World of Computer Science and Information Technology Journal (WCSIT)
ISSN: 2221-0741
Vol. 1, No. 6, 277-282, 2011

Image Deblurring Using Back Propagation Neural Network

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Abstract -Image deblurring is the process of obtaining the original image by using the knowledge of the degrading factors. Degradation comes in many forms such as blur, noise, and camera misfocus. A major drawback of existing restoration methods for images is that they suffer from poor convergence properties; the algorithms converge to local minima, that they are impractical for real imaging applications. Added to its disadvantage, some methods make restrictive assumptions on the PSF or the true image that limits the algorithm's portability to different applications. In conventional approach, deblurring filters are applied on the degraded images without the knowledge of blur and its effectiveness. In this paper, concepts of artificial intelligence are applied for restoration problem in which images are degraded by a blur function and corrupted by random noise. The proposed methodology adopted back propagation network with gradient decent rule which consists of three layers. This methodology uses highly nonlinear back propagation neuron for image restoration to get a high quality restored image and attains fast neural computation, less computational complexity due to the less number of neurons used and quick convergence without lengthy training algorithm. Specific experiments are carried out and the results explore that this work can have extensive application expansion.

Keywords: Image restoration; deblurring ; BPN ; blur parameter ; point spread function.

1. INTRODUCTION

Image restoration refers to the recovery of an original image from degraded observations[1]. The purpose of image restoration is to "compensate for" or "undo" defects which degrade an image. In cases like motion blur, it is possible to come up with a very good estimate of the actual blurring function and "undo" the blur to restore the original image[2]. In cases where the image is corrupted by noise, the best may hope to do is to compensate for the degradation it caused. In this paper, a neural network approach is introduced to implement image restoration used in image processing techniques. The original solution of the blur and blur parameters identification problem is also presented in this paper. A neural network based on back propagation neurons is used for the same blur parameter identification. Three types of blurs and noises are considered: gaussian, motion and disk[3]. The parameters of the corresponding operator are identified using a back propagation neural network. After identifying the type of blur and its parameters, the image can be restored using deblurring methods. Conservative image restoration methods are considered as the preliminary work and comparison is made between BPN and conventional methods. The paper is organized as follows: Section 2 deals with the construction of the framework for image deblurring using BPN. Section 3 deals with the preprocessing images with conservative methods. Section 4 converses the proposed neural network methodology for deblurring the images with high probability of restoration. Section 5 explains the experimental results and restored images. Section 6 concludes with future enhancement.

II. FRAMEWORK FOR IMAGE DEBLURRING USING BACK PROPAGATION NEURAL NETWORK

Firstly, the image can be selected from multi source to initiate the processing. After image is been selected, preprocessing step is been done and image is tested for noises and blur that are predominant and uses filters which is suited for removing the noise and blur to enhance the image for the best output for next process. The parameters extracted from blur type are trained using BPN and network is simulated to restore the image. The proposed figure is given in figure 1.

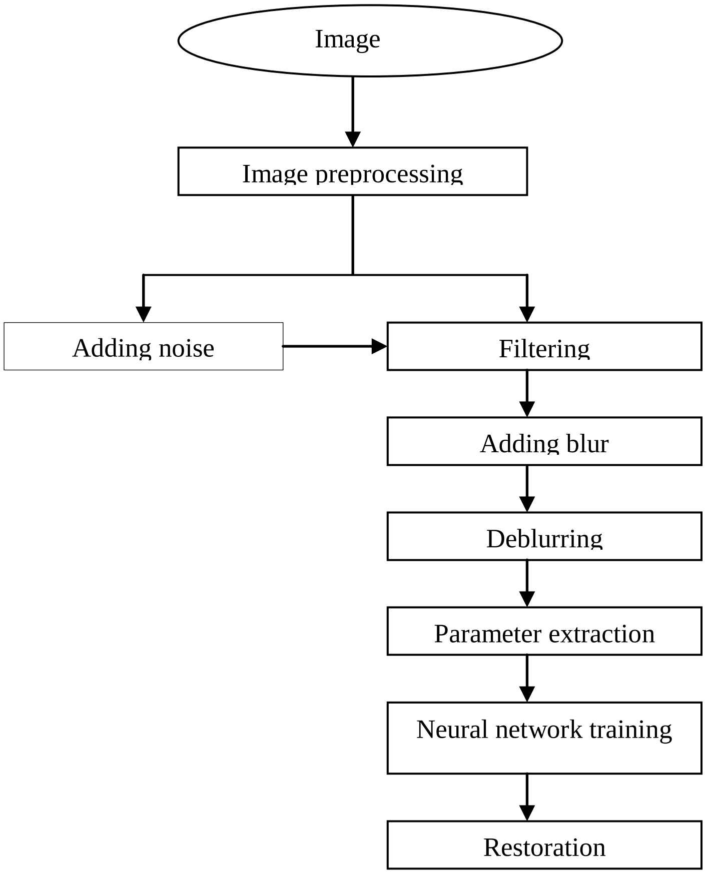

Figure 1: Frame work for the proposed methodology

III. IMAGE PREPROCESSING WITH CONSERVATIVE DEBLURRING METHODS

The goal of digital image preprocessing is to increase both the accuracy and the interpretability of the digital data during the image processing phase. Preprocessing helps to improve the image such that it increases the chance for high accuracy rate in next consecutive module of image processing. In this paper, the preprocessing techniques are used for enhancing the contrast of the image for removing noise and helps segmentation phase to isolate the objects of interest in the image. In image deblurring, it seeks to recover the original sharp image by using a mathematical model of the blurring process[7]. The key issue is that some information are lost ,but this information is “hidden” and can only be recovered if the details of the blurring process is known. Two types of deblurring methods are being adopted for experimentation. They are

- ✓ Deblurring with convolution Lucy Richardson algorithm.
- ✓ Deblurring with convolution Wiener algorithm.

A. Deblurring with convolution Lucy Richardson algorithm

In the Richardson-Lucy algorithm, no specific statistical noise model is assumed. This method does not require apriori information about the original image. This function can be effective when the PSF is known but less performance when there is additive noise in the image. It only works when the noise is not too strong and works well for Gaussian blur. Figure1 shows the implementation of Lucy Richardson algorithm for Gaussian blur.

Figure 2 : Deblurring images using Lucy Richdarson algorithm for Gaussian blur

B. Deblurring with convolution Wiener algorithm

The Wiener filter is a linear filter. The filter tries to minimize the mean square error between the image acquired and its restored estimate[4]. Wiener deconvolution can be used effectively when the frequency characteristics of the image and additive noise are known, to at least some degree. In the absence of noise, the Wiener filter reduces to the ideal inverse filter.

Figure 3: Deblurring images using Wiener algorithm for motion blur

Figure 4: Deblurring images using Wiener algorithm for disk blur

Figure 3 and 4 shows the implementation of Wiener algorithm for motion and disk blur accordingly.

IV. PROPOSED METHODOLOGY

A major drawback of existing restoration methods for images is that they suffer from poor convergence properties; the algorithms converge to local minima, or are so computationally demanding, that they are impractical for real imaging applications. Another disadvantage is that some methods make restrictive assumptions on the PSF or the true image that limits the algorithm's portability to different applications. In simple , deblurring filters are applied on the degraded images without the knowledge of blur and its effectiveness. The original machine intelligent solution of the blur and blur parameters identification problem is presented in this paper which is handled by BPN. A neural network based on Back propagation neurons is used for the blur and blur parameters identification [6]. It is shown that using simple single-layered neural network, it is possible to identify the type of the distorting operator. The parameters of the corresponding operator are identified using a similar neural network. After the type of blur and its parameter is been identified from the image, it is restored back by same neural network.

A. Parameter estimation

Blur parameters are fed as a training input to the adopted BPN network. It takes the blur parameters from the blur patterns of the selected image. Point spread function is the main reason for the blur's PSF and it is a degree to which an optical will blur the point of light.

The blurred spot of the single point is called the point spread function. The noise level will also be removed by the appropriate filter according to the blur identified.

- Gaussian{0.0113,0.0838,0.0113,0.0838,0.6193,0.0838, .0113,0.0838,0.0113}
- Disk {0,0,0,0.0012,0.0050,0.0063,0.0050,0.0012}
- Motion {0.1111,0.1111,0.1111,0.1111,0.1111,0.1111,0.1111, 0.1111, 0.1111}

B. Back Propagation Neural Network

Back propagation is the generalization of the Widrow-Hoff learning rule to multiple-layer networks and nonlinear differentiable transfer functions [8]. Input vectors and the corresponding target vectors are used to train a network until it can approximate a function, associate input vectors with specific output vectors. Networks with biases, a sigmoid layer, and a linear output layer are capable of approximating any function with a finite number of discontinuities. The BPN explained here contains three layers. These are input, hidden, and output layers. During the training phase, the training data is fed into to the input layer. The data is propagated to the hidden layer and then to the output layer. This is called the forward pass of the back propagation algorithm [5]. In forward pass, each node in hidden layer gets input from all the nodes from input layer, which are multiplied with appropriate weights and then summed. The output of the hidden node is the nonlinear transformation of the resulting sum. Similarly each node in output layer gets input from all the nodes from hidden layer, which are multiplied with appropriate weights and then summed. The output of this node is the non-linear transformation of the resulting sum. The output values of the output layer are compared with the target output values. The target output values are those that attempt to teach the network. A feed-forward network has a layered structure. Each layer consists of units which receive their input from units from a layer directly below and send their output to units in a layer directly above the unit. There are no connections within a layer. The input units are merely 'fan-out' units; no processing takes place in these units. The activation of a hidden unit is given in eq (1)

$$y_k(t+1) = F_k(S_k(t)) = F_k\left(\sum_j w_{jk(t)y_j}(t) + \phi_{k(t)}\right) \ldots\ldots(1)$$

In most applications, a feed-forward network with a single layer of hidden units is used with a sigmoid activation function for the units.

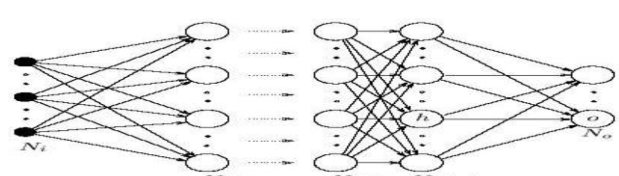

Figure 5: Network for training the neurons

A number of new deblurring methodologies have been developed in recent years and has interest in new aspects of image deblurring problems. Motivated by the biological neural network in which the processing power lies in a large number of neurons linked with synaptic weights in which back propagation neural network model attempt to achieve a good performance via dense interconnection of simple computational elements. Back propagation neural network model have great potential in areas where high computation rates are required and the current best systems are far from equaling human performance. Deblurring of a high quality image from a degraded recording is a good application area of neural nets. Figure 6,7 and 8 shows the deblurring experimentation results using BPN.

Figure 6: Deblurring with Lucy Richardson algorithm for Gaussian blur using BPN

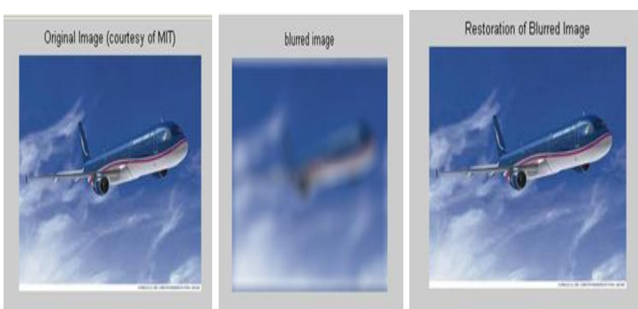

Figure 7 :Deblurring with Wiener algorithm for motion blur using BPN

Figure 8 :Deblurring with wiener algorithm for disk blur using BPN

V.EXPERIMENTAL RESULTS

During training, the progress is constantly updated in the training window. The performance, the magnitude of the gradient of performance and the number of validation checks are of the most interest. The magnitude of the gradient and the number of validation checks are used to terminate the training.

The gradient will become very small as the training reaches a minimum of the performance. If the magnitude of the gradient is less than 1^{e-5}, the training will stop. This limit can be adjusted by setting the parameter. The number of validation checks represents the number of successive iterations that the validation performance fails to decrease. If this number reaches the default value, the training will be stopped.

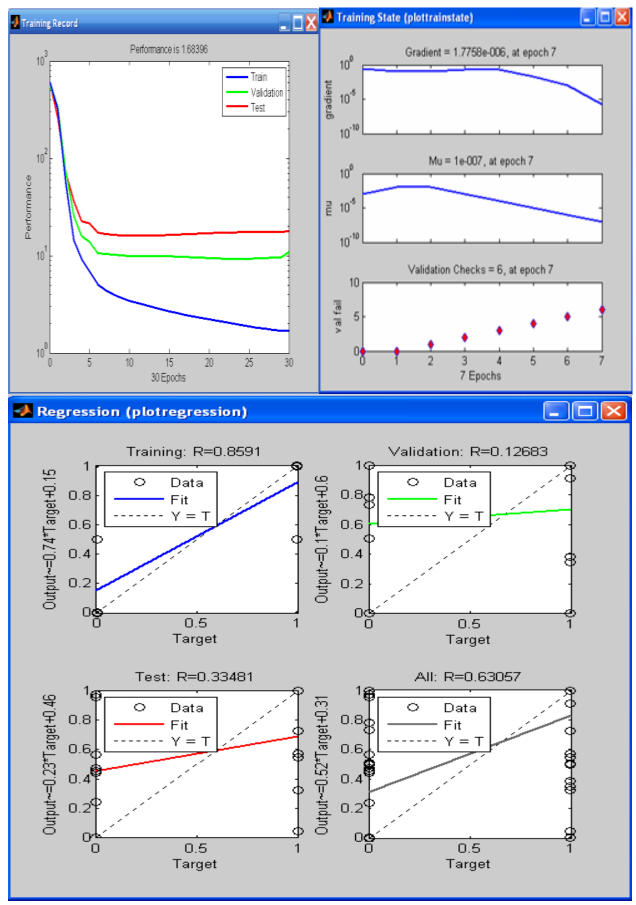

Figure 9: (a).Performance plot (b).Training plot (c).Regression plot

The above training data indicates a good fit. The scatter plot is helpful in showing that certain data points have poor fits. Figure 9 exhibits the performance of BPN on taken datasets.

Table 1: Time performance evaluation between conventional methods and BPN

Images taken	Blur and deblurring technique	Deblurring using conservative methods	BPN
  	Gaussian, Lucy Richardson	1.921347 sec 1.920124 sec 1.928011 sec	1sec 0.9sec 1sec
  	Disk, Wiener	2.259984 sec 2.238644 sec 2.123222 sec	2sec 2sec 2sec
  	Motion, Wiener	1.307713 sec 1.290718 sec 1.092352 sec	1sec 1sec 1sec

Mean square error

The mean squared error E_i of an individual program i is evaluated by the eq (2)

$$MSE = \frac{1}{MN}\sum_{i-1}^{M}\sum_{1-1}^{N}\left[g(i,j) - f(i,j)\right]^2 \quad \ldots\ldots\ldots\ldots(2)$$

where, M and N are the total number of pixels in the horizontal and the vertical dimensions of image. g denotes the noise image and f denotes the filtered image.

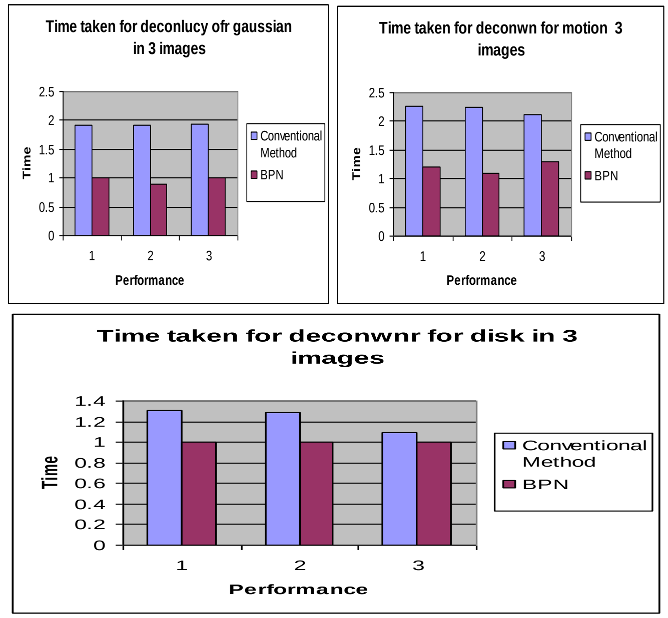

Figure 10: Performance evaluation between conventional method and BPN based on time

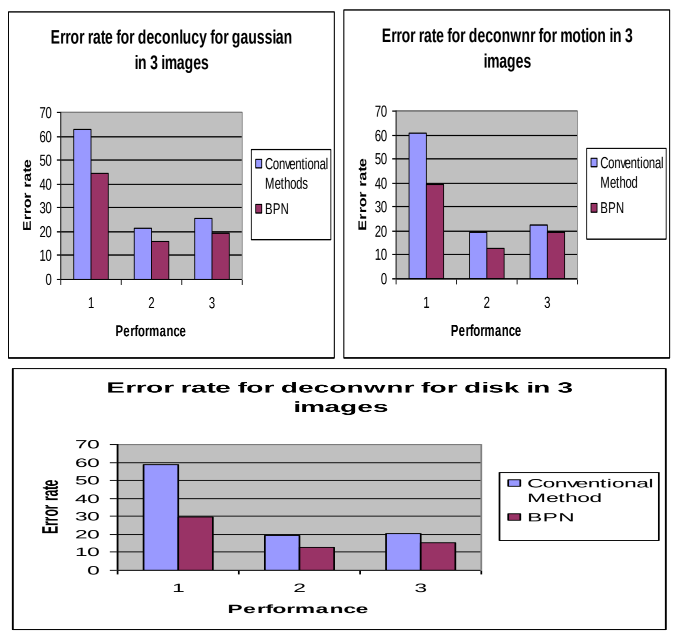

Figure 11: Performance evaluation between conventional method and BPN based on MSE

VI. CONCLUSION

Neural network based deblurring is being implemented and it will be more useful for all types of image processing applications. This attempt is very useful in identification of what type of a blur it is and it also helps working with different noises and other restoration techniques. Once the neural network is trained, images can be restored without having prior information about the model of noise/blurring with which the image is corrupted. It also gives the original information from the degraded image. Based on the identification of the proper technique for removing the specific blur in the image is also carried out accordingly and the image is restored by using back propagation neural network. The method is proposed with the aim of providing efficient and effective restoration and the work can be extended for neural network based segmentation also.

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