Multi-focus Image Fusion Algorithm Based on Motivated Pulse Coupled Neural Networks Using Nonsubsampled Contourlet Transform

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Abstract. In this paper, a multi-focus image fusion algorithm based on motivated pulse coupled neural networks using nonsubsampled contourlet transform (NSCT) is proposed. Firstly, NSCT is used to decompose the source image in multi scale and multi directions to obtain the low frequency coefficients and high frequency coefficients. Secondly, Fourier transform method is used for saliency detection. We choose the coefficients which have larger saliency for high frequency coefficients. In the process of choosing the low frequency, the spatial frequency is used as the input of the Pulse coupled neural network (PCNN) to obtain the firing times of the low frequency. If the firing times of two images are not the same, then we choose coefficients which have larger firing times. Otherwise, coefficients which have larger saliency will be chosen. Lastly, inverse transformation of NSCT is used to obtain the fused image. The proposed method is compared with four other common methods, and the experimental results show that the proposed method performs better on both subjective and objective evaluation indicators.

Introduction

Due to the limited depth-of-focus of optical lenses in CCD devices, it is often not possible to obtain an image that contains all of the relevant objects in focus [1]. To get an all-in-focus image, multi-focus image fusion is an effective way to solve this problem. Multi-focus image fusion is to combine information from multiple images captured by different sensors for the same scene in order to produce images to get better human visual perception or machine recognition [2]. Basically, the fusion techniques can be divided into the following two categories: spatial domain fusion and transform domain fusion [1]. The spatial domain fusion includes averaging, spatial frequency [3], HIS transform [4] and so on. The transform domain fusion includes discrete wavelet [5], curvelet transform [6], Contourlet transform [7], Nonsubsampled contourlet transform [8] and so on.

In this paper, a multi-focus image fusion algorithm based on motivated pulse coupled neural networks using nonsubsampled contourlet transform is proposed. The experimental results show that the proposed method performs better on both subjective and objective evaluation indicators.

NSCT and PCNN in Image Fusion

Nonsubsampled Contourlet Transform

Nonsubsampled contourlet transform (NSCT) provides flexible multiresolution, anisotropy, and directional expansion for images [9]. Compared with Contourlet transform, it is shift invariance and overcomes the pseudo Gibbs phenomenon near singular point. Therefore, the NSCT method is more suitable for image fusion. The NSCT transform firstly employs a nonsampled pyramid filter bank to perform multiscale decomposition (NSP) of the image, and then uses the Nonsubsampled directional filter banks (NSDFB) to decompose the resulting subband images.

Pulse Coupled Neural Network

PCNN is a feedback network containing multiple neurons, which consist of three parts: the receptive
part, the modulation part and the pulse generator. When used in image fusion, PCNN is a single layer pulse coupled neural cells with a two-dimensional connection. The number of neurons equals to the number of pixels of the input image.

The Proposed Image Fusion Method

The fusion process of the proposed method is shown in figure 3 (refer with: Fig. 1). Firstly, NSCT is used to decompose the source image in multi scale and multi directions to obtain the low frequency coefficients and high frequency coefficients. Secondly, Fourier transform method is used for saliency detection. We choose the coefficients which have larger saliency for high frequency coefficients. In the process of choosing the low frequency, the spatial frequency is used as the input of the PCNN to obtain the firing times of the low frequency. If the firing times of two images are not the same, then we choose coefficients which have larger firing times. Otherwise, coefficients which have larger saliency will be chosen. Lastly, inverse transformation of NSCT is used to obtain the fused image.

Spatial frequency can be calculated as below (refer with: Eq. 1):

\[
S_{i,j} = \sum_{k \in \mathbb{N}} \left( I_{i,j}^{k} - I_{i-1,j}^{k} \right)^2 + \left( I_{i,j}^{k} - I_{i,j-1}^{k} \right)^2
\]

We use spectral residual method to conduct saliency detection, the detection flow is illustrated in figure 2.

Fusion Rule of the Low Frequency

A method based on motivated PCNN and saliency detection is used in the rule of choosing low frequency. Firstly, calculate the spatial frequency of the low frequency (refer with: Eq. 2).

\[
S_{i,j}^A = \sum_{k \in \mathbb{N}} \left( I_{i,j}^{k} - I_{i-1,j}^{k} \right)^2 + \left( I_{i,j}^{k} - I_{i,j-1}^{k} \right)^2\kappa
\]

\[
S_{i,j}^B = \sum_{k \in \mathbb{N}} \left( I_{i,j}^{k} - I_{i-1,j}^{k} \right)^2 + \left( I_{i,j}^{k} - I_{i,j-1}^{k} \right)^2\kappa
\]

Let \( S_{i,j}^A \) and \( S_{i,j}^B \) be the inputs of PCNN, calculate the firing times mapping \( \text{Firing\_times}^A \) and \( \text{Firing\_times}^B \) respectfully. Then, calculate the saliency detection map \( \text{saliencyMap}^A \) and \( \text{saliencyMap}^B \) of \( \text{coeffs}_A\{\text{low}\} \) and \( \text{coeffs}_B\{\text{low}\} \). The fusion rules are:

- If \( \text{Firing\_times}^A > \text{Firing\_times}^B \), \( \text{coeffs}\{\text{low}\} = \text{coeffs}_A\{\text{low}\} \).
If $Firing\_times^A < Firing\_times^B$, $coeffs\{low\} = coeffsB\{low\}$;
If $Firing\_times^A = Firing\_times^B$, the coefficients are chosen by saliency map;

**Fusion Rule of the High Frequency**

The coefficients of the high frequency part are chosen according to saliency Map. Calculate the saliencyMap$^A$ and saliencyMap$^B$ of the high frequency coefficients and coefficients which have larger saliency will be chosen as the fused coefficients.

**Experiments and Discussions**

**Evaluation Indicators**

In this paper, we use four indicators to evaluate the quality of the fused images, namely structural similarity index(SSIM), standard deviation(SD), mutual Information(MI) and edge based evaluation indicators ($Q_{AB/F}^A$).

**Simulations for Parameter Selection**

We conducted simulations of linking strength, and the results are given by both MI and SD. The results show that the performance is the best when linking strength equals to 2.1 (refer with: Fig. 3, Fig. 4).

![Figure 3. The relation between the linking strength and MI.](image1)

![Figure 4. The relation between the linking strength and SD.](image2)

**Simulations for the Proposed Method and other Four Methods**

We have done three simulations for the proposed method and other four methods, namely the general NSCT based method, wavelet based method, combined contourlet and PCNN based method and combined PCNN and NSCT based method. Three sets of images are used, named lab, clock and Pepsi. (refer with: Fig. 5, Fig. 6, Fig. 7).

![Figure 5](image3)

![Figure 6](image4)

![Figure 7](image5)
Evaluation Indicators and Results for the Three Sets of Images

As the results shown below (refer with: Table. 1, Fig.8-Fig.12), the proposed method performs better both in human visual perception and evaluation indicators. The results of proposed method are clearer than other method. Compared with Combined contourlet and PCNN, Combined PCNN and NSCT, the proposed method has clearer edges and image contrast.

Table 1. Evaluation indicators of three sets of images.

<table>
<thead>
<tr>
<th>Method</th>
<th>Image lab</th>
<th>Image clock</th>
<th>Image pepsi</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>SD</td>
<td>SSIM</td>
<td>MI</td>
</tr>
<tr>
<td>Method 1</td>
<td>45.46</td>
<td>0.94</td>
<td>4.83</td>
</tr>
<tr>
<td>Method 2</td>
<td>45.68</td>
<td>0.92</td>
<td>4.61</td>
</tr>
<tr>
<td>Method 3</td>
<td>45.48</td>
<td>0.92</td>
<td>4.72</td>
</tr>
<tr>
<td>Method 4</td>
<td>45.74</td>
<td>0.94</td>
<td>4.04</td>
</tr>
<tr>
<td><strong>proposed</strong></td>
<td><strong>47.3</strong></td>
<td><strong>0.91</strong></td>
<td><strong>4.91</strong></td>
</tr>
</tbody>
</table>
Summary
In this paper, the link strength of PCNN is experimentally investigated, and the proper link strength is chosen as the coefficient of PCNN. On the other hand, compared with the general PCNN, this paper makes the PCNN performance better by using the spatial frequency of the pixel as input instead of the pixel as the input of the PCNN. And the saliency detection method based on Fourier transform is introduced, which makes the fused image clearer and suitable for human eyes. The proposed method achieves higher value of SD, SSIM, MI and QABF than other four methods, it performs better on both subjective and objective evaluation indicators. The proposed method is a good way for multi-focus image fusion.

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References


