Brain Tumor Edge Detection Based on GWT & DWT Fusioning

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Abstract— Brain tumor Edge detection plays a vital role in medical image processing. Edge of the image is one of the most significant features which is mainly used for image analyzing process. An edge is in general a border which separates the adjacent zones of image having distinct brightness. The development of an edge detector is often based on a specific characteristic of the image. An important property of the edge detection method is its ability to extract the accurate edge line with good orientation, and much literature on edge detection has been published in the past three decades. It is encountered in the areas of feature selection and feature extraction in Computer Vision. An edge detector accepts a digital image as input and produces an edge map as output. The edge maps of some detectors include explicit information about the position and strength of the edges and their orientation. An efficient algorithm for extracting the edge features of images using Gabor Wavelet and fusion technique is proposed in this work. Gabor wavelets can effectively abstract local and discrimination features. In textural analysis and image segmentation, GW features have achieved outstanding results, while in machine vision, they found to be effective in object detection, recognition and tracking. The most useful application of the Gabor Wavelets is for edge detection. Gabor wavelet along with DWT and fusion based approach is highly effective at detecting both the brain tumor location and orientation of edges. The results proved that the performance of proposed method is superior to conventional Gabor Wavelet and other edge detection algorithms. The performance of the proposed method is proved with the help of Entropy, PSNR & spectral analysis is also computed for proposed method edge detected output image, gabor wavelet edge detected output image, original input MRI brain image.

Key words: Digital Image Processing, Edge detection, GWT, DWT, Fusion

I. INTRODUCTION

Bjoern H. Menze, et.al [1] proposed Multimodal Brain Tumor Image Segmentation Benchmark (BRATS) organized in conjunction with the MICCAI 2012 and 2013 conferences. They found that different algorithms worked best for different sub-regions (reaching performance comparable to human inter-rater variability), but that no single algorithm ranked in the top for all sub-regions simultaneously. Fusing several all good algorithms using a hierarchical majority vote yielded segmentations that consistently got ranked above all individual algorithms, indicating remaining opportunities for further methodological improvements. The BRATS image data available and found through an online evaluation system as an ongoing benchmarking resource. Evaluating the accuracy of automated routines in longitudinal settings including both pre- and postoperative images are important directions for future work along with further algorithmic developments. Finally they concluded, by using BRATS they generated the largest public dataset available for this task and they evaluated a large number of state-of-the-art brain tumor segmentation methods

A. Brain Tumor

Brain tumors are created by abnormal and uncontrolled cell division in brain itself. Identification of tumor involves tests like CT and MRI. MRI plays an efficient role in identifying location, size and type of brain tumor. This makes this technique a very special one for the brain tumor detection. A brain tumor is known an uncontrolled growth of solid mass formed by the undesired cells either normally found in the different part of the brain such as glial cells, neurons, lymphatic tissue, blood vessels, pituitary and pineal gland, skull, or spread cancers mainly located in other organs. Brain tumors are divided based on the type of tissue involved in the brain, the positioning of the tumor in the brain, whether it is benign tumor or malignant tumor and other different considerations. Brain tumors are occurred at the solid portion that permeate the surrounding tissues or distort the surrounding structures. There are different types of brain tumors

1) Pre-Malignant Tumor
2) Malignant Tumor

B. Problem Statement

Edge detection is used to characterize the intensity changes in the image in terms of the physical processes that have originated them. An intermediate target of edge detection is the detection and characterization of significant intensity changes. This work discusses this part of the edge detection problem. To characterize the types of intensity changes derivatives of different types, and possibly different scales, are needed. BasicallyEdge detection consists of two steps, a filtering step and a differentiation step. Gradient based edge detectors have no smoothing filter, and they are only based on a discrete differential operator. The main drawbacks of zero crossing based operators are re-responding to some of the existing edges and very sensitive to noise. The problem with canny operator is that these two thresholds are not easily determined and low threshold produces false edges, but a high threshold misses important edges.

C. Scope of Work

In this work, an image is decomposed into sub bands using discrete wavelet transform. Thereafter we are applying Gabor wavelet transform is applied LL (Approximate band) of DWT decomposed image. Then we are fusing this Gabor wavelet transformed image with HH (Diagonal Band) of DWT decomposed image. The results of proposed method are better than that of the Gabor wavelet transform method. From proposed method the exact size and shape of tumor can be identified efficiently. Spectral analysis is computed for proposed method output.

II. PROPOSED METHOD

A. Edge Detection

An edge is in general a border which separates the adjacent zones of image having distinct brightness. The development of an edge detector is often based on a specific characteristic of the image. One of the property of the edge detection method is its ability to extract accurate edge lines with good orientation . An edge detector accepts a digital image as input and produces an edge map as output. The edge maps of some detectors include explicit information about the position and strength of the edges and their orientation.we are using gradient based image edge detection in our proposed method.

B. Wavelet Approach

Wavelet transforms are classified into discrete wavelet transforms (DWTs) and continuous wavelet transforms (CWTs). The Discrete Wavelet Transform (DWT) has been a successful technique used in edge detection. . The 2-D discrete wavelet transform decomposes the image into sub-images, 3 details and 1 approximation. The approximation looks just like the original; only on ¼ the scale. The 2-D DWT is an application of the 1-D DWT in both the horizontal and the vertical directions. DWT separates image into low pass filter and high pass filter and again low & high pass filter divides into a lower resolution approximation image (LL) as well as horizontal (HL), vertical (LH) and diagonal (HH) detail components. DWT is used for edge detection.

C. Edge Detection Using Conventional Gabor Wavelet

Gabor wavelets can effectively abstract local and discrimination features. In textural analysis and image segmentation, GW features have achieved outstanding results, while in machine vision, they found to be effective in object detection, recognition and tracking. The most useful application of the Gabor Wavelets is for edge detection.For given an input image I(x, y), the Gabor Wavelet features are extracted by convolving I(x,y) with G(x,y) as in equation

$$\Phi(x,y)=G(x,y)\otimes I(x,y) \qquad (1)$$

Where $\otimes$ denotes the 2-D convolution operation .The Gabor wavelets (GWs) respond strongly to edge if the edge direction is perpendicular to the wave vector ($\omega \cos \theta$, $\omega \sin \theta$). When hitting an edge, the real and imaginary parts of $\Phi(x, y)$ oscillate with the characteristic frequency in- stead of providing a smooth peak.

D. Discrete Wavelet Transform

DWT can be implemented by filtering operations with well-defined filter coefficients. In order to compute forward DWT, the input signal (x) is filtered separately by a low-pass filter (h~) and a high pass filter (g~). The two output streams are sub-sampled again by simply dropping the alternate output samples in each stream to produce the low-pass (yL) and high-pass (*yH*) sub band outputs as shown in Fig2. The original signal can be reconstructed by a synthesis filter bank (h, g) starting from *yLandyH*. The two filters (h~, *g*~) constitutes the analysis filter bank.. Given a discrete signal *x* (*n*), the output signals *yL*(*n*) and *yH*(*n*) can be computed as

$$y_l(n) = \sum_{i=0}^{t_l-1} h(i) * x(2n-i) \,,$$
$$y_H(n) = \sum_{i=0}^{t_n-1} g(i) * x(2n-i) \qquad (2)$$

Where τ *L* and τ *H* are the lengths of the low-pass (h~) and high-pass (g~) filters respectively. For inverse transform, both *yLandyH*are first up-sampled by inserting zeros in between two samples and then filtered by low-pass (*h*) and high-pass (*g*) filters respectively. Then they are added to obtain the signal (*x*').

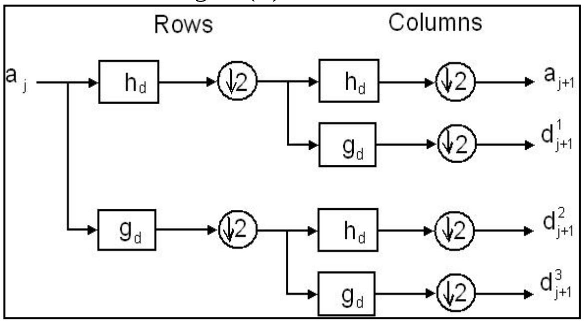


Fig. 1: One-level 2D DWT decomposition scheme

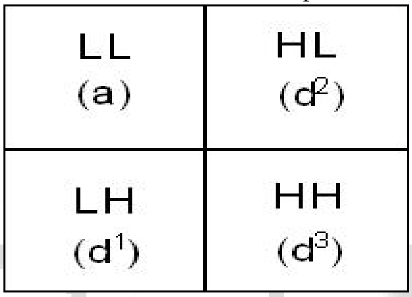


Fig. 2: 2D DWT coefficients' image

For multi-resolution wavelet decomposition, the low-pass sub band (*yL*) is further decomposed in a similar fashion in order to get the second-level of decomposition, and the process is repeated. The inverse process follows similar multi-level synthesis filtering to reconstruct the signal. Image signals are two-dimensional signals. In order to increase the quality of the low resolution image, preserving the edges is essential. Therefore, DWT and SWT have been employed in order to preserve the high frequency components of the image. In this correspondence, one level DWT is used to decompose an input image into different sub band images.

E. Image Fusion

The term Fusion means in general an approach to extraction of information acquired in several domains. Most recently, with the evolution of wavelet based multi resolution analysis concepts, the multi-scale wavelet decomposition has begun to take the place of pyramid decomposition for image fusion. Actually, the wavelet transform can be considered one special type of pyramid decompositions. It retains most of the advantages for image fusion but has much more complete theoretical support. The real Discrete Wavelet Transform (DWT) has the property of good compression of signal energy. Perfect reconstruction is possible using short support filters. The unique feature of DWT is the absence of redundancy and very low computation. Therefore, DWT has been used extensively for Multi Resolution Analysis (MRA) based image fusion

F. Proposed Block Diagram

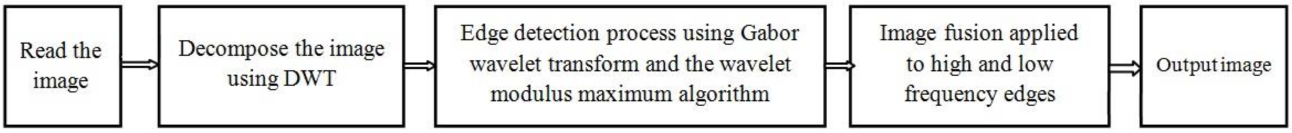


Fig. 3: Proposed block diagram

G. *Algorithm*

1) Take any color or gray scale image as input image
2) If it is color image convert into gray scale image
3) Now apply Discrete Wavelet Transform to the input image
4) The resultant image will be decomposed into 4 sub bands
5) Apply Gabor wavelet to the LL band
6) Now fuse resultant image with HH band
7) Tumor size and shape can be identified efficiently, Tumor part can be detected.

H. *Spectral Analysis*

Fourier Transform is used to decompose an image into its sine and cosine components. The output of the transformation represents the image in the Fourier or frequency domain, while the input image is the spatial domain equivalent. In a wide range of applications Fourier transform is used, such as image analysis, image filtering, image reconstruction and image compression. As we are using only digital images, we will restrict this discussion to the Discrete Fourier Transform (DFT).

The DFT contains only a set of samples which is large enough to fully describe the spatial domain image. The number of frequencies corresponds to the number of pixels in the spatial domain image, i.e. the image in the spatial and Fourier domain is of the same size.

For a square image of size N×M, the two-dimensional DFT is given by:

$$F(k,l)=\sum_{i=0}^{n-1}\sum_{j=0}^{m-1} f(i,j)\, e^{-i2\pi(\frac{ki}{n}+\frac{lj}{m})} \qquad (3)$$

where f(a,b) is represented the image in the spatial domain and the exponential term is the basis function corresponding to each point F(k,l) in the Fourier space. The equation can specifies as the value of each point F(k,l) is obtained by multiplying the spatial image with the corresponding base function and summing the result. The basic functions are cosine and sin waves with increasing frequencies, DC-component of the image represents F(0,0) the which corresponds to the average brightness and F(N-1,M-1) represents the highest frequency.

In a similar way, the Fourier image can be re-transformed to the spatial domain. The inverse Fourier transform is given by:

$$\boldsymbol{f(a,b)} = \frac{\mathbf{1}}{\boldsymbol{N^2}}\sum_{k=0}^{N-1}\sum_{l=0}^{M-1} \boldsymbol{F(k,l)}\boldsymbol{e}^{i2\pi(\frac{ka}{n}+\frac{ib}{m})} \qquad (4)$$

Note the $\frac{1}{N^2}$ normalization term in the inverse transformation. This normalization is sometimes applied to the forward transform instead of the inverse transform, but it should not be used for both.

To obtain the result for the above equations, a for each image point double sum has to be calculated. However, because the Fourier Transform is separable, it can be written as

$$F(k,l)=\frac{1}{N}\sum_{b=0}^{N-1} \boldsymbol{P(k,b)}\boldsymbol{e}^{-i2\pi \mathrm{ib}/\mathrm{N}} \qquad (5)$$

Where

$$P(k,b)=\frac{1}{N}\sum_{a=0}^{N-1} \boldsymbol{f(a,b)}\boldsymbol{e}^{-i2\pi ka/N} \qquad (6)$$

Even with these computational savings, the ordinary one-dimensional DFT has $\boldsymbol{N^2}$ complexity. The Fast Fourier Transform (FFT) reduced to N$\boldsymbol{log_2^N}$ to compute the one-dimensional DFTs. This is a significant improvement, in particular for large images. There are various forms of the. The mathematical details are well described in the literature. The Fourier Transform produces a complex number valued output image which can be displayed with two images, either with the real and imaginary part or with magnitude and phase.

I. *Advantages*

1) Gabor filter for edge detection is based on frequency and orientation representations. .
2) 2D Gabor filter is a Gaussian kernel function modulated by a sinusoidal plane wave.
3) They can be designed for a number of dilations and rotations.
4) In general, the expansion is not applied for Gabor wavelets.
5) It is well suited for a specific spatial location in distinctive between the objects of an image.
6) The main important activations can be extracted from the Gabor space in order to create a sparse object representation.
7) Gabor wavelets are used for “feature extractions.

J. *Applications*

1) Satellite image analysis
2) Smoothing and image de-noising
3) Fingerprint verification
4) Biology for cell membrane recognition, to distinguish the normal from the pathological membranes
5) DNA analysis, protein analysis
6) Industrial supervision of gear-wheel
7) Computer graphics and multi-fractal analysis

III. RESULTS

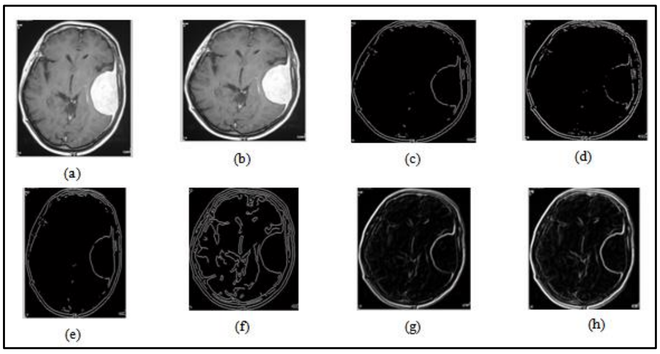


Fig.No.4: (a) Original image, (b) Grayscale image, (c) Prewitt image, (d) Robert image, (e) Sobel image, (f) canny image, (g) Gabor image, (h) Proposed method image

A. *Performance Measures*

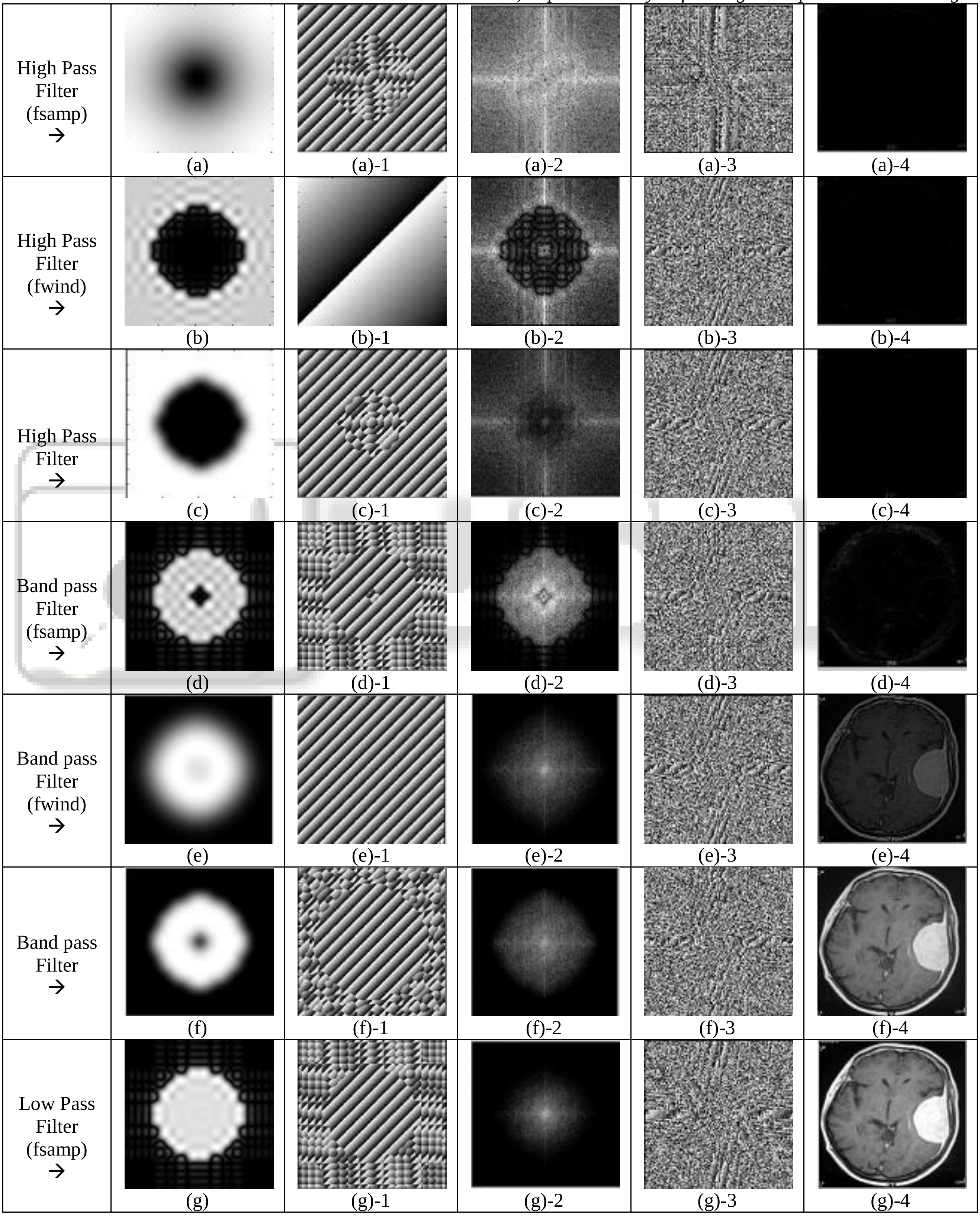
ALGORITHM	ENTROPY OF BRAIN IMAGE
CANNY	1.7328
PREWITT	1.6706
ROBERT	1.6810
SOBEL	1.6704
GABOR WAVELET	3.0979
PROPOSED METHOD	3.5766

Table 1: Entropy of brain image

PSNR PERFORMANCE=22.07 DB

B. *Results of Spectral Analysis:-*

1) *Spectral Analysis for Original Input MRI Brain Image*



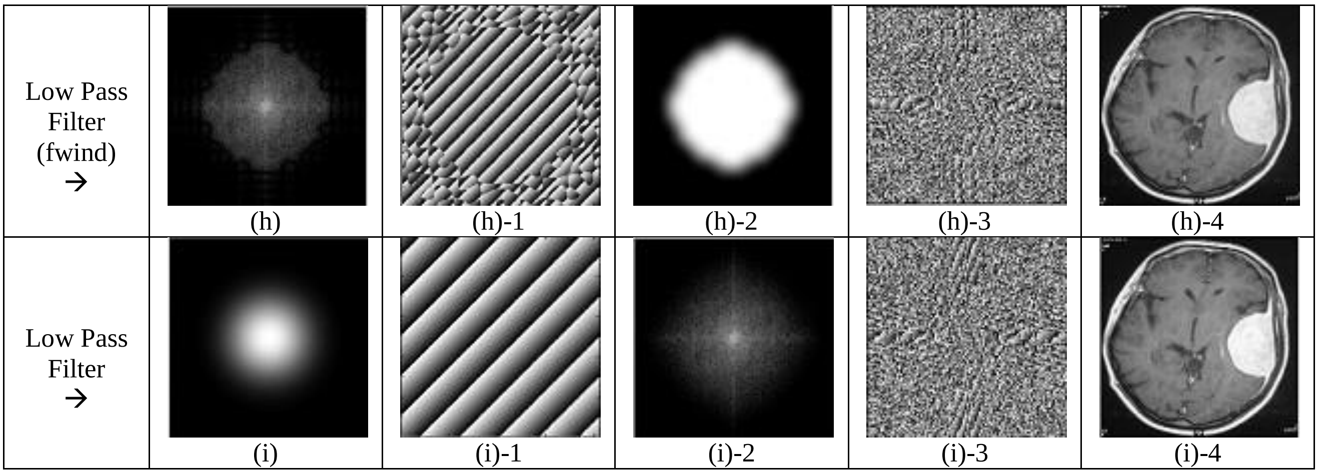
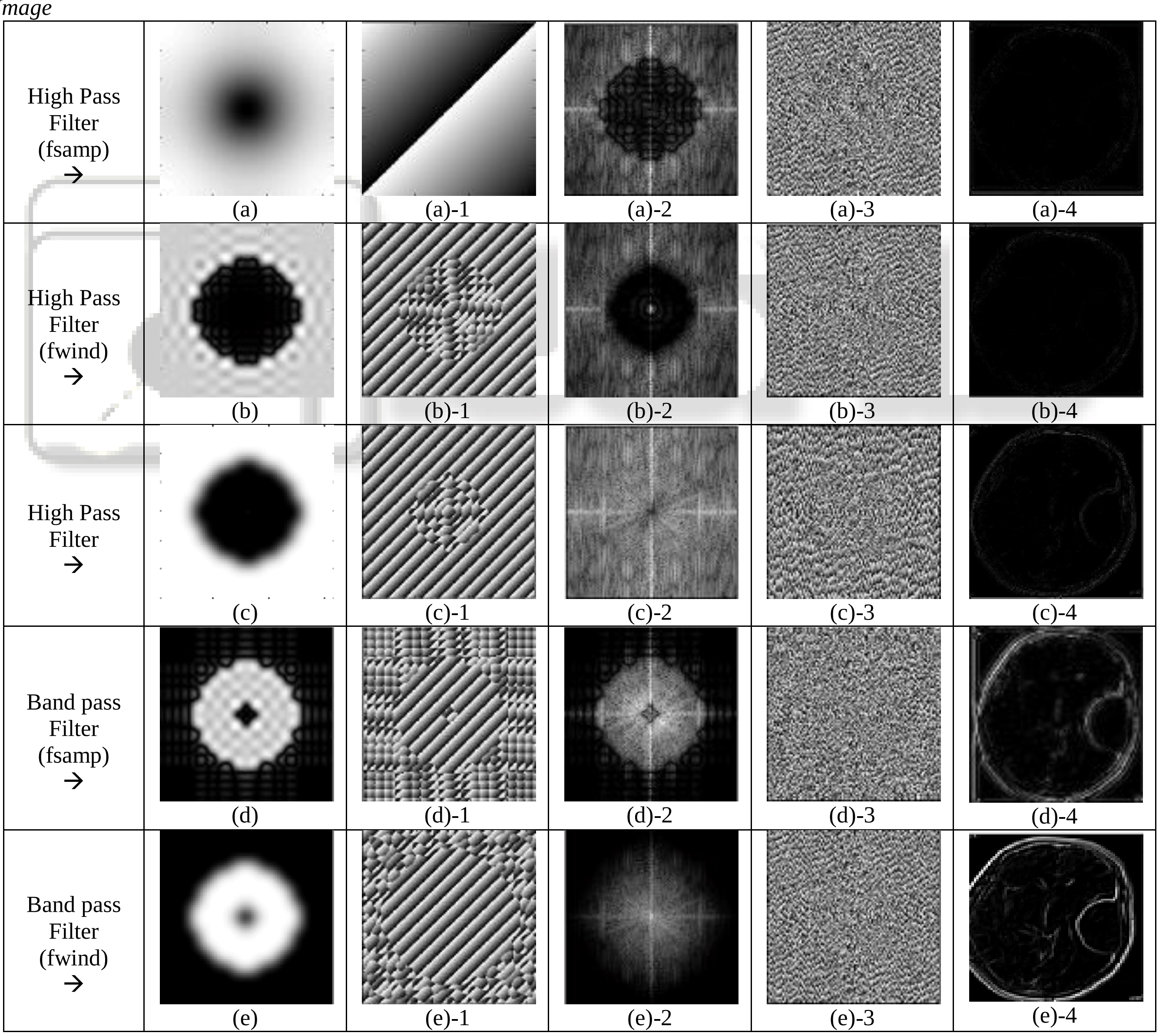


Fig. 5: (a),(b),(c),(d),(e),(f),(g),(h) and (i) :-Magnitude Images, (a)-1,(b)-1,(c)-1,(d)-1,(e)-1,(f) 1,(g)-1,(h)-1 and (i)-1 :-Phase Images, (a)-2,(b)-2,(c)-2,(d)-2,(e)-2,(f)-2,(g)-2,(h)-2 and (i)-2 : Log Magnitude Images, (a)-3,(b)-3,(c)-3,(d)-3,(e)-3,(f)-3,(g)-3,(h)-3 and (i)-3 :-Phase Images, (a)-4,(b)-4,(c)-4,(d)-4,(e)-4,(f)-4,(g)-4,(h)-4 and (i)-4 :-Inverse FFT Images

2) Spectral Analysis for Gabor wavelet Edge Detected Image



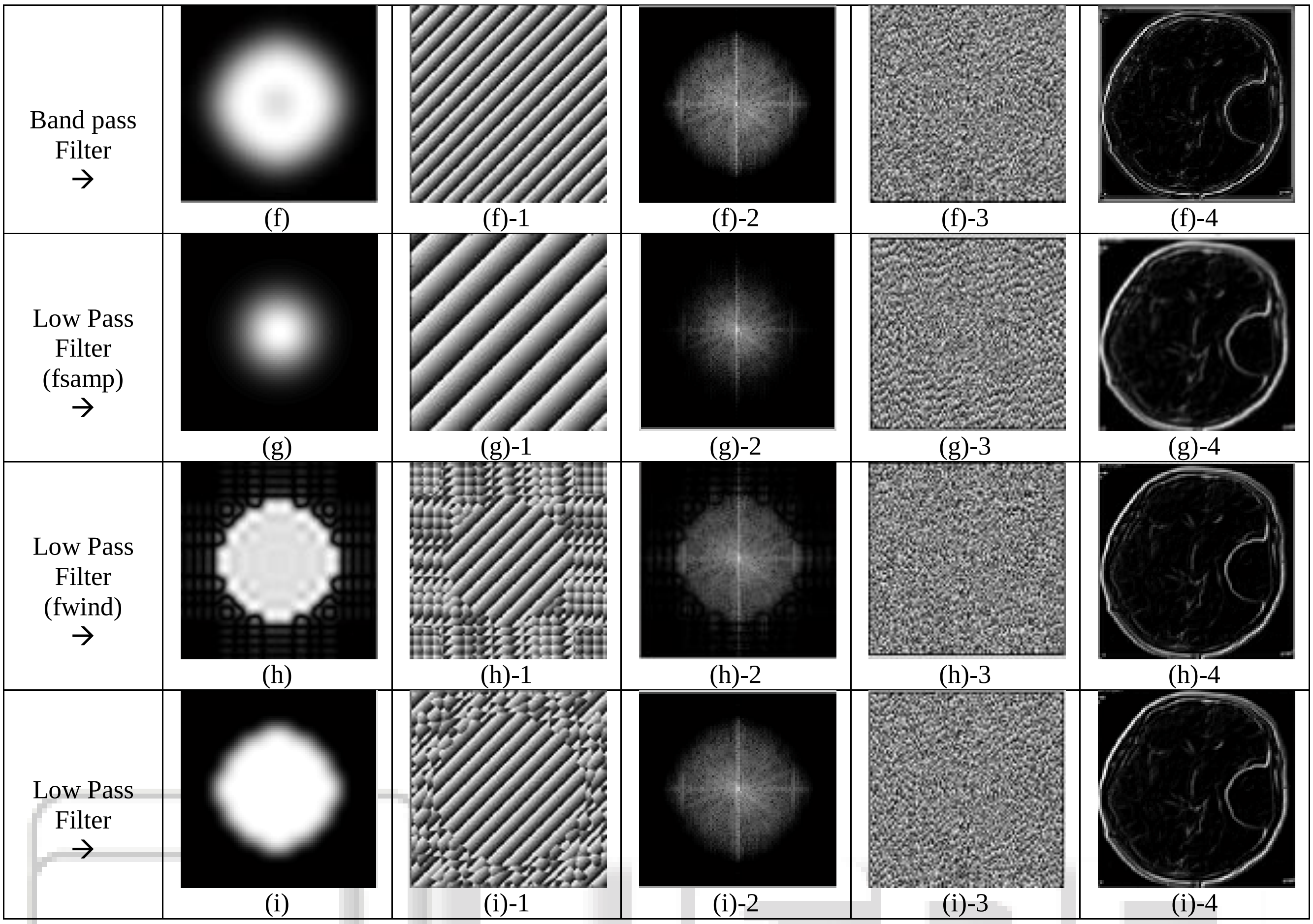
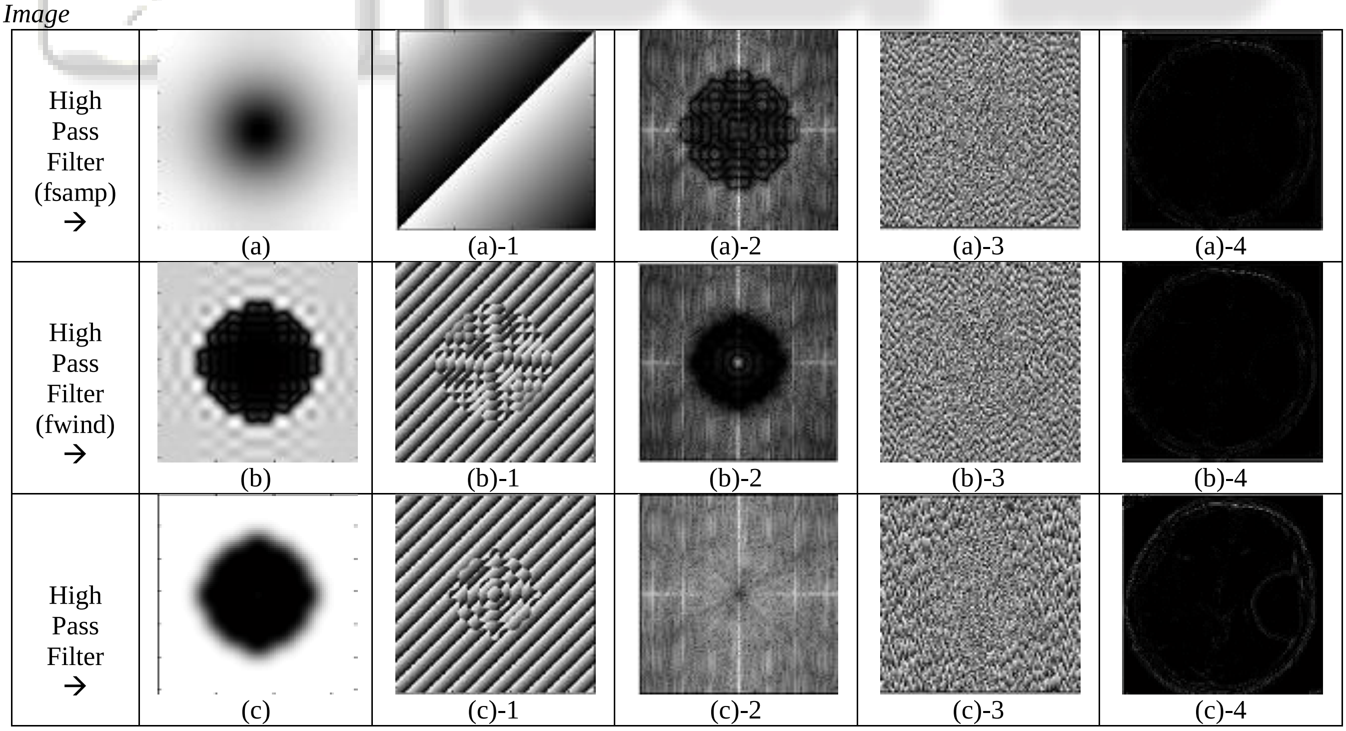


Fig. 6: (a),(b),(c),(d),(e),(f),(g),(h) and (i) :-Magnitude Images, (a)-1,(b)-1,(c)-1,(d)-1,(e)-1,(f)-1,(g)-1,(h)-1 and (i)-1 :-Phase Images, (a)-2,(b)-2,(c)-2,(d)-2,(e)-2,(f)-2,(g)-2,(h)-2 and (i)-2 :-Log Magnitude Images, (a)-3,(b)-3,(c)-3,(d)-3,(e)-3,(f)-3,(g)-3,(h)-3 and (i)-3 :-Phase Images, (a)-4,(b)-4,(c)-4,(d)-4,(e)-4,(f)-4,(g)-4,(h)-4 and (i)-4 :-Inverse FFT Images

3) Spectral Analysis for Proposed Method Edge Detected Image



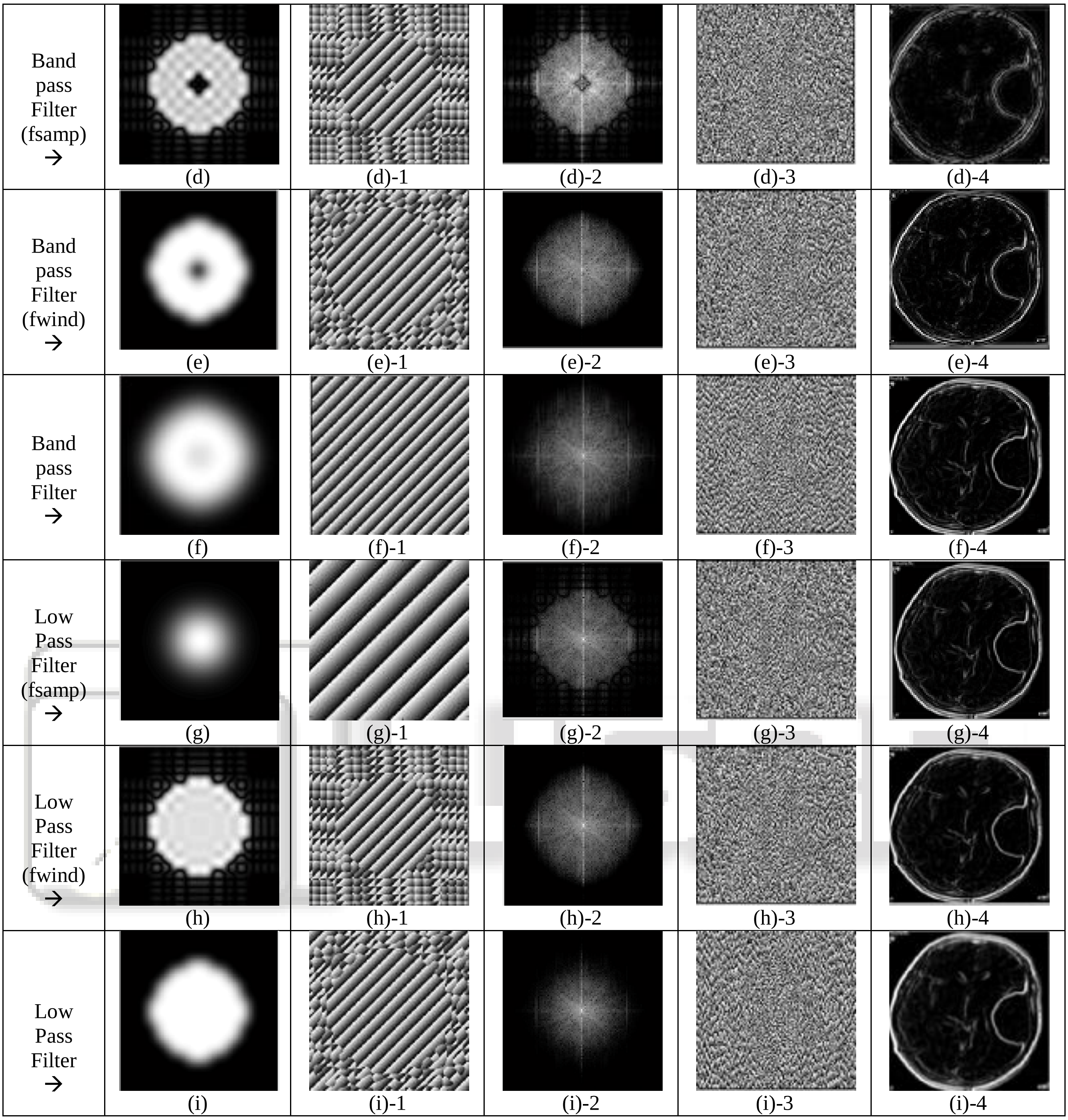
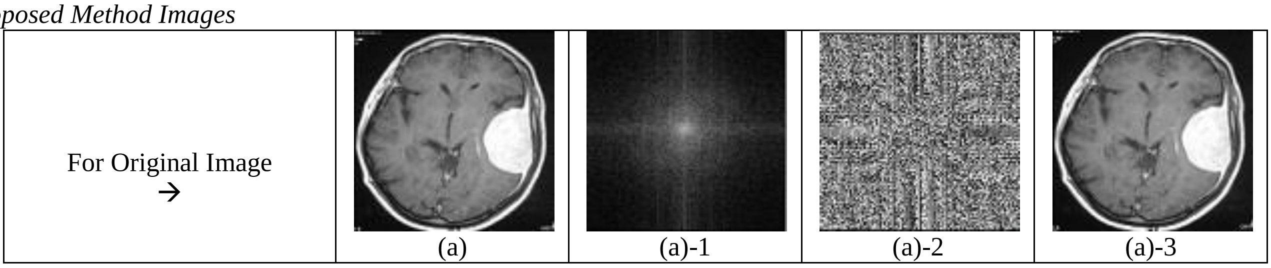


Fig. 7: (a),(b),(c),(d),(e),(f),(g),(h) and (i) :-Magnitude Images, (a)-1,(b)-1,(c)-1,(d)-1,(e)-1,(f)-1,(g)-1,(h)-1 and (i)-1 :-Phase Images, (a)-2,(b)-2,(c)-2,(d)-2,(e)-2,(f)-2,(g)-2,(h)-2 and (i)-2 :-Log Magnitude Images, (a)-3,(b)-3,(c)-3,(d)-3,(e)-3,(f)-3,(g)-3,(h)-3 and (i)-3 :-Phase Images, (a)-4,(b)-4,(c)-4,(d)-4,(e)-4,(f)-4,(g)-4,(h)-4 and (i)-4 :-Inverse FFT Images

4) Final Spectral Analysis for Original, Gabor and Proposed Method Images



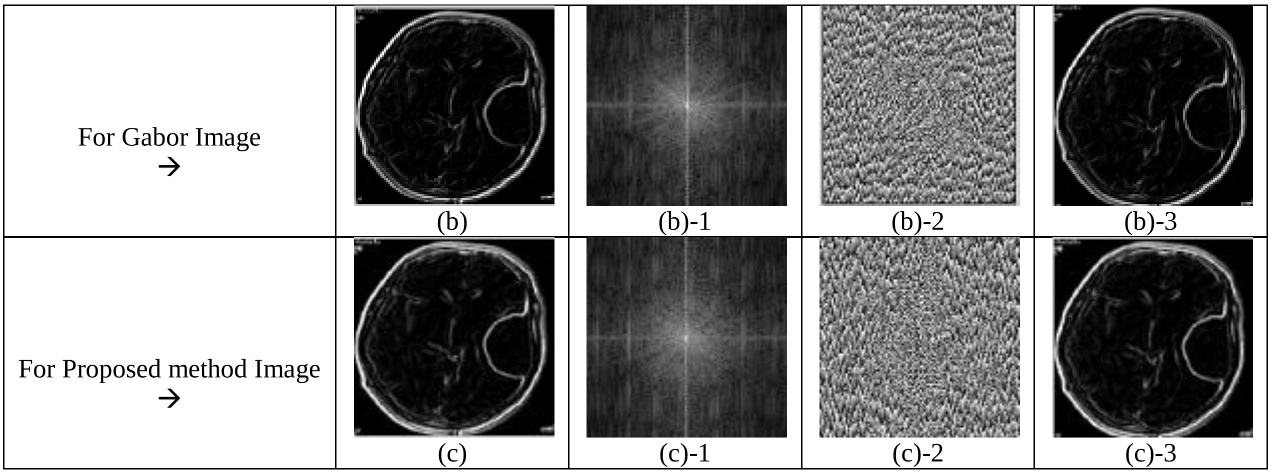


Fig. 8: (a), (b), (c): Input Images, (a)-1, (b)-1, (c)-1: Log Magnitude Images, (a)-2, (b)-2, (c)-2: Phase Images, (a)-3, (b)-3, (c)-3: Spectral Image for Input Images

Low pass filter: Let the low frequencies pass and eliminates high frequencies. Frequency analysis is applied on image, Image is the combination of group of pixels for each and every pixel frequency analysis is applied and it is sampled then displays output with magnitude and phase generates image with overall shading. The function of gain of filter at every frequency is called the amplitude response (or magnitude response).Low pass filter is used to find imaging details. Low pass filter with windowing function is also calculated and it is shown in fig.(h),(h)-1,(h)-2,(h)-3,(h)-4,(h)-5.Low pass filtered image and its spectrum is calculated.In all these we computed magnitude, phase, inverse FFT. Magnitude is used to find intensity. Phase is used for occurrence of integrity and to reconstruct the detected part of tumor.

High pass filter: Let the high frequencies pass and eliminates low frequencies, Frequency analysis is applied on image, Image is the combination of group of pixels for each and every pixel frequency analysis is applied and it is sampled then displays output with magnitude and phase. High pass filter it acts like edge enhancer. High pass filter is used especially to find edges .High pass filter with windowing function is also calculated and it is shown in fig (b),(b)-1,(b)-2,(b)-3,(b)-4,(b)-5. High pass filtered image and its spectrum is calculated.

Band pass filter: This filter allows to cut low and high frequencies of signal An ideal band pass filter would have a completely flat pass band (e.g. with no gain/attenuation throughout) and would completely attenuate all frequencies outside the pass band., Frequency analysis is applied on image, Image is the combination of group of pixels for each and every pixel frequency analysis is applied and it is sampled then displays output with magnitude and phase. Band Pass filter is used especially to select band of frequencies. Band pass filter with windowing function is also calculated and it is shown in fig (e),(e)-1,(e)-2,(e)-3,(e)-4..Band pass filtered image and its spectrum is calculated.

IV. Conclusion

Many algorithms and techniques are available in recent days to detect edges of an image. All techniques and algorithms have it's own advantage and disadvantage. In our work edge detection methods are classified into five categories such as gradient based edge detection, zero crossing based edge detection, Gaussian based edge detection, Laplacian of Gaussian (LoG) based edge detection and transform based edge detection. Some of the conventional edge detection approaches such as sobel, canny, prewitt, Robert and LoG have been implemented and results for various types of images are shown. Similarly wavelet transform based edge detection approaches namely Gabor wavelet and simplified Gabor techniques are implemented for various types of images and those images are given. The experimental results shows that canny provides better result than other classical approaches and Gabor wavelet provides better result than other transform based approach. Spectral analysis is also computed.

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