Multispectral and Panchromatic Images Fusion by Adaptive PCNN

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Abstract. As for low resolution of remote sensing images, a novel image fusion algorithm by adaptive PCNN was proposed. The multi-spectral image is firstly converted from RGB to lαβ color space. Then, the input images are adaptively decomposed by simplifying traditional PCNN model and defining image definition as the coupled joint coefficient. The largest entropy ignition time series are finally sent to decision factor to achieve the ultimate fusion image. The experimental results show that the proposed method can not only solve the difficult problem about how to set traditional PCNN parameters adaptively, but also on subjective and objective evaluation, its fusion effect on subjective and objective performance evaluation is better than that of other multi-resolution fusion algorithms such as wavelet transform.

Keywords: Image fusion, pulse-coupled neural network (PCNN), color space conversation, adaptive parameter setting.

1 Introduction

Multispectral and panchromatic image fusion technology has been widely used in environmental observation and surface plants classification [1]. At present, the pixel-level image fusion algorithms can be divided into IHS color space transform method, pyramid decomposition method and wavelet transform method [2]. Among them, IHS method can retain high resolution of panchromatic image, but lead to very serious spectral distortion. Multi-scale analysis methods easily separate the inter-linkages between pixels and bring about high algorithmic complexity [3].

As the single-layer network, pulse coupled neural network (PCNN) is well suited to deal with real-time image fusion, because it can carry out pattern recognition and target classification without training [4]. For example, multi-source image fusion algorithm based on local contrast PCNN model is proposed, which is combined with FPF filters to achieve the best option [5]. The multi-channel PCNN model is used to image fusion, which is combined with Laplace transform based on image block [6].

In the paper, a novel image fusion algorithm based on adaptive PCNN is proposed, which is combined with human visual feature according to PCNN model principle. On one hand, this algorithm not only can achieve adaptive processing by defining

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image clarity as the coupling coefficient β, but also avoid the mutual influence of multi-parameter adjustments by simplifying traditional PCNN model. On the other hand, the use of master-slave parallel dual-channel adaptive PCNN structure can solve the problem of high algorithm complexity caused by combination of PCNN model and other multi-resolution algorithms. Experimental results show that compared with other algorithms, it can effectively retain spectral information of multispectral images, and improve spatial resolution.

2 Adaptive PCNN Fusion Principle and Model

2.1 PCNN Model Theory

PCNN is evolved from the mathematical model according to pulse synchronous vibration phenomenon of cat visual cortex, which is put forward by Eckhorn [7]. Every neuron is composed of the reception, modulation and pulse generator. The reception mainly has two functions including feedback input domain and connection input domain, which are respectively connected with the adjacent neuron through weighted synapsis functions M and W. In addition, the external stimulus S is add into the feedback input field. So the mathematical formulae are as follows:

$$F_{ij}[n]=e^{\alpha_F\delta_n}F_{ij}[n-1]+S_{ij}+V_F\sum_{kl}M_{ijkl}Y_{kl}[n-1] \tag{1}$$

$$L_{ij}[n]=e^{\alpha_L\delta_n}L_{ij}[n-1]+V_L\sum_{kl}W_{ijkl}Y_{kl}[n-1] \tag{2}$$

Where F_{ij} is defined as the neuron feedback of point (i, j), L_{ij} is coupled connective function, Y_{kl} is neuron output of $(n-1)$ time iteration, V_F and V_L are respectively the inherent potential of F_{ij} and L_{ij}. Weighted connective matrix M and W as information transfer degree between adjacent neuron and central neuron require iterative computing according to exponential decay rule.

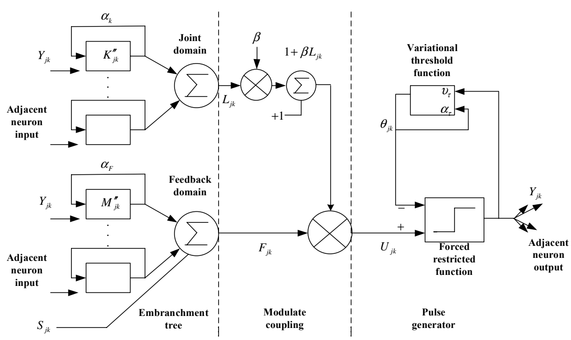


Fig. 1. PCNN neuron model

Internal neuron activity is formed of the two above-mentioned functions by non-linear multiplication, where β is defined as connective coefficient among synapsis. When the neuron is stimulated by external inspiration and influenced by the adjacent feedback input domain and coupling connection domain, internal neuron activity isn't gradually increasing until it is greater than dynamic threshold Θ . Then neurons stimulate excitement and bring timing pulse timing sequence. At the same time, Θ is suddenly increasing and then gradually reduced by means of exponential rule. So this process can be described as:

$$U_{ij}[n] = F_{ij}[n](1+\beta L_{ij}[n]) \tag{3}$$

$$Y_{ij}[n] = \begin{cases} 1 & U_{ij}[n] > \Theta_{ij}[n] \\ 0 & others \end{cases} \tag{4}$$

$$\Theta_{ij}[n] = e^{\alpha_\Theta \delta_n} \Theta_{ij}[n-1] + V_\Theta Y_{ij}[n] \tag{5}$$

From the above analysis, we can see that PCNN is a multi-parameter neural network model and its application depends largely on parameters setting, so there is a problem of finding the optimal parameters. But so far the connection factor, threshold amplification factor and the number of iterations have been set through repeated experiments. Thus, this situation isn't suited for PCNN further application.

2.2 Improved PCNN Model

In order to solve the problem of poor adaption in image fusion, the traditional PCNN model is improved and a novel adaptive PCNN expansion model in master-slave parallel mode is proposed in this paper.

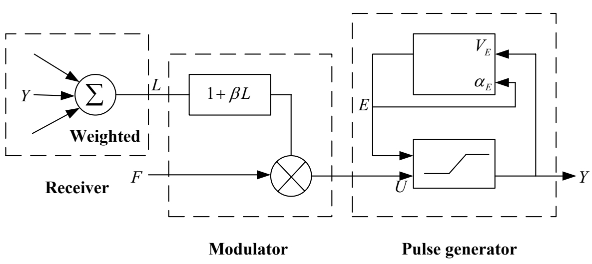


Fig. 2. Simplified PCNN neuron structure

From the above figure, we can see that the simplified PCNN model not only reduces parameters setting, but also maintains several important features of the original model to some extent. Firstly, it retains connective characteristics and the neurons in similar situation have the synchronize output pulse. Secondly, internal activities are formed by the output and connection domain according to the non-linear way. Thirdly, the dynamic threshold is still declined by means of exponential rule. When the neurons output the pulse, the threshold will be reset as V_E . The mathematical expressions of whole process are as

$$H_{ij}^{k}[n] = f^{k}(Y[n-1]) + S_{ij}^{k} \tag{6}$$

$$U_{ij}^{k}[n] = I_{ij}^{k}(1 + \beta_{ij}^{k} H_{ij}^{k}[n]) + \sigma \tag{7}$$

$$Y_{ij}[n] = \begin{cases} 1 & U_{ij}[n] > E_{ij}[n-1] \\ 0 & others \end{cases} \tag{8}$$

$$E_{ij}[n] = \exp(-\alpha_E)E_{ij}[n-1] + V_E Y_{ij}[n] \tag{9}$$

Where I_{ij}^{k} is defined as external incentive input of k $(k = 1, 2)$ channel, where point (i, j) is pixel gray value of input image. Function $f(\bullet)$ is the impact of adjacent on neurons on its own. σ is the internal balance factor of neurons. U_{ij}, Y_{ij} and E_{ij} are respectively the internal activity, pulse output and dynamic threshold of each neuron.

Connective coefficient is directly related to the weighted value of fusion image shared by input source image. In this model, each neuron (i, j) has its own connection coefficient β_{ij}^{k}, which reflects different coupling differences among neurons and adaptively adjusts according to different stimulus. Therefore, can enter the incentive to adjust the different adaptive. It is assumed that I_1 and I_2 are defined as the source input images, β_{ij}^{1} and β_{ij}^{2} are connection coefficients of the corresponding channels, so the mathematical expressions are as follows:

$$\beta_{ij}^{1} = \frac{1}{1 + e^{-\eta D(i,j)}}, \beta_{ij}^{2} = \frac{1}{1 + e^{\eta D(i,j)}} \tag{10}$$

In above formulae, $D(i, j)$ is defined as mean filter for input $d(i, j)$ to remove the wrong definition value, namely $D(i, j) = \sum_{m=-r/2}^{r/2} \sum_{n=-r/2}^{r/2} d(i+m, j+n)$. The input $d(i, j)$ is represented as $d(i, j) = g(I_1(i, j)) - g(I_2(i, j))$ and $g(I(i, j))$ is neighborhood clarity of image $I(i, j)$ by means of gradient method.

$$g(I(i,j)) = \sqrt{\begin{matrix}[I(i,j) - I(i+1,j)^2 + I(i,j) - I(i-1,j)^2 + \\ I(i,j) - I(i,j+1)^2 + I(i,j) - I(i,j-1)^2]\end{matrix}} \tag{11}$$

From above formula, we come to conclusion that β_{ij}^{1} is a increasing function, while β_{ij}^{2} is a declined function. It means that the point is more clearly, thus the connective coefficient of corresponding neuron is greater, which lead to higher weighted value in fusion image. So the adaptive setting of β_{ij}^1 and β_{ij}^2 is completed.

3 The Process of Fusion Algorithm

3.1 Algorithm Steps

There is the processing of image fusion algorithm based on adaptive PCNN model in figure 3. The whole process is described in detail as follows:

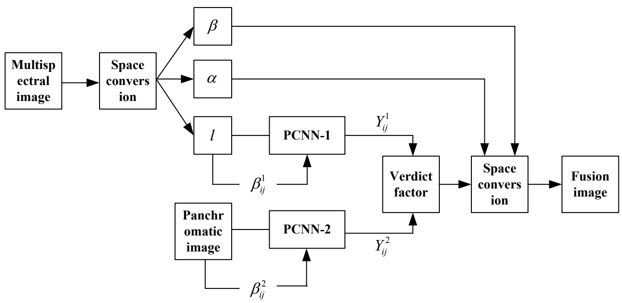


Fig. 3. Adaptive PCNN image fusion

(1) Color space conversion
Registered multi-spectral image is transformed from RGB to $l\alpha\beta$ color space, which is proposed by Welsh [8]. In this color space, l is defined as the achromatic channel, α is defined as the yellow - blue channel and β is defined as the red-green) channel. These three channels are orthogonal relationship.

$$\begin{bmatrix} L \\ M \\ S \end{bmatrix} = \begin{bmatrix} 0.3811 & 0.5783 & 0.0402 \\ 0.1967 & 0.7244 & 0.0782 \\ 0.0241 & 0.1288 & 0.8444 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{12}$$

$$\begin{bmatrix} l \\ \alpha \\ \beta \end{bmatrix} = \begin{bmatrix} 1/\sqrt{3} & 0 & 0 \\ 0 & 1/\sqrt{6} & 0 \\ 0 & 0 & 1/\sqrt{2} \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & -2 \\ 1 & -1 & 0 \end{bmatrix} \lg \begin{bmatrix} L \\ M \\ S \end{bmatrix} \tag{13}$$

(2) PCNN parameters setting
In this algorithm, the gray pixel of l channel is selected as the input of main PCNN neurons, and each neuron is linked with other neurons in its neighboring 3×3 domain. The connective coefficient β_{ij}^1 is calculated according to formula

(10)-(11).The output of each neuron has only two situations: firing or not firing. The main parameter settings are as follows: the balance factor $\sigma = -0.1$, the decay time of threshold $\alpha_E = 0.5$, the threshold magnification factor $V_E = 220$, the internal activity U, pulse output Y and coupling output H are set as zero.

The gray pixel of panchromatic image is selected as the input of slaved PCNN neuron. The connective coefficient β_{ij}^2 is calculated according to formula (10)-(11), too. The difference between main and slaved PCNN channel is that the external stimulus S is removed in slaved PCNN. The main parameters are as follows: threshold decay time and magnification factor of slaved PCNN are less than that of main PCNN, and other parameter settings are the same.

(3) Adaptive fusion processing

According to the above parameters setting, the pixel value of l channel and panchromatic image is input into PCNN, then the received signals of each neuron are integrated based on formula (6) - (9). In this algorithm, the connective weighting function of adjacent neurons $f(\bullet)$ in main and slaved PCNN is the reciprocal of Euclidean distance square [9], namely weighted matrix of neuron ij and kl is as follows:

$$M_{ijkl} = W_{ijkl} = \frac{1}{(i-k)^2 + (j-l)^2} \tag{14}$$

The acts of main PCNN neurons are as follows: neurons with larger pixel value are first ignited and carried out pulse, which neurons with similar pixel and adjacent location are ignited one after the other based on pulse coupling characteristics. So the neurons clusters of synchronous pulse are formed and image decomposition will be completed. The acts of slaved PCNN neurons are as follows: all neurons are naturally ignited, and then the connection between neurons depends on their own coupling intensity. Each region has ignition phenomenon by controlling the number of iterations, and then feature points are selected. On determining the number of iterations, the maximum entropy principle [10] is used and then ignition time maps Y_{ij}^1 and Y_{ij}^2 with the largest entropy are obtained after dual-channel PCNN decomposition. Then they are input into verdict factor according to ignition situation of neurons to determine whether the target is in l channel image or in panchromatic image.

$$F(i,j) = \begin{cases} I_A(i,j) & Y_{ij}^1(i,j) > Y_{ij}^2(i,j) \\ I_B(i,j) & Y_{ij}^1(i,j) < Y_{ij}^2(i,j) \\ (I_A(i,j) + I_B(i,j))/2 & Y_{ij}^1(i,j) = Y_{ij}^2(i,j) \end{cases} \tag{15}$$

(4) Color space inversed conversion

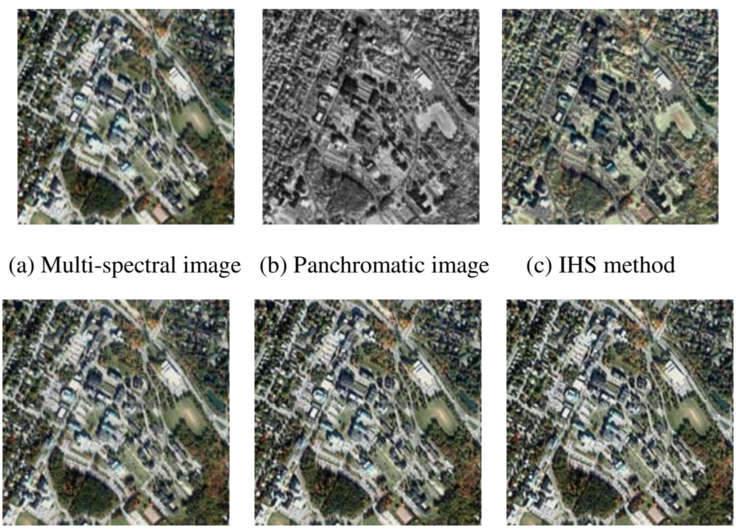
The l channel image that is obtained by $l\alpha\beta$ space conversion on original multispectral image is replaced by gray fusion image $F(i,j)$ that is input from verdict factor. Then the final fusion image of RGB space is obtained by means of $l\alpha\beta$ inversed conversion on the new component l, α and β.

$$\begin{bmatrix} \Gamma \\ \Omega \\ \Psi \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & -1 \\ 1 & -2 & 0 \end{bmatrix} \begin{bmatrix} 1/\sqrt{3} & 0 & 0 \\ 0 & 1/\sqrt{6} & 0 \\ 0 & 0 & 1/\sqrt{2} \end{bmatrix} \begin{bmatrix} l \\ \alpha \\ \beta \end{bmatrix} \tag{16}$$

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \begin{bmatrix} 4.4679 & -3.5873 & 0.1193 \\ -1.2186 & 2.3809 & -0.1624 \\ 0.0497 & -0.2439 & 1.2045 \end{bmatrix} \begin{bmatrix} 10^{\Gamma} \\ 10^{\Omega} \\ 10^{\Psi} \end{bmatrix} \tag{17}$$

4 Simulation and Analysis

To verify the algorithm performance, the simulation makes use of two groups of remote sensing images to simulate and contrast with the common methods such as IHS, discrete wavelet transform(DWT), Contourlet algorithm [11]. The multispectral and panchromatic image photographed by IKONOS satellite in Fredericton of Canada is adopted in the first experiment, while the Nanking zone images photographed by Quick Bird satellite is adopted in the second experiment. In the first experiment,



(a) Multi-spectral image (b) Panchromatic image (c) IHS method

(d) DWT+IHS (e) Contourlet+IHS (f) proposed method

Fig. 4. Fusion results of different methods in IKONOS

DWT algorithm uses the biorthogonal wavelet "bior4.4" and decomposition is 4 levels, while the decomposition of Contourlet algorithm is 5 levels. The above fusion methods use the low-frequent coefficients to substitute the intensity component and use the maximum regional energy as the high-frequent coefficients in order to validate the impact of different multi-scale decomposition tools on fusion performance. In the second experiment, the parameters settings of above algorithms is unchanged, but the pictures are appended into Gaussian white noise, which the mean is 0 and variance is 0.05 in order to validate the effects of noise interference on different algorithms. In the proposed algorithm, the initial value of parameters is set according to Step (2). The simulation results are shown in Figure 4 and 5.

(a) Multi-spectral image (b) Panchromatic image (c) IHS method

(d) DWT+IHS (e) Contourlet+IHS (f) proposed method

Fig. 5. Fusion results of different methods in Quick Bird

The results of the objective evaluation on the above fusion methods are shown in Table 1 and 2. The edge maintainability and spectral distortion [12] are compared in the average of three-band R, G, and B.

Table 1. Fusion Performance of Different Methods in IKONOS

Fusion Method	Edge Maintainability	Spectral Distortion	SNR
IHS method	0.6560	46.9975	12.1286
DWT +IHS method	0.7148	28.7321	18.5569
Contourlet+IHS method	0.7256	23.4805	18.5102
The proposed method	0.7260	21.8591	19.4394

Table 2. Fusion Performance of Different Methods in Quick Bird

Fusion Method	Edge Maintainability	Spectral Distortion	SNR
IHS method	0.3783	2.9020	30.2798
DWT +IHS method	0.3929	2.4462	33.8287
Contourlet+IHS method	0.4135	2.1515	34.4391
The proposed method	0.4303	2.0417	34.9347

From Fig. 4, 5 and Table 1, 2, the conclusions are as below:

(1) From the view of edge maintainability, the effect of IHS algorithm is the worse owing to no directional information extraction. Although DWT+IHS and Contourlet+IHS methods can achieve detailed integration in each frequent band, "virtual shadow" is appeared in fusion image owing to the sub-sampled processing of multi-resolution decomposition. The effect of the proposed method is the best owing to the scale and displacement invariance of improved model.

(2) From the view of spectral distortions, the relationship among each channel of IHS space conversion isn't orthogonal so the color distortion fusion image is obvious. Although IHS space conversion is combined with DWT and Contourlet transform, the effect isn't satisfied owing to its own shortcoming. In the proposed method, orthogonal $l\alpha\beta$ space conversion is used to reduce the cross distortion of each color channel.

(3) From the view of SNR, IHS algorithm has the worst anti-noise ability; DWT + IHS and Contourlet + IHS methods carry out direction decomposition on image pixels with noise, which easily leads to signal-to-noise-aliasing. The proposed method has the optimal anti-noise ability, which removes majority of high frequent noise by neuron coupling.

(4) From the view of calculation complexity, for the image with $N \times N$ sizes the number of the proposed method are less than that of DWT+IHS method about $\frac{4}{3}KN^2$ times, and less than that of Contourlet+IHS method about $\frac{2}{3}(K+2)N^2$, which K is the length of filter.

5 Conclusion

With the problem of multi-parameter setting of traditional PCNN model, a novel image fusion algorithm based on adaptive PCNN model and $l\alpha\beta$ color space conversion is proposed in this paper. It can achieve self-adaptive processing by means of simplifying traditional PCNN model and defining image definition as the coupled joint coefficient. The experimental results show that the proposed method can adequately take the correlation between pixels and noise influence into account the correlation between pixels and noise impact, and then the fusion effect is better than that of other multi-resolution decomposition algorithms both in subjective visual analysis and objective evaluation standards.

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