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Performance Analysis of ICA Using Tuning Parameters Size

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Abstract— Remote sensing has played a vital role in change detection of the hyperspectral images. In past some years, several improvements have been made in change detection techniques. The objective of this paper is also to propose such an improvement in Independent Component Analysis (ICA) by introducing certain tuning parameters in the FastICA algorithm. The algorithm can be run with different approaches and under different criteria with these parameters and thus making the algorithm much efficient. A comparison is made between the two important techniques of change detection that are PCA and ICA. The better performance of ICA to remove correlation efficiently among the components found from a given hyperspectral data has been assured by experimental results.

Keywords— Hyperspectral Images, Remote Sensing, Tuning parameters, PCA, FastICA

I. INTRODUCTION

Change detection is the process of identifying differences in the characteristic or state of an object over a time period. Change detection based on remote sensing is widely applicable in many applications. It helps to take a huge-scale view of landscape over a long period of time to detect changes in it properly. Change detction is very important for monitoring environmental changes and resources management [1].

The “hyper” in hyper spectral means “over” as in “too many” and refers to the large number of measured wavelength bands covering a wide spectral range. Hyperspectral remote sensing attracts much interest from researchers and practitioners because the high spectral resolution of an acquired image provides the potential of more accurate object detection, object classification, and their identification [2]. In most hyperspectral imagers a series of narrow and contiguous wavelength bands is used to measure reflectance. The spectrum for one pixel in a hyperspectral image looks very much like a spectrum measured in a spectroscopy laboratory. It can provide much more detailed information about the surface than a multispectral pixel spectrum that is useful to improve the performance of change detection. Multispectral images were classified into broad categories of image classification methods. Hyperspectral images helps to perform more detailed image analysis. To fulfill this potential, new image processing techniques have been discovered. In a hyperspectral image, all the information about reflectance across the entire spectral range of the sensor is contained by a single pixel producing what is called a spectral signature.

Several techniques have been discovered and enhancements have been made to measure the change detection more efficiently. Among them, Principal Component Analysis (PCA) and Independent Component Analysis (ICA) are being focused.

Principal component analysis (PCA) is often used to detect change over time in remotely sensed images. Commonly, projections are found along the two eigenvectors for data consisting of two variables which represent the same spectral band covering the same geographical region acquired at two different time points. PCA reduces the number of correlated variables associated with a given data set into a new set of variables which are uncorrelated but retain most of the variability that are associated with original variables of the data set. Basically, PCA technique uses as input a set of images and apply a linear transformation on them so as to produce output images in such an organized manner that they are linearly independent. In such a way, all unchanged pixels shared by a set of images lie in a narrow cluster along the principal axis equivalent to first principal component while the changed pixels tend to lie far away from the principal axis. The original data is transformed to make it uncorrelated. Thus, PCA can distinguish changed and unchanged area easily by using principal components [3].

Independent component analysis (ICA) is an extension of PCA. ICA aims to recover independent sources given only sensor observations that are unknown linear mixtures of the unobserved independent source signals. ICA not only removes the correlation among the signals (second-order statistics) but also reduces higher-order statistical dependencies. Thus it tries to remove dependency from the signals. ICA has shown success in unsupervised recognition, blind source separation and feature extraction [4]. It automatically extracts each source from the observation of linear combinations of these sources. ICA algorithm obtains components that are independent of each other and related to different land-variation categories [5]. Most popular ICA method is FastICA.

The paper is organized in foue sections. Following this introduction, the proposed method for change detection in hyperspectral image is presented in section II. All the results obtained from ICA and PCA using hyperspectral data with explanation are represented in third section. Both the change detection techniques are also compared in this section. Finally, in section IV general conclusion is provided.

II. PROPOSED WORK

Many change detection techniques such as image differencing, change vector analysis etc. have been developed and their use depends on the application. Principal Component Analysis has been widely used to select the features and create a change map but still it suffers from some drawbacks that lead researchers to a new change detection technique named Independent Component Analysis which is more useful to reduce problem's dimensionality for source separation and compress data [6]. ICA is the most suitable to analyze multidimensional signals and much more efficient than PCA. ICA has proven good performances with respect to PCA in various fields, such as object recognition and geoscience applications [7].

The objective of this paper is to make some more enhancements in ICA so that it can work more efficiently and provide more flexibility. From given multidimensional signals, FastICA estimates the independent components. FastICA has some advantages as compared to other ICA algorithms that are mentioned below:

1. The algorithm finds directly independent components of (practically) any non-Gaussian distribution using any nonlinearity. While in many algorithms, non-linearity is chosen on basis of some estimate of the probability distribution function.
2. The performance of the method can be optimized by choosing a suitable nonlinearity. One can obtain algorithms that are robust and/or of minimum variance.
3. The independent components can be estimated one by one, as done in projection pursuit. It decreases the computational load of the method in cases where only some of the independent components need to be estimated and is also useful in exploratory data analysis.
4. The FastICA has most of the advantages of neural algorithms: It is parallel, computationally simple, distributed and requires little memory space [8].
5. FastICA can be applied in a particular dimension reduced area after dimension reduction to find independent components so that the particular area can be observed more carefully [9].

TABLE I DIFFERENT TUNING PARAMETERS AND THEIR VALUES.

S.No.	Tuning Parameter	Parameter Value
1.	Approach	Deflation
		Symmetric
2.	Number Of Dimensions	1 to 188
3.	Non-linearity	Pow3 (g(u)=u^3)
		Tanh (g(u)=tanh(a1*u))
		Gauss (g(u)=u*exp(-a2*u^2/2))
		Skew (g(u)=u^2)
4.	Stabilization	On or Off
5.	Epsilon(Convergence Criteria)	0.0001(default)

The proposed FastICA uses the fixed-point algorithm with several tuning parameters. These parameters are being discussed here.

1. The approach to find the components can be specified. Either all the independent components can be estimated in parallel using a 'symmetric' approach or one by one as in projection pursuit using 'deflation' approach.
2. Data dimensions can be reduced to reduce the complexity by estimating small number of independent components from a large data sets.
3. Non-linearity used in the fixed-point algorithm can be chosen from a set of values. Moreover, fine-tuning of data can also be enabled or disabled.
4. Convergence parameter and maximum number of iterations to find each component can be controlled to converge algorithm.
5. Stabilization parameter controls whether the program uses the stabilized version of the algorithm or not.

Table 1 shows all the tuning parameters with their possible values. We can choose different values of non-linearity to enable or disable fine-tuning of the output data.

III. RESULTS AND DISCUSSION

The AVIRIS "Cuprite" subimage scene, of size 250*190, shown in Fig.1, was collected in Nevada in 1997. The image had 224 bands with 0.4- to 2.5-_m spectral range in original. After water absorption bands and low-SNR bands were removed, 188 bands were used in the experiment. This image scene is well understood mineralogically, and a spectral library of pure minerals is available. The experiment involved the use of FastICA and PCA to find the independent components and principal components respectively.

A. Experimental Results For FastICA

FastICA was run with the tuning parameters as shown in Table 2. Before finding the components, data is whitened by FastICA so as reduce the whole work of ICA and provide better illumination in the image. The plot for this whitened data is shown in Fig. 2.

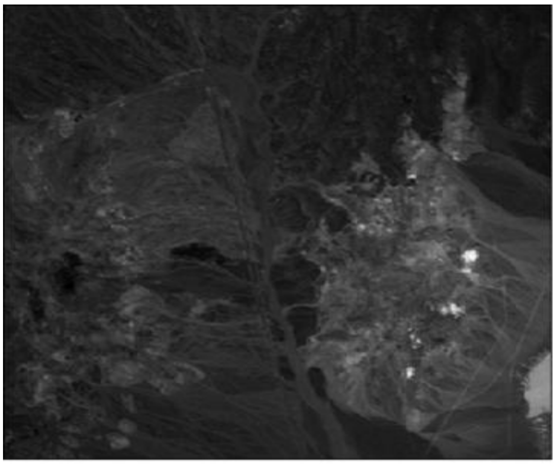

Fig. 1 Spectral band number 50 (827 nm) of the Cuprite AVIRIS image scene.

TABLE 2 THE TUNING PARAMETERS SPECIFIED FOR EXPERIMENT WITH FASTICA.

S.No.	Tuning Parameter	Parameter Value
1.	Approach	Deflation
2.	Number Of Dimensions	4
3.	Non-linearity	Pow3 (g(u)=u^3)
4.	Stabilization	Off
5.	Epsilon(Convergence Criteria)	0.0001
6.	Maximum Number of Iterations	1000

The algorithm outputs the four independent components from a set of several components. These four independent components are shown in Fig. 3. When the light falls on a spatial surface composed of several source then some of the energy gets reflected back by those sources. . Each pixel then, is modeled as a linear sum of all the radiated energy curves of materials making up the pixel. The reflectance corresponding to the pixels of these four independent components is shown in Fig. 4. The independent components are shown spatially in Fig. 3 while Fig. 5 is showing the same components by plotting their eigenvectors and values.

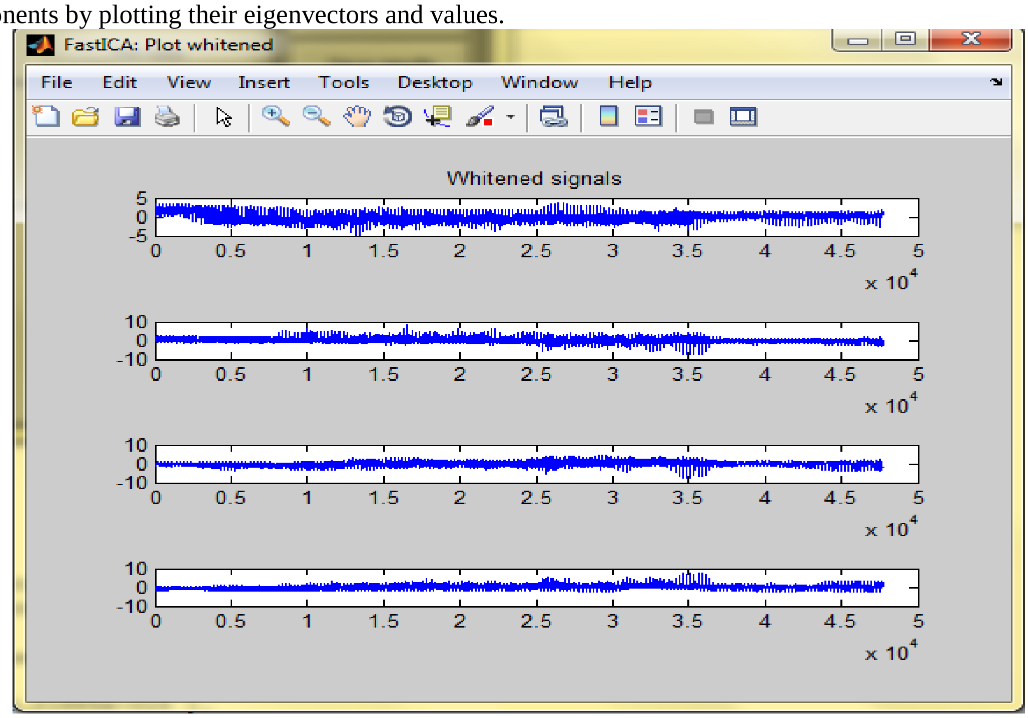

Fig. 2 Whitened signals plotted using FastICA.

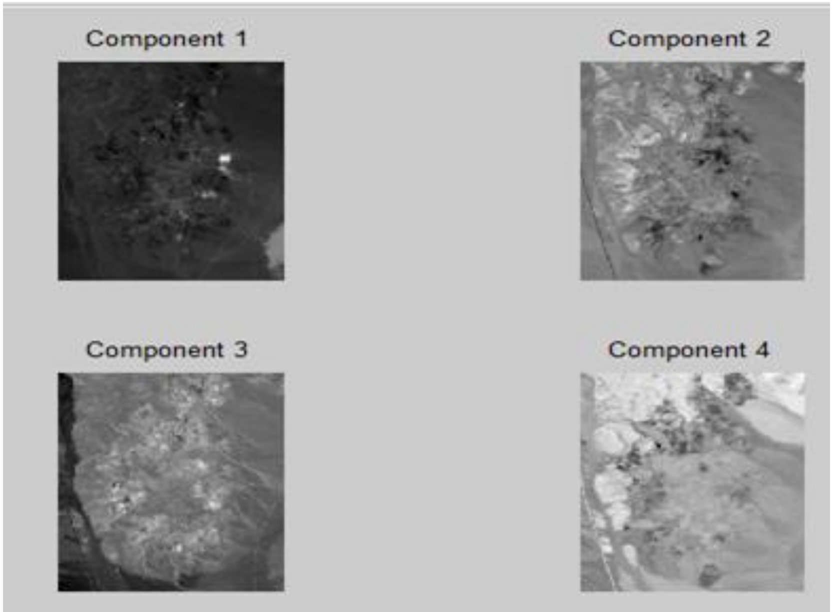

Fig. 3 First four independent components found using FastICA.

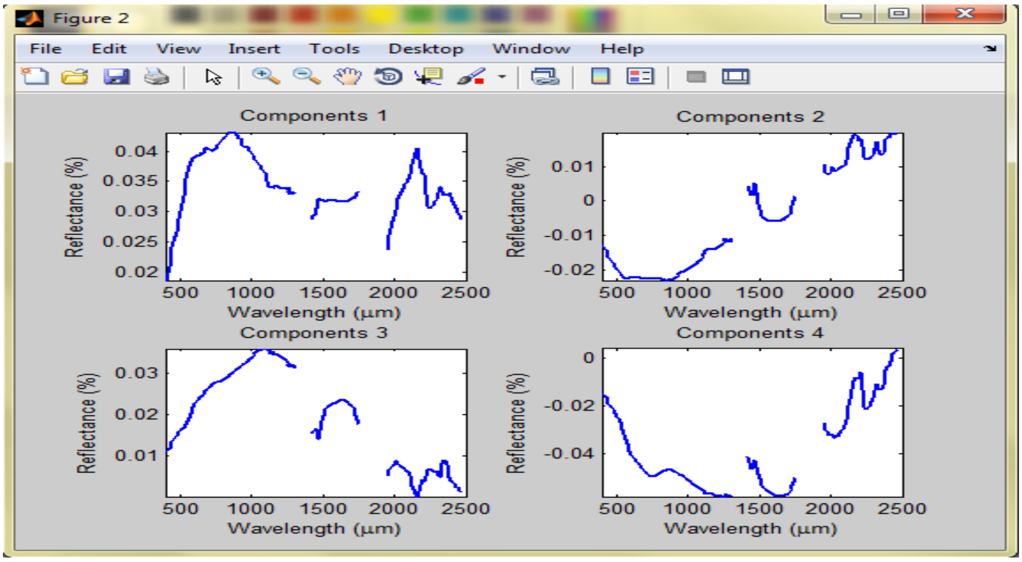

Fig. 4 Reflectance corresponding to first four independent components found using FastICA.

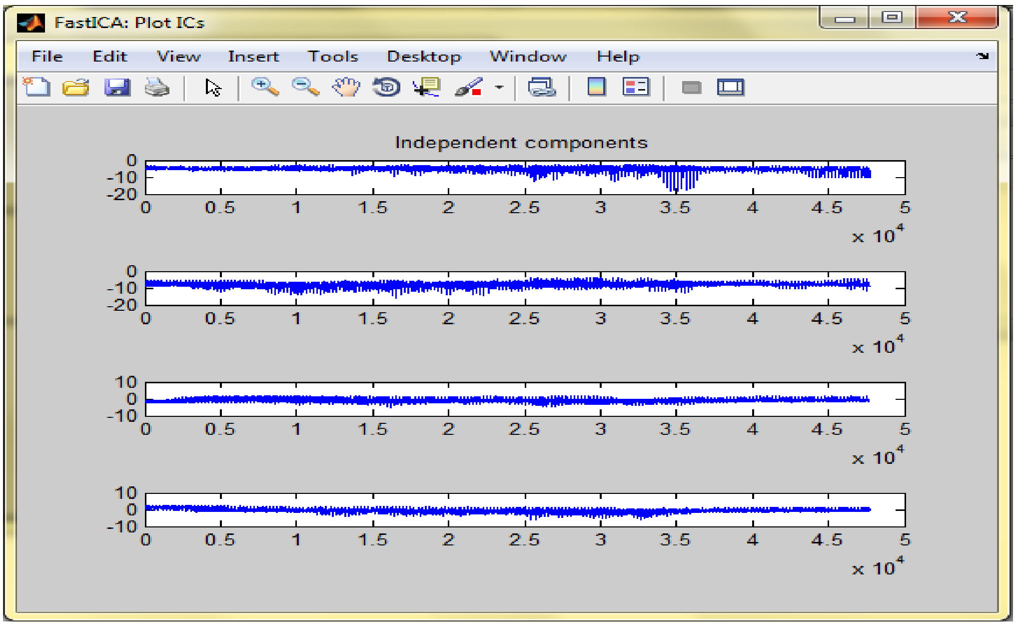

Fig. 5 Plots for first four independent components found using FastICA.

B. Experimental Results For PCA

PCA aims at finding the linearly independent principal components. The plots for the first four principal components computed by the PCA algorithm are shown in Fig. 6 when the same data was used with PCA.

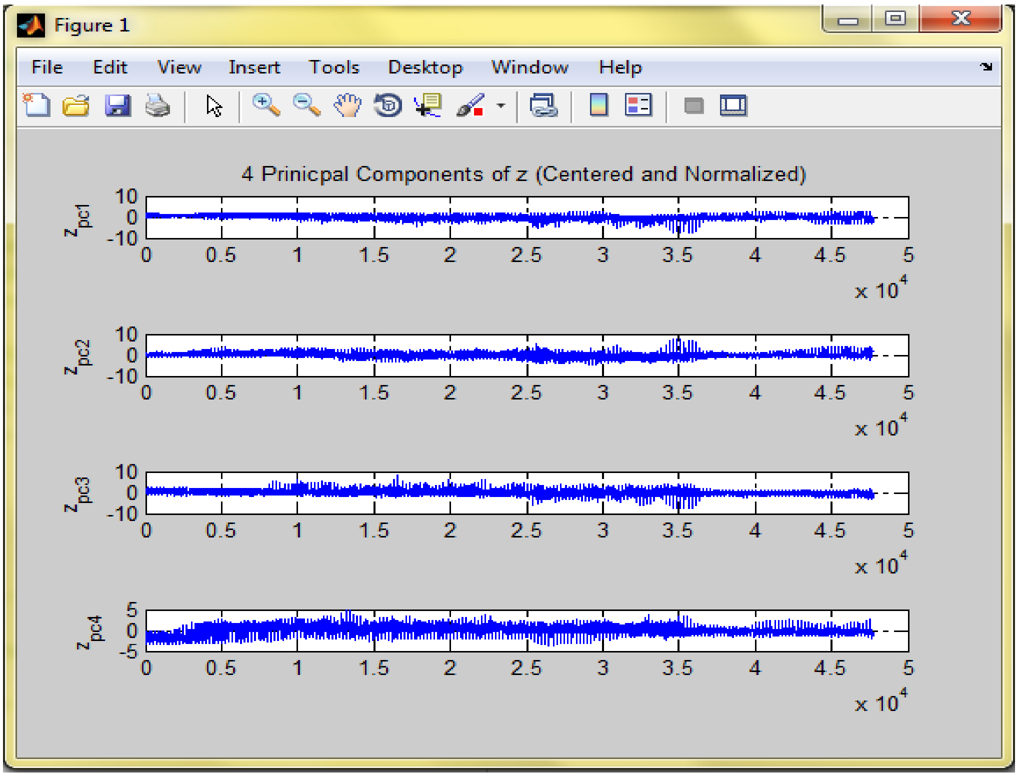

Fig. 6 Plots for first four principal components found by PCA.

C. Comparison Between PCA and ICA

Both ICA and PCA were used on the same image data set to find the uncorrelated statistically independent and linearly independent components respectively. In this experiment, after finding the components, the image data was reconstructed from these components by both the algorithms so as to measure the deviation of reconstructed data from the actual data. The results obtained by ICA are as shown in Fig. 7 and by PCA are as shown in Fig. 8. From the graph, it is very much clear that the variance of components generated by the PCA is less than the variance for components generated by ICA.

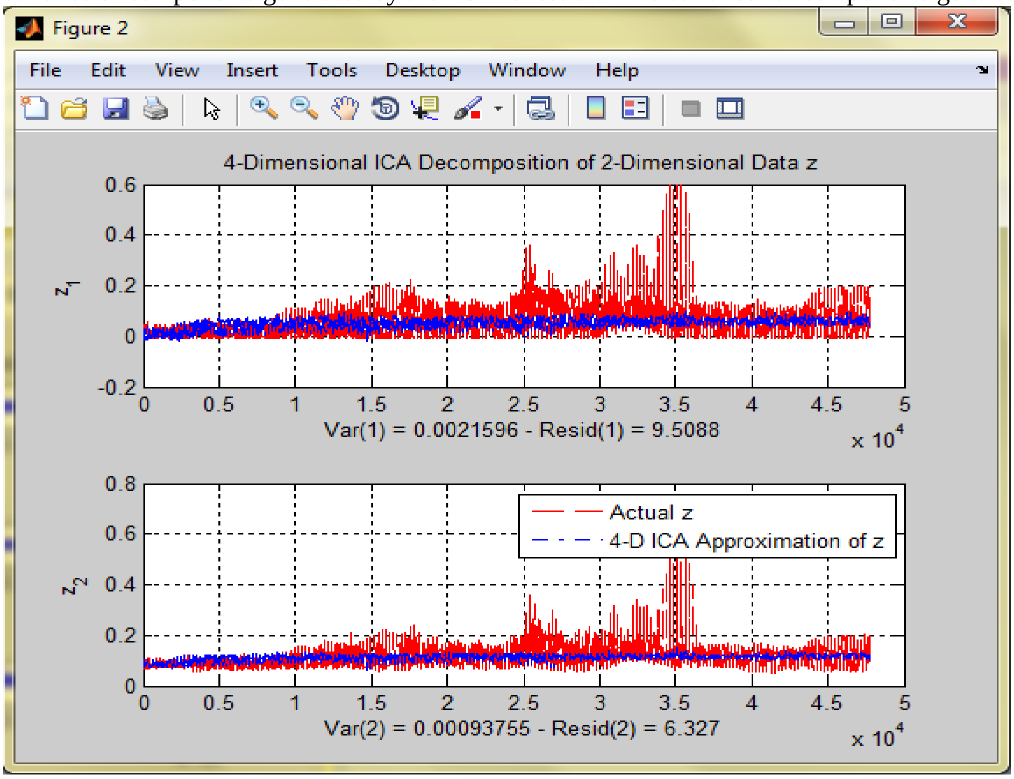

Fig. 7 Deviation of Actual data from the ICA approximation of same data.

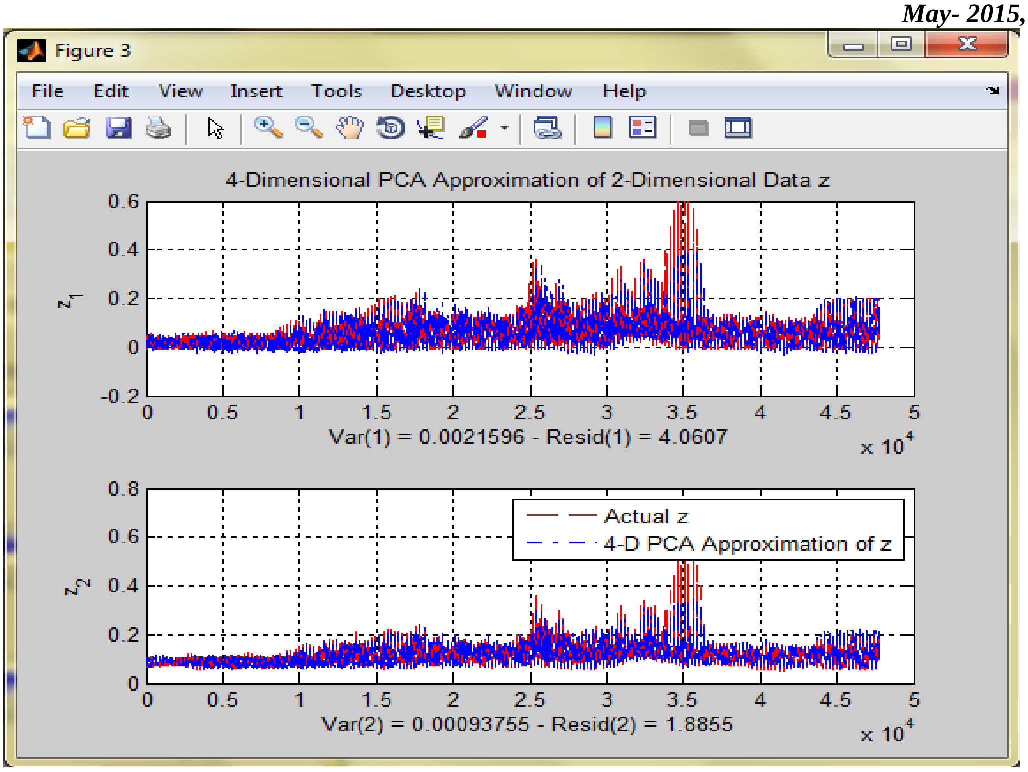

Fig. 8 Deviation of Actual data from the PCA approximation of same data.

IV. CONCLUSIONS

ICA consists in finding a linear decomposition of data into statistically independent components. In the recent past, ICA has been proposed as a tool to analyse and unmix hyperspectral data [10].This paper addresses the impact of the tuning parameters on the performance of the FastICA. In this experiment, our main findings are-

1. It is easy to find independent components of different non-Gaussian distribution using different non-linearity.
2. Finding independent components one by one as in projection pursuit reduces the computational load.

By choosing suitable values of these parameters, one can easily run an algorihm that is robust, computationally simple and requires less storage space.

Also, the graphs make it very clear that the ICA produces more deviation between the actual and approximated data which shows that ICA performs better than PCA to generate more uncorrelated independent components. The main aim of ICA or PCA is to remove the correlation among the components and ICA does it very well than PCA. Moreover, the variance of components generated by the PCA is less than the variance for components generated by ICA. Thus, the introduction of these tuning parameters has made the ICA more efficient.

REFERENCES

[1] Chen Wu, Bo Du, Liangpei Zhang, "A Subspace-Based Change Detection Method for Hyper-spectral Image ", IEEE Journal of selected topics in applied earth observations and remote sensing, vol. 6, no. 2, April 2013.

[2] Qian Du, Ivica Kopriva and Harold Szu, "Independent-component analysis for hyperspectral remote sensing imagery classification", Optical Engineering 017008-1, vol-45(1) , January 2006.

[3] Vijay Kumar, Rahul Gupta, "Change Detection on SAR data using PCA Algorithm", International Journal of Computers and Technology, Vol.4, No.2(Mar-Apr 2013).

[4] P.Comon, "Independent Component Analysis: A new concept", Signal Process, vol. 36, pp. 287-314, 1994.

[5] Vikrant Gulati, Pushp Araj Pal, "Enhancement of ICA Algorithm Using MatLab for Change Detection in HyperSpectral Images ", IJESRR, Volume 1, Issue 5, October, 2014.

[6] Jing Wang and Chein-I Chang, "Independent Component Analysis-Based Dimensionality Reduction With Applications in Hyperspectral Image Analysis", IEEE Transactions on Geoscience and Remote Sensing, VOL. 44, NO. 6, JUNE 2006.

[7] A.Villa and J. Chanussot, "On The Use Of ICA For Hyperspectral Image Analysis", *IGARSS,* 978-1-4244-3395-7, 2009.

[8] Aapo Hyvärinen and Erkki Oja, "Independent Component Analysis: Algorithms and Applications", Neural Networks, vol. 13, no. 4-5, pp. 411-430, 2000.

[9] Neha Kumari and Dr. Rajat Gupta, "A Performance Analysis of Unsupervised Change Detection Method for Hyper spectral Images", International Journal On Recent And Innovation Trends in Computing and Communication, vol. 2, issue 5, May 2014.

[10] Jose M.P. Nascimento and Jose M.Bioucas Dias, "Does independent component analysis play a role in unmixing hyperspectral data?", IEEE Transactions on Geoscience and Remote Sensing, Vol. 43, No.1, Jan 2015.