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iseNo Models and De-noising Techniques:A Review

Prof A.Janardhan[1], Prof. K.Kishan Rao[2]

[1,2]Electronics and Communications Engineering Department,

Sreenidhi Institute of Science and Technology, Hyderabad, (India)

ABSTRACT

Noise removal is an active research topic in imaage processing. Various noises degrade the image quality during capturing ,coding and transmission stages of image . Image processing is basically extracting important information from the images. Hence, de-noising of corrupted image is a preprocessing step in image processing and retaining the important features like edge details as much as possible. The search for efficient denoising algorithm or techniques is an ongoing challenge at the interchange of functional analysis and statistics. In this paper a review of different noise models that are relevant to 1D and 2D signals such as image processing and various de-noising algorithms both spatial and transform domain techniques and their salient features are presented.

Keywords-Gaussian Noise; Rayleigh noise; Salt and Pepper noise s, de-noising spatial ,transform

I. INTRODUCTION

Many Practical developments, of considerable interest in the field of signal denoising, need continuous and uniform review of relevant noise theory. Noise usually presents during signal acquisition, coding, transmission, and processing steps. This additive noise corrupts the original information such as voice, image and video signal. Due to this reason some questions such as how much original signal is corrupted? how we can reconstruct the signal? etc., arises in researchers mind, .In image processing noise can be easily detected by the amount of pixels that are corrupted and the challenge is removal of noise from image without changing its actual features. Figure 1 depicts noise degradation and restoration model [1]. To remove noise from an image we must have knowledge of type of noise and and its associated noise distribution model.

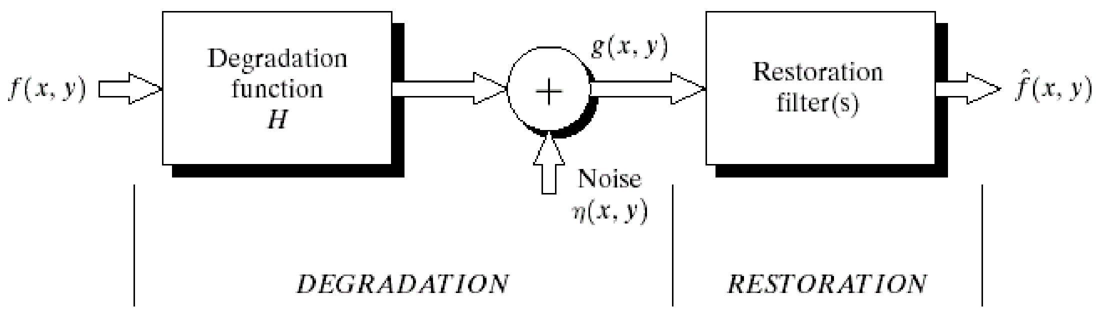


Fig. 1 Noise degradation / restoration model

Based on statistical concepts of noise theory, we start with noise and the role of noise in signal distortion. Noise is a random signal and is characterized by its mean and standard deviation. Most common types of noise are additive noise and multiplicative noise. Signal degradation is most prevailing problems in signal processing and based on how noise corrupts data we can have additive noise model and multiplicative noise models. Signals distorted due to various types of noises such as Gaussian noise, Flicker noise, Impulse or Salt and Pepper noise, and many more are fundamental noise types in signal processing. These noise sources are present in the vicinity of signal capturing devices, faulty memory location or may be introduced due to imperfection / inaccuracy in the signal capturing devices like microphones, Geo-phones, EEG sensors ,cameras, misaligned lenses, weak focal length, scattering and other adverse conditions may be present in the atmosphere. This makes careful and in-depth study of noise and noise models are essential ingredient in signal denoising. This leads to selection of proper noise model for signal de-noising systems .

In this paper, different noise models are explained in section II, section III deals with different de-noising methods including spatial and transform domain methods and section IV concludes this paper.

II. NOISE MODELS

Based on how the noise is corrupting the data, noise models are classified in to Additive noise and Multiplicative noise. One very common noise model is the additive noise model in which one can see , noise is added to true signal or data samples. Multiplicative noise on the other hand is still a model but in this model our true data samples are being multiplied by noise samples.

Digital noise may arise from various kinds of sources as mentioned in section I. In some sense, points spreading function (PSF) and modulation transfer function (MTF) have been used for timely, complete and quantitative analysis of noise models. Probability density function (PDF) or Histogram is also used to design and characterize the noise models. Some of noise models , their types and categories in signal processing [2] are explained in sub sections 2.1 to 2.5

2.1 Gaussian Noise Model

It is also called as electronic noise because it arises in amplifiers or detectors. Gaussian noise caused by natural sources such as thermal vibration of atoms and discrete nature of radiation of warm objects [2].

Gaussian noise generally disturbs the signal amplitude and gray values in digital images. That is why Gaussian noise model essentially designed and characteristics by its PDF or normalizes histogram with respect to gray value. This is given as

$$P(g) = \sqrt{\frac{1}{2\pi\sigma^2}} e^{-\frac{(g-\mu)^2}{2\sigma^2}} \quad \text{………………..…. (1)}$$

Where g = gray value, s = standard deviation and μ = mean. Generally Gaussian noise mathematical model represents the correct approximation of real world scenarios. In this noise model, the mean value is zero, variance is 0.1 and 256 gray levels in terms of its PDF, which is shown in Fig.2.

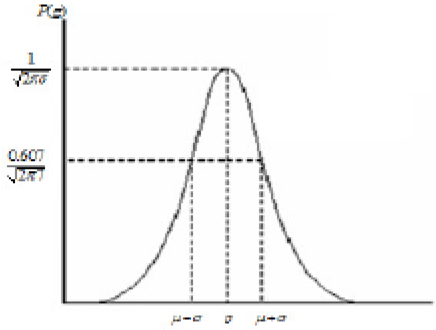


Fig. 2 PDF of Gaussian Noise

2.2 White Noise

White noise or Thermal noise: (a.k.a. Johnson–Nyquist noise?) refers to thermal agitation of electrons in charge carriers. In other words, a sensor will show some signal not because of receiving photons (or whatever they record) but because the electron is warm enough to have electron movement occasionally count as signal. Its frequency content is much like that of white noise.White noise refers to a statistical model for signals and signal sources, rather than to any specific signal. White noise is a signal (or process), named by analogy to white light, with a flat frequency spectrum, when plotted as a linear function of frequency (e.g., in Hz). In other words, the signal has equal power in any band of a given bandwidth (power spectral density) when the bandwidth is measured in Hz. For example, with a white noise audio signal, the range of frequencies between 40 Hz and 60 Hz contains the same amount of sound power as the range between 400 Hz and 420 Hz, since both intervals are 20 Hz wide.

2.3 Flicker or Brownian Noise (Fractal Noise)

Colored noise has many names such as Brownian noise or pink noise or flicker noise or 1/f noise. In Brownian noise, power spectral density is proportional to square of frequency over an octave i.e., its power falls on ¼ th part (6 dB per octave). Brownian noise caused by Brownian motion.

Brownian motion seen due to the random movement of suspended particles in fluid. Brownian noise can also be generated from white noise, which is shown in Fig.3. However this noise follows non stationary stochastic process. This process follows normal distribution. Statistically fractional Brownian noise is referred to as fractal noise. Fractal noise is caused by natural process.

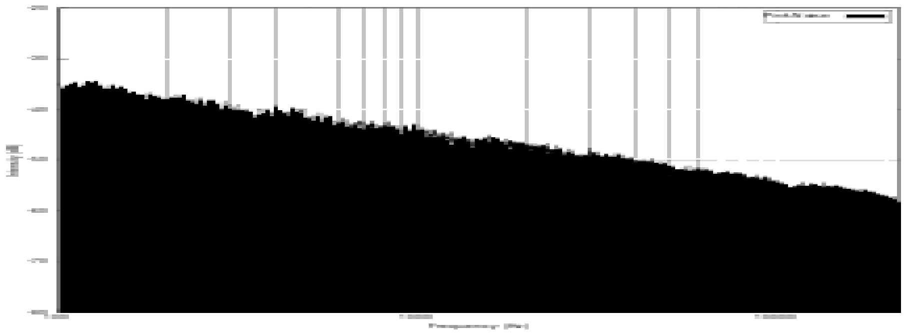
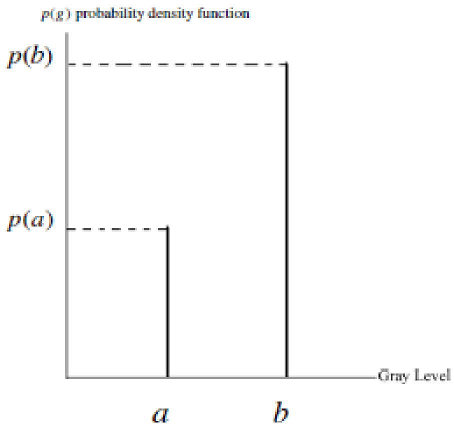


Fig. 3 Flicker Noise

2.4 Impulse Noise (Salt and Pepper Noise)

This is also called data drop noise because statistically its drop the original data values. This noise is also referred as salt and pepper noise.



$$P(g) = \begin{cases} Pa & \text{for } g = a \\ Pb & \text{for } g = b \\ 0 & \text{otherwise} \end{cases}$$ ....(2)

Fig. 4 Impulse Noise

Fig.4 shows the PDF of Salt and Pepper noise or impulse noise, if mean is zero and variance is 0.05. Here we will meet two spike one is for bright region (where gray level is less) called 'region a' and another one is dark region (where gray level is large) called 'region b', clearly seen here are the PDF values are minimum and maximum in 'region a' and 'region b', respectively . Salt and Pepper noise generally corrupted the digital image by malfunctioning of pixel elements in camera sensors, faulty memory space in storage, errors in digitization process and many more.

2.5 Rayleigh noise

Rayleigh noise or fading is a statistical model for the effect of a propagation environment on a radio signal, such as that used by wireless devices.

Rayleigh fading models assume that the magnitude of a signal that has passed through such a transmission medium (also called a communications channel) will vary randomly, or fade, according to a Rayleigh distribution — the radial component of the sum of two uncorrelated Gaussian random variables.

Rayleigh fading is viewed as a reasonable model for tropospheric and ionospheric signal propagation as well as the effect of heavily built-up urban environments on radio signals. Rayleigh fading is most applicable when there is no dominant propagation along a line of sight between the transmitter and receiver. How rapidly the channel fades will be affected by how fast the receiver and/or transmitter are moving. Motion causes Doppler shift in the received signal components. For example the power variation over 1 second of a constant signal after passing through a single-path Rayleigh fading channel with a maximum Doppler shift of 10 Hz and 100 Hz. These Doppler shifts correspond to velocities of about 6 km/h (4 mph) and 60 km/h (40 mph) respectively at 1800 MHz, one of the operating frequencies for GSM mobile phones. This is the classic case of Rayleigh fading , in particular the 'deep fades' where signal strength can drop by a factor of several thousand, or 30–40 dB.

The probability density function is given as:

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$$P(g)=\begin{cases}\frac{2}{b}(g-a)e^{\frac{-(g-a)^2}{b}} & \text{for } g \geq a \\ 0 & \text{for } g < a\end{cases}$$ ………………………………... (3)

Where mean $\mu = a+\sqrt{\frac{\pi b}{4}}$ and variance $\sigma^2 = \frac{b(4-\pi)}{4}$; are given as respectively

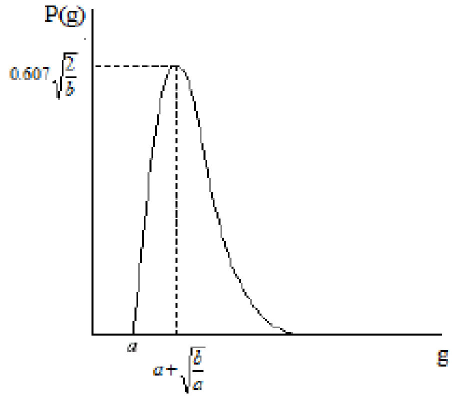

Fig. 5 Rayleigh distribution

III. DENOISING TECHNIQUES

The term "signal denoising" is general, it is usually devoted to the recovery of a digital signal that has been contaminated by additive white Gaussian noise (AWGN), rather than other types of noise (e.g., non-additive noise, Poisson/Laplace noise, etc.)

There is a wide range of applications in which denoising is important. Examples are medical image/signal analysis, data mining, radio astronomy and there are many more. Each application has its special requirements. For example, noise removal in medical signals requires specific care, since denoising which involves smoothing of the noisy signal (e.g., using low-pass filter) may cause the lose of fine details, as can be seen in Figure 6.

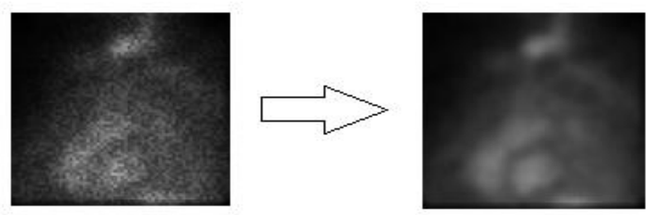

Fig. 6 Typical result of Low Pass Filtering for denoising

There are many approaches in the literature for the task of denoising, which can be roughly divided into two categories: denoising in the original signal domain spatial domain (e.g., time or space) and denoising in the transform domain [3] (e.g., Fourier or wavelet transform) as shown in figure 7.

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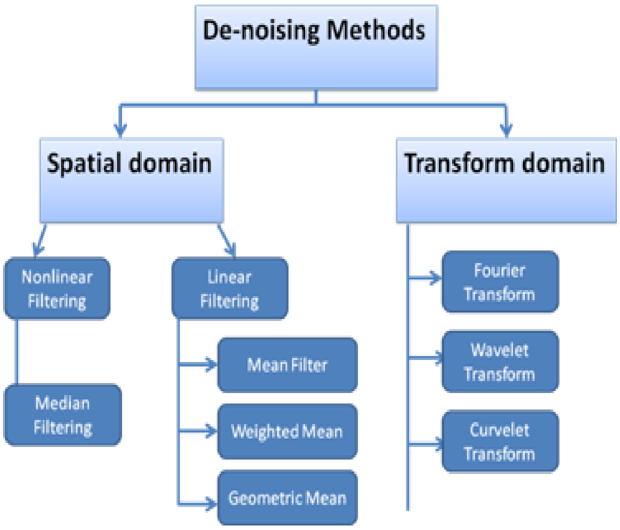

Fig. 7 : Denoising Techniques/methods

3.1. Non-linear Filtering (Median Filtering)

Median filtering is a nonlinear method used to remove noise from images. It is widely used as it is very effective at removing noise while preserving edges. It is particularly effective at removing 'salt and pepper' type noise. The median filter works by moving through the image pixel by pixel, replacing each value with the median value of neighbouring pixels. The pattern of neighbours is called the "window", which slides, pixel by pixel over the entire image 2 pixel, over the entire image. The median is calculated by first sorting all the pixel values from the window into numerical order, and then replacing the pixel being considered with the middle (median) pixel value. The following example shows the application of a median filter to a simple one dimensional signal. A window size of three is used, with one entry immediately preceding and following each entry. x =3,3,9,4,5,2,3,8,6,2,2,9,

y[1] = median[3 3 9] = 3,

y[6] = median[3 6 8] = 6,

y[2] = median[3 4 9] = 4,

y[7] = median[2 6 8] = 6,

y[3] = median[4 9 52] = 9

y[8] = median[2 2 6] = 2 3 3 9 4 52 3 8 6 2 2 9 9 3

y[4] = median [3 4 52] = 4

y[9] = median[2 2 9] = 2 y[5] = median[3 8 52] = 8 y[10] = median[2 9 9] = 9 y =3,4,9,4,8,6,6,2,2,9 . For y[1] and y[9], extend the left-most or right most value outside the boundaries of the image same as leaving left-most or right most value unchanged after 1-D median

3.2. Linear Filtering

Average (or mean) filtering is a method of 'smoothing' images by reducing the amount of intensity variation between neighbouring pixels. The average filter works by moving through the image pixel by pixel, replacing each value with the average value of neighbouring pixels, including itself. There are some potential problems: ¾ A single pixel with a very unrepresentative value can significantly affect the average value of all the pixels in its neighbourhood. 9 ¾ When the filter neighbourhood straddles an edge, the filter will interpolate new values for pixels on the edge and so will blur that edge. This may be a problem if sharp edges are required in the output.

The example given below shows the application of an average filter to a simple one dimensional signal. Size of window of three is used as an example, with one entry immediately preceding and following each entry and following each entry. Window for x[4]→y[4] x= y[1] = round((3+3+9)/3)= 5 y[6] = round((3+8+6)/3)= 6 y[2] = round((3+9+4)/3)= 5 y[7] = round((8+6+2)/3)= 5 [3] d((9+4+52)/3) 22 [8] d((6+2+2)/3) 3 3 3 9 4 52 3 8 6 2 2 9 9 10 y[3] = round((9+4+52)/3)= 22 y[8] = round((6+2+2)/3)= 3 y[4] = round((4+52+3)/3)= 20 y[9] = round((2+2+9)/3)= 4 y[5] = round((52+3+8)/3)= 21 y[10] = round((2+9+9)/3)= 7 y= 5 5 22 20 21 6 5 3 4 7.

For y[1] and y[9], extend the left-most or right most value outside the boundaries of the image

ii) Weighted mean Filtering

Weighted mean filter differs from mean filter in that specified pixels within a local neighborhood are repeated a given number of times in the computation of the mean value.

iii) Geometric mean filtering

In the geometric mean filter method, the color value of each pixel is replaced with the geometric mean of color values of the pixels in a surrounding region. A larger region (filter size) yields a stronger filter effect with the drawback of some blurring.The geometric mean is defined as:

$$G = \sqrt[n]{a_1 \cdot a_2 \cdots a_n} \quad \text{....................(4)}$$

The geometric mean filter is better at removing Gaussian type noise and preserving edge features than the arithmetic mean filter. The geometric mean filter is very susceptible to negative outliers.

3.3.Transform domain filtering

The transform domain filtering methods can be divided according to the choice of the basis functions. The basis functions can be further classified as data adaptive and non data adaptive.

Non-data adaptive transform domain method such as Discrete Wavelet Transform (DWT) contains the methodology of image de-noising that follows in the following steps

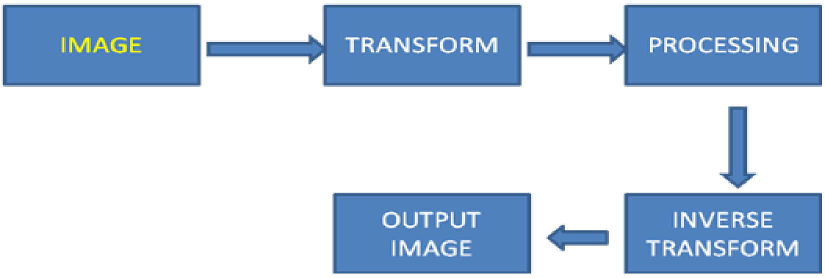

Fig. 8.Block diagram of Wavelet Denoising.

Step-1: Transform the noisy image into orthogonal domain by 2D discrete wavelet transform.

Step-2 Apply hard or soft thresholding to the noisy detail coefficients of the wavelet transform.

Step-3. Perform inverse discrete wavelet transform to obtain the de-noised image.

Choice of Wavelets, Curve lets and Contourlets:

Recently, a new member of the emerging representation family of multiscale geometric transform called contourlet transform that was developed to overcome limitations of traditional multi-resolution common representation such as wavelets. The curvelet, like the wavelet transform, is a multi scale transform, with frame elements indexed by location parameters and scale. The curvelet transform was designed to represent singularities and edges along curves much more efficiently than traditional transforms, i.e. using many coefficients for a given accuracy of reconstruction. So, in order to represent an edge to squared error 1/N requires 1/N wavelets and only about $1/\sqrt{N}$ curvelets [4]. But contourlet transform [5] is an efficient directional multiresolution expansion that is digital, thus contourlets transform is multiscale, local and directional contour segments and it is constructed via filter banks and can be viewed as an extension of wavelets with directionality than it Inherits the rich wavelet theory and algorithms, it starts with a discrete-domain construction that is amenable to efficient algorithms, and then investigates its convergence to a continuous-domain expansion [4]. The expansion is defined on rectangular grids i.e. seamless transition between the continuous and discrete worlds.

In transform domain method, threshold plays an important role in the denoising process. Finding an optimum threshold is a tedious process. A small threshold value will retain the noisy coefficients resulting noise in the restored image or signal whereas a large threshold value leads to the loss of coefficients that carry image signal details. A trade off is required in choosing the threshold.

Data Adaptive Transform method:.

Independent Component Analysis is widely used in signal and image processing as data adaptive transform domain filtering method. In ICA transform [7] data is represented as it can be define the ICA and it is a random vector X consists of finding a linear transform as shown in equation 5".

$$X=AS \quad ....(5)$$

Such that the sources or components Si are as independent as possible, with respect to some optimizing function that measures independence. As this definition of ICA is general definition and no assumptions on the data are made. ICA is the decomposition of random vector in linear components which are "as independent as possible". Here, 'independence' should be understood in its strong statistical sense: it goes beyond second order decorrelation and thus involves the non-gaussianity of the data. The ideal measure of independence is the higher order cumulates like kurtosis and mutual information. In addition to the basic assumption of statistically independence, by imposing the following fundamental restrictions, the noise free ICA model can be defined[8,9] if.

1. All the independent components Si, with the possible exemption of one component, must be non-Gaussian

2. The number of observed linear mixtures m must be at least as large as the number of independent components n; i.e. m> p

3.The matrix A must be of full column rank We can invert the mixing matrix as in equation 6.

$$S = A^{-1} X \quad ....(6)$$

Thus to estimate one of the independent components, we can consider a linear combination of Xi Let us denote this by equation 7.

$Y= b^TX= b^T AS$ ....(7)

Hence if b were one of the rows of $A-^1$, this linear combination bTX would actually equal one of the independent components . But in practice we cannot determine such 'b' exactly because we have no knowledge of matrix A, but we can find an estimator that gives a good approximation.

IV. CONCLUSION

Many of linear and non linear filtering algorithms have been developed to reduce noise from corrupted signals and images to enhance quality. The most common type of noise is the white or Gaussian noise where its power is uniformly distributed over the spectral and spatial spaces and its mean is zero. Linear filtering is an efficient technique to deal with additive noise while non-linear filters are efficient to deal with the multiplicative and function based noise. If we are moving to the transform domain method then non adaptive basis function based on contourlet , curvelet or wavelet transform domain method provides better de-noising while preserving the details of image like edges. The main assets of the this transform are:

1. The ability to compact most of the signal's energy into a few transformation coefficients, which is called energy compaction. 2. The ability to capture and represent effectively low frequency components (such as image backgrounds) as well as high frequency transients (such as image edges). 3. The variable resolution decomposition with almost uncorrelated coefficients. 4. The ability of a progressive transmission, which facilitates the reception of an image at different qualities.

Data adaptive basis function based method like independent component analysis (ICA) is a higher order statistical method suitable for multidimensional and multivariate data analysis and processing. De-noising of natural images by ICA methods are strongly data adaptive as de-noising processes do not require the noise free image in general and hence more efficient than curvelet , wavelet transform domain methods . This paper concludes that dual filtering in cascade - one filtering method followed by another filtering would perform better. Suppose , we use wavelet or curvelet transform to remove additive noise and then use ICA to separate components the performance would be much better as signal is denoised before applying to ICA. On the other hand wavelet transform may cause loss of information while denoising which may be useful for ICA for classification purposes.

REFERENCES

[1] Noorpet Kaur Gill and Anand Sharma, Noise Models and De-noising Techniques in Digital Image Processing, Phil. IJCMS,Volume 5,Issue 11.November 2016

[2] Prabhishek Singh and Raj Shree, A comparative study to Noise models and Image restoration Techniques, IJCA 2016,Volume 149-N0.1

[3] Vandana Roy and Dr Shailaja Shukla,Spatial and Transform Domain Filtering Method for Image De-noising: A Review,IJMECS 2013,7,41-49.

[4] Jean-Luc Stark,Fionn Murtagh and Jalal M Faditi,SPARSE IMAGE AND SIGNAL PROCESSING-Wavelets,Curvelets,Morphological Diversity , Cambridge University Press Cambridge,NEW YORK,Melbourne,Madrid,Singapore,Delhi,Dubai Tokyo, Cambridge University Press 32 Avenue of the Americas,New York NY 10013 2473,USA..

[5] Do and Vetterli,The Counterlet Transform:An efficient Directional Multi Resolution Image Representation.IEEE Transactions on Image Processing.14:2091-2016,2005

[6] Negar Riazifar and Mehran Yazdi,Effectiveness of Countourlet vs Wavelet Transform on Medical Image Compression a comparative study, World Academy of Science,Engineering and technology 49,2009

[7] Aapo Hyvarinen and Erkki Oja,Independent Component Analysis: Algorithms and Applications, Neural Networks Research center,Finland. 2000

[8] Te-Won Lee, Independent Component Analysis Theory and Applications, Kulwer Academic Publisher.Boston.1998

[9] A.Cichocki,Shun-ichi Amar, 'Adaptive blind signal and Image processing learning algorithms and Applications, John Wiley and Sons Ltd 2002.