International Journal of Engineering and Advanced Technology (IJEAT)
ISSN: 2249 – 8958, Volume-1 Issue-3, August 2012

# Hybrid Filtering Technique for Image Denoising using Artificial Neural Network

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***Abstract*— Image enhancement and restoration in a noisy environment are fundamental problems in image processing. Various filtering techniques have been developed to suppress noise in order to improve the quality of images. Many filters for image processing are designed assuming a specific noise distribution. In the medical field image processing play an important role because most of the diseases are diagnosed by means of medical images. In order to use these images for the diagnosing process, it must be noiseless. However, most of the images are affected by noises and artifacts. Hence an effective technique for denoising medical images particularly in Computed Tomography (CT) is necessary, which is a significant and most general modality in medical imaging. In order to achieve this denoising of CT images, an effective CT image denoising technique is proposed. The proposed technique remove the Additive white Gaussian Noise from the CT images and improves the quality of 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 Adaptive Neuro-Fuzzy Inference System (ANFIS). In the testing phase, the input CT image is examined using this trained ANFIS and then to enhance the quality of the CT image thresholding is applied and then the image is reconstructed. Hence, the quality enhanced and the denoising CT images are obtained in an effective manner.***

***Index Terms*— CT image; denoising; Additive White Gaussian Noise (AWGN); multi-wavelet transformation; Adaptive Neuro- Fuzzy Inference System (ANFIS); thresholding.***

## I. INTRODUCTION

The quality of digital medical images has become an important issue today. To achieve the best possible diagnoses, it is important for medical images to be sharp, clear, and free of noise and artifacts [1]. Though, the technologies used to improve resolution and quality of noisy images remains an issue in many medical images applications [12]. Removing noise in these digital images remains as one of the major challenges in the study of medical imaging [13].

Denoising of ultrasound images is particularly challenging due to their peculiar texture [3]. The presence of noise will degrade the quality of image, and even conceal image details, which affects the subsequent image segmentation, feature extraction and recognition, quantitative analysis, and most importantly disease diagnosis [4] [15]. Several denoising methods that have been proposed such as neighborhood filtering, total variation minimization, Wiener filtering, Gaussian scalar mixture, methods based on partial differential equation [5] Adaptive low pass filtering, adaptive median filtering, geometric filter and others manage to remove substantial amounts of speckle, but also tend to over smooth the features [6]. To avoid this, Gaussian filters have been largely used in some applications. However, they have the disadvantage of blurring the edges due to the averaging of non similar patterns [7]. Image quality is a very essential feature in medical imaging. But, degradation of medical images due to different kinds of noises is highly probable. In order to avoid this problem, many edge preserving filters have been proposed. Probably the most well-known is the Anisotropic Diffusion Filter (ADF) [8] [9] [10]. ADF respects edges by averaging pixels in the orthogonal direction of the local gradient. However, such filtering usually erases small features and transforms image statistics due to its edge enhancement effect resulting in unnatural images [9]. Finally, an inverse transform is used to estimate only the signal value in the central pixel of the window [16]. And then wavelet based filters have also been applied to image denoising [11]. Some wavelet based techniques [18] find the correlation of wavelet coefficients between consecutive scales to distinguish noise from meaningful data. The method is based on the fact that wavelet coefficients related to noise are less correlated across scales than coefficients associated with edges. If the correlation is smaller than a threshold, a given coefficient is set to zero. To determine a proper threshold, a noise power estimate is necessary for this technique, which may be difficult to obtain for some images [17].In thispaper, we propose an effective noise reduction technique for the medical images especially for the CT images using window based multi-wavelet transformation and Artificial Neuro-Fuzzy Inference System (ANFIS).

The proposed technique is comprised of three phases; they are preprocessing, training and testing. In the preprocessing phase the input CT image which is affected by the AWGN is transformed using multi wavelet transformation and the obtained multi-wavelet coefficients are given as input to the ANFIS for the training process and noiseless image samples are used as training samples. Subsequent to the training process, in the testing process the input image which is pre processed earlier in the preprocessing phase is tested using the trained ANFIS. After the completion of the testing process the denoised image is reconstructed.

## II. LITERATURE REVIEW

Ahmed Badawi et al. [19] have proposed an enhancement model to greatly reduce speckle and preserve image features in medical ultrasound images. They have been able to greatly improve the performance of the existing filtering methods, namely edge enhancing (EE) and coherence enhancing (CE) diffusion. The enhancement method has been tested using various ultrasound images to determine the amount of speckle reduction, edge, and coherence enhancements.

**Manuscript received on August, 2012.**

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Scatterer density weighted nonlinear anisotropic diffusion (SDWNAD) for ultrasound images have consistently outperformed. SDWNAD has been shown to greatly reduce speckle noise while preserving image features such as edges, orientation coherence, and scatterer density. The superior performance of SDWNAD over nonlinear coherent diffusion (NCD), speckle reducing anisotropic diffusion (SRAD), adaptive weighted median filter (AWMF), wavelet shrinkage (WS), and wavelet shrinkage with contrast enhancement (WSCE), has made these methods ideal preprocessing steps for automatic segmentation in ultrasound imaging.

Thangavel et al. [21] have discussed that removing noise from the original image has been a challenging research in image processing. Generally there has been no common enhancement approach for noise reduction. Several approaches have been introduced and each has its own assumption, advantages and disadvantages. The speckle noise has been commonly found in the ultrasound medical images. They have proposed different filtering techniques based on statistical methods for the removal of speckle noise. A number of successful experiments have validated the proposed filtering model. The quality of the enhanced images has been measured by the statistical quantity measures: Signal-to-Noise Ratio (SNR), Peak Signal-to- Noise Ratio (PSNR), and Root Mean Square Error (RMSE). Ratha Jeyalakshmi et al. [23] have discussed that Ultrasound images contain speckle noise which degrades the quality of the images. Eliminating such noise has been an important preprocessing task. They have described and analysed an algorithm for cleaning speckle noise in ultrasound medical images. Mathematical Morphological operations have been used in their algorithm. The algorithm has used a different technique for reconstructing the features that are lost while removing the noise. For morphological operation it has also used arbitrary structuring elements suitable for the ultrasound images which have speckle noise.

Guangming Zhang *et al.* [25] have discussed that the curvelet transform is a multiscale transform that has directional parameters occurring at all scales, locations, and orientations. They have proposed a model for CT medical image de-noising, which has used independent component analysis and curvelet transform. Firstly, a random matrix has been generated to separate the CT image into a separated image for estimation. Then curvelet transform has been employed to optimize the coefficients. At last, the coefficients have been selected for the image reconstruction by performing the inverse of the curvelet transform. The approach has been capable of removing more noises and reserve more details, and its efficiency has been better than that of other traditional de-noising approaches.

## III. PROPOSED WORK

In medical field, digital image processing plays a vital role in diagnosing diseases and the images used for processing must be a denoised one. In our work, we utilize CT images and improve their quality. The proposed work is comprised of 3 phases namely preprocessing, training and testing. Let I be the original CT image with M × N dimension where $0 \le m \le M-1$, $0 \le n \le N-1$ . This image is utilized for the further processes in our work. Let Iwg be an image affected by AWGN. The noise corrupted image Iwg is to be denoised and the image is to be preprocessed in the preprocessing phase. Figure.1 depicts the proposed CT image denoising technique.If you are using *Word*, use either the Microsoft Equation Editor or the Math Type add-on (http://www.mathtype.com) for equations in your paper (Insert | Object | Create New | Microsoft Equation *or* MathType Equation). “Float over text” should *not* be selected.

### A. Preprocessing

In the preprocessing phase, $I_{wg}$ is applied to the multiwavelet transformation based on windows to generate its duplicate $I''_{wg}$ . From the $I_{wg}$ and $I''_{wg}$ , 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 $I_{wg}$ is processed and a window of pixels $I'_{wg}$ is obtained. Let w be the window of pixels extracted from the image $I_{wg}$ and $I'_{wg}$ with a window step size of w size which is applied throughout the image to obtain $w_x$ , $0 \le x \le n_w - 1$ windows. In the same way the windowing process is performed in the image $I'_{wg}$ and $w'_y$ , $0 \le y \le n_w - 1$ windows are obtained. Here $n_w$ indicates the number of windows. Subsequently, the obtained window of pixels is converted into multi-wavelet transform domain which is shown

$$W(i,j) = F_{GHM}(i,j) . w_x(i,j) . F_{GHM}^T(i,j) \quad (1)$$

$$W'_Y(i,j) = F_{GHM}(i,j) . W'_Y(i,j) . F_{GHM}^T(i,j) \quad (2)$$

Where, $0 \le i \le W_M - 1$ , $0 \le j \le W_N - 1$ and $W_M$* $W_N$ represents the window size. In (1) and (2) $F_{GHM}$ is the concatenated filter coefficient of GHM multi-wavelet transformation, $W_X$ and $W'_Y$ are nothing but $W_X$ and $W'_Y$ in the multi-wavelet domain, respectively. For every $W_X$, $W'_Y$ that are closer to*Wx* are selected based on L2 norm distance ( *L2 xy* ), which can be computed using (3),

$$L2_{XY} = \sqrt{\sum_{i=0}^{W_M-1} \sum_{j=0}^{W_N-1} (w_X(i,j) - W'_Y(X,Y))^2} \quad (3)$$

Where $WL2_{XY}$

$$WL2_{XY} = \begin{cases} W_Y & IF\ L2_{XY} \le L2_T \\ \varnothing & ELSE \end{cases} \quad (4)$$

### B. Training Phase

ANFIS is a class of adaptive networks that act as a fundamental framework for adaptive fuzzy inference systems [1]. Figure.2 shows the ANFIS architecture. 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 (5)

Where fi is the output and pi , qi and ri are the designed parameters that are assigned during the training algorithm of the ANFIS. Output of each node in every layer is denoted by $O_i^1$ where i specifies 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:

$$O_i^1 = \mu Ai\,(x) \quad (6)$$

$$O_i^1 = \mu Bi\,(x) \quad (7)$$

i = 1, 2

Where µAi (x) and µBi (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.

$$O_i^2 = W_i = \mu Ai\,(x)\ \mu Bi\,(y) \quad (8)$$

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.

$$O_i^3 = W_i{}' = \frac{W}{W_1 + W_2} \quad (9)$$

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

$$O_i^4 = W_i' F_i = W_i'(P_i x + Q_i x + r_i) \quad (10)$$

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.

$$O_i^5 = \frac{\sum_{i=1}^{2} W_i F_i}{\sum_{i=1}^{2} W_{ii}} \quad (11)$$

The training efficiency is improved by employing ahybrid learning algorithm to justify the parameters of input and output membership functions. The two parameter sets in the ANFIS architecture that require tuning are the antecedent parameters (the parameters associated with the input membership functions) and the consequent parameter (the parameters associated with the output membership functions).

The output of ANFIS will be a linear combination of the consequent parameters is the premise parameters can be assumed as fixed. So, the output can be written as:

$$f = W_1{}'f_1 = W_2{}'f_2 \quad (12)$$

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. ANFIS utilizes hybrid learning algorithm in which the least square method is used to identify the consequent parameters in the forward pass and the gradient descent method is applied to determine the premise parameters in the backward pass. Thus, the ANFIS system is generated for the denoising operation and the generated ANFIS system is utilized for the testing phase.

### *C. 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 III.A. Then the coefficient is applied to the generated ANFIS system. The ANFIS system analyzes the image and eliminates the added AWGN noise from the image and then the 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 $I_{final}'$ is denoised and hence the obtained image can be utilized for clinical diagnoses.

## IV. RESULT & DISCUSSION

In this proposed work, the CT image denoising technique using ANFIS has been implemented in the working platform of MATLAB.

The performance has been evaluated for the image which is corrupted through the AWGN with different noise levels. The quality of the final denoised and enhanced CT has been evaluated by calculating the PSNR values as

$$PSNR\,(I_{WG}) = 20\,Log_{10}\left(\frac{M-1}{\sqrt{\frac{1}{MN}\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}\left(I(m,n) - I_{wg}(m,n)\right)^2}}\right) \quad (13)$$

$$PSNR\,(I_{final}{}') = 20\,Log_{10}\left(\frac{M-1}{\sqrt{\frac{1}{MN}\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}\left(I(m,n) - I_{final}{}'(m,n)\right)^2}}\right) \quad (14)$$

The PSNR for noisy and denoised image, respectively, can be determined. The PSNR values of noisy and denoised images with different noise levels are given in the Table I and the image results for *I*1 and *I* 2 are shown in the Figure. 3 and Figure. 4, respectively. The following figure depicts the ANFIS structure for the proposed CT image denoising technique.

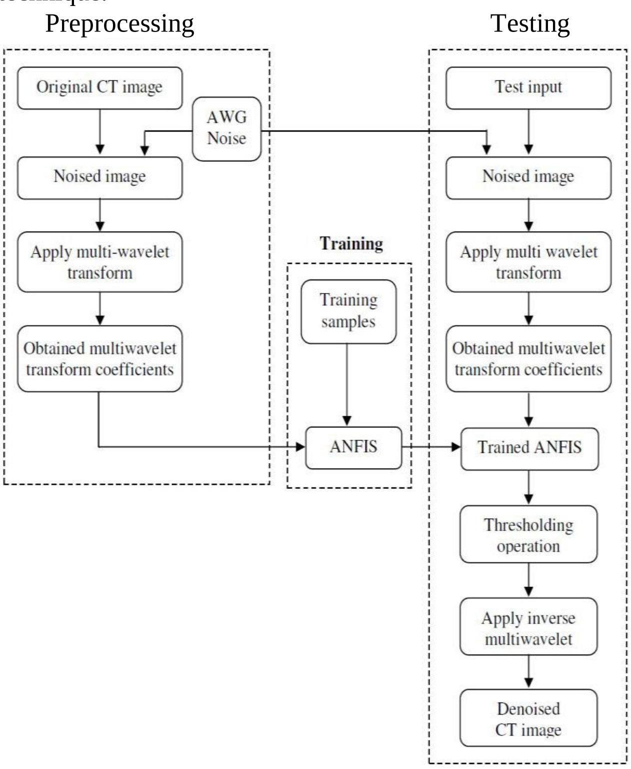


**Fig. 1 Roposed Denoising Technique**

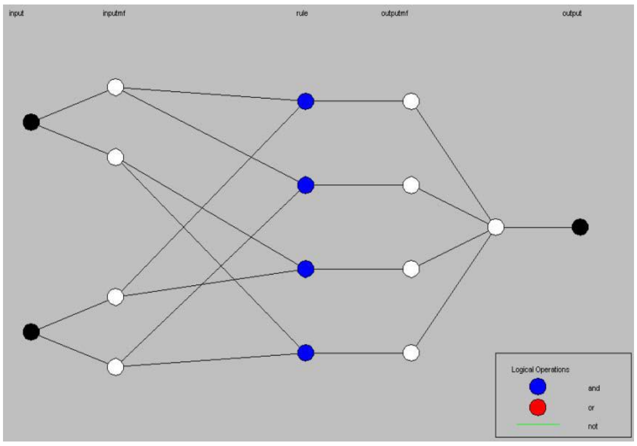


**Fig. 2 Generated ANFIS Structure for the Proposed Denoising Technique**

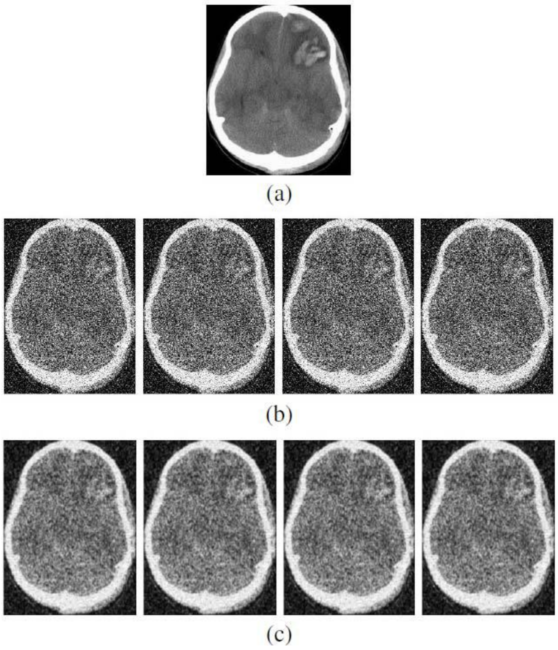


**FIG. 3 Image Results for (A) Original Ct Image (B) Awgn Corrupted Ct Image, Withadded Noise Levels Σ=10, 20, 30 and 40 and (C) Denoised CT Image**

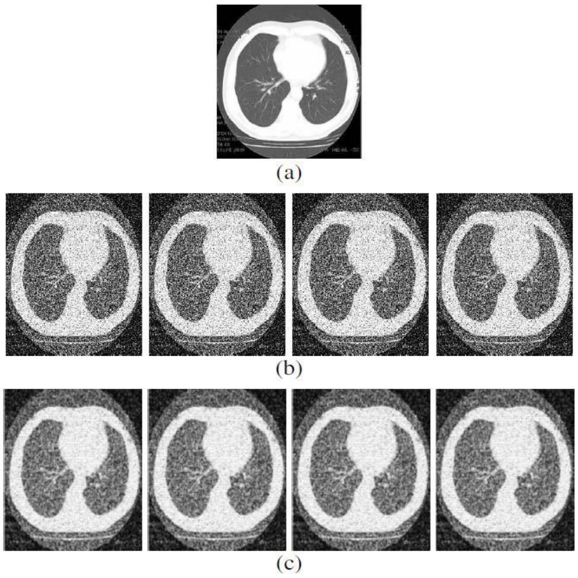


**Fig 4. Image Results for (A) Original Ct Image (B) Awgn Corrupted Ct Image, With Added Noise Levels □ = 10, 20, 30 and 40 and (C) Denoised CT Image**

The PSNR values of two test CT images are shown in the table I. The given PSNR of noisy images at the mentioned levels and the corresponding denoised images the performance of the proposed denoising technique. The Figure 2 depicts the generated ANFIS structure. Figure 3 and Figure 4 illustrate the performance of the proposed denoising technique original, noisy and denoised CT images. The results shows that the noise is removed from the represented CT images using our proposed image denoising technique using ANFIS.

**Table I - PSNR Values of the Images I1 and I2of the Noised Image and the Denoised Image**

| Sl. No | Noise Level | I1 WITH AWGN | Denoised I1 | I2 WITH AWGN | Denoised I2 |
|---|---|---|---|---|---|
| 1 | 10 | 11.6921 | 18.3971 | 11.9532 | 18.3268 |
| 2 | 20 | 9.4082 | 16.2510 | 9.8219 | 16.1863 |
| 3 | 30 | 8.7240 | 15.1981 | 8.6958 | 14.8633 |
| 4 | 40 | 8.153271 | 14.4760 | 8.0673 | 14.0315 |

## V. CONCLUSION

In this paper, an effective CT image denoising technique is proposed and the proposed technique is comprised of preprocessing, training and testing phases. The AWGN affected CT images are applied with the multi-wavelet transformation in the preprocessing phase. In the training phase, the ANFIS is trained through the sample images and the CT images are tested through different sample images. In the testing process the input CT image is tested in this trained ANFIS and then to enhance the quality of the CT image, thresholding is applied. The technique has been evaluated using different levels of AWGN corrupted CT images. The denoising of CT images has been performed well and it has also offered a good PSNR for the denoised images. Hence from the obtained results, it can be concluded that the proposed denoising technique effectively removes the AWGN from the CT images by using the multi-wavelet transformation, ANFIS and thresholding and also it improves the quality of the CT image. The obtained denoised CT images are of good quality which can be utilized for effective and precise disease diagnosis.

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