# A Novel Image Registration and Denosing Method for Multiple Sequence for MRI and CT Image

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**ABSTRACT**
The Medical Images normally have a problem of high level components of noises. There are different techniques for producing medical images such as Magnetic Resonance Imaging (MRI), X-ray, Computed Tomography and Ultrasound, during this process noise is added that decreases the image quality and image analysis. Image denosing is an important task in image processing, use of spectral subtraction improves the quality of an image and reduces noise level. Noise reduction is an important step for any complicated algorithms, in computer vision and image processing. In this paper proposed a hybrid method for medical image denosing for improvement of CT and MRI image for brain stroke and brain tumor. The process of CT and MRI image gets the high component value of noise in environment. For the reduction of these noise used wavelet transform domain method. The wavelet transform method is well recognized method for noise reduction. In wavelet transform method the local noise component value are not considered. Then after the denosing process noise are still remain in CT and MRI image. For these low components value collection used multiple sequences. And finally used self-organized map network.

**Keyword: - Noise, SOM, PSNR, Image.**

## INTRODUCTION

The need for efficient image restoration methods has grown with the massive production of digital images and movies of all kinds, often taken in poor conditions. No matter how good cameras are, an image improvement is always desirable to extend their range of action [4]. The rapid development of medical imaging technology and the introduction of new imaging modalities, such as functional magnetic resonance imaging (fMRI), calls for new image processing methods including specialized noise filtering, enhancement, classification and segmentation techniques. Some of the recent multiresolution denosing methods for medical ultrasound and MRI imaging and their applications in some clinical investigations of the human brain. For the image with complex local structure, a single or fixed scale cannot effectively represent local structure with different size essentially. Therefore, searching an adaptive, multi-scale and sparse representation turns to the core of image processing. It is well known that the wavelet transform is the most appropriate tool to multi-scale decomposition. Different scales of image are separated effectively via wavelet, which makes each sub-band have a more unitary structure. Considering diversity of image and separation efficiently, we choose a most suitable wavelet for each layer to replace traditional method of using a fixed wavelet. Image denosing as a low-level image processing operator is an important front-end procedure for high-level visual tasks such as object recognition, digital entertainment, and remote sensing imaging [12]. In real camera systems, the noise has various sources, such as fixed pattern noise, thermal noise, and quantization noise.

For the issue of image denoising, in order to avoid the traditional multi-scale sparse representation methods, which used blocks of different sizes as a base function to represent image, the non-separable wavelets were taken. Their advantages included revealing the multi-scale structure, depicting the texture structure under different scales, and separating different directions and different types of singularity structure in a certain extent [6]. The two main limitations in image accuracy are categorized as blur and noise. Blur is intrinsic to image acquisition systems, as digital images have a finite number of samples and must satisfy the Shannon–Nyquist sampling conditions. The second main image perturbation is noise.

## II GAUSSIAN NOISE

Gaussian noise is evenly distributed over the signal [Um98]. This means that each pixel in the noisy image is the sum of the true pixel value and a random Gaussian distributed noise value. As the name indicates, this type of noise has a Gaussian distribution, which has a bell shaped probability distribution function given by,

$$F(g) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-(g-m)^2/2\sigma^2}$$

…………………… (1)

Where g represents the gray level, m is the mean or average of the function and σ is the standard deviation of the noise.

Graphically, it is represented as shown in Figure 1. When introduced into an image.

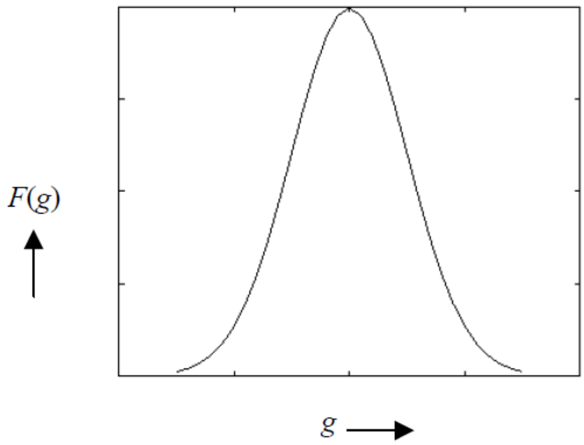


**Figure 1: Gaussian distribution.**

## III WAVELET DOMAIN NOISE FILTERING

The discrete wavelet transform translates the image content into an approximation subband and a set of detail subbands at different orientations and resolution scales. Typically, the band-pass content at each scale is divided into three orientation subbands characterized by horizontal, vertical and diagonal directions. The approximation subband consists of the so-called scaling coeffcients and the detail subbands are composed of the wavelet coefficients. Here we consider a non-decimated wavelet transform [2] where the number of the wavelet coeffcients is equal at each scale.

- Multiresolution - Image Details Of Different Sizes Are Analyzed At The Appropriate Resolution Scales
- Sparsity - The Majority Of The Wavelet Coefficients Are Small In Magnitude
- Edge Detection - Large Wavelet Coefficients Coincide With Image Edges
- Edge Clustering - The Edge Coefficients Within Each Subband Tend To Form Spatially Connected Clusters
- Edge Evolution Across Scales - The Coefficients That Represent Image Edges Tend To Persist Across The Scales

In developing an efficient and robust denoising method for medical ultrasound images one has to take into account the following Adaptation to expert defined features of interest. For an experienced radiologist, speckle noise, which is in medical literature also referred to as \texture" , may present useful diagnostic information . The desired degree of speckle smoothing should ideally depend on the expert's knowledge and on the application at hand like the enhancement for visual inspection or a preprocessing for an automatic segmentation. For an automatic segmentation it is usually preferred to keep the sharpness of the boundaries between different image regions and to smooth out the speckled texture. For a visual interpretation smoothing the texture may be less desirable. Adaptation to spatial context. - In most natural" images including the medical ultrasound images there typically exist a significant spatial correlation [8]. A spatially adaptive denoising can be based on statistical context models like Markov random fields or simply on adapting certain filter parameters based on measurements from a local window around each pixel.

A critical view on the used noise models. - A majority of the speckle filters assume fully developed speckle which is modelled as a multiplicative noise and often simplify that a logarithmic operation transforms speckle into additive white Gaussian noise. Such a speckle model seems to be too simplistic in the case of medical ultrasound images for different reasons. Speckle is not necessarily fully developed and there exist a pronounced spatial correlation. Moreover, the ultrasound devices themselves usually perform a pre-processing of the raw data including even a logarithmic compression. Thus in the displayed medical ultra sound images the noise differs significantly from the often assumed multiplicative model [16].

## IV PROPOSED METHOD

In this section, we discuss image denosing methodology based on SOM neural network model. The image features are extracted from the image using wavelet transform function. SOM acts as a clustering mechanism that projects N-dimensional features from the WT function into an M-dimensional feature space. The resulting vectors are fed into an SOM that categorizes them onto one of the relearned noise classes. The proposed scheme is work along with MS. The MS process the collection task of local intensity of medical image data. The collected noise value combined with high intensity image value and generates vector value for the process. They mapped features from each frame of the word onto the SOM output to form a trajectory of winner nodes for a given word. The SOM learns this trajectory for each denosing constraints value is comprised of a hierarchical organization of SOM and SOM. SOM receives inputs from the WT function bank and maps onto an M-dimensional space where M is the dimensionality of the SOM output node distribution. The transformed feature vectors are fed into the SOM, which classifies them. We call the feature space generated from the WT function output as primary feature space and M-dimensional feature space from SOM output as secondary feature space. The vectors from the secondary feature space are called secondary feature vectors.

## PROCESSING OF PROPOSED ALGORITHM

Step1. Initially input image passes through WT function and decomposed into two layers different value.
Step2.the layers value different higher and lower part.
Step3. The collection of lower intensity value used MS (multiple sequences)
step4. MS collects the local noise value after that combined with high intensity value.
Step5. After collecting total noise value convert into feature vector image data passes through self organized map network
Step6. In phase of feature mapping in feature space of SOM network create a fixed cluster according to threshold of details of image part.
Step7. Here show steps of processing of SOM network

**1)** Initialize each node’s weights.
**2)** Choose a random vector from training data and present it to the SOM.

**3)** Every node is examined to find the Best Matching Unit (BMU).
**4)** The radius of the neighborhood around the BMU is calculated. The size of the neighborhood decreases with each iteration.
**5)** Each node in the BMU’s neighborhood has its weights adjusted to become more like the BMU. Nodes closest to the BMU are altered more than the nodes furthest away in the neighborhood.
**6)** Repeat from step 2 for enough iteration for convergence.
**7)** Calculating the BMU is done according to the Euclidean distance among the node’s weights ($W_1$, $W_2$, … , $W_n$) and the input vector’s values ($V_1$, $V_2$, … , $V_n$).
1) This gives a good measurement of how similar the two sets of data are to each other.
**8)** The new weight for a node is the old weight, plus a fraction (L) of the difference between the old weight and the input vector… adjusted (theta) based on distance from the BMU.
**9)** The learning rate, L, is also an exponential *decay* function.
1) This ensures that the SOM will converge.
**10)** The lambda represents a time constant, and t is the time step
Steps 8. After processing of SOM network out data of image
Step 9. Finally gets denosie image and calculate the value of PSNR and SIM value.

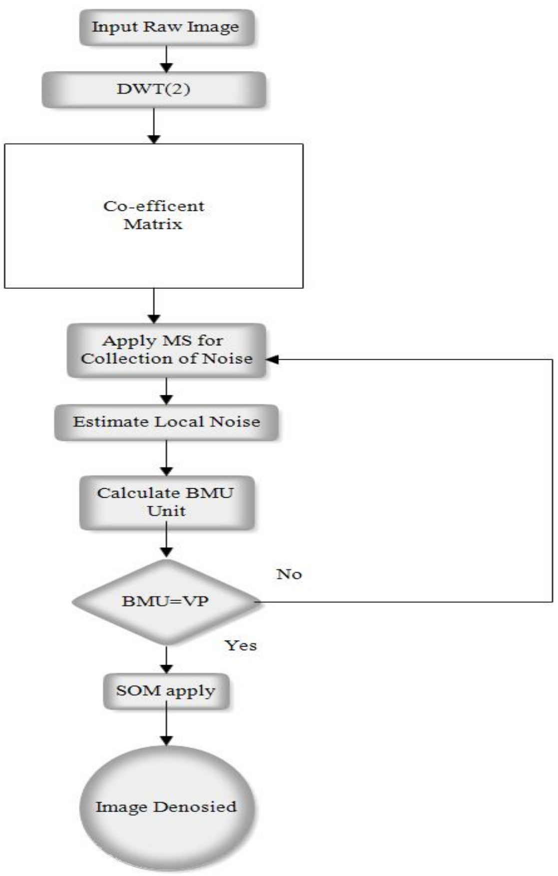


Figure 2: Shows that propsoed model of medical image denosing.

**V EXPERIMENTAL RESULT AND ANALYSIS**

To investigate the effectiveness of the proposed method for image denoising and image filtration. We perform some experimental task; all these tasks perform in matlab 7.8.0 software and well famous image data set such as CT and MRI images of head. For experimental evaluation of our proposed algorithm for image denoising we used very famous image such as Head, Head MRI, Head front CT scan. All images are gray scale and size of resolution is 512*512.

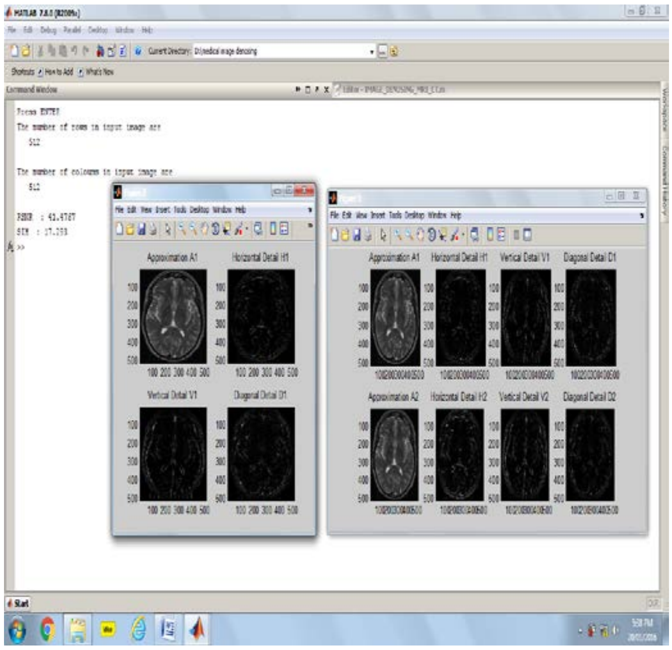

**Figure 3: shows that preprocessing of transformation function of first and second stage for MS method with the approximation, horizontal, vertical and diagonal detail of CT1 image.**

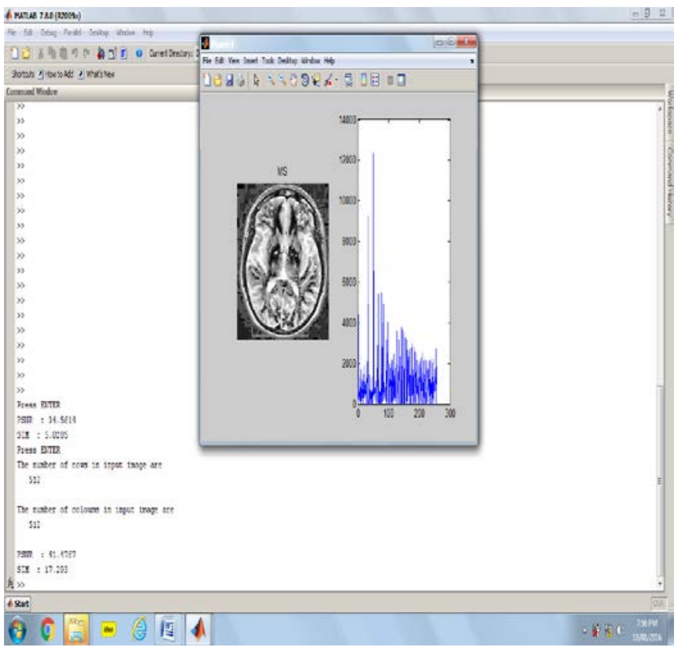

**Figure 4: shows that output image of CT1 for denoised MS method**.

| Denoised method | PSNR | SIM |
|---|---|---|
| Wavelet | 34.5614 | 5.0285 |
| MS | 41.4767 | 17.293 |
| Proposed Method | 75.4616 | 25.4693 |

**Table 1: shows the PSNR and SIM values of all method applied on CT1 image.**

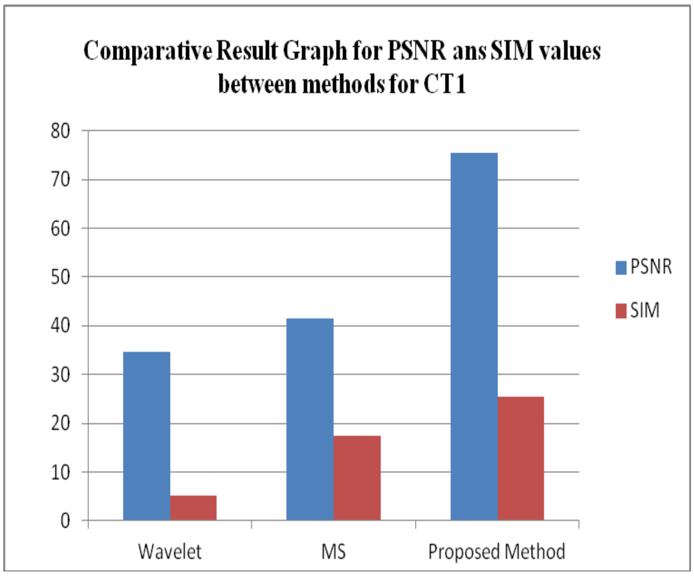


**Figure 5: shows that comparative result graph for PSNR and SIM values between methods wavelet, MS and proposed for image MRI1.**

## VI CONCLUSION AND FUTURE WORK

In this papera hybrid of SOM-MS method based on wavelet transform function and neural networks is proposed. SOM were used to find correlation between noised and original DWT coefficients and approximation. Experimental results showed capability of proposed method to remove noise in terms of PSNR and visual quality. Different architectures and different activation functions is considered. The experimental results show the mean with the traditional denoising methods, the proposed threshold-based denoising digital image denoising algorithm for mixed digital image denoising is relatively clear, especially in the more noise, more complex cases", can show its good performance. In future we used optimizations method for the reduction of time and improvement of quality of image.

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