Illumination Normalization Among Multiple Remote-Sensing Images

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***Abstract*—Changes of illumination have a huge effect on image quality during imaging process. One method that compares high and low resolution images to compute MTF in image quality assessment requires images to be in the same illumination conditions. Thus, it is necessary to do illumination normalization. This letter presents a novel method by combining gradient domain method and improved singular value equalization, which can achieve a good result of illumination normalization. The gradient domain method can bring the contrasts of multiple images to the same level while the improved singular value equalization can make their intensity means close to each other. We also suggest a parameter named p to assess the illumination consistency quantitatively. Experimental results demonstrate that the proposed method has a good performance in visualization and quantitative assessment.**

***Index Terms*—Gradient domain method, illumination normalization, image contrast enhancement, quantitative assessment, singular value equalization.**

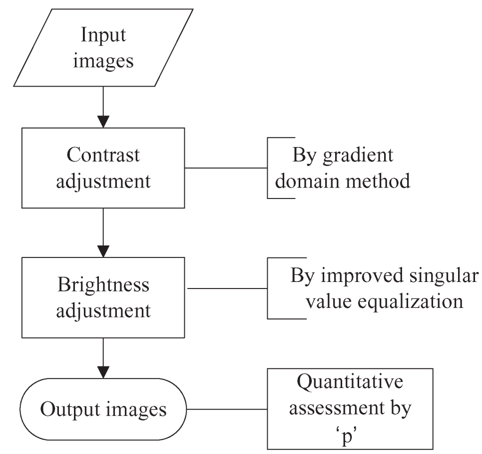

Fig. 1. Flow chart of our method.

I. Introduction

ILLUMINATION is an important element for image quality. Changes of the source of light cannot only affect the brightness of the image, but also lead to details lost and distortion. Comparison of high and low resolution images based method [1] estimates the MTF of low resolution image by computing the MTF of high resolution image on the condition that the two images to be compared have a good state of illumination homogeneity. However, it is hard to meet the requirements. Therefore, illumination normalization is needed for these kinds of remote-sensing images.

Currently most image enhancement methods can be used for illumination correction. Histogram equalization [2], gamma correction [2] and Retinex [3] are traditional methods, which are popular but cannot maintain average brightness level and may result in either under or over saturation in processed images. Majumder's [4] and Fattal's [5] gradient domain method have a good effect on contrast enhancement. Simultaneously they can achieve the effect of correcting uneven illumination. However, these methods can only correct illumination in a single image and cannot make illumination among images consistent. There are two ways to solve the problem. One is histogram specification [2], which is simple and practical, but may cause problems as traditional methods mentioned before. The other way is to extract characteristics that are not sensitive to illumination, such as Scale-Invariant Feature Transform (SIFT) [6]. However, this way just avoids the problem and does not solve it.

The singular value equalization method proposed by Demirel *et al.* [7] is a good way to adjust the brightness of images to be consistent. They proposed an improved method [8] (DWT-SVD) combined discrete wavelet transform and singular value decomposition, which has a better effect on contrast enhancement. But when the images have a big difference in contrast and brightness, the result may not turn out as we expect. The affine illumination model proposed by Pedro *et al.* [9] can compensate illumination variations in a series of multispectral images of a static scene. However, it does not meet our demands. The satellite images to be normalized are random. The senses of the images may be different and the number of the images is arbitrary.

This letter proposes a general illumination normalization method that can normalize illumination of multiple remote sensing images exactly. To the best of our knowledge, no illumination normalization method has been published for multiple remote sensing images so far. As shown in Fig. 1, we use gradient domain method to adjust contrasts of the images firstly. This process can bring their contrasts to the same level and eliminate uneven illumination in each image. Then the brightness is adjusted by improved singular value equalization. Finally, the illumination of the output images will look consistent.

Manuscript received November 6, 2013; accepted December 13, 2013. Date of publication January 10, 2014; date of current version March 14, 2014. This work was supported by Grants from the Qing Lan Project and the Programme of Introducing Talents of Discipline to Universities under Grant B13022.

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Digital Object Identifier 10.1109/LGRS.2013.2295794

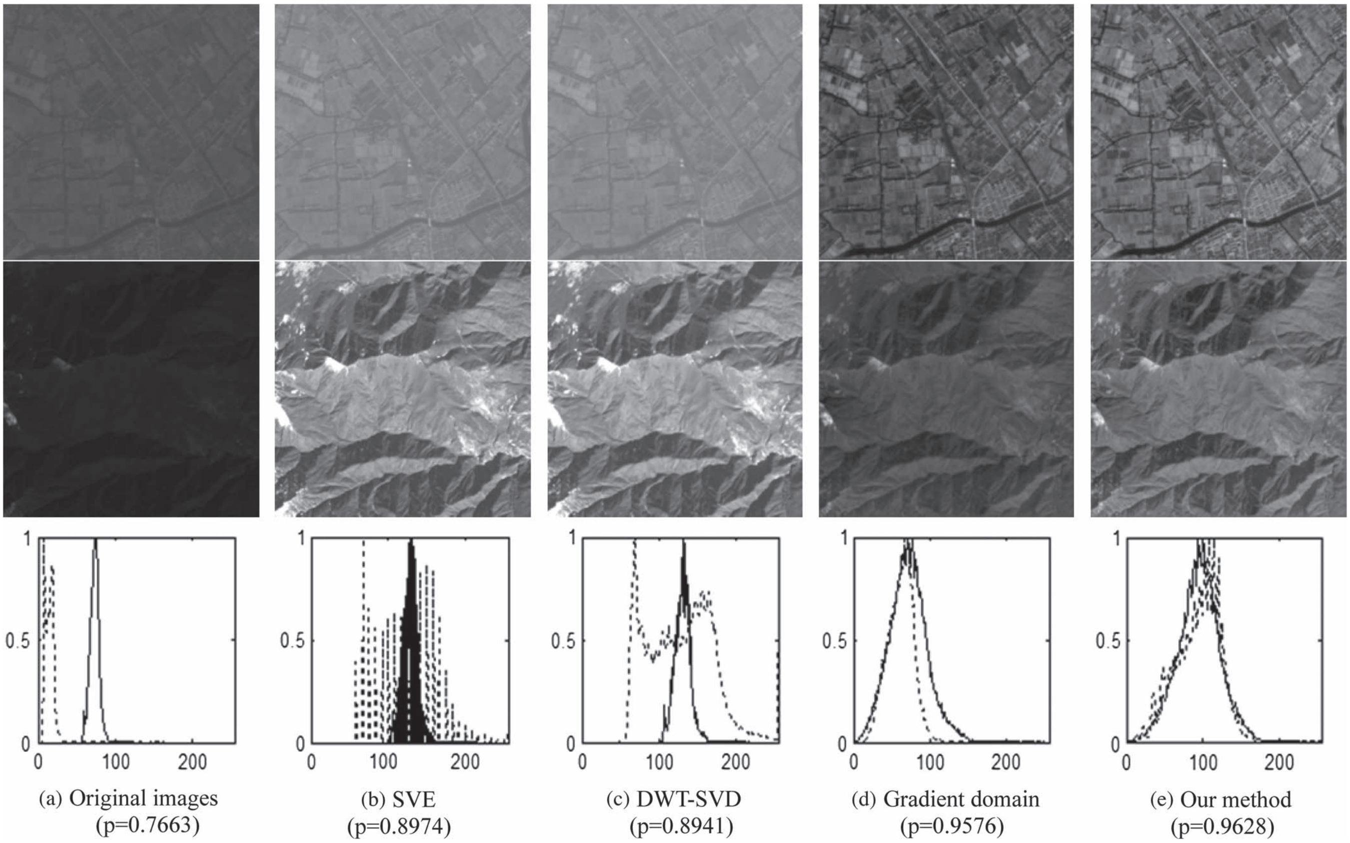

Fig. 2. Images of different places and same time (solid line is the first image and dashed line is the second image). (a) Original images $(\mathrm{p} = 0.7663)$. (b) SVE $(\mathrm{p} = 0.8974)$. (c) DWT-SVD $(\mathrm{p} = 0.8941)$. (d) Gradient domain $(\mathrm{p} = 0.9576)$. (e) Our method $(\mathrm{p} = 0.9628)$.

We also suggest a parameter named p to assess the illumination consistency. So we can evaluate the performance of the method visually and quantitatively.

II. Contrast Adjustment by Gradient Domain Method

Gradient domain methods of image enhancement can effectively compress the dynamic range of original images, increase contrast and enhance fine details in darker regions, thus providing visual improvement of images. We choose gradient domain methods to eliminate uneven illumination of an image.

Fattal *et al.* [5] proposed a method that compresses the dynamic range by using a gradient manipulation process of multiplying the gradient magnitude with a function of local gradient magnitude, expecting to enhance the fine details in darker regions while compressing the dynamic range. Besides a new low dynamic range image is reconstructed from the modified gradient field in least mean square sense. The method takes the following basic steps: obtain the gradient field of the original image, treat the field using a manipulation function, and reconstruct the enhanced image from the modified field. It needs to be pointed out here that all the steps stated above are carried out in the logarithmic domain.

The function of gradient domain method is to adjust contrast to the same level. The results of this method can be seen in Figs. 2(d), 3(d), and 4(d) in Section V. When the contrast is low or inconsistent, the effect is obvious as Fig. 2 shows.

III. Brightness Adjustment by Improved Singular Value Equalization

The singular value equalization (SVE) technique is based on the singular value decomposition (SVD). Each image can be represented by a matrix which contains the pixel intensity values. Generally speaking, for any image matrix I, the SVD can be defined as

$$\mathrm{I} = U_I \Sigma_I \mathrm{V}_I^T \tag{1}$$

where U and V are orthogonal square matrices and Σ_I matrix contains the sorted singular values on its main diagonal. Σ_I contains the intensity information of the given image, which means that the maximum singular value of Σ_I contributes more than other singular values. The original SVE equalize a dark image and a bright image in such a way that the mean intensity values of the two images increase or decrease toward the neighborhood of gray value 128, respectively. To make the method satisfy our requirements, we improve the method by replacing the gray value 128 with the intensity mean, M, of all images to be normalized so that the mean of each image will get close to M.

For a group of images to be normalized $(\mathrm{I}_1, \mathrm{I}_2, \ldots, \mathrm{I}_n)$, M is the intensity mean of all images. We introduce a new image, I_M, with the single value M. The SVD of this new image is calculated and the maximum singular value $(\max(\Sigma_{I_M}))$ is used to calculate the transformation factor, ξ, as follows:

$$\xi = \frac{\max(\Sigma_{I_M})}{\max(\Sigma_{I_i})} \quad (\mathrm{i} = 1, \ldots, \mathrm{n}). \tag{2}$$

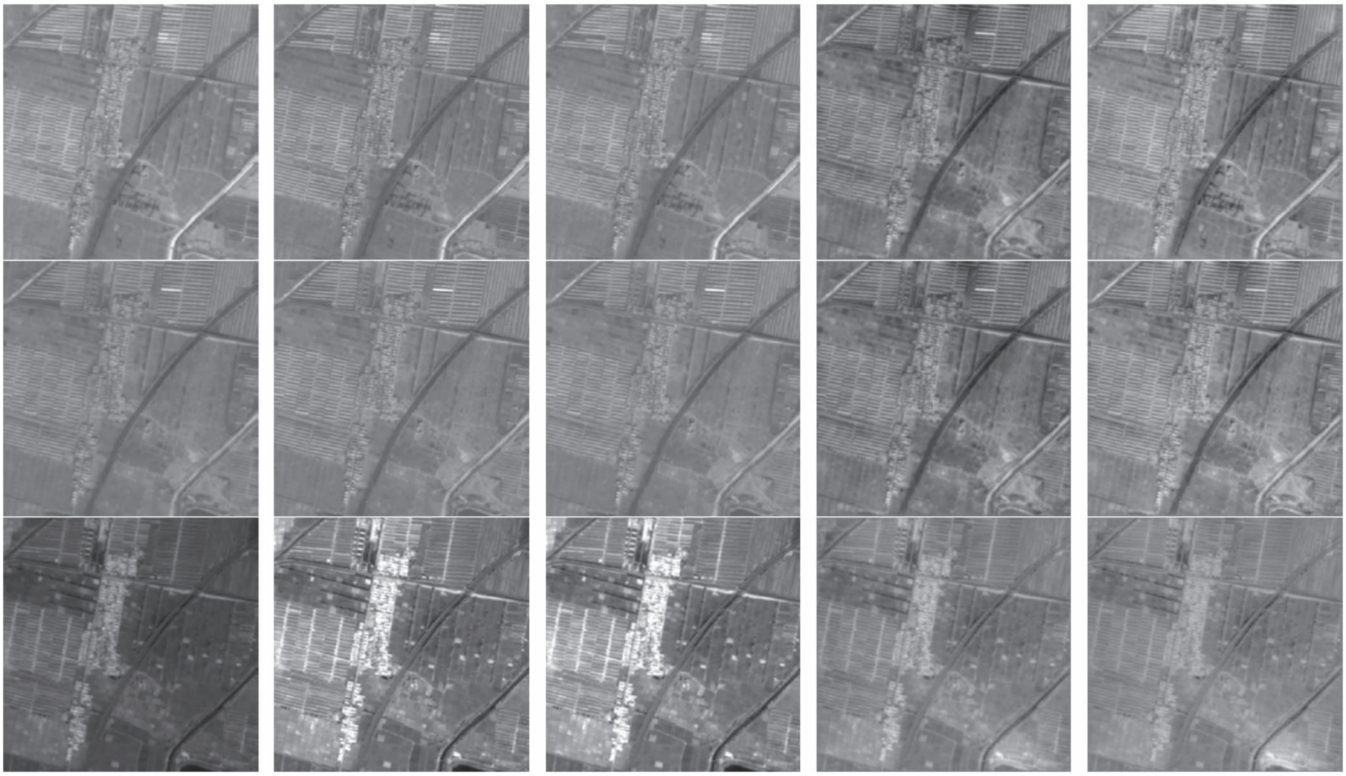

Fig. 3. Images of same place and different time. (a) Original images $(\mathrm{p} = 0.7727)$. (b) SVE $(\mathrm{p} = 0.9065)$. (c) DWT-SVD $(\mathrm{p} = 0.9051)$. (d) Gradient domain $(\mathrm{p} = 0.9188)$. (e) Our method $(\mathrm{p} = 0.9758)$.

It is straight forward that ξ is greater than 1 if the image I_i's mean intensity value is lower than M. Otherwise, if the image I_i's mean intensity value is greater than M, ξ is lower than 1. Now a new singular value matrix, $\overline{\Sigma}_{I_i}$, can be defined as

$$\overline{\Sigma}_{I_i} = \xi \Sigma_{I_i} \tag{3}$$

$\overline{\Sigma}_{I_i}$ can be referred as singular value matrix of the equalized image. Using this equalized matrix, a new image $\overline{I}_\iota$ can be constructed by using these three matrices of U_{I_i}, $\overline{\Sigma}_{I_i}$, $\mathrm{V}_{I_i}^T$ by applying the following equation:

$$\overline{I}_\iota = U_{I_i} \overline{\Sigma}_{I_i} \mathrm{V}_{I_i}^T. \tag{4}$$

The intensity of the image has been adjusted by the singular value matrix. Section V will show the results of our method.

IV. Quantitative Assessment of Illumination Normalization

This section introduces a parameter, p, to quantitatively assess illumination consistency. The main idea of p is to measure the similarity of multiple images' histograms. Because the more their histograms match, the better their illumination consistency is.

As the scenes of images are different, it is hard to compare illumination among different images. If we can evaluate illumination of images, it is more supportive to compare illumination directly. Now there are two main methods to evaluate illumination: Retinex theory [11] and homomorphic filtering [2]. We adopt the first one.

A. Extracting Illumination Image

According to Retinex theory, an image can be decomposed into illumination and reflection. For an image S

$$\mathrm{S(x, y) = R(x, y)L(x, y)} \tag{5}$$

where R is reflection and L is illumination. The R is computed as

$$\mathrm{R(x, y)} = \log \mathrm{S(x, y)} - \log \left[\mathrm{F(x, y)} * \mathrm{S(x, y)}\right] \tag{6}$$

where S(x, y) is the input image. F(x, y) is a Gaussian function

$$\mathrm{F(x, y)} = \frac{1}{\sqrt{2\pi\sigma}} \mathrm{e}^{-\frac{\mathrm{x}^2+\mathrm{y}^2}{2\sigma^2}}. \tag{7}$$

The illumination image is the Gaussian filtering result, namely F(x, y) $*$ S(x, y).

B. Histogram Similarity of Illumination Images

Now we can compare illumination images for evaluating illumination consistency. For a group of images, we firstly

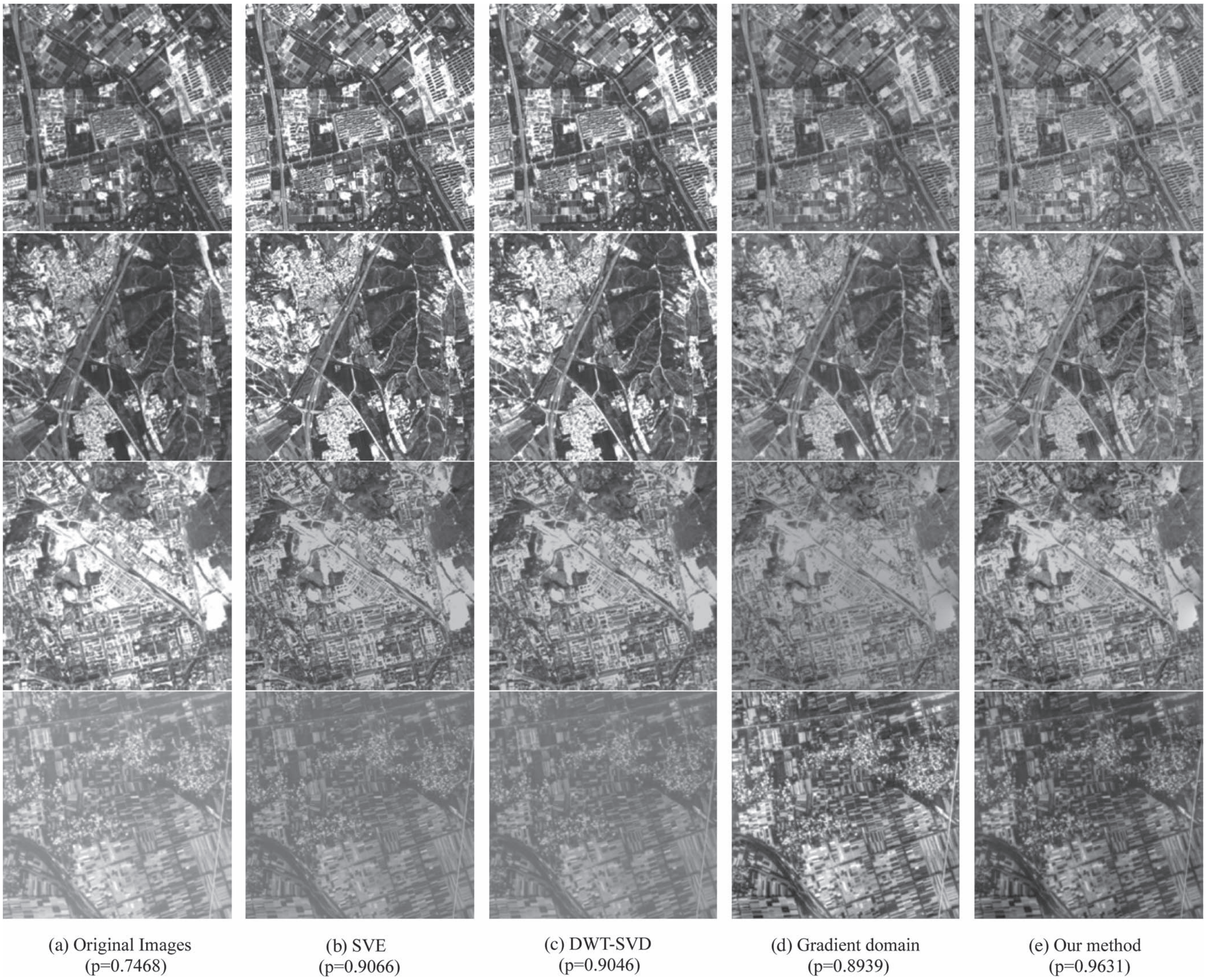

Fig. 4. Images of different places and different time. (a) Original Images ($\mathrm{p} = 0.7468$). (b) SVE ($\mathrm{p} = 0.9066$). (c) DWT-SVD ($\mathrm{p} = 0.9046$). (d) Gradient domain ($\mathrm{p} = 0.8939$). (e) Our method ($\mathrm{p} = 0.9631$).

compute the mean histogram of them, and then compare each histogram to the mean histogram. The formulation is

$$\mathrm{p} = 1 - \frac{\Sigma_{\mathrm{i}=1}^{\mathrm{k}} \Sigma_{\mathrm{j}=0}^{255} |\mathrm{G_i(j)} - \mathrm{A(j)}|\, \mathrm{W_j}}{\mathrm{k} \cdot \mathrm{N} \cdot \mathrm{W_{max}}} \tag{8}$$

where k is the number of the images. G_i is a vector indicating the histogram of ith image. $\mathrm{G}_i(j)$ is the number of pixels whose value is j. A is the mean histogram. A(j) is the number of pixels whose intensity value is j. $\mathrm{W_j} = |\mathrm{M} - \mathrm{j}| + 1$.N is the size of images. $\mathrm{W_{max}} = \max(|\mathrm{M} - \mathrm{j}|)$ is the weight when illumination difference is huge, such as black image and white image. In our experiments $\mathrm{W_{max}}$ is set to be 128. The parameter p is between 0 and 1, which can quantitatively evaluate illumination consistency of images. The bigger p is, the more consistent images are.

V. Experiments and Analysis

This part will show the results of experiments and analyze the effects of our method through visualization and quantitative assessment parameter p. The images used in the experiment come from Resource Satellite 2th 02C and Resource Satellite 3th.

Our method can normalize illumination of any amount of images. Because of the limitation of letter, we only show three results of 2, 3, and 4 images as a group, including three conditions: same time different places, same place different time and different time different places. We show the results of SVE [7], DWT-SVD [8], gradient domain method [5] and our method.

Fig. 2 is two images at the same imaging time but in different places. The first column is the original images and their histograms. The other columns are the results of SVE, DWT-SVD method, gradient domain method and our method, respectively. It is obvious that the histograms of the images are better matching than before. Comparing the histograms and p values, we can find out that the bigger p is, the more consistent the images are. Fig. 3 is three images in the same place but at different time. Their illumination is different. From visualization and p values we can find that the effect of our

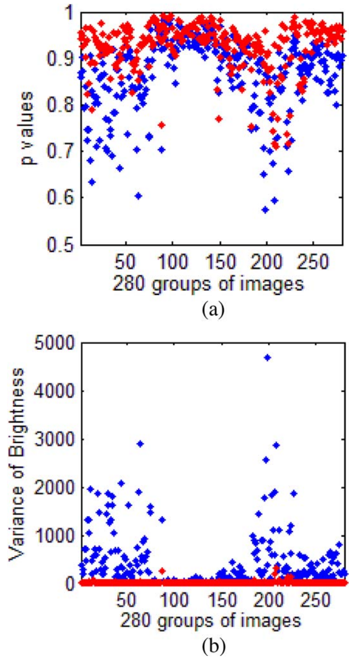

Fig. 5. Scatter diagram of 280 groups of images (Blue and red dots represent original and processed images, respectively). (a) Changes of p values. (b) Changes of variance of brightness.

method is better than others. Fig. 4 is four images at different time and in different places. The third image is over exposed while the fourth image is under exposed. Our method has normalized the illumination of the 4 images.

The SVE, DWT-SVD and gradient domain method concentrate on image contrast enhancement. Our purpose is illumination normalization. But they can bring us illumination changes in visualization. So our experiments make comparisons with the three methods. The DWT-SVD method applies SVD to low-low subband image after discrete wavelet transform. It pursues good performance in contrast enhancement and does not care consistency. As we analyzed, gradient domain method is good at contrast consistency. We improved SVE to make it good at brightness consistency. Then our method combines their advantages to get illumination consistency. Fig. 5 is the statistic data of our method. There are 280 groups of images. Every group has four images. In Fig. 5(a) p values of the processed images, represented by red dots, are almost higher than the original ones, represented by blue dots. In Fig. 5(b) red dots is lower than blue ones. In conclusion their p values rise and variances of brightness descend, which indicates that their illumination is normalized.

Table I shows brightness, contrast and p of each column in Fig. 2. We can find that SVE method can keep the brightness close and Gradient domain method is good at adjusting contrast to the same level. Our method can correct both brightness and contrast to achieve illumination consistency.

TABLE I
PARAMETERS OF IMAGES IN FIG. 2

	brightness	contrast	p
Original images	73.3	5.7	0.7663
	15.0	6.5	
SVE	127.0	9.9	0.8974
	123.2	41.4	
DWT-SVD	130.8	10.0	0.8941
	128.7	42.8	
Gradient domain	71.8	24.9	0.9576
	61.6	17.6	
Our method	94.5	27.5	0.9628
	93.8	28.8	

VI. CONCLUSION

We propose an illumination normalization method based on gradient domain method and improved singular value equalization. First, contrast is modified through gradient domain method. Then we adjust the mean of each image to the mean of all images using improved SVE. Finally, a group of images achieve consistent illumination. This letter also proposes a quantitative assessment for illumination consistency of images. It abstracts an illumination image from the original image, compares the similarity of histograms of each illumination image and constrains the value between 0 and 1. Experimental results demonstrate that our method is available to normalize illumination of images.

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