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Modern Approach of Enhancement for Computed Tomography Image with Frequency Domain Filtering Technique

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Abstract: Computed tomography image enhancement is the processing of medical images to improve their appearance to human viewers, in terms of better contrast and visibility of features of interest, or to enhance their performance in subsequent computer-aided analysis and diagnosis. In this paper, various frequency domain filtering techniques are applied on the computed tomographic image for improve their performance. These techniques are mathematical techniques that are aimed at realizing improvement in the quality of a given image. The result is another image that demonstrates certain features in a manner that is better in some sense as compared to their appearance in the original image. Basic aim of paper is to improve the image quality of the CT image. Various image quality measures have been applied to find the performance of the image enhancement.

Keywords: Computed Tomography, Laplacian filtering, Medical imaging, PSNR, RMSE.

I. INTRODUCTION

Medical imaging [1, 6, 7] deals with the interaction of all forms of radiation with tissue and the design of technical systems to extract clinically relevant information, which is then represented in image format. Medical images range from the simplest such as a chest X-ray to sophisticated images displaying temporal phenomena such as the functional magnetic resonance imaging (fMRI) [1, 6].

Medical imaging systems detect different physical signals arising from a patient and produce images. An imaging modality is an imaging system which uses a particular technique. Some of these modalities use ionizing radiation, radiation with sufficient energy to ionize atoms and molecules within the body and others use non-ionizing radiation. Ionizing radiation in medical imaging comprises x-rays and γ-rays, both of which need to be used prudently to avoid causing serious damage to the body and to its genetic material. Non-ionizing radiation, on the other hand, does not have the potential to damage the body directly and the risks associated with its use are considered to be very low. Examples of such radiation are ultrasound, i.e. high-frequency sound, and radio frequency waves.

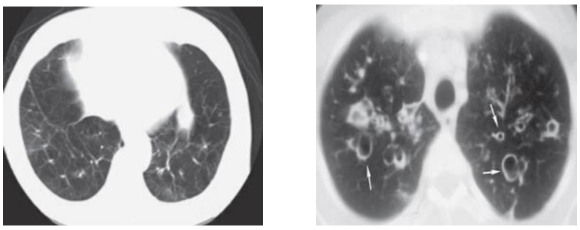
Medical imaging involves a good understanding of imaging medium and object, physics of imaging, instrumentation, and often computerized reconstruction and visual display methods. Though there are a number of medical imaging modalities available today involving ionized radiation, nuclear medicine, magnetic resonance, ultrasound, and optical methods, each modality offers a characteristic response to structural or metabolic parameters of tissues and organs of human body.

Medical imaging is a process of collecting information about a specific physiological structure (an organ or tissue) using a predefined characteristic property that is displayed in the form of an image. For example, in X-ray radiography, mammography and computed tomography (CT), tissue density is the characteristic property that is displayed in images to show anatomical structures. The information about tissue density of anatomical structures is obtained by measuring attenuation to X-ray energy when it is transmitted through the body. On the other hand, a nuclear medicine positron emission tomography (PET) [1, 6, 7] image may show glucose metabolism information in the tissue or organ. A PET image is obtained by measuring gamma-ray emission from the body when a radioactive pharmaceutical material, such as flurodeoxyglucose (FDG) [1, 6] is injected in the body. FDG metabolizes with the tissue through blood circulation eventually making it a source of emission of gamma-ray photons. Thus, medical images may provide anatomical, metabolic or functional information related to an organ or tissue.

The basic process of image formation requires an energy source to obtain information about the object that is displayed in the form of an image. Some form of radiation such as optical light, X-ray, gamma-ray, RF or acoustic waves, interacts with the object tissue or organ to provide information about its characteristic property. The energy source can be external (X-ray radiography, mammography, CT, ultrasound), internal [nuclear medicine: single photon emission computed tomography (SPECT); positron emission tomography (PET)], or a combination of both internal and external such as in magnetic resonance imaging where proton nuclei that are available in the tissue in the body provides electromagnetic RF energy based signals in the presence of an external magnetic field and a resonating RF energy source. As described above, image formation requires an energy source, a mechanism of interaction of energy with the object, an instrumentation to collect the data with the measurement of energy after the interaction, and a method of reconstructing images of information about the characteristic property of the object from the collected data. The following imaging modalities are commonly used for medical applications today.

Tomographic imaging, of which x-ray computed tomography (CT) is an example, is a technique that was developed for producing transverse images, by scanning a slice of tissue from multiple directions using a narrow fan-shaped beam. The data from each direction comprise a one-dimensional projection of the object, and a transverse image can be retrospectively reconstructed from multiple projections. The body can be compared to a loaf of sliced bread, and a transverse image can be produced as if it were a selected slice viewed face-on . The slice thickness can be reduced to 1mm or so, so that very little super positioning occurs. Indeed, if many transverse images are obtained, the data can be presented as an image in any plane, or even as a three-dimensional composite image.

CT imaging is the primary digital technique for imaging the chest, lungs, abdomen and bones due to its ability to combine fast data acquisition and high resolution, and is ideally suited to three-dimensional reconstruction. It is particularly useful in the detection of pulmonary (i.e. lung) disease, because the lungs are difficult to image using ultrasound and MRI. It is often used to diagnose diffuse diseases of the lung such as emphysema, which involves a sticky build-up of mucus in the lungs, and cystic fibrosis, which leads to irreversible dilation of the airways (Fig. 1).



(i) (ii)

Figure-1 .CT image of a patient with (i) emphysema, showing damage to both lungs, and (ii) cystic fibrosis, showing dilated airways and the presence of small, opaque areas filled with mucus (arrows).

II. FREQUENCY DOMAIN FILTERING

A. *Laplacian Filters:*

The directional sensitivity of the filters means it is necessary to apply rotated variants of the kernels several times and combine the outputs to get a direction insensitive output. Often it is more convenient to use a more isotropic single kernel. The simplest and commonest of these is the Laplacian, the 3 X 3 kernel of which is shown in Fig. 2 together with its corresponding Fourier spectrum. The Laplacian is formally a *second derivative* filter[1, 5] – it measures, effectively, the gradient of the gradient. The advantage of a second derivative filter for edge detection is that it will usually define edges more precisely than a first derivative filter.

-1	-1	-1
-1	8	-1
-1	-1	-1

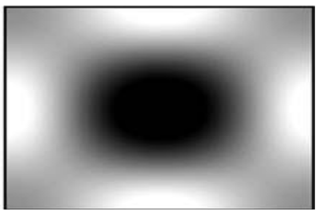


Figure. 2 A Laplacian kernel calculates the second derivative of the image intensity. The 3 X 3 Laplacian kernel and its Fourier spectrum are shown here. Note that the sum of the kernel elements is zero, so the output is not scaled. The Fourier spectrum confirms that convolution with this kernel acts as a high pass filter

How can tell that the Laplacian calculates the second derivative of pixel intensities? This is not immediately obvious looking at the kernel, but it makes sense if we think about what is happening in any single line through the center of the kernel: The sequence of kernel elements is -1,8,-1. In other words, the kernel is the sum of four 3 X 1 kernels (one vertical, one horizontal, and two diagonal) whose elements are [-1 2 -1]. Any one of these 3 X 1 kernels is the sum of two 2 X 1 difference kernels with elements [-1 1] and [1 -1], or the *difference* between two identical difference kernels with elements [-1 1] where the second kernel is displaced one pixel from the first. The 2 X 1 kernels calculate the intensity differences between one particular pixel and those on either side of it. Subtracting one offset kernel from the other gives the 3 X 1 kernel [-1 2 -1] that calculates the difference between the differences – in other words, the second derivative! In contrast to the Roberts Cross filter [5] we now have a single central kernel element so there is no confusion about where to put the output.

The sum of the elements of the Laplacian is zero. If it is applied to a neighborhood in which all the gray scale intensities are identical the output will be zero. Thus any region of constant intensity will become black in the filtered image. When the intensity of the central pixel differs substantially from its neighbors, as may be the case for noise, the output of the Laplacian is very high because it sums *all* differences between a pixel and its eight neighbors. Although the Laplacian filter [1, 5] is good for edge detection it has a tendency to exaggerate lines and noise even more than edges. For this reason it is sometimes used as a point defect detector. This effect is demonstrated in Fig. 3 where we see a test pattern comprised of mid-gray features: a rectangle, a narrow line, and a series of very small (almost invisible) points comprised of single pixels. When a 3 X 3 Laplacian kernel is applied to this image the edges of the rectangle are isolated as expected. However, the line feature is enhanced more than the edges of the rectangle, and the previously very faint points become quite distinct.

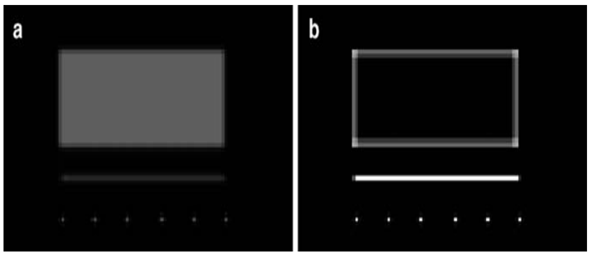


Figure. 3 Demonstration of edge selection and point and line exaggeration of Laplacian kernel. (a) Test image. (b) Effect of convolution with 3X 3 Laplacian. Note that the originally inconspicuous point features (single pixels of same intensity as large rectangle) are strongly enhanced, the line feature less so, and the edge of the gray rectangle less again. This is a notable characteristic of Laplacian filters

-1	-1	-1
-1	9	-1
-1	-1	-1

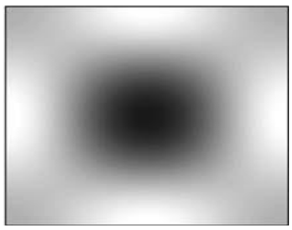


Figure. 4 3x3 'High Boost' kernel and its corresponding Fourier spectrum. Note that the sum of the kernel elements is one so the image intensity in homogeneous regions will be unchanged. The gray center of the Fourier spectrum indicates that low frequencies are only partially attenuated so tonal detail is retained

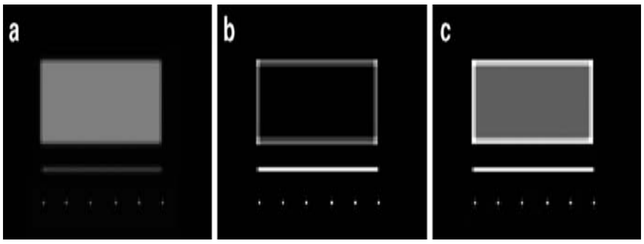


Figure. 5 High Boost filter demonstration. (a) Original image. (b) Laplacian only. (c) High boost. Note that the high boost filter retains tonal information (the center of the rectangle)

Often the aim is not to isolate the edges in an image but to *enhance* them. This can be achieved by adding the output of a Laplacian high pass filter to the original image. This is equivalent to adding a one to the central element of the Laplacian convolution kernel (Fig. 4). The resulting filter is referred to as a *High Boost* filter because its effect is to increase the relative intensity of high spatial frequencies (Fig. 5).

B. LoG Filters:

One way to get around the propensity of the Laplacian filter to exaggerate noise is to smooth the image before application of a high pass or high boost filter. In Fig. 6 we can see that smoothing prior to application of the high boost filter reduces the final intensity of the point features (representative of noise) and, to a lesser extent, the line feature [5]. Note also that the degree of enhancement of the edge of the rectangle is reduced.

Instead of performing two convolution operations, the smoothing and then the high boost, the separate smoothing and high boost kernels can be combined into one kernel. Closely related to this combined filter is the *Laplacian of Gaussian* or LoG filter which combines a Laplacian high pass filter with a Gaussian low pass filter. The Fourier spectrum of the LoG filter should look familiar. It is very similar to the frequency domain band pass filter created by multiplication of a high pass filter mask with a low pass filter mask[5].

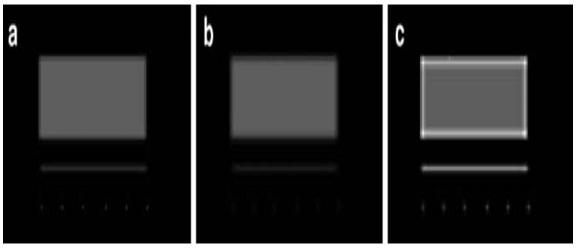


Figure. 6 Application of a smoothing filter prior to the high boost filter. (a) Original image. (b) Smoothed original. (c) High boost applied to image b. In comparison with Fig. 3.34 the point features, which simulate noise, are much less strongly enhanced

C. High-Pass Filtering:

High-pass filtering [7, 8] is used for image sharpening and extraction of high-frequency information such as edges. The low-frequency information is attenuated or blocked depending on the design of the filter. An ideal high-pass filter has a rectangular window function for the high-frequency pass-band. Since the noise in the image usually carries high-frequency components, high-pass filtering also shows the noise along with edge information. An ideal 2D high-pass filter with a cut-off frequency at a distance $D0$ from the origin in the frequency domain is defined as:

$$H(u, v) = \begin{cases} 1 & \text{if } D(u, v) \geq D0 \\ 0 & \text{otherwise} \end{cases}$$

As described above for an ideal low-pass filter[1, 5, 8], the sharp cut-off characteristic of the rectangular window function in the frequency domain causes the ringing artifacts in the filtered image in the spatial domain. To avoid ringing artifacts filter functions with smoother fall-off characteristics such as Butterworth and Gaussian are used. A Butterworth high-pass filter of *n*-th order is defined in the frequency domain as:

$$H(u, v) = \frac{1}{1 + [D0/D(u,v)]^{2n}}$$

III. EXPERIMENT RESULT

Table 1 reports the performance of the filters upon the computed tomography image. Figure 7(a) shows the original image. The other images in figure 7 shows the results for the (a) unsharp filter, (b) laplacian filter with and without Gaussian, (c) high boost filtering, (d) average filter and adaptive filter.

With regard to Table 1, consider the unsharp filter with the standard function and parameter value and the proposed unsharp filter with the scale factor 0.58. It has been clearly observed that root mean square value(RMSE) is low and peak signal to noise ratio(PSNR) value is high for unsharp filter. However, from the visual observation as well as from the quality measurement value, the performance of the unsharp filter in Sr.no. 1 is better than the unsharp scale factor performance.

For the filtering method as mentioned in the Sr.no 3 to 9 which are the laplacian methods with the various mask as mentioned in the fig 7(d to j). These filters are popularly used for detecting and enhancing the edges of the medical images. From the table 1, it is clearly observed that mean square error(MSE) of the proposed laplacian 4 with mask[-1-1-1;0 0 0;1 1 1] performs better result as compared to the other laplacian filters. However, from the figure 7(g) the corresponding figure for the said mask detects the edges efficiently compared to the other laplacian filters. Hence, it is conclude that the performance of the proposed laplacian filter 4 is highly enhanced as compared to the other laplacian filters.

Now coming towards the high boost filters as mentioned there result are grouped into two parts i.e. group1 &2. Group1 is a serial no 10, 11, 12, and 13 with z values 12, 11, 10 and 9 respectively and group2 is serial no 14 and 15 with A=5/6 and 3/5. From the visual perception and from the analysed values it is clearly indicated that the high boost filter with z=11 has achieve the higher significant outcome as compared to the other high boost filters with any other z value. The other high boost filters with A=5/6 and 3/5 are used for the quality improvement of the medical images. The high boost filter with A = 5/6 having the PSNR value (24.95), AD (0.50), MEAN(161.88) and STD(93.61) whereas the high boost filter with A=3/5 has PSNR(21.32), RMSE(21.88), AD(0.83), MEAN(161.55) and STD(96.30). Hence from the above values as well as from the visual quality, it has been clearly proved that the performance of the high boost filter having A=5/6 is not only better than the high boost filter with a=3/5 but also the any other filter as defined in our experiment.

Table 1: Performance of the filters upon the CT image

Sr. No	Filtering method	MSE	RMSE	PSNR	AVG DIFF	MEAN	STD
1	ct_unsharp_std_func	769	27.73	19.27	1.61	160.77	97.68
2	ct_unsharp_filt_scle_factor58pt	1518	38.97	16.31	-20.76	183.15	91.70
3	ct_laplacian_log	9658	98.27	8.28	39.86	122.52	115.50
4	ct_laplacian	9318	96.53	8.43	49.43	112.92	116.11
5	ct_laplace5	9130	95.55	8.52	53.23	109.15	117.70
6	ct_laplace4	9051	95.14	8.56	55.45	106.93	117.36
7	ct_laplace3	9855	99.27	8.19	59.02	103.36	118.01
8	ct_laplace2	9357	96.73	8.41	48.45	113.93	115.93
9	ct_laplace1	7391	85.97	9.44	50.43	111.95	116.48
10	ct_high_boost_filter_z12	1312	36.22	16.95	-16.92	179.31	93.54
11	ct_high_boost_filter_z11	750	27.38	19.38	-2.18	164.57	97.61
12	ct_high_boost_filter_z10	1505	38.80	16.35	19.17	143.21	101.06
13	ct_high_boost_filter_z9	4503	67.10	11.59	41.41	120.97	108.87
14	ct_high_boost_filter_56	208	14.42	24.95	0.50	161.88	93.61
15	ct_high_boost_filter_35	479	21.88	21.32	0.83	161.55	96.30
16	ct_avg99	610	24.71	20.27	1.09	161.29	90.02
17	ct_adpt_filter	1183	34.40	17.39	-0.18	162.57	77.70

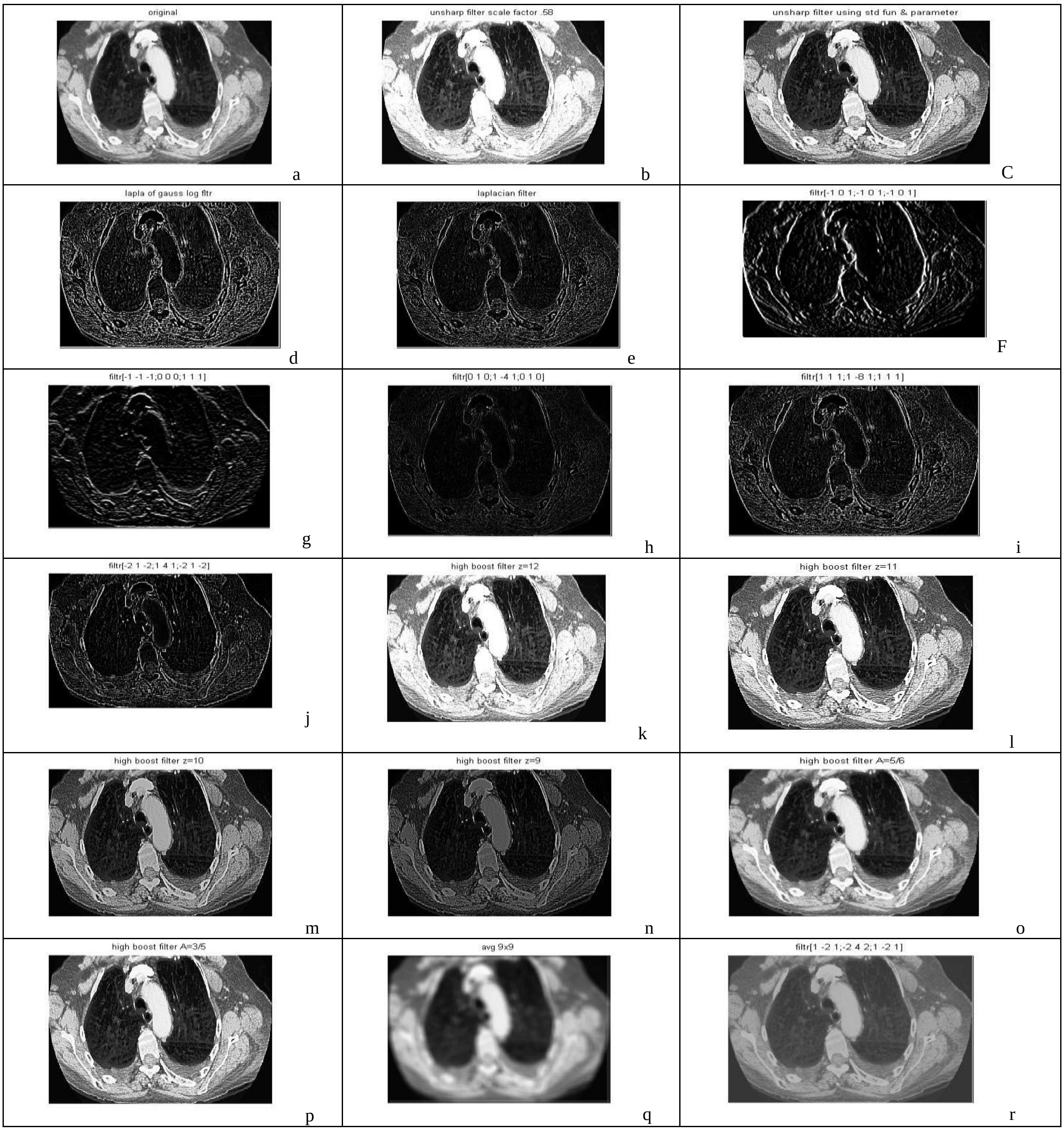


Figure 7: Output images of the filtering methods for the CT image.

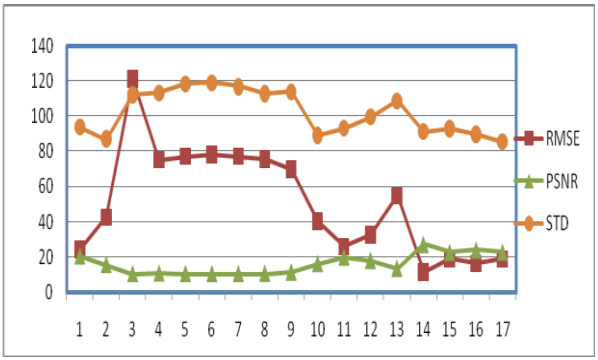


Figure 8: Graphical Analysis for RMSE, PSNR and STD

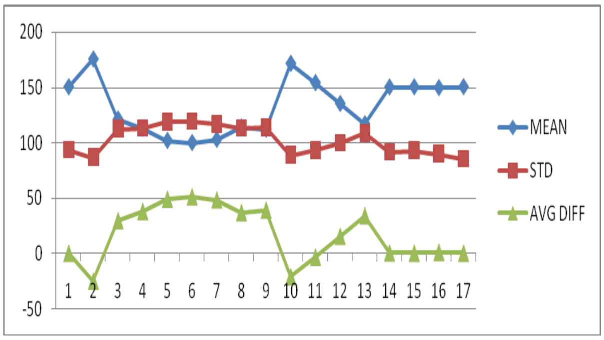


Figure 9: Graphical Analysis for MEAN, STD and Avgas Difference

VI. CONCLUSION

This research has been devoted to the medical image enhancement based upon the frequency domain filtering that can be applied to enhance the noisy computed tomography medical image. The trade-off between noise elimination and detail preservation was analyzed using the MSE, RMSE, PSNR, AD, MEAN and STD and visual criteria. Thus a comparison between the qualities and performance of various filtering techniques were deduced using these criteria. Effectiveness of each filter is dependent on the type of image, the error criterion used, the nature and amount of contaminating noise. It was seen that the high boost filtering with z=11 and A=5/6 and the proposed laplacian filter 4 is highly enhanced as compared to the other filters. These fillters performed well for the image enhancement; this can be clearly seen with its considerable improvement in PSNR and producing visually more pleasing images.

IV. REFERENCES

[1]. Rafael C. Gonzalez University of Tennessee, Richard E. Woods. Digital image processing Third Edition 2008. Pearson Education.

[2]. Rafael C. Gonzalez University of Tennessee, Richard E Woods, Steven L. Eddins. Digital image processing using MATLAB. Fourth impression 2008. Pearson Education.

[3]. Anke Meyer-Base. Pattern recognition for medical imaging 2004. Elsevier academic press.

[4]. Bernard Jahn. Digital image processing, fifth revised edition. Springer-Verlag Berlin Heidelberg New York.

[5]. Roger Bourne, Fundamentals of Digital Imaging in Medicine by Springer-Verlag London Limited 2010.

[6]. Geoff Daugherty, Digital Image Processing for Medical Applications, Cambridge University Press 2009.

[7]. Atam P Dhawan, H K Huang, Day-Shik Kim. Principles and Advance Method in Medical Imaging and Image Analysis, World Scientific Publishing Co. Pvt. Ltd 2008.

[8]. Isaac h Bankman Handbook of medical image processing and analysis, Elsevier Inc 2009.

[9]. J.C. Russ, The Image Processing Handbook (fifth edition), CRC Press, 2007.

[10]. Sankar Seramani, Zhou Jiyan. "Denoising of MR images using non linear anisotrophic diffusion filtering as preprocessing steps". http: // www.ijbst.org-a.googlepages.com /IJBST_1_1_17-21.pdf IJBST (2008), 1(1):17-21.

[11]. Tarek A Mahmoud, Stephen Marshall. Medical image enhancement using threshold decomposition driven adaptive morphological filter. 16th European Signal Processing Conference (EUSIPCO 2008), Lausanne, Switzerland, August 25-29, 2008.

[12]. Vivian E Pera, Erica L. Heffer, Spatial second–derivative image processing: an application to optical mammography to enhance the detection of breast tumors. Journal of Biomedical Optics 8(3), 517–524 (July 2003).

[13]. Mrs. Firouz Abdullah Al-Wassai, Dr. N V Kalyankar. Arithmetic and frequency filtering methods of pixel based image fusion techniques. IJCSI International Journal of Computer Science Issues, Vol. 8, Issue 3, No. 1, May 2011.pp 113-122.

[14]. Hadi sadoghi Yazdi, Farank Homayouni. Impulsive noise suppression of images using adaptive median filter. International Journal of Signal Processing, Image Processing and Pattern Recognition. Vol. 3, No. 3, September, 2010. Pp 1-12.

[15]. Mr. Salem Saleh, Dr V N Kalyankar. Removal Salt & Pepper noise from image by using adaptive median filter. International journal of advance research in Computer Science. Vol 2 No 2 Mar-Apr 2011. 431-434.

[16]. Jin-Hyuk Hong, Sung-Bae Cho, Ung-Keun Cho. A novel Evolutionary approach to image enhancement filter design: methods and applications. IEEE Transactions on Systems, Man, and Cybernetics—Part B: Cybernetics, Vol. 39, No. 6, December 2009.PP 1446-1457.

[17]. Andrzej Zadorozny and Hong Zhang. Contrast enhancement using Morphological scale space. Proceedings of the IEEE International Conference on Automation and Logistics Shenyang, China August 2009. pp 804-807.

[18]. Kubler, Ron Kikinis. and Ferenc A. Jolesz . Nonlinear Anisotropic Filtering of MRI Data. IEEE Transactions on Medical Imaging. vol. 1 I . No. 2. June 1992.pp 221-232.

[19]. P. Jagatheeswari, S. Suresh Kumar, M. Rajaram. A novel approach for contrast enhancement Based on histogram equalization followed by median filter. ARPN Journal of Engineering and Applied Sciences. VOL. 4, NO. 7, SEPTEMBER 2009.pp 41-45.

[20]. Ambica Verma, Priyanka Gupta, Ramandeep Singh Enhancement of ultrasound images using fuzzy sets and comparing the results of Radon and Fourier transforms. International Journal of Computer Sci ence and Technology IJCST Vol. 2, Issue 2, June 2011 pp 184-187.

[21]. Milindkumar V. Sarode, Dr. Prashant R. Deshmukh. Performance Evaluation of Noise Reduction Algorithm in Magnetic Resonance Images. IJCSI International Journal of Computer Science Issues, Vol. 8, Issue 2, March 2011. Pp 198-202.

[22]. Dr. Samir Kumar Bandyopadhyay. Diagnosis of Breast Abnormalities in Mammographic Image. International Journal of Computer Science and Technology IJCST Vol. 2, Issue 1, March 2011.pp 69-71.