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Genetic Algorithms Based Artificial Neural Networks for Blur Identification and Restoration of Degraded Images

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Abstract: In this research paper, we present a n novel idea of using genetic algorithms to search global minimum of the error performance surface of a blind image restoration problem using artificial neural networks. The artificial neural network was based on autoregressive moving average network with random Gaussian process in which the noisy and blurred images are modeled as continuous associative networks, where as auto-associative part determines the image model coefficients and the hetero-associative part determines the blur function of the system. The weights of the network were first of all initialized using genetic algorithm after then iterative gradient based algorithm was used to minimize the error function therefore, self-organization like structure of the proposed neural network provides the potential solution of the blind image restoration problem. The beauty of the algorithm lies in the fact that estimation and restoration are implemented simultaneously.

Key Words: Blind Image Restoration, ARMA Model, Neural Networks, Genetic Algorithms, Blur Identification

Introduction

Images are produced to provide useful information about a phenomenon of interest. Unfortunately, physical imaging systems are imperfect therefore a recorded image invariably represents a degraded version of the original image or scene. The degradation may be due to relative motion between the camera and the original scene, or to a miss-adjustment of the lens system (defocusing) (Andrews and Hunt; 1977). The ultimate goal in image restoration is the recovery of the original scene from a degraded version. The first step in this process in this process is the ability to identify the type of degradation that the image has suffered. A model of the system that causes the degradation might be obtained by the physical nature of the problem, but in most real life situations sufficient a prior information to determine the Point Spread Function (PSF) of the blurring system is rarely available(Jain, 1981). The development of a suitable model for development of a suitable model for discrete images requires a trade off between the accuracy of representation and its utility in image identification and restoration (Katsaggelos, 1991).

Tekalp *et al.*, used Auto Regressive Moving Average (ARMA) process for blue identification and restoration of where Auto Regressive (AR) part determines the image model coefficients and the Moving Average (MA) part determines the blue function of the system. They assumed that the images of natural scenes are smooth in nature therefore, they can be represented as a Gauss Markov random process and can be statistically modeled as a Noncausal Minimum Variance Representation (NMVR) with non systematic support S_a (Sezan and Tekalp, 1990). The state space image model was:

$$\hat{x}(i,j) = \sum_{(k,l)\in s_a} a_{k,l}\, x(i-k, j-l) + v_1(i,j) \qquad (1)$$

where $a_{k,l}$ are NMVR coefficients and S_a is the noncausal support, $x(i,j)$ is the undegraded image and $v_1(i,j)$ is the zero mean white Gaussian noise with variance σ_{v1}^2. The degraded image was assumed to be a convolutional sum between image and blurring function with a noncausal support, S_h and an addition of white noise.

$$\hat{y}(i,j) = \sum_{(m,n)\in s_h} h_{m,n}\, \hat{x}(i-m, j-n) + v_2(i,j) \qquad (2)$$

where $h_{m,n}$ is space invariant Point Spread Function (PSF) which is the blur caused by relative motion between camera and object, $\hat{x}(i,j)$ is undegraded image, $\hat{y}(i,j)$ is the estimate of the observed distorted image and $v_2(i,j)$ is zero mean white Gaussian noise with variance σ_{v2}^2. It is statistically independent of $v_1(i,j)$. A three-layer neural network structure was used to restore the blur function and the original image simultaneously (Zhou *et al.*, 1988) . The structured neural network was decomposed into two adaptive associative networks. The operation between the first and second layer was auto-associative excited by random Gaussian noise while between second and third layer is hetero-associative. The output of third layer was the estimate of the observed image (Chao-Ming Cho and Hon-Son Don, 1991). The output of the second layer was the estimated true image while the weights between second and third layer were the estimate of the blurring function $h_{m,n}$. The weights were updated through feedback using gradients method where cost function was the square of the error between observed and the estimate of the blurred image (Lagendijk *et al.*, 1988; Lagendijk *et al.*, 1990). There were many local minima in the error performance surface, and it was unavoidable for the algorithm to get stuck in a local minima and the flat plateau. Although different methods have been proposed to get out of local minima like Brains method and adding momentum terms. But these methods have not been found satisfactory. Therefore, one usually runs the algorithm several times with different random initial configuration and chooses the configuration with lowest stress.

In this paper, we propose a novel neural network structure in which we will find the initial configuration of weights of the neural network by using the genetic algorithms. The genetic algorithms are proposed to be used to find the global minima of the error performance surface. After finding the initial weights gradient-based algorithm will be used to converge to the solution. It is the usage of genetic algorithm to search the global minima of the error performance surface (May *et al.*, 1997), which is the main motivation of this work. The image and degradation models for the proposed net are given in Eq. 5 and 6.

Image and Degradation Models: The true image model is represented in Eq. 1 and the blurred image modeled is shown in Eq. 2. There are practical difficulties in estimating $a_{k,l}$, and $h_{m,n}$ due to high computational complexity of PSF's with large support, instability of the algorithm, and non-unique solution. These problems can be overcome by using the following assumptions (Kundur and Hatzinakos, 1996):

1. The positive PSF i.e., $h_{m,n}$ limits the ambiguous solutions.
2. Both PSF's i.e., $h_{m,n}$ are symmetric and zero phase. This is for the stability and uniqueness of the solution.
3. The PSF has known parametric form consisting of only few parameters. This lowers the computational complexity.
4. In general, the image formation system is assumed not to absorb or generate energy. So that, the total energy in the object is equal to that of the observed image i.e.,

$$\sum_{(m,n)\in S_h} h_{m,n} = 1 \qquad (3)$$

Neural Networks for Restoration of Image: A feed-forward three-layer neural network structure can be presented to identify the blur function and restore the degraded image, simultaneously. This structured network was decomposed into two adaptive associative networks (May *et al.*, 1997).

1. The operation between the first layer L_1 and the second layer L_2 was assumed to be equivalent to that of an auto-associative network, which is excited by a random Gaussian process.
2. The information then passes forward from the second layer L_2 to the third layer L_3 by hetero-associative process.
3. The output of the third layer L_3 is the estimate of the observed blurred image.

The weights of the two associative networks were initialized using the genetic algorithm and the updated using gradient based algorithm. When the networks have converged to stable states, weights of the hetero-associative network equal to the coefficients of unknown blur function.

Procedure for Neural Network: This artificial neural network consists of three 2-D structured layers L_1, L_2 and L_3 with $M_1{\times}N_1$, $M_2{\times}N_2$ and $M_3{\times}N_3$ neurons respectively. The procedure of the operation of the neural network can be explained as follows:

1. Initially, the inputs to the first layer L_1 are assumed to be a random Gaussian process image with no information about the original image. $a_{k,l}$ are weights of connection between layers L_1 and L_2 which are initiated using genetic algorithm and then updated to optimize the solution. The operation between the first and the second layer will be according to Eq.(1).
2. The neuron values of the second layer L_2, i.e. $\hat{x}(i,j)$, are then feedback to the corresponding neurons of the first layer L_1 i.e., $x(i,j)$ for the next iteration, according to the following equation.

$$x(i,j) = \hat{x}\_(i,j) \qquad (4)$$

3. The operation between second layer L_2 and third layer L_3 defines the hetero-associative operation or MA process. The output of the $(i,j)^{th}$ neuron of the third layer will be calculated according to Eq. 2. The structure of the proposed neural network is shown in Fig.1.

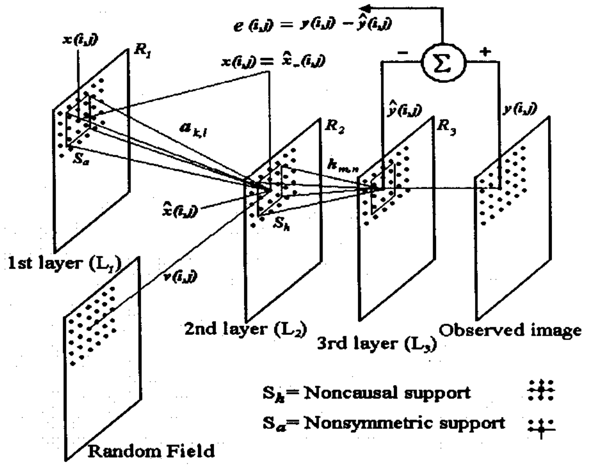

Fig. 1: The Structure of the proposed Artificial Neural Network Based on ARMA Model

Identification and Restoration Processes: The identification and restoration processes are implemented simultaneously by using a dynamic iterative algorithm to minimize the error function of the neural network. The hetero-associative errors in the layer L_3

$$E_y(w) = \frac{1}{M_3 \times N_3} \sum_{(i,j)\in R_3} \{y(i,j) - \hat{y}(i,j)\}^2 \qquad (5)$$

and the auto-associative error in L_2 is

$$E_x(w) = \frac{1}{M_2 \times N_2} \sum_{(i,j)\in R_2} \{x(i,j) - \hat{x}(i,j)\}^2 \qquad (6)$$

Genetic Algorithm: One main desire is to find out optimized synaptic weights that will give better restored image and exact or close point spread function.. In order to get out o local minima, a searching algorithm (G.A) is used to search global minima.

The Genetic Algorithm is being used to find weights of the feedforward neural network, which are closed to the desired solution. One proposed neural net consists of two layers and each layer contains a set of weights $a_{k,l}$ and $h_{m,n}$,

$$
\begin{aligned}
W &= W_x, W_y \\
W_x &= [a_{k,l}] \\
W_x &= [h_{m,n}]
\end{aligned} \tag{7}
$$

where W_x *and* W_y are sets of floating point numbers. The ordinary rule of thumb for choosing the population size is to choose it five to six times the length of a chromosome.

Initialization: The genes rêpresenting weights were produced by using a pseudo random generator. The values of the genes were floating between 0 and 1 but the sum of all weights in a layer must be equal to zero according the fifth assumption of image models otherwise layer would generate energy (Rawlins, 1991).

Fitness Criterion: The fitness criterion denoted by F is taken as

$$
\begin{aligned}
F &= \frac{F_x + F_y}{2} \\
F_x &= \frac{1}{1 + E_x} \\
F_y &= \frac{1}{1 + E_y}
\end{aligned} \tag{8}
$$

where

Cross-over, Reproduction and Next Generation: The population in a generation is sorted out according to the fitness criterion in a descending order. The top one third was given a chance to produce five children per pair. The next one third was given chance to produce 3 children per pair. They were similar to child 1 and child 2 and child 3 as given above. The last one third was given a chance to produce only one child per pair, which is similar to child 1. For selection of a new generation, the rule for the survival of the fittest is being used. All the parents and children are sorted in a descending order of fitness after calculating the fitness of the children. The ones equal to the number of population were chosen for the next generation. So the new population was a blending and overlap of the previous and the present with no fixed percentage for either generation (Davis, 1991).

Mutation: Mutation is the process in which genes are randomly mutated (changed). Mutation plays an important role when every new generation does not seem to improve the fitness.

Termination Criterion: When the fitness of the best chromosome is the new population was almost same as that of the best chromosome in the previous population, the program is terminated. Quantitatively the criterion for termination was;

$$|F_{new} - F_{prev}| \leq 0.01 \tag{9}$$

Gradient-Based Algorithm: A gradient-based algorithm was used to train and optimize the network by minimizing the squares of errors. Specifically the weights between L_2 and L_3, which only depend on E_y, were updated as

$$h_{p,q}^{new} = h_{p,q}^{old} - \alpha_l \frac{\partial E_y(w)}{\partial h_{p,q}} \tag{10}$$

The solution of the differential is given as

$$\frac{\partial E_y(w)}{\partial h_{p,q}} = \frac{2}{M_3 \times N_3} \sum_{(i,j)\in R_3} \{y(i,j) - \hat{y}(i,j)\}\hat{x}(i-p, j-q) \tag{11}$$

Fig.2: Original Undistorted Image

Fig. 3: Blurred or Degraded Image

Fig. 4: Image Restored Using Neural Network

Table 1: Real and Estimated Blur Parameter

	Real blur parameters	Estimated blur parameters
l_1	0.2	0.0675235
l_2	0.055	0.0540259
l_3	0.05	0.0472884
l_4	0.035	0.0337958
l_5	0.035	0.0337912
l_6	0.03	0.0304172
SNRI		1.17322

The weights of the auto-associative network are related to E_x in L_2 and E_y propagated form L_3. Therefore, the coefficients of the linear part of the auto-associative network are iteratively updated by Eq. (16)

$$a_{u,v}^{new} = a_{u,v}^{old} - \beta \frac{\partial\{E_y(w) + E_x(w)\}}{\partial a_{u,v}} \quad (12)$$

We find the following updating equation for $a_{u,v}$,

$$a_{u,v}^{new} = a_{u,v}^{old} + \beta \sum_{(i,j)\in R_2} [\delta(i,j) + d(i,j)] x(i-u, j-v) \quad (13)$$

where

$$\delta(k,l) = \frac{2}{M_3 \times N_3} \sum_{(m,n)\in R_3} h_{m-k,n-l}\{y(i,j) - \hat{y}(i,j)\} \text{ and}$$

$$d(i,j) = \frac{2}{M_2 \times N_2}\{x(i,j) - \hat{x}(i,j)\}$$

Simulation Studies: The algorithm has been applied on linear motion blur or de-focussed images. The blurred images were obtained by using a 5×5 linear Gaussian blur functions with 30db white Gaussian noise. These blurred images represented the out of focus or linear motion blur. Fig. 2, 3 and 4 shows the original undistorted image, blurred image and restored image using neural network, respectively. As a measure of goodness of the restoration, the percentage Mean Square Error (MSE) and improvement in the Signal to Noise Ratio (SNRI) was used (Kundur and Hatzinakos, 1996). SNRI was defined as follows:

$$SNRI = \frac{MSE\ (y)}{MSE\ (\hat{x})} \quad (14)$$

where MSE was given as:

$$MSE\ (\hat{x}) = 100 \frac{\sum_{i,j} \{c\hat{x}(i,j) - f(i,j)\}^2}{\sum_{i,j} f^2(i,j)} \quad (15)$$

The value of c can be calculated using the following relation:

$$c = \frac{\sum_{i,j} f(i,j)\hat{x}(i,j)}{\sum_{i,j} f^2(i,j)} \quad (16)$$

Here $y(i,j)$ is the given blurred image and $\hat{x}(i,j)$ is the restored image. This performance measure can only be evaluated for controlled experiments because undistorted image $f(i,j)$ is required as well. Table 1 shows the real and estimated blur parameters. It also shows the SNRI of the restored image.

Conclusion

In this research, we have used multilayer neural networks for blur identification and restoration of degraded images. These degraded and noisy images were modeled as continuous associative networks in which auto-regressive part is used to model the characteristics of an image called image model while the other part hetero associative part modeled the blurring or degradation process. The weights of the neural network were updated using gradient-based algorithms but due to ill convergent properties gradient based algorithms stuck into the local minima or flat plateaus. Therefore, we used genetic algorithms in order to initialize weights of the neural network. After properly initializing weights gradient based algorithms showed better convergence properties. Because of space invariance of the blur function, massive parallelism of local neighborhood is used. In the future work space-variant nonlinear blurs will be considered and instead of simple square error function, magnitude of gradients of the neighborhood will be taken into account.

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