Fast Guided Filter-Based Multi-Focus Image Fusion through Focus Region Detection

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ABSTRACT

In an efficacy method of information fusion, multi-focus image fusion has been attracting great interests in applications like image processing and computer vision. This paper proposes a multi- focus image fusion method based on focus region detection using mean filter and fast guided filter. Firstly, a novel focus region detection method is presented, which uses fast guided filter to refine the rough focus maps obtained by mean filter and difference operator. An initial decision map is got via the pixel-wise maximum rule, and optimized to generate final decision map by using fast guided filter again. Finally, the fused image is obtained by the pixel-wise weighted-averaging rule with the final decision map. Experimental results demonstrate that the novel focus region detection method has stronger robustness to different noises, and higher computational efficiency than other focus measures. Our proposed method implements efficiently and outperforms some state- of-the-art approaches both in visual effect and objective evaluation.

1. INTRODUCTION

Image fusion, which combines complementary information from different images to generate an image , has been an active topic in many applications, such as digital photography, remote sensing, surveillance, and medical diagnosis[1]. Overcoming the limited depth of the field for optical lenses, multi-focus image fusion obtains an all-in- focus image, and has been widely used in image processing and computer vision. In the past three decades, a large number of multi-focus image fusion methods have been proposed, mostly concerning transform domain and spatial domain methods[2-6].

For transform domain-based methods, the source images are decomposed into different transform coefficients, which are fused by certain fusion rules. Then the fused image is generated by reconstructing the fused coefficients. In this framework, with the development of multi-scale theories, a variety of multi-scale transforms are proposed and applied in image fusion, mainly including pyramid transform, wavelet transform , contourlet transform , shearlet transform etc. In addition, robust principal component analysis sparse representation, multi- scale transform and sparse representation , pulse- coupled neural network methods have also been discussed[7-8]. If spatial consistency is not well considered in the fusion process, the above methods may lose some spatial information, and result in brightness or color distortion . Different from transform domain-based methods, spatial domain- based methods directly fuse source images into intensity values.

Spatial domain-based methods are simple to implement, and preserve much spatial information. The simplest method calculates the average of source images pixel-by-pixel, but it leads to many detail loss, contrast reducing, and high sensitivity to noise. Aiming to make full use of spatial context, a number of block and region based- methods have been proposed. Focus measure, as a measure of image clarity, is the key to block and region-based methods. Almost all of focus measures depend on high-frequency information such as gradient or edge . The classic focus measures are variance, spatial frequency (SF) , sum of the modified Laplacian (SML) , etc. Compared with other focus measures, SML performed better for measuring image clarity , and frequency-selective weighted median is more robust to noise . To measure image clarity well, some novel focus measures or detection methods have been presented recently, such as surface area , multi-scale morphology (MSM), multi-scale weighted gradient , convolutional neural network , and boundary extraction . These focus measures or detection methods perform well for focus region detection, but suffer from computational efficiency or robustness to noise[9-10].

Recently, as an efficient edge-aware filter, guided filter can well preserve global salient edges and local shapes, and has been widely used in image fusion. Firstly, because guided filter preserves spatial consistency of structures, applied guided filter to optimize the weighted coefficients of base layers and detail layers, and obtained satisfied fusion image[11-13]. This advantage of guided filter solves the problem of spatial domain-based methods, that is the misalignment of decision map with object boundaries. guided filter is mostly used for spatial consistency verification of decision map or weight map in image fusion . Secondly, different scale details can be extracted by setting different parameters of guided filter. Guided filter is also used to multi-scale decomposition in visible and infrared image fusion[14-15]. Thirdly, due to preserving local shapes, guided filter is used to detail enhancement in image fusion, such as infrared detail enhancement , multi-spectral detail enhancement In 4addition, employed guided filter to extract salient features in focus region, and obtained initial decision map by using a mixed focus measure, which combines the variance of image intensities and the energy of the image gradient fusion method through fast guided filter- based focus region detection. Firstly, the proposed method employs image mean filter and difference operator to get rough focus maps, which are refined by fast guided filter with the corresponding source images serving as guidance images, and gets accurate focus maps. Secondly, an initial decision map is obtained by taking the pixel-wise maximum rule of the corresponding accurate focus maps, and the initial fusion image is fused with the pixel-wise weighted-averaging rule. Thirdly, the initial decision map is optimized into a final decision map using small region removal strategy and guided filter. Finally, the source images are fused by the pixel-wise weighted-averaging rule with the final decision map, and the desired fusion image is obtained

2. PROPOSED FUSION METHOD

The proposed method in this paper uses fast guided filter-based focus region detection for multi-focus image fusion (named as FGFDF). Two source images are pre- registered are considered as input for the method. The fusion scheme includes four steps. Firstly,the mean filter and difference operator are used to get the rough focus maps, are then refined by fast guided filter to produce the accurate focus maps. Secondly, an initial decision map is obtained by taking the pixel-wise maximum rule of the corresponding refined focus maps. Thirdly, an initial decisionmap is optimized into a final decision map using small region removal strategy and fast guided filter. Finally, the source images are fused by the pixel-wise weighted-averaging rule with the final decision map, and the resultant image is obtained.

Focus region detection is quite an important step in MFIF. In this section, a new focus region detection method based on mean filter and fast guided filter (MFGF)is proposed, which contains three steps as follows:

Step1: Simple average filter fm is used to blur the source images and the mean-filtered images M1 and M2 are produced, as shown in Eq. (1) and Eq. (2).

$$M_1(x,y) = I_1(x,y) * f_m \qquad (1)$$

$$M_2(x,y) = I_2(x,y) * f_m \qquad (2)$$

where * represents a convolution operator.

Step2: Compared to the focus region of source image, the corresponding region of mean-filtered image are blurred. The absolute values of the difference between the source images and the mean- filtered images are calculated, and the part of high frequency information is extracted to generate rough focus maps RFM1 and RFM2, as shown in Eq. (3) and Eq. (4).

$$RFM_1(x,y) = \left| I_1(x,y) - M_1(x,y) \right| \qquad (3)$$

$$RFM_2(x,y) = \left| I_2(x,y) - M_2(x,y) \right|, \qquad (4)$$

where || represents an absolute operator.

Step3: Due to the high-frequency information in guidance image is transferred to output image, the high frequency information of the rough focus maps are enhanced by fast guided filter with source images serving as guidance image. Therefore, the rough focus maps RFM1 and RFM2 are refined by fast guided filter serving as guidance images, and the accurate focus maps AFM1 and AFM2 are obtained which have more high frequency information than rough focus maps, as shown in Eq. (5) and Eq. (6).

$$AFM_1(x,y) = FGF(I_1(x,y), RFM_1(x,y)) \qquad (5) \quad AFM_2(x,y) = FGF(I_2(x,y), RFM_2(x,y))$$

(6)

where FGFr,( ) represents an fast guided filter operator, r and ε are the parameters of fast guided filter.

Initial decision map

AFM1 and AFM2 represent the focus measure of the source images. Therefore, an initial decision map is obtained by taking the pixel-wise maximum rule of the corresponding accurate focus maps AFM1 and AFM2, as shown in Eq. (7).

$$IDM(x,y)=\begin{cases}1, AFM_1(x,y)>AFM_2(x,y)\\ 0, otherwise\end{cases} \quad (7)$$

Final decision map

To obtain fused image with more accuracy , fast guided filter is used again to verify spatial consistency with the initial fusion image IIF serving as guidance images, and generates the desired final decision map FDM, as shown in Eq. (9).

$$I_{IF}(x,y)=IDM(x,y)I_1(x,y)+(1-IDM(x,y))I_2(x,y) \quad (8)$$

$$FDM(x,y)=FGF_{r,\varepsilon}(I_{IF}(x,y),IDM(x,y)) \quad (9)$$

Fused result

With the final decision map FDM, the source images are fused together by the following pixel-wise weighted-averaging rule, and the final fused image IF is obtained, as shown in Eq. (10)

$$I_F(x,y)=FDM(x,y)I_1(x,y)+(1-FDM(x,y))I_2(x,y) \quad (10)$$

3. EXPERIMENTAL RESULTS & DISCUSSION

To conduct the experiments on image pairs, a PC with an Intel® coreTM 4.00GHz and 1TB RAM with win 10;64-bit OS having MATLAB2018a used as software environment. The proposed framework effectiveness is verified on three pairs of multi-focus images. These source images are taken from standard site. All these source images are accurately registered and their size is 256 x 256 pixels. In this we are taking two inputs, left side blurred and right side blurred to get the output of proposed method.




(a)Left focus image (b)Right focus image (c)Existed method (d)Proposed method




(a)Left focus image (b)Right focus image (c)Existed method (d)Proposed method




(a)Left focus image (b)Right focus image (c)Existed method (d)Proposed method

Experimental results demonstrate that this method can be competitive with or even outperform the state-of-the-art fusion methods in terms of both subjective visual perception and objective evaluation metrics.Performance evaluation of image fusion can be divided into subjective evaluation and objective evaluation. Objective evaluation is determined according to statistical parameter like mean, standard deviation. The subjective evaluation is concluded according to visual effects and some parameters are the entropy, image definition etc. Here some standard performance metrics likes QP,QG,QY,QFMI [16-23] are determined.

The quality metrics which are mentioned in above section are listed in table as shown below. In the table, higher value is showed in bold .The efficiency of proposed is tested based on three image pairs.

Table.1. Objective assessment of Fused image

Quality Metrics		Q_G	Q_P	Q_Y	Q_{CB}	Q_{FMI}
Fast Guided Filter	Clock	**0.6795**	0.7301	**0.9882**	0.7045	**0.6135**
Guided Filter	Clock	0.6732	**0.8125**	0.9780	**0.7630**	0.6045
Fast Guided Filter	Lytro	0.5803	0.6210	0.9862	0.6150	0.5898
Guided Filter	Lytro	**0.7118**	**0.8636**	**0.9885**	**0.7865**	**0.5963**
Fast Guided Filter	Book	0.6585	0.9228	0.9781	**0.8428**	0.6250
Guided Filter	Book	**0.6731**	**0.9315**	**0.9826**	0.8367	**0.6291**

From the table it is seen that, for clock image –fused image has good quality in terms of Q_G,Q_Y,Q_{FMI} .For lytro image, proposed method is not showing good results but visual quality of fused image is more compared with guided filter. For book image, fused image has good quality metrics like Q_{CB} but visual quality of fused image is more compared with guided filter.

4. CONCLUSION

In multi-focus image fusion, focus region detection is quite important to produce quality image as fused one. In proposed method, fast guided filter is applied to find decision maps accurately and this solve the misalignment problem related to object boundaries. Because of good smoothing property and less computational complexity of fast guided filter ,fused image is having more clarity,quality,more information and having robustness to noise. Our method gives good results both objectively and subjectively than guided filter based focus region detection method.

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