Journal of Information Hiding and Multimedia Signal Processing ©2017 ISSN 2073-4212
Ubiquitous International Volume **8**, Number **4**, July **2017**

UAV Motion-Blurred Image Restoration Using Improved Continuous Hopfield Network Image Restoration Algorithm

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Received December, 2016; revised April, 2017

Abstract. *The performance of blind detection algorithm based on Hopfield neural network depends on the choice of activation function. According to this principle, we change the activation function of continuous Hopfield image restoration algorithm to improve the performance. Compared with the previous algorithm, the improved algorithm greatly speeds up the convergence rate without reducing the quality of the repaired image. The new algorithm can resolve unmanned aerial vehicle (UAV) motion-blurred image restoration, combining with the estimated point spread function (PSF). The experimental results show the superiority of the new algorithm.*
Keywords: Hopfield neural network, Activation function, Image restoration, UAV motion-blurred image

1. **Introduction.** With the help of UAV, it is easier to take photos in terrible environment. However, we may still get the motion blur image which is hard to recognize resulting from relative movements, posture changes, mechanical vibrations, effects of atmospheric turbulence and so on. Therefore, we use the image restoration algorithm to overcome the problems and restore the original image.

Zhou's team firstly used Hopfield neural network to restore image [1], they compared the cost function and the energy function of the Hopfield neural network model and found the contacts between recovery and neural network parameters. But Zhou's model is too large and low-efficiency. Paik's team updated the model, with the shortcoming that the state of the neural network changed discontinuously [2]. Wang et al [3] and Wu et al [4] proposed a continuous Hopfield neural network image restoration algorithm and improved it. Further, the stability of that algorithm is proved by Han et al [5]. Latterly, Wu et al [6] proposes the fast image restoration algorithm using neural network based on the harmonic model. The quality of PSF that estimated according to blurred image, directly affects the image restoration, Li et al [9] proposed a PSF estimation algorithm based on strong edge detection which calculated faster, cost less memory and had higher precision, and it can combine with the continuous Hopfield image restoration algorithm to recover UAV Motion-blurred Image. This paper firstly applies the Hopfield neural network with improved activation function [7][8] for image restoration, it replaces the activation function to accelerate the convergence of the algorithm and improve the time complexity and noise immunity. The experimental results show that the performance of the improved algorithm is better.

2. UAV Image Degradation and Restoration Model Introduction.

2.1. Image degradation model.

When the UAV is in the air, there will be relative motion between the imaging device and the ground, so a corresponding motion blur happens when taking photos. The quality of motion-blurred image depends on the fuzzy size which is caused by the speed, altitude, exposure time, the focal length and so on.

In general, with the help of short exposure time, we do not need to think the speed and altitude change in the moment of exposure. The image blur is mainly generated by the UAV's uniform linear motion. In this case, the structure of motion blur depends on the properties of PSF[10]. The degradation model of UAV motion-blurred is given by

$$\mathbf{z} = \mathbf{W}\mathbf{x} + \mathbf{n} \tag{1}$$

where $\mathbf{z}$,$\mathbf{x}$ and $\mathbf{n}$ represent the lexicographically ordered original, degraded image and additive noise respectively. The function of $\mathbf{W}$ is equal to the PSF, which can be considered as a block Toeplitz matrix. If we handle an image with the size of $M \times N$, x and z are $MN \times 1$ vectors and $\mathbf{W}$ is $MN \times MN$ matrix.

We set the PSF function

$$w(i,j) = \begin{cases} \frac{1}{2} & i = 0, j = 0 \\ \frac{1}{16} & |i|, |j| \le 1, (i,j) \ne (0,0) \end{cases} \tag{2}$$

so the matrix $\mathbf{W}$ has the following form:

$$\mathbf{W} = \begin{bmatrix} \mathbf{W_0} & \mathbf{W_1} & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{W_1} \\ \mathbf{W_1} & \mathbf{W_0} & \mathbf{W_1} & \cdots & \mathbf{0} & \mathbf{0} \\ \vdots & \vdots & \vdots & \cdots & \vdots & \vdots \\ \mathbf{W_1} & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{W_1} & \mathbf{W_0} \end{bmatrix} \tag{3}$$

where

$$\mathbf{W_0} = \begin{bmatrix} \frac{1}{2} & \frac{1}{16} & 0 & \cdots & 0 & \frac{1}{16} \\ \frac{1}{16} & \frac{1}{2} & \frac{1}{16} & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \cdots & \vdots & \vdots \\ \frac{1}{16} & 0 & 0 & \cdots & \frac{1}{16} & \frac{1}{2} \end{bmatrix} \tag{4}$$

$$\mathbf{W_1} = \begin{bmatrix} \frac{1}{16} & \frac{1}{16} & 0 & \cdots & 0 & \frac{1}{16} \\ \frac{1}{16} & \frac{1}{16} & \frac{1}{16} & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \cdots & \vdots & \vdots \\ \frac{1}{16} & 0 & 0 & \cdots & \frac{1}{16} & \frac{1}{16} \end{bmatrix} \tag{5}$$

In eq. (3) $\mathbf{0}$ means zero matrix.

2.2. **Image restoration model.** Image restoration process is to inverse image degradation. We take the estimated PSF and the collected image as the inputs of the network. The restored image as the output is generated after the neural network converges.

We estimate PSF with strong edge characteristic of the image. Firstly we calculate the gradient of the target image and retains the significant edge with threshold values expressed as:

$$P_x = \begin{cases} u_x, & |u_x| > \tau \\ 0, & |u_x| \le \tau \end{cases} \tag{6}$$

$$P_y = \begin{cases} u_y, & |u_y| > \tau \\ 0, & |u_y| \le \tau \end{cases} \tag{7}$$

where u_x and u_y represent the partial derivation along the x and y direction of the image,τ is the threshold value. Then, we can get the PSF:

$$\arg\min_h \{||g_x - h * P_x||^2 + ||g_y - h * P_y||^2 + \alpha||h||^2\} \tag{8}$$

$$s.t. \sum_{i,j} h_{i,j} = 1, h_{i,j} \ge 0 \tag{9}$$

where (g_x, g_y) represents the gradient of the original image[9].

Image restoration is transformed into to get the minimum of the energy function. The energy function can be expressed as following:

$$E = \frac{1}{2}\mathbf{x}^T\mathbf{T}\mathbf{x} - \mathbf{B}^T\mathbf{x} \tag{10}$$

with $\mathbf{T} = \mathbf{W}^T\mathbf{W} + \lambda\mathbf{C}^T\mathbf{C}, \mathbf{B} = \mathbf{W}^T\mathbf{z}$. And $\mathbf{C}$ is the regularization operator which is usually taken as Laplacian operator, and λ is the harmonic parameter.

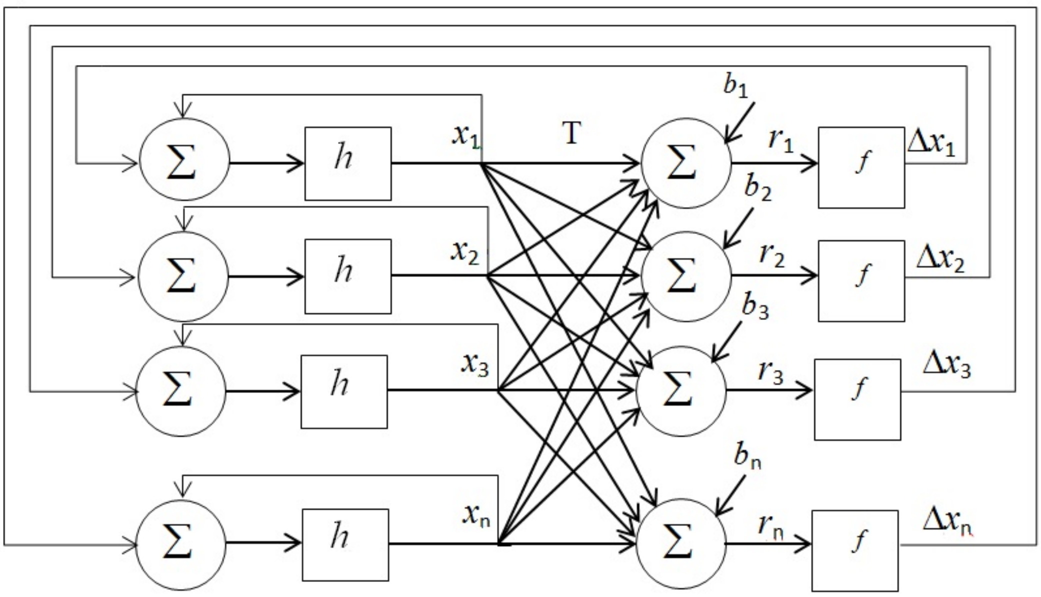

Figure 1. Paik model network

3. **Improved Continuous Hopfield Image Restoration Algorithm.**

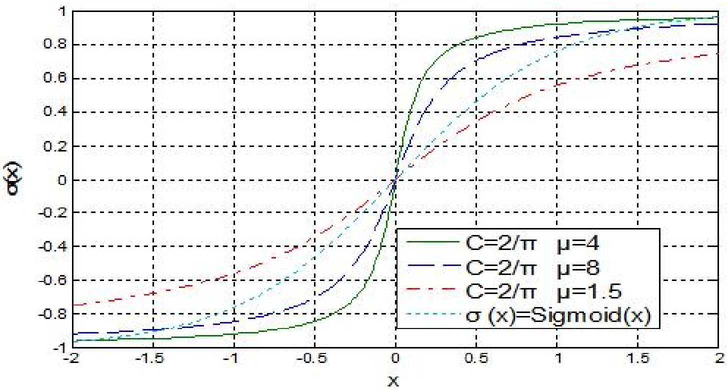

FIGURE 2. The curve of new activation function and Sigmoid activation function

3.1. **Hopfield image restoration algorithm.** On the basis of Zhou's model, Paik proposed a modified network, whose neuron had the value ranging from 0 to 255 [2].The neuron state in Paik's model changed in the following rules:

$$x_i(t+1) = h(x_i(t) + \Delta x_i), i = 1, \cdots MN \tag{11}$$

$$h(x) = \begin{cases} 0, & x < 0 \\ x, & others \\ 255, & x > 255 \end{cases} \tag{12}$$

$$\Delta x_i = f(r_i) = \begin{cases} -1, & r_i < -\theta_i \\ 0, & others \\ 1, & r_i > \theta_i \end{cases}, \theta_i = \frac{1}{2}t_{ii} > 0 \tag{13}$$

$$r_i = b_i - \sum_j t_{ij} x_j(t) \tag{14}$$

where b_i and t_{ij} are the elements of the matrix **B** and **T** respectively.

The network structure is given in Figure 1.

FIGURE 3. Image segmentation method

For full parallel, the convergence point could not correspond exactly to the minimum energy, which affected the quality of rehabilitation. This drawback drived Wang to propose the continuous Hopfield neural network algorithm for image restoration. That was, firstly normalize the gray value of images and make the value between -0.5 to 0.5, and then replace eq.(13) with a monotone continuous function.

3.2. **Improved hopfield image restoration algorithm.** Compared with Paik's model, the time complexity of the continuous Hopfield neural network algorithm has been remarkablely improved. The time complexity is always a key topic of this article. Conventional activation function of neural network is: $f_1(u_i) = ru_i, r > 0$ or $f_2(u_i) = \frac{1-e^{-ru_i}}{1+e^{-ru_i}}, r > 0$ [5].

Among currently literatures that solved practical problems with neural network[11][12][13], the major neural networks used the traditional Sigmoid function as the activation function. With the new activation function, the blind detection algorithm based on Hopfield neural network makes the signal recovery time shorter and the network easier to reach the global optimum [7][8]. Referring to these ideas, we introduce the arc tangent function as the new activation function of continuous Hopfield neural network algorithm for image restoration. The form of new activation function is:

$$\sigma(x) = C \times art\tan(\mu x)[7] \tag{15}$$

where C and μ are used to control the trend of function. Figure 2 shows the new activation function graph with different parameters and the traditional sigmoid function curve.

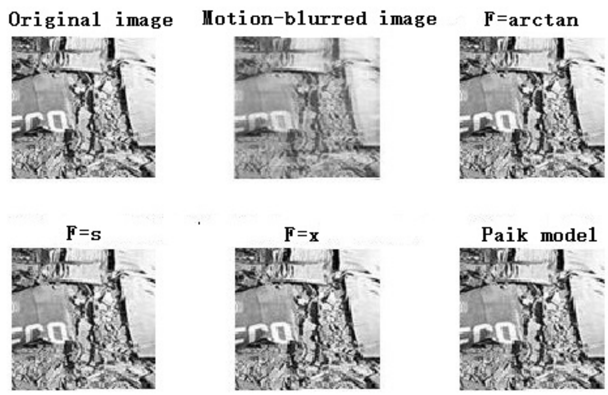

FIGURE 4. Restored image

The form of new activation function is similar to the conventional Sigmoid function, so the network converges quickly with input values of neurons. Besides, it also significantly reduces the sensitivity of neurons on the input values in the vicinities of the origin and enhances anti-jamming capability. The new activation function can improve the convergence speed and noise immunity of a Hopfield neural network.

During the simulation with Matlab R2014a, the image with the size of $M \times N$ needs a weight matrix with size of $MN \times MN$.If the size of image is $\frac{1}{k}M \times N$, that of the weight matrix would be $\frac{1}{k^2}MN \times MN$.

Obviously, in order to reduce the algorithm complexities of time and space, we can respectively process the different parts of the image, and then merge them into one image. Select the appropriate k can greatly reduce the time complexity. The image can be divided with the method showed in Figure 3.

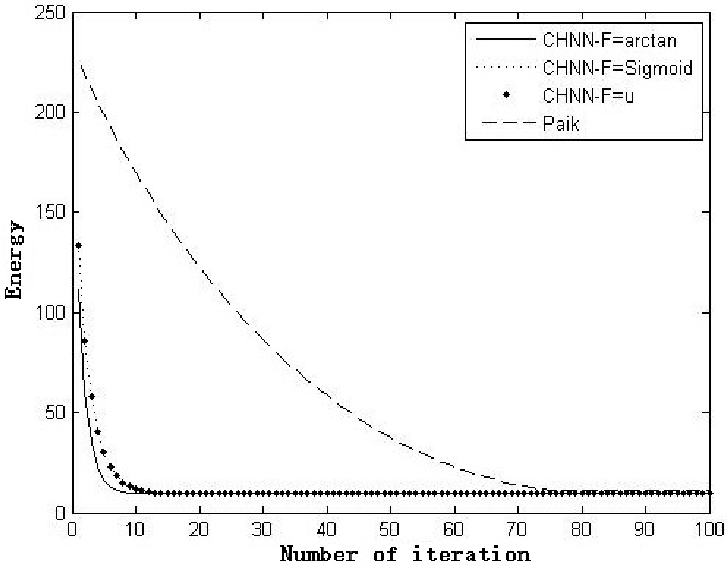

FIGURE 5. Iterations and energy function

4. **UAV Blurred Image Restoration Image Restoration Experiment.** Combined with the foregoing analysis of the PSF estimation of UAV motion-blurred image and improved Hopfield neural network algorithm description, we apply the comprehensive algorithm to restore UAV motion-blurred image. Due to the space limitation, this paper mainly analyzes the performance of improved continuous Hopfield neural network algorithm, and its comparison to the previous algorithm and Paiks model. The experimental results show the convergence rate of the improved algorithm is much faster.

We use a BMP format image for experiment. In order to get results quickly we split the image, and select one for the experiment. The size of the selected image is 100×99. After adding additive white Gaussian noise to the image, the signal to noise ratio (SNR) is 20dB. We take Laplacian operator as regularization operator with cyclic matrix model. We use SNR improvement as an evaluation expressed as:

$$\Delta SNR = 10\log_{10}\frac{||z-x||^2}{||\hat{x}-x||^2} \tag{16}$$

where $x, \hat{x}$ and z represent the original image, restored image and degraded image, respectively.

For Paik's model in full parallel manner, the value of λ is particularly important. If it is unsuitable, the SNR improvement would first increase, then decrease, finally achieve the convergence, resulting in the evaluation criteria out of the function. Setting $\lambda = 0.001$ would make the experimental results better. The experiment would compares Paik's model with the continuous Hopfield neural network algorithm with those activation functions:

$$f_1(u_i) = ru_i(r = \frac{2}{||T||_2} - 0.001) \tag{17}$$

$$f_2(u_i) = \frac{1-e^{-ru_\mathrm{i}}}{1+e^{-ru_\mathrm{i}}}(r = \frac{4}{||T||_2} - 0.001) \tag{18}$$

$$\sigma(x) = C \times art\tan(\mu x)(C = \frac{\pi}{2}, \mu = \frac{5}{||T||_2} - 0.001) \tag{19}$$

The traditional activation function makes the algorithm achieve optimal performance. The Matlab R2014a serves as the experimental tool. The restored image shown in Figure 4 are a little different using different algorithms. The convergence and the SNR improvement of those algorithms would show the advantages and disadvantages of those algorithms. Figure 5 and Figure 6 respectively represent the relationship of iterations between the energy function and the SNR improvement. By observing the results, we find that the continuous Hopfield neural network image restoration algorithm is better than Paik's model in convergence speed and SNR improvement and the improved algorithm with new activation function is better than the previous ones. So if we select the appropriate activation function, we can improve the performance of continuous Hopfield neural network algorithm for image restoration.

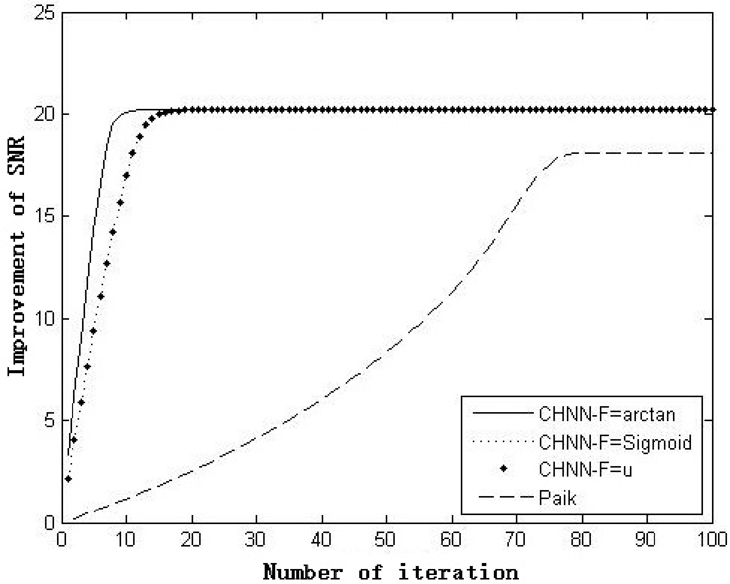

FIGURE 6. Iterations and SNR improvement

5. **Conclusions.** In this paper, we combined the PSF estimation algorithm with Hopfield neural network algorithm for the UAV captured image restoration scenarios. We introduce the principle that a new activation function can improve the performance of continuous Hopfield neural network algorithm. Simulation results demonstrate that the improved algorithm can quickly converge energy function to minimum point, and improve the SNR. After analyzing the simulation data, we find that continuous Hopfield neural network algorithm with traditional activation function needs 17 times of iterations to converge, but with novel activation function, it only needs 8 times to convergence. The convergence rate increases substantially. For larger amounts of data, it will be more advantageous in saving processing time.

Acknowledgment. The authors would like to thank the support of this work by Grants from the National Natural Science Foundation of China (NSFC) (No.61302155,No.61274080) and the introduction of talent Project of Nanjing University of Posts and Telecommunications(No.NY2l4052).

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