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Matching of Multi-exposure Images

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***Abstract*—In this paper, a method for matching multi-exposure images is introduced. By extracting feature points from the brightness-spaces which are built by multiplying the contrast stretching function with a series of parameters by the input image, we can obtain interesting points robustly even under large illumination, rotation and scale changes. We use the scale invariant feature transform (SIFT) description to describe these points. The experimental results show that the proposed algorithm has good effects on dealing with the matching of multi-exposure images and better than the SIFT method, especially, upon the extracting the correct matching numbers.**

Keywords-multi-exposure image matching, brightness-spaces, invariant feature points

I. INTRODUCTION

Recently, with the rapid development of economy and technology, digital camera is becoming a common device in the real life. However, because of the constrains of the properties in charge-coupled device (CCD) and analog-digital converter (ADC), the dynamic range of digital camera is very limited, it is difficult to achieve a complete record of light information. When the filming scene dynamic range exceeds the scope of the camera collection, it usually controls the range of brightness information which is achieved by changing the time for exposure. But no matter how to adjust the time, that always still exist overexposed or underexposed areas which leads to some detail losses of highlighting or the darkness department. A group of images with different exposure but same scene can provide more information than a single image. Darker images can provide some details of bright scene, and lighter images can provide the details of the shadow scene [7]. The necessary task is to obtain a series of matching images. In this paper, we describe a feature point detection method for matching a set of multi-exposure images. It is not only useful for scene understanding but also for computer vision systems.

Feature points extraction is an important part for image matching. One of the earliest feature points extraction algorithms is the Moravec corner detector [1]. This method defines a large intensity variation in every direction as the feature points. Harris and Stephens [2] improve the Moravec detector by applying Taylor series expansion, using image derivatives to estimate the autocorrelation of a image. Shi and Tomasi [3] use the eigenvalues of the auto-correlation matrix as the corner measure. Recently, scale and affine invariant methods [8] [9] have been put forward. One of the most popular algorithms is the scale invariant feature transform (SIFT) [4]. The method extracts feature points by choosing the extrema of difference-of-Gaussian (DoG) filtered images with different scale Gaussian kernels, eliminating edge responses and low contrast points.

This paper proposes a method which extracts feature points based on brightness-spaces and scale-invariant for multi-exposure image matching. First, building brightness-space images by multiplying the contrast stretching function with a series of parameters by the input images. Second, extracting feature points at each layer of brightness-space images using the SIFT method. Then, adding the feature points to all brightness-spaces as feature points of the images and describing each point based on the local histogram of the gradient vectors. Finally, matching the standard and the reference images which are different in exposure. The main procedure of multi-exposure images matching is shown in Fig.1.

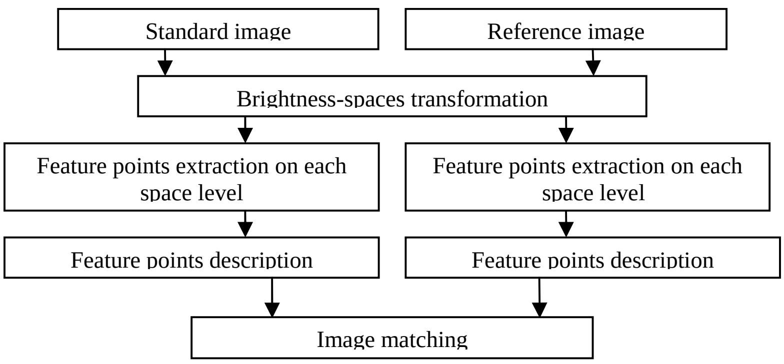


Figure 1. The proposed matching flow chart

II. OVERVIEW OF SIFT

One of the most popular method used feature points detectors is the scale invariant feature transform (SIFT) [4]. The algorithm extracts feature points by constructing a Gaussian pyramid and searching for local eatrema over location and scale in a series of difference-of-Gaussian (DoG) images. $L(x, y, \sigma)$ is the convolution of a Gaussian function $G(x, y, \sigma)$ whose scale is variable with an input image $I(x, y)$.

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y) \quad (1)$$

where $*$ is the convolution operation, and

$$G(x, y, \sigma) = \frac{1}{2\pi} e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (2)$$

$$\begin{aligned} D(x, y, \sigma) &= (G(x, y, k\sigma) - G(x, y, \sigma)) * I(x, y) \\ &= L(x, y, k\sigma) - L(x, y, \sigma) \end{aligned} \quad (3)$$

III. MATCHING BASED ON THE BRIGHTNESS-SPACES AND SCALE-INVARIANT METHOD

We can not obtain the whole scene details through a single image due to the over- or under-exposure by common digital camera. Under-exposure images can provide some details of bright scene, and over-exposure images can provide the details of the shadow ones. Here give an example of a nature scene at six different exposure levels [6]. As is shown in Fig. 2.

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

Figure 2. (a)-(f) Multiple exposures images of a door to a dark room, these images are of size 338×31 pixels.

A. Building brightness-space images and selecting feature points

As described above in the introduction, we will establish the brightness-space images by multiplying the contrast stretching function with a series of parameters and the input images. We select the sigmoid function as the contrast stretching function in the experiments [5].The sigmoid function is as follows:

$$I_c(x, y) = \frac{1}{1 + e^{-\gamma(I(x,y)-c)}} \quad (4)$$

where $I(x,y)$ is the normalized gray value in the range [0,1], c is the contrast center around which the contrast is stretched, and γ determines the slope of the sigmoid function.

After we obtain a group of images in different contrast parameters, the scale invariant feature point extracting method which extracts feature points by constructing a Gaussian pyramid and searching for local extrema over location and scale in a series of difference-of-Gaussian (DoG) images is used at each brightness-space level:

$$L_c(x, y, \sigma) = G(x, y, \sigma) * I_c(x, y) \quad (5)$$

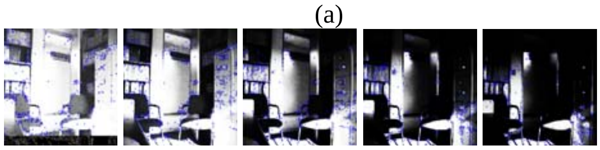
$$\begin{aligned} D_c(x, y, \sigma) &= (G(x, y, k\sigma) - G(x, y, \sigma)) * I_c(x, y) \\ &= L_c(x, y, k\sigma) - L_c(x, y, \sigma) \end{aligned} \quad (6)$$

where $L_c(x, y, \sigma)$ is the convolution of a Gaussian function at the contrast center.

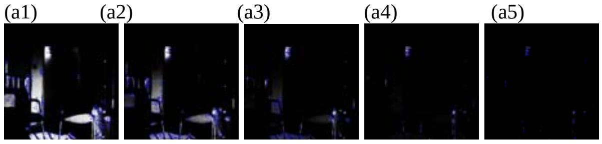
The next step is to eliminate edge responses and low contrast points at each brightness-spaces level. Fig. 3 and Fig. 4 show the results of feature points detection at several contrast centers c.

c=0, n=586

(a)



c=0.1, n=884 (a1) c=0.2, n=896 (a2) c=0.3, n=788 (a3) c=0.4, n=659 (a4) c=0.5, n=542 (a5)

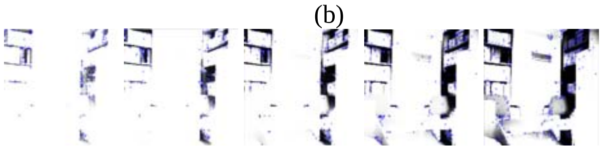


c=0.6, n=457 (a6) c=0.7, n=411 (a7) c=0.8, n=239 (a8) c=0.9, n=89 (a9) c=1, n=41 (a10)

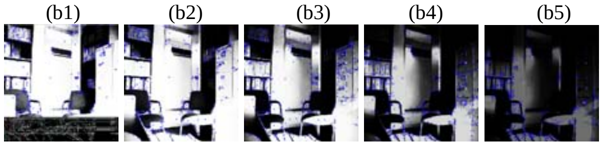
Figure 3. The scale feature point extracting at different contrast centers c, where n is the point numbers at this brightness, $\gamma = 20$.

c=0, n=675

(b)



c=0.1, n=255 (b1) c=0.2, n=285 (b2) c=0.3, n=307 (b3) c=0.4, n=426 (b4) c=0.5, n=588 (b5)



c=0.6, n=709 (b6) c=0.7, n=711 (b7) c=0.8, n=796 (b8) c=0.9, n=754 (b9) c=1, n=640 (b10)

Figure 4. The scale feature point extracting at different contrast centers c, where n is the point numbers at this brightness, $\gamma = 20$.

B. Feature point description

In this section, we have got the feature points using the SIFT descriptor [4]. Building a 128 dimensions feature vector by computing and accumulating the gradient magnitude and orientation for each feature point which is invariance to image rotation in some extent. Image gradient magnitude and orientation are obtained by following forms:

$$m(x,y)=\sqrt{(I(x+1,y)-I(x-1,y))^2+(I(x,y+1)-I(x,y-1))^2} \tag{7}$$

$$\theta(x,y)=\tan^{-1}((I(x,y+1)-I(x,y-1))/I(x+1,y)-I(x-1,y))) \tag{8}$$

where $m(x, y)$ is the gradient magnitude, $\theta(x, y)$ is the orientation.

C. Image Matching

According to the Minimum Euclidean distance of the feature vectors of the two source images, matching points can be found [4]. All of the parameters, distratio and vals, determine the matching numbers. A group of multi-exposure image matching result using our method is shown in Figure.9 (a).

IV. EXPERIMENTAL RESULTS

In this section, we will give the experimental results of our method under a set of image exposure, rotation, and scale; and compare with the classical SIFT method under the same conditions. It can be proved from the experiments that our method can obtain better results than the classical methods.

There are four experimental data sets, which are shown in Fig.5-8 [6]. Fig. 5-8 (a) are the standard image, Fig. 5 (b)-(f), Fig. 6 (b)-(f), Fig.7.(b)-(g), and Fig.8.(b)-(g) are the different exposure images. From the figures we find that our method gains more correct matching points than the classical SIFT method.

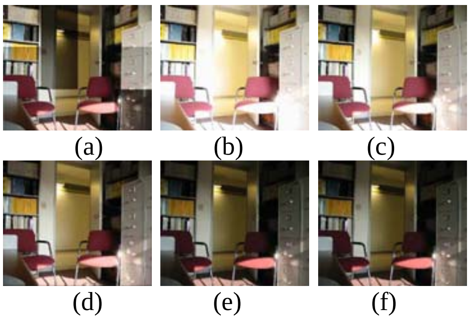


Figure 5. (a) the standard image, (b)-(f) Multiple exposures images of an office room, these images are of size 768×1024 pixels.

The proposed method is used to match the standard image and the different exposure images in each group respectively. In our method, the value of parameter c is 0, 0.2, 0.4, 0.6, and 0.8. The results are shown in Figure 9-12.

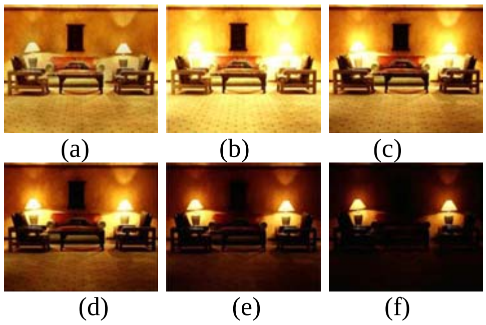


Figure 6. (a) the standard image, (b)-(f) Multiple exposures images of an indoor scene, these images are of size 231×3434 pixels.

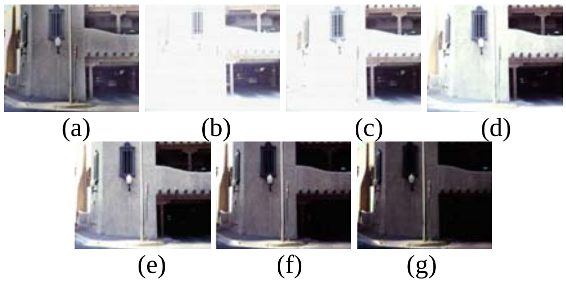


Figure 7. (a) the standard image, (b)-(g) Multiple exposures images of a garage scene, these images are of size 222×348 pixels.

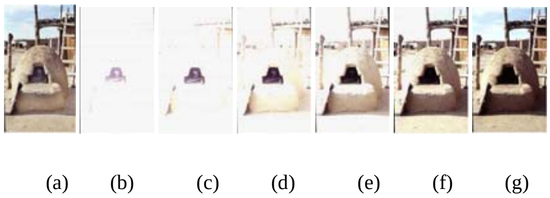


Figure 8. (a) the standard image, (b)-(g) Multiple exposures images of an igloo scene, these images are of size 341×236pixels.

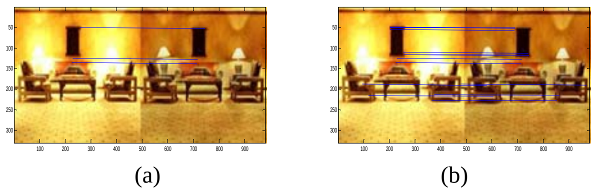


Figure 9. (a)is the result of SIFT, (b)is the result of the proposed method, distratio=0.55, vals=0.15.

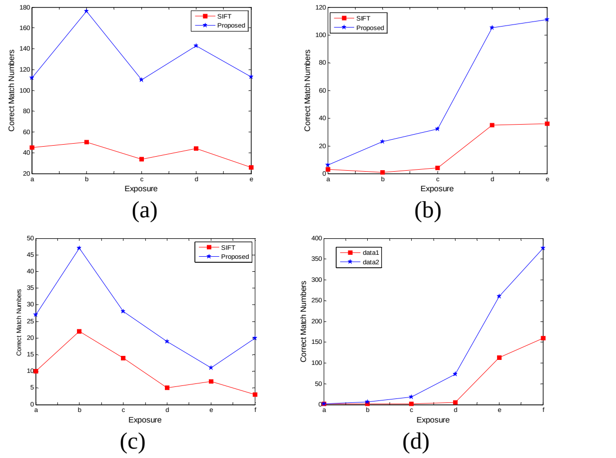


Figure 10. (a), (b), (c) and (d) are the results of compared with classical method SIFT in different exposures for data set 1, data set 2, data set 3, and data set 4, respectively.

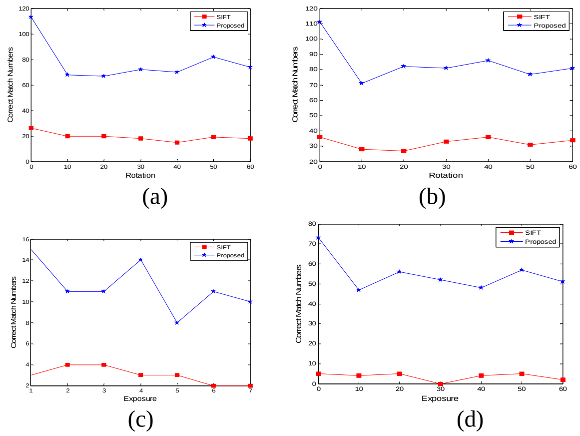


Figure 11. (a), (b), (c) and (d) are the results of compared with classical method SIFT in different rotation for data set 1, data set 2, data set 3, and data set 4, respectively.

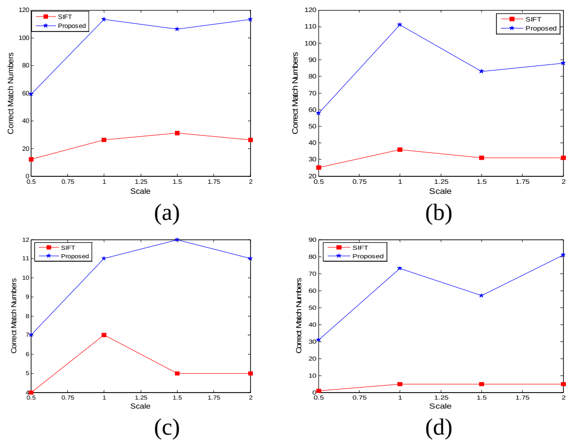


Figure 12. (a), (b), (c) and (d) are the results of our method compared with SIFT in different scale for data set 1, data set 2, data set 3, and data set 4, respectively.

Fig. 9 (a) is the result of the proposed method which gets thirteen correct match numbers, and Fig. 9 (b) is the result of SIFT method which only get three correct match numbers under the same conditions.

Fig. 10 is the result of the proposed method and the SIFT method under rotation change. The rotation is 0, 10, 20, 30, 40, 50, and 60. From the charts we can find that our method gets more correct match numbers than SIFT.

Fig. 11 is the result of the proposed method and the SIFT method under scale change. The scale is 0.5, 1, 1.5, and 2. From the charts we can find that our method gets more correct match numbers than SIFT.

V. Conclusions

In this paper, we propose a method, brightness-spaces and scale-invariant, to detect interest points. In our method we can solve the problem of the multiple-exposure image matching. From the above series of experiments, we can conclude that our method can obtain greater matching results on the conditions of multi-exposures, as well as larger rotation and scale changes. Through observing and anglicizing these figures, we found that our method has much more advantages than the classical SIFT method in the total correct matching numbers, which is very important in image registration.

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