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A Hybrid Patching Scheme for High Dynamic Range Imaging

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***Abstract*—It is very challenging to synthesize a high dynamic range (HDR) image by using a set of differently exposed low dynamic range (LDR) images that are captured with moving objects. This is due to the fact that the moving objects cause ghosting artifacts in the synthesized HDR image. To remove these artifacts, an anti-ghost algorithm is necessary for detection and patching of motion regions, and the patching plays an important role in the synthesis of an HDR image with moving objects. In this paper, a hybrid scheme for patching of motion regions is introduced. The proposed patching scheme is a scheme which is composed of a pixel level intensity mapping function (IMF) and a block level template matching. Experimental results show that the proposed patching scheme outperforms existing IMF based patching schemes.**

I. Introduction

The image generated by ordinary cameras is presented by 8-bits numbers, so its dynamic range is limited to $[0, 255]$. This is far from adequate as the visible radiance in real scene has a dynamic range larger than 10^3. A solution to overcome the limitation is sequentially capturing multiple LDR images of the same scene by using different exposures, and then synthesizing these images into a high dynamic range image [1].

Although taking multi-exposure images only takes very short interval, it is still very hard to make all involved objects stationary during image capturing, especially in outdoor scenes. In practice, the captured multi-exposure images often contain some moving objects, such as people and vehicles. These moving objects cause ghosting artifacts in the motion areas of synthesized HDR image. To deal with this problem, many movement detection and anti-ghost schemes have been developed for HDR synthesis. Khan et al. introduced an iteratively weighting function to reduce the effect of moving objects [2]. A Gaussian kernel function is applied to measure the similarity between neighboring pixels. The pixel that is obviously different with its ambient pixels will get small weighting factor, and contribute less to the synthesis of HDR image. While this scheme is able to reduce the ghosting effect, but the ghosting effect is generally still visible in the output. A camera response function (CRF) based algorithm was proposed in [3]. The CRF is estimated by an accumulative histogram [4], which is less affected by moving objects. With estimated CRF and exposure time, the pixel color can be predicted from one image to another image. If the difference between a pixel and its predicted value is larger than a threshold, the pixel will be marked as invalid pixel and removed. The performance of this method relies on the accuracy of estimated CRF and high contrast between moving objects and background.

To avoid the distortion introduced by inaccurate CRF, entropy based algorithms were introduced in [5] and [6]. The local entropy is computed from the histogram constructed from pixels falling in a small window. The pixels that have large entropy variance with their counterparts will be marked as moving objects and eliminated from HDR synthesis. But this entropy comparison method is not exhaustive enough, as it is difficult to justify whether high entropy is introduced by moving objects or spatial diversity. In [7], pixel gradient was adopted to detect motion areas along image sequence. It is assumed that moving objects would cause gradient discrepancy of co-located pixels. It is also mentioned in [7] that this assumption is incorrect for under/over exposure areas, and therefore this method may not be able to detect the moving objects in these areas.

In this paper, a new anti-ghost scheme for synthesis of HDR image with moving objects is proposed. Different from existing anti-ghost schemes, which typically tend to remove moving objects from synthesized HDR, the proposed scheme aims to give clear presentations of moving objects. Then the real scene occurred during shooting time can be recorded in an HDR image.

To achieve this purpose, a hybrid scheme is developed for patching of moving objects along input image sequence. With integration of a bi-directional movement detection scheme [8], the proposed hybrid scheme can make the moving objects consistent along images. It consists of two parts: an IMF based patching scheme and a block-level template matching based patching scheme. The IMF based scheme can transfer information of moving objects from one image to another image, and the intensity diversity between images is minimized by IMF. The transferred information is mapped to proper intensity values without introducing any visible artifacts. The block level matching scheme exploits spatial similarity of neighboring pixels, as well as the correlation of successive images. Some matching blocks, which are highly similar with moving objects, can be found and used to reconstruct the moving objects.

The rest of this paper is organized as follows. In Section 2, the moving pixel detection scheme in [8] is briefly introduced. The hybrid patching algorithm is presented in Section 3. Then experimental results are provided in Section 4 to demonstrate the performance of proposed scheme. Conclusion remarks are given in Section 5.

II. A Pixel Level Detection of Moving Regions

Let $Z_{k,l}(p)$ denote image intensity of the lth color channel at position p when the kth LDR image is captured, i.e. p is a spatial position, l indexes over color channels of red, green and blue, and k indexes over exposure time Δt_k.

The movement detection scheme in [8] implemented pixel level comparison between two images. An input image Z_k is compared with its reference image $\hat{Z}_k$. For a given position p, if the similarity between pixel $Z_k(p)$ and $\hat{Z}_k(p)$ is high, i.e.

$$\frac{\sum_{l=1}^{3} 2\Phi_{k,l}(p)\Psi_{k,l}(p)+1}{\sum_{l=1}^{3}[\Phi_{k,l}^2(p)+\Psi_{k,l}^2(p)]+1} > Thr_k(p). \tag{1}$$

$Z_k(p)$ will be marked as valid pixel, and this detection result is used to initialize a weighting matrix w_k. $w_k(p)=1$ if $Z_k(p)$ is valid and 0 otherwise.

$\Phi_{k,l}(p)$ and $\Psi_{k,l}(p)$ in Equation (1) are constructed by using a bi-directional mapping method as

$$\Phi_{k,l}(p)=\begin{cases} \Lambda_{l,\pi(k),k}(\hat{Z}_{k,l}(p)); & w(Z_{k,l}(p)) \le w(\hat{Z}_{k,l}(p)) \\ Z_{k,l}(p); & \text{otherwise} \end{cases}, \tag{2}$$

$$\Psi_{k,l}(p)=\begin{cases} \Lambda_{l,k,\pi(k)}(Z_{k,l}(p)); & w(Z_{k,l}(p)) > w(\hat{Z}_{k,l}(p)) \\ \hat{Z}_{k,l}(p); & \text{otherwise} \end{cases}, \tag{3}$$

where the weighting function $w(z)$ is defined as [1], $\pi(k)$ corresponds to the exposure time of image $\hat{Z}_k$ and its value is updated as follows:

$$\pi(k)=\begin{cases} k+1; & \text{if } k<k_0 \\ k-1; & \text{if } k>k_0 \end{cases}, \tag{4}$$

and $\Lambda_{l,k,\pi(k)}$ and $\Lambda_{l,\pi(k),k}$ are two IMFs [4]. $\Lambda_{l,k,\pi(k)}$ maps intensity value in the kth image into its reference image and $\Lambda_{l,\pi(k),k}$ vice versa.

The threshold $Thr_k(p)$ in Equation (1) is adaptive to the values of $Z_{k,l}(p)$, $\hat{Z}_{k,l}(p)$, Δt_k, and $\Delta t_{\pi(k)}$. It is computed as

$$Thr_k(p)=\frac{2(1-\xi_k(p))}{1+(1-\xi_k(p))^2}, \tag{5}$$

where $\xi_k(p)$ is computed as

$$\xi_k(p)=\max_{1\le l\le 3}\{\alpha_1+\max\{\epsilon(\Phi_{k,l}(p)),\epsilon(\Psi_{k,l}(p))\}\}\varrho(k,\pi(k)),$$

the scale factor $\epsilon(z)$ and the ratio of two exposure times $\varrho(k,\pi(k))$ are defined as

$$\epsilon(z)=\begin{cases} 0; & \text{if } z>127 \\ \alpha_2(1-\frac{2z}{255})^{(50-\frac{10z}{51})^{16}}; & \text{otherwise} \end{cases},$$

$$\varrho(k,\pi(k))=\sqrt{\frac{max\{\Delta t_k,\Delta t_{\pi(k)}\}}{min\{\Delta t_k,\Delta t_{\pi(k)}\}}},$$

and $\alpha_i (i=1,2)$ are two constants.

III. A Hybrid Patching Scheme

All pixels in motion regions are marked as invalid. To improve the quality of final image, it is necessary to reconstruct new pixels by using all available information for the replacement of pixels in the motion regions. The patching of motion regions plays an important role in the synthesis of an image for an HDR scene with moving objects.

In this section, we shall introduce a hybrid scheme for the patching of motion regions. The proposed patching scheme is composed of a pixel level IMF based patching scheme and a block level template matching based patching scheme. In other words, invalid pixels $Z_k(\vec{p})$ of image Z_k are replaced by the co-located pixels $\hat{Z}_k(p)$ or spatially neighboring pixels $Z_k(h)$, as defined in Equation (6)

$$Z_k(\vec{p})=\begin{cases} \Lambda_{\pi(k),k}(\hat{Z}_k(p)); & \text{if } \hat{Z}_k(p)\in\Omega(\hat{Z}_k(p)) \\ Z_k(h); & \text{otherwise} \end{cases}. \tag{6}$$

A. A pixel level IMF based patching scheme

It is straightforward to reconstruct pixels by using the IMF $\Lambda_{\pi(k),k}$ and corresponding pixels in reference image $\hat{\mathbf{Z}}_k$. But the pixel level patching scheme is not applicable when the IMF is not one to one mapping function, especially in those regions with mapping error larger than the Weber ratio [9]. So $\Omega(\hat{Z}_k(p))$ in Equation (6) is defined as

$$\Omega(\hat{Z}_k(p))=\begin{cases} 0\le\hat{Z}_k(p)<Thr_{\Lambda_{\pi(k),k}}; & \Delta t_{\pi(k)}>\Delta t_k \\ Thr_{\Lambda_{\pi(k),k}}<\hat{Z}_k(p)\le 255; & \Delta t_{\pi(k)}<\Delta t_k \end{cases}, \tag{7}$$

which is an intensity range that IMF can provide reliable mapping from reference image to current image.

$Thr_{\Lambda_{\pi(k),k}}$ in Equation (7) should be correlated with the gradient of $\Lambda_{\pi(k),k}$ in luminance domain, since large gradient indicates that IMF trends to map one intensity values to a set of intensity values. $Thr_{\Lambda_{\pi(k),k}}$ indicates the intensity boundary that IMF can map pixel without introducing visible artifacts or information loss. It is computed as

$$Thr_{\Lambda_{\pi(k),k}}=\begin{cases} \min_{0<z\le 255}\{z|\nabla(\Lambda_{\pi(k),k}(z))>\gamma(z)\}; & \Delta t_{\pi(k)}>\Delta t_k \\ \max_{0<z\le 255}\{z|\nabla(\Lambda_{\pi(k),k}(z))>\gamma(z)\}; & \Delta t_{\pi(k)}<\Delta t_k \end{cases}. \tag{8}$$

$\gamma(z)$ is the Weber ratio that indicates visible luminance diversity. $\nabla(\Lambda_{\pi(k),k}(z))$ is the gradient of $\Lambda_{\pi(k),k}(z)$, and it is computed as $(\Lambda_{\pi(k),k}(z)-\Lambda_{\pi(k),k}(z-1))$.

B. A block level template matching based patching scheme

A template matching based scheme is provided in this subsection to patch invalid pixels that cannot be filled in effectively by using IMF mapping.

Z_k is divided into small blocks. Let $B_{k,i}$ denote a block at position i in Z_k. If $B_{k,i}$ contains invalid pixels, a matching search, spanning a searching window, is conducted to find a best-matching block. The pixels of best-matching block will be used to replace the invalid pixels in $B_{k,i}$.

The matching criteria between $B_{k,i}$ and candidate block $\hat{B}_{k,j}$ is calculated by using the Mean Absolute Difference (MAD) as

$$MAD_{sum} = MAD_k + MAD_{\pi(k)} + MAD_{k,\pi(k)}. \quad (9)$$

The aim of this MAD criteria is to achieve smooth connection in spatial domain, as well as the consistency between the filling pixels and co-located pixels in reference image. So the candidate block with minimum MAD_{sum} in a pre-defined searching window will be selected for the patching of the corresponding block. If two candidate blocks get the same MAD_{sum}, the block with more valid pixels is selected by the proposed template matching based scheme.

MAD_k in Equation (9) measures the spatial similarity of valid pixels in $B_k(i)$ and their counterparts in the candidate block $\hat{B}_k(j)$ as

$$MAD_k = \frac{\sum_{u=p} |B_{k,i}(u) - \hat{B}_{k,j}(u)|}{Num_p}. \quad (10)$$

MAD_k can be used to ensure that $B_{k,i}$ and $B_{k,j}$ are highly similar in the spatial domain. But MAD_k cannot guarantee consistency between Z_k and $\hat{Z}_k$, as it only takes single image information into consideration.

Temporal similarity between the co-located blocks are measured by $MAD_{\pi(k)}$ and $MAD_{k,\pi(k)}$. They are defined as

$$MAD_{\pi(k)} = \frac{\sum_{u=\vec{p}} |B_{\pi(k),i}(u) - \hat{B}_{\pi(k),j}(u)|}{Num_{\vec{p}}}, \quad (11)$$

$$MAD_{k,\pi(k)} = \frac{\sum_{u=\vec{p}} |B_{\pi(k),i}(u) - \Lambda_{k,\pi(k)}(\hat{B}_{k,j}(u))|}{Num_{\vec{p}}}. \quad (12)$$

It is worth mentioning that the proposed block patching is conducted in an iterative manner. In the first iteration, only blocks at boundary of moving object are patched, as they include more valid pixels and their neighboring pixels are more reliable for computation of MAD in Equation (9). The blocks inside moving object are patched in subsequent iterations with the necessary information provided by the patched boundary blocks.

IV. Experimental Results

In this section, we verify the proposed patching scheme by integrating it with the moving pixel detection scheme in [8] and the HDR synthesis scheme in [1].

A set of four differently exposed LDR images with movement in head and body of a human subject is used for testing, as shown in Figure 1. In our experiments, the block size is selected as 16×16, and the searching window size is set as 48×48 pixels. The first image is selected as initial referencing image.

The moving object detection and patching results of Figures 1(b) and 1(c) are presented in Figure 2. To verify the performance of proposed block-based patching scheme, we compare it with spatial interpolation and pixel level IMF patching scheme in [8]. The window area in the initial reference image, Figure 1(a), is over exposed. In this case, the IMF cannot get reliable information from the reference image to reconstruct pixels for replacement of invalid pixels in other images. As such, there is obvious "hole" in Figure 2(c). The artifacts caused by the IMF based patching scheme in Figure 2(c) propagate to Figure 2(d), as the image in Figure 2(c) is used as the reference image of the image in Figure 2(d). The spatial interpolation scheme fills invalid pixels with wrong information. The pixels belonging to window glass are filled by the information from window frame. The result in Figure 2(e) displays serious artifacts in motion regions. The images produced by proposed hybrid method are presented in Figures 2(a) and 2(b). The contents of pixels that are neighboring to moving objects are taken into consideration. By doing this way, it will prevent wrong replacements of invalid pixels, which in turn allowing information of motion regions to be reliably restored.

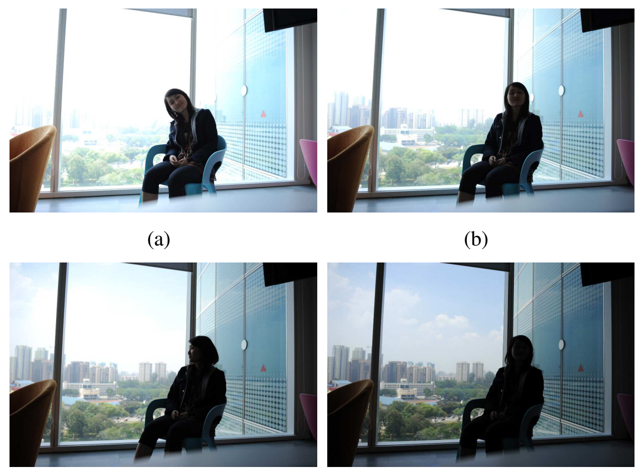

(a) (b) (c) (d)

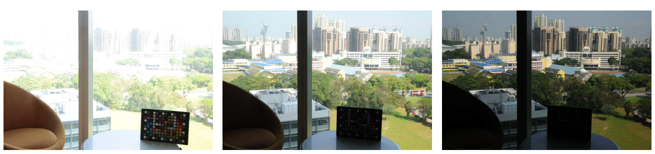
Fig. 1. A set of multi-exposure images captured in dynamic scene. (a-d) input images from high exposure to low exposure.

We also compare the proposed method with the commercial software Photoshop CS5, Photomatix 3.0 and FDRTools [10]. Two sets of multi-exposure images are used for comparison, one is the sequence presented in Figure 1 and the other is shown in Figure 3. Anti-ghost schemes have been embedded into commercial software to deal with the moving objects in HDR synthesis. As can be seen, all of them are not capable to totally remove ghosting artifacts from the final images. Compared to them, no ghost artifact is seen by using the proposed scheme. The contents of motion areas are also preserved very clearly in the synthesized image. Furthermore, the visual quality in background area, which is not affected by moving objects, also can be improved by proposed scheme. As shown in Figure 4(b), the sky area has obvious color shifting. This is because moving objects cause inaccurate estimation of CRF. In the results of proposed method, this kind of artifacts has been eliminated, as the moving objects have been corrected

(a) (b) (c) (d) (e) (f)

Fig. 2. Patching results from proposed method, IMF and spatial interpolation. (a) and (b) patching results of proposed scheme; (c) and (d) patching results of IMF; (e) and (f) patching results of spatial interpolation.

before the estimation of CRF.

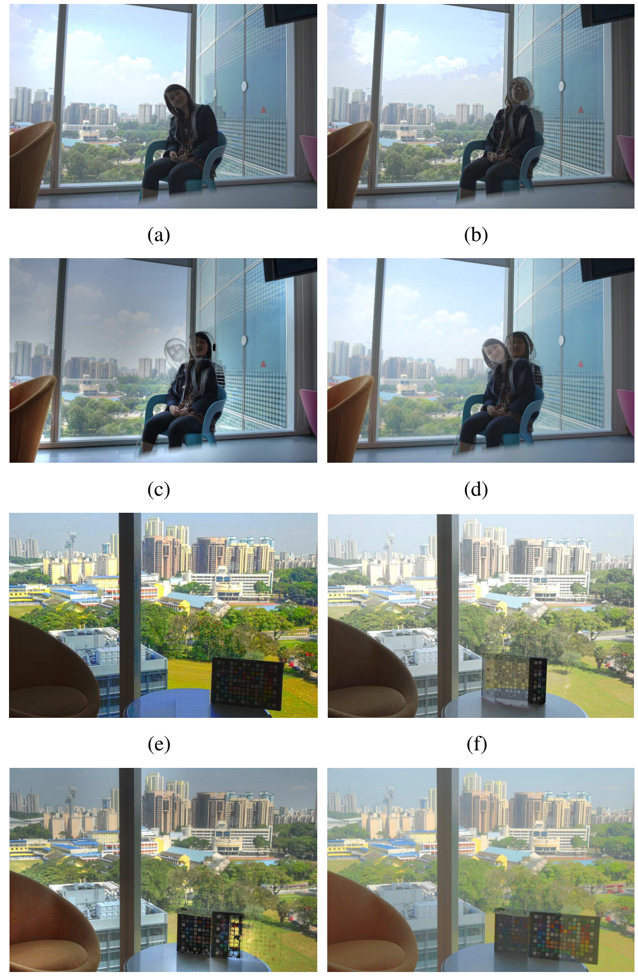


(a) (b) (c)

Fig. 3. A set of multi-exposure images with moving object.

V. Conclusion

In this paper, we propose a hybrid patching scheme for the synthesis of ghosting-free HDR image in dynamic scene. The proposed scheme includes a pixel level intensity mapping function based patching scheme and a block level template matching based patching scheme. By using the proposed method, moving objects are reconstructed with proper information, and ghosting artifacts are thus eliminated from the synthesized image.



(a) (b) (c) (d) (e) (f) (g) (h)

Fig. 4. Comparison between proposed method and commercial software. (a) and (e) results of proposed method; (b) and (f) results of Photoshop CS5; (c) and (g) results of Photomatix3.0; (d) and (h) results of FDRTools.

References

[1] P. E. Debevec and J. Malik, "Recovering high dynamic range radiance maps from photographs", *Proceeding of SIGGRAPH*, pp. 369-378, August 1997.

[2] E. A. Khan, A. O. Akyuz and E. Reinhard, "Ghost removal in high dynamic range images", *Proceedings of IEEE International Conference on Image Processing*, pp.2005-2008, 2006.

[3] T. Grosch, "Fast and robust high dynamic range image generation with camera and object movement", *Vision, Modeling and Visualization*, pp.277-284, 2006.

[4] M. D. Grossberg and S. K. Nayar, "What can be known about the radiometric response from images", *Proceedings of European Conference on Computer Vision*, pp. 189-205, 2002.

[5] K. Jacob, C. Loscos and G. Ward, "Automatic high-dynamic range image generation for dynamic scenes", *IEEE Computer Graphics and Applications*, Vol. 128, No. 2, pp.84-93, Feburay 2008.

[6] G. Jing, C. E. Siong and D. Rajan, "Foreground motion detection by difference-based spatial temporal entropy image", *Proceedings of IEEE Region 10 Conference*, Vol.A, pp. 379-382, 2004.

[7] W. Zhang and W. K. Cham, "Gradient-directed composition of multi-exposure images", *Proceedings of Computer Vison and Pattern Recognition*, pp. 530-536, June 2010.

[8] Z. Li, S. Rahardja, Z. Zhu, S. Xie and S. Wu, "Movement detection for the synthesis of high dynamic range images", *Proceedings of International Conference on Image Processing*, pp. 3133-3136, September 2010.

[9] R. C. Gonzalez and R. E. Woods, "Digital image processing", Second Edition, 2002.

[10] PHOTOMATIX and FDRTOOLS, http://www.hdrsoft.com/, http://www.fdrtools.com/.