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Research Article

IMAGE ENHANCEMENT OF MEDICAL IMAGES USING DIFFERENT FILTERING TECHNIQUES IN THE SPATIAL AND FREQUENCY DOMAIN: A COMPARATIVE ANALYSIS

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Abstract

In The field of medical imaging advances so rapidly that all of those working in it, scientists, engineers, physicians, educators and others, need to frequently update their knowledge in order to stay abreast of developments. While journals and periodicals play a crucial role in this, more extensive, integrative publications that connect fundamental principles and new advances in algorithms and techniques to practical applications are essential. In this paper the emphasis is laid upon the use of image enhancing in medical images and how suitably one can choose the most appropriate one to implement. Techniques in both spatial and frequency domain have been implemented and its effectiveness has been analysed.

Key words: Domain, Techniques, Frequency.

INTRODUCTION

The principal objective of image enhancement is to process a given image so that the result is more suitable than the original image for a specific application (Signals and Systems, 1983). In general it accentuates or sharpens image features such as edges, boundaries, or contrast to make a graphic display more helpful for display and analysis (Digital image processing, 1987). The enhancement doesn't result in either increasing the inherent information content of the data or alters the actual acquired data, but it increases the dynamic range of the chosen features so that they can be detected easily (Digital Image Processing, ?). Enhancement results in providing the richness of the information. Given practical conditions it enables to perceive the depth of information. Depending on the area of application the most suitable one could be selected. When looking into medical images, the images are in general grey scale images. The acquisition sensors are different for different images (Digital Image Processing, ?). The resolution differs. Image resolution can be defined in many ways. It quantifies the capability of the sensor to observe or measure and distinguish the smallest object with clarity (Mitra and Li, 1991). The resolution of images is accessed in various ways i.e.

Pixel: difference between pixel measures

Spatial: closeness (pixel values per unit length)

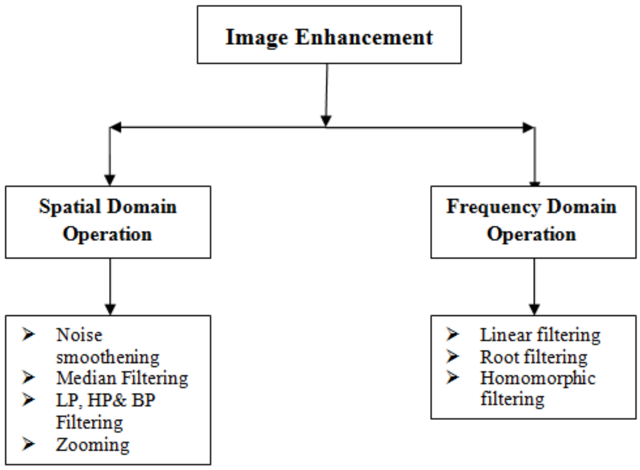
Temporal: precision of a measurement with respect to time

Spectral: based on spectral features and bands

Radiometric: finely represent or distinguish differences of intensities (expressed as bits)

Enhancements help in quantifying the resolution property, leading to the term "image quality" (Digital Image Processing and Pattern Recognition, ?).

The type of image and its application significantly influences the selection of the image processing techniques at every stage. What enhancement needed and suitable for general image and medical image are far different as the outcome of the processing is very unique for each (Fundamentals of Digital Image Processing, ?). Here the first or initial levels of image enhancement have been implemented and observations have been made (Digital Image Processing, ?). The schematic representation of the flow of methodology followed is as given below:



In the following experiment the various filters have been used across different modalities of medical images. The similarity and differences are observed and analysed to compare the modalities (Medical Instrumentation for Health Care, ?).

- Median filter
- Mean filter
- Laplacian of Gaussian
- Homomorphic filter
- Low pass and High pass filter

Median Filter

The median filter is a nonlinear filter. Its success in filtering depends upon the number of the samples used to derive the output, as well as the spatial configuration of the neighborhood used to select the samples. The median filter provides better noise removal than the mean filter without blurring (Introduction to Biomedical Imaging. ?).

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However, the median filter could result in the clipping of corners and distortion of the shape of sharp-edged objects. Median filtering with large neighborhoods could also result in the complete elimination of small objects (Introduction to Medical Imaging Physics, ?). This filter is effective than mean sometimes as it is more robust and the pixel values of the edges are preserved better than mean (Introduction to Biomedical Engineering, 2005). Generally we use the median filter to have a great deal of effectiveness in removing noise on images where less than half of the pixels in a smoothing neighborhood have been affected (Principles of Medical Imaging, 2012) It allows high spatial frequency detail to pass. Studies have shown that median filtering is less effective for Gaussian noise removal (Christensen's, 1990).

Mean Filter

The mean filter can suppress Gaussian and uniformly distributed noise effectively in relatively homogeneous areas of an image (Fundamentals of Medical Imaging, ?). However, the operation leads to blurring at the edges of the objects in the image, and also to the loss of fine details and texture. Regardless, mean filtering is commonly employed to remove noise and smooth images (Biomedical Image Analysis, ?). The blurring of edges may be prevented to some extent by not applying the mean filter if the difference between the pixels that are being processed and the mean of its neighbours is greater than a certain threshold; this condition however makes the filter nonlinear (Biosignal and Biomedical Image Processing, ?). The effectiveness of the filter varies based on whether the noise is Gaussian or salt and pepper .Surveys point out that this filter is very efficient in Gaussian noise removal. But the variance matters (Image Fusion Algorithms, 2008).

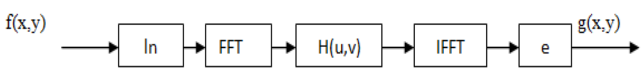
Laplacian of Gaussian

Laplacian filters are derivative filters used to find areas of rapid change in images. Since derivative filters are very sensitive to noise, it is common to smooth the image, using a Gaussian filter before applying the Laplacian. This two-step process is called the Laplacian of Gaussian (LoG) operation (Multisensor data fusion Pfeiffer, 1976). These filters are proved to be good for highlighting edges of an image.LoG filter approximation with the difference of two differently sized Gaussians is possible and they are known as a **DoG** filter`Difference of Gaussians') .Their applications are widely in biological visual processing.Another approximation to the LoG that is much faster to compute is the DoB filter (`Difference of Boxes'). It is designed by using two mean filters of different sizes and the difference between two mean produces a kind of squared-off approximate version of the LoG (Mathematical Equations for Homomorphic Filtering in Frequency Domain, ?).

$$LOG(X,Y) = \frac{1}{\pi\sigma^4}\left[1 \quad \frac{X^2+Y^2}{2\sigma^2}\right]e^{-\frac{x^2+y^2}{2\sigma^2}}$$

Homomorphic Filter

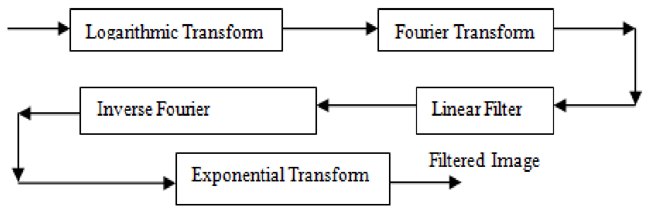
Images can be basically characterized either based on illumination or reflectance. Illumination is relates to looking into the slow spatial resolution whereas reflectance is relates to sudden or sharp changes on an image (Computer Vision and Image Processing, ?). Hence illumination associate to the low frequencies of the Fourier transform of the natural log of an image and high frequencies with reflectance. A good deal of control rather than approximation can be gained on these two components by the use of homomorphic filtering (Ramponi *et al*., 1996). The illumination and reflectance components can be filtered individually by homomorphic filtering method.



Images are sometimes acquired under poor illumination. Under this condition, the same uniform region will appears brighter on some areas and darker on others. This undesired situation will leads to several severe problem in computer vision based system. The pixels might be misclassified, leading to wrong segmentation results, and therefore contribute to inaccurate evaluation or analysis from the system (Cornsweet, 1970). Therefore, it is very crucial to process this type of images first before they are fed into the system. One of the popular methods used to enhance or restore the degraded images by uneven illumination is by using homomorphic filtering (Ramponi, 1998). This filter is modified from Gaussian high pass filter, which is known as Difference of Gaussian (DoG) filter.

$$H(u,v) = (\gamma_H \quad \gamma_L\left[1 \quad exp\left\{ \quad c\frac{D(u,v)^2}{D_0}\right\}\right] + \gamma_L$$

Where constant c has been introduced to control the steepness of the slope, D0 is the cut-off frequency, D(u,v) is the distance between coordinates (u,v) and the centre of frequency at (0,0). For this filter, three important parameters are needed to be set by the user. They are the high frequency gain γ H, the low frequency gain γ L, and the cut-off frequency D_0. If γ H is set greater than 1, and γ L is set lower than 1, the filter function tends to decrease the contribution made by the illumination (which occupies mostly the low frequency components) and amplify the contribution made by the reflectance (which occupies most of the high frequency components)(Lee and Park, 1990).



Block Diagram of Homomorphic Filtering

Low pass Filter

Edges and sharp transitions in the gray levels contribute to the high frequency content of its Fourier transform, so a low pass filtergenerally smoothenimages (Guillon *et al*., 1998).

Ideal low pass filter:

1. The ideal low-pass filter smoothens out the image, which is good for removing noise.
2. The edges remain fairly sharp (better than mean filter).
3. But it creates “ringing” artifacts around the edges.

$$H(u,v) = \begin{cases} 1 & \text{if } D(u,v) \leq D_0 \\ 0 & \text{else} \end{cases} \quad H(u,v) = \frac{1}{1 + [D(u,v)/D_0]^{2n}}$$

D_0 is the cut-off frequency, D(u, v) is the distance between coordinates (u,v) and the centre of frequency at (0,0). When all frequencies to be are inside the circle with radiusD_0 , then it is an ideal low pass filter. Fora nth order Butterworth Low pass filter has the cutoff frequency locus at a distance D_0 from the origin (De Vries, 1990).

High pass Filter

A high pass filter attenuates the low frequency components without disturbing the high frequency information in the Fourier transform domain. It sharpens edges (Lambrecht, 1996). Here again D_0 is the cut-off frequency, D(u,v) is the distance between coordinates (u,v) and the centre of frequency at (0,0).

$$H(u,v) = 1 - H_{lp}(u,v)$$

$$\begin{cases} 1 & \text{if } D(u,v) \leq D_0 \\ 0 & \text{if } D(u,v) > D_0 \end{cases} \quad H(u,v) = \frac{1}{1 + [D_0/D(u,v)]^{2n}}$$

MATERIALS AND METHODS

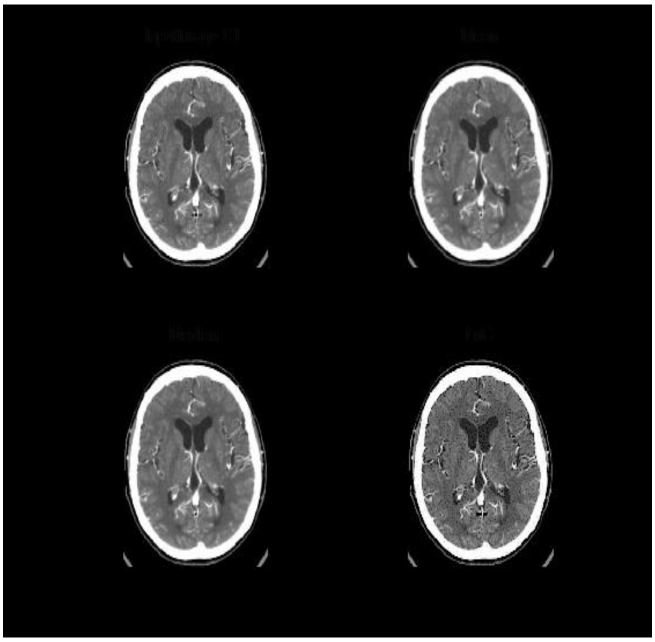
Images

Three imaging techniques are considered in the experiment. A section of the human body scanned using different techniques such as CT (Computerized

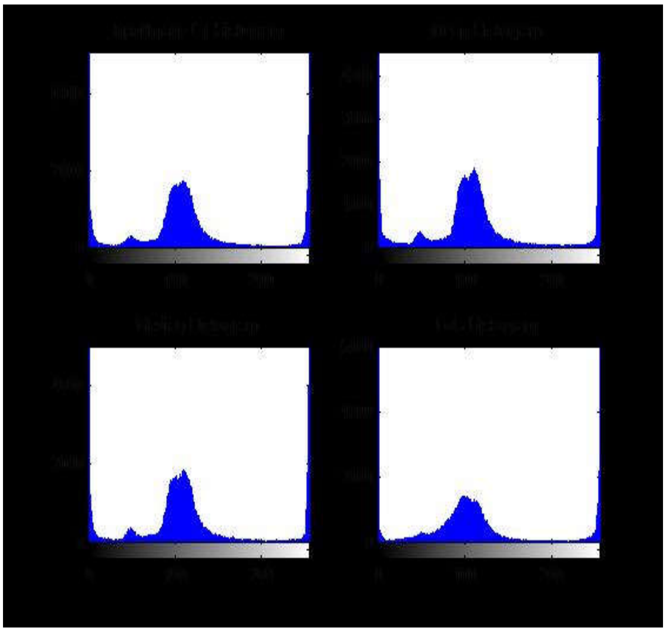
Tomography), MRI (Magnetic resonance Imaging) and PET (Positron emission tomography) is used for analysis. Each imaging technique differs from the other, and this leads to varied outputs images and probable noise ranges. So it is necessary to analyse and filter each image considering its specific feature. The images considered here are CT, MRI and PET (Widrow and Stearns, 1985). Application of the filters in both spatial and frequency domain have been executed and their outcomes have been observed (Hou and Andrews, 1978). The following experimental study was applied on three images of the same section of the brain. For further analysis and a more accurate study, a larger database can be considered (Keys, 1981).

ANALYSIS AND DISCUSSIONS

The first set of filters considered were, Mean, Median and LoG

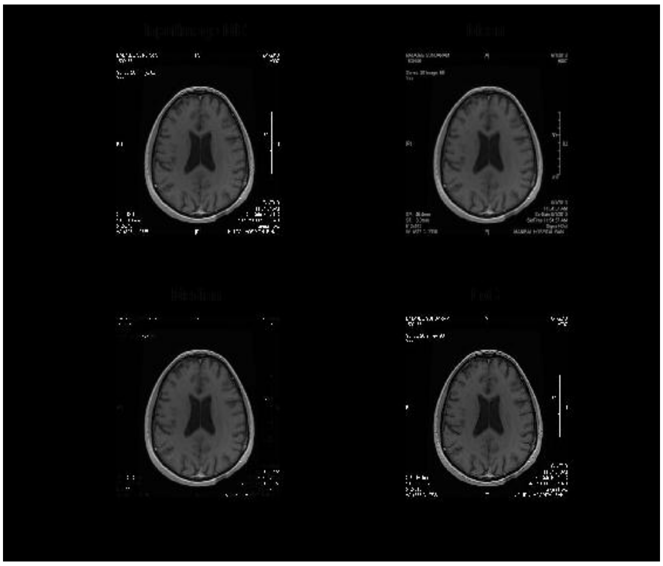


CT : Image

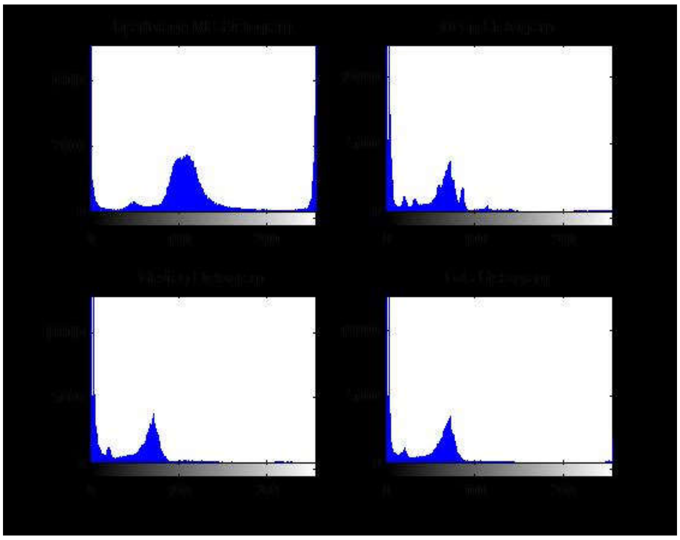


CT: Histogram

Figure 2.2. A(i) originalmean filteredoriginal, mean filtered, median filtered LoG filtered, median filtered, LoG filtered

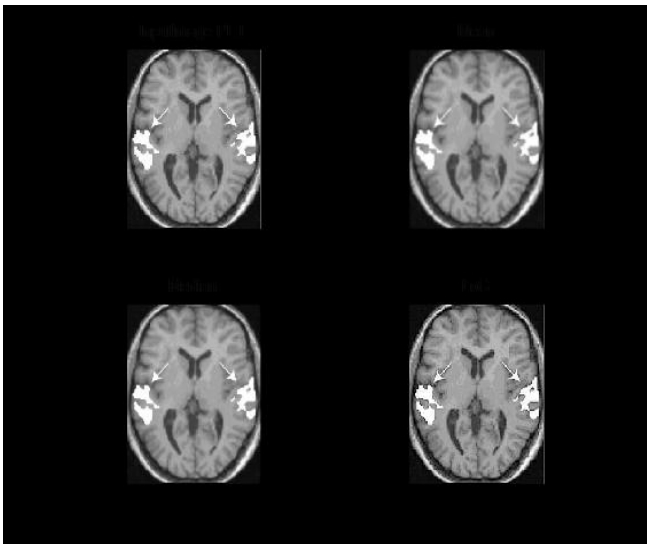


MR : Image

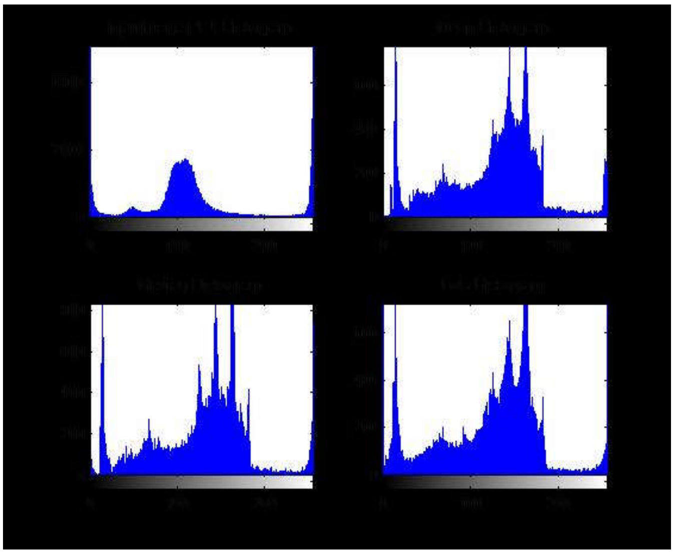


MR : Histogram

Figure 2.2. A(ii). Original, mean filtered, original, mean filtered, median filtered LoG filtered median filtered, LoG filtered

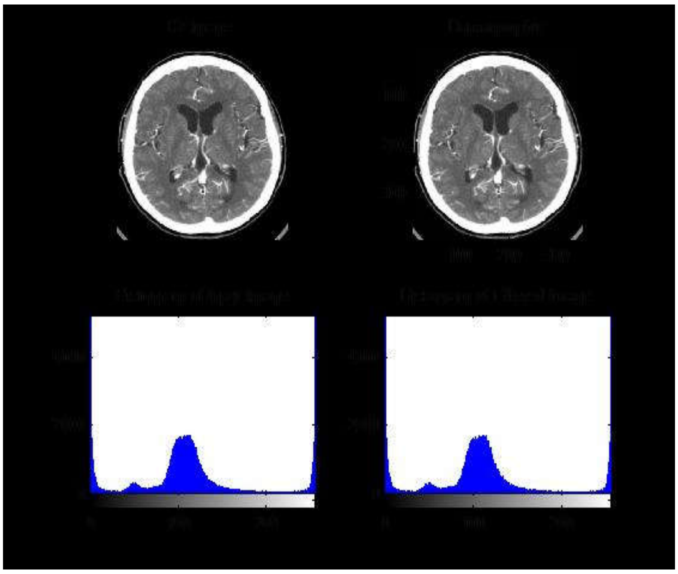


PET : Image

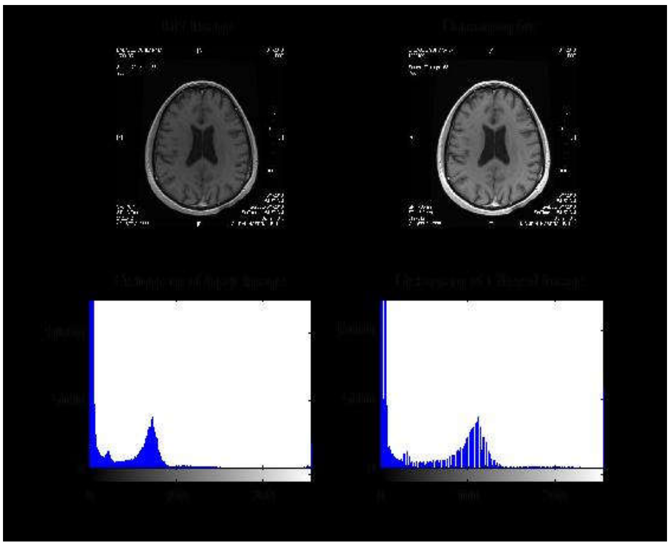


PET: Histogram

Figure 2.2. A(iii). Original, mean filtered, original, mean filtered, median filtered LoG filtered median filtered, LoG filtered

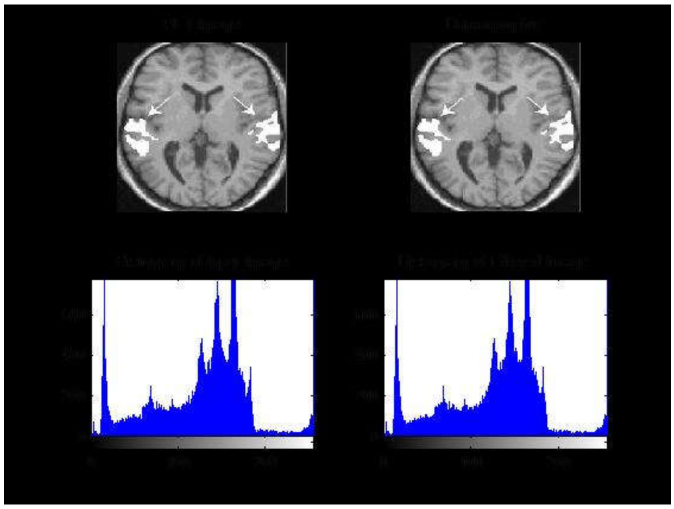


i. CT original & homomorphic filtered



ii. MR original & homomorphic filtered

Figure 2.2B



iii. PET original & homomorphic filtered

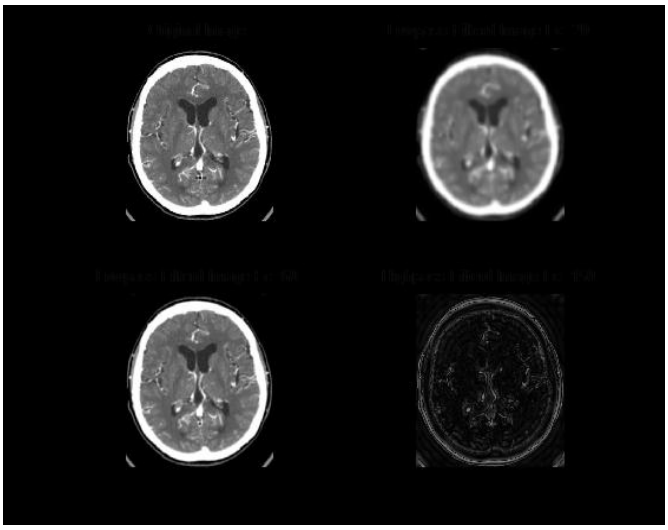


Figure 2.2 C

Original **lowpass f_c= 20,**
lowpassf_c= 60 **highpassf_c= 150**

From the above outputs the following observations may be made:

- For the CT image, the mean and median filter do not produce any significant or consequential alterations. These filters maybe skipped or avoided while processing these type of images. The LoG filter adds noise to the image. And hence is to be avoided.
- For the MR image, the mean and median filters provide very little enchancement and so maybe be eliminated. The LoG filter provides almost similar results and maybe avoided aswell.
- For the PET image, the mean filter blurs the image significantly and hence causes more harm than gain, and should be avoided. The median filter increases image clarity while the LoG filter proves to be extremely efficient. It enhances the bone matter and allows for easy segmentation in further processing.

The histogram plots for ecah of the images is provided for a better visual understanding of the filtering process. These histograms only substantiate the results thus obtained (Boyle and Thomas, 1988). It is evident from the histograms that the CT and MR images are least affected by these filters, while there are significant alterations in the PET image. Henceforth for any initial level of processing CT and MR images other types of filters could be considered (Davies, 1990).

Homomorphic filtering was applied to each of the images and the outputs are as follows

Homomorphic filtering provides effective results only for the MR image, where it clearly enhances bone matter over the rest. This differentiation can be taken advantage of by thresholding for further processing (Vernon, 1991).

Low pass and High pass filtering

None of the above filtering techniques proved effective for CT images.This might be a direct consequece of the fact that the predominant noise in CT images is random or Poisson ditributed (Luft *et al*., 2006) (Stark, 2000). So, we considered ideal lowpass and highpass filters, which maybe used preceeding other imaging techniques. The outputs are as follows:

Low pass filtering below 60Hz leads of blurring of the image which maybe undesirable. But a cutoff frequency above 60Hz proves useful in eliminating high frequency noise (Yang Yu and Hong Zhao, 2006) (Resolution enhancement, 2010). High pass filtering, darkens the image, but at the same time enhances the high density features such as bone matter. Both these filters are only pre-processing filters and should be followed by other filters for proper feature extraction.The images taken for filtering are CT.

Conclusion

In this work we have taken different medical images like MRI, CT, and PET for removing noises from by applying the various filtering techniques like Median Filtering, Mean Filtering and Homomorphic Filtering. Through this work we have observed that the choice of filters for de-noising the medical images depends on the type of noise and type of filtering technique, which are used. It is remarkable that this saves the processing time. This experimental analysis will improve the accuracy of MRI, CT and PET images for easy diagnosis.

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