NONLINEAR RESTORATION OF SPATIALLY VARYING BLURRED IMAGES USING SELF-ORGANIZING NEURAL NETWORK

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Abstract

An efficient nonlinear restoration of spatially varying blurred images with noise is presented using a self-organizing neural network (SONN). The proposed method can effectively restore the blurred images by using the region classification and learning property of SONN adapted for the blur sensitivity of the receptive field. In addition, receptive fields are adaptively overlapped to eliminate the block effect within the restored images. The proposed method eliminates the need to calculate the gradient, gradient step size, or Hessian of error surface, which affect the performance of the least squares method or of the constraint optimization. Simulation results for the space-variant blurred pepper image show the performance improvement of about 4.86 dB or 3.57 dB, as compared to that of the Richardson-Lucy algorithm or that of conventional neural networks, respectively.

Ⅰ. Introduction

In our observation of the world, it often happens that we can only obtain a distorted version of the signal in which we are interested. Sometimes inappropriate instrumentation or atmospheric turbulence causes the distortion. The distortion may be space-invariant or space-variant. In general, the former can be characterized by an underlying system. The latter is difficult to express explicitly only with underlying system. That is, space-invariant can be expressed as a convolution but space-variant as a superposition. Various methods such as the inverse filter [1], Wiener filter [1], Kalman filter [2], SVD (singular value decomposition) pseudo-inverse [1,3], and many other model-based approaches have been proposed for image restoration. One of the major drawbacks of most image restoration algorithms is computational complexity, and many assumptions such as wide sense stationarity (WSS) and/or availability of the second-order image statistics have been made to obtain computationally feasible algorithms. Furthermore, knowledge on the power spectrum or on the correlation matrix of the undegraded image is required. The Kalman filter approach can be applied to non-stationary image, but it is computationally intensive. Katsaggelos *et al.* [4] estimated the degree of blur for space-invariant blurred images. But his technique needs the power spectrums or the correlation matrices of original images, and also needs a hypothesis for boundary condition. Fisher *et al.* [5] restored the blurred images using the modified Richardson-Lucy algorithm based on constraint optimization theory.

Artificial neural networks that perform extremely rapid computations seem to be very attractive for image restoration, image processing, and pattern recognition. Zhou *et al.* [6,7] restored the degraded images using the Hopfield Neural Networks with blurring model. And Ravichandran *et al.* [8,9] made an adaptive filter using self-organizing feature map learning algorithm to remove the impulse noise, which is generated in mark recognition and reconstruction from coded images.

In this paper, an efficient nonlinear restoration method of gray-level images, blurred by spatially varying blur-functions and contaminated by noises, is presented. The proposed method can effectively restore the space-variant blurred image by using the region classification and the learning property of SONN adapted for the blur sensitivity of the receptive field. In addition, receptive fields are adaptively overlapped to eliminate the block effect within the restored images. The proposed method eliminates the calculation of the gradient, gradient step size, or Hessian of error surface, which affect the performance in the least squares method and/or the constraint optimization methods, *etc.* We show the performance of the proposed restoration method for the space-variant blurred pepper image, and compares it with other restoration methods such as the Richardson-Lucy algorithm and conventional neural networks in peak-to-peak of signal to noise ratio (PSNR) and in improved signal to noise ratio (ISNR).

Ⅱ. SONN-based restoration of the space-variant blurred image

Ⅱ-1. Degradation Model

The blurred image is modeled as

$$b = Ds \tag{1}$$

where b and s denote the vectors representing the lexicographical ordering of the blurred and the ideal image, respectively. The matrix D is the blur operator.

In case of space-variant blur, D represents a superposition. The blurred image can be expressed as

$$b(i,j) = \sum_{(k,l)\in S_d(i,j)} d(i,j;k,l)s(k,l) + v, \quad (i,j) \in S_b \tag{2}$$

where $d(i,j;k,l)$ and $s_d(i,j)$ denote the point spread function and its support region at pixel position (i,j), and S_b denote the receptive field of SONN in blurred image. And the observation noise v accounts for both sensor noise and noise introduced by other components of the imaging system and approximated by a zero-mean Gaussian random noise which is additive and uncorrelated to the image.

Ⅱ-2. Restoration using SONN

Fig. 1 is the restoration procedure using the proposed SONN.

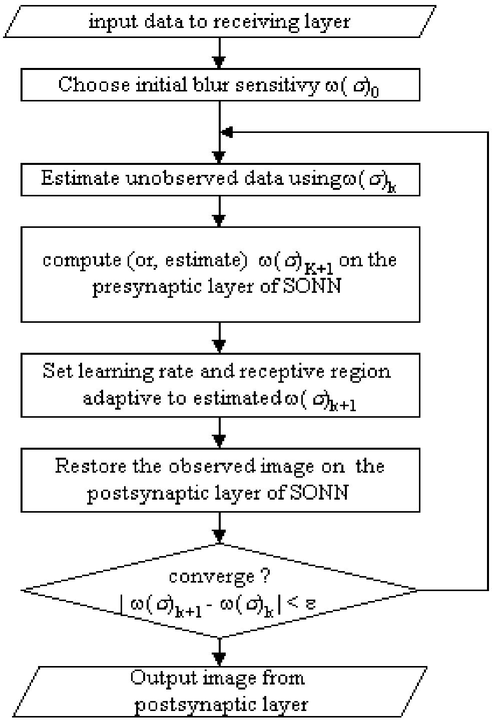


Fig. 1. Adaptive restoration procedure of spaces-variant blurred image.

To effectively restore the spatially varying blurred image, we use the region classification property of SONN to detect the degraded regions, and learning rate is adaptively adjusted to the blur quantity in receptive field. In addition, receptive fields are adaptively overlapped to alleviate the block effect within the restored images.

The architecture of the SONN is shown in Fig. 2, which is composed of the pre-synaptic layer to detect the blur in input image and the post-synaptic layer to restore the input image by adaptive learning based on the information of pre-synaptic neurons. Especially the pre-synaptic neurons are bipolar neuron, which has fan-in function to get observed image and fan-out function to post-synaptic layer.

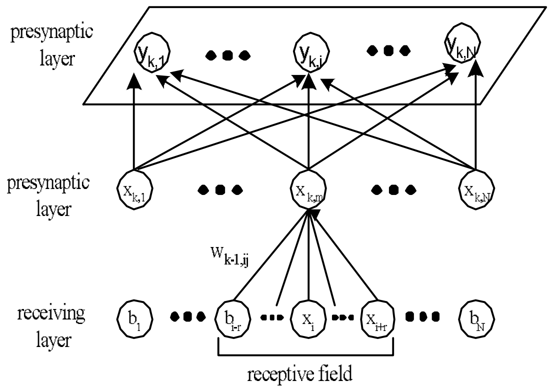


Fig. 2. The architecture of the SONN .

In Fig. 2, $w_{k,ni}$ denote the synaptic weight in k-th iteration between a neuron n in pre-synaptic layer and a neuron i in post-synaptic layer.

Flusser *et al.* [10] directly analyzed the features of the blurred image without the original image. And they showed that the central moments (l_2-norm) were invariant to blur. And we define the sensitivity of receptive field as a measure of blur and adjust the receptive field region based on local variance of blurred image.

Let the blur sensitivity of the receptive field be w and the post-synaptic neuron y_c be the winning neuron. In SONN, the blur sensitivity w is considered as the blur quantity in receptive field and restores that region by adjusting the post-synaptic weight to the blur sensitivity.

The weights of post-synaptic layer are updated as follows:

$$y_c(n+1) = y_c(n) + \eta_{eff}(n)[x(n) - y_c(n)] \tag{3}$$

$$\eta_{eff}(n) = \eta_p + (w - p)\eta(1 - \eta_p) \tag{4}$$

where, p denote the Gaussian integer $\lceil w \rceil$, and η_p is recursively determined from the initial learning rate as follows:

$$\eta_p = \eta_{p-1} + \eta(1 - \eta_{p-1}) \quad (5)$$

The learning mechanism of post-synaptic layer for p=3 is shown in Fig 3.

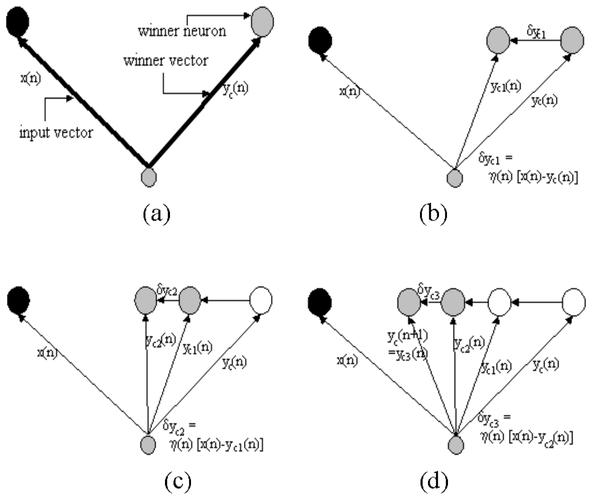


Fig. 3. Learning process of the post-synaptic layer

Fig. 3(a) shows the detected wining neuron y_c and from Fig3 (b) to (d) show the weight modification mechanism using the sensitivity of locally specified receptive field.

To adjust the receptive field s_p, in which neuron (i, j) is a center of SONN in proportion to the blur sensitivity, the local variance of that is calculated as follows

$$\sigma_{ij} = \frac{1}{(2m+1)}\frac{1}{(2n+1)}\sum_{k=-m}^{m}\sum_{l=-n}^{n}(x_{(i+m,j+n)} - \mu_{ij})^2, \quad (k,l)\in S_p \quad (6)$$

where μ_{ij} denotes the local mean and can be defined as follows.

$$\mu_{ij} = \frac{1}{(2m+1)}\frac{1}{(2n+1)}\sum_{k=-m}^{m}\sum_{l=-n}^{n}x_{(i+m,j+n)}, \quad (k,l)\in S_p \quad (7)$$

To imitate the characteristics of the human sight, the blur sensitivity can be defined as follows.

$$w_\sigma(i,j) = \frac{g_{p-p}}{g_{\max} - g_{\min}} \cdot \left(\frac{1}{\sigma_h^2 + 1}\right) \quad (8)$$

g_{p-p} means the difference between maximum and minimum brightness of the obtained image, and m_{ax} and m_{in} mean maximum and minimum brightness, respectively.

The blur sensitivity is about 1 for edge area and 0 for flat area, respectively.

Ⅲ. Simulation results and Discussions

Simulation is conducted on the 128×128 sized partial pepper image which is blurred by spatially varying blurring function with 1~4 blurring parameter and has 20dB additive Gaussian random noise. On the other hand, the receptive field s_p is adjusted to the region of (m-σ_L) to (m+σ_L) at current processing pixel position m and locally estimated variance σ_L which exploits the similarity of the general Gaussian density function and the PSF (point spread function).

Figure 5 shows the restoration results in 3-dimensional mesh formed image.

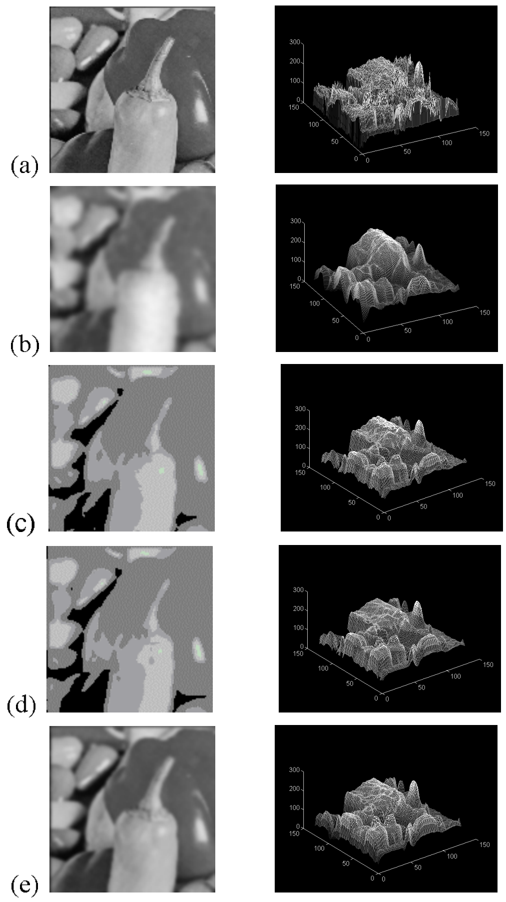
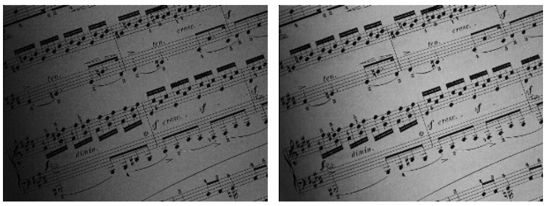


Fig. 4. Restoration of the spatially varying blurred synthetic image: (a) partial peppers image, (b) degraded image, (c) restored image by using Richardson-Lucy Algorithm, (d) restored image by the conventional neural networks, and (e) restored image by the proposed method

Table 1. Comparison of restoration efficiency.

Methods / Images	Richardson-Lucy Algorithm		Conventional Neural networks[6]			SONN with fixed receptive field			SONN with adaptive receptive field		
	PSNR	ISNR	PSNR	ISNR	Iteration	PSNR	ISNR	Iteration	PSNR	ISNR	Iteration
Blurred peppers	25.12	5.8	26.34	7.0	72	25.29	6.0	94	30.82	10.3	83
Blurred peppers with noise	24.39	5.1	25.68	6.4	85	24.92	5.6	114	29.25	8.9	79

The restoration results are summarized in Table 1. Simulation results in Table 1 for the space-variant blurred pepper image show the better performance of about 4.86 dB or 3.57 dB as compared to those of the Richardson-Lucy algorithm or the conventional neural networks. As shown in Fig. 5, the proposed method significantly alleviates the degree of the degradation in real image.



(a) (b)

Fig. 5. Restoration of a spatially varying blurred musical note image: (a) degraded image in imaging context and (b) restored image by the proposed method.

Ⅳ Conclusion

We present an efficient self-organizing neural network-based nonlinear restoration of spatially varying blurred gray-level images. The proposed method can effectively restore the degraded image by using region classification of SONN to detect the location of the degraded regions, and adaptive learning to the blur sensitivity of receptive field. In addition, receptive fields are adaptively overlapped to eliminate the block effect within the restored images. Simulation results for the space-variant blurred pepper image show the performance improvement of about 4.86 dB or 3.57 dB as compared to the Richardson-Lucy algorithm or to the conventional neural networks. The restoration results of the proposed method for camera acquired image lead significantly to temper the degree of the degradation.

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