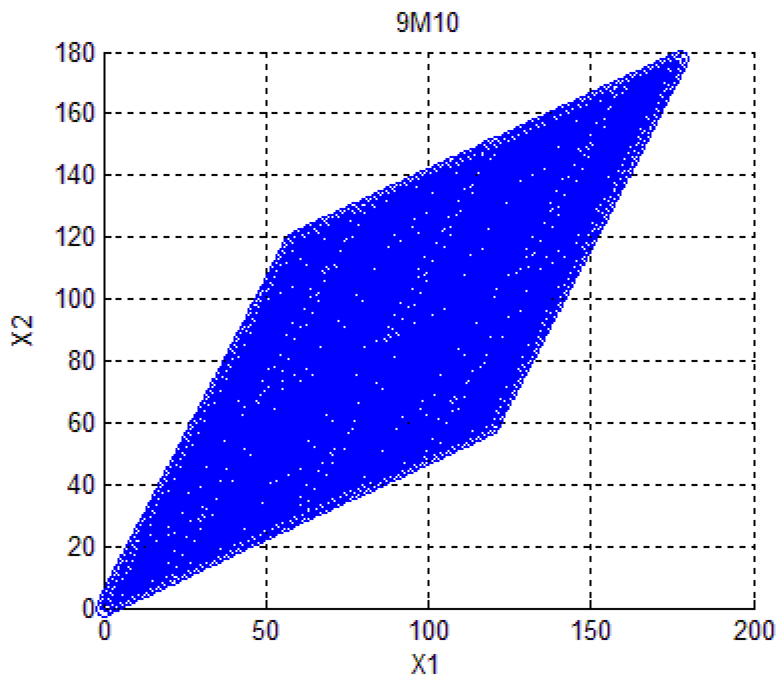


Figure 31 Scatter plot of mixture $\boldsymbol{X_1 and\ X_2(9M10)}$ ($\boldsymbol{K_{11} = 0.467\ K_{12} = 0.23\ K_{21} = 0.33\ K_{22} = 0.667}$) Horizontal axis is labeled as $\boldsymbol{X_1}$ and vertical axis $\boldsymbol{X_2}$

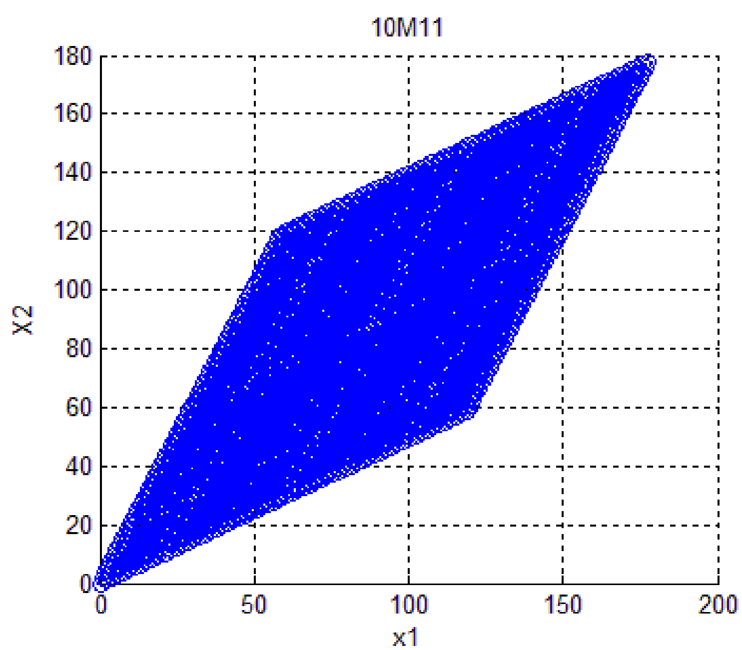


Figure 32 Scatter plot of mixture $\boldsymbol{X_1 and\ X_2(10M11)}$ ($\boldsymbol{K_{11} = 0.467\ K_{12} = 0.23\ K_{21} = 0.33\ K_{22} = 0.667}$) Horizontal axis is labeled as $\boldsymbol{X_1}$ and vertical axis

4.3 Separation with scatter graphical method

Figure 33: Separated image 1M2

Figure 34: Separated image 2M3

Figure 35: Separated image 3M4

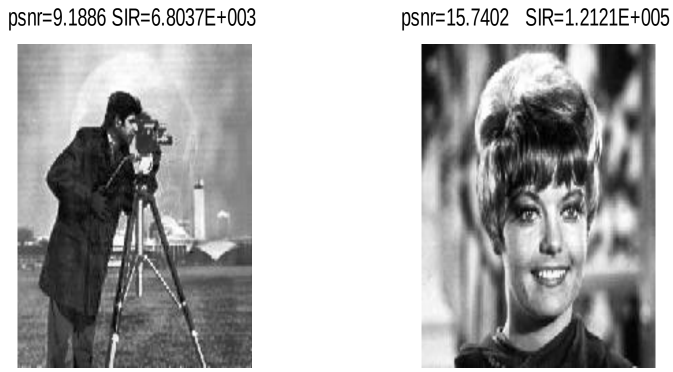


Figure 36: Separated image 4M5

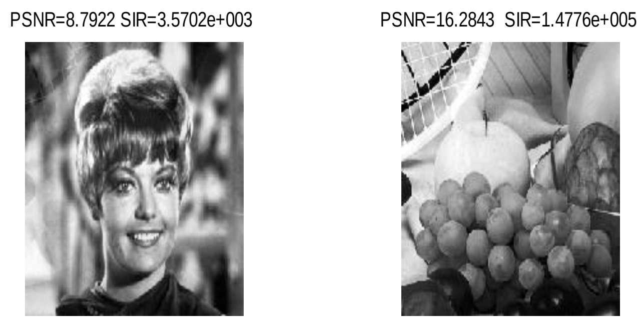


Figure 37: Separated image 5M6

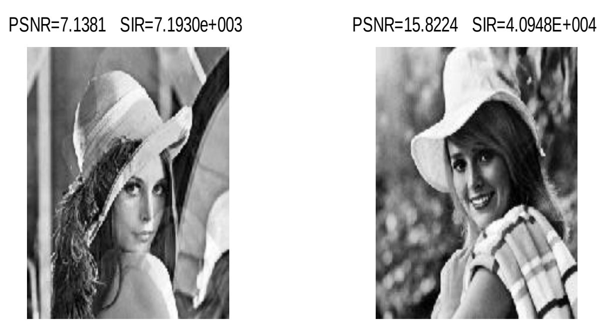


Figure 38: Separated image 6M7

Figure 39: Separated image 8M9

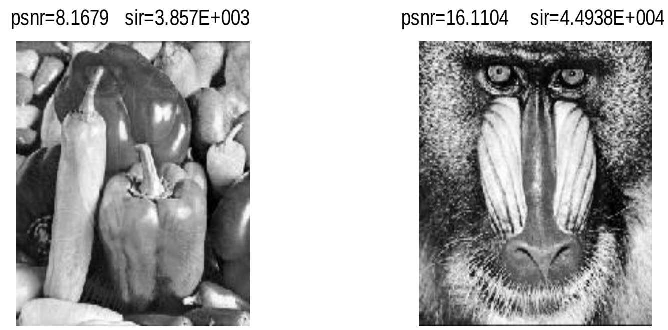


Figure 40: Separated image 9M10

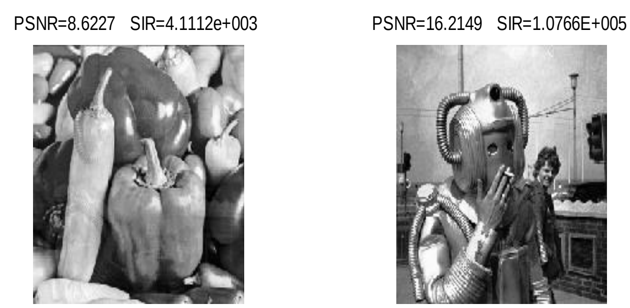


Figure 41: Separated image 10M11

4.4 Fused and separate image with SVD based ICA method

Format with a resolution of 512 x 512 pixels. Few original images, mixed images and separated images are shown in

Figure 42: 1M2

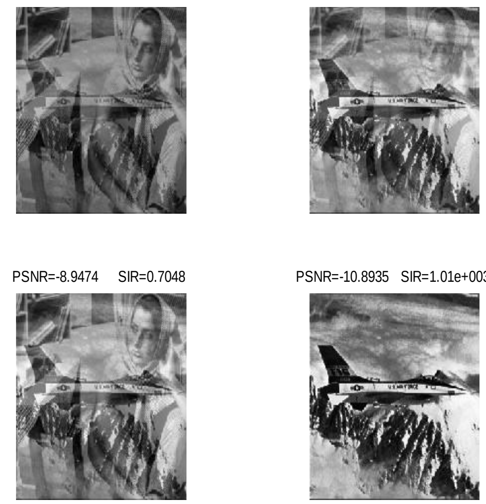


Figure 43: 2M3

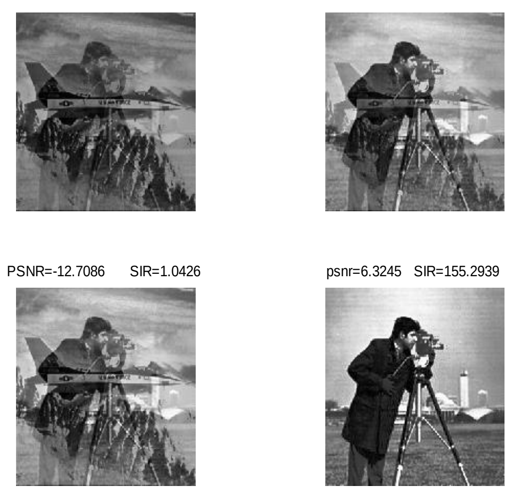


Figure 44: 3M4

Figure 45: 4M5

Figure 46: 5M6

Figure 47: 6M7

Figure 48: 7M8

Figure 49: 8M9

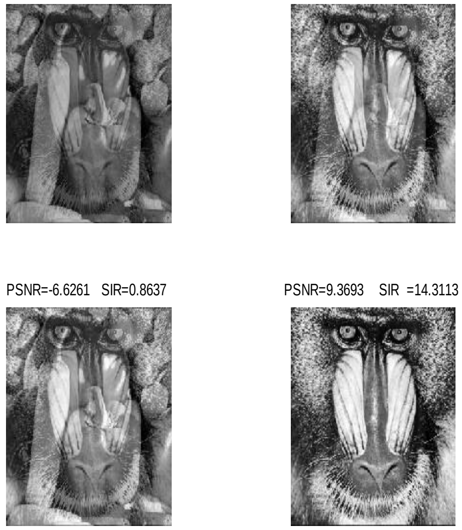


Figure 50 9M10

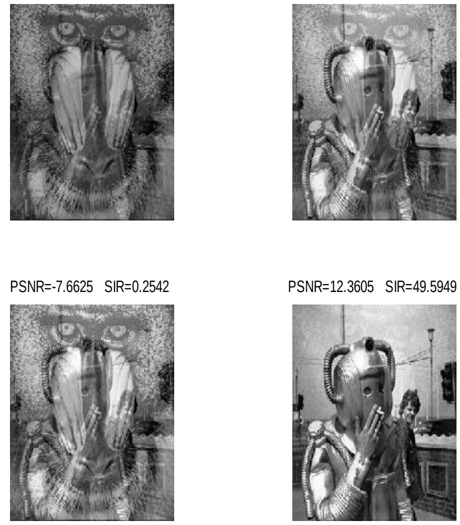


Figure 51 10M11

4.5 Result

For the image separation of mixed images, the given algorithm has been applied on 55 mixed image pairs and their performance is evaluated in terms of PSNR and signal to interference ration (SIR). These fused images for $\boldsymbol{k_{11}}$ = 0:467; k_{12}= 0:29; k_{21} = 0:33; and k_{22} = 0:67 are generated using randomly chosen 11 images in the bitmap

$$K=\begin{bmatrix} K_{11} & K_{12} \\ K_{21} & K_{22} \end{bmatrix}$$

$$\text{Actual matrix}=\begin{bmatrix} 0.465 & 0.23 \\ 0.33 & 0.667 \end{bmatrix}$$

TABLE:1 ESTIMATED MATRIX COEFFICIENT FOR 55 COMBINATION OF IMAGE

	Estimated Coefficient			
MIXTURE	**k11**	**k12**	**k21**	**k22**
1M2	0.52	0.23	3.30E-01	6.62E-01
1M3	0.52	0.23	0.33	6.62E-01
1M4	0.52	0.23	3.30E-01	6.62E-01
1M5	0.52	0.23	3.30E-01	6.70E-01
1M6	0.52	0.23	0.33	0.6621
1M7	0.52	0.23	0.33	6.70E-01
1M8	0.5371	0.205	3.30E-01	6.58E-01
1M9	0.52	0.23	3.30E-01	6.62E-01
1M10	0.52	0.23	0.33	6.62E-01
1M11	0.52	0.23	3.30E-01	6.62E-01
2M3	0.52	0.23	3.31E-01	6.62E-01
2M4	0.52	0.23	3.31E-01	6.62E-01
2M5	0.52	0.23	3.31E-01	6.62E-01
2M6	0.52	0.23	3.31E-01	6.62E-01
2M7	0.52	0.23	3.31E-01	6.62E-01
2M8	0.52	0.23	3.31E-01	6.62E-01
2M9	0.52	0.23	3.31E-01	6.62E-01
2M10	0.52	0.23	3.31E-01	6.62E-01
2M11	0.52	0.23	3.31E-01	6.62E-01
3M4	0.52	0.23	3.30E-01	6.62E-01
3M5	0.52	0.23	3.30E-01	6.62E-01
3M6	0.52	0.23	3.30E-01	6.62E-01
3M7	0.52	0.23	3.30E-01	6.62E-01
3M8	0.52	0.23	3.30E-01	6.62E-01
3M9	0.52	0.23	3.30E-01	6.62E-01
3M10	0.52	0.23	3.30E-01	6.62E-01
3M11	0.52	0.23	3.30E-01	6.62E-01
4M5	0.52	0.23	3.30E-01	6.62E-01
4M6	0.5175	0.2324	3.33E-01	6.54E-01
4M7	0.52	0.2345	3.31E-01	6.62E-01
4M8	0.5214	0.2324	3.33E-01	6.62E-01
4M9	0.529	0.23	3.30E-01	6.62E-01
4M10	0.52	0.23	3.30E-01	6.62E-01
4M11	0.52	0.23	3.30E-01	6.62E-01

5M6	0.521	0.23	3.30E-01	6.62E-01
5M7	0.521	0.23	3.30E-01	6.62E-01
5M8	0.521	0.23	3.30E-01	6.62E-01
5M9	0.521	0.23	3.30E-01	6.62E-01
5M10	0.521	0.23	3.30E-01	6.62E-01
5M11	0.521	0.23	3.30E-01	6.62E-01
6M7	0.52	0.23	3.30E-01	6.62E-01
6M8	0.52	0.23	3.30E-01	6.62E-01
6M9	0.52	0.23	3.30E-01	6.62E-01
6M10	0.52	0.23	3.30E-01	6.62E-01
6M11	0.52	0.23	3.30E-01	6.62E-01
7M8	0.529	0.23	3.30E-01	6.62E-01
7M9	0.5214	0.2324	0.333	0.6621
7M10	0.52	0.23	3.30E-01	6.62E-01
7M11	0.5195	0.2304	3.28E-01	6.56E-01
8M9	0.5195	0.2304	3.26E-01	6.60E-01
8M10	0.52	0.23	3.30E-01	6.60E-01
8M11	0.52	0.23	3.30E-01	6.60E-01
9M10	0.52	0.23	3.30E-01	6.60E-01
9M10	0.52	0.23	3.30E-01	6.60E-01
10M11	0.521	0.23	3.32E-01	6.62E-01

TABLE2: Result with scatter method

	Scatter Method			
Mixture	**PSNR1**	**PSNR2**	**SIR1**	**SIR2**
1M2	9.6594	17.0704	1.97E+01	2.35E+01
1M3	8.6195	14.9952	17.9967	2.31E+01
1M4	8.9315	17.2053	2.00E+01	2.35E+01
1M5	8.9297	16.1687	1.87E+01	2.33E+01
1M6	10.5535	17.9277	20.4357	24.1486
1M7	8.4327	15.3123	18.391	2.35E+01
1M8	8.0001	14.05	1.89E+01	2.32E+01
1M9	8.1524	15.8216	1.88E+01	2.29E+01
1M10	8.5861	15.441	18.5419	2.29E+01
1M11	10.1432	17.7997	2.00E+01	2.39E+01
2M3	8.189	15.2778	1.86E+01	2.29E+01
2M4	8.3965	16.4529	1.92E+01	2.32E+01
2M5	8.0667	15.5065	1.87E+01	2.27E+01
2M6	10.4343	17.2393	1.98E+01	2.45E+01
2M7	9.659	16.6811	1.92E+01	2.41E+01
2M8	8.8603	16.4541	1.92E+01	2.30E+01
2M9	8.2974	15.4847	1.85E+01	2.30E+01
2M10	9.1212	15.9276	1.87E+01	2.31E+01
2M11	8.6252	15.5362	1.87E+01	2.35E+01
3M4	8.7393	16.0909	1.91E+01	2.32E+01
3M5	8.914	15.9317	1.88E+01	2.37E+01
3M6	7.593	14.844	1.86E+01	2.25E+01
3M7	9.0929	15.9142	1.93E+01	2.34E+01
3M8	7.5967	14.9875	1.84E+01	2.27E+01
3M9	8.3119	16.4637	1.92E+01	2.27E+01
3M10	8.6335	15.967	1.89E+01	2.32E+01
3M11	7.8449	15.967	1.93E+01	2.26E+01
4M5	9.1886	15.7402	1.89E+01	2.35E+01
4M6	8.3921	20.0371	1.85E+01	2.45E+01
4M7	9.4675	16.9361	1.94E+01	2.35E+01
4M8	7.9197	15.1941	1.84E+01	2.33E+01
4M9	8.0899	14.4259	1.82E+01	2.31E+01
4M10	7.7423	14.6461	1.83E+01	2.23E+01

4M11	10.9179	16.796	1.95E+01	2.53E+01
5M6	8.7922	16.2843	1.84E+01	2.36E+01
5M7	7.3808	15.2394	1.82E+01	2.30E+01
5M8	8.6753	16.4496	1.87E+01	2.36E+01
5M9	8.0841	16.1758	1.84E+01	2.32E+01
5M10	7.0187	14.6529	1.89E+01	2.30E+01
5M11	7.8965	16.2391	1.89E+01	2.30E+01
6M7	7.3784	15.5158	1.88E+01	2.31E+01
6M8	8.8499	16.2622	1.84E+01	2.35E+01
6M9	7.9465	16.5462	1.87E+01	2.33E+01
6M10	8.0192	15.9821	1.84E+01	2.35E+01
6M11	9.2758	19.628	1.95E+01	2.40E+01
7M8	7.1381	15.8224	1.94E+01	2.27E+01
7M9	7.0183	15.0601	18.3038	22.8362
7M10	7.9323	15.5138	1.87E+01	2.34E+01
7M11	7.021	18.9086	1.89E+01	2.28E+01
8M9	8.0279	14.5488	1.83E+01	2.29E+01
8M10	8.5334	15.5712	1.84E+01	2.33E+01
8M11	8.4392	15.961	1.87E+01	2.30E+01
9M10	8.1679	16.1104	1.87E+01	2.31E+01
9M10	8.6227	16.2149	1.88E+01	2.35E+01
10M11	7.2353	15.6431	1.79E+01	2.28E+01

TABLE 3:RESULT WITH SVD BASED ICA METHOD

	SVD BASED ICA METHOD			
Mixture	PSNR1(DB)	PSNR2(DB)	SIR1(DB)	SIR2(DB)
1M2	-7.4206	16.4746	3.67E-01	2.50E+01
1M3	-7.1387	-10.7684	-0.844	2.25E+01
1M4	-8.3258	5.7458	5.71E-01	1.02E+01
1M5	-7.8728	23.9131	-4.60E-01	2.51E+00
1M6	-6.7542	-7.871	1.1739	28.3935
1M7	-8.0362	3.8823	-0.5897	9.83E+00
1M8	-7.2695	-0.9374	-1.05E-01	1.30E+01
1M9	-7.7478	0.0131	1.31E-02	1.19E+01
1M10	-7.0801	-0.0688	-0.1412	7.04E+00
1M11	-6.9482	8.2268	6.60E-01	8.81E+00
2M3	-8.9474	-10.8935	1.71E+00	1.91E+01
2M4	-8.8413	6.0913	2.36E+00	1.05E+01
2M5	-8.8347	27.0881	2.05E+00	3.12E+00
2M6	-7.3649	-7.9569	2.62E+00	2.90E+01
2M7	-7.9178	2.4864	2.52E+00	9.05E+00
2M8	-8.2172	-0.7394	2.37E+00	1.31E+01
2M9	-8.5692	10.8848	1.86E+00	1.26E+01
2M10	-8.0404	-0.4832	1.86E+00	6.63E+00
2M11	-8.0404	-0.4832	1.92E+00	9.54E+00
3M4	-12.7086	6.3245	4.18E+00	1.03E+01
3M5	-12.8127	21.7522	3.43E+00	2.31E+00
3M6	-12.6839	-7.7158	3.15E+00	3.48E+01
3M7	-12.8027	3.3066	4.51E+00	9.54E+00
3M8	-12.7064	-0.194	4.00E+00	1.39E+01
3M9	-12.4338	10.1715	4.65E+00	1.18E+01
3M10	-12.5983	-0.5745	3.57E+00	6.45E+00
3M11	-12.6775	10.0347	4.77E+00	9.57E+00
4M5	-7.0768	23.4242	7.99E-01	2.64E+00
4M6	-7.0768	-7.8897	1.56E-01	3.25E+01
4M7	-6.4233	2.8085	1.39E+00	9.20E+00
4M8	-7.6565	-0.1213	8.34E-01	1.36E+01
4M9	-7.5095	9.8922	-1.38E-01	1.22E+01
4M10	-6.8738	0.6985	6.09E-01	7.83E+00
4M11	-6.8229	8.043	7.13E-01	8.65E+00
5M6	-0.6609	-7.8222	-3.47E+00	3.32E+01

5M7	-2.4179	4.1361	-3.41E+00	1.01E+01
5M8	-1.0397	-0.8788	-3.21E+00	1.31E+01
5M9	-2.3293	10.1985	-3.18E+00	1.22E+01
5M10	-1.9318	0.9787	-2.85E+00	8.02E+00
5M11	-2.4712	10.2388	2.85	9.63E+00
6M7	-12.076	3.8299	3.11E+00	9.76E+00
6M8	-11.4094	9.5666	2.19E+00	1.33E+01
6M9	-11.4094	9.5666	2.66E+00	1.20E+01
6M10	-11.528	-0.3748	2.23E+00	6.63E+00
6M11	-11.1159	8.0751	3.02E+00	8.72E+00
7M8	-11.1159	8.0751	5.48E-01	1.32E+01
7M9	-7.5023	10.8317	-0.331	12.6775
7M10	-6.7196	-0.3428	-8.00E-03	6.66E+00
7M11	-7.6743	11.2705	5.12E-02	9.61E+00
8M9	-8.59	10.7803	3.53E-01	1.25E+01
8M10	-7.8121	0.2276	4.00E-01	6.93E+00
8M11	-8.0086	11.0895	9.42E-01	9.92E+00
9M10	-6.6261	9.3693	8.64E-01	6.79E+00
9M10	-6.6261	9.3693	8.64E-01	9.42E+00
10M11	-7.6625	12.3605	2.54E-01	1.09E+01

TABLE 4: PERCENTAGE ERROR

	Percentage error			
Mixture	**k11**	**k12**	**k21**	**k22**
1M2	19.82422	27.34375	3.57E+01	2.61E+01
1M3	23.92578	32.8125	36.71875	2.69E+01
1M4	23.92578	32.8125	3.67E+01	2.69E+01
1M5	23.92578	32.8125	3.67E+01	2.69E+01
1M6	23.33984	32.03125	38.80208	28.41796875
1M7	23.33984	32.03125	36.71875	2.69E+01
1M8	21.38672	33.07292	3.62E+01	2.41E+01
1M9	23.33984	32.03125	3.57E+01	2.61E+01
1M10	23.33984	32.03125	36.71875	2.69E+01
1M11	22.75391	31.25	3.57E+01	2.61E+01
2M3	23.33984	32.03125	3.67E+01	2.69E+01
2M4	23.33984	32.03125	3.57E+01	2.61E+01
2M5	23.33984	32.03125	3.57E+01	2.61E+01
2M6	23.33984	32.03125	3.57E+01	2.61E+01
2M7	22.75391	31.25	3.70E+01	2.71E+01
2M8	23.33984	32.03125	3.46E+01	2.53E+01
2M9	23.33984	32.03125	3.46E+01	2.53E+01
2M10	23.33984	32.03125	3.67E+01	2.69E+01
2M11	23.33984	32.03125	3.67E+01	2.69E+01
3M4	23.92578	32.8125	3.57E+01	2.61E+01
3M5	23.33984	32.03125	3.46E+01	2.53E+01
3M6	23.33984	32.03125	3.67E+01	2.69E+01
3M7	23.33984	32.03125	3.57E+01	2.61E+01
3M8	23.33984	32.03125	3.57E+01	2.61E+01
3M9	23.33984	32.03125	3.57E+01	2.61E+01
3M10	23.33984	32.03125	3.67E+01	2.69E+01
3M11	23.33984	32.03125	3.67E+01	2.69E+01
4M5	23.33984	32.03125	3.67E+01	2.69E+01
4M6	22.16797	32.03125	3.67E+01	2.53E+01
4M7	23.33984	32.03125	3.57E+01	2.61E+01
4M8	23.33984	32.03125	3.57E+01	2.61E+01
4M9	23.33984	32.03125	3.57E+01	2.61E+01
4M10	23.33984	32.03125	3.57E+01	2.61E+01
4M11	23.33984	32.03125	3.57E+01	2.61E+01

5M6	23.33984	32.03125	3.46E+01	2.53E+01
5M7	23.33984	32.03125	3.57E+01	2.61E+01
5M8	23.33984	32.03125	3.57E+01	2.61E+01
5M9	23.33984	32.03125	3.57E+01	2.61E+01
5M10	23.33984	32.03125	3.67E+01	2.69E+01
5M11	23.33984	32.03125	3.57E+01	2.61E+01
6M7	23.33984	32.03125	3.59E+01	2.63E+01
6M8	23.33984	32.03125	3.36E+01	2.45E+01
6M9	23.33984	32.03125	3.57E+01	2.61E+01
6M10	23.33984	32.03125	3.57E+01	2.61E+01
6M11	22.16797	32.03125	3.67E+01	2.53E+01
7M8	23.33984	32.03125	3.57E+01	2.61E+01
7M9	23.33984	32.03125	35.67708	26.07421875
7M10	23.33984	32.03125	3.57E+01	2.61E+01
7M11	22.16797	32.03125	3.67E+01	2.53E+01
8M9	22.16797	32.03125	3.54E+01	2.47E+01
8M10	23.33984	32.03125	3.57E+01	2.61E+01
8M11	23.33984	32.03125	3.57E+01	2.61E+01
9M10	23.33984	32.03125	3.57E+01	2.61E+01
9M10	23.33984	32.03125	3.57E+01	2.61E+01
10M11	23.33984	32.03125	3.57E+01	2.61E+01

Compression of PSNR for scatter method and SVD based Ica method

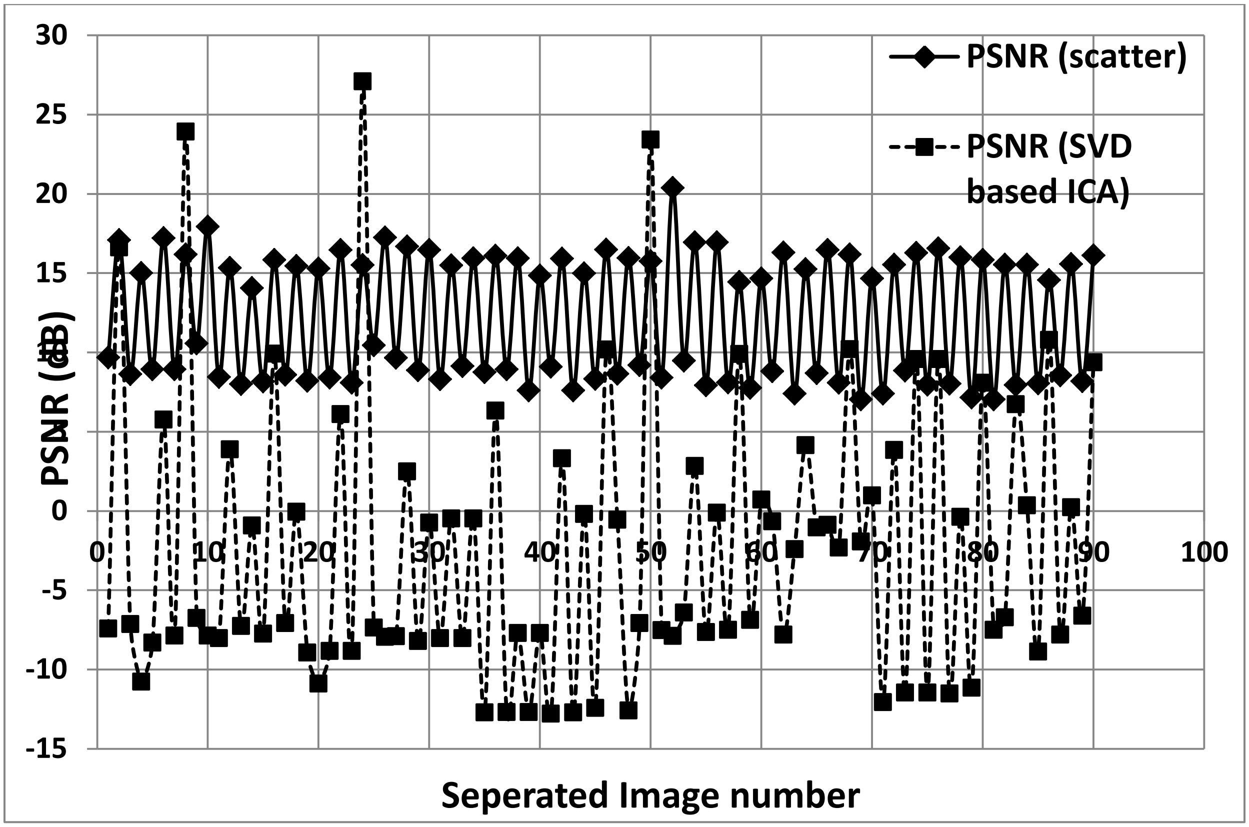


Figure 52: PSNR of separated image

Comparison of SIR between scatter method and SVD based Ica method

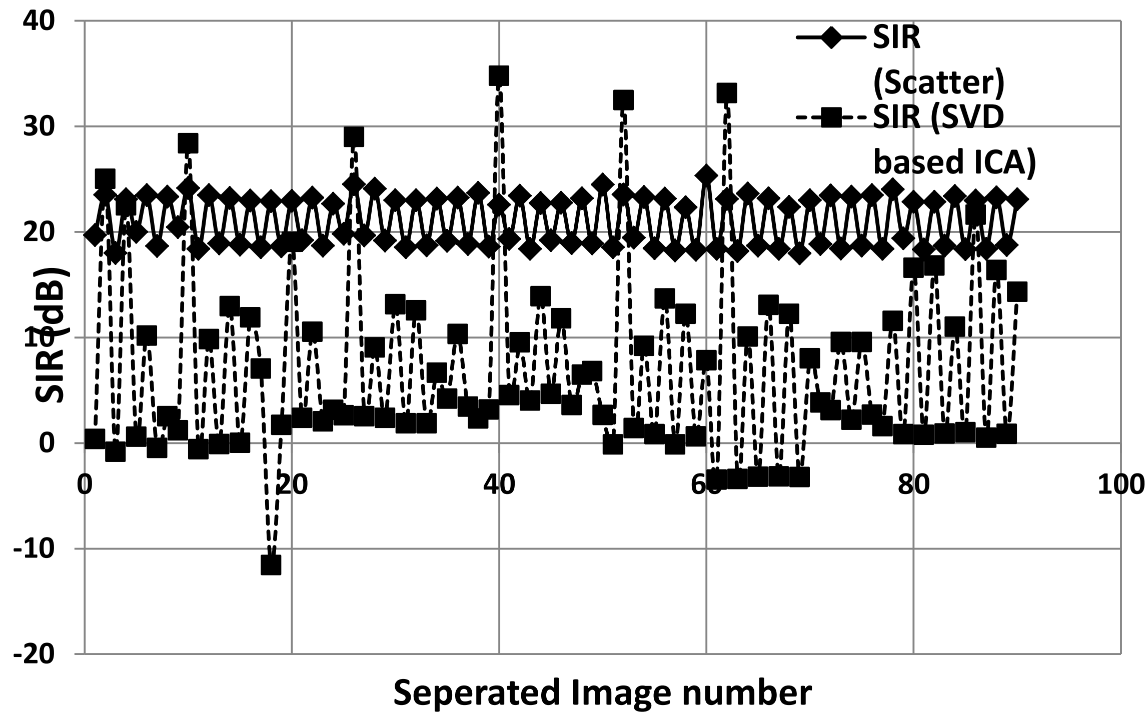


Figure 53 SIR of separated image

4.6 Performance evaluation and compression

The performance of the scatter based techniques with the presented algorithm is compared with SVD based ICA method. It can be observed from fig. 52 and 53 that both PSNR and SIR for scatter based method is more than the SVD based ICA method for all mixed image separation. The average PSNR and average SIR for scatter based technique is more than 12 dB and 21 dB respectively, while for SVD based ICA method average PSNR is around -2.5 dB and average SIR is 7.2 dB. Also, the average percentage error of mixing coefficient estimates for 45 mixtures is calculated and is given in table.

4.7 Conclusion

The given algorithm for image separation based on scatter plot successfully separates the histogram equalized mixed images and performs better than SVD based ICA technique. In this thesis, we have to separate image with scatter graphical method and SVD based

ICA method. Main problem of how can we estimate the mixing matrix? Since the image separation aims at estimating both the original image separation and the mixing matrix using only the observation .Our aim to estimate mixing matrix gives estimate of source 2d signal. Some information about the source and on the basis of information we are trying to calculate mixing coefficient with the help of scatter graphical method and SVD based ICA method .Some limitations of find the mixing matrix are-

(1) Image sources are independent to each other (2) fused images are noise free

In this thesis, we assume that we have the idea about the distribution of sources, different type of graphical structures and by analysis of these structures; we can estimate the mixing coefficient easily. We can take two images having weighting coefficient i.e (k_{11} k_{12} k_{21} k_{22}.all the different cases for the all two observed fused image

Mixture		**Structure**	**Estimating Coefficient**
X1	**X2**	**Straight Line**	$\boldsymbol{k_{11} = k_{12} = k_{21} = k_{22}}$
X1	**X2**	**rhombus**	$\boldsymbol{k_{11} = k_{22}, k_{12} = k_{21}}$

4.8 Future work

In this thesis I have described uniform and non-Gaussian distribution as the prior information about the original image with the help of scatter graphical method and SVD based ICA method. I will try more than two fused images separated with scatter method, compare them with fast ICA method, minimize the mean square error and improve PSNR in future.

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