REDUCTION OF GHOST EFFECT IN EXPOSURE FUSION BY DETECTING THE GHOST PIXELS IN SATURATED AND NON-SATURATED REGIONS

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ABSTRACT

This paper proposes a multiple exposure image fusion algorithm with reduced ghost. The basic idea is to adjust the weight map in the conventional fusion method in such a way that the ghost pixels are excluded. For this, pixels that cause ghost effect are detected in both of the saturated and non-saturated regions. In order to detect ghost pixels in the non-saturated region, we use the photometric relation and Gaussian mixture modeling (GMM) of a zero mean normalized cross correlation (ZNCC) map between a given exposure image and the reference. From this, we can also obtain static region where we construct an intensity mapping function (IMF) to detect the ghost pixels in saturated regions. Experimental results show that the proposed method generates high quality image without noticeable ghost effect, and yields less artifacts than the conventional methods.

Index Terms— Ghost effect, Exposure fusion

1. INTRODUCTION

The dynamic range of commercial image sensors and display devices are often much less than that of real world scenes. As a result, the pixels in the dark or bright regions are prone to be saturated. Hence there have been many approaches to generate a photo with less saturated pixels from the multiple photos of the same scene with different exposures. The most popular methods for this purpose may be the high dynamic range imaging (HDRI) [1] and the exposure fusion [2]. The HDRI is to generate a high dynamic range image from the multiple exposure photos, based on the given or estimated camera response function (CRF). That is, the dynamic range of each pixel value is actually extended beyond the range of common image sensors by using the camera parameters and the change of pixel intensities depending on the exposure. For displaying this HDR image on a display device, the range of each pixel value is adaptively compressed to fit the lower range of the display device, which is called the tone-mapping process. The latter approach, i.e., the exposure fusion is to generate a well exposed image without generating the HDR image, by the weighted addition of multiple exposure images. This method first generates weight map for each image, where higher weights are given to the pixels with high quality (well contrasted, more color-saturated, well exposedness). Then the weights are multiplied to the pixels, and all the weighted images are added to generate the high quality fused image. This method is shown to provide comparable quality to that of HDRI, while requiring no CRF estimation and less computations.

High quality images with less saturated pixels are usually obtained by the above stated approaches, from two or more differently exposed images. However, these approaches cause another problem when there are moving objects or hand trembling while taking the multiple photos. Specifically, the moving objects may cause the ghost effect and blurring. Hence there have also been many researches to reduce the ghost effect in the case of HDRI, which seem to have some problems in certain situations [3, 4]. There is also a patch based method [5] which removes ghost successfully. However if the difference of brightness among the neighboring patch is large, this causes some visible seams. In the case of methods based on the addition of multiple images, the median threshold bitmap [6] is used for the fusion with less ghost effect. This is simple but fails to remove the ghost when the scene is over or under exposed for the whole sequence. Zhang et al [7] used the gradient directions to detect the pixels in the moving objects but it may not work well in the scenes that have some tiny changes.Recently we also proposed an image fusion based method [8] where the photometric relation and ZNCC are used to adjust a weight of pixels that can cause the ghost effect. This works well in most cases, but it cannot distinguish between still and moving objects if there are saturated pixels in the reference image. More precisely, since the saturated pixels do not provide enough information to detect the ghost pixels, this method generates a bit insufficient quality when it has somewhat undistinguishable regions.

To alleviate this problem, we first select a reference image and classify it into two regions : saturated and non-saturated region. Main contribution of this paper is to detect ghost pixels in the two regions independently. In the non-saturated region, two conditions are defined, the photometric relation and ZNCC, which tell whether the pixel is in the boundary of a moving object. We modify our previous algorithm by constructing a GMM of the ZNCC map and detect ghost pixels by formulating the Gaussian function as an energy function. Furthermore we obtain exact static region and construct an

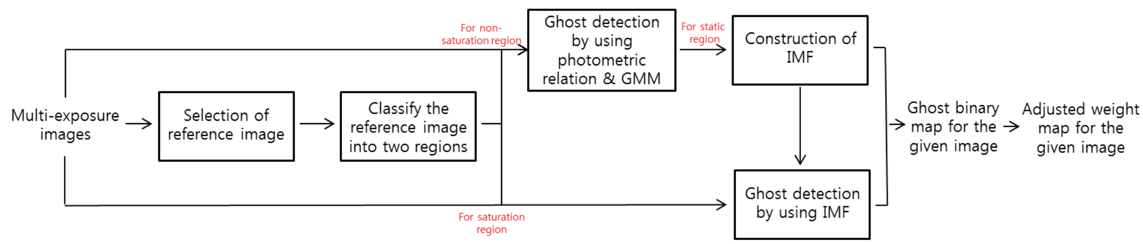


Fig. 1. Block diagram of the proposed method.

IMF to detect ghost pixels in this region. Experimental results show that the proposed method generates high quality image without noticeable ghost effect compared with the conventional methods and also with our previous approach.

2. PROPOSED ALGORITHM

Fig. 1 shows the block diagram of the proposed method. From multi-exposure images, we first select one as a reference which has the least saturated pixels. In order to detect the ghost pixels, most of previous methods usually use low-level features, such as color, texture and shape, which are directly extracted from the images. However the features extracted from the pixels in the saturation region are meaningless so that they do not provide enough information to distinguish between static and moving objects. Hence for ghost detection, we use information that can be obtained in the non-saturation regions. For this purpose, we need to classify the reference image into two regions : saturation and non-saturation region. For each of multi-exposure images, we detect ghost pixels for in each of the regions and then adjust the weight for those by assigning to zero.

2.1. GHOST DETECTION IN NON-SATURATION REGION

We detect ghost pixels for non-saturation region by using the photometric relation and a ZNCC map.

2.1.1. THE PHOTOMETRIC RELATION

The reciprocity law means that total the exposure X is equal to the irradiance E times exposure time Δt. Then a pixel value Z in the low dynamic range image is defined by CRF which is generally a monotonic increasing function. Hence we can define an inequality from photometric relation [8] as

$$Z_1 < Z_2 \quad when \quad \Delta t_1 < \Delta t_2$$

where Z_1 and Z_2 mean pixel values related with exposure time Δt_1 and Δt_2 respectively. If there is a certain pixel that does not satisfy the above condition, the pixel is considered a ghost pixel in the boundary of moving objects. In this case,

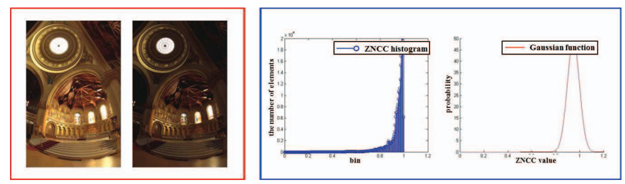


Fig. 2. Two static images and the distribution of ZNCC which can be modeled as a single Gaussian distribution

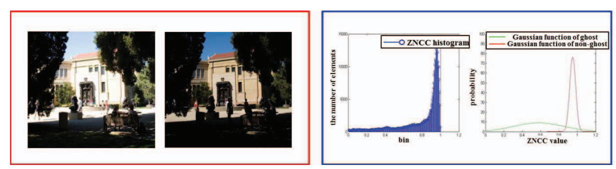


Fig. 3. Two dynamic images and the distribution of ZNCC which can be modeled as sum of two Gaussian distributions

the weight for the pixel must be set to zero. In this way, we assign binary value $O(p) \in \{0, 1\}$ at every pixel location p : when above equation is not satisfied, $O(p) = 0$, otherwise $O(p) = 1$. From the binary image O, we perform connected component (CC) analysis using an 8-neighborhood system. In this process, we suppress small CCs (containing less than 2 pixels) for the removal of isolated noise.

2.1.2. ZNCC MAP

Although the above condition is helpful for alleviating the ghost effect, there are some pixels that satisfy the photometric relation but can cause the ghost effect. To resolve this problem, this paper proposes another condition, i.e, a ZNCC map between a given exposure input and a reference one.

Consider any two images which have no difference except for exposure time as Fig. 2. Ideally all ZNCC values must be one because the images has no change of background and/or motion objects. However due to the noise, the ZNCC values are normally distributed centered on 1. On the contrary, Fig. 3 shows another set of multi-exposure images that has some moving objects. Since the ZNCC values in the moving objects are small, the distribution of ZNCC values from these images is composed of two or more Gaussian distributions : one and the others are referred to non-ghost and ghost. In this paper, we model the distribution of ZNCC values as sum of two Gaussian pdf (Gaussian mixture model). By using the Expectation Maximization algorithm, we estimate the parameters that specify the two Gaussian density function. Then we generate a binary map to determine the pixels which cause ghost effect by using an energy minimization approach. This gives less noisy and more accurate result than the thresholding approach. Let us define a binary label map $A = \{A_f | f \in F\}$ where $A_f \in \{"Ghost", "Non-ghost"\}$. After that we find the binary label map by formulating the energy $E(A)$ and minimizing the energy by using graph cut method [9]. The energy in graph cut method is formulated as

$$E(A) = \sum_{f \in F} R_f(A_f) + \gamma \cdot \sum_{(f,g) \in N} S(A_f, A_g)$$

where F is the set of all data pixels, N contain all unordered pairs of neighboring pixels, and γ is a weighting factor for a balance between data cost R_f and smoothness cost S. In our case, the data cost is constructed as a negative of log-likelihoods for two Gaussian density function. Also, the smoothness cost S is designed as

$$S(A_f, A_g) = B_{\{f,g\}} \times \delta(A_f, A_g)$$

where $B_{\{f,g\}}$ means edge cue by pixel intensity difference of a given image and δ denotes kronecker delta function.
Finally we define a binary ghost map G^{Non} for non-saturation region as

$$G^{Non}_{ij,k} = \begin{cases} 0 \quad if \quad O_{ij,k} = 0 \quad or \quad A_{ij,k} = "Ghost" \\ 1 \qquad\qquad\qquad\qquad\qquad\qquad \text{otherwise} \end{cases}$$

where $O_{ij,k}$ and $A_{ij,k}$ are binary maps of the photometric relation and ZNCC map respectively.

2.2. GHOST DETECTION IN SATURATION REGION

To detect ghost pixels in the saturation region which have no information, we use an IMF [10] that is defined to measure the difference of intensity values of two images in a static scene. In our case, the IMF between a given exposure image and the reference is perfectly estimated because we have found static region for non-saturation region in the above section. Hence we estimate the IMF in the static region by fitting a polynomial of order four as Fig. 4. The pixel locations where there is no scene change from the reference should follow the IMF with a certain width η. So we define a binary ghost map G^{Sat} for saturation region as

$$G^{Sat}_{ij,k} = \begin{cases} 0 \quad if \quad |I_{ij,k} - IMF(I_{ij,ref})| > \eta \\ 1 \qquad\qquad\qquad\qquad\qquad \text{otherwise} \end{cases}$$

where $I_{ij,k}$ and $I_{ij,ref}$ indicate pixel values related with the k-th exposure image and the reference at (i, j) pixel location.

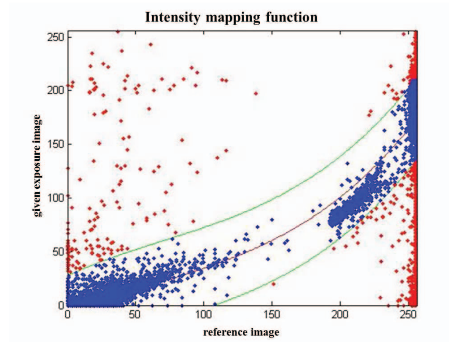


Fig. 4. An IMF between a given exposure image and the reference (blue point and red point indicate non-ghost and ghost pixels).

Finally, we construct a binary ghost map $G_{ij,k}$ for a given exposure image as

$$G_{ij,k} = \begin{cases} 0 \quad if \quad G^{Non}_{ij,k} = 0 \quad or \quad G^{Sat}_{ij,k} = 0 \\ 1 \qquad\qquad\qquad\qquad\qquad \text{otherwise} \end{cases}$$

and apply the morphological operation to the map for motion of a textureless object. So we modify the weight by using the dilated ghost map as

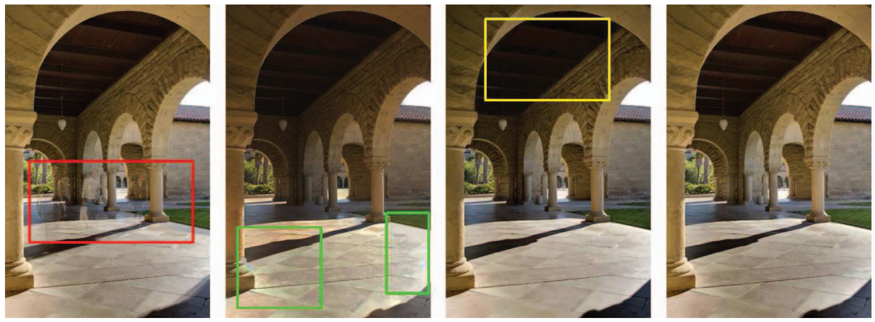
$$\hat{W}_{ij,k} = W_{ij,k} \times dilation(G_{ij,k})$$

where $\hat{W}_{ij,k}$ and $W_{ij,k}$ mean modified weight map and the conventional one.

3. EXPERIMENTAL RESULTS

The experiments with many set of multiple exposure images are performed, which include the experiments with the images used in [5]. All the results are obtained by using a 33×33 patch for the ZNCC calculation and the weight factors of quality measures as $\omega_C = \omega_S = \omega_E = 1$. We compare the proposed method with the conventional exposure fusion [2], the ghost-removal algorithm based on the HDRI method [5], and fusion based method [8]. The conventional exposure fusion generates a well exposed image, but it suffers from the ghost effect as can be observed in the first column in Fig. 5. Orazio et al [5] used a patch based method based on the HDRI, which removes the ghost successfully, but some visible seam remains as shown in the second column in Fig. 5. The fusion based method [8] generates a high quality image with almost no noticeable ghost effect, but it has somewhat saturated regions as observed in the third column in Fig. 5. The proposed method produces a ghost free image which has few saturated pixel, so we can see more details of the image.

(a)



(b)

Fig. 5. Experimental results. (a) Sculpture garden sequence, (b) Arch sequence. Left to right : results of [2], [5], [8] where artifacts are observed in the box (red : ghost effect, green : color distortion, yellow : less details), and the proposed method

4. CONCLUSIONS

We have proposed a new weighted image fusion method which reduces the ghost effect and produces a high quality output, where the output image is the weighted addition of multiple exposure images. For this, we have found some conditions to detect ghost pixels which occur in the moving objects. Specifically, the pixels for given exposure images are independently detected in saturated and non-saturated regions of a reference image. In the non-saturated regions, we have tested the photometric and created a binary map by minimizing a well designed energy function formulated as GMM of a ZNCC. Also, an IMF from static region is used to detect ghost pixels in saturated region. The experiments show that the proposed method removes ghost effect efficiently, and generates a high quality image with more details and without artifacts that are found in the existing methods.

5. ACKNOWLEDGEMENT

This research was supported by Basic Science Research Program through the National Research Foundation of Korea(NRF) funded by the Ministry of Education, Science and Technology (Grant No. 2011-0001271).

6. REFERENCES

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