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A novel multi-focus image fusion method using PCNN in nonsubsampled contourlet transform domain

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ABSTRACT

A novel multi-focus image fusion method using modified pulse coupled neural network (PCNN) in nonsubsampled contourlet transform (NSCT) domain is presented in this study. Different scales and directions are obtained by image decomposition using the NSCT at first. Then to retain more edges and textures, the edge feature is used to motive the improved PCNN model. The coefficients in the NSCT domain with large firing times are selected as coefficients of the fused image. To testify the performance of our proposed algorithm, simulation experiments are conducted on it. The experimental results showed that the proposed algorithm produces better results compared to other state-of-the-art algorithms neither visual effects nor objective indicators.

1. Introduction

Image fusion has been developed for many years. The mechanism of image fusion combines relevant information contained in different images into a single composite image. Multi-focus image fusion is an important part of image fusion research which utilizes the clear parts of multiple images from the same scene to generate a new image. The new image is available for computer for further image analysis, target recognition and image understanding.

Multi-resolution analysis methods have been widely used in image fusion, which includes wavelets, Laplacian pyramid and gradient pyramid, the ratio of low pass pyramid and contrast pyramid. The traditional wavelet transform can capture the limited direction information, but cannot capture the outline information and will cause pseudo-Gibbs phenomena around singularities. To solve these problems, some researchers put forward stationary contourlet transform (SCT) [1] and àtrous wavelet transform (AWT) [2]. However, the fused images by these methods were poor in retaining edge information. The nonsubsampled contourlet transform (NSCT) put forward by da Cunha et al. also could solve these problems with its shift invariance, anisotropy and rich directions [3].

Pulse coupled neural network (PCNN) was proposed by Eckhorn in 1900, which owns some excellent characters, such as global coupling and pulse synchronization [4]. In spite of good performance of many multi-focus image fusion methods based on PCNN or discrete wavelet transform, there still exist problems which cannot meet the high quality needs of the fused images. Some researchers have used spatial frequency-energy of Laplacian [5] or the improved sum-modified Laplacian (SML) [6] to motivate PCNN. Furthermore, authors in Ref. [5] proposed PCNN based on block processing, which can save the calculated time in a sense. But it will cause the vague phenomenon at the edge. The energy of edge (EOE) was introduced to stimulate the PCNN in this study since human eyes are sensitive to the edge information and traditional PCNN is modified to simplify the calculation. The linking coefficient β is also changed according to the edge features.

2. Nonsubsampled contourlet transform

Nonsubsampled contourlet transform (NSCT) is a redundant transform which consists of nonsubsampled pyramid (NSP) and nonsubsampled directional filter bank (NSDFB). NSCT inherits the feature of contourlet transform. It is a flexible MSD-based method and owns more strength expression ability of edge information than wavelet or contourlet transform. Besides, it avoids the frequency aliasing emerges in wavelet or contourlet transform by removing up-sampling and down-sampling in the process of

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decomposition and reconstruction. Therefore, it satisfies perfect reconstruction conduction and shift invariance [3].

3. Modified pulse coupled neural network

The traditional PCNN is a feedback network. A single neuron of PCNN is consists of three parts: the receptive field, the modulation field, and the pulse generator as shown in (Fig. 1).

Through analyzing the basic PCNN's structure above, there are many parameters need to be determined, which made a great effect on its practical applications. Some researchers proposed simplified PCNN models according to practical applications. However, these models did not get the ideal results in image fusion. A modified PCNN model is adopted in this paper. Besides, the linking coefficient β and external stimulus play a key role in PCNN, which directly decide the performance of PCNN. In the literature [4], the author points out that the U will produce false decisions when linking with low-intensity pixel of the image that just below the potential θ. He proposed that the Sigmoid function can be used for processing datum. Sigmoid response of output is used as a feedback to the L channel in this paper. The modified PCNN model is described by the following equations [1–7]:

$$F_{i,j} = S_{i,j} \tag{1}$$

$$L_{i,j}[n] = V_L \sum_{k,l \in D} W_{i,j,k,l}(Y_{k,l}[n-1]X_{i,j}[n-1]) + \exp(-\alpha_L)L_{i,j}[n-1] \tag{2}$$

$$U_{i,j}[n] = F_{i,j}[n](\alpha_U + \beta_{i,j}L_{i,j}[n]) \tag{3}$$

$$\theta_{i,j}[n] = L_{i,j}V_\theta Y[n] + \exp(-\alpha_\theta)\theta_{i,j}[n-1] \tag{4}$$

$$Y_{i,j}[n] = step(U_{i,j}[n] - \theta_{i,j}[n]) \tag{5}$$

$$X_{i,j}[n] = 1/(1+\exp(-2(U_{i,j}[n] - \theta_{i,j}[n-1]))) \tag{6}$$

$$T_{i,j}[n] = T_{i,j}[n-1] + Y_{i,j}[n] \tag{7}$$

where i and j denote the pixel space coordinate, D denotes the neighborhood around the pixel at position (i, j), m and n are the decomposed scale and direction, α_U is the weighted factor, α_L and α_θ are the delay constants. $W_{i,j,k,l}$ is the synaptic weight, V_L and V_θ are the amplitude gain, n denotes the iteration number currently, step is the step response, when $U_{i,j}$ exceeds $\theta_{i,j}$, it will output 1, otherwise it will output 0.

The linking coefficient $\beta(1>\beta>0)$ is a key role in PCNN which decides the lifting range and exciting character. In general, the weighting coefficient is a constant, which is a limitation for adaptation. Some measures are made to strength the self-adaptive in our study. Since human eyes are more sensitive to region than to signal pixel, to make use of the surrounding information, the size

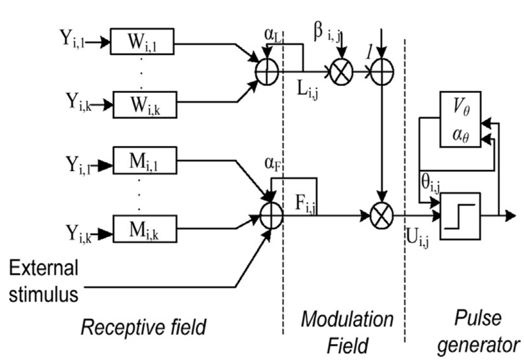

Fig. 1. Basic PCNN neuron model.

of the region around $S_{i,j}$ is chosen as $(2N+1)\times(2M+1)$. The region feature $D_{i,j}$ is computed using Eq. (8):

$$D_{i,j} = \sum_{i=-N}^{N}\sum_{j=-M}^{M} S_{i,j} \tag{8}$$

At last, the Sigmoid activation function is used to calculate the linking coefficient $\beta_{i,j}$ as shown in Eq. (9):

$$\beta_{i,j} = \frac{2}{(1+\exp(-kD_{i,j}))} - 1 \tag{9}$$

where k is the weighting constant which is obtained from experiment or experience.

4. Image fusion method based on EOE-PCNN-NSCT

4.1. Energy of edge

The original image fusion methods based on PCNN used image pixel gray value i.e. the feature of images as the external stimulus. Some researchers have introduced PCNN into wavelet or contourlet domain, these methods achieved some certain effect, but will cause pseudo-Gibbs phenomena around singular points as the result of lacking the shift-invariance. To solve this problem, some new methods were proposed based on SCT or AWT, which reduced the phenomena to some extent. Recently, a new image fusion method was proposed by the authors in Ref. [8]; this method combines NSCT with SF and get better result in fused image. Moreover, the author pointed out that the SML or EOL can be utilized as the external input of PCNN, which would improve the performance. We can know that human eyes are sensitive to edge information. So the EOE can denote the edge feature better than EOL, SF and SML. We choose the EOE as the external stimulus of PCNN in NSCT domain, which is computed by Eq. (10).

$$S_{i,j} = \sum_{i,j \in D} w(i,j)LE(i,j) \tag{10}$$

where $w(i, j)$ is the weighted factor and the sum of its elements equals to 1, D is the neighborhood window around position (i, j), $LE(i, j)$ is calculated using Eq. (11).

$$LE(i,j) = (E_1 * Z(i,j))^2 + (E2 * Z(i,j))^2 + (E3 * Z(i,j))^2 \tag{11}$$

where $Z(i, j)$ is the coefficient in NSCT domain, $E1, E2, E3$ denote the directional filtering operators, which are shown as follows:

$$E1 = \begin{vmatrix} -1 & -1 & -1 \\ 2 & 2 & 2 \\ -1 & -1 & -1 \end{vmatrix} \quad E2 = \begin{vmatrix} -1 & 2 & -1 \\ -1 & 2 & -1 \\ -1 & 2 & -1 \end{vmatrix} \quad E3 = \begin{vmatrix} -1 & 0 & -1 \\ 0 & 4 & 0 \\ -1 & 0 & -1 \end{vmatrix}$$

The edge feature can be extracted by three filtering operators defined above.

4.2. The EOE-PCNN-NSCT-based image fusion method

According to the discussion above, we get our image fusion method. Firing times is regarded as the criteria for selecting fusion coefficient. The larger firing times is corresponding to the position with larger image information. The flowchart of the proposed image fusion method in this paper is shown in Fig. 2.

Supposed the source images have been registered, the fusion method can be conducted on them. The process of the image fusion algorithm is as follows: