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MULTI-FOCUS IMAGE FUSION USING GUIDED FILTERING

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Abstract: - Multi-focus image fusion plays an important role in image processing and machine vision applications. In frequent occasions, captured images are not focus throughout the image because the optical lenses that are commonly used for producing image have limited depth of field. Therefore only the objects that are near the focal range of the camera are clear while other parts are blurred. Image fusion is the process of combining information from two or more images of a scene into a single composite image that is more informative and is more suitable for visual perception or computer processing. A fast and effective image fusion method is proposed for creating a highly informative fused image through merging multiple images. A novel guided filtering-based weighted average technique is proposed to make full use of spatial consistency
For fusion of the base and detail layers.

Keywords: - Multi-focus, visual perception and guided filtering

1 Introduction

In this section we propose a new type of explicit image filter, called guided filter. The filtering output is locally a linear transform of the guidance image. This filter has the edge-preserving smoothing property like the bilateral filter, but does not suffer from the gradient reversal artefacts. It is also related to the matting Laplacian matrix, so is a more generic concept and is applicable in other applications beyond the scope of ”smoothing”. Moreover, the guided filter has an O (N) time (in the number of pixels N) exact algorithm for both gray-scale and color images. Experiments show that the guided filter performs very well in terms of both quality and efficiency in a great variety of applications, such as noise reduction, detail smoothing/ enhancement, HDR compression, image matting/feathering, haze removal, and joint up sampling.

Image fusion is an important technique for various image processing and computer vision applications such as feature extraction and target recognition. Through image fusion, different images of the same scene can be combined into a single fused image. The fused image can provide more comprehensive information about the scene

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Which is more useful for human and machine perception. For instance, the performance of feature extraction algorithms can be improved by fusing multi-spectral remote sensing images. The fusion of multi-exposure images can be used for digital photography.

In these applications, a good image fusion method has the following properties. First, it can preserve most of the useful information of different images. Second, it does not produce artefacts. Third, it is robust to imperfect conditions such as mis-registration and noise. A large number of image fusion methods have been proposed in literature. Among these methods, multiscale image fusion and data-driven image fusion are very successful methods. They focus on different data representations, e.g., multi-scale coefficients, or data driven decomposition coefficients and different image fusion rules to guide the fusion of coefficients. The major advantage of these methods is that they can well preserve the details of different source images. However, these kinds of methods may produce brightness and color distortions since spatial consistency is not well considered in the fusion process. To make full use of spatial context, optimization based image fusion approaches, e.g., generalized random walks, and Markov random fields based methods have been proposed. These methods focus on estimating spatially smooth and edge aligned weights by solving an energy function and then fusing the source images by weighted average of pixel values. However, optimization based methods have a common limitation, i.e., inefficiency, since they require multiple iterations to find the global optimal solution. Moreover, another drawback is that global optimization based methods may over-smooth the resulting weights, which is not good for fusion. To solve the problems mentioned above, a novel image fusion method with guided filtering is proposed in this paper. Experimental results show that the proposed method gives a performance comparable with state-of-the-art fusion approaches. Several advantages of the proposed image fusion approach are highlighted in the following.

1. Traditional multi-scale image fusion methods require more than two scales to obtain satisfactory fusion results. The key contribution of this paper is to present a fast two-scale fusion method which does not rely heavily on a specific image decomposition method. A simple average filter is qualified for the proposed fusion framework.

2. A novel weight construction method is proposed to combine pixel saliency and spatial context for image fusion. Instead of using optimization based methods, guided filtering is adopted as a local filtering method for image fusion.

3. An important observation of this paper is that the roles of two measures, i.e., pixel saliency and spatial consistency are quite different when fusing different layers. In this paper, the roles of pixel saliency and spatial consistency are controlled through adjusting the parameters of the guided filter.

2. Guided Image filtering

Recently, edge-preserving filters have been an active research topic in image processing. Edge-preserving smoothing filters such as guided filter , weighted least squares, and bilateral filter can avoid ringing artefacts since they will not blur strong edges in the decomposition process.

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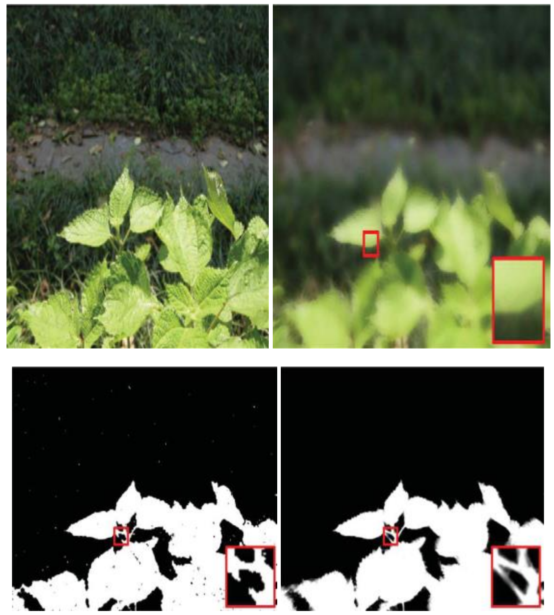

Fig 2.1: Two examples of guided filtering

Among them, the guided filter is a recently proposed edge-preserving filter, and the computing time of which is independent of the filter size. Furthermore, the guided filter

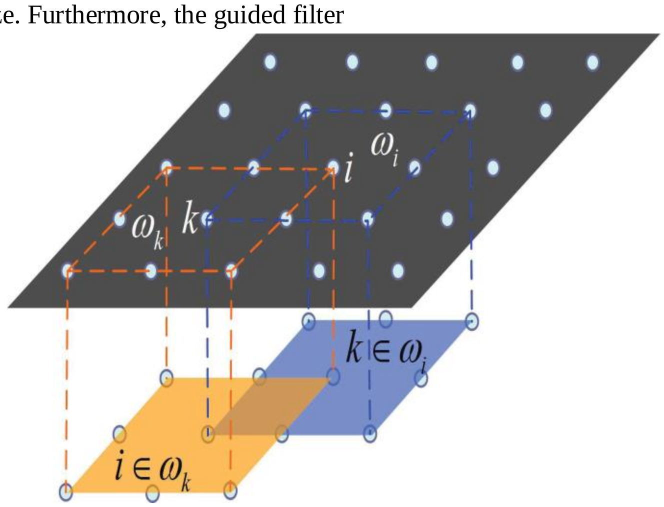

Fig. 2.2: Illustration of window choice.

is based on a local linear model, making it qualified for other applications such as image matting, up-sampling and colorization. In this paper, the guided filter is first applied for image fusion. In theory, the guided filter assumes that the filtering output O is a linear transformation of the guidance image I in a local window ω_k centered at pixel k.

$O_{i=}a_kI_{I+}b_K \forall_I \ {}^{\varepsilon}\omega_K$

Where ωk is a square window of size (2r+1)×(2r+1).

2.2.1 Two-Scale Image Decomposition

As shown in Fig. 2.3, the source images are first decomposed into two-scale representations by average filtering. The base layer of each source image is obtained as follows:

Bn = In * Z

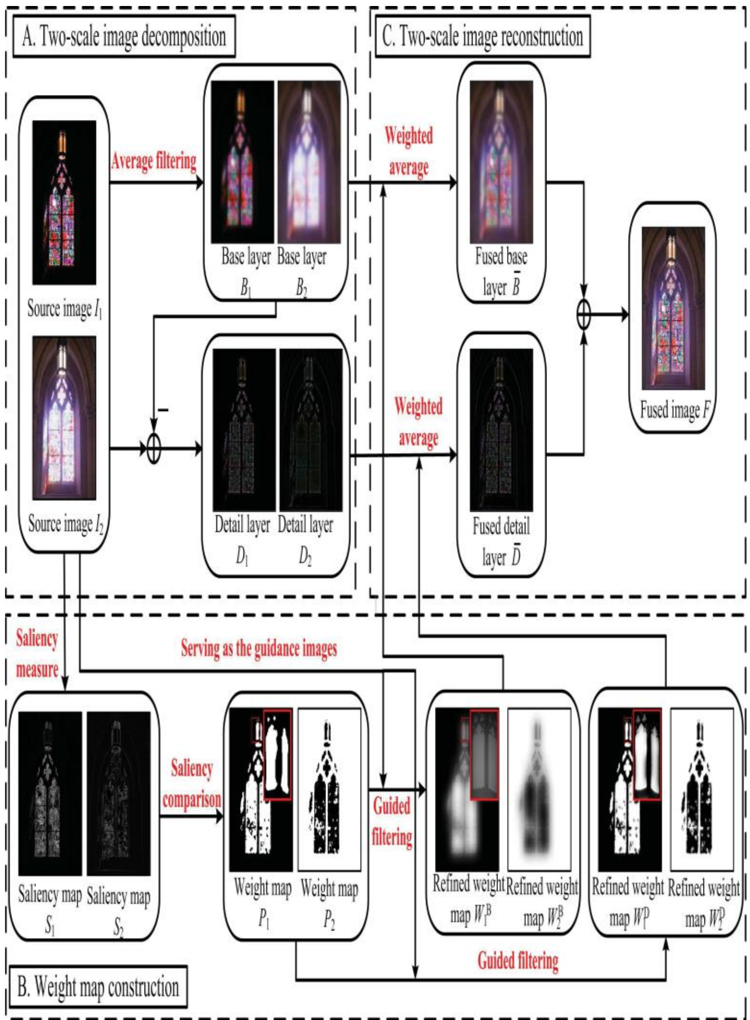

Fig 2.3 Schematic diagram of the proposed image fusion method based on guided filtering.

Where In is the nth source image, Z is the average filter, and the size of the average filter is conventionally set to 31×31. Once the base layer is obtained, the detail layer can be easily obtained by subtracting the base layer from the source image.

Dn = In − Bn.

The two-scale decomposition step aims at separating each source image into a base layer containing the large-scale variations in intensity and a detail layer containing the small scale details.

2.2.2 Weight Map Construction with Guided Filtering

In this section, an interesting alternative to optimization based methods is proposed. Guided image filtering is performed on each weight map Pn with the corresponding source image In serving as the guidance image.

$W_n^B = G_{r1,\alpha1}(P_n, I_n)$
$W_n^D = G_{r2,\alpha2}(P_n, I_n)$
Where r1, α1, r2, and α2are the parameters of the guided filter, W_n^B and W_n^D n are the resulting weight maps of the base and detail layers. Finally, the values of the N weight maps are normalized such that they sum to one at each pixel k.

2.2.3 Two-Scale Image Reconstruction

Two-scale image reconstruction consists of the following two steps. First, the base and detail layers of different source images are fused together by weighted averaging. Then, the fused image F is obtained by combining the fused base layer B and the fused detail layer D
F = B + D.

2.3 Example of Guided Filter

Fig. 2.4 (top) shows an example of the guided filter with various sets of parameters. Though the guided filter is an edge-preserving smoothing filter like the bilateral filter, it avoids the gradient reversal artifacts that may appear in detail enhancement and HDR compression. Fig. 2.5 shows a 1-D example of detail enhancement. Given the input signal (black), its edge-preserving smoothed output is used as a base layer (red). The difference between the input signal and the base layer is the detail layer (blue). It is magnified to boost the details. The enhanced signal (green) is the combination of the boosted detail layer and the base layer. An elaborate description of this method can be found in. For the bilateral filter (Fig. 2.5 left), the base layer is not consistent with input signal at the edge pixels. This is because few pixels around them have similar colors, and the Gaussian weighted average has little statistical data and becomes unreliable. So the detail layer has great fluctuations, and the recombined signal has reversed gradients as shown in the figure.

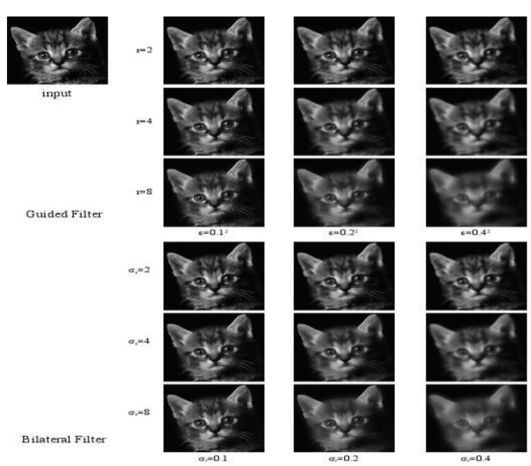

Figure 2.4: The filtered images of a gray-scale input

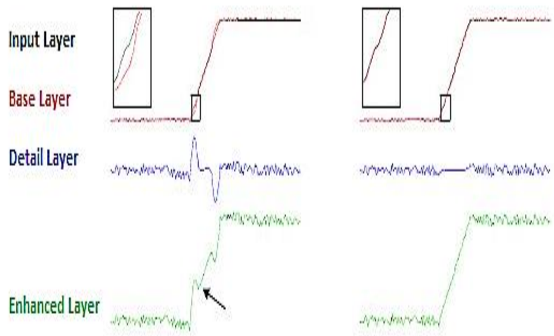

Fig. 2.5-1D illustration for detail enhancement. See the text for explanation.

2.4 Detail Enhancement

The method for detail enhancement is described in Section 2.3. For HDR compression, we compress the base layer instead of magnifying the detail layer. Fig. 2.6 shows an example for detail enhancement. The results using the bilateral filter are also provided. As shown in the zoom-in patches, the bilateral filter leads to gradient reversal artifacts.

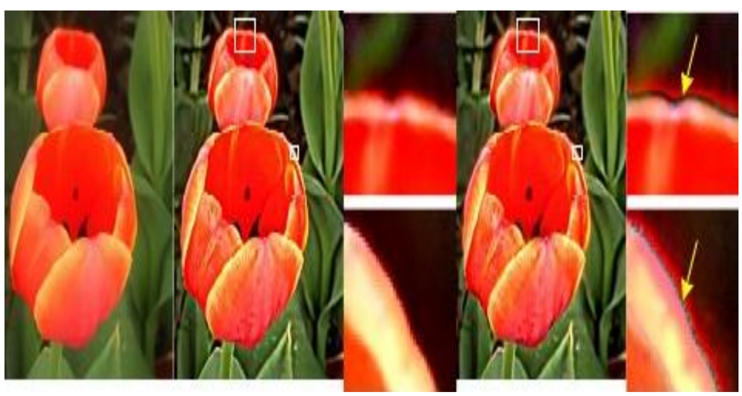

Fig 2.6: Detail enhancement.

2.5 Flash/No-flash Denoising

In it is proposed to denoise a no-flash image under the guidance of its flash version. Fig. 2.7 show a comparison of using the joint bilateral filter and the guided filter. The gradient reversal artifacts are noticeable near some edges in the joint bilateral filter result.

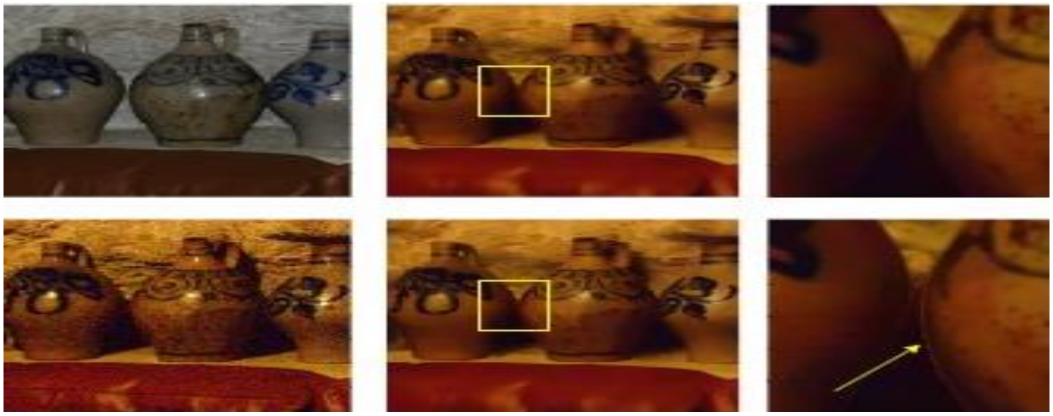

Fig. 2.7. Flash/no-flash denoising

2.5 Matting/Guided Feathering

We apply the guided filter as guided feathering: a binary mask is refined to appear an alpha matte near the object boundaries

Fig. 2.8. Guided Feathering.

(Fig. 2.8). The binary mask can be obtained from graph-cut or other segmentation
Methods, and is used as the filter input p. The guidance I is the color image. A similar function "Refine Edge" can be found in the commercial software Adobe
Photoshop CS4. We can also compute an accurate matte using the closed-form solution. In Fig. 2.8 we compare our results with the Photoshop Refine Edge and the closed-form solution. Our result is visually comparable with the closed form solution in this short hair case. Both our method and Photoshop provide fast feedback (<1s) for this 6-mega-pixel image, while the closed-form solution takes about two minutes to solve a huge linear system.

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3. Conclusion

In this paper, we have presented a novel filter which is widely applicable in computer vision and graphics. Different from the recent trend towards accelerating the bilateral filter , we define a new type of filter that shares the nice property of edge-preserving smoothing but can be computed efficiently and exactly. Our filter is more generic and can handle some applications beyond the concept of ”smoothing”. Since the local linear model can be regarded as a simple case of learning, other advanced models/features might be applied to obtain new filters. Furthermore, the proposed method is computationally efficient, making it quite qualified for real applications. At last, how to improve the performance of the proposed method by adaptively choosing the parameters of the guided filter can be further researched.

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