A Novel Approach For Image Fusion

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Abstract— A new fusion method is been proposed for creating highly informative fused images from multiple images of the same scene.The proposed method is based on a two-scale decomposition of an image into base and detailed layer and then fusing the image by using a weighted guided filter. An edge awareness is being incoperated to Guided filter to adress the problem of halo artifact. Experimental results shows that the proposed method can obtain better performance for fusion of multifocus,multimodel and multiexposure images.

Keywords— multiple images, Base layer, detailed layer, edge weighting, halo artifact,multifocus,multimodel,multiexposure

INTRODUCTION

Image Fusion is important in many image analysis tasks in which image data are acquired from multiple sources. The goal of image fusion is to combine relevant information from two or more source images into one single image such that the single image contains as much information from all the source images as possible. The source imagesinvolved in such applications can be taken at different times and/or using different sensors. As a result, some source images may contain certain occlusions and source images from different sensors show different physical features. The fused image can provide more comprehensive information about the scene which is more useful for human and machine perception.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 [1]. For instance, the performance of feature extraction algorithms can be improved by fusing multi-spectral remote sensing images [3]. The fusion of multi-exposure images can be used for digital photography [4].A significant challenge in data and information fusion is the fusion of images with different focus points so as to create an all-in-focus image.Image fusion has been used extensively in various areas of image processing such as remote sensing, biomedical imaging, nondestructive evaluation etc. For example, in optical remote sensing, due to physical and technical constraints, some sensors provide excellent spectral information but inadequate spatial information about the scene. On the other hand, there are sensors that are good at capturing spatial information but which fail to capture spectral information reliably. Fusing these two types of data provides an image that has both the spatial and the spectral information. Therefore, only the fusedimage needs to be stored for subsequent analysis of the scene.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 artifacts. Third, it is robust to imperfect conditions such as mis-registration and noise. From the perspective of fusion, features of the observed images that are to be fusedcan be broadly categorized in the following three classes.

1) Common features: These are features that are present in all the observed images.

2) Complementary features: Features that are present only in one of the observed images are called complementary features.

3) Noise: Features that are random in nature and do not contain any relevant information are termed as noise.

Note that the above categorization of the features is local in nature. A fusion algorithm should be able to select the feature type automatically and then fuse the information appropriately. For example, if the features are similar then the algorithm should perform an operation similar to averaging but in the case of complementary features, should select the feature that contains relevant information.

A novel image fusion method with weighted 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,weighted 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 weighted guided filter.

An edge-aware weighting is introduced and incorporated into the GIF [14] to form a weighted GIF (WGIF)[2]. In human visual perception, edges provide an effective and expressive stimulation that is vital for neural interpretation of a scene [17]. Larger weights are thus assigned to pixels at edges than pixels in at areas. There are many methods to compute the edge-ware weighting. Local variance in 3×3 window of a pixel in a guidance image is applied to compute the edge-aware weighting. The weighting can be easily computed via the box filter in [14] for all pixels in the guidance image. The localvariance of a pixel is normalized by the local variances of all pixels in the guidance image. The normalized weighting is then adopted to design the WGIF. Due to the proposed weighting, the WGIF can preserve sharp edges like the global filters [1], [2], [4], [8]. As a result, halo artifacts can be reduced/avoided by using the WGIF. Similar to the GIF in[14], the WGIF also avoids gradient reversal. In addition, the complexity of the WGIF is O(N) for an image with N pixels which is the same as that of the GIF in [14].Hence we improve the quality of the fused image by incoporating theWGIF into the fusion algorithm.

PROPOSED FUSION METHOD

In this project a novel image fusion method based on guided filtering is done. This method utilizes the average filter to get the two-scale representations, which is simple and effective. More importantly, the weighted guided filter is used in a novel way to make full use of the strong correlations between neighborhood pixels for weight optimization.In order to remove the halo artifacts that were the main diadvantage of GIF we have incorporated an edge-aware weighting (weighted guided image filter (WGIF))into the guided image filter (GIF)[14].

Two-scale Image Fusion :

The source images are first decomposed into two-scale representations by average filtering. The base layer of each source image is obtained as follows:

$$B_n = I_n * Z$$

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.

Weight Map Construction using weighted guided filter:

The weight map is constructed as follows. First, Laplacian filltering is applied to each source image to obtain the high-pass image Hn. Then, the local average of the absolute value of Hn is used to construct the saliency maps Sn. The measured saliency maps provide good characterization of the saliency level of detail information. Next, the saliency maps are compared to determine the weight maps as follows:

$$P_n^k = \begin{cases} 1 \text{ if } S_n^k = \max\left(S_1^k, S_2^k, \ldots, S_N^k\right) \\ 0 \text{ otherwise} \end{cases}$$

Normally the weight maps that is constructed in this way may not be perfect it is liable to have noise hence we need to enhance it by using some technique. In this paper e propose a new method ie,weighted guided filtering based approach.

It is known that local filtering based edge-preserving smoothing techniques suffer from halo artifacts. Here a weighted guided image filter (WGIF) is introduced by incorporating an edge-aware weighting into an existing guided image filter (GIF) to address the problem. The WGIF inherits advantages of both global and local smoothing filters in the sense that:the complexity of the WGIF is O(N) for an image with N pixels which is same as the GIF and WGIF can avoid halo artifacts like the existing global smoothing filters.

An edge-aware weighting ΓG(p') is defined by using local variances of 3×3 windows of all pixels as follows:

$$\Gamma_G(p') = \frac{1}{N}\sum_{p=1}^{N}\frac{\sigma^2_{G,1}(p') + \varepsilon}{\sigma^2_{G,1}(p) + \varepsilon}$$

Where ε is a small constant and its value is selected as $(0 : 001 \times L)^2$ while L is the dynamic range of the input image. All pixels in the guidance image are used in the computation of ΓG(p'). In addition, the weighting ΓG(p') measures the importance of pixel p' with respect to the whole guidance image. Due to the box filter in [1], the complexity of ΓG(p') is O(N) for an image with N pixels.

The key assumption of the WGIF is a local linear model between the guidance image G and the filltering output Ẑ. The model ensures that the output Ẑ has an edge only if the guidance image G has an edge.The proposed weighting ΓG(p') is incorporated into the cost function E(ap' ; bp') as follows:

$$E = \sum_{p \in \Omega_{\varsigma 1}(p')} [(a_{p'}G(p) + b_{p'} - X(p))^2 + \frac{\lambda}{\Gamma_G(p')} a^2_{p'}]$$

The optimal values of ap' and bp' are computed as:

$$a_{p'} = \frac{\mu_{G\odot x,\varsigma_1}(p') - \mu_{G,\varsigma_1}(p')\,\mu_{X,\varsigma_1}(p')}{\sigma^2_{G,\varsigma_1}(p') + \frac{\lambda}{\Gamma_G(p')}}$$

$$b_{p'} = \mu_{X,\varsigma_1}(p') - a_{p'}\mu_{G,\varsigma_1}(p')$$

The final value of Ẑ (p) is given as follows:

$$\hat{Z} = \bar{a}_p G(p) + \bar{b}_p$$

For easy analysis, the images X and G are assumed to be the same. Consider the case that the pixel p' is at an edge. The value of ΓX(p0) is usually much larger than 1. ap' in the WGIF is closer to 1 than ap' in the GIF [13]. This implies that sharp edges are preserved better by the WGIF than the GIF. In addition, the complexity of the WGIF is O(N) for an image with N pixels which is the same as that of the GIF. The weighted Guided image filtering is performed on each weight map *P*n with the corresponding source image *I*n serving as the guidance image.

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 and the fused detail layer .

RESULT AND ANALYSIS

Experiments are performed on three image databases, i.e., the outdoor images (natural,industrial) and indoor images (with different focus points and exposure settings), the multi-focus image database which contains 10 pairs of multi-focus images, and the multi-exposure and multi-modal image database which contains 2 pairs of color multi-exposure images and 8 pairs of multi-modal images. The testing images have been used in many related papers [3][10],[17][21].Figure 1 shows the multi-focus database.Further, Figure 2 shows the multi-exposure and multi-modal database.

Fig 1: Multifocus Image Database

Fig 2:Multimodal and multiexposure Image Database

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Figure 3 shows the fusion result of a multiexposure image

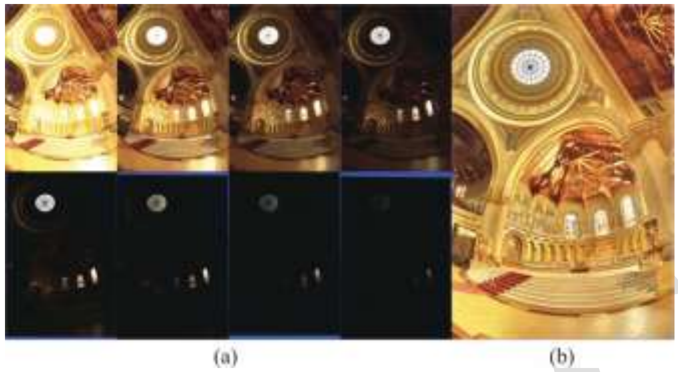

Fig 3(a) The input source image (b) The fused image

For evaluating the quality of the fused image we use Visual Information Fidility (VIF) measure.Because subjective evaluation is not adequate for assessing work in an automatic system, using an objective image fusion performance metric is a common approach to evaluate the quality of different fusion schemes. In this paper, a multi-resolution image fusion metric using visual information fidelity (VIF) is presented to assess fusion performance objectively. This method has four stages: (1) Source and fused images are filtered and divided into blocks. (2) Visual information is evaluated with and without distortion information in each block. (3) The visual information fidelity for fusion (VIFF) of each sub-band is calculated. (4) The overall quality measure is determined by weighting the VIFF of each sub-band.We have the comparison between the two filters in terms of information that they are having which can be plotted into a graph.Here we have the VIFF measure evaluated for different images of our database ploted in a graphical format as shown in figure 4 :

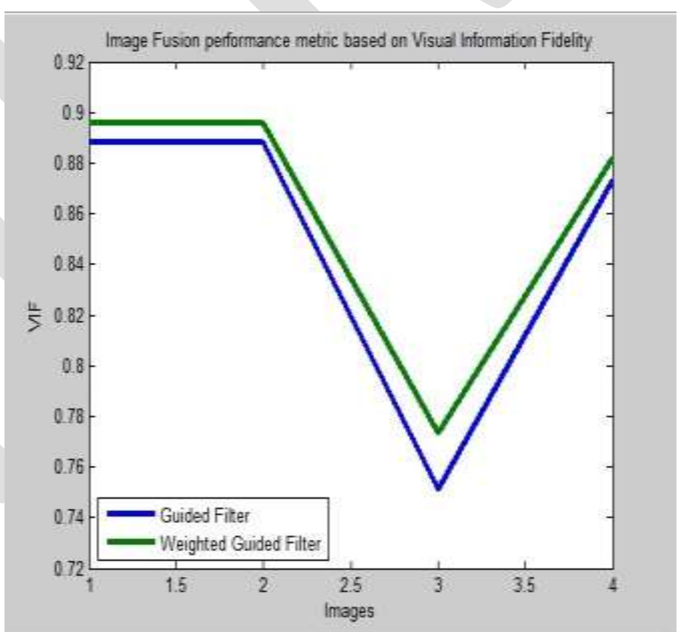

Fig 4: Comparison of GIF and WGIF using VIFF values.

CONCLUSION

In this paper, a novel image fusion method has been proposed. Fusion of the image based on weighted Guided Filter were incoporated in our project. This method utilizes the average filter to get the two-scale representations, which is simple and effective. More importantly, the guided filter is used in a novel way to make full use of the strong correlations between neighborhood pixels for weight optimization.Encouragingly, this method is very robust to image registration.A weighted guided image filter (WGIF) is proposed in this paper by incorporating an edge-aware weighting into the guided image filter (GIF). The WGIF preserves sharp edges as well as existing global filters, and the complexity of the WGIF is O(N) for an image with N pixels which is almost the same as the GIF.Furthermore, the proposed method is computationally efficient, making it quite qualified for real applications.

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