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A Multi-Focus Image Fusion Algorithm Based on Weighted Multi-Scale Morphological Gradients and Uniform Segmentation

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Abstract: Multi-focus image fusion is a technique used to create a single image that is entirely in focus by merging the focused regions from multiple images. This paper presents an approach to multi-focus image fusion that combines uniform segmentation with a weighted multi-scale morphological gradient focus measurement. During the creation of the focus degree measurement map of the source image, multi-scale morphological gradients are first obtained through multi-scale morphological operations. These gradients are then adjusted using scale weighting and distance weighting. For image segmentation, to minimize the occurrence of image blocks containing both focused and defocused pixels, the image is uniformly divided into 2x2 pixel blocks. The focus degree value of each block is determined by the values within a 6x6 pixel range that includes the block and its surrounding pixels. Experimental results demonstrate that this method enhances the accuracy of focus degree measurement, particularly in smooth regions of the image.

Keywords: Multi-focus image fusion, weighted multiscale morphological gradient, uniform segmentation.

1. Introduction

Usually a camera is used to shoot a scene to obtain its picture, and different objects in the scene have different distances from the camera. Depth-of-Field (DOF) of the camera is the range of distance, objects within which appear to be sharp in the photograph [1].Part of the object of interest is not in focus, so the image obtained is usually a partial area focus picture. In order to get a single image which contains multiple focused objects of interest, it can be achieved by multi focused image fusion. At present, image fusion technology has been widely used in various digital image processing applications, such as remote sensing image fusion, clinical medical image fusion and visual image fusion. In recent years, a variety of algorithms have been proposed for multi-focus image fusion. These algorithms can generally be divided into two categories: algorithms based on the transform domain and algorithms based on the spatial domain[2].

The spatial domain-based algorithm uses image pixels as the basis for image feature extraction and image fusion. Compared with the transform domain-based fusion algorithm, the spatial domain-based algorithm can retain more of the original image information.

In this paper, we propose a multi-focus image fusion algorithm in the spatial domain based on weighted multi-scale morphological gradients and uniform segmentation. The uniform segmentation provides decomposition of image block pairs, and weighted multi-scale morphological gradients enable focus measurement of image block pairs. The fusion decision map is obtained by measuring the pair-focus situation and the fusion of the focus area of the image is achieved.

2. Proposed Algorithm

The goal of this paper is to generate a fully focused image by multi focus image fusion. The method steps are as shown in Figure 1. Firstly, Calculate the weighted multi-scale morphological gradient of the source image; Secondly, Decompose the source image by uniform segmentation and measure the focus of each block pair to get the preliminary fusion decision map; Thirdly, Realize the fusion of the multi focus image according to the fusion decision map and fusion rules. When the fusion image is generated according to the decision fusion image, the corresponding fusion image is generated by directly copying the source image with full focus pixels. This method can improve the ability of image decomposition and focus measurement, and more retain the original image information.

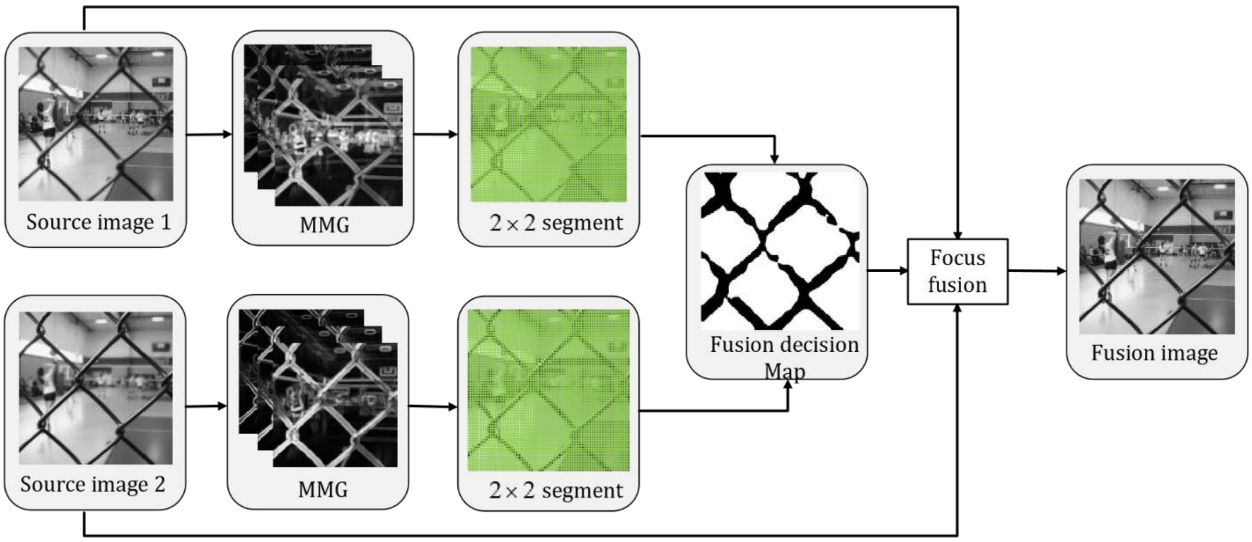


Figure 1. Fusion framework of proposed method

2.1. Image Focus Measure

The gradient information of image can be extracted by morphological gradient operator, and the gradient information of image on multiple scales can be extracted by different morphological gradient operators. Compared with the focus region, the image has a clear boundary, and the edge of the defocused region tends to diverge outward, so the gradient information on multiple scales is combined as the focus measurement. But in the smooth region of the image, the pixel value changes smoothly, and the corresponding gradient value is small. The gradient value of the smooth focus area and the corresponding defocus area are relatively small, so the focus block and the defocus block in the smooth area are more difficult to distinguish, and the gradient value of the smooth area is easily affected by the noise pixels [].In order to solve this problem, we weighted the combined multi-scale gradient at each pixel position to increase the difference between the focus measurement values of the focus block and the defocus block in the smooth region, so as to improve the discrimination effect between the focus block and the defocus block. Therefore, we design a weighted multi-scale morphological gradient for image focus measurement. The detailed steps are described as follows.

Firstly, the multi-scale morphological structure elements are constructed.

$$SE_s = \underbrace{SE_1 \oplus SE_1 \cdots \oplus SE_1}_{s}, \qquad s \in \{1, 2, \cdots, n\} \quad , \tag{1}$$

Where SE_1 is the basic morphological structural element with radius r, and s is the number of scales.

Secondly, the morphological gradients of images at different scales are calculated.

$$MG_s(x,y) = I(x,y) \oplus SE_s - I(x,y) \ominus SE_s \ , \tag{2}$$

Where I(x, y)represents the source image, and represent the morphological dilation and erosion operators, respectively, which are defined as

$$I(x,y) \oplus SE = \max_{(u,v)} \left(I(x-u, y-v) \right) + SE(u,v) \tag{3}$$

$$I(x,y) \ominus SE = \min_{(u,v)} \left(I(x-u, y-v) \right) - SE(u,v) \tag{4}$$

Where (x, y) represent the pixel coordinates of the source image, and (u, v) represent the pixel coordinates of the structural elements.

Thirdly, all multiscale gradients are combined into one multiscale morphological gradient.

$$MMG(x,y) = \sum_{s=1}^{n} w_s \cdot MG(x,y) \tag{5}$$

Where w_s is the gradient weight at scale s, which is defined as follows.

$$w_s = 1/(2 \times s + 1) \tag{6}$$

The boundary of the image in the focus area is clearly fixed, but the boundary of the image corresponding to the defocus area is blurred and divergent. Small-scale gradients within a short distance can reflect relatively clear boundary information, and large-scale gradients over a long distance can reflect relatively fuzzy boundary information. Therefore, when multi-scale gradients are combined, small-scale gradients are assigned larger weights. Gradients are assigned smaller weights, so that the different contributions of gradients at different scales to the merged gradients are achieved, and the focus information of the image is better reflected. Fourthly, at the pixel coordinate (x, y), the weighted value of the multi-scale morphological gradient in the local window is calculated.

$$WMMG(x,y) = \sum_{i=x-T}^{x+T} \sum_{j=y-T}^{y+T} \frac{MMG(i,j)}{\sqrt{(i-x)^2 + (j-y)^2} + 1} \tag{7}$$

Where T determines the size of the local window, and (i, j) represents the coordinates of each gradient in the local window.

In equation 7, WMMGis a weighted sum of MMG in a window with the pixel coordinate (x, y) asthe center and the size $(2 \times T + 1) \times (2 \times T + 1)$. In a local window, as T increases, the window size becomes larger, so the range of gradients that contribute toWMMGis larger. At the same time, the contribution weight of the gradient value of each position in the local window is determined by its spatial distance to the center position. Its weight is inversely proportional to the distance. Therefore, the WMMG value of each position is mainly contributed by the gradient value of nearby points. For smooth areas in a multi-focus image, the WMMG value of the focus area is much larger than the WMMG value of the corresponding defocus area, and at the same time, the noise gradient can be partially suppressed. Therefore, the accuracy of the focus detection of the image can be improved.

2.2. Image Block Focus Measure Method

After obtaining the multi-scale morphological gradient maps of the two source images, use them as the focus degree measurement maps A_1 and A_2 of the source image.

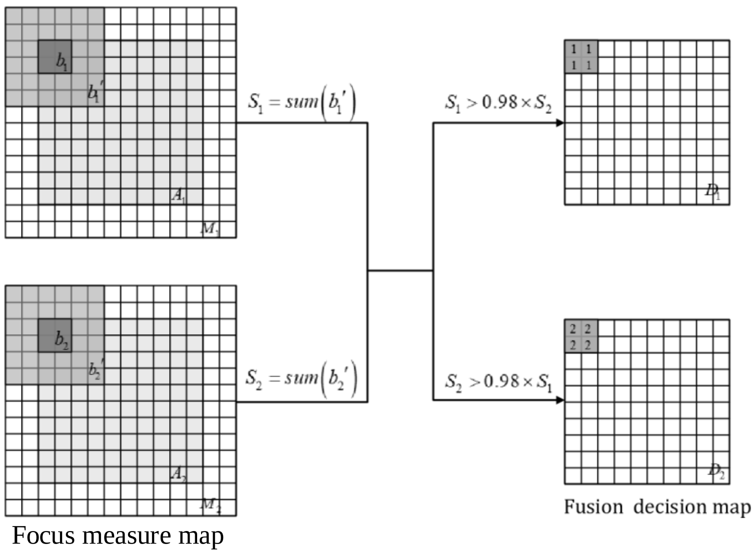


Figure 2. Image block focus determination

Firstly, A_1 and A_2 are evenly divided into 2×2 size image blocks, the image blocks are marked as b_1 and b_2, and then the sum of all values in the 6×6 size range centered on the image block is used as the focus judgment value of the image block. The formula is as follows:

$$S_i = \sum\sum_{(x,y)\in b_i'} M_i(x,y), \quad i = 1,2 \tag{8}$$

Where S_i is the focus determination value of the image block, $M_i(x,y)$ is the expanded degree of focus measurement map after "zero-filling".

Secondly, For each image block pair, according to the image block focus determination value, the corresponding image block focusing situation can be divided into three categories: focused block, defocused block and uncertain block. The initial fusion decision map can be generated by determining the focus of the image block. If the focus determination value of the sub-block of image 1 is greater than 0.98 times the focus determination value of the sub-block of image 2, the position corresponding to image 1 is the focus block and the position corresponding to image 2 is a defocus block, the value corresponding to the initial fusion decision map is 1; on the contrary, the position corresponding to image 1 is the defocus block, the position corresponding to image 2 is the focus block, and the value corresponding to the initial fusion decision map is 2; Determine the block pair, the value of the corresponding initial fusion decision map is 0, and the formula is as follows:

$$D(x,y)=\begin{cases}1, & if\ S_1>0.98\times S_2\\ 2, & if\ S_2>0.98\times S_1\\ 0, & otherwise\end{cases} \tag{9}$$

Where $D(x,y)$ is fusion decision map.

2.3. Focused Fusion

After obtaining a more accurate fusion decision map, directly copy the corresponding focus area of the source image to generate a fully focused fusion image according to the fusion decision map. For the case where the focus measurement values of the same pair are equal, take the average pixel value of the region as the fusion image pixel value. The fusion formula is as follows.

$$I_F(x,y)=\begin{cases} I_i(x,y), & D(x,y)=i, \quad i=1,2\\ \frac{1}{2}\sum_{i=1}^{2} I_i(x,y), & D(x,y)=0, \quad i=1,2\end{cases} \tag{10}$$

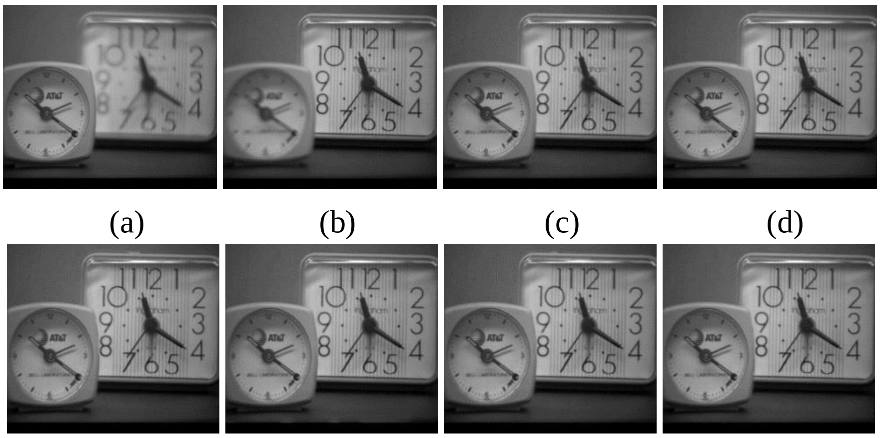
Where I_F (x, y,) is fused image, I_i (x, y) is the source image and D(x, y) is fusion decision map.

3. Experimental Results and Discussions

In order to illustrate the effectiveness of the proposed algorithm, we compare this algorithm with existing algorithms, including IM (Image matting)algorithm[3], Boundary finding (BF) algorithm[4], DSIFT algorithm[5], Multi-scale weighted gradient (MWGF) algorithm[6], MST_SR algorithm [7], and 10 pairs of source images include ‘net’, ‘leopard’, ‘girl’, ‘opengl’, ‘flower’, ‘lab’, ‘disk’, ‘wine’, ‘clock’, ‘seascape’. For the comparison of the fusion results of different methods, qualitative comparison and quantitative comparison are performed.

3.1. Qualitative Comparison

The qualitative comparison of the fused images is based on the subjective evaluation of human vision. One way is to look at the visual effect of the fused image; the other way is to make a difference between the fused image and the source image.



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

(e) (f) (g) (h)

Figure 3. Multi-focus ‘Clock’ images and fused images. (a-b) The source images, (c-h) The fusion images by using IM algorithm, BF algorithm, DSIFT algorithm, MWGF algorithm, MST_SR algorithm, respectively.

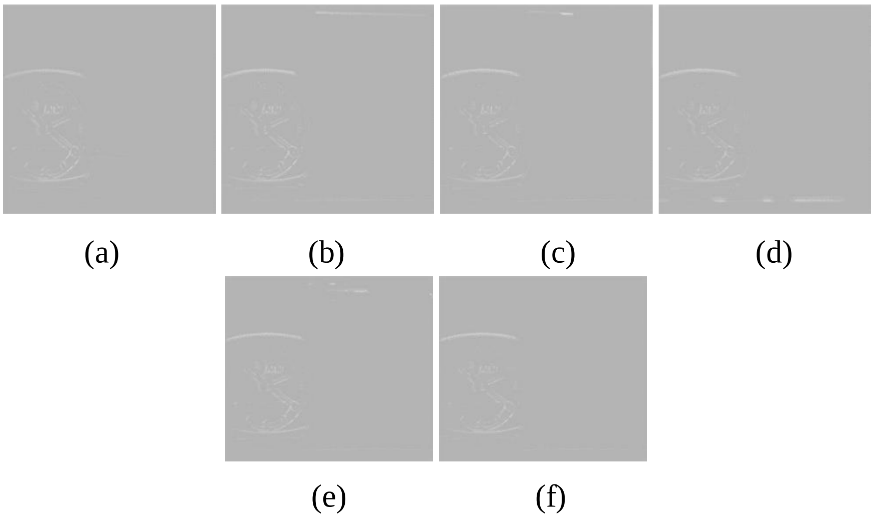


Figure 4. Differences between different methods fused images and Figure3.(b)

3.2. Quantitative Comparison

We choose 5 commonly used indicators to objectively evaluate the quality of the fused image. These indicators include Tsallis entropyQ_{TE} [8], nonlinear related information entropyQ_{NCIE} [9], edge retention fusion quality indicator Q_{AB} $_{F}$/ [10], phase-based fusion indicator Q_{P} [11], and standardized mutual information indicatorQ_{MI} [12].

Table 1. The average objective evaluation of 10 groups of images by different methods

method	IM	BF	DSIFT	MWGF	MST_SR	Proposed
Q^{TE}	1.19063	1.22408	1.22438	1.15811	0.99411	1.23039
Q^{NCIE}	0.84407	0.84618	0.84612	0.84216	0.83316	0.84664
$Q^{AB/F}$	0.76894	0.76538	0.76692	0.76111	0.78494	0.76456
Q^{P}	0.83636	0.84698	0.84666	0.84797	0.80671	0.84704
Q^{MI}	6.01581	6.18201	6.18846	5.85449	5.03343	6.21513

Table 2. The average time consumed by different methods

method	IM	BF	DSIFT	MWGF	MST_SR	Proposed
Time/s	3.21436	1.27657	7.43227	3.17474	0.21107	2.14327

4. Conclusion

This paper introduces a new weighted multi-scale morphological gradient evaluation index for source image focus degree measurement. This index improves the accuracy of source image focus evaluation by enhancing the focus evaluation ability of the smooth area of the image. The establishment of a fusion decision map correctly laid the foundation. Finally, in this chapter, 10 sets of different multi-focus images are used to compare the five existing methods with the method in this paper, which verifies the effectiveness and superiority of the method in this paper.

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