Image Fusion Algorithm Based On Orientation Information Motivated Pulse Coupled Neural Networks*†

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***Abstract* - Pulse Coupled Neural Networks (PCNN) is a visual cortex-inspired neural networks and characterized by the global coupling and pulse synchronization of neurons. It has been proven suitable for image processing and successfully employed in image fusion. However, in most PCNN-based fusion algorithms, only single pixel value is input to motivate PCNN neuron. This is not effective enough because humans are often sensitive to features, not only pixel value. In this paper, novel orientation information is considered as features to motivate PCNN. Visual observation and objective performance evaluation criteria demonstrate that the proposed algorithm outperforms typical wavelet-based, lapacian pyramid transform-based and PCNN-based fusion algorithms.**

Index Terms* – *Image fusion, Pulse Coupled Neural Networks, Orientation information, Wavelet transform, Image Processing.

I. INTRODUCTION

Image Fusion is a rapidly developing research area in remote sensing, computer vision and weapon detection, etc. It aims at combing multiple sensors data to provide more reliable and accurate information [1]. In image fusion, how to combine information in multiple images is the core problem.

Pulse Coupled Neural Networks (PCNN) is a novel biological 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 [2]. It is characterized by the global coupling and pulse synchronization of neurons and has been proven suitable for image processing [3].

Pulse Coupled Neural Networks (PCNN) is a novel biological 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 [2]. It is characterized by the global coupling and pulse synchronization of neurons and has been proven suitable for image processing [3].

Recently, PCNN has been employed in image fusion in [4]-[8]. Owing to the coupling links in neurons, PCNN successfully utilize the local image information of images. Thus, coupling characteristic of PCNN benefits image fusion. In these PCNN-based methods, value of single pixel in spatial or multi-scale decomposition domain is used to motivate one neuron. There exists a one-to-one correspondence between pixels and neurons. It can be seen that value of pixel is considered as the original image information in these methods.

In fact, humans are often sensitive to edges and directional features, etc. In this paper, novel orientation information (OI) in spatial domain is adopted as one type of feature to motivate neurons. We believe that features, orientation information as an example, to motivate PCNN will be more reasonable than the traditional way. Furthermore, blocked orientation information measurement is employed to reduce the computing complexity. Experimental results on visual observation and objective evaluation criterion demonstrate that the orientation information motivated PCNN (OI-PCNN) outperforms wavelet-based, lapacian pyramid transform-based and PCNN-based fusion algorithms.

II. EXTRACT ORIENTATION INFORMATION

The image orientation information measure proposed by Wang [9] is defined as (1). It is an effective way to present the piecewise smoothness property of the images. For a given image x, we use x_{ij}^{k} to denote the pixels in the k-th block centred at (i,j) pixel. The orientation information I_{ij}^{k} in the block is defined as:

$$I_{ij}^{k} = d_{\theta_{\max}} - d_{\theta_{\min}} \tag{1}$$

where

$$d_{\theta_{\max}} = \max_{0^o \le \theta \le 180^o} \left(d_\theta\right),$$
$$d_{\theta_{\min}} = \min_{0^o \le \theta \le 180^o} \left(d_\theta\right),$$
$$f_{A_L} = \sum_{(i,j)\in A_L} x(i,j),$$
$$f_{A_R} = \sum_{(i,j)\in A_R} x(i,j),$$
$$d_\theta = \left|f_{A_L} - f_{A_R}\right|$$

A_L and A_R denotes the left and right region in a given block as shown in Fig.1. The extent of the given block

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is $(2w_x+1)\times(2w_y+1)$. l_θ is the line through the pixel (i,j) . Through orientation information measure, all the image pixels will be detected and angle direction could be calculated in spatial domain. In order to reduce the complexity, images in spatial domain are firstly decomposed into blocks and orientation information is measured in each block in this paper. The orientation information is considered as the feature in each block.

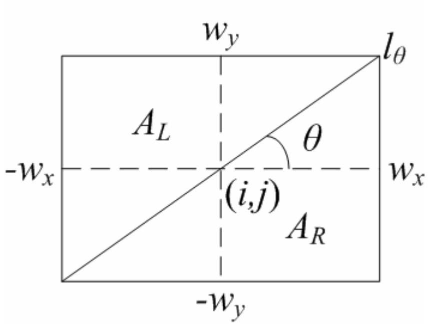

Fig.1 Orientation measurement.

Figs.2 (a) and 2(b) show a pair of visual and 94 GHz millimetre-wave (MMW) images. Figs.2 (c)-(f) are zoom in images labelled in (a) and (b). The visual image provides appearance of men, Fig.2(c) as an example, while the MMW image shows a gun hidden in coat, Fig.2 (f) as an example. They are obtained from the same scene by two sensors and utilized as the source images for our experiments in which image fusion is applied in weapon detection. In Fig.2, label S_1 is corresponding to S_3 and label S_2 is corresponding to S_4 . Figs.2 (g)-(j) are the orientation information of Figs.2 (c)-(f) using the definition of (1) and the block size is 4×4 . It can be seen that orientation information denotes the directional edge and texture of images. I_{ij}^k is large if sharp intensity transition exists between two sides of an edge.

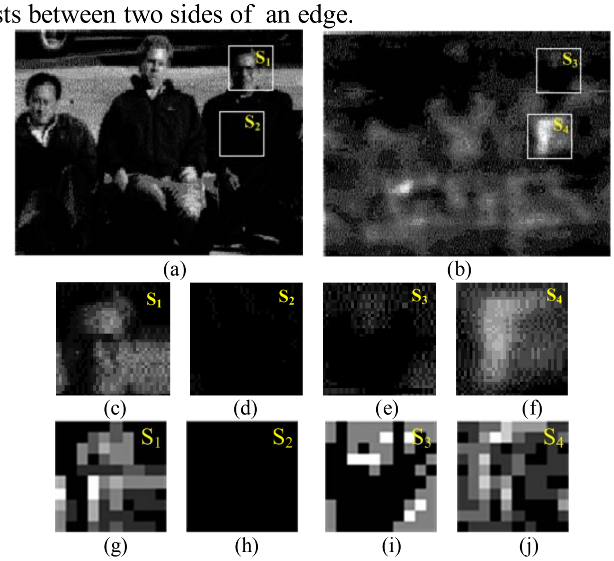

Fig.2 Source images and orientation information measure: (a) visual image, (b) millimeter-wave image, (c)-(f) zoom in images labeled in (a) and (b), (g)-(j) orientation information of Figs. (c)-(f).

III. 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 [3].In image processing, PCNN is a single layer pulse coupled neural cells with a two-dimensional connection [4] as shown in Fig.3.

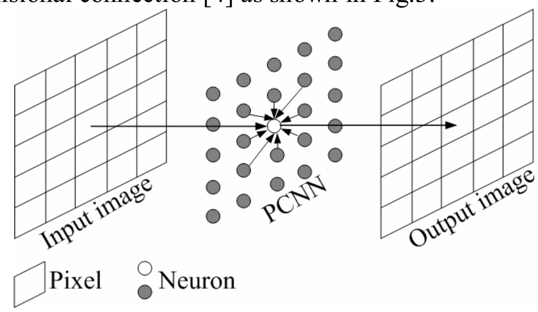

Fig.3 Connection model of PCNN neuron.

In the existed PCNN-based fusion algorithms [4]-[8], pixels in spatial domain or MSD domain are input to PCNN, there exists a one-to-one correspondence between the pixels and the neurons. Each neuron is connected with neighbouring neurons in linking range. The output of each neuron results in two states, namely firing and non-firing. Then the sum of neuron firing times will generate a firing map whose size is equal to the images in spatial or MSD domain and value of each pixel in firing map is equal to sum of neuron firing times[7][8].

We summarize these algorithms as Fig.4. It can be seen that value of pixels in spatial or MSD domain is considered as the original image information in the existed algorithms. However, a pure use of pixels is not effective enough because humans are often sensitive to edges and directional features. We believe that it will be more reasonable that features, rather than value of pixels, are employed to motivate PCNN.

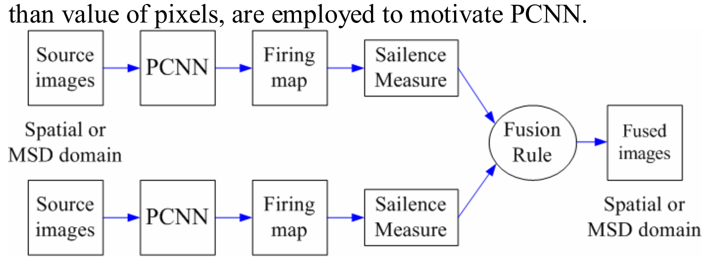

Fig.4 Schematic diagram of existed PCNN-based fusion algorithms.

IV. ORIENTATION INFORMATION MOTIVATED PCNN-BASED FUSION ALGORITHM

In this paper, orientation information introduced in section II is considered as one type of feature to motivate PCNN. We name it as orientation information motivated PCNN, OI-PCNN for short. The proposed OI-PCNN-based fusion algorithm is implemented as follows:

(1) Decompose the source images into blocks and measure the orientation information in each block.
(2) Orientation information of each source image is input to PCNN and pulse of neurons generated according to (2). Then sum of firing times $T_{ij}^k(n)$ is calculated as (3).

$$
\begin{cases}
F_{ij}^{k}(n)=I_{ij}^{k} \\
L_{ij}^{k}(n)=\exp(-\alpha_L)L_{ij}^{k}(n-1)+V_L\sum_{p,q}W_{ij,pq}Y_{pq}(n-1) \\
U_{ij}^{k}(n)=F_{ij}^{k}(n)*(1+\beta L_{ij}^{k}(n)) \\
\theta_{ij}^{k}(n)=\exp(-\alpha_\theta)\theta_{ij}^{k}(n-1)+V_\theta Y_{ij}^{k}(n-1) \\
Y_{ij}^{k}(n)=\begin{cases}1, if: U_{ij}^{k}(n)>\theta_{ij}^{k}(n) \\ 0, otherwise\end{cases}
\end{cases} \quad (2)
$$

$$T_{ij}^{k}(n)=T_{ij}^{k}(n-1)+Y_{ij}^{k}(n) \quad (3)$$

(3) Get the decision map D_{ij}^{k} based on (3), which is the fusion rule proposed in this paper. That is block of source images with larger orientation information is selected as the blocks of the fused images.

(4) Perform the majority filtering on the decision map D_{ij}^{k} to guarantee the consistency in the fused image.

(5) Reconstruct the fused image $x_{F,ij}^{k}$ according to the filtered decision map D_{ij}^{k} by using (4) and (5).

$$D_{F,ij}^{k}=\begin{cases}1, if: T_{1,ij}^{k}(n)\geq T_{2,ij}^{k}(n) \\ 0, if: T_{1,ij}^{k}(n)<T_{2,ij}^{k}(n)\end{cases} \quad (4)$$

$$x_{F,ij}^{k}=\begin{cases}x_{1,ij}^{k}, if: D_{ij}^{k}=1 \\ x_{2,ij}^{k}, if: D_{ij}^{k}=0\end{cases} \quad (5)$$

In s (2) (3) (4) (5), the feeding input F_{ij}^{k} is equal to the normalized orientation information I_{ij}^{k} in k-th block centred at (i,j) pixel. The linking input L_{ij}^{k} is equal to the sum of neurons firing times in linking range. W_{ij} is the synaptic gain strength. α_L is the decay constants. V_L and V_θ are the amplitude gain. β is the linking strength. U_{ij}^{k} is total internal activity. θ_{ij}^{k} is the threshold. Subscripts p,q are the size of linking rang in PCNN. n denotes the iteration times. If U_{ij}^{k} is larger than θ_{ij}^{k}, then the neuron will generate a pulse $Y_{ij}^{k}=1$, also called one firing times. In fact, sum of Y_{ij}^{k} in n iteration is often defined as (3) and employed to represent image information. Rather than analyse $Y_{ij}^{k}(n)$, one often analyse $T_{ij}^{k}(n)$ instead. $x_{F,ij}^{k}$, $x_{1,ij}^{k}$ and $x_{2,ij}^{k}$ denote the pixels in the k-th block of the fused image and two source images respectively.

The schematic diagram of the OI-PCNN-based algorithm is shown in Fig.5. Compared with the existed PCNN-based algorithm, orientation information of pixels, not pure use of value of single pixels, is used to motivate PCNN in the new algorithm.

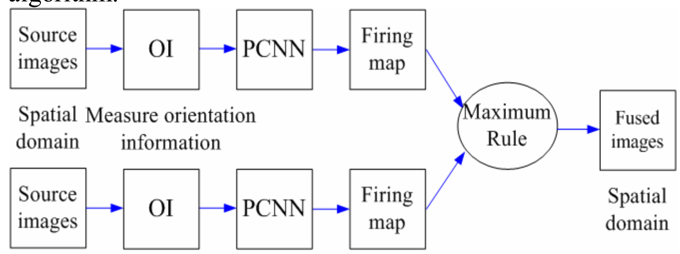

Fig.5 Schematic diagram of existed OI-PCNN-based fusion algorithms.

V. EXPERIMENTAL RESULTS AND EVALUATION

The performance evaluation criteria of image fusion are still a hot topic in the research of image fusion [1]. Besides visual observation, objective performance evaluation criteria are used in this paper, such as spatial frequency (SF) [10], mutual information (MI) [11], MAE [12] and Q_E [13]. SF stands for the gradient of images and MI essentially computes how much information from source images is transferred to the fused image. MAE indicates the spectral difference between source images and fused image. The last Q_E use correlation, luminance distortion and contrast distortion to measure the fused images. The higher the Q_E is, the more the saliency information of source images are contained in the fused image.

In the experiments, parameters of PCNN set as $p\times q=3\times 3$, $\alpha_L=0.06931$, $\alpha_\theta=0.2$, $\beta=0.2$, $V_L=1.0$, $V_\theta=20$, $W=\begin{bmatrix}0.707 & 1 & 0.707 \\ 1 & 0 & 1 \\ 0.707 & 1 & 0.707\end{bmatrix}$, and the maximal iterative number is $n=200$.

Figs.6 (a) and (b) shows the orientation information of source images. It can be seen that orientation information represents edge and texture feature. Sharp edge means large orientation information, while texture means small orientation information. On the other hand, if one block is smooth and without rich texture or sharp edges, the orientation information is very small. Figs.6 (c) and (d) show the firing maps, which are the output when orientation information is input to PCNN. Owe to the global coupling and pulse synchronization of PCNN, neighbouring pixels with the similar orientation information are divided into the same group. Pixels in the same group compose the firing maps in form of regions. Meanwhile, large orientation information generates large firing times, shown in high grey value in Figs.6(c) and (d).So, it is reasonable to use orientation to motivate PCNN, and select the pixels with the large firing times.

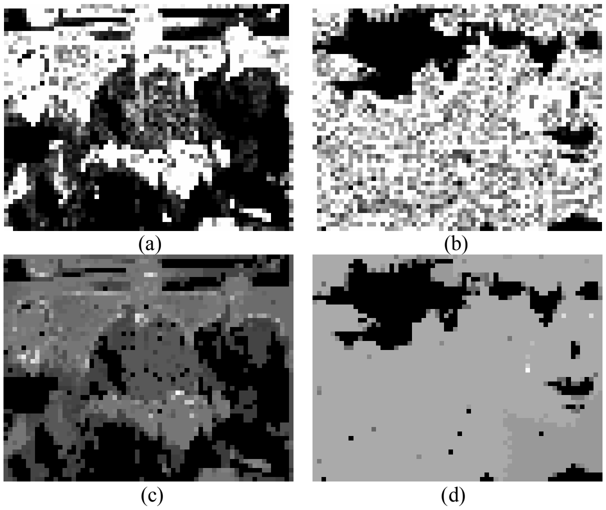

Fig.6 Orientation information and firing map. (a) Orientation information of Fig.2 (a), (b) Orientation information of Fig.2 (b), (c) Firing map of Fig.6 (a), Firing map of Fig.6 (b).

To evaluate the performance of the proposed fusion algorithm, it is compared with wavelet-based fusion algorithm [1], laplacian pyramid transform (LPT)-based fusion algorithm [1] and PCNN-based fusion algorithm [7].In [1], the summarized fusion rule of wavelet-based and LPT-based fusion algorithms is that maximum absolute value of pixels is employed as the fusion rule in high-frequency domain and average rule in low-frequency domain. While in [7] only value of single pixel is used to motivate PCNN.

The fused results are shown in Fig.7. From the visual observation, fused image of OI-PCNN is obviously clear than that of other algorithms. Particularly, brightness of OI-PCNN's fused image is the best. Because nonlinear operation on coefficients in MSD domain may induce the side effect of "ring" in wavelet-based and LAP-based algorithms. Fig.8 shows the difference images between the fused results and source image Fig.2 (b). We can see that texture, which is not attracted in the fusion process, of the proposed algorithm is the least. It demonstrates that the new algorithm best preserve the features of source images.

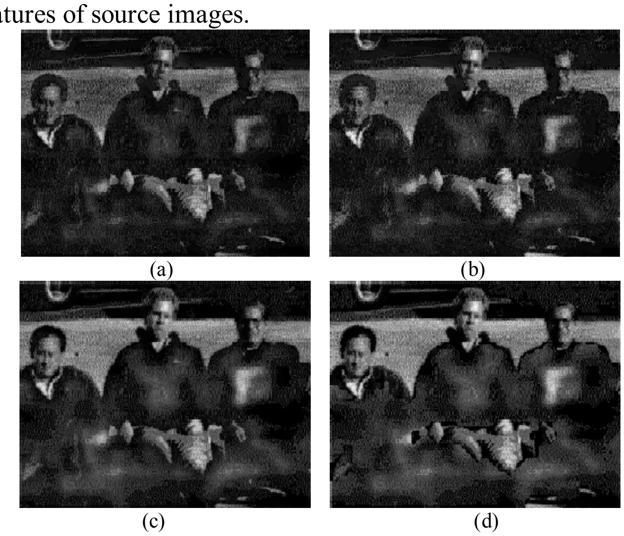

Fig.7 Fused results of different algorithms. (a)-(d) are the fused results of wavelet, LPT, PCNN,OI-PCNN based algorithms.

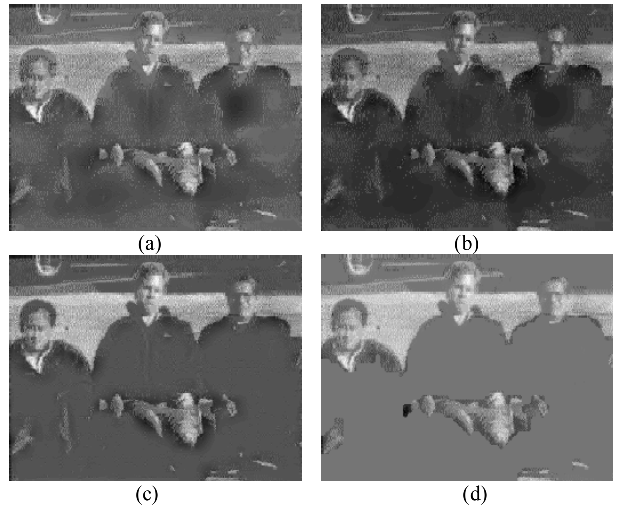

Fig.8 Difference images between the fused results and source image Fig.2 (b). (a)-(d) are the results that fused images of wavelet, LPT, PCNN,OI-PCNN based algorithms minus Fig.2 (b).

Besides the visual observation, the objective performance evaluation criteria are shown in Tab. 1. The highest SF consists with the fact that the new algorithm produces the clearest fused image. The largest MI and demonstrate that information of source images are best transferred into fused image in our algorithm ,while the lowest MAE indicates our algorithm preserve the best spectral characteristics of source images. All the comparisons, no matter visual observation or objective performance evaluation criteria, demonstrate that OI-PCNN outperforms other typical fusion algorithms.

TABLE I
OBJECTIVE PERFORMANCE EVALUATION CRITERIA(OEPC) OF DIFFERENT ALGORITHMS

OEPC	Wavelet	LPT	PCNN	OI-PCNN
SF	2.4126	2.5448	2.8209	2.9165
MI	1.2197	1.3016	2.0996	3.2624
MAE	7.036	7.2492	6.7298	6.3461
Q_E	0.4746	0.4855	0.6486	0.761

VI. Conclusion and Discussion

Orientation information motivated PCNN is proposed in this paper and successfully employed in information. Orientation information, rather than pure use of pixel value, is evidenced more reasonable to motivate PCNN. The OI-PCNN-based algorithm can well preserve spatial characteristics of source images and efficiently transfer the information from source images to fused image. We also believe that it may be more reasonable that other image features are used to motivate PCNN. Furthermore, PCNN could be associated with bandelet [14] and contourlet [15] 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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