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A Hybrid Method of Medical Image De-nosing Using Subtraction Transform and Radial Biases Neural Network

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Abstract**—** Image processing plays an important role in medical science for the analysis of heart attack and brain stroke. During the capturing of medical image some noise is induced and makes medical image blurred and unclear. So image de-nosing process is required to make the image noise free .In this paper we propose an image de-nosing method using subtraction transform and RBF neural network. The subtraction transform used basically in the field of voice noise reduction. the RBF neural network model is very efficient due to single layer network. The process of CT and MRI gets the high component value of noise in environment. For the reduction of these noise we have used spectral subtraction de-noising method. The spectral substation method is well recognized method for voice noise reduction. In spectral subtraction method the local noise component value are not considered. In this paper, we discuss image de-nosing methodology based on RBF neural network model comprised of radial biases neural network (RBF). The image features are extracted from the image using SSD function. RBF acts as a clustering mechanism that projects N-dimensional features from the SSD function into an M-dimensional feature space. The resulting vectors are fed into an RBF that categorizes them onto one of the relearned noise classes.

Keywords**—** Medical Image, Noise, Subtraction Transform, RBF

I. INTRODUCTION

In this paper proposed a hybrid method for medical image de-nosing. The medical image de-nosing process is very challenging job for the process of medical disease diagnose. The de-noise image helps for the analysis such as brain stroke, brain tumor and other serious medical disorder[1]. The removal of noise from noisy data to obtain the unknown signal is often referred to as de-nosing. However, there are other filtering techniques that use other statistical estimates such as the median. The Non- Local Means (NLM) filter is one of the most popular de-noise approaches and there have been many improvements regarding its weight function and parameter optimization. The recently proposed nonlocal means algorithm offered remarkably promising results. Unlike previous de-noise methods that rely on the local regularity assumption, the NLM exploits the spatial correlation in the entire image for noise removal[2]. It can adjust each pixel value with a weighted average of other pixels whose neighborhood has a similar geometrical configuration. Since image pixels are highly correlated while noise is typically independently and identically distributed, averaging of these pixels results in noise cancellation and yields a pixel that is similar to its original value. The feature extraction of MR images is done with the consideration of moment invariant functions. They are several groups of moment invariants with respect to the more common degradations image scaling and rotation, image affine transforms, as well as image blurring was given by Chen. In current research trend spectral subtraction technique is very useful for high intensity image de-nosing process. In the process of high intensity of image de-nosing process some local intensity of noise value are not considered[3,4]. The local value noise degraded the performance of image de-nosing process. For the collection of local noise intensity value used genetic algorithm for searching purpose of local value and integrated with self-organized map network for the de-nosing process. The spectral subtraction method is developed by Boll is a popular noise reduction technique due to its simple underlying concept and its effectiveness in enhancing speech degraded by additive noise. The technique is based on the direct estimation of the short-term spectral magnitude. The basic principle of the spectral subtraction method is to subtract the magnitude spectrum of noise from that of the noisy speech. A radial basis function (RBF) is a real-valued function whose value depends only on the distance from the origin. If a function 'h' satisfies the property $h(\boldsymbol{x})=h(\|\boldsymbol{x}\|)$, then it is a radial function[14]. Their characteristic feature is that their response decreases (or increases) monotonically with distance from a central point. The centre, the distance scale, and the precise shape of the radial function are parameters of the model, all fixed if it is linear [2]. II in this section discuss subtraction transform and RBF III. Section describes proposed work in section IV discusses experimental result and finally discuss conclusion and future work in section V.

II. SSD AND RBF FUNCTION

The spectral subtraction method is developed by Boll is a popular noise reduction technique due to its simple underlying concept and its effectiveness in enhancing speech degraded by additive noise. The technique is based on the direct estimation of the short-term spectral magnitude[1]. The basic principle of the spectral subtraction method is to subtract the magnitude spectrum of noise from that of the noisy speech. The noise is assumed to be uncorrelated and additive to the speech signal the conventional power spectral subtraction method substantially reduces the noise levels in the noisy speech. However, it also introduces an annoying distortion in the speech signal called musical noise. Due to the inaccuracies in the short-time noise spectrum estimate, large spectral variations exist in the enhanced spectrum causing these distortions. Also, occasional negative estimates of the enhanced power spectrum can occur. In such cases, the negative spectral components are floored to zero or to some minimal value, causing further distortions in the time signal.

Additive Noise Model

Assume that a windowed sequence n(k) has been added to a windowed image signal s(k), with their sum denoted by x(k). Then, x (k) = s (k) + n (k)

Taking the Fourier transform gives $X(e^{j\omega}) = S(e^{j\omega}) + N(e^{j\omega})$

Where $x(k) \leftrightarrow X(e^{j\omega})$

$$X(e^{j\omega}) = \sum_{k=0}^{L-1} x(k) e^{-j\omega k}$$

Where L is the window length

$$x(k) = \frac{1}{2\pi}\int_{-\pi}^{+\pi} X(e^{j\omega}) e^{j\omega k}\, dw$$

Spectral Subtraction Estimator

The spectral subtraction filter $H(e^{j\omega})$ is calculated by replacing the noise spectrum $N(e^{j\omega})$ with spectra which can be readily measured. The Magnitude $|N(e^{j\omega})|$ of $N(e^{j\omega})$ is replaced by its average value $\mu(e^{j\omega})$ taken during non-image activity, and the phase $\theta_N(e^{j\omega})$ on $N(e^{j\omega})$ is replaced by the phase $\theta_x(e^{j\omega})$ of $X(e^{j\omega})$. These substitutions result in the spectral subtraction estimator

RBF Neural Network

A radial basis function (RBF) is a real-valued function whose value depends only on the distance from the origin. If a function 'h' satisfies the property $h(\boldsymbol{x})=h(\|\boldsymbol{x}\|)$, then it is a radial function. Their characteristic feature is that their response decreases (or increases) monotonically with distance from a central point. The centre, the distance scale, and the precise shape of the radial function are parameters of the model, all fixed if it is linear [14]. A typical radial function is the Gaussian which, in the case of a scalar input, is

$$H(X)=\exp((-(x-c)^2)/(r^2)) \ldots\ldots\ldots\ldots (1)$$

Its parameters are its centre *c* and its radius *r*.

A Gaussian RBF monotonically decreases with distance from the centre. In contrast, a multi-quadric RBF which, in the case of scalar input monotonically increases with distance from the centre. Gaussian-like RBFs are local (give a significant response only in a neighborhood near the centre) and are more commonly used than multi-quadric-type RBFs which have a global Response. Radial functions are simply a class of functions. In principle, they could be employed in any sort of model (linear or nonlinear) and any sort of network (single-layer or multi-layer). RBF networks have traditionally been associated with radial functions in a single-layer network. In the Figure 4.4, the input layer carries the outputs of FLD function. The distance between these values and centre values are found and summed to form linear combination before the neurons of the hidden layer. These neurons are said to contain the radial basis function with exponential form. The outputs of the RBF activation function is further processed according to specific Requirements.

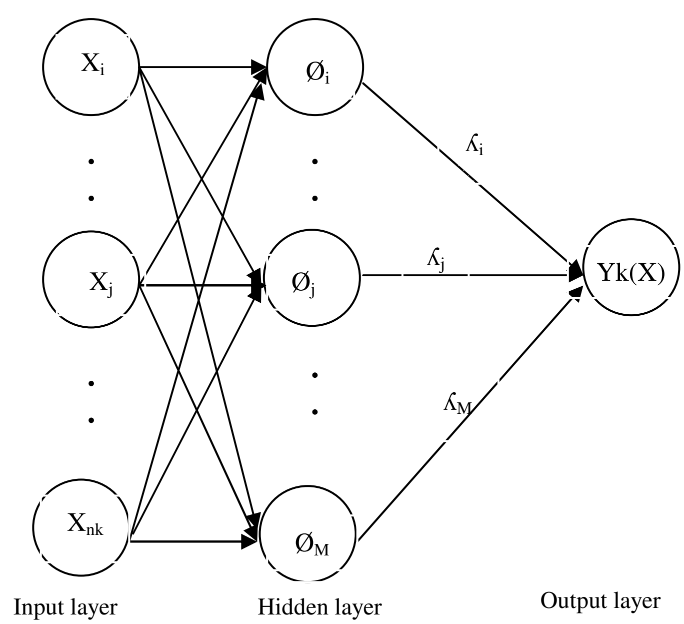

Figure 1 Structure of Radial Basis Function Neural Network.

III. PROPOSED ALGORITHM

In this section, we discuss image de-nosing methodology based on RBF neural network model comprised of radial biases neural network (RBF). The image features are extracted from the image using SSD function. RBF acts as a clustering mechanism that projects N-dimensional features from the SSD function into an M-dimensional feature space. The resulting vectors are fed into an RBF that categorizes them onto one of the relearned noise classes. 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 RBF output to form a trajectory of winner nodes for a given word. The RBF learns this trajectory for each de-nosing constraints value is comprised of a hierarchical organization of RBF.
RBF receives inputs from the SSD function bank and maps onto an M-dimensional space where M is the dimensionality of the RBF output node distribution. The transformed feature vectors are fed into the RBF, which classifies them. We call the feature space generated from the SSD function output as primary feature space and M-dimensional feature space from RBF output as secondary feature space. The vectors from the secondary feature space are called secondary feature vectors.

Step for proposed methodology.

1. Input degraded image
2. Perform subtraction transform and image decomposed in layers.
3. Estimate coefficient of subtraction transform.
4. Apply soft thresholding of subtraction transform
5. Check value of coefficient of subtraction transform
6. Decide the size of vector input 4*4
7. Trained the network.
8. Apply target value of activation function
9. Find PSNR with SIM variance
10. Image denoised result.

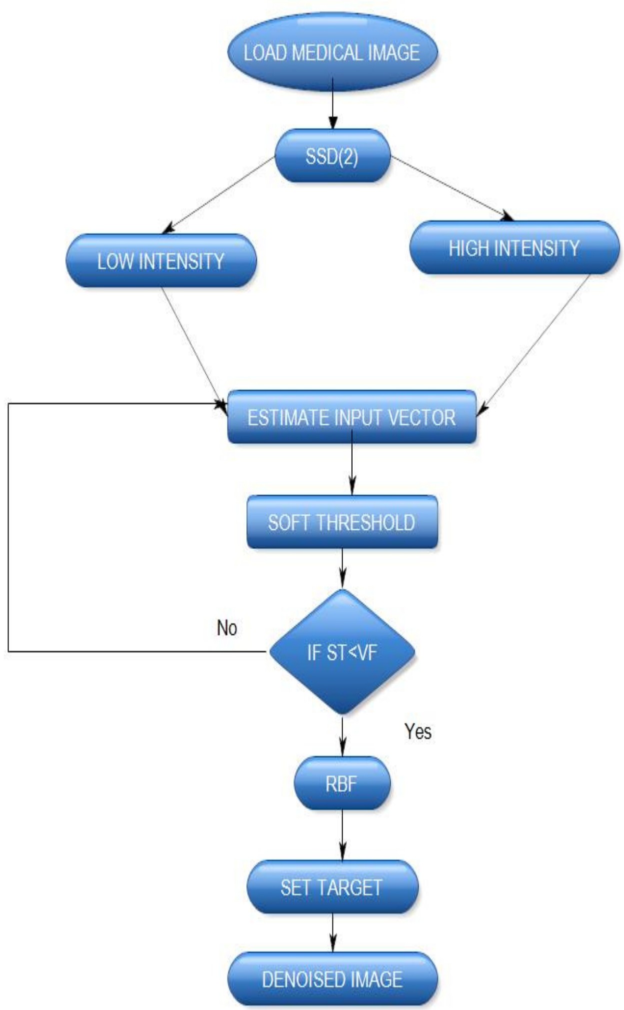

Figure 2 proposed model of medical image de-nosing using RBF and SSD transform

IV. EXPERIMENTAL RESULTS

For the evaluation of performance of proposed algorithm used MATLAB software and some standard medical image and measure two parameter PSNR and SIM, also implement two algorithm SSD and ADF

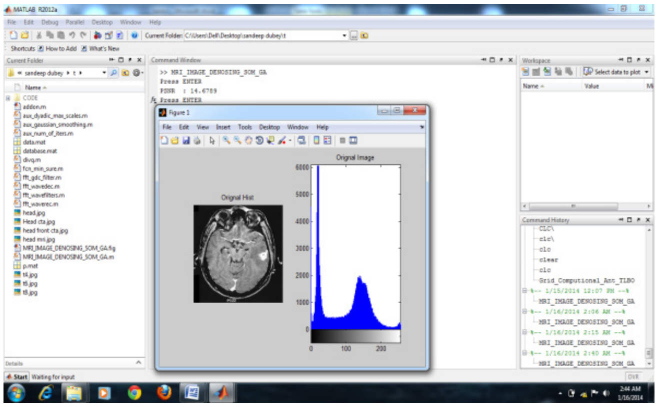

Fig:1 shows that input image Head MRI for denoise method SSD.

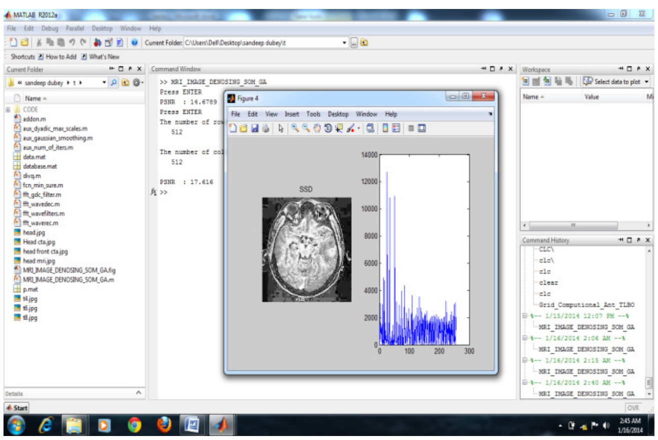

Figure 2shows that input image Head MRI for de-noised method SSD and PSNR value of improved image is 17.61.

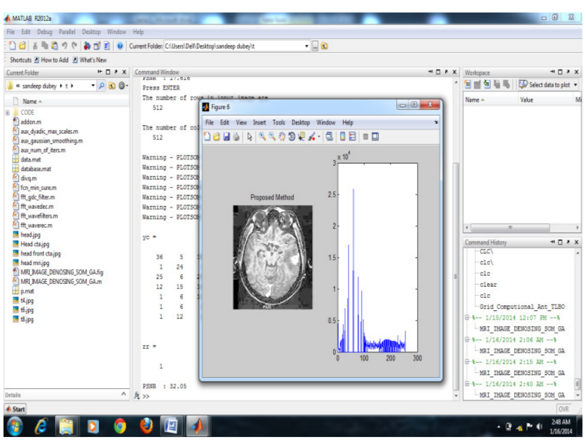

Figure 3 shows that input image Head MRI for proposed method and PSNR value of improved image is 32.05.

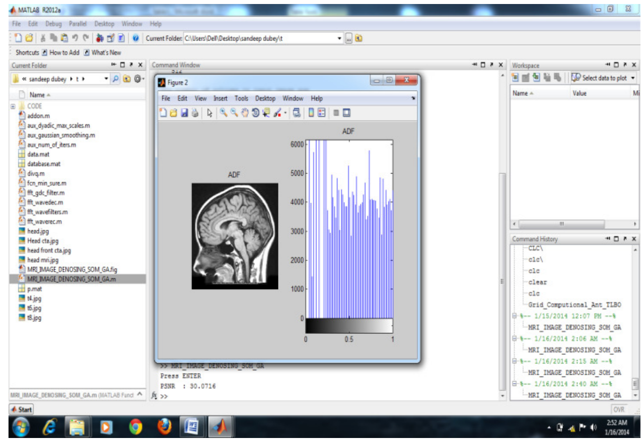

Figure 4 shows that input image Head front CTA scan for ADF method, and PSNR value of improved is 30.07.

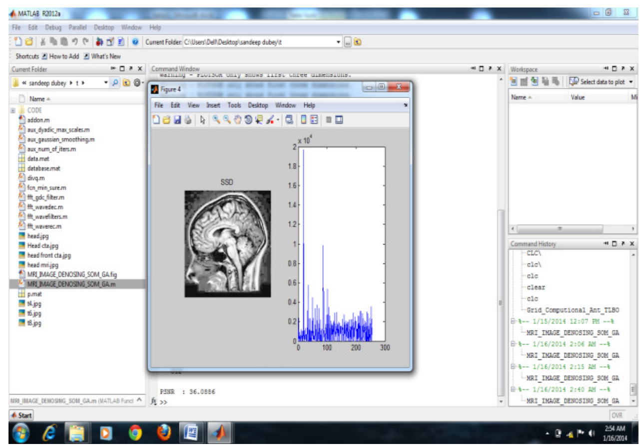

Figure 5 shows that input image Head front CTA scan for proposed method, and PSNR and SIM value of improved is 65.65.

For Head image resolution 512* 512 and variance 0.006

De-noised method	SIM(DB)	PSNR(DB)	Image Type
ADF	28.34	34.5614	HEAD
SSD	34.56	41.4767	HEAD
RBF	48.641	26.36	HEAD
Proposed Method	56.79	75.46	HEAD

Table 5.4.1 shows the PSNR and SIM value of all method applied on Head image.

For Head MRI image resolution 512* 512 and variance 0.006

De-noised method	SIM(DB)	PSNR(DB)	Image Type
ADF	8.34	14.67	HEAD MRI
SSD	6.43	17.61	HEAD MRI
RBF	14.641	22.36	HEAD MRI
Proposed Method	20.56	32.05	HEAD MRI

Table 2 shows the PSNR value of all method applied on HEAD MRI image

For Head front CTA scan image resolution 512* 512 and variance 0.006

De-noised method	SIM(DB)	PSNR(DB)	Image Type
ADF	19.34	30.07	HEAD Front CTA
SSD	21.43	36.08	HEAD Front CTA
RBF	48.583	21.55	HEAD Front CTA
Proposed Method	34.54	65.65	HEAD Front CTA

Table 3 shows the PSNR value of all method applied on Head font

CTA scan image.

Figure 6 shows that comparative result analysis of head image of three methods. Result indicates that increase value of PSNR and SIM

Figure 7shows that comparative result analysis of head MRI image of three methods. Result indicates that increase value of PSNR and SIM.

Figure 8 shows that comparative result analysis of head CT front image of three methods. Result indicates that increase value of PSNR and SIM.

CONCLUSION AND FUTURE WORK

In this paper proposed a hybrid method for medical image denosing. The proposed method is combination of two different functions one is subtraction transform and another is RBF neural network. The RBF neural network is single layer network and processing is very efficient. Our experimental result shows that proposed method is better than ADF and SSD. For the evaluation of parameter used two parameter one is PSNR and other is SIM. The increasing value of PSNR and SIM shows that method is efficient but suffered from time complexity. Due to training of neural network model, the process of algorithm takes more time. In future reduces the time complexity of algorithm.

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