

Image fusion based on MPCNN and DWT in PCB failure detection

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Abstract

The traditional contact-type printed circuit board (PCB) test methods have been unable to meet the needs of the fault detection and maintenance of a variety of increasingly complex electronic equipment. The visible and infrared respectively reflects the background information and the radiation information of PCB, so we can fuse the visible image and infrared image of the board together, and use the new fusion image to locate and identify the abnormal high temperature components or areas of the circuit board. A novel fusion algorithm of multi-sensor image is proposed based on Discrete Wavelet transform (DWT) and pulse coupled neural networks (PCNN) in this paper. Firstly, the IR and visible images are decomposed by DWT, then a fusion rule in the DWT is given based on the PCNN. This algorithm uses the local entropy of wavelet coefficient in each frequency domain as the linking strength, then its value can be chosen adaptively. After processing PCNN with the adaptive linking strength, new fire mapping images are obtained. According to the fire mapping images, the firing time gradient maps are calculated and the fusion coefficients are decided by the compare-selection operator with firing time gradient maps. Finally, the fusion images are reconstructed by wavelet inverse transform. The proposed algorithm of image fusion using modified pulse coupled neural networks (MPCNN) and DWT results in better quality of fused image with Entropy, Average grads, Cross-Entropy as compared to conventional image fusion Algorithms.

Keywords: PCNN image-fusion, DWT, PCB, failure detection

1 Introduction

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 [1] Image fusion is introduced into PCB failure detection, more abundant and comprehensive complementary information could be obtained through infrared and visible image, which could improve the accuracy and validity of PCB failure detection. Image fusion is the process of combining information from two or more images of a scene into a single composite image, which is more informative and suitable for human visual perception or computer processing [2, 3]. Most image fusion algorithms are based on multi-resolution analysis including Wavelet Transform, PCNN, etc. Conventional PCNN image fusion algorithms have been successful used in image fusion and could retain more details. However, in these algorithms, the value of single pixel is used to motivate on neuron. In fact, humans are sensitive to edges, directional features, etc. So, a pure use of single pixels is not enough. For the second question, the linking strength of PCNN neurons based on experiment or experience is great and has caused great inconvenience to the application of image fusion. Due to joint information representation at the spatial spectral domain, wavelet transform becomes the most popular multi-scale decomposition domain method in image fusion. This paper

proposed a new method for image fusion based on DWT and PCNN. Experimental results demonstrate that the proposed algorithm outperforms typical DWT-based, and conventional PCNN-based in terms of objective criteria [4, 5].

2 Conventional PCNN model

PCNN is a novel biologically neural network, which was developed by Eckhorn based on the experimental observations of synchronous pulse bursts in cat and monkey visual cortex. The basic model of PCNN neuron is shown in Figure 1, which comprises three parts: receptive field, modulation field and pulse generator. The neuron receives input signals from other neurons and external sources from two channels viz. F channel and L channel in the receptive field. F channel is the feeding input F_{ij} , which receives the input from external source and output of other neurons. L channel is the linking input L_{ij} which receives the input from other neurons output. The feeding field is modulated by linking field to calculate the internal activity U_{ij} . θ is the dynamic threshold. Matrixes M/V_F , W/V_L and V_θ are the linking weight/magnify coefficient of the feeding back field, the linking weight/magnify coefficient of the linking field, the threshold magnify coefficient, respectively; α_F and α_θ are the decayed constants associated with F , L , u ; b , n and Y_{ij} are the linking strength, the iteration number and the

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pulse output, respectively. The discrete mathematical equations of each neural can be described as follows:

$$F_{ij}[n] = \exp(-\alpha_F) F_{ij}[n-1] + V_F \sum m_{ijkl} Y_{kl}[n-1] + I_{ij}, \quad (1)$$

$$L_{ij}[n] = \exp(-\alpha_L) L_{ij}[n-1] + V_L \sum W_{ijkl} Y_{kl}[n-1], \quad (2)$$

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

$$\theta_{ij}[n] = \exp(-\alpha_\theta) \theta_{ij}[n-1] + V_\theta Y_{ij}[n-1], \quad (4)$$

$$Y_{ij} = \begin{cases} 1, & U_{ij}[n] \geq \theta_{ij}[n] \\ 0, & U_{ij}[n] < \theta_{ij}[n] \end{cases}, \quad (5)$$

where (1), (2) and (3) are the mathematical models of the receptive feeding input, receptive linking input and modulating coupler, respectively; (4) and (5) are the step function of the pulse generator and the expression of variable threshold function respectively [6, 7]

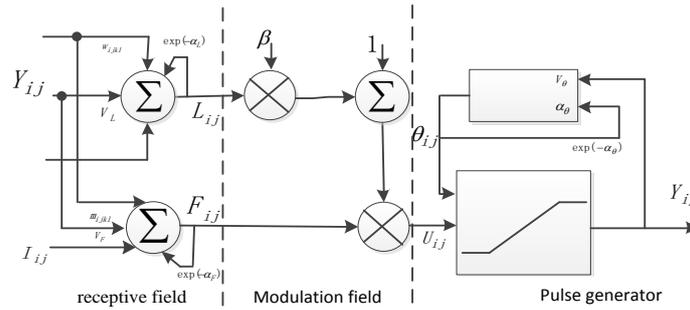


FIGURE 1 The Basic Model of PCNN Neuron

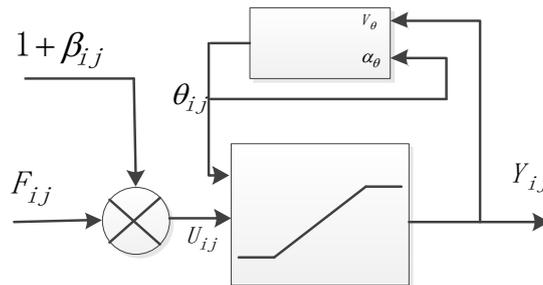


FIGURE 2 The MPCNN Model

3 Modified PCNN

The conventional PCNN model has the limitation of slow processing because of large number of iterations and computational complexity, which makes it unsuitable for image processing applications where large amount of data are to be handled. In practical application, to meet the demand of the situation should be simplified, easy for hardware implementation in saving cost and overhead at the same time, therefore according to different purposes, many scholars put forward different degrees of the simplified PCNN model, this paper uses the modified model according to the actual needs of image fusion [8-11]. The MPCNN model is shown in Figure 2. The expressions of MPCNN are listed as follows:

$$F_{ij}[n] = I_{ij}, \quad (6)$$

$$L_{ij}[n] = \sum_{kl} w_{ijkl} Y_{kl}[n-1], \quad (7)$$

$$U_{ij}[n] = F_{ij}[n](1 + \beta L_{ij}[n]), \quad (8)$$

$$U_{ij}[n] = F_{ij}[n](1 + \beta L_{ij}[n]), \quad (9)$$

$$Y_{ij} = \begin{cases} 1, & U_{ij}[n] \geq \theta_{ij}[n] \\ 0, & U_{ij}[n] < \theta_{ij}[n] \end{cases}. \quad (10)$$

The number of parameters to be determined will decrease if the PCNN model is simplified, but for a special image the key parameters are still needed to be selected by experiments or empirically.

4 Image fusion based on DWT and MPCNN

Image fusion based on Discrete Wavelet transform (DWT) is to decompose the original images into a series of frequency channels and combine the different features and details at multiple decomposition levels and in multi-frequency bands, which is suitable for multi-scale properties of the human vision system. In this paper, DWT and MPCNN are combined effectively to display their own advantages. Suppose that there are two original images with the same size denoted I and A, which are both accurately registered and F is the final fusion image. The new fusion scheme is shown in Figure 3.

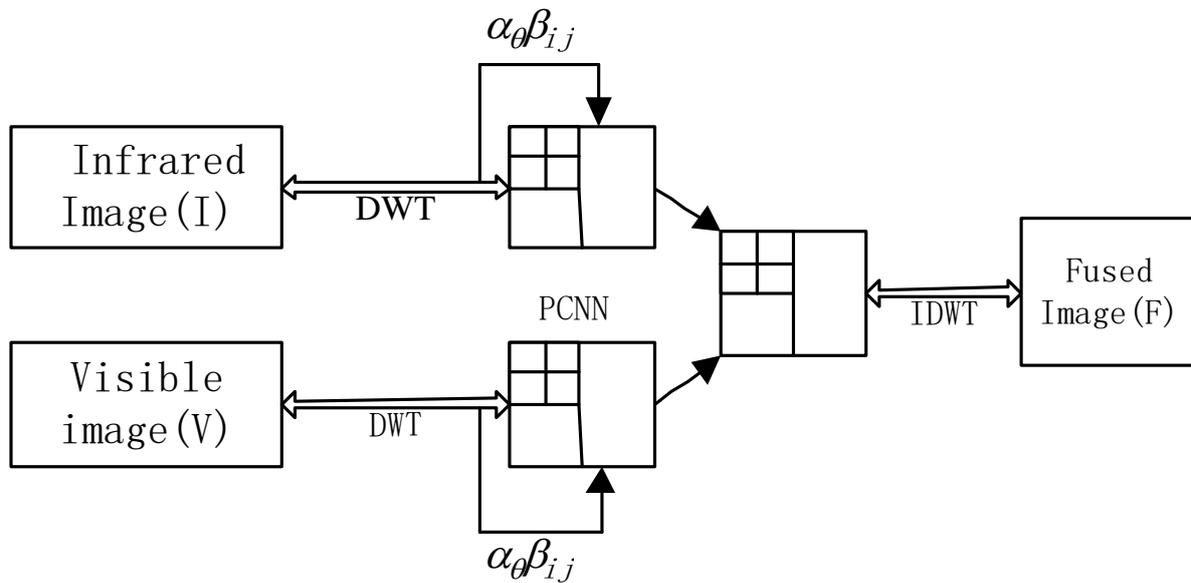


FIGURE 3 The new fusion scheme

The concrete steps of the new fusion algorithm can be described below [8-10].

Step 1: Get Wavelet Pyramid by DWT to infrared and visible images which are matched. Let $C(i,j)$ denote the wavelet coefficients of wavelet domain (i,j) . Let β_{ij} denote the local entropy of window. The clearer the pixel is, the larger the linking strength β is, and accordingly, the greater the linking extent of the corresponding neuron is. The parameter β_{ij} can be expressed with the following formula:

$$\beta_{i,j} = -\sum_{i=1}^M \sum_{j=1}^N P_{i,j} \log P_{i,j}, \tag{11}$$

$$P_{i,j} = \frac{c(i,j)}{\sum_{i=1}^M \sum_{j=1}^N C_{i,j} \log C_{i,j}}, \tag{12}$$

where β_{ij} is the linking strength of the neuron ij

Step 2: Let β_{ij} denote the linking strength of the PCNN, the wavelet coefficients are mapped to the corresponding gray range; the output of threshold function decay with time to the minimum gray when all the pixels in the image are the ignition.

Step 3: Setting the initial values of the MPCNN's parameters;

Step 4: For each iteration the following steps were done to MPCNN. Let V_{min} and V_{max} denote the minimum and V_{min} fire threshold, let t denote iteration time. The parameter α_θ can be expressed with the following formula

$$\alpha_\theta = -\frac{\ln\left(\frac{V_{min}}{V_{max}}\right)}{t}. \tag{13}$$

The input neurons of MPCNN were computed according to Equations (6), (7), (8), (9), (10) calculate the linking strength β_{ij} according to (11) and (12).

Step 5: Reconstruct the original image by using an inverse DWT, thus obtaining the fused image F [8-18].

5 Experimental results and conclusion

The performance evaluation criteria of image fusion are still a hot topic in the research of image fusion. Besides visual observation, objective performance evaluation criteria are used in this paper, such as Entropy, Average grads, Cross-Entropy etc.

In this section, the example, which is conducted by MATLAB 2012a on a PC with Intel P8700, is given to prove the validity of the proposed fusion technique. The related source images are PCB infrared and visible images whose size is 512×512 . To illustrate the proposed fusion method, several experimental results are presented in this section. Parameters of PCNN is set as $t = 20$ PCNN

iteration time: $w = \begin{bmatrix} 0.707 & 1 & 0.707 \\ 1 & 0 & 1 \\ 0.707 & 1 & 0.707 \end{bmatrix}$ linking synapse.

To evaluate the performance of the proposed fusion algorithm, it is compared with DWT-based fusion algorithm, and PCNN-based. The fusion results are shown in Figure 4 and the objective performance evaluation criteria are shown in Table 1.

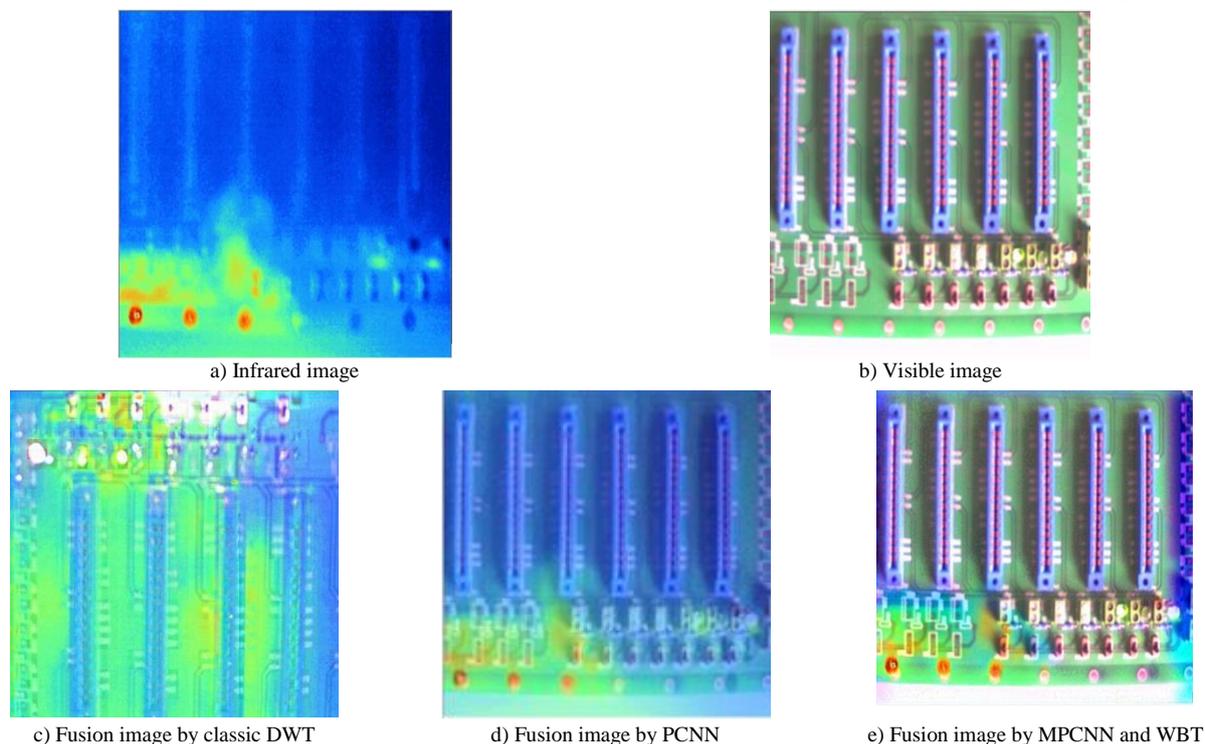


FIGURE 4 Fusion results using different algorithms

TABLE 1 Evaluation of statistical parameters

Method	Entropy	Average grads	Space frequencies	Standard deviation	Cross-Entropy
classic WBT	5.8199	3.9318	13.7498	66.5730	0.4709
PCNN	7.4947	5.2122	12.1433	62.4376	0.5022
MPCNN&WBT	7.7698	8.2097	17.0698	63.6202	0.7029

PCNN is a mammal visual cortex-inspired neuron networks and has been widely employed in image processing. The combination of DWT and MPCNN can make full use of the multi-resolution characteristics of DWT and the global couple and pulse synchronization characteristics of PCNN. The experimental results in Figure 4 and Table 1 show that the new method presented in this paper can improve the fusion effect. the entropy of the new algorithm are larger indicating the fused image contains more information, and the average gradient of the new algorithm is larger indicating that the fused image is more clear and contains more details and texture features.

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