Multi-modal Image Fusion with KNN Matting

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Abstract. A single captured image of a scene is usually insufficient to reveal all the details due to the imaging limitations of single senor. To solve this problem, multiple images capturing the same scene with different sensors can be combined into a single fused image which preserves the complementary information of all input images. In this paper, a novel K nearest neighbor (KNN) matting based image fusion technique is proposed which consists of the following steps: First, the salient pixels of each input image is detected using a Laplician filtering based method. Then, guided by the salient pixels and the spatial correlation among adjacent pixels, the KNN matting method is used to calculate a globally optimal weight map for each input image. Finally, the fused image is obtained by calculating the weighed average of the input images. Experiments demonstrate that the proposed algorithm can generate high-quality fused images in terms of good visual quality and high objective indexes. Comparisons with a number of recently proposed fusion techniques show that the proposed method generates better results in most cases.

Keywords: Image fusion, KNN matting, Laplician filtering, weighted average.

1 Introduction

Image fusion is able to fuse the complementary information preserved in different images of the same scene, so as to obtain a single fused image which provides more comprehensive information. The fused images are usually more useful for human and machine perception, and thus, image fusion has been widely applied for digital photography, object detection and related applications [1].

Recently, a large number of image fusion methods have been proposed such as multiscale image fusion and optimization based fusion. Multiscale fusion aims at proposing different multi-scale coefficients and novel fusion rules to guide the fusion of coefficients [2,3]. Since the multi-scale coefficients provide an accurate representation of images, these methods can well preserve the details of different images [2]. However, since spatial information is not considered, multi-scale based methods cannot ensure the color and brightness consistency of the fused image [4]. To solve this problem, optimization based image fusion approaches, e.g., generalized random walks [5], and matting based method [6] have been proposed

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Fig. 1. An example of image matting. (a) Input images and clicks. (b) Alpha matte obtained by the closed form matting method [7]. (c) Alpha matte obtained by the KNN matting method [8].

for fusion of multi-exposure and multi-focus images. These methods first estimate accurate weights by solving an energy function. The source images are then fused together by weighted average of pixel values. In [6], robust matting has been successfully applied for fusion of multi-focus images. However, this method relies heavily on the accurate estimate of initial weights. More importantly, the method is designed only for multi-focus image fusion.

In order to extend image matting for fusion multi-modal images captured by different imaging sensors, a novel KNN matting based fusion method is proposed in this paper. Experimental results show that the proposed method gives a performance comparable with state-of-the-art fusion approaches including the traditional robust matting based fusion method [6].

2 Image Matting

Image matting is a technique to accurately distinguish foreground objects from background [7]. Specifically, an input image I can be represented as a combination of foreground color F and background color B.

$$I = \alpha \times F + (1 - \alpha) \times B \tag{1}$$

where $\times$ represents the multiplication operation element by element, α ranging from 0 to 1 is the foregrounds opacities which is usually named as the alpha matte. The objective of image matting is to calculate the alpha matte α, the foreground color F, and the background color B from a single image I. Obviously, this problem is under constrained which has infinite solutions. Therefore, in most cases, user inputs and prior assumptions are required in addition to the original image.

Fig. 1 gives an example of image matting. Taking Fig. 1(a) as the inputs which contain the input image, and user clicks (black point indicates that this pixel is a background pixel, white point indicates that this pixel is a foreground pixel), different matting algorithms are able to obtain different matting results shown in Fig. 1(b) and (c). It can be seen that, although there has only few user

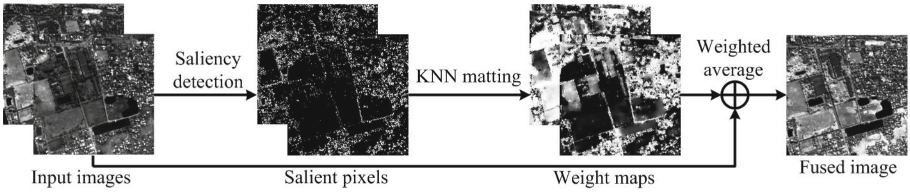

Fig. 2. A schematic of the proposed KNN matting based image fusion method

clicks as inputs, the KNN matting method [8] is still able to obtain an accurate alpha matte which can distinguish the foreground object from the background. By contrast, the closed form matting method [7] fails in detecting the accurate foreground object in this example. Therefore, the KNN matting is expected to be a more suitable solution for the proposed matting based image fusion method.

3 Proposed Method

Fig. 2 summarizes the main processes of the proposed KNN matting based fusion method (GFF). First, an laplacian filter is utilized to detect the salient pixels in each input image. Then, taking the detected salient pixels and the input images as the inputs of KNN matting, the weight maps α used for image fusion can be estimated. Finally, the fused image is obtained by weighted average of input images.

3.1 Salient Pixels Detection

In order to detect the salient pixels of each input image, Laplacian filtering is applied to each source image I_n to obtain the filtered image H_n.

$$H_n = I_n * L \tag{2}$$

where L is a 3×3 Laplacian filter, I_n refers to the nth input image. Then, these pixels give much higher salience values are assigned as salient pixels.

$$S_n^i = \begin{cases} 1 & \text{if } H_n^i - \max_{m,m \neq n} H_m^i > \sigma, \\ 0 & \text{otherwise.} \end{cases} \tag{3}$$

where i refers to the ith pixel, σ is a free threshold to control the number of detected salient pixels. In this paper, the parameter σ is fixed as 0.1 for all experiments.

Fig. 3(c) and (d) shows the detected salient pixels of Fig. 3(a) and (b), respectively. It can be seen that the major function of the Laplician filter is to find the rough positions of the salient objects in each input image.

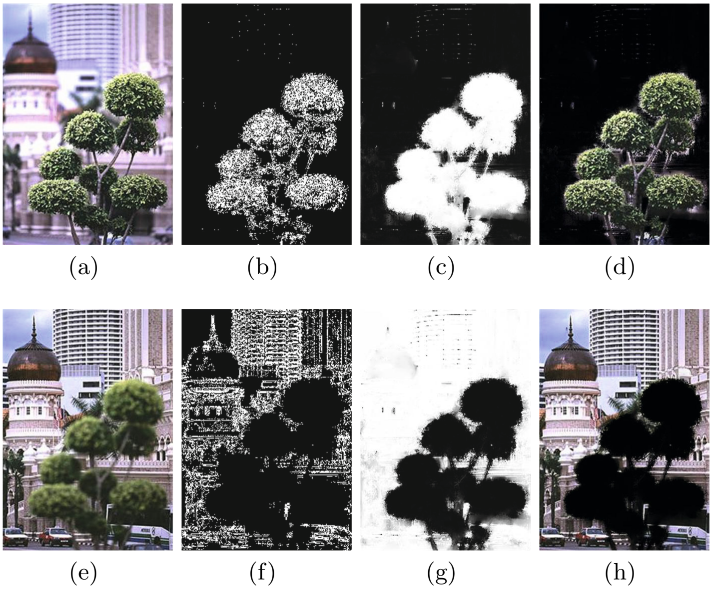

Fig. 3. (a) and (e) Input images. (b) and (f) Salient pixels detected by Laplician filtering. Weight maps α_1 (c) and α_2 (g) estimated by the KNN matting method [8]. Accurate salient objects of the input images obtained by $\alpha_1 \times I_1$ (d) and $\alpha_2 \times I_2$ (h).

3.2 KNN Matting and Fusion

After salient pixel detection, through considering the spatial consistency between adjacent pixels, KNN matting is used to estimate the accurate weight map for image fusion. Specifically, the detected salient pixels are considered as the input clicks of the KNN matting algorithm. The detailed description of the KNN matting method can be found in [8]. Here, the KNN matting step is represented using a KNN function as follows.

$$\alpha_n = \mathrm{KNN}\left\{I_n, S_n\right\} \tag{4}$$

For this function, the inputs are the input images I_n (see Fig. 3(a) and (e)), and the salient pixel maps S_n (see Fig. 3(b) and (f)). The outputs are the resulting alpha matte α_n for each input image I_n (see Fig. 3(c) and (g)). As shown in Fig. 3, the salient object in each input image can be detected accurately by calculating the multiplication between the alpha matte and the corresponding input image pixel by pixel. Therefore, the fused image can be easily constructed by calculating a weighed sum of the input images with the alpha mattes serving as weight maps as follows.

$$F = \sum_{n=1:N} \alpha_n \times I_n \tag{5}$$

where N is the number of input images.

4 Experiments

4.1 Experimental Setup

In this section, the proposed KNN based fusion method (KNNF) is compared with three recently proposed image fusion methods, i.e., the robust matting based multifocus fusion method (RMMF) [4], the guided filtering based fusion method (GFF) [6], and the recursive filtering based fusion method (RFF) [9]. These methods are implemented by using the default parameters given by the corresponding authors. For the proposed KNNF method, the default parameters given in [8] is adopted for the KNN matting algorithm. Furthermore, four widely used image fusion quality metrics, i.e., Q_0, $SSIM$, Q_w, and MI have been used to test the objective fusion performance of different methods. A detailed description of these quality metrics can be found in [9].

4.2 Fusion Results

The first experiment is performed on the multispectral images shown in Fig. 4(a) and (b), where the two images are two different bands of a multispectral image. In order to compare the performance of different methods clearly, the details in the input images and the fused images are magnified for close-up comparison. As shown in Fig. 4, the RMMF method may produce false details which are not existed in the input images. Although the RFF and GFF methods are

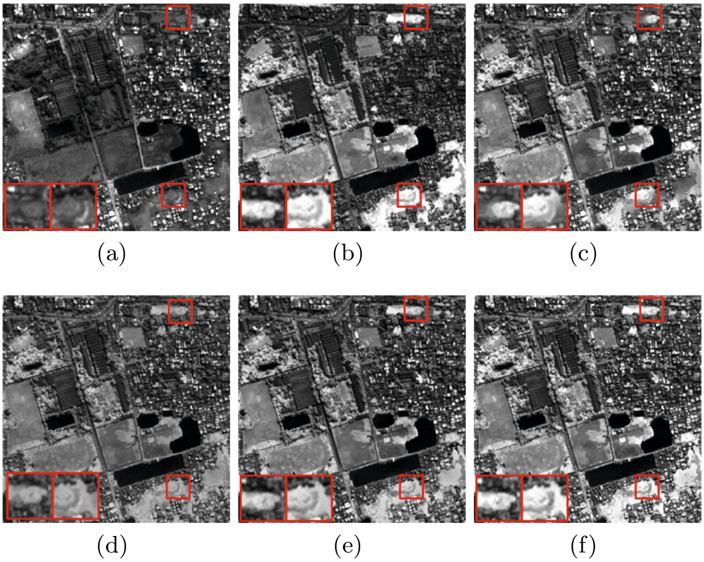

Fig. 4. Input multi-spectral images and fused images obtained by different fusion methods. (a) and (b) Input images. Fused images obtained by the RMMF method (c), RFF (d), GFF(e), and proposed KNNF method (f).

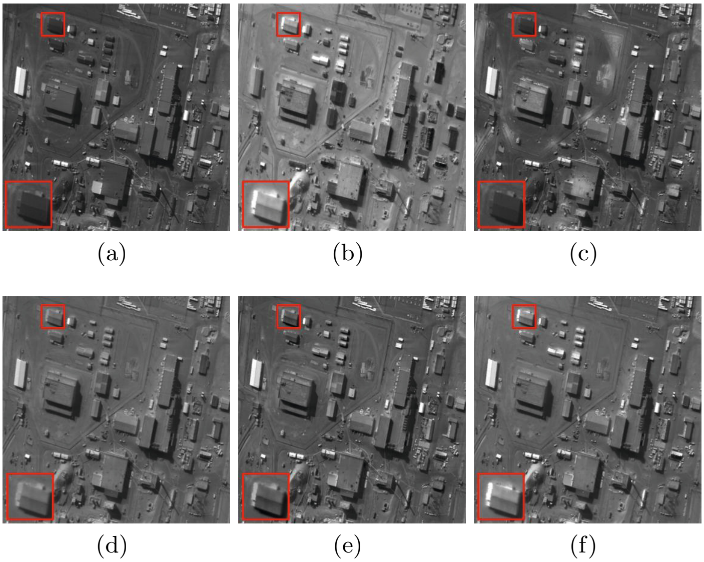

Fig. 5. Input multi-spectral images and fused images obtained by different fusion methods. (a) and (b) Input images. Fused images obtained by the RMMF method (c), RFF (d), GFF(e), and proposed KNNF method (f).

able to preserve the complementary information of input images, image contrast may be decreased in the fused images especially for the result obtained by the RFF method. By contrast, the proposed KNNF method can well preserve most of useful information in the input images without decrease the contrast of the fused image. Table 1 compares the objective performances of different methods. As shown in this table, the proposed KNNF method gives the best fusion performance for the first experiment in terms of the highest value of all four quality indexes.

Another multispectral image fusion example is presented in Fig. 5. This figure shows that the proposed method is able to preserve most useful information in the input images. By contrast, the results generated by RMMF may lose some important image details. The RFF and GFF methods may decrease the local contrast of fused images. Similar to the first experiment, table 1 also shows that the proposed KNNF method gives the best objective performances for the second experiment.

The third experiment is performed on multi-modal medical images. Two medical images are captured by using different senors and thus able to reveal different types of details about an human's brain. Fig. 6 shows that the RMMF, RFF, and GFF methods may fail in detecting some salient brain structures. By contrast, the proposed KNNF can preserve the salient information of different images. Furthermore, Table 1 shows that the proposed KNNF method gives the best performance in terms of the highest value of most quality indexes, except ranking as third for the Q_0 Metric.

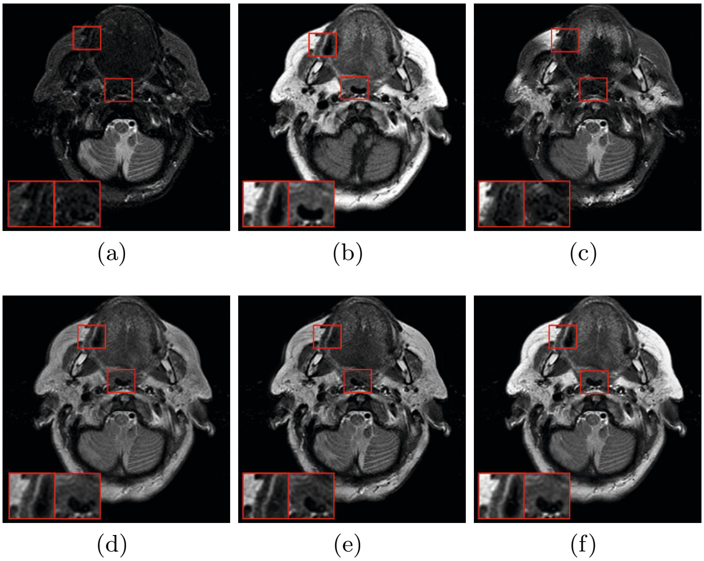

Fig. 6. Input multi-modal images and fused images obtained by different fusion methods. (a) and (b) Input images. Fused images obtained by the RMMF method (c), RFF (d), GFF(e), and proposed KNNF method (f).

Table 1. Objective Performances of Different Image Fusion Methods Measured by Four Objective Quality Indexes

Experiment-1				
Metrics	RMMF	RFF	GFF	KNNF
Q_0	0.7315	0.7047	0.7679	**0.7707**
$SSIM$	0.8099	0.5668	0.7455	**0.8984**
Q_w	0.7274	0.698	0.773	**0.779**
MI	0.3239	0.2979	0.2995	**0.3513**
Experiment-2				
Metrics	RMMF	RFF	GFF	KNNF
Q_0	0.4975	0.5885	0.6095	**0.6136**
$SSIM$	0.6346	0.4921	0.6764	**0.6791**
Q_w	0.6045	0.6451	0.7046	**0.7248**
MI	0.4104	0.3342	0.4035	**0.4154**
Experiment-3				
Metrics	RMMF	RFF	GFF	KNNF
Q_0	0.4206	0.5476	**0.5596**	0.5463
$SSIM$	0.5442	0.5142	0.7006	**0.8316**
Q_w	0.3738	0.5733	0.6588	**0.7893**
MI	0.3038	0.3041	0.3054	**0.3482**

5 Conclusions

A novel image fusion method based on KNN matting is presented in this paper. The proposed method utilizes the Laplician filter to detect the salient pixels of each source image, which is simple and effective. More importantly, the KNN matting is used to make full use of the spatial correlations between neighborhood pixels for weight estimation. Experiments show that the proposed method can well preserve the complementary information of multiple input images captured by different sensors. The proposed method can achieve competitive subjective and objective performances compared with several recently proposed image fusion methods. Therefore, it will be quite useful in real applications.

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