MULTI-DOMAIN MEDICAL IMAGE ENHANCEMENT USING DEEP LEARING

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Abstract:
Medical image processing has been a revolution in the modern medical science. In an ideal world we would be able to diagnose, treat and cure patients without causing any harmful side effects. The use of medical imaging has enabled doctors to see inside a patient without having to cut them open. Medical imaging also helps us learn more about neurobiology and human behaviours. Brain imaging is being used to understand why some people become long-term cocaine addicts and some do not. Medical imaging brings scientists from biology, chemistry and physics together and the technologies developed can often be used in many disciplines. In this paper, medical images are enhanced in frequency and time domain. Local transformation histogram technique is employed for contrast enhancement; afterwards images are enhanced overall using Fuzzy-Neural technique. The proposed technique is implemented on the working platform of MATLAB 2018b. Parameters like PSNR, Entropy, MSE are expected to be fairly better than original images.
Keywords: Medical Images, Laplacian Filter, PSNR, Deep learning, Neuro-fuzzy

1-INTRODUCTION

With the discovery of x-ray in 1895, images were routinely acquired for medical diagnostics. Nurtured by the amassed use of direct digital imaging systems, digital image processing has become increasingly important in health care. In addition to originally digital methods such as computed tomography (CT) or magnetic resonance imaging (MRI), initially analogue imaging modalities such as endoscopy or radiography have now been equipped with digital sensors. Digital images are composed of individual pixels (this acronym is formed from the words "picture" and "element"), where discrete brightness or color values are assigned. They can be efficiently processed, objectively evaluated and made available in many places at the same time by means of appropriate communication networks and protocols.

The usually used word "medical image processing" means the provision of digital image processing for medicine. Medical image processing includes five major areas

1. Image creation includes all the steps from taking the image to forming a digital image matrix.
2. Image picturing refers to all types of operation of this matrix, resulting in an optimized output of the image.

3. Image analysis contains all the steps of processing, which are used for measurable measurements as well as abstract explanations of medical images. These steps require a-prior knowledge on the nature and content of the images, which must be integrated into the algorithms on a high level of abstraction. Thus, the process of image analysis is very precise, and developed algorithms can rarely be transferred directly into other domains of applications.
4. Image management involves all the techniques that provide the efficient storage, communication, transmission, archiving and access (retrieval) of image data. A simple gray scale radiograph in its novel condition may need several megabytes of storage capacity, and density techniques are applied. The procedures of telemedicine are also a part of image management.
5. Image enhancement: in contrast to image examination, which is also stated to as high-level image processing, low-level processing or image enhancement represents manual or automatic techniques, which can be recognized without a-prior information on the specific content of images. This type of algorithm has alike effects regardless of what is presented in an image.

1.1-BIOMEDICAL IMAGE PROCESSING

Biomedical image processing is akin in concept to biomedical signal processing in several dimensions. It contains the analysis, improvement and display of images captured via x-ray, ultrasound, MRI, nuclear medicine and optical imaging technologies. Image renovation and modeling techniques allow instant processing of 2D signals to create 3D images.

Image Smoothing and Restoration Filtering shows a major role in image enhancement. Diffusion filters are well agreed and used as influential tools in image analysis for several decades. Diffusion filters can be congregated as linear and nonlinear, or isotropic and anisotropic diffusion filters. Formulation of diffusion filtering processes with partial differential equations (PDEs) shaped a solid backbone for a common framework - a top-down methodology - for scale-space analysis. Give’s interesting relations between biological mechanisms behind vision and scale space analysis. Morel and Solomon introduced a deep mathematical and physical understanding of this methodology for multi-scale image smoothing and restoration.

1.2-IMAGE ENHANCEMENT

Contrast enhancement, Image enhancement techniques have been broadly used in many presentations of image processing where the idiosyncratic quality of images is important for human interpretation. Contrast is an important factor in any subjective valuation of image quality. Contrast is created by the difference in luminance echoed from two adjacent surfaces. In other words, contrast is the alteration in visual possessions that makes an object distinguishable from other objects and the experience.

Gray-level histogram is supreme contrast enhancement means make use of the gray-level histogram, created by counting the number of times each gray-level value occurs in the image, then dividing by the total number of pixels in the image to create a dispersal of the percentage of each gray level in the image. The gray-level histogram defines the statistical distribution of the gray levels in the image but comprises no spatial information around the image. Contrast enhancement processes amend the relative brightness and darkness of objects in the scene to advance their visibility. The contrast and tone of the image can be reformed by mapping the gray levels in the image to novel values through a gray-level transform. The mapping function redistributes the current gray level GL to a new gray level GL′. Improved medical images are anticipated by a surgeon to assist diagnosis and interpretation because medical image abilities are often worsened by noise and other data acquisition devices, illumination conditions, etc [1].

In spatial domain techniques, we openly deal with the image pixels. The pixel values are influenced to achieve preferred enhancement. In frequency domain methods, the image is paramount transferred into the frequency domain. It means that the Fourier Transform of the image is figured first. All the enhancement processes are performed on the Fourier transform of the image and then the Inverse Fourier transform is executed to get the resultant image. These enhancement processes are performed in order to revise the image brightness, contrast or the dispersal of the grey levels [2].

Identifying the edges of low contrast structures is one of the supreme mutual tasks performed by those inferring medical images. Low contrast assemblies need to be resolved in all kinds of digital medical images; e.g., X-ray imaging, computed tomography (CT), magnetic resonance (MR), digital mammography, ultrasound, angiography and nuclear medicine [3].

Histogram equalization is a usually used technique for image enhancement. When an image is aligned, its grey levels should spread till the margins of the intact scale. Also, the pixel number at each grey level should be made as nearby as possible. Thereby, the new image after equalization would probably extract a better contrast conclusion for human vision, and details in some dark or bright sections could also show up. For continuous images, histogram equalization is fairly simple to complete, and owns exact solution. However, for discrete images, things develop different. Usually, several minor grey levels would combine into only one grey level if the discrete images were equalized in the same way as the continuous images. More importantly, the facts included in the minor grey levels will be lost after image equalization, although equalization itself is imaginary to make details clearer after enhancement [4].

2-LITRETURE SURVEY

Jais Jose et. al (2021,) a new multi-modality algorithm for medical image fusion constructed on the Adolescent Identity Search Algorithm (AISA) for the Non-Subsampled Shearlet Transform was projected to obtain image optimization and to reduce the computational cost and time. The NSST was a multi-directional and multi-dimensional illustration of a multiscale and multi-directional wavelet transform. The input source image was moldy into the NSST sub-bands at the initial stage. The margin measure was modulated by the Adolescent Identity Search Algorithm (AISA) that welded the sub-band in the NSST thereby reduced the complication and increased the computational speed. The proposed method was confirmed under different real-time disease datasets such as Glioma, mild Alzheimer's, and Encephalopathy with hypertension that encompassed similar pairs of images and analyzed different evaluation measures such as Entropy, standard deviation, structural similarity index measure, Mutual information, Average gradient, Xydeas and Petrovic metric, Peak-signal to-noise-ratio, processing time. The investigational findings and discussions point out that the proposed algorithm outperformed other approaches and offers high quality fused images for an accurate diagnosis.

2. **Tawsif ur Rahman ET. AL (2021),** a novel U-Net model was projected and related with the standard U-Net model for lung segmentation. Six diverse pre-trained Convolutional Neural Networks (CNNs) (ResNet18, ResNet50, ResNet101, InceptionV3, DenseNet201, and ChexNet) and a shallow CNN model were inspected on the plain and segmented lung CXR images. The novel U-Net model presented an accuracy, Intersection over Union (IoU), and Dice coefficient of 98.63%, 94.3%, and 96.94%, respectively for lung segmentation. The gamma correction-based improvement technique outperforms other techniques in identifying COVID-19 from the plain and the segmented lung CXR images. Organization performance from plain CXR images was faintly better than the segmented lung CXR images; however, the dependability of network enactment was significantly improved for the segmented lung images, which was witnessed using the conception technique. The accuracy, precision, sensitivity, F1-score, and specificity were 95.11%, 94.55%, 94.56%, 94.53%, and 95.59% correspondingly for the segmented lung images. The planned approach with very reliable and comparable concert will boost the fast and robust COVID-19 detection using chest X-ray images.
3. **Sreedhar Kollem et. al (2021),** proposed an improved partial differential equation (PDE)-based total variation (TV) prototypical that enhanced grey and coloured brain tumor images attained by magnetic resonance imaging. A non-sub sampled contour let transform was functional to images from standard databases that transformed into low pass and high pass (or bandpass) contourlet coefficients. A established version of the power-law transform method was used on the lowpass contourlet factors, and an adaptive threshold method was applied to the highpass (or bandpass) contourlet coefficients. The inverse contourlet transform was fulfilled on all the enhanced contourlet coefficients to produce a complete brain tumour image. Finally, the PDE-based TV model was pragmatic to this image to produce the denoised image. The presentation of the advised method was considered in terms of the peak signal-to-noise ratio, mean square error, and structural similarity index. Proposed way achieved the best peak signal-to-noise ratio, mean square error, and structural similarity index of 77.9846 dB, 0.00012612, and 97.895%, respectively, compared to the conventional PDE+modified transform-based gamma correction, adaptive PDE+generalized cross-validation, parallel magnetic resonance imaging, and Berkeley wavelet transform+support vector machine methods.
4. **Sushruta Mishra et. al (2021),** provided a detailed analysis of algorithms based on deep learning that was used in clinical image with regards to recent works and their future approaches. Technique provided some important knowledge and the way of approaching deep learning concept in the field of healthcare image analysis. Afterwards, authors discussed the challenges that were faced when it was applied to medical images and some open research issues. In the end, a successful medical image processing was presented where implementation was done by deep learning.

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5. Upendra and Sandeeep (2021), the proposed framework included genetic algorithm, histogram sub-division and modified probability density function (PDF). A novel approach of subdivision was applied to the histogram using the exposure threshold and optimal threshold for preserving the brightness and reducing the information loss. To make the proposed technique more adaptive, the threshold parameters were optimized by utilizing the concept of genetic algorithm, guided by the proposed multi-objective fitness function. Then, the PDF of each sub-histogram was modified to enhance the image quality. The experimental results showed that, the proposed GAAHE technique performed superior over other existing enhancement techniques.

6. Jais et. al (2021), a new multi-modality algorithm for medical image fusion based on the Adolescent Identity Search Algorithm (AISA) for the Non-Subsampled Shearlet Transform was proposed to obtain image optimization and to reduce the computational cost and time. The NSST was a multi-directional and multi-dimensional example of a multiscale and multi-directional wavelet transform. The input source image was decomposed into the NSST subbands at the initial stage. The boundary measure was modulated by the Adolescent Identity Search Algorithm (AISA) that fuses the sub-band in the NSST thereby reducing the complexity and increasing the computational speed. The proposed method was tested under different real-time disease datasets such as Glioma, mild Alzheimer's, and Encephalopathy with hypertension that includes similar pairs of images and analyzed different evaluation measures such as Entropy, standard deviation, structural similarity index measure, Mutual information, Average gradient, Xydeas and Petrovic metric, Peak-signal to-noise-ratio, processing time. The experimental findings and discussions indicate that the proposed algorithm outperforms other approaches and offers high quality fused images for an accurate diagnosis.

7. Wei Li et. al (2021), a multimodal medical image fusion technique that united the advantages of non-sub-sampling contour let transform (NSCT) and fuzzy entropy was planned to provide a basis for clinical diagnosis and improve the accuracy of objective recognition and the quality of fused images. An image was initially decomposed into low- and high-frequency sub bands through NSCT. The equivalent fusion rules were accepted in accordance with the different features of the low- and high-frequency components. The membership degree of low-frequency coefficients was calculated. The fuzzy entropy was also figured and subsequently used to director the fusion of coefficients to reserve image details. High-frequency modules are bonded by maximizing the regional energy.

8. Phu-Hung Dinh (2021), a novel approach, including two algorithms, was proposed to address the above-mentioned limitations. The first algorithm was based on the Grasshopper optimization algorithm (GOA) to find optimal parameters with the aim of fusing low-frequency components. That allowed fused image to have good contrast. The second algorithm was based on the Kirsch compass operator to create an efficient rule for the fusion of high-frequency components. This allowed the fused image to significantly preserve details transferred from input images

9. Ramesh et. al, (2021), the article presented a review with an objective to give some thought regarding the different segmentation for medical image and novel LB method to advance interest for future investigation and exploration in medical image segmentation. The paper in attendance a short review of medical image segmentation techniques based on Thresholding, Region-based, Clustering, Edge detection, Model-based and the novel method Lattice Boltzmann method (LBM). Author sketched several segmentation techniques applied to medical images, highlight that none of these problematic areas has been acceptably settled, and all of the algorithms depicted are available for broad improvement. Since LBM has the remunerations of speed and flexibility of modeling to guarantee excellent image processing quality with a sensible amount of computer resources, we predict that this method will become a new research hotspot in image processing.

10. Guofen and Huang (2021), the article proposed a novel medical image fusion algorithm based on this research objective. First, the input image was decomposed into structure, texture, and local mean brightness layers using a hybrid three-layer decomposition model that can fully extract the features of the original images without the introduction of artifacts. Secondly, the nuclear norm of the spots, which were attained using a sliding window, is calculated to construct the weight maps of the structure and texture layers. The weight map of the local mean brightness layer was constructed by calculating the local energy. Finally, remapping functions were applied to enhance each fusion layer, which reconstructs the final fusion image with the inverse operation of decomposition. Subjective and objective experiments confirmed that the proposed algorithm had a distinct advantage compared with other state-of-the-art algorithms.

3-RESEARCH METHODOLOGY

3.1 PROBLEM STATEMENT

As we had gone through several diagnostic & disease detection research papers, we noted that more focus had been put on the stages like segmentation and classification, due to the negligence of image quality enhancement further stages throughput is not good enough to yield maximum classification accuracy. This motivates us to work upon the basic and fundamental step of image detection using an innovative technique namely fuzzy-neural enhancement. We are expecting better PSNR, Entropy, CNR and MSE value at the final stage. Here we propose a fuzzy based Algorithm to improve the data efficiency and quality of the detection of the image. The algorithm designed will be incorporation of regression based neural network analysis and Fuzzy rule based model. This fuzzy neuro algorithm is designed for the enhancement of the image.

3.2 OBJECTIVES

The objectives of our research are formulated from the drawbacks of previous research, in previous articles we found researchers are providing heed towards the top layer processing in medical image processing like segmentation and classification, without focusing over basic foundation layers like preprocessing. Therefore we set our objectives as under.

1. Amphasis over preprocessing like denoising and unwanted sections to be removed.
2. Multi-layered enhancement techniques in time as well as in frequency domains.

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3. Fuzzy neural enhancement in post stage of enhancement.
4. PSNR, CNR and Antropy parameters are kept in view while processing images in the process.

3.3 PROPOSED WORK

In this research work different medical images are collected for the purpose of enhancement. Following are the medical images considered.

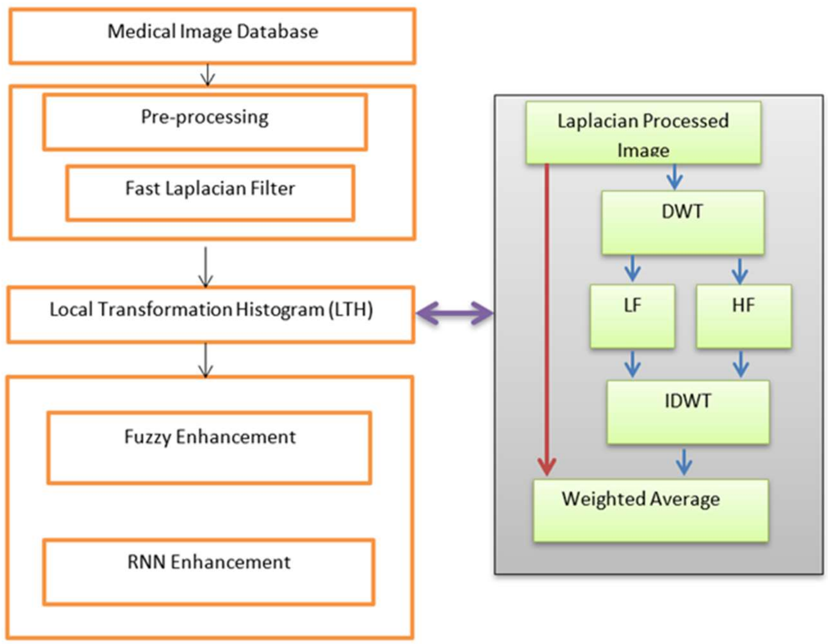

Figure 3.1- Implementation plan flow diagram

MR images: Magnetic resonance imaging (MRI), also known as nuclear magnetic resonance imaging, is a scanning technique for creating detailed images of the human body. The scan uses a strong magnetic field and radio waves to generate images of parts of the body that can't be seen as well with X-rays, CT scans or ultrasound. For example, it can help doctors to see inside joints, cartilage, ligaments, muscles and tendons, which makes it helpful for detecting various sports injuries. MRI is also used to examine internal body structures and diagnose a variety of disorders, such as strokes, tumors, aneurysms, spinal cord injuries, multiple sclerosis and eye or inner ear problems. It is also widely used in research to measure brain structure and function, among other things.

Figure 3.2: MRI image

FINGERPRINT IMAGING: The unique nature of a fingerprint makes it ideal for use in automated recognition systems. A fingerprint is made of a series of ridges and grooves. Once a fingerprint is captured the system locates the minutiae points. These minutiae points occur where the lines of the ridges begin, end, branch off and merge with other ridge lines. These points are then mapped and a line is drawn between each point. This creates a map of how each point relates to the other points. The map is then stored as a data stream called a minutia template in a database for future comparison with other presented fingerprints. It is important to note that during the entire process no fingerprint images are stored on the system and a fingerprint image cannot be recreated from the minutiae template.

Figure 3.3: Fingerprint Imaging

3.4- PREPROCESSING

The preprocessing of images aims at selectively removing the redundancy present in captured images without affecting the details that play a key role in the overall process. Re-sizing of an image is performed by the process of the interpolation. It is a process which re-samples the image to determine values between defined pixels. Thus, a resized image

contains more or less pixels than that of the original image. The intensity values of additional pixels are obtained through interpolation if the resolution of the image is increased.

Filtering Uncertainties are introduced into the image such as random image noise, partial volume effects and intensity non uniformity artifact (INU), due to the movement of the camera. This results in smooth and slowly varying change in image pixel values and leads to information loss, SNR gain and degradation of edge and finer details of image.

3.5- LAPLACIAN FILTERING

In digital image processing, we use a Laplacian filter to compute the second-order derivative of an image to detect edges. We need a Laplacian filter so that we can extract the features of the image in a better way. The better we can extract the features of the image, the better we will make the model to train.

As we have discussed earlier, in the Laplacian filter, we are interested in finding the second-order derivatives of the image vertically and horizontally. So the equation of this scenario is given below.

$$\nabla F(X,Y) = \frac{\partial^2 F}{\partial X^2} + \frac{\partial^2 F}{\partial Y^2}$$

In this equation,

X is the columns index of the pixel.

Y is the row index of the pixel.

F(X,Y) represents the intensity of the image at pixel

MR images filtered in preprocessing by Laplacian filter are depicted as under.

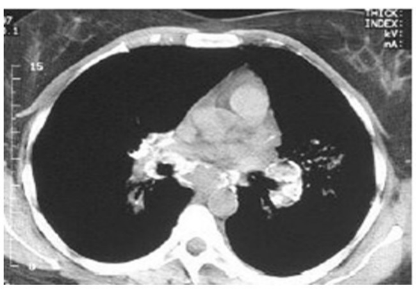

Figure 3.5 MR image

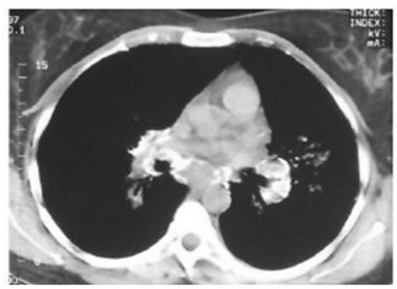

Figure 3.6 Filtered image

Brain images filtered by wiener filter are show as under in figure 3.7 and 3.8.

Figure 3.7 Input Brain Image

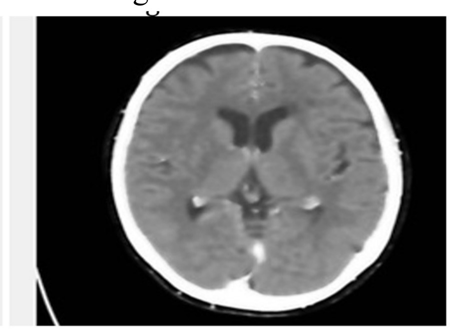

Figure 3.8 filtered Brain Image

X-ray images filtered by weiner filter to reduce noise and other spikes are as under in figure 3.9 and 3.10.

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Figure 3.9- X-ray input image

Figure 3.10 Weiner filtered image

Filtration of fingerprint images by weiner fitler are depicted as under in figure 3.11 and 3.12

Figure 3.11- fingerprint input image

Figure 3.12 weiner filtered image

3.6-LOCAL TRANSFORM HISTOGRAM

In this technique input image is converted into the frequency domain using DWT (Discrete Wavelet transform), then CLAHE (contrast limited adaptive histogram equalization) is applied to the LL band, afterward I-DWT transformations are done to convert image back into time domain. The process is deeply explained as under:

3.7-DISCRETE WAVELET TRANSFORM

A wavelet, in the sense of the Discrete Wavelet Transform (or DWT), is an orthogonal function which can be applied to a finite group of data. Functionally, it is very much like the Discrete Fourier Transform, in that the transforming function is orthogonal, a signal passed twice through the transformation is unchanged, and the input signal is assumed to be a set of discrete time samples. Both transforms are convolutions. The Discrete Wavelet Transform
(DWT), which is based on sub-band coding, is found to yield a fast computation of Wavelet Transform. It is easy to implement and reduces the computation time and resources required. In DWT, the most prominent information in the signal appears in high amplitudes and the less prominent information appears in very low amplitudes. Data compression can be achieved by discarding these low amplitudes. The wavelet transform enables high compression ratios with good quality of reconstruction. Recently, the Wavelet Transforms have been chosen for the

3.8-CONTRAST LIMITED ADAPTIVE HISTOGRAM EQUALIZATION

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While performing AHE if the region being processed has a relatively small intensity range then the noise in that region gets more enhanced. It can also cause some kind of artifacts to appear in those regions. To limit the appearance of such artifacts and noise, a modification of AHE called Contrast Limited AHE can be used. The amount of contrast enhancement for some intensity is directly proportional to the slope of the CDF function at that intensity level. Hence contrast enhancement can be limited by limiting the slope of the CDF. The slope of CDF at a bin location is determined by the height of the histogram for that bin. Therefore if we limit the height of the histogram to a certain level we can limit the slope of the CDF and hence the amount of contrast enhancement.

The only difference between regular AHE and CLAHE is that there is one extra step to clip the histogram before the computation of its CDF as the mapping function is performed. Hence CLAHE is implemented in the same function titled AHE in ahe.cpp. The program

"AHE" takes an additional optional parameter which specifies the level at which to clip the histogram. By default no clipping is performed. Valid values for clipping fall in the range from 1 to 1/bins.

Clipping the histogram itself is not quite straightforward because the excess after clipping has to be redistributed among the other bins, which might increase the level of the clipped histogram. Hence the clipping should be performed at a level lower than the specified clip level so that after redistribution the maximum histogram level is equal to the clip level.

To identify the point at which the clipping should be performed, I am using the binary search method as specified in the paper "Adaptive Histogram Equalization and its Variations". Following is an overview of the clipping algorithm.

The function to clip the histogram and other histogram related functions are implemented in the C++ file , where in Image is the input image, bins specifies the number of bins to use for calculating the cdfs, window size specifies the window size to use and clipLevel specifies histogram clipping level for contrast limited AHE Homogeneous CLAHE is only effective for images which contain relatively homogenous ere enhanced noise or artifacts may appear due to AHE. Following are some example images where performing CLAHE is effective. Effect of CLAHE on several images are depicted below in figure 3.13.

Figure 3.14: CLAHE enhanced images

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3.9-NEURO-FUZZY NETWORK FOR IMAGE ENHANCEMENT

Fuzzy based enhancement of image is done which is followed by three steps i.e Fuzzification, Membership modification, Defuzzification. Fuzzy Enhancement on an image is done as in following steps. Define Fuzzy Limit, To Develop Histogram, Develop Fuzzy Histogram and Develop Final Histogram.

Feedforward In this text feedforward networks are the networks we will first explore (even if we will use different topologies later). The neurons are grouped in the following layers: One input layer, n hidden pro- network of processing layers (invisible from the out- layers side, that’s why the neurons are also referred to as hidden neurons) and one output layer. In a feedforward network each neuron in one layer has only directed connections to the neurons of the next layer (towards the output layer). On the next page the connections permitted for a feedforward network are represented by solid lines. We will often be confronted with feedforward networks in which every neuron is connected to all neurons of the next layer (these layers are called completely linked). To prevent naming conflicts the output neurons are often referred to as Ω.

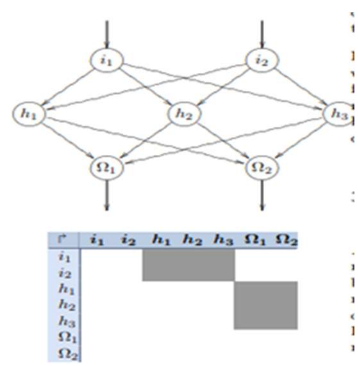

Figure 3.15: A feed forward network with three layers: two input neurons, three hidden neurons and two output neurons

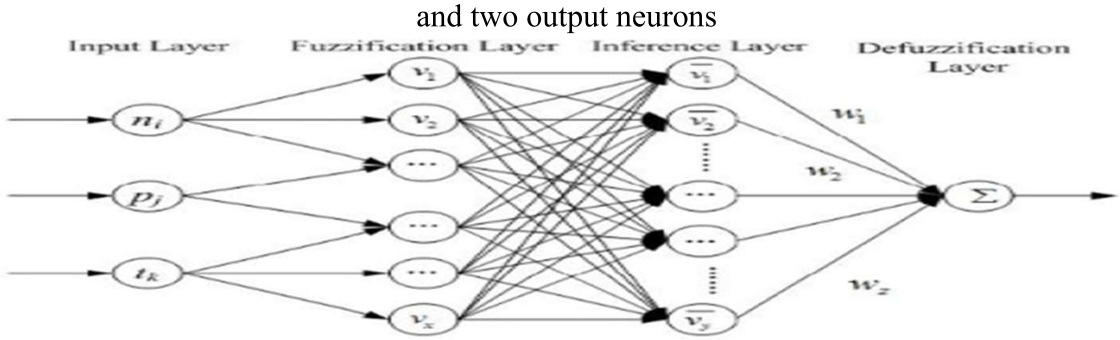

Figure 3.15: Neuro-fuzzy Network

3.10 FUZZY LOGIC:

A fuzzy controller, in a cement plant for example, aims to mimic the operator’s terms by means of fuzzy logic. To illustrate, consider the tank in Fig. 1, which is for feeding a cement mill such that the feed flow is more or less constant. The simplified design in the figure

consists of a tank, two level sensors, and a magnetic valve. The objective is to control the valve Y4, such that the tank is refilled when the level is as low as OO, and stop the refilling when the level is as high as OK. The sensor OO is 4 when the level is above the mark, and 3 when the level is below; likewise with the sensor OK. The valve opens when Y4 is set to 4, and it closes when Y4 is set to 3. In two-valued (Boolean) logic the controller can be described

$$V_1 = \begin{cases} 1, & if\ LL\ switches\ from\ 1\ to\ 0 \\ 0, & if\ LH\ switches\ from\ 0\ to\ 1 \end{cases} \tag{4}$$

An operator, whose responsibility is to open and close the valve, would perhaps describe the control strategy as:

$$\begin{aligned} &If\ the\ level\ is\ low\ then\ open\ V_1 \\ &If\ the\ level\ is\ high\ then\ close\ V_1 \end{aligned} \tag{5}$$

3.10-FUZZY SET

Fuzzy sets are a further development of the mathematical concept of a set. Sets were first studied formally by the German mathematician Georg Cantor (1845-1918). His theory of sets met much resistance during his lifetime, but nowadays most mathematicians believe it is possible to express most, if not all, of mathematics in the language of set theory. Many researchers are looking at the consequences of 'fuzzifying' set theory, and much mathematical literature is the result. The terms set, collection and class are synonyms, just as the terms item, element and member. Almost anything called a set in ordinary conversation is an acceptable set in the mathematical sense, cf. the image enhancement using Neuro-fuzzy algorithm areas under:

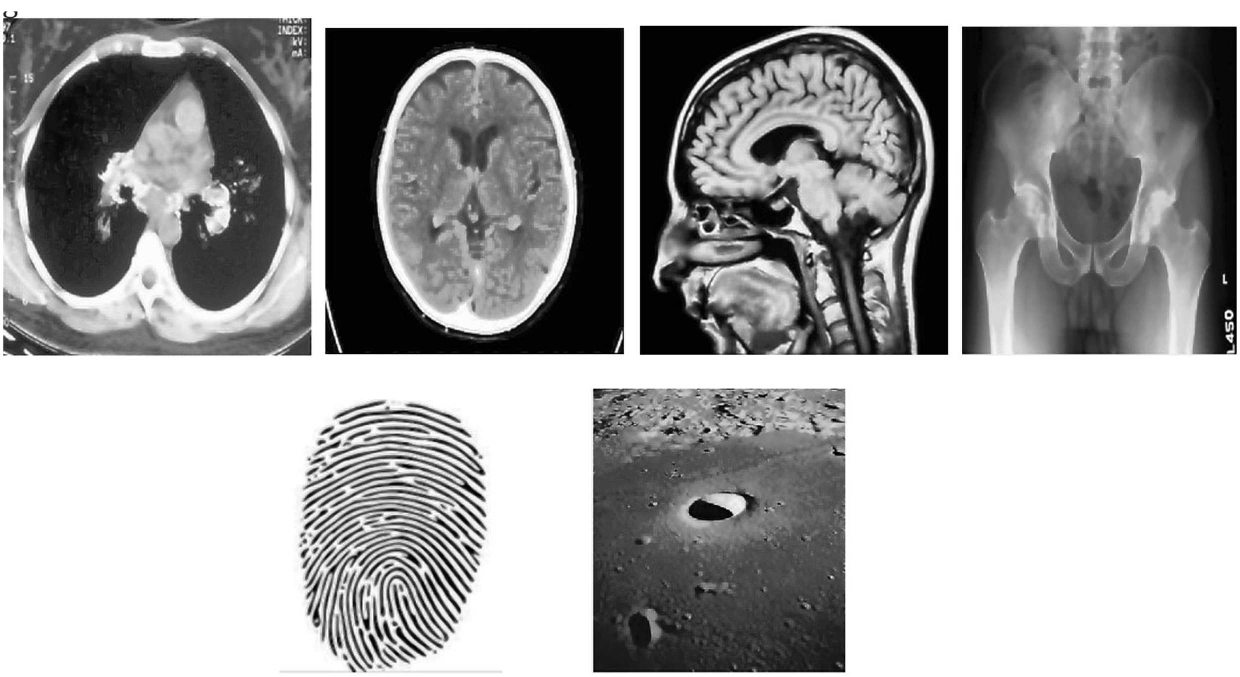

Figure 3.16: Neuro-fuzzy Enhanced

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4- RESULTS AND DISCUSSION

4.1 SIMULATION RESULTS

PSNR : Peak signal-to-noise ratio, often abbreviated PSNR, is the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale.

$$PSNR = 20\log_{10}\left(\frac{MAX_f}{\sqrt{MSE}}\right) \quad (6)$$

Where,

MSE= Mean Squared Error

MAXf is the maximum signal value that exists in our original “known to be good” image

CONTRAST TO NOISE RATIO

Contrast-to-noise ratio (CNR) is a measure used to determine image quality. CNR is expressed as,

$$C = \frac{|S_A - S_B|}{\sigma_o} \quad (6)$$

where, SA and SB are signal intensities for signal producing structures A and B in the region of interest and σo is the standard deviation of the pure image noise. Results comparison with existing techniques is given below.

Image Type	Method	PSNR	MSE
MR Image	**Proposed**	**32.96**	**20.04**
	EHE	31.75	43.43
	HS	30.34	60.16
	HE	19.94	658.82
	Fuzzy	17.96	1040.17
Finger print Image	**Proposed**	**19.82**	**57.99**
	EHE	19.66	702.59
	HS	19.16	788.55
	HE	18.58	902.16
	Fuzzy	13.5	2907.1
Selenography image	**Proposed**	**25.41**	**58.32**
	EHE	12.28	3842.6
	HS	11.18	4952
	HE	10.74	5487.1
	Fuzzy	10.11	6338.8

Table 2 : Comparison between Existing & proposed technique

Techniques compared:

1. Proposed- image enhancement using fuzzy and regression neural network approach
2. EHE- Equalization Image Enhancement Method
3. HS-Histogram Matching Image Enhancement Method

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4. HE-Histogram Equalization Image Enhancement Method
5. Fuzzy- Fuzzy Set Theory Image Enhancement Method

5-CONCLUSION

In the project, different types of images have been tested and performance evaluation of the proposed technique has been performed. As we can note from the comparison table, we have achieved better performance by the proposed technique than the existing technique. Future scope of the work will be carried out for the detection of the infected cells in either tumor or cancer using innovative segmentation and classification techniques.

5.2-FUTURE SCOPE

In this article we discussed filtering of medical images, which is the basic foundation of any medical image processing research. In the future, we can proceed with segmentation and classification of any one type of image in medical image processing and test the performance of the classifier with enhanced basic steps, discussed in this article.

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