

EVALUATION OF GABOR FILTER PARAMETERS FOR IMAGE ENHANCEMENT AND SEGMENTATION

D. K. SOMWANSHI¹, R. PANCHARIYA², ABHAY KRISHAN³

Abstract— This work provides the knowledge about the working of Gabor filters for ten different types of images. A comparative study is based on the output of the noisy and the filtered images using Gabor filter. This process of getting the noisy images is based on three types of images: Gaussian, Poisson and Speckle. Finally an algorithm is developed that performs all the filtering techniques on the input image and the statistical parameters are calculated as per the comparison between output and input images. These statistical parameters are displayed graphically and they are compared for both the noisy and the filtered images. For the evaluation of the performance of Gabor filters statistical parameters like signal to noise ratio, correlation coefficient and Structure similarity are used and the MATLAB codes required in calculating these parameters are developed. These parameters are used to calculate the image quality of the output image obtained from Gabor filter, based on the values of these parameters the results of all the output images is discussed

Index Terms—Gabor Filter, Gaussian, Poisson, MATLAB.

INTRODUCTION

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This paper work is carried out to study the analysis of Gabor filtered output images and the noisy images. For this analysis, we are testing the values of various quality parameters like SNR, Correlation and SSIM. For getting the noisy images, we are using three types of noises, Gaussian, Poisson and Speckle noises. For segmentation purposes, we are selecting a particular area of the original images and this area is different for all the images. For segmentation analysis, we are using the comparison of three output images as: Original image segmentation, Gabor filtered output segmentation and noised output segmentation. These three output images are having the same dimensions for their comparison. The various parameters of the Gabor filter play a major role in deciding the output image. The size, phase, orientation and frequency of the output image are selected by the Gabor filter. The image features are measured by employing an appropriate Gabor filter with adaptively chosen size, orientation, frequency and phase for each pixel. An image property called phase divergence is used for the selection of the appropriate filter size. Characteristic features related to the change in brightness, texture and position are extracted for each pixel at the selected size of the filter. 2-D Gabor filter is easier to tune the direction and radial frequency band-width, and easier to tune center frequency, so they can simultaneously get the best resolution in spatial domain and frequency domain. Gabor filter outputs can be modeled as Gaussian's and develop algorithm for selecting optimal filter parameters.

GABOR FILTERS

A Gabor filter is a linear filter whose impulse response is defined by a harmonic function multiplied by a Gaussian function. Because of the multiplication-convolution property (Convolution theorem), the Fourier transform of a Gabor filter's impulse response is the convolution of the Fourier transform of the harmonic function and the Fourier transform of the Gaussian function. Gabor filters are directly related to Gabor wavelets, since they can be designed for number of dilations and rotations

However, in general, expansion is not applied for Gabor wavelets, since this requires computation of biorthogonal wavelets, which may be very time-consuming. Therefore, usually, a filter bank consisting of Gabor filters with various scales and rotations is created. The filters are convolved with the signal, resulting in a so-called Gabor space.

This process is closely related to processes in the primary visual cortex. The Gabor space is very useful in e.g., image processing applications such as iris recognition and fingerprint recognition. Relations between activations for a specific spatial location are very distinctive between objects in an image. Furthermore, important activations can be extracted from the Gabor space in order to create a sparse object representation. The Gabor Filters have received considerable attention because the characteristics of certain cells in the visual cortex of some mammals can be approximated by these filters. In addition these filters have been shown to possess optimal localization properties in both spatial and frequency domain and thus are well suited for texture segmentation problems. Gabor filters have been used in many applications, such as texture segmentation, target detection, fractal dimension management, document analysis, edge detection, retina identification, image coding and image representation. A Gabor filter can be viewed as a sinusoidal plane of particular frequency and orientation, modulated by a Gaussian envelope.

$$h(x, y) = s(x, y)g(x, y)$$

$s(x, y)$: Complex sinusoid

$g(x, y)$: 2-D Gaussian shaped function, known as envelope

$$s(x, y) = e^{-j2\pi(u_0x+v_0y)}$$

$$g(x, y) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2}\right)}$$

where $s(x, y)$ is a complex sinusoid, known as the carrier, and $g(x, y)$ is a 2-D Gaussian-shaped function, known as the envelope.

The complex sinusoid is defined as follows, $s(x, y) = \exp(j(2\pi(u_0x + v_0y) + P))$

where (u_0, v_0) and P define the spatial frequency and the phase of the sinusoid respectively. This sinusoid can be represented as two separate real functions, conventionally allocated in the real and imaginary part of a complex function.

The real part and imaginary part of this sinusoid are

$$\text{Re}(s(x, y)) = \cos(2\pi(u_0x + v_0y) + P)$$

$$\text{Im}(s(x, y)) = \sin(2\pi(u_0x + v_0y) + P)$$

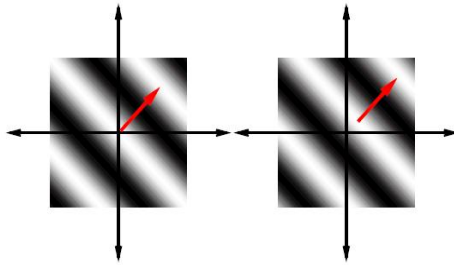
The parameters u_0 and v_0 define the spatial frequency of the sinusoid in Cartesian coordinates. This spatial frequency can also be expressed in polar coordinates as magnitude F_0 and direction ω_0 :

$$F_0 = \sqrt{u_0^2 + v_0^2}$$

$$\text{i.e. } \omega_0 = \tan^{-1}\left(\frac{v_0}{u_0}\right)$$

$$u_0 = F_0 \cos \omega_0$$

$$v_0 = F_0 \sin \omega_0$$



The real and imaginary parts of a complex sinusoidal

Using this representation, the complex sinusoid is

$$s(x, y) = \exp(j(2\pi F_0(x \cos \omega_0 + y \sin \omega_0) + P))$$

where (x_0, y_0) is the peak of the function, a and b are scaling parameters of the Gaussian, and the $_r$ subscript stands for a rotation operation such that

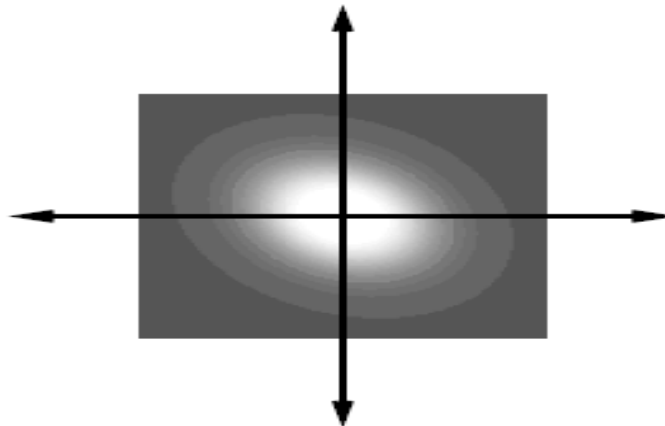
The Gaussian envelope

The Gaussian envelope looks as follows:

$$\omega_r(x, y) = K \exp(-\pi(a^2(x-x_0)_r^2 + b^2(y-y_0)_r^2))$$

$$(x-x_0)_r = (x-x_0)\cos\theta + (y-y_0)\sin\theta$$

$$(y-y_0)_r = -(x-x_0)\sin\theta + (y-y_0)\cos\theta$$



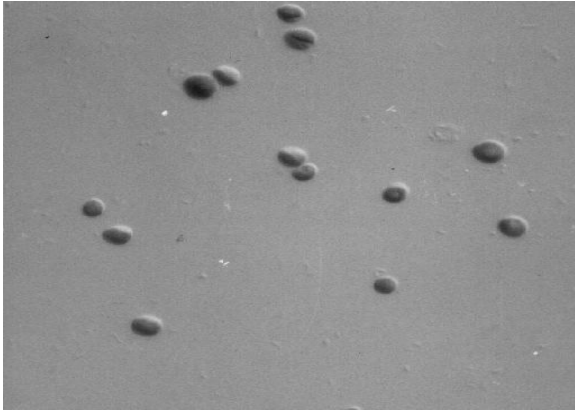
A Gaussian envelope

MATERIALS AND METHODS

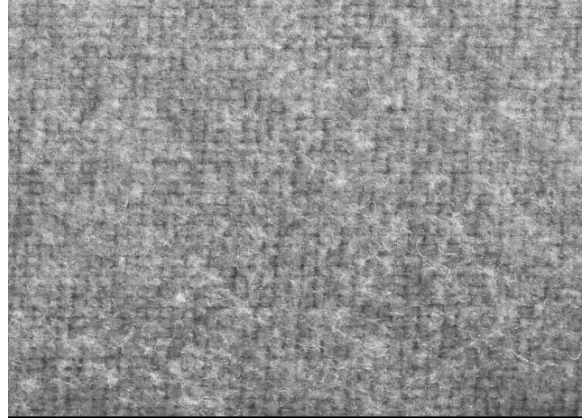
Images as Inputs

Gabor filters needs some types of images as the input. These images require the process of computer algorithms as per the input image. These computer algorithms yield two types of images from Computer Algorithm: noisy image

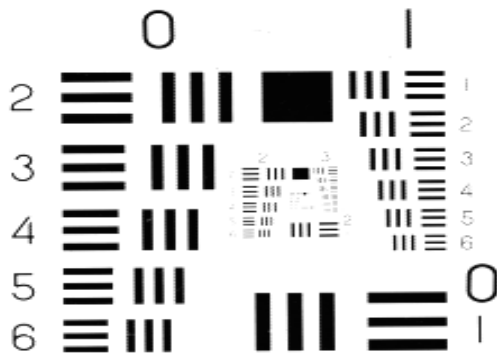
and magnitude image. The magnitude image is comparing with the noisy image, which gives the advantages of Gabor filters in various parameters. There are ten original standard images:-



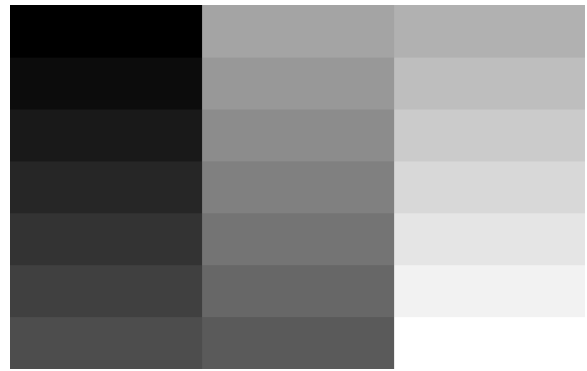
ALGAE.tif



BLANKET.tif



COUNTING.tif



GRAY.tif



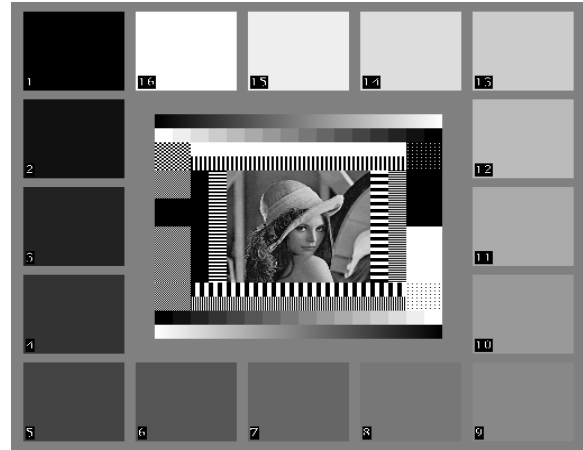
JUNGLE.tif



MOON.tif



LENA.JPG



TESTPAT.tif



TOPVIEW.tif



ULTRASONIC.tif

NOISES

- **Gaussian noise-** This type of noise adds normal distributed noise to the original image. The noise is independent of the image it is applied to. The value of the pixel is altered by the additive Gaussian noise as $J(k, l) = x(k, l) + n$

Where n is the noise, $n \sim N(0, v)$, being distributed normally with variance v . the noisy pixels which are generated are anywhere between black and white,

distributed according to the Gaussian curve. The width of the curve is adjusted with the mean and the variance parameter.

- **Poisson noise-** Poisson noise is generated from the data instead of adding artificial noise to the data. If I , the original image, is double precision, then input pixel values are interpreted as means of Poisson distributions scaled up by $1e12$. Poisson noise generates a noise sequence of integer numbers

having a Poisson probability

$$\text{distribution, } p(x) = \frac{\mu^x}{x!} \cdot e^{-\mu}$$

- **Speckle noise-** Speckle adds multiplicative noise to the image according to the following formula: $J = I + n * I$

where n is an array with the size of an array with the size of the original image, filled with random values resulting from a normal distribution (Gaussian distribution) with mean 0 and are controlled by the variance. With this type of noise, noise generation is dependent on the original image, hence the product in the formula.

Quality metrics

There are various quality metrics in our work. By evaluating the values of those parameters we can compare the values of the noisy and the magnitude images of the output. The values of those parameters lead to best results as per the details of various values by comparing the noisy and the magnitude output values. These are the various working parameters:

- **SNR-** SNR stands for signal to noise ratio. SNR is defined as the ratio of the net signal value to the RMS noise. Where the net signal value is the difference between the average signal and background values, and the RMS noise is the standard deviation of the signal value.
$$\text{SNR} = \frac{\text{Signal}}{\text{RMSnoise}}$$

The net signal is calculated from the difference of the average signal and background values. The RMS or root mean square noise is defined from the signal region. SNR compares the level of desired signal to the level of background noise. The higher the ratio, the less obtrusive the background noise is. SNR in decibel is defined as:

$$\text{SNR} = 10 \log\left(\frac{\sigma_g^2}{\sigma_e^2}\right) \text{ Where, } \sigma_g^2 \text{ is}$$

the variance of the noise free image and σ_e^2 is the variance of error (between the original and the output image). Brighter regions have a stronger signal due to more light, resulting in higher overall SNR.

- **Correlation-** The operation called correlation is closely related to convolution. In correlation, the value of an output pixel is also computed as a weighted sum of neighboring pixels. The correlation coefficient matrix represents the normalized measure of the strength of linear relationship between variables correlation coefficient. Correlation indicates the strength and direction of linear relationship between 2 signals and its value lie between +1 and -1. The correlation is 1 in the case of a linear relationship, -1 in the case of a decreasing linear relationship and some value in between for all other cases, including the degree of linear dependence between the 2 signals. The

closer the coefficient is to either -1 or +1, the stronger the correlation between the signals.

$$COC = \frac{\sum (g - \bar{g})(\hat{g} - \bar{\hat{g}})}{\sqrt{\sum (g - \bar{g})^2 \sum (\hat{g} - \bar{\hat{g}})^2}}$$

- **SSIM-** SSIM stands for structural SIMilarity. The SSIM index is a method for measuring the similarity between two images. The SSIM index is a full reference metric, in other words, the measuring of image quality based on an initial uncompressed or distortion-free image as reference. SSIM is designed to improve on traditional methods like PSNR and MSE, which have proved to be inconsistent with human eye perception. The SSIM metric is calculated on various windows of an image. The measure between two windows of size N X N x and y is:

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + c_1)(2cov_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}$$

with

Where g & \hat{g} are the original and noised images and \bar{g} & $\bar{\hat{g}}$ are the means of the original and the noised images.

- μ_x the average of x ;
- μ_y the average of y ;
- σ_x^2 the variance of x ;
- σ_y^2 the variance of y ;
- cov_{xy} the covariance of y ;
- $c_1 = (k_1L)^2$, $c_2 = (k_2L)^2$ two variables to stabilize the division with weak denominator ;
- L the dynamic range of the pixel-values ;
- $k_1 = 0.01$ and $k_2 = 0.03$ by default.

Working Algorithm using MATLAB

This working Algorithm is the way of doing our work. This is a step by step

procedure that how we implement the images and how we evaluate the working parameters. The main algorithm,

followed in order to fulfill the aim of our work, is as follows:

Step 1:

Read the original standard image (ALGAE.tif, BLANKET.tif, COUNTING.tif, GRAY.tif, JUNGLE.tif, LENA.jpg, MOON.tif, TESTPAT.tif, TOPVIEW.tif, ULTRASONIC.tif)

Step 2:

Apply the Gabor Filter to the original standard image and storing the mainly outputs for the Noisy image and the Magnitude image.

Step 3:

Resize the output noisy and output magnitude images as per the original standard image size as the size of the original image may be. To evaluate various parameters from the original and the output image it is necessary to maintain the same size of the images.

Step 4:

Before calculating the values of the various parameters, it is necessary to convert that output image to

1-Dimensional image because that standard image doesn't work by using the parameters formula in their original form.

Step 5:

Calculate the value of the quality metrics parameters by using the MATLAB command:

SNR (*I*, *J*), Correlation (*I*, *J*), [mssim ssim_map] = ssim_index (*I*, *J*)

This command gives the values of the SNR, Correlation and SSIM where *I* is the original image and *J* is the output image.

Step 6:

After run of all the parameters, all the values of parameters are calculated by changing the Variances and changing the frequency of the Gabor filters. The best value results are collected and plotted all with respect to their particular Variances.

RESULTS:-

Algae.tif:-

For Gaussian noise, SNR gives best result for the variance of 0.3, correlation coefficient gives best result for the variance of 0.1. Similarly, SSIM gives best result for the variance of 0.1. For Poisson noise, SNR gives best result for the variance of 0.5, correlation coefficient gives best result for the variance of 0.1. Similarly, SSIM gives best result for the variance of 0.1. For Speckle noise, SNR gives best result for the variance of 0.3, correlation coefficient gives best result for the variance of 0.1. Similarly, SSIM gives best result for the variance of 0.1.

Blanket.tif:-

For Gaussian noise, SNR gives best result for the variance of 0.1, correlation coefficient gives best result for the variance of 0.3, SSIM gives best result for the variance of 0.7. For Poisson noise, SNR gives best result for the variance of 0.1, correlation coefficient gives best result for the variance of 0.7. Similarly, SSIM gives best result for the variance of 0.7. For Speckle noise, SNR gives best result for the variance of 0.1, correlation coefficient gives best result for the variance of 0.3. SSIM gives best result for the variance of 0.5.

Counting.tif:-

For Gaussian noise, SNR gives best result for the variance of 0.3, correlation coefficient gives best result for the variance of 0.7 and SSIM gives best result for the variance of 0.5.

For Poisson noise, SNR gives best result for the variance of 0.7, correlation coefficient gives best result for the variance of 0.5. Similarly, SSIM gives best result for the variance of 0.5. For Speckle noise, SNR gives best result for the variance of 0.1, correlation coefficient gives best

result for the variance of 0.5 and SSIM gives best result for the variance of 0.3.

Gray.tiff:-

For Gaussian noise, SNR gives best result for the variance of 0.1, correlation coefficient gives best result for the variance of 0.3 and SSIM gives best result for the variance of 0.1.

For Poisson noise, SNR gives best result for the variance of 0.3, correlation coefficient gives best result for the variance of 0.7 and SSIM gives best result for the variance of 0.1.

For Speckle noise, SNR gives best result for the variance of 0.1. Similarly, correlation coefficient gives best result for the variance of 0.1 and SSIM gives best result for the variance of 0.1.

Jungle.tiff:-

For Gaussian noise, SNR gives best result for the variance of 0.5. Similarly, correlation coefficient gives best result for the variance of 0.5 and SSIM gives best result for the variance of 0.3. For Poisson noise, SNR gives best result for the variance of 0.7, correlation coefficient gives best result for the variance of 0.5. Similarly, SSIM gives best result for the variance of 0.5. For Speckle noise, SNR gives best result for the variance of 0.5. Similarly, correlation coefficient gives best result for the variance of 0.5 and SSIM gives best result for the variance of 0.3.

Lena.jpg:-

For Gaussian noise, SNR gives best result for the variance of 0.3, correlation coefficient gives best result for the variance of 0.5 and SSIM gives best result for the variance of 0.3.

For Poisson noise, SNR gives best result for the variance of 0.3, correlation coefficient gives best

result for the variance of 0.7 and SSIM gives best result for the variance of 0.3.

For Speckle noise, SNR gives best result for the variance of 0.1, Correlation coefficient gives best result for the variance of 0.3 and SSIM gives best result for the variance of 0.1.

Moon.tiff:-

For Gaussian noise, SNR gives best result for the variance of 0.1, correlation coefficient gives best result for the variance of 0.3 and SSIM gives best result for the variance of 0.1.

For Poisson noise, SNR gives best result for the variance of 0.5, correlation coefficient gives best result for the variance of 0.7 and SSIM gives best result for the variance of 0.5.

For Speckle noise, SNR gives best result for the variance of 0.1. Correlation coefficient gives best result for the variance of 0.3. Similarly, SSIM gives best result for the variance of 0.1.

Testpat.tiff:-

For Gaussian noise, SNR gives best result for the variance of 0.1. Similarly, correlation coefficient gives best result for the variance of 0.1 and SSIM gives best result for the variance of 0.1. For Poisson noise, SNR gives best result for the variance of 0.5. Similarly, correlation coefficient gives best result for the variance of 0.5 and SSIM gives best result for the variance of 0.5. For Speckle noise, SNR gives best result for the

Effect of Gabor filter for image segmentation

These are the comparison of Image segmentation for various images. There are three segmentation

variance of 0.1. Correlation coefficient gives best result for the variance of 0.7 and SSIM gives best result for the variance of 0.3.

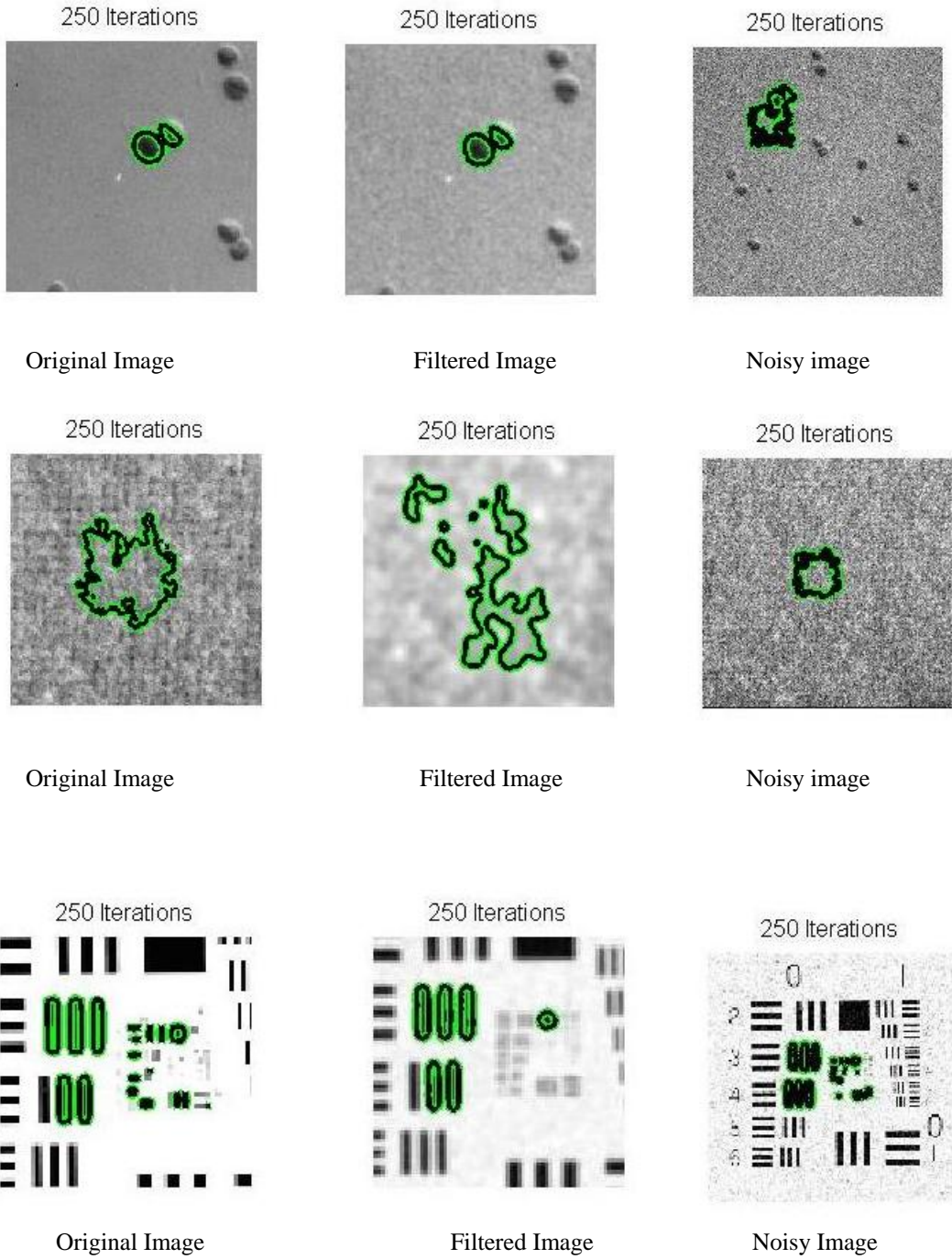
Topview.tiff:-

For Gaussian noise, SNR gives best result for the variance of 0.3, correlation coefficient gives best result for the variance of 0.5. Similarly, SSIM gives best result for the variance of 0.5. For Poisson noise, SNR gives best result for the variance of 0.5, correlation coefficient gives best result for the variance of 0.7. Similarly, SSIM gives best result for the variance of 0.7. For Speckle noise, SNR gives best result for the variance of 0.1. Correlation coefficient gives best result for the variance of 0.5. Similarly, SSIM gives best result for the variance of 0.1.

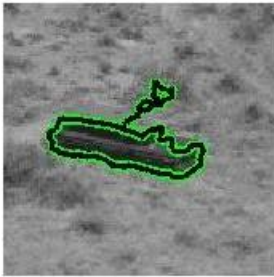
Ultrasonic.tif:-

For Gaussian noise, SNR gives best result for the variance of 0.1, correlation coefficient gives best result for the variance of 0.5. Similarly, SSIM gives best result for the variance of 0.5. For Poisson noise, SNR gives best result for the variance of 0.1, correlation coefficient gives best result for the variance of 0.7. Similarly, SSIM gives best result for the variance of 0.7. For Speckle noise, SNR gives best result for the variance of 0.1. Correlation coefficient gives best result for the variance of 0.7. Similarly, SSIM gives best result for the variance of 0.7.

results for every image. These are the segmentation of Original image and the best values output for Noisy and filtered images.

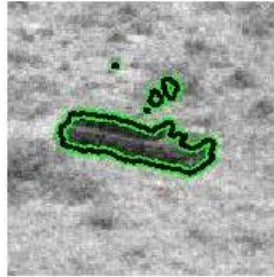


250 Iterations



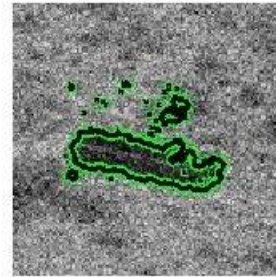
Original Image

250 Iterations



Filtered Image

250 Iterations



Noisy Image

250 Iterations



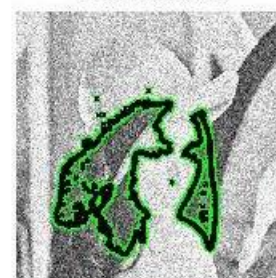
Original Image

250 Iterations



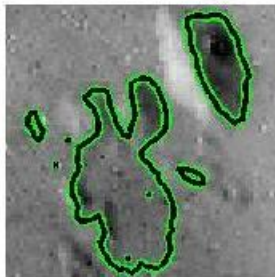
Filtered Image

250 Iterations



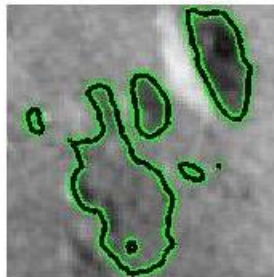
Noisy Image

250 Iterations



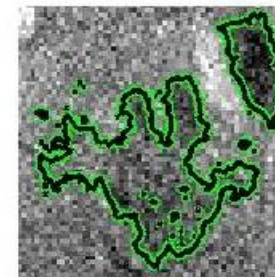
Original Image

250 Iterations



Filtered Image

250 Iterations



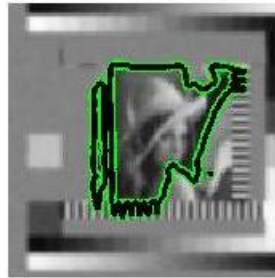
Noisy Image

250 Iterations



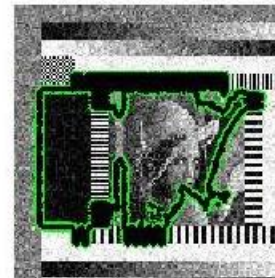
Original Image

250 Iterations

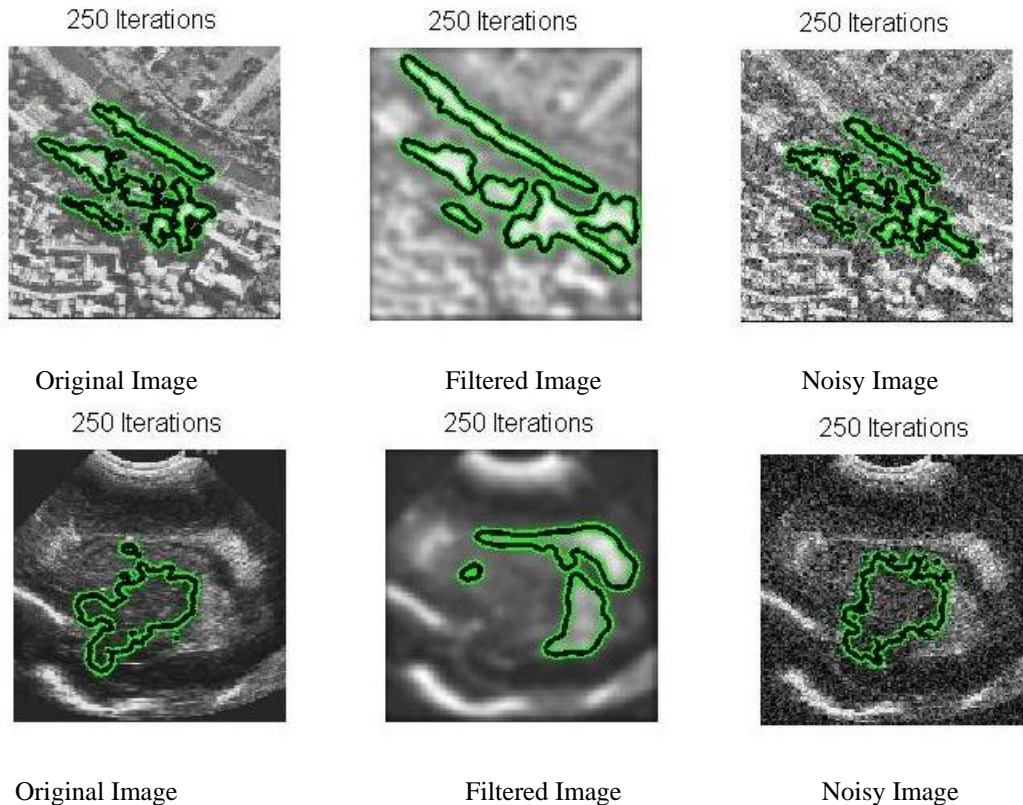


Filtered Image

250 Iterations



Noisy Image



After all the image segmentation has been done, we observe that the images that contain noises not gave good segmentation results after applying Gabor filters. The rest images that do not have noisy are given best results after applying Gabor filters as compared to the original images. In these

figures, Gabor filtered output images give best results as compared to the original image segmentation. And noisy images segmentation clearly indicates bad segmentation as compared to the other two images (original image and Gabor filtered output image).

CONCLUSION AND FUTURE SCOPE

CONCLUSION

This work presents evaluation of Gabor filter's parameters for various noisy and filtered images using Gabor filters. A lot of combinations of these noisy and filtered images have been obtained to find the best values as per the analysis of those two images of the quality metrics, SNR, Correlation and SSIM. The input image formats that have been used in this work are TIFF, TIF

and JPEG and the output image format is having JPEG.

The analysis of all the obtained experimental results, demonstrates that the image noise is significantly reduced after applying Gabor filter. The parameters which are evaluated were Gabor-filtered output images give best output values for all the quality metrics and also give the best results for the image segmentation.

There are ten images in this work. For the analysis of results, we using the variances values (0.1, 0.3,

0.5, 0.7) and for some frequency values (300, 500, 700, 900, 1500)Hz. Each image gives best response for some particular variances values and for some particular frequency values.

- Of all the frequency values that we are using, the frequency value 900 Hz gives the maximum best values for results.
- The frequency values 300, 500 and 700 Hz gives nearly around the same amount of best results.
- The frequency value 1500 Hz gives the least amount of best results.

For all the noises that we are used in this thesis work, each noise will give some different response from the other noises.

- For Gaussian noise, the comparison of noisy and filtered images give the best results mostly for the variances of 0.1 and 0.3.
- For Poisson noise, the comparison of noisy and filtered images give the best results for all the working variances.
- For Speckle noise, the comparison of noisy and filtered images give the best results for the variances of 0.1.

For segmentation results, we can analyze all the three figures in the same plane. These three figures are: segmentation of original image,

segmentation of both the noisy and filtered images that are different for all the ten images that gives best results as per the comparison between noisy and filtered images.

FUTURE SCOPE

The application of Gabor filters has been growing at a very fast rate. Gabor filters can be used for image segmentation, weed image classification, Palmprint recognition, Texture segmentation, for the illumination invariant recognition of color texture, for an automatic inspection system for textile fabrics and many places.

- This work can be further done in the field of texture image segmentation. And also works for various other parameters like MSE etc.
- Moreover, for future work we can use various AI techniques like Radon neural network, Fuzzy, Adaptive, GA in order to attain the best output without performing calculations for each and every combination. This work can be done by using this technique will lead to more efficiency and less tedious work.
- This work can be done using the technique of frequency domain analysis using fractals, FFTs.

REFERENCES

1. Z.-Q. Liu, R.M. Rangayyan and C.B.Frank," Analysis directional features in images using Gabor filters"pp.68-74, 1990 IEEE.
2. Jiang Wen, You Zhisheng and Li Hui,"Segment the Metallograph Images Using Gabor Filter"pp.25-28,1994 International symposium on speech, Image Processing and Neural Networks,13-16 April 1994,Hong Kong.
3. Richard Buse and Zhi-Qiang Liu,"Feature extraction and analysis of handwritten words in Grey-scale images using Gabor filters"pp.164-168, 1994 IEEE.
4. Andreas Teuner, Olaf Pichler and Bedrich J. Hosticka," Unsupervised Texture Segmentation of Image Using Tuned Matched Gabor filters", IEEE transactions on image processing, June 1995.
5. Shuzo Yamamoto, Yoshikazu Nakajima, Shinichi Tamura, Yoshinobu Sato and Seiyo Harino," Extraction of fluorescent dot traces from a scanning Laser Ophthalmoscope Image sequence by Spatio-Temporal Image analysis:Gabor Filter and Radon Transform Filtering", IEEE transactions on biomedical engineering, November 1999.
6. Ian R Fasel, Marian S Barlett and Javier R Movellan," A comparison of Gabor filter methods for automatic detection of Facial landmarks", fifth IEEE international conference on automatic face and Gesture recognition, 2002.
7. C.Klimanee and DT Nguyen," On the design of 2-D Gabor Filtering of Fingerprint Images", IEEE, 2004.
8. Rong Lu and Yi Shen," Image segmentation Based on Random Neural Network Model and Gabor filters" proceedings of 2005 IEEE engineering in medicine and biology 27th annual conference.
9. Ying-Chun Li, Zhan-Chun Li, Yun-Huan Mei and Jian-Xin Zhang," detecting algorithms based Gabor in Microscopic image" proceedings of the fourth International conference on machine learning and cybernetics, Guangzhou, August 2005.
10. Hany Ayad Bastawrous, Takuya Fukumoto, Norihisa Nitta and Masaru Tsudagawa," detection of ground glass opacities in lung CT images using Gabor filters and neural networks", instrumentation and measurement technology conference Ottawa, Canada, May 2005.
11. Hong Wei and Marc Bartels," Unsupervised segmentation Using Gabor wavelets and statistical features in LIDAR Data analysis", Proceedings of the 18th international conference on pattern recognition, 2005.
12. K. L. Mak and P. Peng," An automated inspection system for textile fabrics based on Gabor filters", Department of Industrial and Manufacturing Systems Engineering, The University of Hong-Kong, February 2007.
13. Mohammed Al-Rawi and Jie Yang," Using Gabor Filter for the illumination invariant recognition of color texture", Institute of Image processing and Pattern recognition, Shanghai Jiao Tong University, PR China, December 2007.
14. Jesmin F.khan, Reza R. Adhani and Sharif M.A. Bhuiyan," A customized Gabor filter for unsupervised color image segmentation", Department of Electrical and Computer Engineering, University of Alabama in Huntsville, USA, 2008.
15. Xin Pan and Qiu-Qi Ruan," Palmprint recognition using Gabor-based local invariant features", Institute of information science, Beijing Jiaotong University, PR China, 2008.
16. J. Bossu, Ch. Gee, G. Jones and F.Truchetet," Wavelet transform to discriminate between crop and weed in perspective agronomic images", 21 Bld Olivier de serres, France, 2008.
17. Asnor Juraiza Ishak, Aini Hussain and Mohd Marzuki Mustafa," Weed image classification using Gabor wavelet and gradient field distribution", Department of Electrical, Electronic and Systems Engineering, Faculty of Engineering and built environment,University Kebangsaan Malaysia, Malaysia 2008.
18. Minqin Wang, Guoqiang Han, Yongqiu Tu, Guohua Chen and Yuefang Gao," Unsupervised Texture Image segmentation Based on Gabor Wavelet and multi-PCNN", School of computer Science and Engineering, South China University of Technology, China 2008.
19. Gholam Ali Rezaei Rad and Kaveh Samiee," Fast and modified Image segmentation Method Based on Active Contours and Gabor filter" Electrical Engineering Department of Iran University of Sciences and Technology, 2008.
20. "Natural Coding of Tactile Texture: Comparison of Spatial and Temporal Mechanics for roughness Perception", Charles E. Connor and Kenneth O. Johnson, the Journal of Neuroscience, September 1992.
21. Rafael C.Gonzalez, Richard E.Woods and Steven L.Eddins, "Digital Image Processing Using MATLAB", Pearson Education (Singapore) Pte Ltd., Indian Branch, 482 F.I.E. Patparganj, Delhi 110092, India, 2004.
22. Javier R. Movellan, "Tutorials on Gabor Filters", pp.1-20,GNU Free documentation License 1.1,Kolmogorv Project,2002