Journal of Information Hiding and Multimedia Signal Processing ©2017 ISSN 2073-4212
Ubiquitous International Volume 8, Number 1, January 2017

# Multi-focus Image Fusion Based on Local Clarity of SCM

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Received March, 2016; revised June, 2016

Abstract. *In this paper, a novel image fusion algorithm based on local clarity of spiking cortical model (SCM) is put forward. Firstly, the source images are fused based on local area clarity, and this strategy can keep the focus area of source images. Then, we utilize the SCM to fuse the focus edge of source images. There are five parameters that need to be set in SCM. However, these parameters are hard to get the best combination. Thus, we will utilize biogeography-based optimization algorithm to optimize these parameters. As demonstrated by the experimental results, the proposed method has good quantitative and visual evaluation.*

**Keywords:** Multi-focus image fusion, Local clarity, Spiking cortical model, BBO

1. **Introduction.** The aim of image fusion is to synthesize the main information of source images from different sensors into a single image, and the fusion image can be more accurate and express the image information in a reliable way [1]. Multi-focus image fusion technology can be divided into spatial domain fusion method and transform domain fusion method [2].

In transform domain method, the step of image fusion can be classified into two parts: 1) obtain the corresponding coefficient of transform domain; 2) choose frequency domain coefficients according to different fusion rules and get fusion image by inverse transform. There are many transform domain image fusion methods, such as discrete wavelet transform [3], dual tree complex wavelet transform [4] and shear wave transformation [5]. Nonetheless, transform domain fusion method just has a little direction that can be selected. It is sensitive to noise, and has a higher computational complexity. Thus, it can not be best utilized in real-time applications. The fusion process of spatial domain fusion method is mainly based on the spatial feature of image pixel information. However, this method can easily cause block effect. Moreover, the size of the block is hard to be identified.

Spiking Cortical Model [7] (SCM) is a neural network model based on human visual imaging habits, thus it has been widely applied in image processing field. Nonetheless, there are many parameters that need to be identified in the model. Furthermore, the combination of different parameters will affect the image fusion results. Hence, it needs large computational complexity in the prophase work to obtain the suitable parameters. For solving the parameter problems, we will utilize intelligent optimization algorithm. Biogeography-based optimization [8] (BBO) refers to a new swarm intelligence optimization algorithm and it has a faster convergence rate as well as better estimation performance than the other algorithm. Hence, we will utilize BBO to optimize the model parameters.

Based on the above analysis, a new fusion algorithm based on local clarity is proposed to get the best fusion image. The method can be divided into two steps: 1) Comparing the clarity of the source images local area and extracting the optimal area. 2) Using SCM to fuse the remaining area, and putting forward a fusion rule based on pixel area energy. The rest of this paper is organized as follows. To be specific, section 2 defines the SCM model, and section 3 proposes the image fusion algorithm based on local clarity of SCM. Furthermore, section 4 conducts the performance evaluations for our proposed algorithm. In the end, the paper concludes with Section 5.

2. **Spiking cortical model.** SCM is made up of several interconnected neurons feedback network, it can be divided into three parts: receptive field, modulation field and pulse generator. The SCM neuron model is shown in Figure 1.

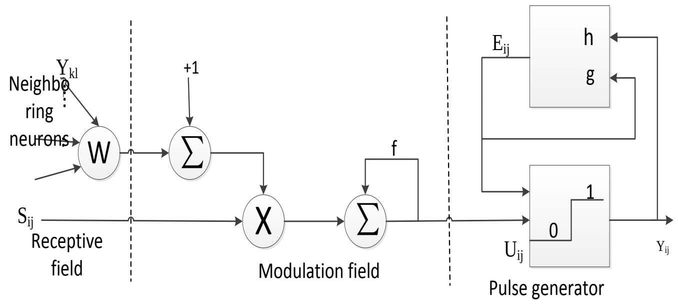


FIGURE 1. the model of SCM

$$E_{ij}(n) = gE_{ij}(n-1) + hY_{ij}(n-1) \tag{1}$$

$$U_{ij}(n) = fU_{ij}(n-1) + S_{ij}\sum_{kl} W_{ijkd}Y_{kl}(n-1) + S_{ij} \tag{2}$$

$$Y_{ij}(n) = \begin{cases} 1, & U_{ij}(n) - E_{ij}(n) > 0 \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

where $U_{ij}(n)$ is internal activity, $S_{ij}$is a stimulus, $Y_{ij}(n)$ is output, $E_{ij}(n)$ is dynamic threshold, $W_{ijkl}$ is synaptic weight matrix applied to the linking field, $f$ and $g$ are decay constants, $h$ is threshold magnitude coefficient. The internal activity of neuron is set to 0. With the increase in the number of iterations, the neuron $(i, j)$ will be fired if the value of $U_{ij}(n)$ is larger than $E_{ij}(n)$. Neurons in the SCM through local coupling constitute a global interconnected neural network. When a neural has been fired, its neighborhood neural with similar status can capture this incentive and send pulse after modulation, realize the ignition ahead of time

3. **Image fusion algorithm based on local clarity of SCM.** The image fusion processing of traditional spatial domain image fusion algorithm is based on pixel level. However, the human visual system is more sensitive to a pixel area. Thus, block effect is the key factor that affects the quality of image fusion. As a result, a new algorithm based on area clarity is put forward to ensure that the final fused image is more suitable for the human eye observation.

3.1. **Image fusion based on local definition.** Define that the size of local area is $M * N$ and calculate the clarity of each local area. Since local average gradient (LAG) can measure the overall activity of images, thus we select it to judge the clarity of source images. LAG can be described as follows.

$$\nabla \bar{g} = \frac{1}{M * N} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} \sqrt{\left(\Delta I_x^2 + \Delta I_y^2\right)/2} \tag{4}$$

Where $\Delta I_x$ refers to the differential value in direction x, while $\Delta I_y$ refers to the differential value in direction $y$. $\Delta I_x$ and $\Delta I_y$ can describe the change degree of image gray and a larger value means that the image has a larger clarity.

When we get the local clarity of the two source images, the fusion rules can be described as follows: If the two fusion areas meet equation (5), it means that the clarity of local region 1 is better than local region 2. Moreover, we keep the local region 1 as the final fusion image.

$$\nabla \bar{g}_1 \geq \nabla \bar{g}_2 \tag{5}$$

3.2. **Image fusion algorithm based on SCM.** As described in section in 3.1, the focus area of source images can be extracted by the fusion strategy, and the main aim of this section is to fuse the edge of focus area. What is more, we will adopt SCM to finish the rest of fusing work.

When the pixel has been fired, the fusing rules can be described as follows:

1) The pixel with more fired number lighter suggests that it has a higher brightness and we will save it as the final fusion pixel.

2) If the pixel of source images has the same number of fired, we will calculate the pixel area energy to fuse image. The fusion strategy can be described as follows:

$$S_{ij} = \beta_{ij}^A S_{ij}^A + \beta_{ij}^B S_{ij}^B \tag{6}$$

Where $S_{ij}$ signifies fusion result of pixel $(i, j)$. $\beta_{ij}^A$ and $\beta_{ij}^B$ refer to the weighting coefficient of fusion, and their values can be calculated by pixel area energy. If the pixel area has a large power value, it indicates that the image information is more abundant and the region should be given with more attention. Additionally, the weight coefficient can be calculated as follows.

$$D(i,j) = M^A(i,j) - M^B(i,j) \tag{7}$$

$$\overline{D}(i,j) = \sum_{m=-r/2}^{2/r} \sum_{n=-r/2}^{2/r} D(i+m, j+n) \tag{8}$$

$$\begin{aligned} \beta_{ij}^A &= \frac{1}{1 + e^{-\eta \overline{D}(i,j)}} \\ \beta_{ij}^B &= \frac{1}{1 + e^{\eta \overline{D}(i,j)}} \end{aligned} \tag{9}$$

Where $M^A(i,j)$ and $M^B(i,j)$ refer to the power of image $A$ and image $B$ in pixel $(i,j)$. The power of image can be calculated as follows:

$$\begin{aligned} M(i,j) = \sum_{i=2}^{m-1} \sum_{j=2}^{n-1} (&-f(i-1,j-1) - 4f(i-1,j) - f(i-1,j+1) \\ &- 4f(i,j-1) + 20f(i,j) - 4f(i,j+1) \\ &- f(i+1,j-1) - 4f(i+1,j) - f(i+1,j+1))^2 \end{aligned} \tag{10}$$

Where $f(i,j)$ denotes the value of pixel $(i,j)$.

3.3. **Parameter optimization based on BBO.** There are several parameters that need to be set in SCM, and they can be analyzed as follows:

1. $f$ denotes the attenuation coefficient of internal activity, and its value depends on the attenuation speed of $U_{ij}(n)$.
2. $g$ and $h$ refer to the attenuation coefficient and amplification coefficient, and their values will affect the change of threshold.
3. $r$ is the local area radius, which will influence the first stage of the fusion effect.
4. $\eta$ is utilized to solve the weighting coefficient and it will affect the result of pixels fusion.

The traditional strategy to determine the parameters of SCM are exhaustive method and experience method. However, exhaustive method will bring large computational complexity, and the experience method cannot make sure that the parameters are suitable for current source image. Thus, to reduce the complexity of the artificial modulation, we will adopt BBO to optimize the parameter values.

BBO algorithm simulates the habitat migration mechanism between species so as to optimize feasible solution. Habitats correspond to the possible solution of optimization problem and Habitat Suitability Index corresponds to the fitness function. When solving optimization problems, the BBO construct multiple habitats X as the initial solution. The algorithm increases the species diversity of habitats and improves the habitat of HIS by exchanging the species migration information to get the optimal solution of the problem. The flow chart can be seen in Fig.2.

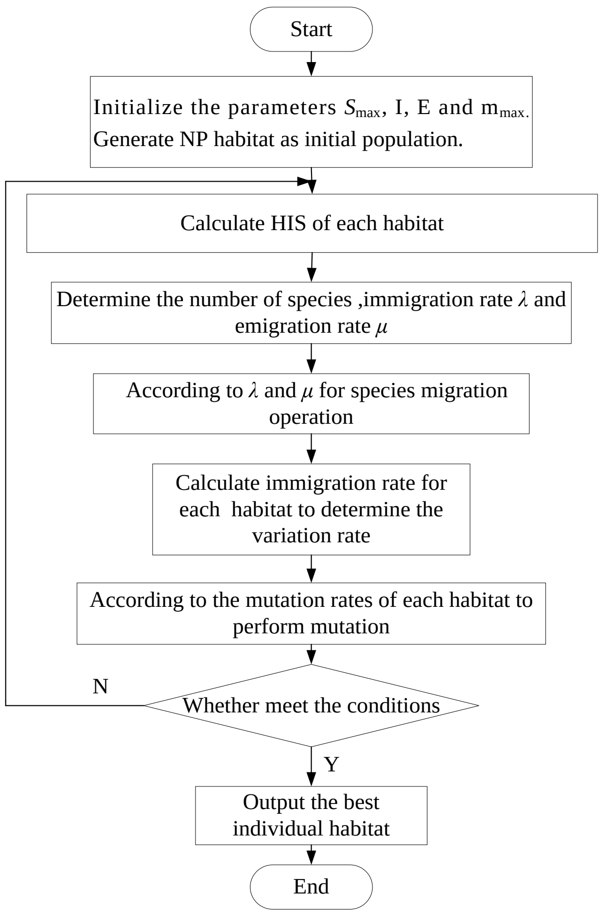


FIGURE 2. The flow chart of BBO

3.4. **Fitness function.** When utilizing BBO algorithm to optimize the parameters, we shall set the fitness function for algorithm. In image fusion evaluation index, the Spatial frequency (SF) [9] mainly expresses the details of the fusion image. Thus, we select SF as the objective function. Spatial frequencies can be described as follows:

$$\begin{aligned} RZ &= \sqrt{\frac{1}{NM}\sum_{\text{n}=1}^{N}\sum_{m=2}^{M}\left(Z\left(n,m\right)-Z\left(n,m-1\right)\right)^{2}} \\ CZ &= \sqrt{\frac{1}{NM}\sum_{m=1}^{M}\sum_{n=2}^{N}\left(Z\left(n,m\right)-Z\left(n-1,m\right)\right)^{2}} \\ SZ &= \sqrt{RZ^{2}+CZ^{2}} \end{aligned} \tag{11}$$

Where $RZ$ refers to the line frequency and $CZ$ refers to the column frequency; $M$ and $N$ refer to the size of the image.

3.5. **Description of fusion algorithm based on local clarity of SCM.** The multi-focus image fusion algorithm based on local clarity of SCM can be summed up as follows.

Step 1: Set the size of local area image as $m*n$. If $\nabla\bar{g}_1 \geq \nabla\bar{g}_2$, we save region 1 as the final fusion image.

Step 2: Use the fusion image finished in step1 to replace the corresponding parts in the source images.

Step 3: Define the initial parameters of SCM and BBO. Initialize a population and each individual represents a SCM.

Step 3: We can get the fitness value, when a SCM finished the process of fusion.

Step 4: Adopt BBO to optimize the fitness function, until the termination conditions are satisfied.

Step 5: Output the final image.

## 4. **Simulation.**

4.1. **Parameters of simulation.** The proposed algorithm is called BBO. To verify the performance of BBO algorithm, such classical algorithms include the pulse coupled neural network (PCNN) [10] in spatial domain discrete wave transform (DWT) [11] in frequency domain, Dual-channel Pulse Coupled Neural Networks (Dual-PCNN) [12], and the fusion rule of maximizing the pixel (MAX). We choose two gray images, including Bottle (512 × 512) and Clock (512 × 512). As shown in Figure 5, they all have two source images with different focus parts, respectively.

With the reference image, AVG, SF and Q [13] are utilized as quantitative assessment metrics to compare various fusion algorithms. Moreover $Q_0$ can describe the similarity between source image and fusion image.

$$Q_0\left(A,F\right)=\left(2\overline{af}/\left(\overline{a}^2+\overline{f}^2\right)\right)\times\left(2\delta_{af}/(\delta_a^2+\delta_f^2)\right) \tag{12}$$

$$Q_0\left(A,B,F\right)=\left(Q_0\left(A,F\right)+Q_0\left(B,F\right)\right)/2 \tag{13}$$

Where $A$ and $B$ refer to source image; $F$signifies fusion image; $\delta_{af}$ signifies the covariance between image $A$ and $F$; $\delta_a$ and $\delta_f$ signify the standard deviation of image $A$and $F$.

The size of population is 30, and the dimension of the problem is 4. The number of iterations is 40. The search range of $\eta$, $f$ and $g$ are initialized in the interval [0, 1]. The parameter $r$ is 16, and $h$ is initialized in the interval [10, 30].

Fig.3 (a)-(b) shows the source images of Bottle, and the fused images of different fusion methods can be listed in Figs. 3(c)–3(g). All of the fusion methods can express the main characteristics of source images. The image fused by MAX is bright, but the contrast of light and shade is bad. The image fused by PCNN is too dark. Merely DWT and BBO can get a better fusion image on the brightness and clarity. Fig.4 (a)-(b) displays the source images of Clock. The fused images of different fusion methods are listed in Figs. 4(c) –4(g). From Fig. 4, it can be seen that Figs. 4(e) and Figs. 4(g) are not as clear as the others. Figs. 7(d) is darker than the other image. Figs. 7(c) and Figs. 7(f) not only keep details well but also have better visual effect.

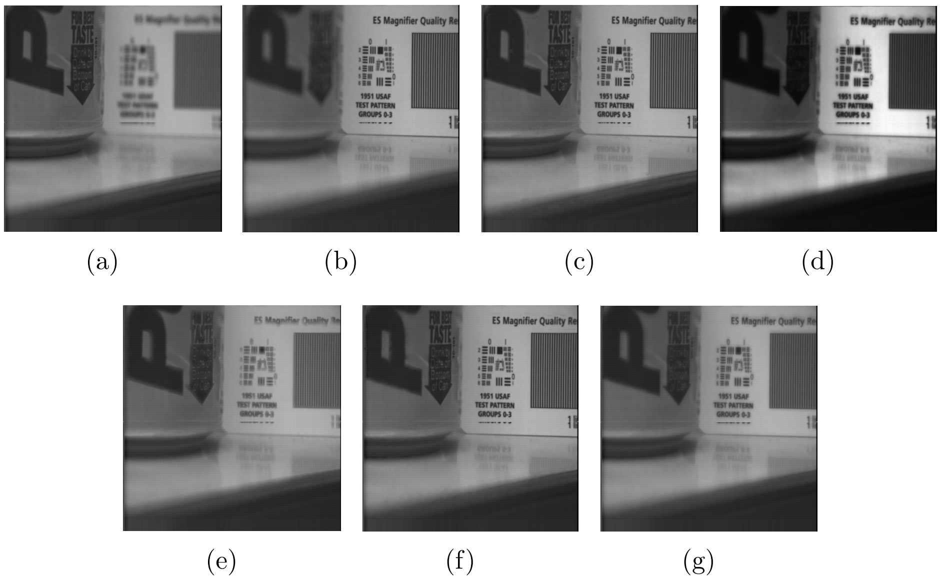


Figure 3. Fusion Results using “Pepsi” grayscale images(a and b) The original images. (c) DWT (d) PCNN (e) MAX (f) BBO (g) Dual-PCNN

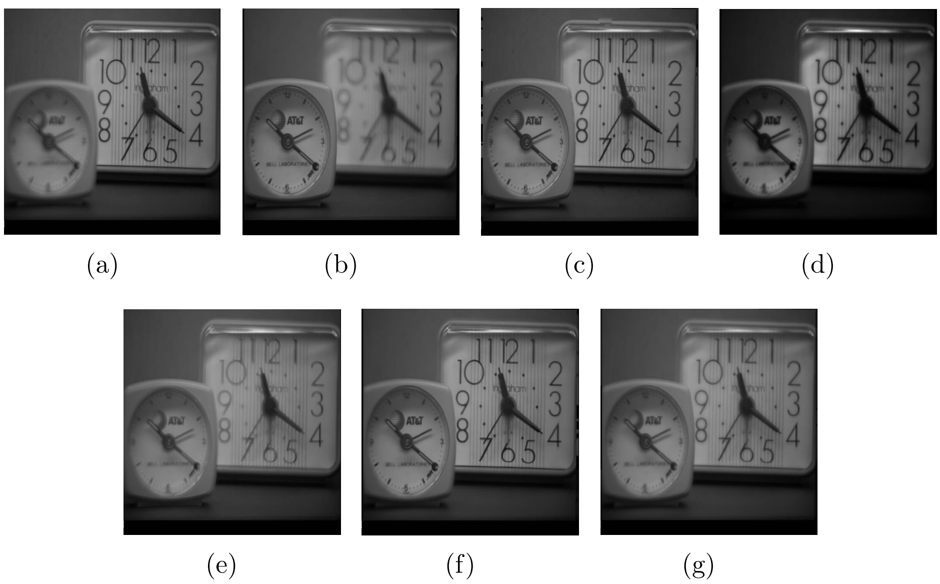


Figure 4. Fusion Results using “Clock” grayscale images(a and b) The original images.(c) DWT (d) PCNN (e) MAX (f) BBO (g) Dual-PCNN

To objectively assess the effect, Table 1 and 2 list the quantitative results by using four measures of AVG, $Q_0$, SF and running time, which demonstrate that our fusion method obtains the best fusion result. Additionally, our method gains the highest AVG, $Q_0$ and SF values compared to the other methods. When BBO is utilized to optimize the model parameters, it needs more time to finish the process. Thus, the presented approach yields higher computational cost than the other methods.

Table 1. Objective evaluation of image fusion experiment

| | AVG | $Q_0$ | SF | t(s) |
|---|---|---|---|---|
| BBO-SCM | **7.5024** | **0.9849** | **27.5721** | 89.32 |
| PCNN | 6.2675 | 0.9609 | 26.3765 | 41.56 |
| Dual-PCNN | 6.7473 | 0.9788 | 26.4340 | 59.22 |
| MAX | 6.2830 | 0.9720 | 24.2529 | **6.38** |
| DWT | 7.3084 | 0.9830 | 27.4911 | 8.74 |

Table 2. image fusion evaluation index experiment

| | AVG | $Q_0$ | SF | t(s) |
|---|---|---|---|---|
| BBO-SCM | **8.1423** | **0.9821** | **16.8874** | 78.54 |
| PCNN | 6.3488 | 0.9576 | 14.0810 | 37.21 |
| Dual-PCNN | 7.8544 | 0.9725 | 16.6876 | 45.18 |
| MAX | 6.2564 | 0.9793 | 13.4978 | **5.32** |
| DWT | 8.0347 | 0.9701 | 16.4757 | 7.17 |

5. **Conclusion.** In this paper, a new multi-focus image fusion technique based on region clarity is put forward. This technique divides the image fusion process into two parts. Firstly, a method based on local area clarity is proposed to keep the focus area of source images. Then, we utilize the SCM to fuse the edge of focusing area of source image. Furthermore, BBO algorithm is adopted to optimize the parameters in SCM. By comparing the other four widely-utilized methods, the proposed technique can get the best details of the expression ability on multi-focus image fusion.

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