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Multi-focus image fusion using pulse coupled neural network

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Abstract

This paper presents a method for multi-focus image fusion by using pulse coupled neural network (PCNN). The registered source images are first decomposed into blocks and the size of the image blocks is 8×8 pixels. Feature maps are obtained by computing the energy of image Laplacian of each block. Input the feature maps into PCNN as external stimulus. The final fused image can be constructed by selecting the image blocks from the source images based on the comparison of the outputs of the PCNN. Experimental results show that the proposed method outperforms some previous fusion methods, both in visual effect and objective evaluation criteria.

Keywords: Multi-focus image fusion; Pulse coupled neural network

1. Introduction

Due to the limited depth-of-focus of optical lenses in CCD devices (e.g. camera with finite depth of field, light optical microscope, etc.), It is often not possible to get an image that contains all relevant objects in focus. In an image captured by those devices, only those objects within the depth of field are focused, while other objects are blurred. To obtain an image with every object in focus, an image fusion process is required to fuse the images taken from the same view point under different focal settings. The fused image gives a better view for human or machine perception.

A more successful image fusion approach that has been explored in recent years is by using multiresolution decompositions (Burt and Kolczynski, 1993; Li et al., 1995; Toet et al., 1989). Unfortunately, many of the multiresolution approaches, such as DWT algorithm, are shift-variant because of an underlying down-sampling process. For example, if there is a movement of the object in the source images or there is misregistration of the source images, the performance of those algorithms will deteriorate. A way to alleviate this problem is by using the discrete wavelet frame transform (DWFT) (Laine and Fan, 1996). However, the implementation of DWFT is complicated and the algorithm is more demanding both computer memory and time. In addition, many multiresolution methods replace coefficients in the transformed domain and the original pixel values of input images are not preserved in the fused resulting image.

Li et al. (2001) introduced a method based on the selection of image blocks from source images. The basic idea underlying the method is to choose the clearer image blocks from source images to construct the fused image. Spatial frequency (SF) is used to distinguish the focused image blocks from the defocused image blocks. It is clear that the method proposed by Li et al. (2001) can avoid the problem of shift-variant, caused by DWT.

In the past few years, several researchers have proposed different image fusion methods based on PCNN

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(Broussard et al., 1999; Kinser, 1997; Li et al., 2005; Miao and Wang, 2005). Miao and Wang (2005) proposed a multi-focus image fusion method based on an improved PCNN model. The source images are inputted to PCNN as the external stimulus. The energy of image gradient is computed for each pixel of the source images as its clarity. The clarity of each pixel is used as the linking strength β of each neuron in the PCNN. The fused image is constructed by comparing the outputs of the PCNN.

In this paper, we propose a multi-focus image fusion method based on the selection of image blocks from source images by using the energy of image Laplacian and PCNN.

The rest of this paper is organized as follows. Energy of image Laplacian is described in Section 2. A brief description of PCNN is given in Section 3. The scheme of image fusion by using PCNN is given in Section 4. Section 5 describes the determination of the parameter values for PCNN. Experimental results can be found in Section 6 and the last section gives some concluding remarks.

2. Energy of image Laplacian

Li et al. (2001) used spatial frequency (SF) to measure the clarity of image blocks. In Literature (Eltoukhy and Kavusi, 2003), energy of image gradients was used to measure the clarity.

SF was introduced by Eskicioglu and Fisher (1995) and the expression for a $K \times L$ pixels image $f(x,y)$ is defined as

$$\mathrm{SF} = \sqrt{(\mathrm{RF})^2 + (\mathrm{CF})^2} \tag{1}$$

where RF and CF are the row frequency

$$\mathrm{RF} = \sqrt{\frac{1}{K \times L} \sum_{x=1}^{K} \sum_{y=2}^{L} [f(x,y) - f(x,y-1)]^2} \tag{2}$$

and column frequency

$$\mathrm{CF} = \sqrt{\frac{1}{K \times L} \sum_{y=1}^{L} \sum_{x=2}^{K} [f(x,y) - f(x-1,y)]^2} \tag{3}$$

respectively.

Energy of image gradient (EOG) is computed as

$$\mathrm{EOG} = \sum_x \sum_y (f_x^2 + f_y^2) \tag{4}$$

where

$$f_x = f(x+1,y) - f(x,y) \tag{5}$$

and

$$f_y = f(x,y+1) - f(x,y) \tag{6}$$

From Eqs. (1)–(6), it is clear that SF is a modified version of EOG.

The image clarity measures, namely focus measures, are deeply studied in the field of autofocusing. In literatures (Krotkov, 1987; Ligthart and Groen, 1982), a focus measure is defined which is a maximum for the best focused image and it generally decreases as the defocus increases. In this paper, we use the energy of image Laplacian as the measure of image clarity. According to literature (Subbarao et al., 1992) and our experiments (Huang and Jing, 2007), the energy of image Laplacian can provide a better performance than SF and EOG.

The energy of image Laplacian (EOL) is computed as

$$\mathrm{EOL} = \sum_x \sum_y (f_{xx} + f_{yy})^2 \tag{7}$$

where

$$\begin{aligned} f_{xx} + f_{yy} = & -f(x-1,y-1) - 4f(x-1,y) \\ & - f(x-1,y+1) - 4f(x,y-1) + 20f(x,y) \\ & - 4f(x,y+1) - f(x+1,y-1) \\ & - 4f(x+1,y) - f(x+1,y+1) \end{aligned}$$

Fig. 1 shows a schematic diagram for evaluating the focus measures (SF, EOG and EOL) by using images with 256 gray levels. This evaluating method consists of the following steps:

Step 1. Decompose the two source images into blocks. Denote the ith image block pair by A_i and B_i, respectively.

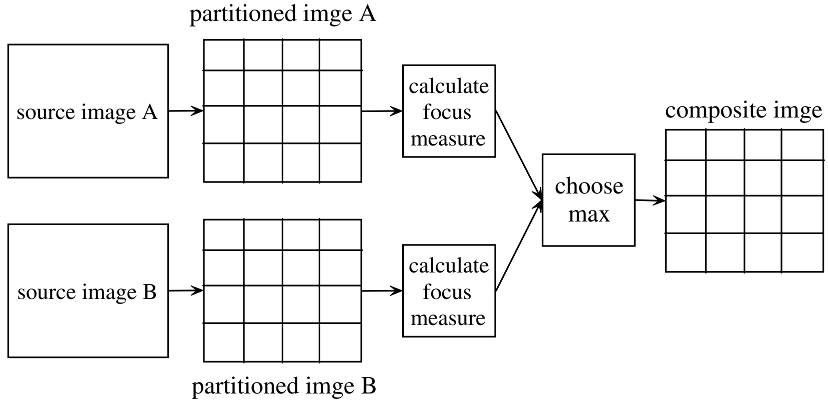

Fig. 1. Schematic diagram for evaluating the focus measures.