A Survey on Types of Noise and Image Denoising Techniques

Parshuram Shingote[1] , Arun Ghandat[2]

[1]Assistant Professor, Computer Engineering Dept., Amrutvahini College of Engineering, Maharashtra, India
[2]Assistant Professor, Computer Engineering Dept., Amrutvahini College of Engineering, Maharashtra, India

ABSTRACT

Now a days, information transmitted in the form of digital images is becoming a major way of communication in the modern age, but the image obtained after transmission is mostly corrupted with noise. The received image needs to processing before it can be used in applications. The important property of a good image denoising model is that it should completely remove or reduce noise as far as possible as well as preserve edges. Image denoising involves the preprocessing of the obtained imag e data to produce a visually high quality image. This paper reviews the existing denoising algorithms, such as filtering methods, wavelet based techniques, and multifractal approach, and also performs their comparative study. Different noise models includ ing additive as well as multiplicative types are used, such as Gaussian noise, speckle noise, salt and pepper noise and Brownian noise. Selection of the denoising algorithm is depends on application. Hence, it is necessary to have knowledge about the type of no ise present in the selected image to select the appropriate denoising algorithm. The image filtering techniques has been proved to be the best when the image is corrupted with salt and pepper noise. The wavelet based technique finds applications in denoising images corrupted with Gaussian noise. The multifractal technique can be used,In the case where the noise characteristics are complex. A quantitative measure of comparison is provided by the signal to noise ratio(SNR) of the image.

Keywords*- Image Denoising, Additive Noises, Multiplicative Noises, Denoising Techniques ,Signal to noise ratio.*

I. INTRODUCTION

A very large portion of digital image processing is contribute to image restoration. This includes research in algorithm development and routine aim oriented image processing. Image restoration is the reduction of degradation that are incurred wh ile the image is being obtained [10]. Degradation comes from blurring and noise due to photo-metric and electronic sources. Blur is a form of bandwidth reduction of the image which caused by the incorrect image formation process such as relative motion betwee n camera and the original scene or by an optical system that is out of focus [10]. When aerial photographs are produced for remote location sensing purposes, blurs are introduced by aberrations in the optical system,atmospheric turbulence and relative mot ion between camera and ground. In addition to these blurring effects, the recorded image is corrupted by noise. A noise is introduced in the transmission medium due to errors during the measurement process, a noisy channel, and during quantization of the data f or digital storage. Each element in the imaging chain such as film, digitizer, lenses, etc. contribute to the degradation.

Image denoising is mostly used in the field of photography or publishing where an image quality was somehow degraded but needs to be improved quality of image before it can be printed. For this type of application we need to know something about the image degradation process in order to develop a model for it. When we have a model for the image degradation process, the reverse process can be applied to the image to restore quality back to the orig inal form. This type of image restoration technique is often used in space exploration to help eliminate artifacts generated by mechanical jitter in a space -craft , to compensate for distortion in the optical system of a telescope. Image denoising mostly finds applications in fields such as astronomy where the resolution limitations are severe, in medical imaging system where the physical requirements for two high quality imaging are needed for analyzing images of unique events, and in forensic study where potentially useful photographic evidence is sometimes of extremely low quality [10]. Let us now consider the array representation of a digital image. A 2 -dimensional digital image can be represented as a 2-dimensional array of data s(x,y), where (x,y) represent the pixel address. The pixel value corresponds to the brightness of the image at location(x,y). Some of the frequently used image types are binary image, gray -scale image and color images [11].

Binary images are the simplest type of image and can take only two discrete values, black and white. Black is represented with the value 0 and white with 1. Note that a binary image is generally obtained from a gray -scale image. A binary images are finds applications in computer vision areas where the general outline information of the image is needed. They are also called to as 1 bit/pixel images. Gray-scale images are known as monochrome or single color or one-color images. The images are used for experimentation purposes in this survey are all gray-scale images. They contain no any color information. They represents the brightness of the images. This image contains 8 bits/pixel data, which means it can have up to 0-255 (256) different brightness levels. A 0 represents black color and 255 denotes white color. The values between 1 to 254 represent the different gray levels. As they contain the intensity information, they are also called as intensity images.

Color images are considered as three band monochrome images, where each band is of a different color. Each band provides the color brightness information of the corresponding spectral band. Typical color images are combination Red, Green and Blue images and are also referred to as RGB images. This is a 24-bits/pixel image.

There are various methods help to restore an image from noisy distortions. Selection of the appropriate method plays a major role in getting the desired high quality image. The denoising techniques tends to be problem specific. For example, a technique that is used for denoise satellite images may not be suitable for denoising medical images. In order to analyze the performance of the various denoising algorithms, a good quality image is taken and some known noise is added to that image. This noise added image would then be given as input to one of the denoising algorithm, which produce an image close to the original high quality image. In case of image denoising methods, the characteristics of the degrading system and assumed that the nois es are to be known before. The image s(x,y) is blured by a linear operation and noise n(x,y) is added to form the lower quality degraded image w(x,y). This is convolved with the restoration method g(x,y) to produce the restored image z(x,y).

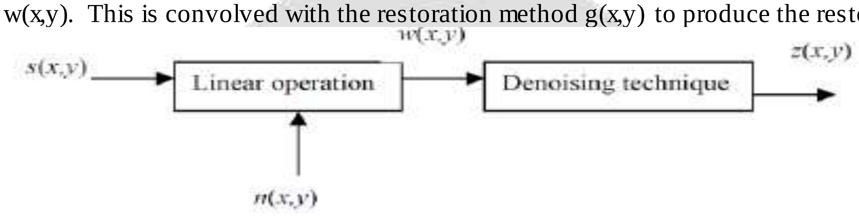

Figure 1.1: Denoising concept

In Figure 1.1 shows the “Linear operation” , is the multiplication or addition of the noise n(x,y) to the signal s(x,y) [Im01]. Once the degraded image w(x,y) is obtained, it is needed to the denoising method to get the denoised image z(x,y). The main focus in this paper is comparing and contrasting several image denoising techniques. Three popular techniques are studied in this paper. Noise removal or reduction can be done on corrupted image by filtering, by wavelet analysis, or by multi fractal analysis. Each technique has its prons and cons. Denoising by wavelets Transform and multi fractal analysis are some of the new approaches. Wavelet techniques consider thresholding and multi fractal analysis is based on improving the Holder regularity o f the degraded image.

II. TYPES OF NOISE

Typically images are corrupted with additive noises modeled with either a Gaussian noise, uniform noise, or salt and pepper distribution. Speckle noise is another type of nose, it is multiplicative in nature. If Noise is present in an image it is either in an additive or multiplicative form. An additive noise follows the rule, $w(x, y) = s(x, y) + n(x, y)$,
While the multiplicative noise follows $w(x, y) = s(x, y)\times n(x, y)$, Where s(x,y) is the original image signal, n(x,y) denotes the noise added into the signal to produce the degraded image w(x,y), and (x,y) represents the pixel value. The above image algebra is done at pixel level. Image addition also finds application in image morphing [11]. By image multiplication, the brightness of the image is get varied.

i. Gaussian Noise

Gaussian noise is evenly distributed over the image signal. That is, each pixel in the corrupted image is the sum of the true pixel values and a Gaussian distributed noise values. This type of noise has a Gaussian distribution, it has a bell shaped probability distribution function given by,

$$F(g) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-(g-m)^2/2\sigma^2}$$

Where in function *g* represents the gray level, *m* represent the mean of the function, and σ represent standard deviation of the noise. Figure 2.1 shows Gaussian noise distribution. When it introduced into an image, Gaussian noise with zero mean and variance as 0.05 would look as in Image 2.1. Image 2.2 illustrates the Gaussian noise with mean (variance) as 1.5 (10) over a original image with a constant pixel value of 100.

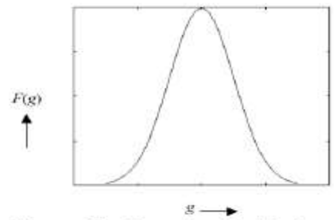

Figure 2.1: Gaussian distribution

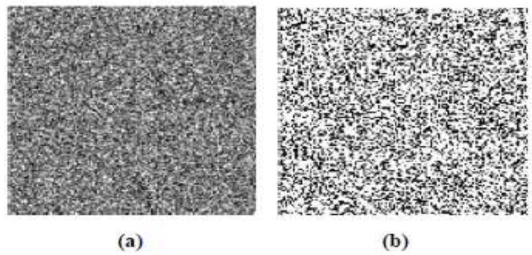

Image 2.1: Gaussian Noise Image (a) mean=0, variance 0.05 (b) mean=1.5, variance 10.

ii. Salt and Pepper Noise

Another type of noise is Salt and pepper noise [11]. It is an impulse type of noise, which is also called to as intensity spikes. This is generally caused due to errors in data transmission and has only two possible values, *a* and *b*.

The probability of each is typically less than 0.1. The corrupted pixels are set alternatively to the minimum or to the maximum value, giving the image a “salt and pepper” like appearance. Unaffected pixels remain unchanged. For an 8-bit image, the typical value for pepper noise is 0 and for salt noise 255. The salt and pepper noise is generally caused by malfunctioning of pixel elements in the faulty memory locations , camera sensors, or timing errors in the digitization process. Figure 2.2 shows the probability density function for Salt and pepper noise. Image 2.3cSalt and pepper noise with a variance of 0.05.

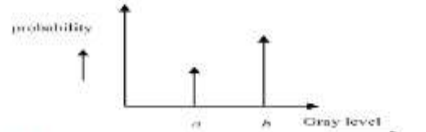

Figure 2.2: PDF for salt and pepper noise

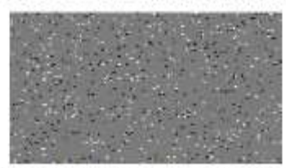

Image 2.3: Salt and pepper noise

iii. Speckle Noise

Speckle noise [Ga99] occurs in almost all coherent imaging systems such as laser, acoustics and SAR(Synthetic Aperture Radar) imagery. It is Multiplicative noise. The source of this noise is attributed to random interference between the coherent returns. Gamma distribution followed by Speckle noise is given as,

$$F(g) = \frac{g^{\alpha-1}}{(\alpha-1)!a^{\alpha}} e^{-\frac{g}{a}}$$

Where variance is $a\alpha$ and g is the gray level. Image 2.4 shows speckle noise with variance 0.05. Figure 2.3 shows gamma distribution.

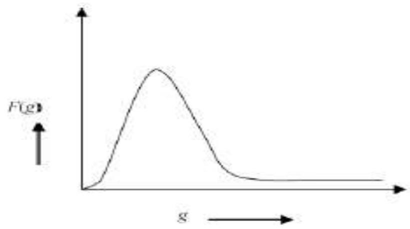

Figure 2.3: Gamma distribution

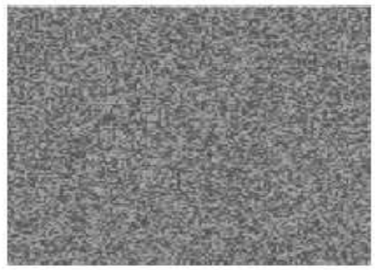

Image 2.4: Speckle noise

iv. Brownian Noise

Brownian noise [12] the category of fractal noise. Brownian noise is a special case of fractal or $1/f$ noise. Brownian noise is obtained by integrating white noise. Figure 2.4 graphically represents Brownian noise.

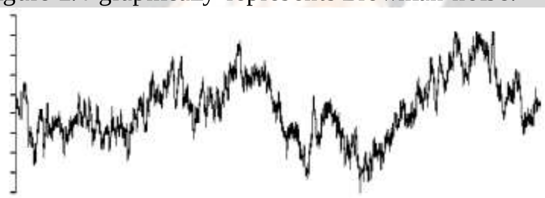

Figure 2.4: Brownian noise distribution

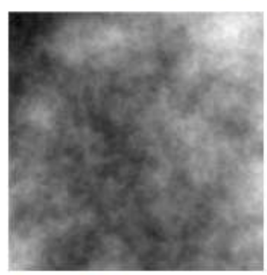

Image 2.5: Brownian noise

III DENOISING TECHNIQUES

a) Linear smoothing

Linear Smoothing is a relatively simple approach to image denoising to convolve a degraded image y with a Gaussian filter k:

$$\hat{x} = y * k$$

This linear operation can be performed in Fourier domain:

$$\hat{X} = Y \odot K$$

Where capital letters denote the Fourier transform of their counterparts and $\odot$ denotes the element wise product. The Gaussian filter k is still a Gaussian in the Fourier domain (i.e. K is also Gaussian).

b) Median filtering

Median filtering is an alternative to linear smoothing . The idea of median filtering is to process an image pixel by pixel. Each pixel is replaced by the median of the value of a set of neighbouring pixels. The method can therefore also be regarded as a filtering technique, though the filter is non-separable or non linear.

c) Denoising using local statistics

This section summarizes the method described by Jong-Sen Lee in 1980 [14]. This algorithm is an early approach to digital image denoising, invented at a time when the cost of computations was much higher. The algorithm can handle both additive noise and multiplicative noise. A clean image x is corrupted with AWG noise n, giving us a noisy image y(additive):

$$y = x + n$$

d) Total variation

The motivation behind image denoising based on total variation [15] is that noisy images have a larger discrete image gradient than noiseless images. Noisy images look grainy and clean images looks smooth. Hence an image which is smooth according to some measure but is close to the original image should yield good denoising results.

e) Anisotropic diffusion

Anisotropic diffusion[16] [17] can be used for image denoising, it is an iterative procedure based on smoothing. The method should fulfil the following requirements: (i) Boundaries of the Object should be preserved, and (ii) noise should be efficiently removed in homogeneous (at) regions. Images can be considered to consist of one region per object, in which case the goal of anisotropic diffusion is to perform smoothing within regions not between regions. Smoothing adapts to the image content.

f) Bilateral Filtering

Bilateral filtering [18][19] like anisotropic diffusion, trying to smooth an image while preserving edges. Bilateral filtering is non iterative. Bilateral filtering is to non-linearly combines nearby image pixel values. The pixels to be combined are chosen based on their geometric proximityand photometric similarity. Domain-filtering and range filtering are two approaches bend in Bilateral filtering.

g) Fields of Experts

The Fields of Experts framework [20][21] is a model for image priors based on MRFs(Markov random fields). The prior probability of an image is modelled using a random field with overlapping cliques, whose potentials are represented as Products of Experts. The framework is applicable to multiple low-level vision tasks, such as denoising and inpainting. Usually, extended cliques are used (3x3 or 5x5), so that image statistics beyond pair wise neighbor hoods are captured. Denoising is achieved using a simple iterative gradient descent approach on a negative log likelihood term.

h) BLS-GSM and other wavelet-based methods

Many image denoising approaches perform denoising on a wavelet decomposition of the degraded image. Wavelet decompositions have the desirable property of locality both in space and in frequency, which is not the case for other transforms e.g Fourier transform. Following are te steps for Wavelet based denoising algorithms , (1) an image is transformed into a wavelet domain, (2) denoising is effected on the wavelet coefficients, and (3) the denoised image is obtained by applying the inverse wavelet transform on the denoised wavelet coefficients.

i) Dictionary-based methods:

Several denoising algorithms are dictionary based for denoising image patches [23, 24, 25, and 26]. This usually assumed that an image x is degraded with AWG noise:

$$y = x + n$$

Denoising is performed patch-wise: Each patch of size k x k with k usually between 8 and 12 is denoised separately and inserted into the denoised image. Usually, averaging is performed in the areas of overlapping patches.

IV. LITERATURE SURVEY

In 2009 Zuofeng Zhou, Jianzhong Cao, Weihua Liu [27] Contour-let is a new effective signal representation tool in many image applications. In this paper, a contour-let-based image-denoising algorithm using adaptive windows which utilizes both the captured directional information by the contour-let transform and the intrinsic geometric structure information of the image is proposed. The adaptive window in each of the contour-let sub band is first fixed by autocorrelation function of contour-let coefficients' energy distribution, and then the local Wiener filtering is used to denoised the corrupted image. Experiments show that the proposed algorithm achieves better performance than current sub-sampled contour-let based image denoising algorithms.

In 2012 Joachimiak, M.; Rusanovskyy, D.; Hannuksela, M.M.; Gabbouj, M., [1] "Multi view 3D video denoising in sliding 3D DCT domain". With the widespread interest in 3D technology areas such as displays, cameras, and processing, the 3D video is becoming widely available. Due to correlation between views in multi view 3D video at the same temporal location, it is possible to perform video processing operations more efficiently comparing to regular 2D video. In order to improve denoising performance for Multi view video, we propose an algorithm based on denoising in 3D DCT domain, which is competitive in performance with state-of-art denoising algorithms and it is suitable for real-time implementation. The proposed algorithm searches for corresponding image patches in temporal and inter-view directions, selects 8 patches with lowest dissimilarity measure, and performs denoising in 3D DCT domain. The novel inter-view image patch search method brings up to 1.62dB gain in terms of average luma Peak Signal-to-Noise Ratio (PSNR), with average gain 0.6-0.8 dB depending on the amount of noise present in test sequences.

In 2013 Kaimal, A.B.; Manimurugan, S.; Anitha, J.,[2] "A modified anti-forensic technique for removing detectable traces from digital images,". The increasing attractiveness and trust on digital photography has given rise to new acceptability issues in the field of image forensics. There are many advantages to using digital images. Digital cameras produce immediate images, allowing the photographer to outlook the images and immediately decide whether the photographs are sufficient without the postponement of waiting for the film and prints to be processed. It does not require external developing or reproduction. Furthermore, digital images are easily stored. No conventional "original image" is prepared here like traditional camera. Therefore, when forensic researchers analyze the images they don't have access to the original image to compare. Fraud by conventional photograph is relatively difficult, requiring technical expertise. Where as significant features of digital photography is the ease and the decreased cost in altering the image. Manipulation of digital images is simpler. With some fundamental software, a digitally recorded image can easily be edited. The most of the alterations include borrowing, cloning, removal and switching parts of a digital image. A number of techniques are available to verify the authenticity of images. But the fact is that number of image tampering is also increasing. The forensic researchers need to find new techniques to detect the tampering. For this purpose, they have to find the new anti-forensic techniques and solutions for them. In this paper a new anti-forensic technique is considered, which is capable of removing the evidences of compression and filtering. It is done by adding a specially designed noise called tailored noise to the image after processing. This method can be used to cover the history of processing in addition to that it can be also used to remove the signature traces of filtering.

In 2013 Hagawa, R.; Kaneko, S.; Takauji, H.,[3] "Using Extended Three-valued Increment Sign for a denoising model of high-frequency artifacts in JPEG images by estimation of specific frequency,". Author presented a robust denoising model for high-frequency artifacts resulted by compressing images into JPEG. In this model, the authors used only simple evaluation value named Extended Three-valued Increment Sign (ETIS). ETIS represents the relationship of adjacent pixels, which one is brighter or almost the same. The authors expected that ETIS difference between Compressed Image and Noise Image would be small except edge region. Then they figured out the sum of the squares of those differences and utilized it in noise estimation. Only quantization process cause the artifacts, then they optimized DCT coefficient matrix in non-linearly based on ETIS, and estimated high-frequency artifacts as an independent approach without smoothing process. In the result, the model succeeded to reject noise with preservation of edge information. In addition, they compared the results with others those applied the traditional method called ε-filter and made sure that their method had similar or better improvement.

In 2013 Jin Xu; Wei Wang; Jinghuai Gao; Wenchao Chen,[4] "Monochromatic Noise Removal via Sparsity- Enabled Signal Decomposition Method,". Monochromatic noise always interferes with the interpretation of the seismic signals and degrades the quality of subsurface images obtained by further processes. Conventional methods suffer from several problems in detecting the monochromatic noise automatically, preserving seismic signals, etc. In this letter, we present an algorithm that can remove all major monochromatic noises from the seismic traces in a relatively harmless way. Our separation model is set up upon the assumption that input seismic data are composed of useful seismic signals and single-frequency interferences. Based on their diverse morphologies, two waveform dictionaries are chosen to represent each component sparsely, and the separation process is promoted by the sparsity of both components in their corresponding representing dictionaries. Both synthetic and field-shot data are employed to illustrate the effectiveness of our method.

In 2013 Abramov, S.; Krivenko, S.; Roenko, A.; Lukin, V.; Djurovic, I.; Chobanu, M.,[5] "Prediction of filtering efficiency for DCT-based image denoising,". The task of prediction practical efficiency of filtering on the basis of the discrete cosine transform (DCT) methods is considered. It is shown that it is possible to estimate the MSE values of images to be processed by means of calculation rather simple statistics of DCT coefficients. Moreover, the quasi-optimal value of threshold parameter for DCT filtering methods can be easy evaluated as well. The results are presented for different additive Gaussian noise levels and a set of gray-scale test images. Developed method provides an opportunity to decide is it worth applying filtering or not.

In 2013 Padmagireeshan, S.J.; Johnson, R.C.; Balakrishnan, A.A.; Paul, V.; Pillai, A.V.; Raheem, A.A., [7] "Performance Analysis of Magnetic Resonance Image Denoising Using Contourlet Transform,". A medical image denoising algorithm using contourlet transform is proposed and the performance of the proposed method is analysed with the existing methods. Noise in magnetic resonance imaging has a Rician distribution and unlike AWGN noise, Rician noise is signal dependent. Separating signal from Rician noise is a tedious task. The proposed approaches were compared with other transform methods such as wavelet thresholding and block DCT. Hard, soft and semi-soft thresholding techniques are described and applied to test images with threshold estimators like universal threshold. The results are compared based on the parameters: PSNR and MSE. Numerical results show that the contour let transform can obtained higher PSNR than wavelet based and block DCT based denoising algorithms.

In 2013 Fedak, V.; Nakonechny, A., [8] "Image denoising based on optimized NLM algorithm,". Images and video are often coded using block based discrete cosine transform (DCT) or discrete wavelet transform (DWT) that cause a great deal of visual distortions. Non- Local Means (NLM) algorithm is chosen by means of comparing complexity and quality of different algorithms and is considered to be the better algorithm for artifacts reduction. Besides, implementation of this algorithm is computationally intensive. In this note, improvements to the non-local means introduced are presented and very effective performance optimization approach is presented. This approach is based on additional memory usage for caching pixels distance in the image.

Table 1: Literature Survey Summary:

Title	Author	Year	Methodology	Description
Contourlet-based Image Denoising Algorithm using Adaptive Windows	Zuofeng Zhou, Jianzhong Cao, Weihua Liu	2009	Contour let Transform with Adaptive Windows	Achieved better performance than current subsampled contourlet based image denoising algorithms
Multi view 3D video denoising in sliding 3D DCT domain	Joachimiak, M.; Rusanovskyy, D.; Hannuksela, M.M.; Gabbouj, M.	2012	Denoising in 3D DCT domain	Up to 1.62dB gain in terms of average luma Peak Signal-to- Noise Ratio (PSNR)
A modified anti-forensic technique for removing detectable traces from digital images	Kaimal, A.B.; Manimurugan, S.; Anitha, J.	2013	Anti-forensic technique	Remove the signature traces of filtering
Using Extended Three-valued Increment Sign for a denoising model of high frequency artifacts in JPEG images by estimation of specific frequency	Hagawa R.; Kaneko S.; Takauji H.	2013	Simple evaluation value named Extended Three-valued Increment Sign (ETIS)	The model succeeded to reject noise with preservation of edge information
Monochromatic Noise Removal via Sparsity-Enabled Signal Decomposition Method	Jin Xu; Wei Wang; Jinghuai Gao; Wenchao Chen	2013	Sparsity-Enabled Signal Decomposition method	Synthetic and field-shot data are employed to illustrate the effectiveness of method
Performance Analysis of Magnetic Resonance Image Denoising Using Contourlet Transform	Padmagireeshan, S.J.; Johnson, R.C.; Balakrishnan, A.A.; Paul, V.; Pillai, A.V.; Raheem, A.A	2013	Contourlet transform	The contour let transform can obtained higher PSNR than wavelet based and block DCT based denoising algorithms
Image de-noising based on optimized NLM algorithm	Fedak, V.; Nakonechny, A.	2013	Optimized NLM algorithm	Improvements to the nonlocal means introduced are presented

V. CONCLUSION

From the above discussion, it can be concluded that for salt and pepper noise, the median filter is optimal. Since selection of the right denoising procedure plays a major role, it is important to experiment and compare the methods. As future research, we would like to work further on the comparison of the denoising techniques. If the features of the denoised signal are fed into a neural network pattern recognizer, then the rate of successful classification should determine the ultimate measure by which to compare various denoising procedures. Besides, the complexity of the algorithms can be measured according to the CPU computing time flops. This can produce a time complexity standard for each algorithm. These points would be considered as an extension to the present work done.

REFERENCES

[1] Joachimiak, M.; Rusanovskyy, D.; Hannuksela, M.M.; Gabbouj, M., "Multiview 3D video denoising in sliding 3D DCT domain," Signal Processing Conference (EUSIPCO), 2012 Proceedings of the 20th European , vol., no., pp.1109,1113, 27-31 Aug. 2012.
[2] Kaimal, A.B.; Manimurugan, S.; Anitha, J., "A modified antiforensic technique for removing detectable traces from digital images," Computer Communication and Informatics (ICCCI), 2013 International Conference on , vol., no., pp.1,4, 4-6 Jan. 2013.
[3] Hagawa, R.; Kaneko, S.; Takauji, H., "Using Extended Threevalued Increment Sign for a denoising model of high-frequency artifacts in JPEG images by estimation of specific frequency," Frontiers of Computer Vision, (FCV), 2013 19th Korea-Japan Joint Workshop on , vol., no., pp.164,169, Jan. 30 2013-Feb. 1 2013.
[4] Jin Xu; Wei Wang; Jinghuai Gao; Wenchao Chen, "Monochromatic Noise Removal via Sparsity-Enabled Signal Decomposition Method," Geoscience and Remote Sensing Letters, IEEE , vol.10, no.3, pp.533,537, May 2013.
[5] Abramov, S.; Krivenko, S.; Roenko, A.; Lukin, V.; Djurovic, I.; Chobanu, M., "Prediction of filtering efficiency for DCT-based image denoising," Embedded Computing (MECO), 2013 2nd Mediterranean Conference on , vol., no., pp.97,100, 15-20 June 2013.
[6] Roenko, A.; Lukin, V.; Djurovic, I., "DCT coefficient statistics in images corrupted by spatially correlated noise," Embedded Computing (MECO), 2013 2nd Mediterranean Conference on , vol., no., pp.156,159, 15-20 June 2013.
[7] Padmagireeshan, S.J.; Johnson, R.C.; Balakrishnan, A.A.; Paul, V.; Pillai, A.V.; Raheem, A.A., "Performance Analysis of Magnetic Resonance Image Denoising Using Contourlet Transform," Advances in Computing and Communications (ICACC), 2013 Third International Conference on , vol., no., pp.396,399, 29-31 Aug. 2013.
[8] Fedak, V.; Nakonechny, A., "Image de-noising based on optimized NLM algorithm," Intelligent Data Acquisition and Advanced Computing Systems (IDAACS), 2013 IEEE 7th International Conference on , vol.01, no., pp.429,432, 12-14 Sept. 2013.
[9] Castleman Kenneth R, Digital Image Processing, Prentice Hall, New Jersey, 1979.
[10] Reginald L. Lagendijk, Jan Biemond, Iterative Identification and Restoration of Images, Kulwer Academic, Boston, 1991.
[11] Scott E Umbaugh, Computer Vision and Image Processing, Prentice Hall PTR, New Jersey, 1998.
[12] 1/f noise, "Brownian Noise," http://classes.yale.edu/99-00/math190a/OneOverF.html, 1999.
[13] Jacques Lévy Véhel, "Fraclab," www-rocq.inria.fr/fractales/, May 2000.
[14] J.S. Lee. Digital image enhancement and noise filteringby use of local statistics. IEEE Transactions on Pattern Analysis and Machine Intelligence (PAMI), 2(2):165 168, 1980.
[15] L.I. Rudin, S. Osher, and E. Fatemi. Nonlinear total variation based noise removal algorithms. Physica D, 60:259{268, 1992.
[16] P. Perona and J. Malik. Scale-space and edge detection using anisotropic di_usion. IEEE Transactions on Pattern Analysis and Machine Intelligence (PAMI), 12(7):629 639, 1990.
[17] G. Gerig, O. Kubler, R. Kikinis, and F.A. Jolesz. Nonlinear anisotropic filtering of mri data. IEEE Transcations on Medical Imaging, 11(2):221{232, 1992.
[18] V. Aurich and J. Weule. Non-linear gaussian _lters performing edge preserving diffusion. In Mustererkennung 1995, 17. DAGMSymposium, pages 538{545. Springer-Verlag, 1995.
[19] C. Tomasi and R. Manduchi. Bilateral _ltering for gray and color images. In International Conference on Computer Vision and Pattern Recognition (CVPR). IEEE, 1998.
[20] S. Roth and M.J. Black. Fields of experts: A framework for learning image priors. In International Conference on Computer Vision and Pattern Recognition (CVPR). IEEE, 2005.
[21] S. Roth and M.J. Black. Fields of experts. International Journal of Computer Vision (IJCV), 82(2):205{229, 2009.
[22] G.E. Hinton. Training products of experts by minimizing contrastive divergence. Neural computation, 14(8):1771{1800, 2002.
[23] J. Mairal, F. Bach, J. Ponce, G. Sapiro, and A. Zisserman. Nonlocal sparse models for image restoration. In International Conference on Computer Vision (ICCV). IEEE, 2010.
[24] J. Mairal, M. Elad, G. Sapiro, et al. Sparse representation for color image restoration. IEEE Transactions on Image Processing (TIP), 17(1):53{69, 2008.
[25] M. Elad and M. Aharon. Image denoising via sparse and redundant representations over learned dictionaries. IEEE Transactions on Image Processing (TIP), 15(12):3736 3745, 2006.
[26] M. Aharon, M. Elad, and A. Bruckstein. K-svd: An algorithm for designing overcomplete dictionaries for sparse representation. IEEE Transactions on Signal Processing (TIP), 54(11):43114 322, 2006.
[27] Zuofeng Zhou; Jianzhong Cao; Weihua Liu, "Contourlet-based image denoising algorithm using adaptive windows," Industrial Electronics and Applications, 2009. ICIEA 2009. 4th IEEE Conference on , vol., no., pp.3654,3657, 25-27 May 2009.

BIOGRAPHIES

	**Er. Parshuram N. Shingote**, Completed M.E. Software Engineering from Dr. Babasaheb Ambedkar Marathwada University,Aurangabad with First Class. Currently Working as Assistant Professor in department of Computer Engineering in Amrutvahini College of Engineering , Sangamner(MH) .Area of research is data mining and image processing.
	**Er. Arun B. Ghandat**, Completed M.Tech in Computer Science from JNTU, Hyderbad with distinction. Currently Working as Assistant Professor in department of Computer Engineering in Amrutvahini College of Engineering , Sangamner(MH) .Area of research is DBMS and image processing, Network Security.