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Image Fusion and Its Separation Using SVD based ICA Method

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Abstract-Image fusion and its separation is a frequently arising issue in image processing field. In this paper we have described image fusion and it's Separation using SVD based Independent Component Analysis technique. Fused image separation using SVD Based ICA Method depend on order of images such as Mean, variance, Skewness and kurtosis. This technique gives better result than any other technique based on Peak signal to noise Ratio and Signal Interference ratio. The work is encouraging and results are also in accordance to the targeted outcome.

Keywords: Real Image, ICA, BSS, PSNR, SIR ,Real Mixture.

I. Introduction

Image Fusion and its separation is very difficult issue in environment of image processing. It is a frequency aliasing issue [1]. Image fusion and its separation has several applications in nature [1]. It plays a very important role in biomedical field, investigation field [6, 9, 11] and Remote sensing field [15]. Biomedical field and remote sensing fields are current issues for of mixed and overlapped images and its separation [7, 8]. In this paper we have focused on separating real image mixture using complex SVD and depending on ICA method. When we take some different images, like Lena Barbara etc. then there is a need to separate these merged images and restore the component layer. Thus the separation of fused images can be formally described as follows. Suppose there are several images, then our focus is to recover the original images from the merged images with the help of SVD algorithm based on ICA method (Independent component analysis). The merged images can seriously disturb human perception as well as many computer vision algorithms such as segmentation and detection. Automatic separation can be achieved by using the diversity of different mixtures from the merged images to the another image whose properties are changed. The separation which is done without strong additional Information about the individual source or constraints in the mixing process is called blind source separation (BSS).The Independent component analysis technique is able to recover statistically independent source Images. We can use SVD Based ICA method for the image Separation from image mixture. Many algorithms have been proposed for image separation like PCA, AMMCA, Convolution Mixture Method etc . PCA uses first and second moments of the measure Data whereas it fails for the fourth order moment and depends on orthogonal data. This is the reason for which we can prefer SVD based ICA for image separation. The main concept of ICA statistics is that the observed data is non-Gaussian and independent. We have carefully chosen many different fused image combination of 11 different samples of proportionate mixtures of mixed image and then we have calculated the PSNR and signal interference ratio of difference between the original image and separated image by SVD Based ICA Method. In this paper a SVD based ICA algorithms of bind source separation based on ICA is introduce on image's. Result of experiment shows that the SVD based ICA approach can separate images and the shown approach can separate every independent component effectively. Experimental result show that the Image –separation can be done from the combined different –images by using the proposed method with an acceptable residual error.

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II. Automatic Image Separation

number of Algorithms have been proposed to separate two-merged image containing transparency and reflections. When only one fused image is present, automatic separation is quite difficult because it is extremely attempted it on simple mixtures [16] and then Levin and Weiss [17] developed a two-image separation system with user's assistances, the system is not automatic. However, when two or more mixtures are available, each slightly different, automatic separation can be achieved "by accurate exploitation of the diversity in different merge image" [16]. Some 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 issue in image processing field 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[1] . Three step have been outlined ,three step in the last that must be apply ,first the rotation of the parallelogram must be computed by finding the maximal and minimal direction of the variance of the information. EASI algorithm was extended to separate complex valued signal Scaling of the principal component (PCA) direction is evaluated by calculating the variance, Third the final rotation is calculated by minimize both the variance and kurtosis of the information this yield an approximately separable probability distribution the three step are each handled in term .To create 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 basic 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

$$\begin{pmatrix} X_1 \\ X_2 \end{pmatrix} = \begin{pmatrix} k_{11} & k_{12} \\ k_{21} & k_{22} \end{pmatrix} \begin{pmatrix} s_1 \\ s_2 \end{pmatrix} \qquad (1)$$

$$X = KS \qquad (2)$$

Problem Statement

To separate mixed/Fused images

Figure(1): image fusion and it's separation

$$X\,(X, Y) = k_{i1}s_1(x, y) + k_{i2}s_2(x, y) \qquad (3)$$

We have proposed many algorithms for image separation but SVD based ICA approach is very efficient technique for separation.

III. Image separation Problem

In signal and image processing, there are more case where a set of observed signals 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 $s(t) = [S_1(t)S_2(t)\ldots\ldots]^T$ an number of images which are random process is generated as a mixture of underlying N two dimensional signal $x(t) = [x_1(t)x_2(t)\ldots\ldots]^T$ [19 20] is given below

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

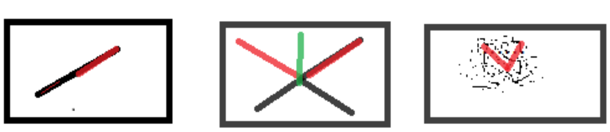
The difficulty of separating mixtures is complicated task when the component layers have both unknown spatial shifts and changing mixing coefficients. Furthermore, if the number of Source image is large, even larger than the number of mixtures, the problem will be particularly complicated. A number of approached have been proposed to separate the method describe here to separate two image relies on reversing the action of the SVD the two statically 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.

IV. SVD BASED INDEPENDENT COMPONENT ANALYSIS

SVD based independent component analysis is the good technique for image separation. In this paper we will calculate 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

V. 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 [18]. 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 considered 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 representing the data. Important concept is considering SVD of the two independent components would generate two principal components. 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) .



(a) (b) (c)

Figure 2: iilustration 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.

VI. ICA ALGORITHM A ICA DEFINATION

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

$$x_j(t) = k_{j1}S_1 + k_{j2}s_{2}.........k_{jn}s_n 1 \le j \le N \qquad (5)$$

SVD based independent component analysis is well developed method [18]. The aim of this method separate independent component from estimate mixing matrix it is applicable for non-Gaussian data.

VII. Concept behind ICA

We can Assume that we tends to observe n linear mixturesx_1, ...,x_n of n independent components

$$x_j = k_{j1}s1 + k_{j2}s_2 \ldots\ldots\ldots\ldots + k_{jn}s_n \text{ for all j. (6)}$$

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.

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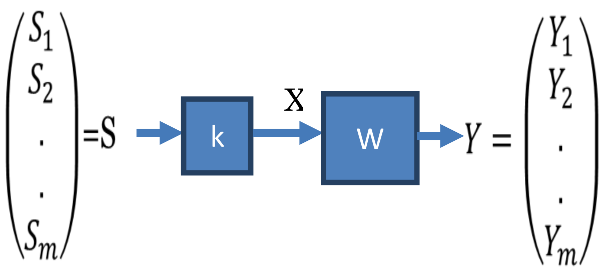

FIGURE 3: ICA ALGORITHM BLOCK DIAGRAM

The independent component calculate is (ICA) of a random vector consist of searching for a linear transformation that reduce 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 $s_2(t)$ algebraic 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 equation

$$x_1\ (t) = a_{11}s_1 + a_{12}s_2 \qquad (7)$$

$$x_2(t) = a_{21}s_2 + a_{22}s_2 \qquad (8)$$

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 many goal that are being tracked , ,then there is significant mixing in the scattered 1d and 2d signal from all of the goal .without a evaluation for clear separation of the goal ,the detector become impractical for recognizing location.

(2) Electroencephalogram(EEG)

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

VIII. SVD METHOD FOR ICA

$$S = K^{-1}X \qquad (9)$$

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 (9). In this situation, we take two different images IMA1 and IMA2. 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.

$$\mathrm{p}(\mathrm{p}_1, \mathrm{p}_2) = \mathrm{p}(\mathrm{p}_1)\mathrm{p}(\mathrm{p}_2) \qquad (10)$$

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 [18]

IX. 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 by $X_1 and X_2$, the linear mixing of these images can be denoted in matrix form as follows:

$$\begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = \begin{bmatrix} k_{11} & k_{12} \\ k_{21} & k_{22} \end{bmatrix} \begin{pmatrix} s_1 \\ s_2 \end{pmatrix} \qquad (11)$$

$$X = K * S \qquad (12)$$

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.

$$S = K^{-1}Y \qquad (13)$$

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.

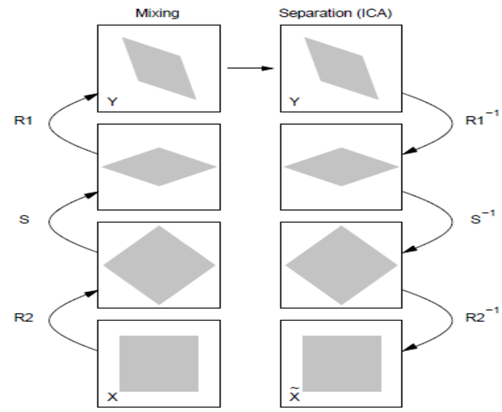

Figure 4: ref [44] graphical depiction of the svd process of mixing of two image .there construction of the image is accomplished by approximating of the svd matrices so as to achieve a separable (statiscally independent) probability distribution of the two images

X. Rotation Of Parallogram

The –first vital step in separating the image is to contain a rotation that aligns the long side and short side of the parallelogram with the major axis [18]. To begin, contain once again figure (4) our first goal 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 denote U*.In a geometrical way of thinking, our goal is to align the long and short axes of the parallelogram with the major axis as depicted in the two top right shaded boxes of fig.(4).The angle of parallelogram relative to the first axes will be indicate byθ 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[18] .the variance at an arbitrary angle of orientation is indicate by

$$var(\theta) = \sum_{j=1}^{N} [x_1(J) x_2(j)] \begin{bmatrix} cos\theta \\ sin\theta \end{bmatrix} \sum_{j=1}^{N} [x_1(J) x_2(j)] \begin{bmatrix} cos\theta \\ sin\theta \end{bmatrix} \qquad (14)$$

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 KThe maximum of with respect to θ can be found by differentiating $var(\theta)$ and setting it equal to 0.and get angle of detection

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XI. Maximum and minimum 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[16] .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

$$S = k^{-1}X \qquad (15)$$

$$var(\theta) = \sum_{j=1}^{N}[x_1\,(J)x_2(j)]\begin{bmatrix}cos\theta\\ sin\theta\end{bmatrix}\sum_{j=1}^{N}[x_1\,(J)x_2(j)]\begin{bmatrix}cos\theta\\ sin\theta\end{bmatrix} \qquad (16)$$

$$\frac{1}{2}atan[-2\sum_{j=1}^{N}\frac{x_1\,(j)x_2(j)}{r^2(j)cos(2\varphi j)} \qquad (17)$$

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

$$\mathrm{U} = \begin{bmatrix}\cos\theta & \sin\theta\\ -\sin\theta & \cos\theta\end{bmatrix} \qquad (18)$$

With the angle θ computed directly from the experimental data.

XII. Scaling Of Parallogram

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

$$\sigma_1 = \sum_{j=1}^{N}[x_1\,(J)x_2(j)]\begin{bmatrix}cos\theta\\ sin\theta\end{bmatrix}\sum_{j=1}^{N}[x_1\,(J)x_2(j)]\begin{bmatrix}cos\theta\\ sin\theta\end{bmatrix} \qquad (19)$$

$$\sigma_2 = \sum_{j=1}^{N}[x_1\,(J)x_2(j)]\begin{bmatrix}\cos\,(\theta - pi/2\\ \sin\,(\theta - pi/2\end{bmatrix}\sum_{j=1}^{N}[x_1\,(J)x_2(j)]\begin{bmatrix}\cos\,(\theta - pi/2\\ \sin\,(\theta - pi/2\end{bmatrix}^2 \qquad (20)$$

$$\begin{bmatrix}\sqrt{1/\sigma_1} & 0\\ 0 & \sqrt{1/\sigma_2}\end{bmatrix} \qquad (21)$$

XIII. Rotation Of 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 stastical moment (fig4) the fourth moment atan ,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 the remaining distribution .The angle that accomplish this task is computed analytically form and the associated rotation matrix U is given by before computing. The rotation matrix or unitary transformation associated then with the rotation of the Parallogram back to its aligned position is then with the angle φcomputed direction from the experiment data.The two image are quite different with one overlooking other

$$var(\theta) = \sum_{j=1}^{N}[x_1\,(J)x_2(j)]\begin{bmatrix}cos\theta\\ sin\theta\end{bmatrix}\sum_{j=1}^{N}[x_1\,(J)x_2(j)]\begin{bmatrix}cos\theta\\ sin\theta\end{bmatrix} \qquad (22)$$

$$\emptyset = \frac{1}{2}atan[-2\sum_{j=1}^{N}\frac{x_1\,(j)x_2(j)}{r^2(j)cos(2\varphi j)} \qquad (23)$$

In polar coordinate x_1(j)=$r_1(j)cos(2\varphi)$ and x_2(j)=$r_1(j)sin(2\varphi)$ (24)

$$U = \begin{bmatrix}cos\theta & sin\theta\\ -sin\theta & cos\theta\end{bmatrix} \qquad (25)$$

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The rotation matrix or unitary transformation associated then with the rotation of the Parallogram back to it’s aligned position is then with the angle φ computed direction from the experiment data The two image are quite different with one overlooking other

XIV. 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

$$\mathrm{p}(s_1)p(s_2) = p(s_1)p(s_2) \tag{26}$$

Appropriate rotation is sought by maximizing the non-Gaussian it

$$k(\varphi) = \sum_{j=1}^{n} x_1(j)x_2(j)\begin{bmatrix} cos\varphi \\ sin\varphi \end{bmatrix}^4 \tag{27}$$

$$k(\emptyset) = \sum_{j=1}^{N} \frac{1}{{x_1}^2(j)+{x_2}^2} x_1(j)x_2(j)\begin{bmatrix} cos\varphi \\ sin\varphi \end{bmatrix}^4 \tag{28}$$

$$\emptyset = \frac{1}{4}tan^{-1}\left[\frac{\sum_{j=1}^{N}[2{x_1}^3(j)x_2(j)-2x_1(j){x_2}^3(j)]/{x_1}^2(j)+{x_2}^2(j)]}{\sum_{j=1}^{N}[\ \ 3\ x_1(j){x_2}^2(j)-\left(\frac{1}{2}\right){x_1}^4(j)-(\frac{1}{2}){x_2}^4(j)]/[{x_1}^2(j)+{x_2}^2(j)}\right] \tag{29}$$

Kurt(y)=E[y4]-3(E[y2])2 (30)

Where $\emptyset$ is image of rotation associated with the unitary matrix U and variable $x_1(j) and x_2(j)$ 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

$$kurt(y) = kurt(q_1s_1) + kurt(q_2s_2) \tag{31}$$

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

XV. Complete 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

$$S = K^{-1}X = V\sum^{-1}U^{*}X \tag{32}$$

$$S = \begin{bmatrix} cos\emptyset & sin\emptyset \\ -sin\emptyset & cos\emptyset \end{bmatrix}\begin{bmatrix} \sqrt{1/\sigma_1} & 0 \\ 0 & \sqrt{1/\sigma_2} \end{bmatrix}\begin{bmatrix} cos\theta & sin\theta \\ -sin\theta & cos\theta \end{bmatrix}\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \tag{33}$$

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

$$\begin{bmatrix} k_{11} & k_{12} \\ k_{21} & k_{22} \end{bmatrix}\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} k_{21} & k_{22} \\ k_{21} & k_{22} \end{bmatrix}\begin{bmatrix} x_2 \\ x_1 \end{bmatrix} \tag{34}$$

$$\mathrm{k}=\begin{bmatrix} k_{11} & k_{12} \\ k_{21} & k_{22} \end{bmatrix} \tag{35}$$

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

$$\begin{bmatrix} k_{11} & k_{12} \\ k_{21} & k_{22} \end{bmatrix}\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} k_{11}/_{\alpha} & k_{12}/_{\delta} \\ k_{21}/_{\alpha} & k_{22}/_{\delta} \end{bmatrix} \tag{36}$$

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

XVI. = SIMULATION

We will take 11 different images. We will fused these images with help SVD based 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 Paper 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.

XVII. 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. 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 5.

Simulation Result by SVD Based ICA METHOD 11 different Original images

Figure 5: ORIGINAL IMAGE

XVIII: Fused image's According to mixing Ratio

IMJ_1: first mixing
IMJ_2: second mixing
K= Mixing Coefficient

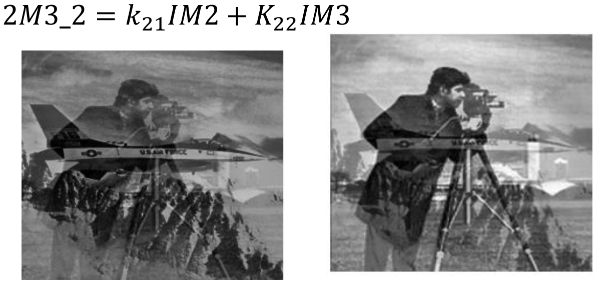
1M2_1 1M2_2

Figure (6) Fused image of 1M2

2M3_1 2M3_2

Figure (7) fused image of 2M3

$$1M2\_1 = k_{11}IM1 + K_{12}IM2$$
$$2M3\_1 = k_{11}IM2 + K_{12}IM3$$
$$1M2\_2 = k_{21}IM2 + K_{22}IM3$$
$$2M3\_2 = k_{21}IM2 + K_{22}IM3$$



3M4_1 3M4_2

Figure (8) fused image of 3M4

4M5_1 4M5_2

Figure (9). Fused image of 4M5

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5M6_1 5M6_2

Figure (10) fused image of 5M6

6M7_1 6M7_2

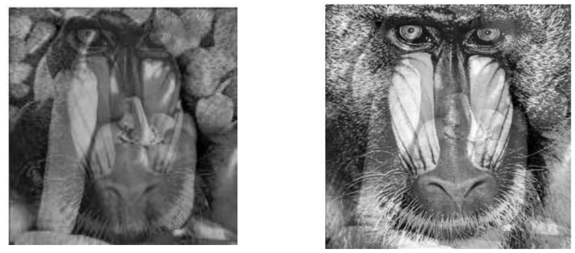
Figure (11) fused image of 6M7

7M8_1 7M8_2

Figure(12) fused image of 7M8

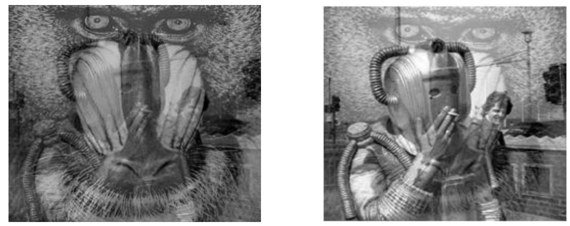
8M9_1 8M9_2

Figure (13) fused image of 8



9M10_1 9M10_2

Figure (14) fused image of 9M10



10M11_1 10M11_2

Figure (15) fused image of 10M11

XIX. Separated image's with SVD Based ICA

Fused and separated images with SVD based ICA Method Separated 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 figures ahead.

Fig (16) Separated image 1M2

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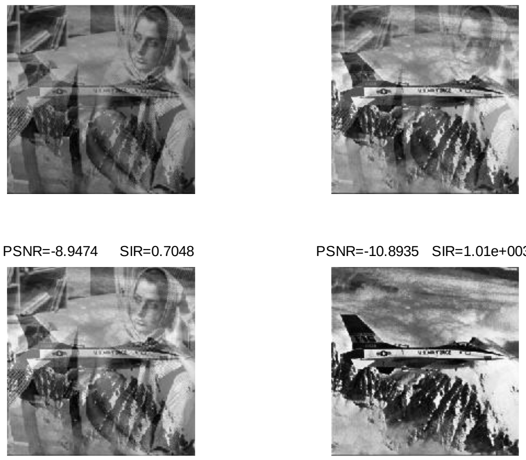

Fig (17) separated Image 2M3

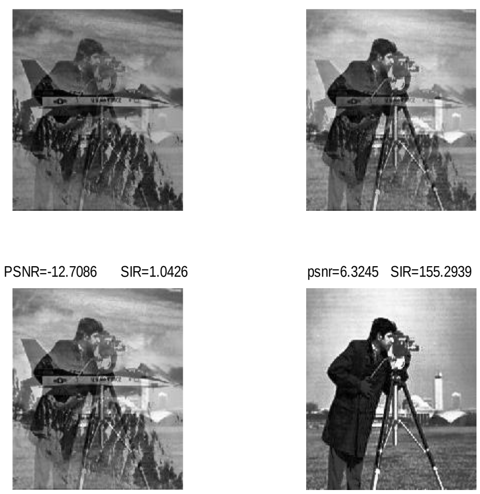

Fig (18) Separated image 3M4

Fig(19) Separated image 4M5

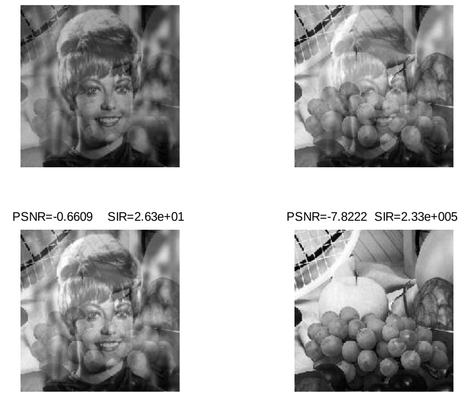

Fig (20) Separated image 5M6

FIG(21) SEPARATED IMAGE 6M7

Fig(22) separated image 7M8

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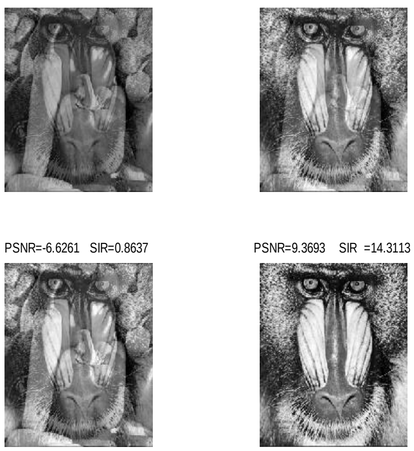
Fig(23) image 8M9separated



Fig(24)separated image 9M10

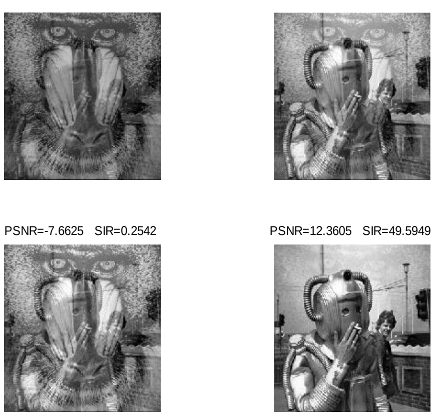


Fig (25)Separated image 10M11

XX. 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

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

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

Table 1: ESTIMATED MATRIX COEFFICIENT FOR 55 COMBINATION OF IMAGE

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

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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

Table 2: Result with SVD Based Ica method
PSNR:**Peak to signal noise ratio**
SIR:**Signal Interference Ratio**

	DB			
Mixture	PSNR1	PSNR2	SIR1	SIR2
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+0	9.20E+0
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		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

Table3: 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

Result of SVD Based ICA method is better Compare to other technique basis on Peak Signal to noise ratio and Signal interference ratio is given by below graph

XXI. Performance evaluation

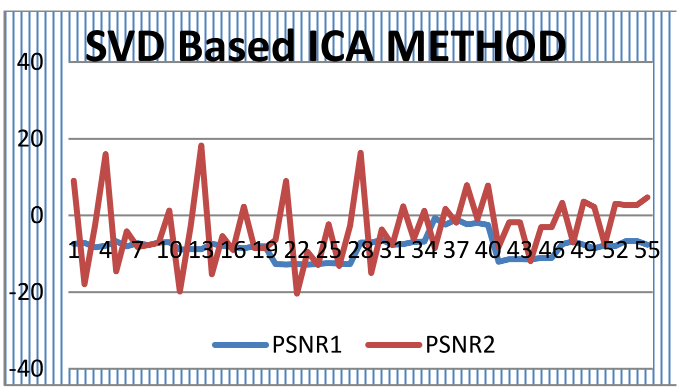
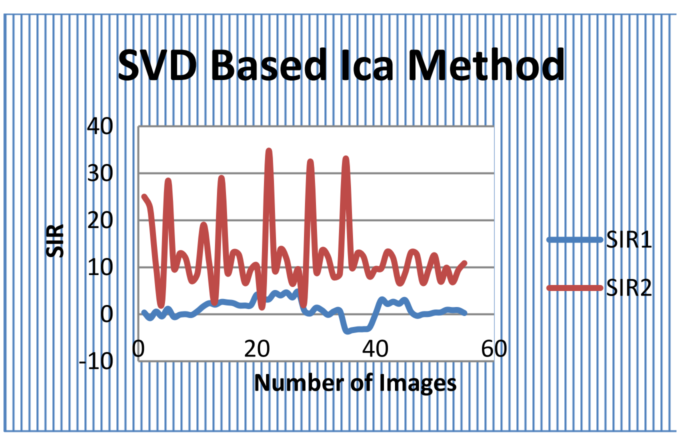


Fig (26) Psnr Of Images



FIG(27) SIGNAL INTERFERENCE RATIO OF IMAGES

XXII. CONCLUSION

We have carefully chosen –several different fused image combinations of 11 different samples of proportionate mixtures of mixed image and then has calculate the PSNR and signal interference ratio of difference between the original image and Separated image by SVD Based ICA Method. In this paper SVD based ICA algorithms give better Result Compare any other technique basis on PSNR and SIR. The results of the work have been encouraging and are in accordance with the theoretical values.

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