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Image Restoration using combined Adaptive Weiner Filter and Radial Basis Function ANN with Sub-block Decomposition for Medical Applications

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ABSTRACT

Image restoration is a critical application in image processing where Artificial Neural Network (ANN) approaches have continuously provided improved results. Here, we propose an adaptive image restoration technique based on combination of Adaptive Weiner Filter (AWF) and Radial Basis Function (RBF) which is a type of ANN with a sub-block decomposition technique. The combination of the AWF and RBF with the sub-block based decomposition provides improved results for medical images. The work initially performs an adaptive image restoration using AWF. In this process a sequence of sub-blocks are extracted from the image and block-wise restoration performed using AWF and then RBF approach. The results when compared to traditional approach as well as RBF ANN sub-block decomposition approach show that the proposed Combined AWF and RBF with sub-block decomposition based approach provides better outcomes. Experimental results show that higher peak signal to noise ratio (PSNR) values are obtained using the sub-block decomposition technique which, however, contributes towards increased computational complexity.

Keywords:- AWF, ANN, restoration, RBFN, sub-block decomposition.

I. INTRODUCTION

Image restoration is a process imparted in the image using certain objective criteria and prior knowledge so that its visual appearance improves considerably. An image may be degraded because of the modification of the gray values of the individual pixels due to some factors, or it may be distorted because the position of the individual pixels may be shifted away from their correct position [1]. Since present-day imaging technology is not perfect, every recorded image is degraded in some sense. Every imaging system has a limit to its available resolution and the speed at which images can be recorded. Various image restoration methods have been proposed in the literature. For the restoration of nonlinear degraded images, the linear filters like Wiener filter and recursive Kalman filter are not suitable. Hence, many nonlinear filtering techniques have been proposed and applied to nonlinear image restoration. Generally, the Order statistics based filters have good behavior in suppressing the additive white noise or impulsive noise and preserving image edges because they have well-design estimators that minimize the mean-square error (MSE) between the filter output and the noise free signal. However, these filters are in general not very effective against nonlinear blur functions [2]. On the other hand, the ANN filters show robust performance for restoration of images degraded by nonlinear distortions [3-7]. ANN systems are massively parallel and distributed processors that have natural propensity for storing and recalling experiential knowledge [3]. As potential tools, ANNs have been successfully applied in image processing mainly due to the ability to generate and recall an internal data representation through pattern examples learning [4]. Some encouraging results on image restoration using neural networks have been reported in literatures [4-8]. Among them, the approaches proposed in [5] and [6] that use a feedforward nonlinear network called the radial basis function networks (RBFN) and the technique of learning by examples show much effectiveness. It is known that the model-based image restoration techniques may fail badly when the assumed model is either incorrect or incomplete. On the contrary, the approaches based on learning by examples can dynamically learn the actual degradation process. Other works report the use of several ANN models for image restoration tasks. Some examples are the Hopfield, Multilayer Perceptron (MLP) and the Self Organizing Map (SOM) networks[4],[8]. Use of these ANNs in image restoration techniques plays very different roles. The Hopfield network tries to find out a stable state of the network as a solution for a constrained least square error measure with a regularization term. This method requires that the blurring matrix is known, and also suffers from the construction of energy function for network weights updating.

The latter method intends to approximate a nonlinear filter through examples learning [7].

Here, we propose an adaptive image restoration technique based on combination of Adaptive Weiner Filter(AWF) and Radial Basis Function (RBF) which is a type of ANN with a sub-block decomposition technique. The combination of the AWF and RBF with the sub-block based decomposition provides improved results for medical images. The work initially performs an adaptive image restoration using AWF. In this process a sequence of sub-blocks are extracted from the image and block-wise restoration performed using AWF and then RBF approach. The results when compared to traditional approach show that the proposed approach provides better outcomes. Experimental results show that higher peak signal to noise ratio (PSNR) values are obtained if the sub-blocks are pre-processed with Adaptive Weiner filtering before RBF ANN technique is applied , however, it contributes towards increased computational complexity.

II. IMAGE RESTORATION TECHNIQUES

Image Restoration has several techniques as per literature. But here we are using a combination of Adaptive Weiner Filter and RBF NN for the purpose.

A. Image Restoration using Adaptive Weiner Filter

Wiener filter is a well known filter technique to remove noise and invert the blurring image simultaneously. This technique is quite popular among medical imaging to enhance the quality of images. The concept of Wiener filter is to approximate F (x, y) from undegraded f(x, y) so that it minimize the mean square error (MSE) between f(x,y) the original image with F(x,y) the estimate restore image. Wiener filter equation was given by

$$F(u,v)=\left[\frac{H^*(u,v)}{|H(u,v)|^2+\dfrac{S_{vv}(u,v)}{S_{ff}(u,v)}}\right]G(u,v) \qquad (1)$$

where $F(u,v)$ is estimate of undegraded image, $H^*(u,v)$ is complex conjugate of $H(u,v)$ (degradation function), $G(u,v)$ is degraded image and $\dfrac{S_{vv}(u,v)}{S_{ff}(u,v)}$ is the ratio of the power spectrum of the noise to the power spectrum of the undegraded image. In order to calculate the estimate of F (u, v), we must know the degradation function H (u, v) or point spread function (PSF) for the image. In this procedure of image restoration, the degradation function was assumed as 2D Gaussian function model. The 2D Gaussian function model can be expressed by

$$f(x,y)=Ae^{-[\frac{(x-x_0)^2}{2\sigma^2{}_x}+\frac{(y-y_0)^2}{2\sigma^2{}_y}]} \qquad (2)$$

where A is a constant which A > 0 and σ is the variance[17]. An advantage of Wiener filter is it takes noise effect into consideration for image restoration but the practical problem is that the information about the undegraded image and the noise is not easily available. Some techniques for calculating the point spread function are proposed in [16]. So the significant part of this filter is to find the power spectrum of noise and power spectrum of original image which are $S_{vv}(u,v)$ and $S_{ff}(u,v)$ respectively. In this experiment, the estimate ratio of $\dfrac{S_{vv}(u,v)}{S_{ff}(u,v)}$ value is treated as constant, so to find the best value of the constant, try and error technique is used.

The adaptive process involves the use of a cost function, which is a criterion for optimum performance of the filter, to feed an algorithm, which determines how to modify filter transfer function to minimize the cost on the next iteration [14]. Weiner filter proves to be a good image restoration technique in the frequency domain but it does not give satisfactory results in the nonstationary environment. So Adaptive Weiner filter is designed using Least Mean Square (LMS) algorithm of the adaptive filters. The conventional LMS algorithm was extended to the 2D case by Hadhoud and Thomas [15]. The steps of the algorithm for adaptive Weiner filtering for a 2-D case maybe summarized as below as given in [12]:

1. Set the step size of the LMS algorithm.

2. Take a very smal value to which the error is to be reduced,say e_{min}=0.000001.

3.Formulate the Weiner filter.

Loop:

4. Get the estimated image in the frequency domain: Compute the 2D inverse FFT to obtain

5. Compute the error e.

6. Update the Weiner filter with 2D LMS weight update equation.

7. Goto step 4 while $e > e_{min}$.

8: If condition 6 is not met, stop.

B. Image Restoration using RBFN

Consider the following image restoration model:

$$g = P(f, n) \quad (3)$$

where P is an blur matrix, f and g are the original and degraded images, respectively, and n is a noise source [4] .

Radial basis function network (RBFN), with the simplicity of its single-hidden layer structure, is a good alternative to multilayer perceptron, especially in the applications requiring local tunable property. Linear output layer and radial basis hidden layer structure of RBFN provide the possibility of learning the connection weights efficiently without local minima problem in a hierarchical procedure so that the linear weights are learned after determining the centers by a clustering process. The construction of RBFN involves three different layers: *Input layer* which consists of source nodes, *hidden layer* in which each neuron computes its output using a radial basis function and *output layer* which builds a linear weighted sum of hidden layer outputs to supply the response of the network [9].

RBFN with one output neuron as shown in Figure 1 implements the input–output relation :

$$y_k = \sum_{j=1}^{N} w_{jk} \phi_j (| x - \mu_j |) + w_{0k} \quad (4)$$

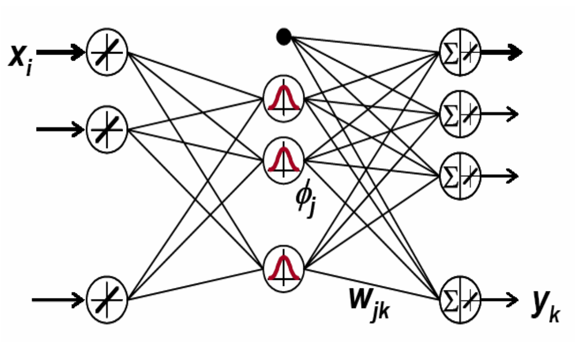

Fig 1. RBF network structure

In designing the RBF network, a key issue that needs to be addressed is how to compute the parameters of the Gaussian units that constitute the hidden layer.

RBF network learning process is a hybrid mechanism consisting of unsupervised selection of RBF centers - self organised selection of centres and supervised learning stage – to estimate the synaptic weights of the output. The K-means clustering algorithm is used for unsupervised selection of RBF centers [9].

III. PROPOSED SYSTEM OF IMAGE RESTORATION USING COMBINED AWF-RBFN INCLUDING SUB-BLOCK DECOMPOSITION TECHNIQUE

The proposed work consists of several parts. The work initially performs an adaptive image restoration using Adaptive Weiner Filter. The image is decomposed into sub-blocks, which are extracted and block-wise filtering is performed. These AWF filtered blocks are again restored using RBF ANN approach. These aspects are described in details in the subsequent sections.

A. *Adaptive Weiner Filtering using sub-block decomposition based technique*

This proposed technique generates a sequence of sub-blocks from the input image. After this step, block-wise adaptive Wiener filtering is performed. The original image of size M by N is divided into smaller blocks each of size M1 by N1. The 2-D image is then converted into a 3D stack form as shown in Figure 2. The above adaptive Weiner filtering is then applied to each block. A restored 2-D image is reconstructed from restored 3-D stack . The flowchart of this proposed technique is shown in Figure 4 [12].

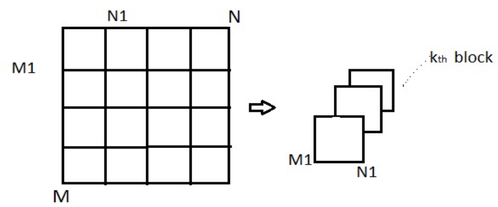

Fig 2. 2-D image converted into 3 D stack

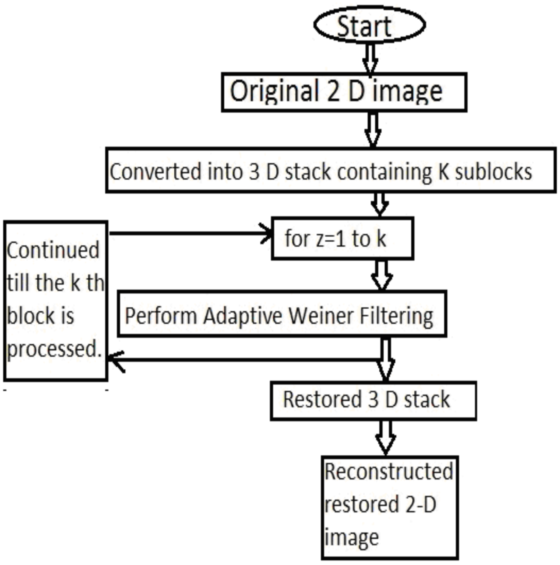

Fig3. Flowchart for restoration using Adaptive Weiner Filtering applied to constituent sub-blocks of the image.

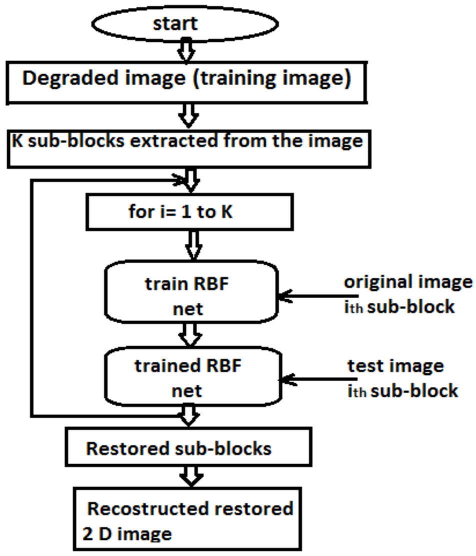

Fig 4. Flowchart for the RBF-ANN sub-block decomposition method.

B. Restoration using RBF ANN with Sub-block Decomposition

In [13], the proposed technique generates a sequence of sub-blocks from the degraded image. After this step, block-wise RBF ANN filtering is performed. The results are compared which show that this second approach provide better outcomes. The original image of size M by N is divided into smaller blocks each of size M1 by N1. The 2-D image is then converted into a 3D stack form as shown in Figure 2. The above restoration process is then applied to each block. A restored 2-D image is reconstructed from restored sub-blocks. Figure 4 shows the flowchart for the sub-block decomposition method.

C. *The proposed technique of Restoration usingAWF- RBF ANN with Sub-block Decomposition*

The work initially performs an adaptive image restoration using AWF. In this process a sequence of sub-blocks are extracted from the image and block-wise restoration performed using AWF and then RBF ANN approach. The flowchart for the proposed algorithm is shown in figure 5.

IV. RESULTS

The results derived are shown for the two separate approaches preferred for the image restoration work. Firstly, the results for restorartion using only RBF NN is shown, which is later compared with the proposed technique of combined AWF –RBF ANN with sub-block decomposition.

A. *Results for restoration using RBF ANN Combined with Sub-block decomposition technique*

The original image is of size 225×225 which is decomposed to extract 9 sub-blocks each of size 75 × 75. The decomposed sub-blocks are processed. A training matrix is formed and applied to the RBF ANN. At the end of the training the RBF is tested. The training of the RBF network is performed with original non degraded image sub-blocks as outputs and the corresponding degraded image sub-blocks as the inputs to the RBF network. The trained network is then tested with degraded test image. The average PSNR value of the sub-blocks for the variation in the error goal is shown in Table 1.

Figure 6 shows degraded image. Figure 7 shows the restored image using this technique with a PSNR value of 54.8271 dB.

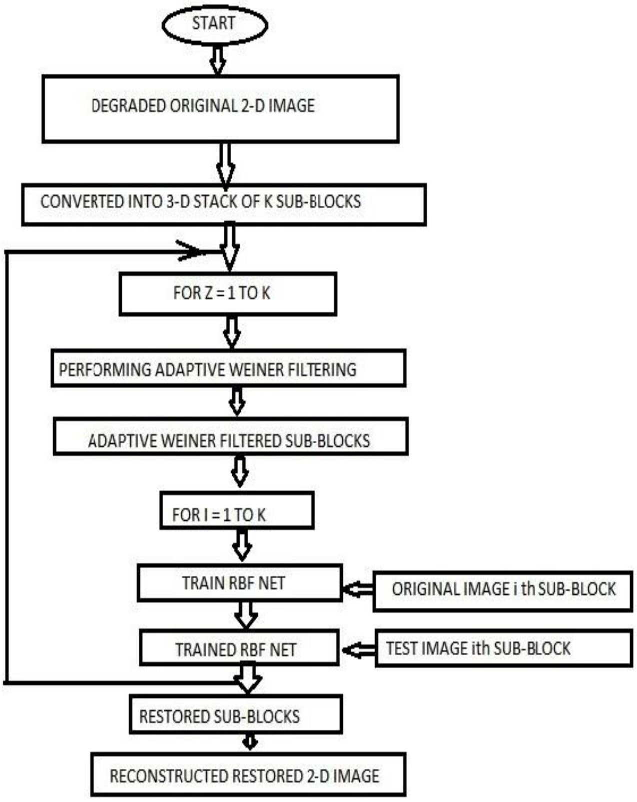

Fig 5. Flowchart for the proposed method of combined AWF – RBFN with sub-block decomposition method.

TABLE I

PSNR(DB) OF THE RESTORED IMAGE FOR VARIATION IN ERROR GOAL AND NO. OF EPOCH USING RBF ANN WITH SUB-BLOCK OF SIZE 75×75.

Error goal	No. of epochs	PSNR(dB)
0.02	21	20.1023
0.002	105	29.6543
0.0002	166	38.8712
0.00002	178	45.4467
0.000002	195	49.8812
0.0000002	201	55.9453
0.00000002	213	60.1258

B. *Results for restoration using combination of Adaptive Weiner filter and RBF ANN with sub-block decomposition*

The methods proposed in [12] and [13] are combined and modified to construct a new algorithm which has given improved results. The original image is of size 225×225 which is decomposed to extract 9 sub-blocks each of size 75 × 75. The decomposed sub-blocks are processed. Adaptive Weiner Filtering is performed on each sub-block and then each restored sub-block is again fed to the RBF NN for further improvement in the restoration process of the sub-blocks. A training matrix is formed and applied to the RBF ANN. At the end of the training the RBF is tested. Table 2 clearly shows that this technique gives better results compared to the previous one. Figure 8 shows the restored image using this technique.

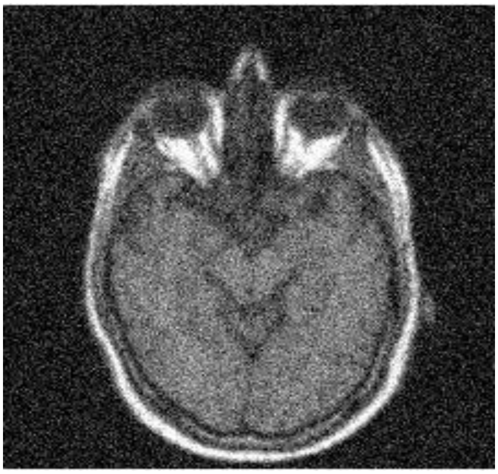

Fig 6. Degraded MRI image

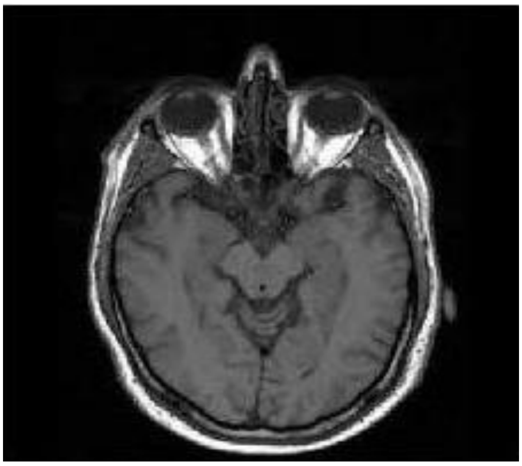

Fig 7. Restored image using RBFN. PSNR (dB) obtained is 54.8271 dB

The proposed technique shows an improvement of the PSNR by 5% to 6%. Since two different restoration techniques are combined into one algorithm, it, however, increases the computational complexity which can be reduced by adopting methods proposed by [11]. Thus the proposed method shows better performance characteristics and is suitable for medical applications.

TABLE III
PSNR(DB) OF THE RESTORED IMAGE FOR VARIATION IN ERROR GOAL AND NO. OF EPOCH USING COMBINED AWF AND RBF ANN WITH SUB-BLOCK OF SIZE 75×75.

.Error goal	PSNR (dB) of the restored image using RBFN with sub-block decomposition (sub-block size 75×75	PSNR (dB) of the restored image using AWF - RBFN with sub-block decomposition (sub-block size 75×75)
0.02	20.1023	21.4532
0.002	29.6543	30.1238
0.0002	38.8712	39.5691
0.00002	45.4467	46.8213
0.000002	49.8812	50.5612
0.0000002	55.9453	57.1024
0.00000002	60.1258	61.9714

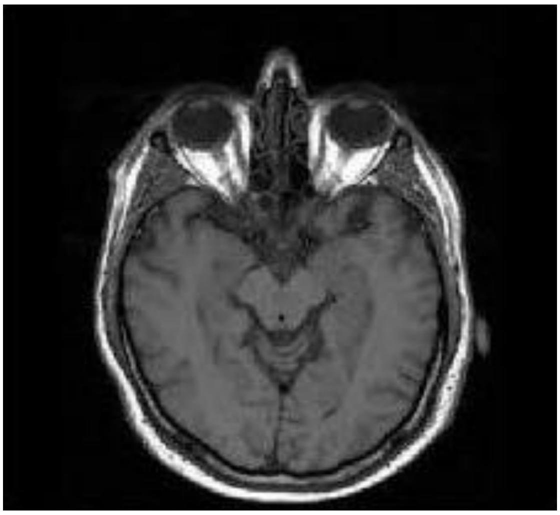

Fig. 8 .Restored image using sub-block decomposition technique. PSNR (dB) obtained is 61.9714 dB

V. CONCLUSIONS

Here we proposed a combination of Adaptive Weiner Filter and RBF NN with sub-block decomposition based image restoration approach. The performance of the proposed algorithm of restoration is tested with PSNR values obtained. But it raises computational complexity marginally. Compared to previously reported work, the proposed technique shows improvement for which the method is found to be suitable for medical applications. The effectiveness of the system is verified using certain medical images. The computational complexity can be reduced by better hardware and improved processing techniques.

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