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Noise Removal using Chebyshev Functional Link Artificial Neural Network with Backpropagation

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Abstract: In this proposed work, we have used an alternate ANN structure called Functional link ANN for image denoising. In contrast to other feed forward neural networks, the FLANN is a single layer structure, which never contain any hidden layer and non-linearity is introduced by enhancing the input pattern with a nonlinear function expansion called Chebyshev functional expansion. With the Chebyshev functional expansion, the network shows very good result in denoising the image corrupted by four different noise called Salt and Pepper noise, Gaussian noise, Speckle noise and Poisson noise. In this paper Gaussian noise is added to the speckle noise to give better result. In particular FLANN structure with Chebyshev functional expansion works best for Poisson noise suppression from an image. Here Back Propagation network is used to train the Chebyshev expanded image. BP network can be used to learn and store a great deal of mapping relations of input-output models, and no need to disclose in advance the mathematical equation that describes these mapping relations. Feed Forward Back Propagation (FFBP) algorithm performs quite well in the presence of different noise while preserving the image features satisfactorily.

Keywords: FLANN, Chebyshev Expansion, Back Propagation, Salt and Pepper noise, Gaussian noise, Poisson noise, Speckle noise.

I. INTRODUCTION

Image Denoising

The major task of image processing is Image denoising. The aim of image denoising is to remove or reduce the noise to give the best quality images for various different applications. In our earlier days, linear models have been used to remove the noises. The advantage of using linear model is easy to implement and it also very speed, but it cannot preserve the edges. The alternative non linearity method is used which better preserve the edges and major features of the image. It becomes the major stream approaches in the field of image denoising [1]. The image filter must adapt the image local statistics, the noise type, and the noise power level and it must adjust itself to change its characteristics so that the overall filtering performance has been enhanced to a high level. One of the most important example of it is neural network based adaptive image filter [2].

Different type of noise

One type of impulse noise is salt and pepper noise which appears in the image when some of the pixels replaced by the outliers whereas the remaining pixels remains unchanged. It was proven that Neural Network with Back propagation along with median filtering work effectively in the removal of salt and pepper noise [3]. One type of statistical noise is Gaussian noise and its having a probability density function which is equal to that of the normal distribution [4]. The most common type of noise is Poisson noise where the intensity value of the pixels changed based on Poisson distribution [5]. Speckle noise is a granular noise which inherently exists in the synthetic aperture radar, medical ultrasound and tomography images [6].

Artificial Neural Network

ANN is a computational model which is used to simulates the functions of biological neural network. It is an adaptive system that changes its construction based on external or internal information that flows through the network during the learning phase. It is used to model the complex relationships between inputs and outputs.

Functional Link ANN

Pal [8], plan the FLANN Architecture, is a solitary layer artificial neural network structure and it is proficient for performing complex choice regions by creating nonlinear decision boundaries [7]. In contrast to linear weighting of the input pattern, the functional link acts on the entire pattern by generating a set of linearly independent functions. The work of Sudhansu [2] and his team shows that the FLANN work more effectively and it requires very less computation compared to Multilayer Feed Forward Neural Network [2]. For the functional expansion of FLANN, we chose the Chebyshev expansion, it was already proven that Chebyshev expansion produce more accuracy compare to other expansions such as trigonometric and exponential expansion [7].

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II.STRUCTURE OF THE FUNCTIONAL LINK NEURAL NETWORK FILTERS

The FLANN is capable of performing complex decision regions by generating nonlinear decision boundaries. There is no need of hidden layers in this network. If network has two inputs, then X is x1 and x2.
An enhanced pattern obtained by using functional expansion is given by

$X = [1\ x_1\ T_1\ (x)\ x_2\ T_2\ (x_2) \ldots\ ]'$. …………**1**

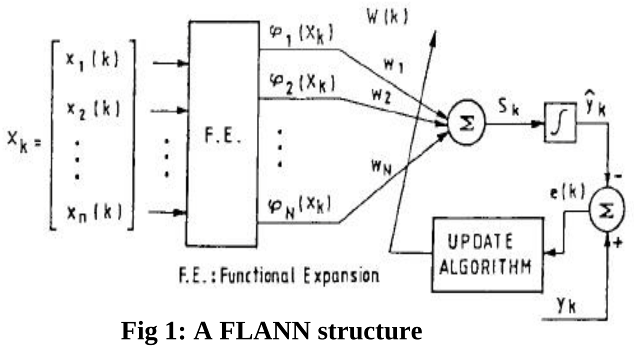

Fig 1: A FLANN structure

In this paper the input pattern of the noisy image is sent to the input node of the FLANN structure and an enhanced pattern is obtained. The target will be the corresponding single pixel from an original image. This process continues iteratively till all pattern of the image gets completed. The whole process continues for 100 times to find out error power with iteration. The BP algorithm used to train the FLANN becomes simple and has a faster convergence due to its single layer architecture. For functional expansion of the input pattern, Chebyshev expansion is chosen individually.

Chebyshev Expansion:

The Chebyshev polynomials are a set of orthogonal polynomials defined as the solution to the Chebyshev differential equation. These higher Chebyshev polynomials for -1<x<1 may be generated using the recursive formula given by

$$T_{n+1} = 2xT_n(x) - T_{n-1}(x) \qquad \ldots 2$$

The first few Chebyshev polynomials are given by

$$\left.\begin{aligned} T_0(x) &= 1 \\ T_1(x) &= x \\ T_2(x) &= 2x^2-1 \\ T_3(x) &= 4x^3-3x \\ T_4(x) &= 8x^4-8x^2+1 \\ T_5(x) &= 16x^5-20x^3+5x \end{aligned}\right\} \ldots \mathbf{3}$$

Chebyshev polynomial expansion needs a less number of computations and is very easy to implement than the other types of polynomial expansion such as trigonometric and exponential expansion which was proven by sudhansu and his team [2]. The Chebyshev polynomial expansion gives better performance for the prediction of financial time series.

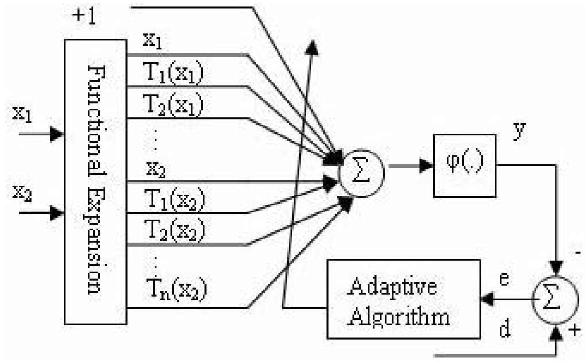

Fig 2: A CHNN Structure

Back Propagation:

Back propagation algorithm is computationally effective and works well with optimization and adaptive techniques, which makes it very attractive in dynamic nonlinear systems. This network is popular general nonlinear modelling tool because it is very suitable for tuning by optimization and one to one mapping between input and output data. The input-output relationship of the network.

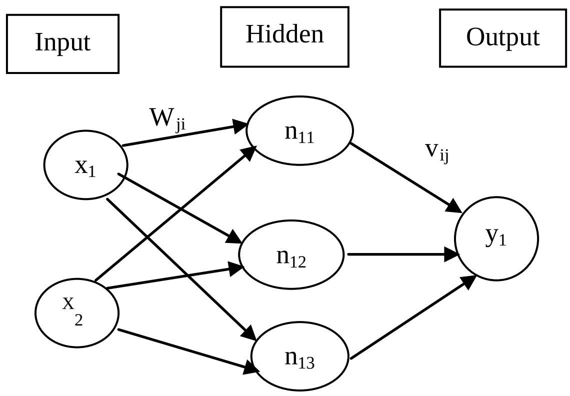

Fig 3: Network Architecture

There are three-layers in BP network, its input node is xi, the hidden node is n_{ij}, and the node of the output layer is y_i. The weight value of network between the input node and hidden layer is w_{ji}, and the weight value of network between the hidden layer and output layer is v_{ij}. The expected value of the output node is y_1, where f(x) is the active function.

III. PROPOSED METHODOLOGY

The following flowchart contain the steps involved in the process. At first the input image is read and convert into grayscale over which noise is added to the image and is made expand using Chebyshev functional link ANN and made to train in Back Propagation. The expanded pattern is used to train by random weight generation and made to produce error. The nonlinear function is used to update weight.

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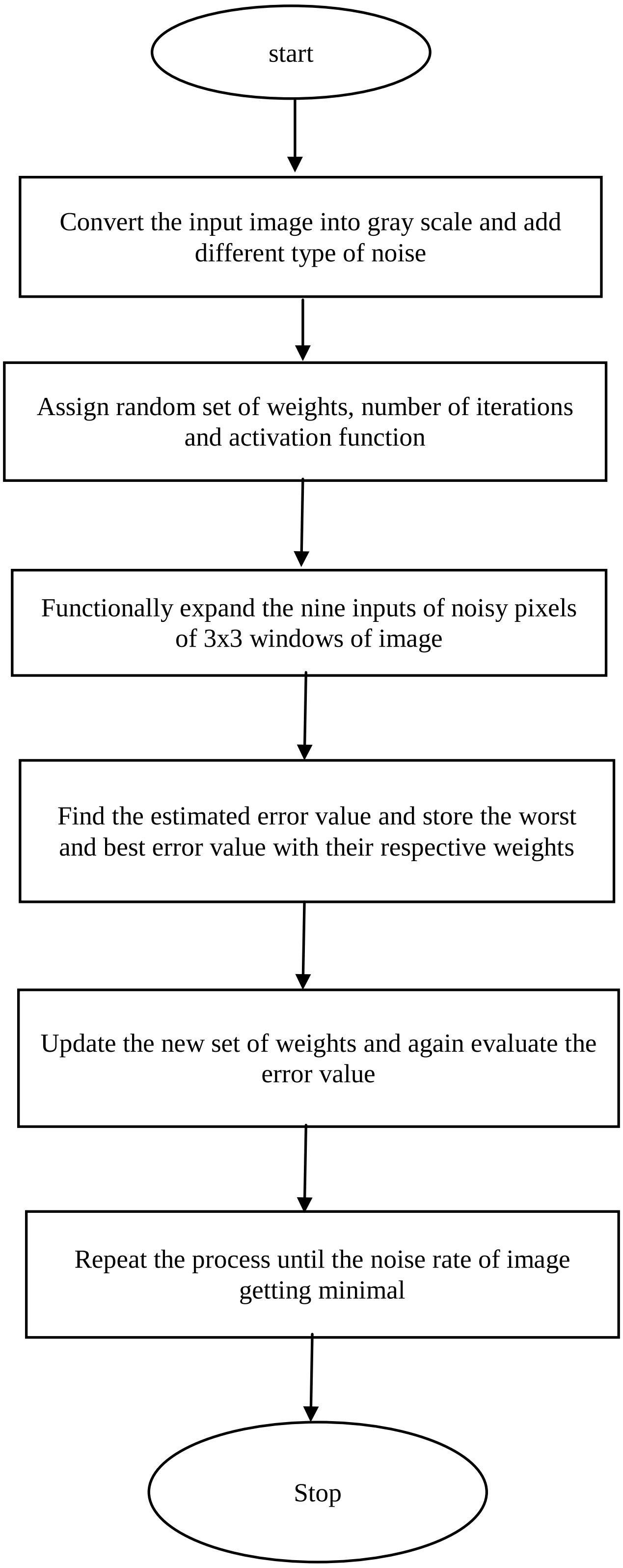

Fig 5: Flowchart for Proposed Methodology

IV. RESULTS AND DISCUSSIONS

Extensive simulation studies were carried out with several examples to compare performance FLANN for denoising of images. This work is carried out with four different noises. Different parameters are decided after experimenting with different values of the parameters. It is observed that large window size, more hidden layer or more numbers of hidden layer neuron does not sure to produce better results. In all types of FLANN the input pattern is expanded in such a way that the total numbers of weights in the ANNs are approximately same. The structure of FLANN is {9-1}. Hence the total number of weights for the FLANN having Chebyshev expansion will be same and be equal to 45. The learning rate for ANN and FLANN is set at 0.03. The number of iterations was set to 3000 for all the models. The BP learning algorithm has been used. The training inputs and corresponding targets were normalized to fall within the interval of [0, 1]. In all the cases the output node has nonlinear function. For the training the neural network, we use the back propagation algorithm. It is supervised learning, hence the test image to which additive noise has been applied have been used. During training, the noisy image is tested window by window where the window size is 3x3 and it is entered into the network in the form of vectors. The associated desire value is the corresponding pixel value from original image, because of this the network do not take into account the border values of the noisy image. Here the images taken are 256X256 size. For the training of the network, a different intensity combination that may arise from noisy image is used. In this Lena image is used which is rich in different patterns. It is important to note that the neural network has a general training and can be applied to any kind of image with different noise. Hence the network trained with four different types of noisy images and can be tested with different type of noisy images.

A.Original Image and noisy images

The following figure is the original Lena Image which is downloaded from the website and the size of the image is 256x256

Fig 6: Original Lena Image

The following is the Converted Gray scale image obtained form the original Lena Image having the same size of the original picture, 256x256.

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Fig 7: Converted Grayscale Image

B. Peak Signal to Noise Ratio

The overall result of filter in term of PSNR value.

Table 1

	PSNR of Input Image	PSNR of Output Image
Lena Image (Fig:8 Speckle Noise)	47.39	24.91
Lena Image 2 (Fig:10 Poisson Noise)	43.67	26.76
Lena Image 3 (Fig:11 Gaussian Noise)	42.78	23.60
Lena Image 4 (Fig 9: Salt and Pepper Noise)	47.42	24.61

The numbers shown correspond to the peak signal-to- noise ratio PSNR value of the images. From this table it can be seen, the nonlinear adaptive filter FLANN having Chebyshev functional expansion have shown better result.

C. Experiments and Results

Experiment – I

In this observation, the simulation works were carried out to predict the performance of the Chebyshev functional link artificial neural network to filter the image which is corrupted by Speckle noise, induced in the image with the PSNR value of 47.39 and after process the image, the network filter the error with the PSNR value of 24.91 which shows 53% of noise getting removed.

Fig 8: Input image corrupted by Speckle Noise

Fig 8.1: Output image denoised from Speckle Noise

Experiment – II

In this observation, the simulation works were carried out to predict the performance of the Chebyshev functional link artificial neural network to filter the image which is corrupted by Salt and Pepper noise, induced in the image with the PSNR value of 47.42 and after process the image, the network filter the error with the PSNR value of 24.61 which shows 52% of noise getting removed.

Fig 9: Input image corrupted by Salt and Pepper Noise

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Fig 9.1: Output image denoised from Salt and Pepper Noise

Experiment – III

In this observation, the simulation works were carried out to predict the performance of the Chebyshev functional link artificial neural network to filter the image which is corrupted by Poisson noise, induced in the image with the PSNR value of 43.67 and after process the image, the network filter the error with the PSNR value of 26.76 which shows 61.28% of noise getting removed.

Fig 10: Input image suppressed by Poisson Noise

Fig 10.1: Output image denoised from Poisson Noise

Experiment IV:

In this observation, the simulation works were carried out to predict the performance of the Chebyshev functional link artificial neural network to filter the image which is corrupted by Gaussian noise, induced in the image with the PSNR value of 42.78 and after process the image, the network filter the error with the PSNR value of 23.60 which shows 56% of noise getting removed.

Fig 11: Input image corrupted by Gaussian Noise

Fig 11.1: Output image denoised from Gaussian Noise

D. Evaluation Parameters

The following table contains the Optimized training parameters for Back Propagation neural network.

Table 2

S.No	Parameters	Achieved
1	Performance error	0.001
2	Learning Rate (LR)	0.1
	No. of epochs taken	
3	to meet	3000
	the performance goal	

V. CONCLUSION

Here we have proposed the use of single layer FLANN structure which is computationally efficient for denoising of image corrupted with different noise. This functional expansion of the input increases the dimension of the input pattern. In the FLANN structure proposed for denoising of image, the input functional expansion is carried out using the Chebyshev polynomials. The prime advantage

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of the FLANN structure is that it reduces the computational complexity without any sacrifice on its performance.

Back Propagation is seen to be quite effective in preserving image boundary and fine details of digital images while eliminating multiple noises. The efficiency of the proposed filter is illustrated applying the filter on various test images contaminated different levels of noise. The Result shows that the proposed filter output images which reveals the pleasant for visual perception. From these works, it is clear that FLANN having Chebyshev Functional expansion is better for Poisson noise suppression than other FLANN structure. Since the FLANN structure having Chebyshev functional expansion requires less computational requirement and satisfactory performance it may be used for online image processing application due to its less computational requirement and satisfactory performance. The new nonlinear adaptive filter FLANN shown satisfactory results in its application to images with additive noise.

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