An Advanced Technique of De-Noising Medical Images using ANFIS

Rupinderpal Singh, Pankaj Sapra, Varsha Verma

Abstract*— Noise reduction has been a traditional problem in image processing. Medical images like X-RAY, CT, MRI, PET and SPECT have minute information about heart, brain, nerves etc. These images are corrupted during transmission. When these are corrupted by noise, it is impossible to rescue a human being from harmful effects. Recent wavelet thresholding based denoising methods proved promising, since they are capable of suppressing noise while maintaining the high frequency signal details. However, the local space-scale information of the image is not adaptively considered by standard wavelet thresholding methods. In this thesis, a new type of technique neural network and fuzzy has been proposed. The proposed technique confiscates the Additive white Gaussian Noise from the CT images and improves the quality of the CT images. The proposed work is comprised of three phases; they are preprocessing, training and testing. In the preprocessing phase, the CT image which is affected by the AWGN noise is transformed using multi wavelet transformation. In the training phase the obtained multi-wavelet coefficients are given as input to the Neural Network and Fuzzy System. In the testing phase, the input CT image is examined using this trained Neural Network and Fuzzy System and then to enhance the quality of the CT image thresholding is applied and then the image is reconstructed. Hence, the denoised and the quality enhanced CT images are obtained in an effective manner.

Index Terms*—Image processing, filters, de-noising, Discrete Wavelet Transform(DCT), neural network, fuzzy logic.

I. INTRODUCTION

Image processing is a form of signal processing for which the input is an image such as a photograph or video frame and the output of image processing may be either an image or the image parameters. An image is a two dimensional function of two real variables. Image= f(x, y) where, x and y are the spatial coordinates known as pixels and f is the amplitude. Before, processing an image is converted into the digital form. Digitization includes, sampling of images and quantization of the sampled values. After converting the image into bit information the processing is performed. The processing technique may be image enhancement, image reconstruction and image compression. Image is processed in two ways:

1. Spatial domain: Spatial domain, refers to the image plane itself, it is based on the direct manipulations of the pixels in the image.
2. Frequency domain: In frequency domain, image is processed in form of sub bands. All types of transformations are applied in frequency domain. e.g DWT, DFT etc.

The purpose of image processing is divided into five groups:

1. Visualization: Observe the objects that are not visible.
2. Image Sharpening and Restoration: To create a better image.
3. Image Retrieval: Seek for the image of interest.
4. Measurement of the Pattern: Measure various objects in an image.
5. Image Recognition: Distinguish the objects in an image.

Medical imaging is the technique and process used to create images of the human body for clinical purposes and diagnosis (medical procedures seeking to reveal, diagnose or examine disease) or medical science. Although imaging of removed organs and tissues can be performed for medical reasons, such procedures are not usually referred to as medical imaging. As a discipline and in its widest sense, it is part of biological imaging and incorporates radiology, nuclear medicine, investigative radiological sciences, endoscopy, medical thermography, medical photography and microscopy (e.g. for human pathological investigations). Measurement and recording techniques which are not primarily designed to produce images, such as electroencephalography (EEG), magneto encephalography (MEG), Electrocardiography (EKG) and others, but which produce data susceptible to be represented as maps, can be seen as forms of medical imaging .Radiation exposure from medical imaging in 2006 made up about 50% of total ionizing radiation exposure in the United States. In the clinical context, "invisible light" medical imaging is generally equated to radiology or "clinical imaging" and the medical practitioner responsible for interpreting (and sometimes acquiring) the images is a radiologist. "Visible light" medical imaging involves digital video or still pictures that can be seen without special equipment. Dermatology and wound care are two modalities that utilize visible light imagery. Diagnostic radiography designates the technical aspects of medical imaging and in particular the acquisition of medical images. The radiographer or radiologic technologist is usually responsible for acquiring medical images of diagnostic quality, although some radiological interventions are performed by radiologists. While radiology is an evaluation of anatomy, nuclear medicine provides functional assessment. Many of the techniques developed for medical imaging also have scientific and industrial applications. Medical imaging is often perceived to designate

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Er.Rupinderpal Singh, Computer Science, Punjab Technical University, CT Institute of Engineering & Management, Jalandhar (Punjab) India
Er.Pankaj Sapra, Computer Science, Punjab Technical University, CT Institute of Engineering & Management, Jalandhar (Punjab) India
Prof. Varsha Verma, Computer Science Punjab Technical University, CT Institute of Engineering & Management, Jalandhar (Punjab) India.

the set of techniques that non-invasively produce images of the internal aspect of the body. In this restricted sense, medical imaging can be seen as the solution of mathematical inverse problems. This means that cause (the properties of living tissue) is inferred from effect (the observed signal). In the case of ultra sonography the probe consists of ultrasonic pressure waves and echoes inside the tissue show the internal structure. In the case of projection radiography, the probe is X-ray radiation which is absorbed at different rates in different tissue types such as bone, muscle and fat. The term noninvasive is a term based on the fact that following medical imaging modalities do not penetrate the skin physically. But on the electromagnetic and radiation level, they are quite invasive. From the high energy photons in X-Ray Computed Tomography, to the 2+ Tesla coils of an MRI device, these modalities alter the physical and chemical environment of the body in order to obtain data.

Type of medical images:

1. **X-ray** : X-rays, for example, are often used to detect broken bones and some types of cancer.
2. **Computer Tomography (CT)** : Computed Tomography (CT) scans, also known as CAT (Computed Axial Tomography) scans, produce multiple cross-sectional images of the body by using special X-rays and computer enhancements. This technology creates an image many times more sensitive and detailed than a simple X-ray can produce.
3. **Magnetic Resonance Imaging (MRI)**: MRI provides extremely detailed images of body tissue, organs, and bones without using X-rays or radiation. Instead, it uses two natural, safe forces: magnetic fields and radio waves.MRI is used to detect a wide range of conditions, including cancer, heart and vascular disease, strokes, and disorders of the joints.
4. **Ultrasound:** Diagnostic medical sonography, is a safe and painless imaging process. It uses high-frequency sound waves, without radiation, to generate images of the internal structures of the body.
5. **Echocardiography:** When ultrasound is used to image the heart it is referred to as an Echocardiogram. It allows physicians to see detailed structures of the heart, including chamber size, heart function, the valves of the heart.

Medical Image De-noising

The arrival of digital medical imaging technologies such as positron emission tomography (PET), magnetic resonance imaging (MRI), computerized tomography (CT) and ultrasound Imaging has revolutionized modern medicine. Today, many patients no longer need to go through invasive and often dangerous procedures to diagnose a wide variety of illnesses. With the widespread use of digital imaging in medicine today, the quality of digital medical images becomes an important issue. To achieve the best possible diagnosis it is important that medical images be sharp, clear, and free of noise and artifacts. While the technologies for acquiring digital medical images continue to improve, resulting in images of higher and higher resolution and quality, removing noise in these digital images remains one of the major challenges in the study of medical imaging, because they could mask and blur important subtle features in the images, many proposed de-noising techniques have their own problems. Image de-noising still remains a challenge for researchers because noise removal introduces artifacts and causes blurring of the images . Noise modeling in medical images is greatly affected by capturing instruments, data transmission media, image quantization and discrete sources of radiation. Different algorithms are used depending on the noise model. Most of images are assumed to have additive random noise which is modeled as a white Gaussian noise. Medical images such as magnetic resonance imaging (MRI) and ultrasound images have been widely exploited for more truthful pathological changes as well as diagnosis. However, they suffer from a number of shortcomings and these includes: acquisition noise from the equipment, ambient noise from the environment, the presence of background tissue, other organs and anatomical influences such as body fat, and breathing motion. Therefore, noise reduction is very important, as various types of noise generated limits the effectiveness of medical image diagnosis.

Techniques to De-noise the Medical Images:

Filters

In image processing filters are mainly used to suppress either the high frequencies in the image that is smoothing the image , or the lower frequencies that is enhancing or detecting edges in the image. The image can be filtered in frequency domain or in the spatial domain. In spatial domain there are two types of filters namely linear filters and non linear filters.

1. Linear filters: It consist of linear operations such as multiplying each pixel in the neighborhood by a corresponding coefficient and summing the result to obtain the results at each point (x , y). The coefficients are arranged as a matrix called filter, mask, or window. Linear filters are of two types:
2. Mean Filter: A mean filter is the optimal linear filter for the Gaussian noise in the sense of the mean square error. This filter acts on the image by smoothing it. It reduces the intensity variations between the adjacent pixels. It is the simple sliding window with the average values of its all neighborhood pixels values including itself. It is implemented with the convolution mask which provides the results that is weighted sum of the values of pixels and its neighborhood. It is also called linear filter. The mask or kernel or the window is square of 3*3. If the coefficients of the mask sum up to 1 then the average brightness is lost and the image it returns is a dark image.
3. Weiner Filter: This method requires the information about the spectra of the noise and original signal and it works well only if the underlying signal is smooth. It implements the spatial smoothing and its complexity corresponds to choosing the window size. It assumes the noise and power spectra of the object a priori.
4. Non-Linear Filters: This method involves a non-linear operation

on the pixels of neighborhood. Median filter is a type of the non-linear filter.

Median Filter: This filter follows the moving window principle. It uses 3*3, 5*5, or 7*7 window. The median of the window is calculated and the center pixel value of the window is replaced with that value.

II. PROPOSED SYSTEM

In the proposed system we can used the concepts of artificial neural networks and fuzzy logic. Artificial neural networks are composed of interconnecting artificial neurons (programming constructs that mimic the properties of biological neurons). Artificial neural networks may either be used to gain an understanding of biological neural networks, or for solving artificial intelligence problems without necessarily creating a model of a real biological system. The real, biological nervous system is highly complex: artificial neural network algorithms attempt to abstract this complexity and focus on what may hypothetically matter most from an information processing point of view. Good performance (e.g. as measured by good predictive ability, low generalization error), or performance mimicking animal or human error patterns, can then be used as one source of evidence towards supporting the hypothesis that the abstraction really captured something important from the point of view of information processing in the brain. Another incentive for these abstractions is to reduce the amount of computation required to simulate artificial neural networks, so as to allow one to experiment with larger networks and train them on larger data sets. Application areas of ANNs include system identification and control (vehicle control, process control), game-playing and decision making (backgammon, chess, racing), pattern recognition (radar systems, face identification, object recognition), sequence recognition (gesture, speech, handwritten text recognition), medical diagnosis, financial applications, data mining (or knowledge discovery in databases, "KDD"), visualization and e-mail spam filtering.

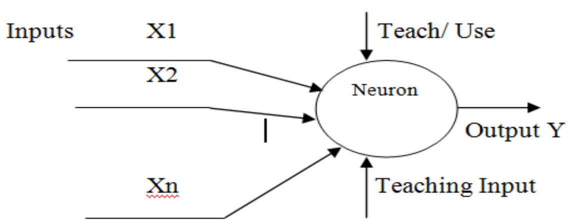

Figure1: Simple Artificial Neural Network.

Back Propagation Algorithm

It is a supervised learning method, and is a generalization of the delta rule. It requires a dataset of the desired output for many inputs, making up the training set. It is most useful for feed-forward networks (networks that have no feedback, or simply, that have no connections that loop). The term is an abbreviation for "backward propagation of errors". Back propagation requires that the activation function used by the artificial neurons (or "nodes") be differentiable.

Phase 1: Propagation Each propagation involves the following steps:

- Forward propagation of a training pattern's input through the neural network in order to generate the propagation's output activations.
- Backward propagation of the propagation's output activations through the neural network using the training pattern's target in order to generate the deltas of all output and hidden neurons.

Phase 2: Weight update For each weight-synapse follow the following steps:

- Multiply its output delta and input activation to get the gradient of the weight.
- Bring the weight in the opposite direction of the gradient by subtracting a ratio of it from the weight.

This ratio influences the speed and quality of learning; it is called the learning rate. The sign of the gradient of a weight indicates where the error is increasing. this is why the weight must be updated in the opposite direction. Repeat phase 1 and 2 until the performance of the network is satisfactory.

The BPNN based approach is a powerful and effective method for image de-noising. Earlier proposed methods suffered from drawbacks such as noise, artifacts and degradation. Although all the spatial filters performs well on the digital images but still suffered from some constraints such as resolution degradation these filters operated by smoothing over a fixed window and it produces artifacts around the object and sometimes caused over smoothing thus causing the blurring of image. Wavelet transform outperforms the filters because of its properties like sparsity, multi resolution and multi scale nature and proved promising as they are capable of suppressing noise while maintaining high frequency signal details. But the limitation with wavelet transform was that the local scale- space information of the image is not adaptively considered by the standard wavelet thresholding methods. Other difficulty was that the soft thresholding function was a piecewise function and does not have high order derivates. A new type of thresholding neural network was presented which outperforms the soft thresholding using wavelet transform but still does not promised a high performance in terms of PSNR, MSE and visual test.

Considering and analyzing the drawbacks of the previous methods we propose a new improved BPNN approach and Fuzzy to de-noise the medical images. This approach includes using both mean and median statistical functions for calculating the output pixels of the NN and Fuzzy. This uses a part of degraded image pixels to generate the system training pattern. Different test, images noise levels and neighborhood sizes are used. Based on using samples of degraded pixels neighborhoods as input, the output of the proposed approach provided a good image de-noising performance which exhibits a promising results of the degraded noisy image in terms of PSNR, MSE and visual test.

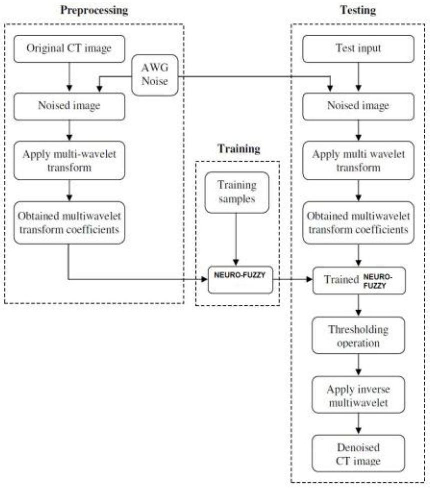

Figure 2: The layout of the proposed system.

Preprocessing:

In the preprocessing phase, *Iwg* is applied to the multiwavelet transformation based on windows to generate its duplicate *Iwg* . From the *I^wg* and *Iwg* , a window of pixels are taken and this window of pixels is subjected to multi wavelet transformation. In this multi-wavelet transformation the noised image *Iwg* is processed and a window of pixels *I* '*wg* .is obtained. Let *w* be the window of pixels extracted from the image *Iwg* and *I* '*wg* with a window step size of *wsize* which is applied throughout the image to obtain wx , $0 \le x \le nw - 1$ windows. In the same way the windowing process is performed in the image *I* '*wg* and ' *y w* , $0 \le y \le nw - 1$ windows are obtained. Here *w n* indicates the number of windows. Subsequently, the obtained window of pixels is converted into multi-wavelet transform domain which is shown below.

$$W_x(i,j) = F_{GHM}(i,j) \,.\, w_x(i,j) \,.\, F^T_{GHM}(i,j)$$

$$W'_y(i,j) = F_{GHM}(i,j) \,.\, w'_y(i,j) \,.\, F^T_{GHM}(i,j)$$

where, $0 \le i \le wM - 1$, $0 \le j \le wN - 1$ and $wM \times wN$ represents the window size. In (1) and (2) *FGHM* is the concatenated filter coefficient of GHM multi-wavelet transformation, *x W* and '*y W* are nothing but *x w* and ' *y w* in the multi-wavelet domain, respectively. For every *x W* , '*y W* that are closer to*Wx* are selected based on L2 norm distance (*L*2 *xy*), which can be computed using (3),

$$L2_{xy} = \sqrt{\sum_{i=0}^{w_M - 1} \sum_{j=0}^{w_N - 1} (|W_x(i,j) - W'_y(x,y)|)^2}$$

Using the *xy L*2 , the '*y W* windows that are closer to the*Wx* , ' *WL*2*xy* can be identified as *xy* = *xy* –φ, where, *WL*2*xy* is given as

$$W_{L2_{xy}} = \begin{cases} W_y & ; \quad if \quad L2_{xy} \le L2_T \\ \phi & ; \quad else \end{cases}$$

Every *xth* window sets in *WL*2*xy* are sorted in ascending order based on their corresponding *L*2 *xy* . From the sorted window set, *n*α number of windows are selected (for every*Wx*) and the remaining windows are discarded, which leads to obtain*Wxk* , where, $0 \le k \le n\alpha - 1$. From every *kth* window that corresponds to the *xth* window, the elements of similar position are subjected to CL multi wavelet transformation to obtain the multi-wavelet coefficient *FCL*(*k*) . This multi-wavelet coefficient is given as input to the Neural Network and Fuzzy inference system for the training process.

Training Phase:

Neural Network and Fuzzy is a class of adaptive networks that act as a fundamental framework for adaptive fuzzy inference systems. For the sake of simplicity, we suppose our FIS has two inputs *x* , *y* and one output *z* ; here *x* = *y* = *FCL* (*k*) where each input has two fuzzy sets A1, A2 and B1, B2. Each circle shows a fixed node, whereas every square indicates an adaptive node. So the rule base system has two if-then rules of Takagi-
Sugeno's type as follows, *Rule i* : *If x is Ai and y is Bi*,

then fi = *pi x* + *qi y* + *ri*

r = 1,2

Where *fi* is the output and *pi* , *qi* and *ri* are the designed parameters that are assigned during the training algorithm of the Neural Network and Fuzzy. Output of each node in every layer is denoted by 1 *Oi* where *i* specify the neuron number of the next layer and *l* is the layer number. The performance of each layer is described in the following:

Layer1: Each node in this layer is an adaptive node and outputs of these nodes are given by:

*Oi*1 =μ *Ai* (*x*)

*Oi*1 =μ *Bi* (*x*)

i = 1, 2

Where μ *Ai* (*x*) and μ *Bi* (*x*) are membership functions that determine the degree to which the given x and y satisfy the quantifiers *Ai* and *Bi*

Layer2: In this layer, each node is a fixed node and determines the firing strength of the related rule.

*Oi*2 =ω*i* = μ *Ai* (*x*)μ *Bi* (*y*) (7)

Layer3: In this layer, every node is a circle node and computes the ratio of firing strength of each rule to the total number of rules to obtain the so-called normalized firing strength. *Oi* = *i* = (8)

Layer4: The output of each adaptive node in this layer is:

*Oi*4 =ω*i fi* =ω*i* (*pi x* + *qi y* + *ri*) (9)

Parameters *pi* , *qi* and *ri* are called as consequence parameters.

Layer5: Final layer, presented with a circle node, calculates the summation of all incoming signals.

$$O_i^5 = \frac{\sum_{i=1}^{2} \omega_i f_i}{\sum_{i=1}^{2} \omega_{ii}}$$

The training efficiency is improved by employing a hybrid learning algorithm to justify the parameters of input and output membership functions.

The output can be rearranged as follows,

$f = (\omega 1x)\, p1 + (\omega 1y)q1 + (\omega 1)r1 + (\omega 2x)\, p2 + (\omega 2\, y)q2 + (\omega 2)r2$

So, the consequent parameters can be adjusted by the least square method. On the other hand, if consequent parameters are fixed, the premise parameters can be adjusted by the gradient descent method. Thus, the Neural Network and Fuzzy system is generated for the denoising operation and the generated Neural Network and Fuzzy system is utilized for the testing phase.

Testing phase

In this phase, the input test image *Itest* of dimension $M \times N$ is processed. Initially, the image affected with AWG noise and is subjected to multi-wavelet transformation as discussed in section. Then the coefficient is applied to the generated Neural Network and Fuzzy system. The Neural Network and Fuzzy system analyzes the image and eliminates the added AWGN noise from the image and then they obtained coefficients are improved by employing the thresholding operation. The thresholding operation is performed based on the threshold *thr* . After the thresholding operation, the image is transformed back to the spatial domain from the frequency domain by employing the inverse multi wavelet transformation to the obtained frequency domain constraints and the denoised image is obtained. The obtained CT image $I\hat{}$ *final* is denoised and hence the obtained image can be utilized for clinical diagnoses.

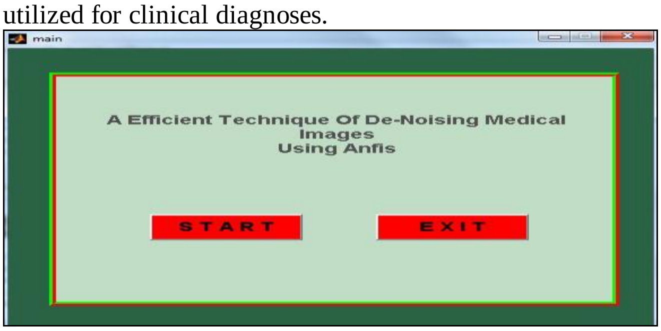

Figure 3: The basic layout of the proposed system

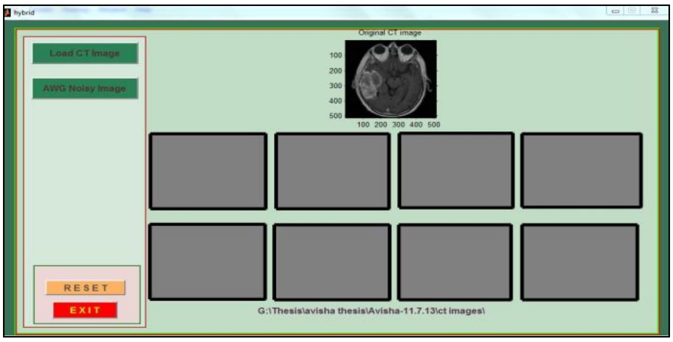

Figure 4: The input image is loaded in to the system.

After loading the input image we will apply some filters method to it.

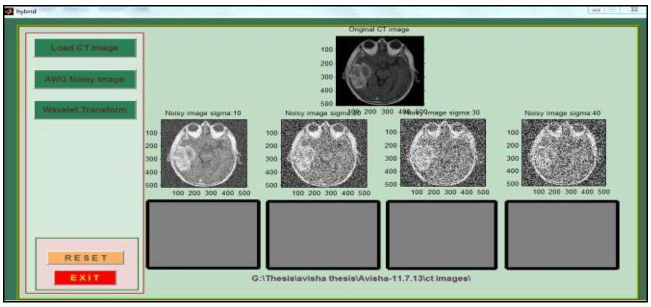

Figure 5: By applying the AVG Filter method.

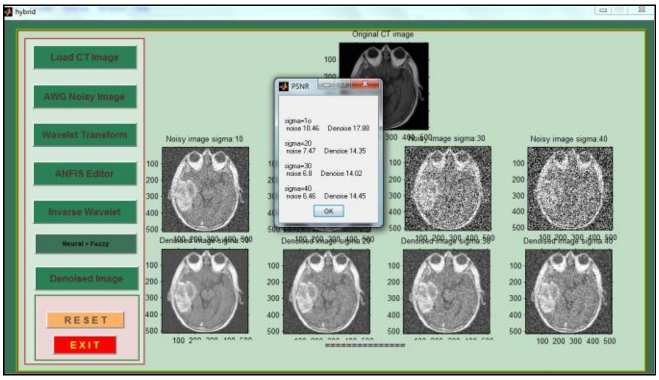

Figure 6: The outcome of the proposed system.

III. CONCLUSION

In this thesis, we implemented the neural networks and fuzzy as a tool for image de-noising and enhancement. BPNN and Fuzzy technique was used. The evaluation also include both mean and median functions. The evaluation was based on the PSNR, MSE. The proposed approach i.e., improved technique for medical image de-noising using Neural Network and Fuzzy exhibit outcomes of noise reduction and image quality improvements, with different noise levels, which qualify it to be suitable for image processing and de-noising. Future work will be using more advanced multi-wavelet transform technique for more better results.

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AUTHOR PROFILE

Er.Rupinderpal Singh, Profile Computer Science, B-tech /M-tech (Pursuing), Membership-CSI, (E-mail: rupindersingh415@gmail.com).

Er.Pankaj Sapra, Profile Computer Science, B-tech /M-tech (Pursuing), Membership-CSI, (E-mail: pankajsapra9999@gmail.com)

Prof. Varsha Verma Profile Computer Science, B-tech/M-tech, Research-Wireless Sensor Network , Publications- IEEE - 01, International Journal - 6, National – 5, International Conference : 05, (e-mail: barkhabright@gmail.com).