Research on ELM-based Image Restoration Algorithm

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Abstract— As the rapid development of the multi-media technology, more and more digital devices are used to take pictures. However, sometimes the images may be degraded due to disoperation, the environment, and system and so on. The main task for image recovery is combining the degraded images and some priori information to acquire the best estimation of the original image by using some kind of restoration algorithm. In this paper, a new image restoration algorithm based on ELM Neural Network and some edge information was proposed, aiming at the fuzzy motion images. As the experiment shows that comparing traditional BP Neural Network, the new restoration algorithm based on ELM Neural Network is simpler, faster, easier to implement, what's more, it's more suitable for real-time processing.

Index Terms—Image Restoration; Neural Network; ELM algorithm; Fuzzy Images; Best Estimation

I. Introduction

As the rapid development of electrical information technology, people always take pictures using digital cameras or cameras embedded in the mobile phones. Due to the bad image function of the equipment, noisy interruption or disoperation etc., a degree of degradation may happen to the images, which may not satisfy the visual requirements of people. There're many factors causing the image degradation, also the degradation principles are very complicated, therefore, it's impossible to develop a mathematical model to express this procedure [1]. In this situation, the image restoration [2], [3], [4], has become one of the hottest topics in the digital image processing area. The main target is to recover the lost information based on the priori knowledge of the degradation image to improve the visual effect.

It has been more than fifty years for image restoration area. The most established technology is to adjust the images from astronomical observation using optical technology; afterwards, the digital restoration technology has been developed in the post treatment process of astronomical observations, and more and more people focused on it. The primary aim of the image restoration is to retrieve the optimum estimation according to the observed and some criterion. The recovering process is called as image non-blind restoration when the degraded factors are known. Inversely, the process, priori knowledge is unknown, is called as image blind restoration. The key point for image non-blind restoration is to estimate the Point Spread Function (PSF) of the imaging model accurately, and then doing the deconvolution using the PSF. However, in the practice application, the imaging systems are totally different and complicated; it's very hard to estimate the PSF accurately. Therefore, the estimation can be done to the fuzzy core only based on the degraded image, which is the image non-blinded restoration. Even if PSF is not necessary for the image non-blinded restoration algorithm, some kinds of constraints, such as imaging system or noise, are also needed. Consequently, this algorithm is also complex and time-consuming. However, it's still more in line with the requirements and becoming more and more popular in the image restoration area.

As the development of the image restoration technology, the traditional method cannot meet the demands, and the researchers start to explore more efficient methods, and using neural network to process the image is one of the most active directions. Comparing to the traditional algorithm, the neural network algorithm offers superiors as following:

1) Highly parallel processing ability. The processing speed is much faster than the traditional sequence processing algorithm.

2) Highly adaptive function. It can find out the inner connection between the samples and outputs.

3) Highly generalization performance. It can process incomplete or noisy data.

II. BP Neural Network

A. Principals

BP network is a kind of multi-layer feed forward neural networks, which is connected by the nodes in input layer, hidden layer and output layer. The structure is as Fig. 1.

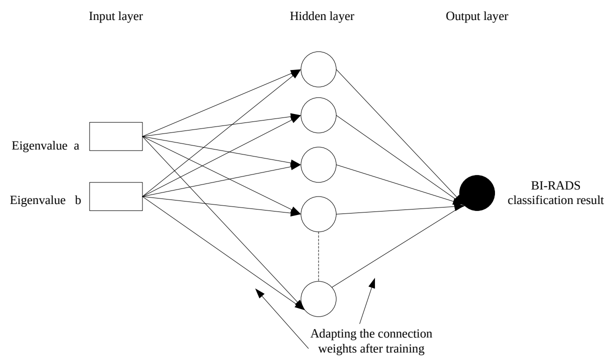

Figure 1. The structure of BP Neural Networks

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It revises the weights by error back-propagation to train the network. The learning process is composed of two parts:

1)Information propagation. It calculates the results based on the input information via input layer and hidden layer;

2)Error revising. It doesn't revise the hidden layer weights according to the back propagated error until all the weights meet the requirement.

The input-output non-linear mapping relationship can be get by BP neural network learning procedure. After that, the subsequent processing to the signal can be finished.

B. Network Training Algorithm

It has been confirmed that three layers feed forward neural networks called Single-Layer Feedforward Network (SLFN) can approximate arbitrary multivariate nonlinear functions [5]. The BP neural network trains the network by error back propagation, and revises the weights by the gradient descent-method. Consequently, the activation function must be differentiable. Normally, Sigmoid function is always chosen to be the output activation function. When the sample is input, all the nodes in every layer must be calculated in sequence as follows:

$$net_j = \sum_i w_{ij} x_i \tag{1}$$

$$o_j = f(net_j) \tag{2}$$

where$i$ means i_{th} node in previous layer of j_{th} node in this layer, o_j means the output of the j_{th} node in this layer, $o_i$means the output of i_{th} node in previous layer, and w_{ij} means the weights among the nodes in this layer.

At the output of the network, y_i means the ideal output, $\hat{y}_i = O_i$ means the real output, the error between them is expressed as follows:

$$E = \frac{1}{2}\sum_j (y_i - \hat{y}_j)^2 \tag{3}$$

Considering the effect of the weights w_{ij} on the error

$$\frac{\partial E}{\partial w_{ij}} = \frac{\partial E}{\partial net_j}\frac{\partial net_j}{\partial w_{ij}} = \delta_j O_i \tag{4}$$

To ensure the error decreasing fastest, the biases of the weights Δw_{ij} should be

$$\Delta w_{ij} = -\eta \frac{\partial E}{\partial w_{ij}} = -\eta \delta_j O_i \tag{5}$$

$$w_{ij}(t+1) = w_{ij}(t) + \Delta w_{ij}(t) \tag{6}$$

The counterpart vectors are as follows:

$$\Delta W(t) = -\eta \frac{\partial E}{\partial W}(t) \tag{7}$$

$$W(t+1) = W(t) + \Delta W(t) \tag{8}$$

The procedure above is so called as gradient descent-based BP neural network. As the curve of the target function has several extreme points, the result will be convergent to local minimum when the initial weights are set differently. If the initial weights are chosen randomly, the output may be convergent to local minimum rather than global minimum, and then the network must be train longer. Previously, the parameters (weights and biases) of different layers are dependent due to all the parameters must be tuned.

III. Image Restoration Algorithm based on ELM

Recently, a new algorithm named as Extreme Learning Machine (ELM) was proposed in [6] by Huang et al. In the Single-Layer Feedforward Neural network (SLFN), the weights of the hidden nodes can be chosen very fast. Comparing the previous methods [7], [8]–[9], in this case, the time consuming will be reduced even by hundreds. Therefore, the algorithm will be so simple that the implementation will be very easy.

A. Introduction of ELM

The ELM was proposed [10] in the SLFN, and initializing the weights and biases in SLFN randomly was the key concept of this algorithm. According to theorem and definition bellowing, the hidden-layer output matrix and the output weights can be calculated easily even if the input weights and biases are not tuned. In this situation, within very few steps and low computational consuming, the network can be trained.

Definition 1[6]: $x_0 \in R_n$is said to be a minimum norm least-squares solution of a linear system Ax = y if for any y $\in R_m$

$$\|x_0\| \le \|x\|, \forall x \in \left\{x : \|Ax - y\| \le \|Az - y\|, \forall z \in R^n\right\} \tag{9}$$

In a linear system, if x_0 is the smallest norm among the least-square solutions, it will be said to be the minimum norm least-squares solutions.

Theorem 1[11]: Let there exist a matrix G such that Gy is the minimum norm least-squares solution of a linear system $Ax = y$. Then it is necessary and sufficient that G = $A^{\dagger}$, $A^{\dagger}$ is the Moore-Penrose generalized inverse of matrix A.

Consider a set of M distinct samples (x_i, y_i) with $x_i \in R_M$ and $y_i \in R_N$, with w_{ij} being the input weights, b_i being the biases, andβ_i being the output weights. Then, a standard SLFN with $\overline{N}$ hidden neurons and $h(x)$ as the activation function is modeled as the following:

$$o_j = \sum_{i=0}^{M-1} w_{ij} x_i + b_{i,} \qquad 0 \le j \le \overline{N} - 1 \tag{10}$$

$$y_k = \sum_{j=0}^{\bar{N}-1} \beta_{jk} h(o_j), \qquad 0 \le k \le N-1 \tag{11}$$

For the error between the estimated outputs y_k and the actual outputs y_k to become the smallest, the SLFN can be modeled as following:

$$\sum_{j=0}^{\bar{N}-1} \beta_{jk} h(\sum_{i=0}^{M-1} w_{ij} x_i + b_i) = y_k, \quad 0 \le j \le \bar{N}-1, 0 \le k \le N-1 \tag{12}$$

which is written compactly as $H\beta = \hat{Y}$, as named by Huang and Babri [12] and Huang [13], where H is called the hidden layer output matrix of the neural network.

It has been shown in [14], [15] that SLFN can be treated as a linear system when the input weights and biases can be chosen randomly. For this linear system $H\beta = Y$, β is said to be a least-square solution when:

$$\left\| H\beta - Y \right\| = \min_{\beta} \left\| H\beta - Y \right\| \tag{13}$$

where $\|\bullet\|$ means a norm in Euclidean space.

According to the Definition 1 and Theorem 1, this linear system $H\beta = Y$, can be solved very simple by the use of the Moore-Penrose generalized inverse [11].

According to the theorem above, in the SLFN, the outputs can be approximated to the target values as good as wished with arbitrary input weights and biases. Whereas, it should be under the condition that the activation function must be infinitely differentiable. The key point for this algorithm is to calculate the weights of the hidden layer by the use of the Moore-Penrose generalized inverse of the hidden layer outputs H.

B. The ELM-based Image Restoration Algorithm

Previously, learning speed has become the bottleneck of the classical learning algorithms' application. In the image restoration area, learning speed is one of the most important factors. Based on the analysis of the ELM algorithm in the SLFNs above, the learning speed is extremely fast, which makes the possibility for the ELM-based algorithm applied in the image restoration area. In this case, a new image restoration algorithm based on ELM has been proposed.

During degradation period, the gray value of every pixel will be affected by the adjacent gray values. Consequently, if the degradation is caused by uniform motion in strait line, all the pixel values not only include the original information, but also include a part of adjacent fuzzy information in the same line. Assuming the size of the training sample is M×N with the length of the movement n. In this case, every value includes the information of the pixel itself and information of adjacent n pixels. Therefore, the input-output relations of the SLFN will be 2×n＋1→1. As the movement will also take effect on the edge information, the high frequency information of the edge will be lost and incorrect in the restoration image, which will cause degrading again so called ringing effect. When the high frequency information estimated, the edge information should be considered separately [16] to complement the input-output relations and enhance the restoration quality of the high frequent part. In this paper, Sobel operator will be used to extract the edge information to be the input of the SLFN, which will fulfill the priority knowledge. Accordingly, the input-output relations will be changed to (2×n＋1)×2→1. The new relations may increase the calculation consuming; however, it can improve the generalization performance. To some extent, it also improve improves the restoration effect.

Constructing a SLFN under following conditions (n is the length of the movement): The number of the nodes in input layer and output layer is (2×n＋1)×2 and 1 respectively with Tan-Sigmoid function and Linear function as the activation function of the hidden layer and output layer.

The flowing of the algorithm is as follows:

- Choosing several high quality clear images to be the training sample.
- Reducing the quality of all the images above using same level degrading model to retrieve counterpart fuzzy images.
- Extracting the edge information of the original images and fuzzy images separately by Sobel operator.
- Preprocessing the original samples with edge information and fuzzy images with edge information in normalization and expressing them as $\hat{y}(x, y)$ and $f(x, y)$.
- Using $f(x, y)$ as input matrix, at the same time, using $\hat{y}(x, y)$ as output matrix.
- Assigning arbitrary input weights matrix **W** and bias matrix **B**, and calculating the hidden layer output matrix **H**.
- Calculating the output weights β: $\beta = H^{\dagger}\hat{Y}$ to receive the input-output relations and the network has been trained.
- Preprocessing the testing fuzzy images as step (4) to be the input matrix I(x,y) of the trained network.
- Denormalizing the output matrix of step (8) to receive the restoration result.

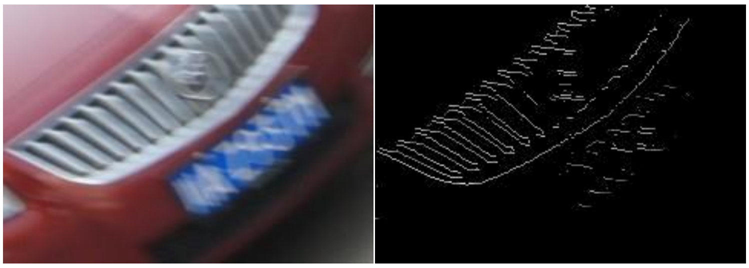
C. Experiment

In this section, several actual fuzzy images are chosen to recover using ELM-based image restoration algorithm, Wiener Filter and traditional BP algorithm. Based on the comparison, the advantage of the new algorithm can be figured out.

First of all, 30 high quality images with size 128×128are chosen to be the training samples, and all are processed under the condition of horizontal movements to get the counterpart fuzzy images. And then, training the neural network constructed in section 3.2 by the ELM-based image restoration algorithm. After all the parameters (input weights, hidden layer weights, biases) are trained out, the recovering process will come to the initial stage.

An image of 1386×693 as Fig. 2(a) is selected to be the testing image. Before restoration, the direction and length of the movement should be estimated. Wang Xiaohong [17] et al has proposed a motion PSF parameters estimation method based on Radon transformation. In this experiment, it’s used to estimate the direction being 32°and length being 17. Based on the estimated result, the image is rotate to horizontal direction as Fig.2 (b), afterwards, the rotated image is cut to rectangle only with the image information as figure 2(c). Considering the parameters estimated, the experiment should be set in several times according to the estimated result. In the experiment, 16, 17 and 18 are chosen to be the length as Fig. 2, Fig. 3 and Fig. 4.

(a) Original image (b) rotated image



(c) cutted image (d) blur_edg

Figure 2. Preprocessing image

(a)wiener_res (b)bp_res (c) ELM_based_res

Figure 3. Estimated Length=16

(a)wiener_res (b)bp_res (c)ELM_based _res

Figure 4. Estimated Length=17

Figure 5. Estimated Length=18

TABLE I COMPARISON OF THE RECOVERING RESULT

Algorithm		wiener	bp	ELM
Time (Seconds)	Training	NA	1183.28	1.093
	Testing	0.738	0.937	0.427
Training RMS		NA	0.1285	0.1245
Testing RMS		NA	0.1583	0.1524
PSNR		22.314	25.3704	25.7437
MSSIM		0.7118	0.7710	0.8071

Seen from TableI, the learning speed of the ELM-based image restoration algorithm is more than 1,000 times faster than BP for this case. The generalization performance obtained by the ELM algorithm is very close to the generalization performance of BP. When the PSF parameters are estimated accurately, the result of our algorithm will be much better than BP and Wiener algorithm, meanwhile, the ringing effect is also reduced.

Seen from the result above, the recovering result is much better than Wiener and BP algorithm especially in the details such as characters, digits and so on. The effect of Wiener depends on the PSF parameters estimation; nevertheless, our algorithm is robust with respect to the estimation process.

IV. DISCUSSION AND CONCLUSION

When taking pictures, many environmental factors may cause them degraded so that it cannot reach our requirement. Hence, how to estimate the original images has become the main target in image restoration area. Some improvements has been made to the traditional BP neural network to develop the ELM-based image restoration algorithm. It also includes the edge information of the images. The result of the experiment has shown that the learning speed of the new algorithm is extremely fast. It can train SLFNs much faster than classical learning algorithms. Unlike the traditional classic gradient-based learning algorithms which intend to reach minimum training error but do not consider the magnitude of weights, it tends to reach not only the smallest training error but also the smallest norm of weights. Thus, the proposed algorithm tends to have the better performance for image restoration.

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