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Image Fusion Algorithm Based on Features Motivated Multi-channel Pulse Coupled Neural Networks

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***Abstract*—Pulse coupled neural networks (PCNN) is a mammal visual cortex-inspired artificial neural networks. Owing to the coupling links in neurons, PCNN is successful to utilize the local information, thus it has been successfully employed in image fusion. However, in traditional PCNN for image fusion, value of per pixel is used to motivate per neuron. In this paper, image feature of per pixel, e.g. gradient and local energy, is used to motivate per neuron and generate firing maps. Each firing map is corresponding to one type feature. Furthermore, a new multi-channel PCNN is presented to combine these firing maps via a weighting function which measures the contribution of these features to the fused image quality. Finally, pixels with maximum firing times, when firing times of source images are compared, are selected as the pixels of the fused image. Experimental results demonstrate that the proposed algorithm outperforms Wavelet-based and Wavelet-PCNN-based fusion algorithms.**

Keywords-Pulse Coupled Neural Networks; image fusion; wavelet transform; image processing

I. INTRODUCTION

Pulse coupled neural networks (PCNN) is a novel biologically neural network, which was developed by Eckhorn et al in 1990 and based on the experimental observations of synchronous pulse bursts in cat and monkey visual cortex[1]. It is characterized by the global coupling and pulse synchronization of neurons and has been proven suitable for image processing [2].Image fusion is an active research field as an aspect of data and information fusion, which is widely applied in remote sensing, computer vision, medical image processing .etc. It combines sensory data from multiple sensors to provide more reliable and accurate information [3].

Recently, PCNN has been employed in image fusion successfully [4]-[7]. PCNN is associated with other image processing methods, especially multiscale decomposition methods, in image fusion to make full use of the characteristics of them. These fusion methods can be divided into two categories. PCNN is utilized in spatial domain (SD) [4] [5] and multiscale decomposition domain (MSD) [6] [7]. The distinctive feature of the two categories is that pixels in SD and pixels of subimages in MSD are connected to PCNN neurons, respectively. Because the multi-frequency and multi-resolution processing mechanism are the same as that of human retina [7].Most fusion algorithms are based on combining the MSD pixels of the source images. MSD-based fusion schemes provide a much better performance than the simple methods studied previously [3]. Thus, the typical PCNN-based fusion algorithm employs PCNN in MSD [6] [7], namely MSD-PCNN. Due to joint information representation at the spatial-spectral domain, wavelet transform becomes the most popular MSD method in image fusion. In this paper, a shift-invariant wavelet transform (SIDWT) in [8] is selected as the wavelet transform to overcome shift-variance of common discrete wavelet transform.

However, in the previous PCNN-based fusion algorithms [4]-[7], only value of per pixel in SD or MSD is utilized to motivate PCNN. In fact, humans are often sensitive to edges and regional features. Due to parameters setting of PCNN, which is still an unsolved problem, PCNN cannot completely extract all the detailed image information. Thus, we propose a feature motivated PCNN to improve its efficiency and overcome this limitation of PCNN. Image feature, not value of per pixel in traditional way, is input to PCNN and generates firing maps. Here, a weighting function is defined to measure the contribution of multiple firing maps to quality of the fused image.

II. MSD-PCNN BASED FUSION ALGORITHM

PCNN is a feedback network and each PCNN neuron consists of three parts: the receptive field, the modulation field, and the pulse generator [2].In image fusion, PCNN is a single layer pulse coupled neural cells with a two-dimensional connection as shown in Fig.1.

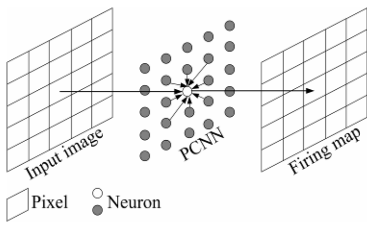


Figure 1. Connection model of PCNN neuron.

Traditional MSD-PCNN fusion algorithms are complemented in [6] [7], In these algorithms value of per pixel in MSD domain is considered as the image information and is input to PCNN as shown in Fig.2.

Figure 2. Traditional value of per pixel motivated PCNN

A pixel in MSD subimages with maximum pixel firing times, which is the sum of pulse in $n_{\max}$ iteration, is selected as the pixel of fused subimages. The selection rule can be described as

$$\begin{cases} I_{F,k}(x,y)=I_{1,k}(x,y), \text{if}: T_{1,k}(x,y,n_{\max}) \geq T_{2,k}(x,y,n_{\max}) \\ I_{F,k}(x,y)=I_{2,k}(x,y), \text{if}: T_{1,k}(x,y,n_{\max}) < T_{2,k}(x,y,n_{\max}) \end{cases}$$

where $I_{1,k}(x,y)$, $I_{2,k}(x,y)$, $I_{F,k}(x,y)$ denote the pixels located at (*x*,*y*) of MSD subimages and fused subimages, $T_{1,k}(x,y,n_{\max})$ and $T_{2,k}(x,y,n_{\max})$ are the firing times of *k*-th MSD subimage after $n_{\max}$ iterations.

This method doesn't make full use of feature of each pixel, e.g. local energy and gradient information. In addition, parameters setting of PCNN are still an unsolved problems, PCNN cannot completely extract all the detailed image information and features motivated PCNN could overcome this limit as well as utilizing the global coupling and pulse synchronization of neurons in PCNN. This is our original intention of features motivated PCNN proposed in this paper.

III. FEATURS MOTIVATED MULTI-CHANNEL PCNN DESIGN IN IMAGE FUSION

A. General Design of Features Motivated Multi-channel PCNN

Suppose $S_k^{\ i}$ denote the *i*-th type feature at the *k*-th MSD subimage. Size of $S_k^{\ i}$ is same as size of subimage and we name $S_k^{\ i}$ as feature map. All the feature maps $S_k^{\ i}\left(i=1,2,3,\cdots,N\right)$ consist of N types feature information. Per feature map will be input to one PCNN and generate one firing map, which represents the sum of firing times located at corresponding pixels. Firing times denote the information of images, which is the processed result by the global coupled and pulse synchronic neurons. Note that number of PCNN and firing maps is same as that of feature maps. The multi-channel PCNN is shown in Fig.3.

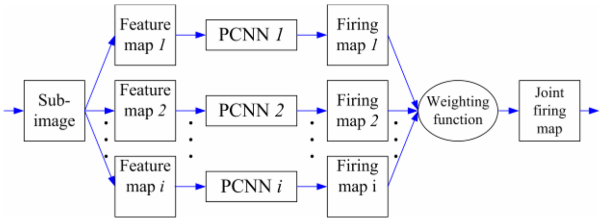


Figure 3. Features motivated multi-channel PCNN.

In multi-channel PCNN, different definitions of features will satisfy different goals for image fusion. A weighting function is designed to measure the contribution of firing maps to the quality of fused image. Suppose $f_k^{\ i}\ \left(i=1,2,3,\cdots,N\right)$ denotes the *i*-th feature firing map corresponding to the *i*-th feature map $S_k^{\ i}$, which belongs to the *k*-th MSD subimage. The weighting function is defined in as follows

$$\tilde{f}_k=\sum_{i=1}^{N} w^i f_k^{\ i}$$

where $\sum_{i=1}^{N} w^i=1, w^i \geq 0$. N is the total number of feature maps. An ideal weight vector $\left\{w^1,w^2,\cdots,w^N\right\}$ will lead to an ideal joint firing map $\tilde{f}_k$, which perfectly represents the information of images via firing times. However, weighting function is one simple form. Other function aiming at an exact fusion purpose may be more reasonable and effective.

Compared with the typical MSD-PCNN fusion algorithm, fusion rules in features motivated multi-channel PCNN (FMMC-PCNN) fusion algorithm can be defined as

$$\begin{cases} I_{F,k}(x,y)=I_{1,k}(x,y), \text{if}: \tilde{f}_{1,k}(x,y,n_{\max}) \geq \tilde{f}_{2,k}(x,y,n_{\max}) \\ I_{F,k}(x,y)=I_{2,k}(x,y), \text{if}: \tilde{f}_{1,k}(x,y,n_{\max}) < \tilde{f}_{2,k}(x,y,n_{\max}) \end{cases}$$

B. Example: Two-channel PCNN in Image Fusion

General design of FMMC-PCNN is introduced in subsection A. In this subsection, two-channel PCNN as an example is presented to evidence the efficiency of multi-channel PCNN in image fusion. In order to overcome shift invariance of discrete wavelet transform, the SIDWT in [8] is selected as the MSD method.

Image gradient energy and local energy in Wavelet domain are used as two-type features here and defined in (1) and (2) respectively, where Ω is the local region (typically 3×3) in Wavelet domain subimages.

$$E_k(x,y) = \sum_{x,y\in\Omega} I^2{}_k(x,y). \quad (1)$$

$$G_k(x,y) = \left(I_k(x,y) - I_k(x+1,y)\right)^2 + \left(I_k(x,y) - I_k(x,y+1)\right)^2. \quad (2)$$

Gradient energy denotes the gradient intensity of images, which is sensitive to human perception. Local energy denotes the local information in Wavelet subimages. They compose gradient energy and local energy feature maps. The two features maps $f_k{}^1$ and $f_k{}^2$ are input to PCNN separately, thus two feature firing maps will be produced. The joint firing map $\tilde{f}_k$ is calculated as in

$$\tilde{f}_k(x,y) = w^1 f_k{}^1 + w^2 f_k{}^2$$

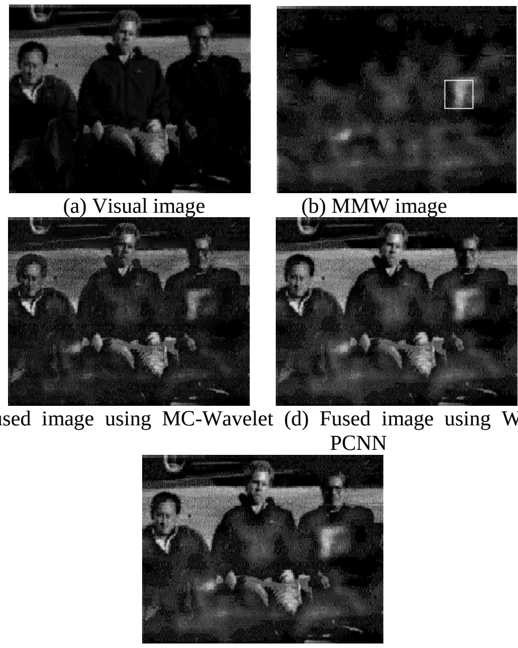
where $w_1 + w_2 = 1, w^1, w^2 \geq 0$.

IV. EXPREIMENTAL RESULTS AND DISCUSSIONS

In experiments, SIDWT is selected as the wavelet because of it is a shift-invariant wavelet form. The decomposition level of SIDWT is set as 4.To demonstrate the performance of FMMC-PCNN fusion algorithm, two typical algorithms in wavelet domain, as the MSD fusion algorithms, maximum-coefficients-based algorithm (MC-Wavelet) [3] and Wavelet-PCNN algorithm [6], are compared. In MC-Wavelet, maximum absolute value of pixels is employed as the fusion rule in high frequency and average rule in low frequency. While in Wavelet-PCNN, single pixel firing times of PCNN is employed as the fusion rule in both high frequency and low frequency. The parameters of PCNN are the same in Wavelet-PCNN and FMMC-PCNN. In order to show the weight vector's impact on the performance of FMMC-PCNN, weight vector $\{w_1, w_2\}$ of two channels FMMC-PCNN is set as in three groups shown in Table I.

Weapon detection is an increasingly important application of image fusion. Fig.4 (a) and Fig.4 (b) show a pair of visual and 94 GHz millimeter-wave (MMW) images. The visual image Fig.4 (a) provides appearance of men while the MMW image shows a gun hidden in coat. Landform analysis is another application of image fusion. Fig.5 (a) and Fig.5 (b) show a pair of two spectral images of the land, recorded by Daedalus scanner, distinctively represents vegetation and water area. In Fig.4 (d) and Fig.4 (e), gun and human appearance are obviously clearer than that of Fig.4(c).In Fig.5 (d) and Fig.5 (e), trees and land features are also clearer than that of Fig.5(c).It demonstrates that PCNN-based fusion algorithms, as for Wavelet-PCNN and FMMC-PCNN, could preserve image information better than MC-Wavelet. In addition, Fig.5 (e) is more consistent than Fig.5 (d), because regional information is considered in FMMC-PCNN than Wavelet-PCNN.

Fig.6 (a) and Fig.6 (b) are the difference images that MMW image subtracts fused results of FMMC-PCNN than Wavelet-PCNN, respectively. White pixels, which represent the gun hidden in coats, i.e. the tag square region in Fig.4 (b), are of interest. Thus, less detailed information in difference image indicates more preserved information and better fused results. Fig.6 (b), the difference image of the proposed algorithm, demonstrates the FMMC-PCNN fusion algorithm nearly extracts the entire region we are interested in MMW image. The same conclusion could be drawn in Fig.6 (c) and Fig.6 (d).

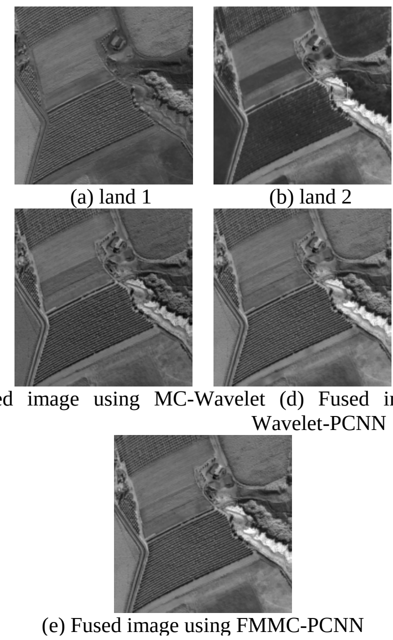


(a) Visual image (b) MMW image

(c) Fused image using MC-Wavelet (d) Fused image using Wavelet-PCNN

(e) Fused image using FMMC-PCNN

Figure 4. Fused results of visual and MMW images.

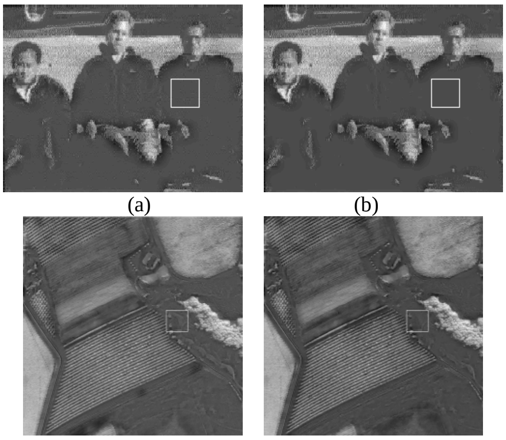


(a) land 1 (b) land 2

(c) Fused image using MC-Wavelet (d) Fused image using Wavelet-PCNN

(e) Fused image using FMMC-PCNN

Figure 5. Fused results of two spectral images.



(a) (b) (c) (d)

Figure 6. Difference images between source images and fused images of Wavelet-PCNN and FMMC-PCNN algorithms :(a) difference image between Fig.4 (b) and Fig.4(d),(b) difference image between Fig.4 (b) and Fig4.(e),(c) difference image between Fig.5 (b) and Fig.5(d),(d) difference image between Fig.5 (b) and Fig.5(e)

Besides visual observation, a robust objective evaluation criterion, mutual information (MI) in [9] is adopted. It measures the information that the fused image inherited from the source images. The larger the MI is, the better the algorithm do in terms of inherited information. In Table I, MI of three algorithms is compared. The largest MI proves that fused images of FMMC-PCNN are strongly correlated with the source images and more image features are preserved in the fusion than the other two algorithms. However, MI may be slightly varied with weight vector. All of the comparison indicates that the proposed algorithm outperforms MC-Wavelet and Wavelet-PCNN fusion algorithms.

TABLE I. COMPARISON ON MUTUAL INFORMATION

Source images	**FMMC-PCNN**		**Wavelet-PCNN**	**MC-Wavelet**
	Weight vector	***MI***	***MI***	***MI***
Visual and MMW	w^1=0.3,w^2=0.7	2.1507	2.0917	1.2198
	w^1=0.5,w^2=0.5	2.2013		
	w^1=0.7,w^2=0.3	2.2115		
Land 1 and Land 2	w^1=0.3,w^2=0.7	3.0421	2.8147	1.6865
	w^1=0.5,w^2=0.5	3.0544		
	w^1=0.7,w^2=0.3	2.9853		

V. CONCLUSION AND DISCUSSION

The features motivated multi-channel PCNN model in image fusion is proposed. Compared with the traditional PCNN model in image fusion, multi-features of images, rather than value of per pixel in multi-scale domain are used to motivate PCNN. And a new multi-channel PCNN is presented to combine the firing maps via a weighting function which measures the contribution of these features to the fused image quality. Experimental results in image fusion demonstrate that the FMMC-PCNN outperforms typical PCNN in extracting detailed information of images. However, FMMC-PCNN needs consummated features of images, e.g. phase and directional features, to motivate PCNN in consideration of many other applications, such as segmentation and so on. In summarization, we hope FMMC-PCNN will extend the PCNN application in image processing. Furthermore, PCNN could be associated with bandelet [10] and contourlet [11] and employed in image fusion to make use of their highlight in image feature extraction and global coupling links of PCNN. In addition, the OI-PCNN could also be applied in other image processing tasks, i.e. segmentation, feature extraction and so on.

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