Suppression for Luminance Difference of Stereo Image-Pair Based on Improved Histogram Equalization

Zhao Liling [1,2], Zheng Yuhui [3], Sun Quansen[1], Xia Deshen[1]

1School of Computer Science and Technology, NJUST, Nanjing, China .2School of Information and Control Engineering, NUIST, Nanjing, China.3School of Computer Science and Technology, NUIST, Nanjing, China
zhaoliling@nuist.edu.cn, zheng_yuhui@nuist.edu.cn, cnsunquansen@mail.njust.edu.cn, deshen_x@263.com

Abstract. In order to recover the depth and obtain the 3-D coordinates of the feature points in front of binocular stereo camera, high-precision stereo matching is very important. Image gray based matching method is a major approach with its simple calculation and low complexity. Generally the matching accuracy relates to the luminance difference of the image-pair and higher accuracy needs lower luminance difference. Histogram equalization is commonly used when the luminance difference of the image-pair being balanced, but the image gray dynamic range will be changed and artifact will be appearance. In order to overcome these drawbacks, an improved histogram equalization method was proposed. This method combines the local information and middle axis histogram equalization to balance the brightness. Both theoretical analysis and experimental results show that this approach can suppresses luminance difference and improve matching accuracy of stereo image-pair effectively.
Keywords: stereo image-pair; luminance difference; middle axis histogram equalization

1 Introduction

With the increasing application in 3-D vision technology, demand for higher timeliness and accuracy are increasing. Image gray based method and feature extraction based method are commonly used. But gray based method has an important position, because the mathematical models, convergence speed, positioning accuracy and error estimates with quantitative analysis and research findings is simple and low complexity [1]. However, this method has an assumption that the same target in the left and right image has the same gray value. This assumption does not meet the actual situation. In fact, image acquisition process will be interfered by differences light and brightness between the stereo camera, so the brightness of the same target in the left and right images will have a greater difference. Therefore, when using gray based method for better match and accuracy fundamentally, suppression for luminance

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difference of stereo image-pair is necessary. To transform the image and suppression for luminance difference, histogram equalization and related improvements are often used. But, most kinds of method has its drawbacks. In this paper, a new image equalization method was proposed. This method combines the local information and middle axis histogram equalization. Experimental results show that, the proposed method can effectively correct brightness differences, keep the image gray dynamic range and can improve the matching accuracy with little image details lost.

2 Essential difference in histogram equalization

Luminance difference of stereo image-pair can be reflected in different gray of the same object in image-pair and different dynamic range in image histogram. An appropriate method to adjust the image histogram of stereo image-pair to be the same is necessary. If we consider two images I_1 and I_2, whose cumulative histogram are H_1 and H_2. In order to make H_1 and H_2 to be the same, we have to choose a cumulative histogram H and contrast them to be as correspond H. If H is the identity function on [0,1], each image I_i becomes $H_i(I_i)$, i.e. each histogram is equalized. All of the approach based on histogram equalization can be attributed to select the appropriate mapping rule H.

Proposition 1: if $I_i : \Omega \to [0,1]$ ($\Omega \subseteq R^2$, $i = 1, 2$) is the image-pair, h_i is the image histogram of I_i, the cumulative histogram $H_i : [0,1] \to [0,1]$ of I_i is:

$$H_i(x) = \int_0^x h_i(t)dt$$

Proposition 2: if F_i: [0,1] $\to$ [0,1] is a continuous monotonically increasing function, then $F_i = H^{-1} \circ H_i$, and $F_i(I_i)$ is a new image, the cumulative histogram of the new image is: $H_i = H \circ F_i^{-1}$

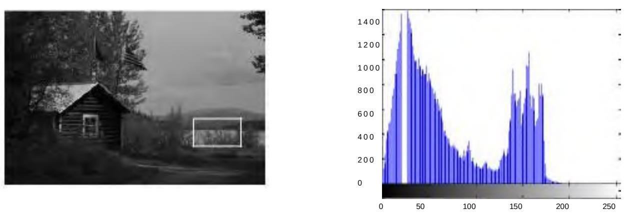
2.1 Histogram equalization

The selection of H in histogram equalization (HE) approach is the cumulative histogram of the image itself. Histogram equalization is the approach that nonlinearly stretching the original grayscale of the image according to the mapping rule.

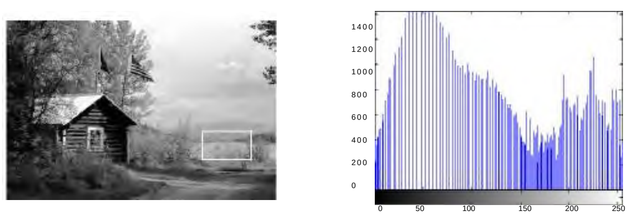
Therefore, the result is to make the number of pixels of each grayscale roughly the same and the distribution of the image histogram changing into a "uniform" distribution. But, this approach has many drawbacks, such as reducing of image grayscale, disappearance of image detail, through enhancement, artifact etc.[2]. See Fig.1, details after histogram equalization is almost not distinguishable from the vegetation, especially in the right part of the image (see in particular the part in the rectangular zone).

2.2 Histogram specification

Histogram specification (HS) is a transformed approach based on histogram equalization. It is diversified especially in selecting the appropriate mapping rule H . As for stereo image-pair, if one of the images is chosen as a reference, the other image is specified by the reference cumulative histogram H , the two images will be as the same image histogram. I_1 is not changed, I_2 is changed into $H_1^{-1} \circ H_2(I_2)$. The method maintains the original gray dynamic range with the lower blind transformation. If the images have similar gray dynamic range, this approach is appropriate. But, if the images have large differences in brightness. See Fig.2, artifacts are obvious especially in the left part of the image (see in particular the part in the rectangular zone).

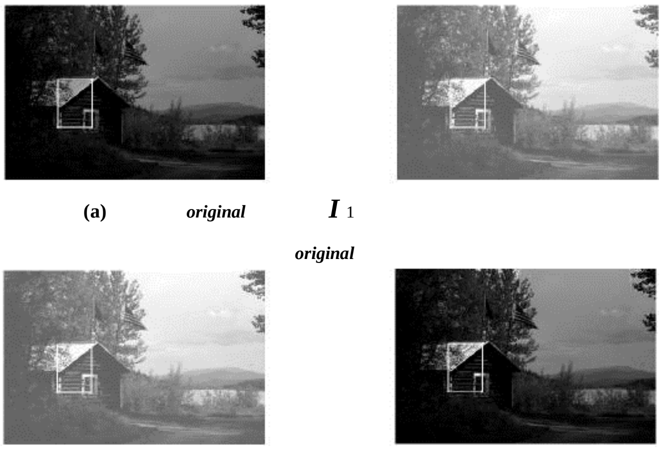


(a) Image r, the corresponding histogram hr



(b) Image rafter histogram equalization, the histogram hr'

Figure 1: Effect of histogram equalization



(a) *original* I_1 (b) *original* I_2

(c) I_1 *after HS* (d) I_2 *after HS*

Figure 2: Effect of histogram specification

2.3 Middle axis histogram equalization

Through the analysis above, both approaches have shortcomings. Histogram equalization flattens the global original image histogram dynamic range. While, histogram specification produces a certain loss of image detail and artifact, although it can maintain the original image histogram dynamic range better. These shortcomings will reduce the stereo matching accuracy. Thus, the change level of image gray dynamic range and the lost of original image detail must be considered when selecting the appropriate mapping rule before correcting stereo image-pair brightness. Obviously, if the axis located in the middle of the two cumulative histograms is made as the mapping rule, the image cumulative histogram of the pair will be transformed closer. We can easily find the balance relationship between the image histogram

dynamic range and image detail. Suppose that the image pairs I_1 and I_2 , their cumulative histogram is H_1 and H_2 , the middle of the curve located in the two images cumulative histogram is H . I_1 and I_2 have the same cumulative histogram H_i $= H \circ F_i$ and the image-pair with the same gray-scale dynamic range. In

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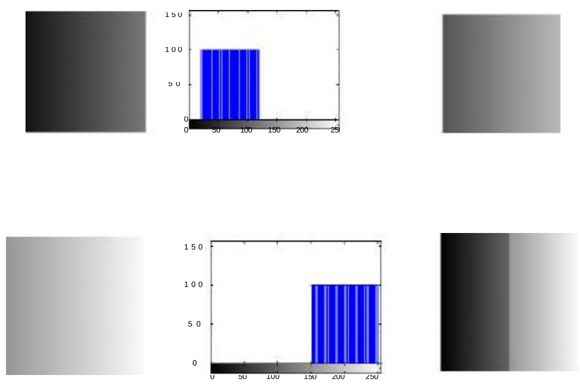
conclusion, this approach can not only reduce the image histogram dynamic range change, but also maintain image detail without increasing or decreasing obviously.

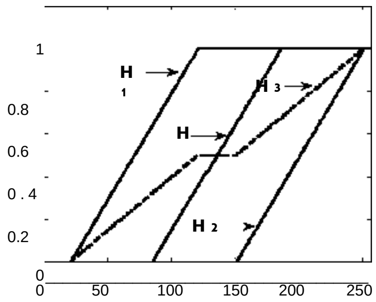
3 Theory of middle axis histogram equalization

To illustrate the theory of middle axis histogram equalization, two artificial gray images which has distinct gray dynamic range was made. One has higher gray value, while the other has lower value. See Fig.3, The cumulative histograms contains four lines placed in a unified coordinate, H_1 and H_2 is the cumulative histograms of original image, H_3 is the numerical average of H_1 and H_2, H is the average position of H_1 and H_2, H is a straight line. Obviously, H_3 is not the best average result of H_1 and H_2, because of the new structure in transformed image, see Fig. 3(d). This new structure will affect the further application [3]. H maybe the better average which can be calculated from $H = \left[\frac{H_1^{-1} + H_2^{-1}}{2}\right]^{-1}$. Image transformed by the middle axis will has the same gray dynamic range and maintain image detail without increasing or decreasing obviously, see Fig. 3(e).



(a) I_1 **and** *the corresponding image histogram* **(b)** *Image after* H

(c) I_2 **and** *the corresponding image histogram* **(d)** *Image after* H_3



(e) ***Cumulative histogram*** H, H_1, H_2, H_3

Figure 3: *original images* and the corresponding image histogram, *transformed images* after the corresponding cumulative histograms

4 Proposed algorithm

In this paper, we note global middle axis image equalization as GMIE. A new approach combining the local and GMIE was proposed. The new approach is named as block adaptive middle axis image equalization (BAMIE). The BAMIE based approach can make every pixel adapt to its surroundings, better result can be obtained on luminous difference correction and therefore more details can be maintained.

Generally, the size of I_1 and I_2 is set to $M \times N$, a real-time window size is W and step length is $W/2$, two zero matrix I_1' and I_2' with the same size as I_1 and I_2. The steps of BAMIE are as follows: take I_{1w} with size of W in I_1 and take I_{2w} with size of W in I_2 from the top left pixel of the image; calculate the cumulative histogram of I_{1w} and I_{2w}, marked as H_{1w} and H_{2w}; calculate the middle axis H of H_{1w} and H_{2w} according to $H = \left[\frac{1}{2}\left(H_1^{-1} + H_2^{-1}\right)\right]^{-1}$; calculate the nonlinear mapping model F_1 and F_2 from H, H_{1w} and H_{2w} based on image equalization, $F_1 = H^{-1} \circ H_{1W}$, $F_2 = H^{-1} \circ H_{2W}$; transform the window image gray value through the formula in(4), that is $I_{1W}' = F_1(I_{1W})$, $I_{2W}' = F_1(I_{2W})$; put I_{1W}' and I_{2W}' into I_1' and I_2' in the corresponding position; reuse steps (2) - (6

), and cumulate the I_{1w} and I_{2w} into ${}_1I$ and ${}_2I$ when the window moving every time, until all of image histogram is transformed; calculate every pixel value with weighted according to cumulate times (brief mathematical derivation in annex, a new image-pair ${}_1I$ and ${}_2I$ are obtained at last.

5 Experiments and discussions

In order to illustrate our algorithm effectiveness, we choose a standard image-pair and a real remote sensing image-pair contrast with the results from histogram equalization (HE), histogram specification (HS) and GMIE.

5.1 Effects on gray dynamic range

Fig.5~Fig.10 shows an example of applying the proposed algorithm BAMIE and also the results of applying histogram equalization (HE), histogram specification (HS) and GMIE. Although the angle variation between both views is small, the light difference is existed. We can see clearly that the number of pixels of each gray roughly the same and the distribution of the image histogram changing into a "uniform" distribution after histogram equalization; the histogram is changed obviously after each image histogram specification on the other; after GMIE the histogram has almost the same gray dynamic range but not smooth; after BAMIE the histogram has the same appearance especially. In short, histogram after BAMIE became more identical and satisfied with the assumption of stereo matching. The gray dynamic range changes the same after BAMIE.

5.2 Effects on image details and spectrum

If we scan some image details (Fig.5 and Fig.8), we can see that the details in BAMIE are rich and visible. This algorithm is an effective way to perform this transformation on discrete data. Generally, the composition of an image by a function doesn’t maintain the property “to be well sampled, according to Shannon-Whittaker sampling theorem”. Now, we want to get the match map of the area, the image must be well sampled if we want a good precision. In order to check the effects of the different transformations on the spectrum experimentally, we made the following example: we specify I_1 on I_2 , and we compute the modification of I_1 via HE, HS, GMIE and BAMIE. From the Fig.11(a)~(e) and table 1, we can see that the spectrums of I_1 via BAMIE remain more in the central square than that of others and the spectrums energy become balance between the image-pair. Most natural images have a spectrum really concentrated in the center of its support. It follows that after a transform like a histogram modification, the spectrum sprawls but doesn't go much out of its support. The ratios of energy presented illustrate that our algorithm is really useful in the applications of stereo matching.

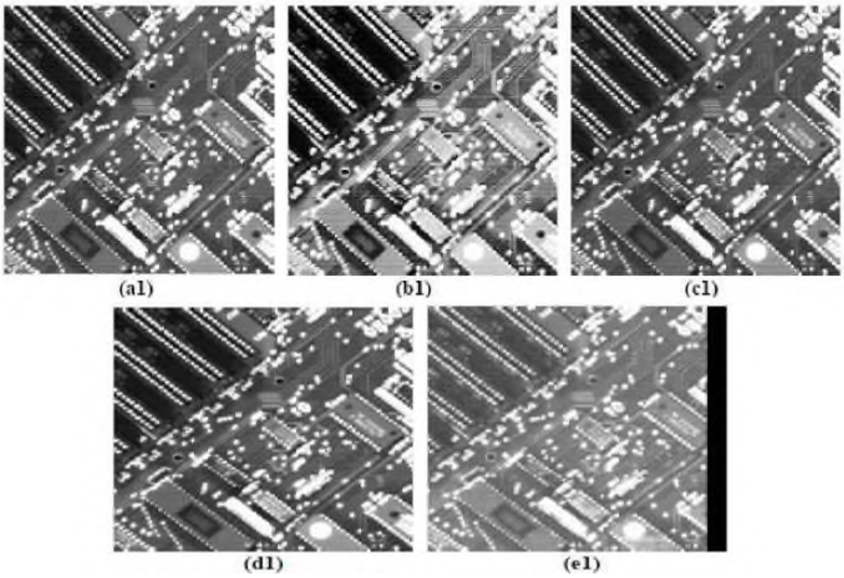
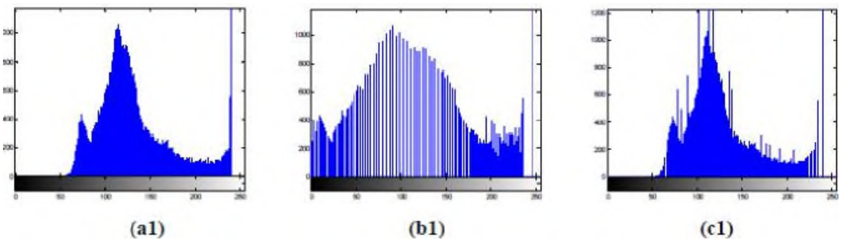


Figure 5: The original image-pair and the transformed image-pair by HE, HS, AMIE, BAMIE



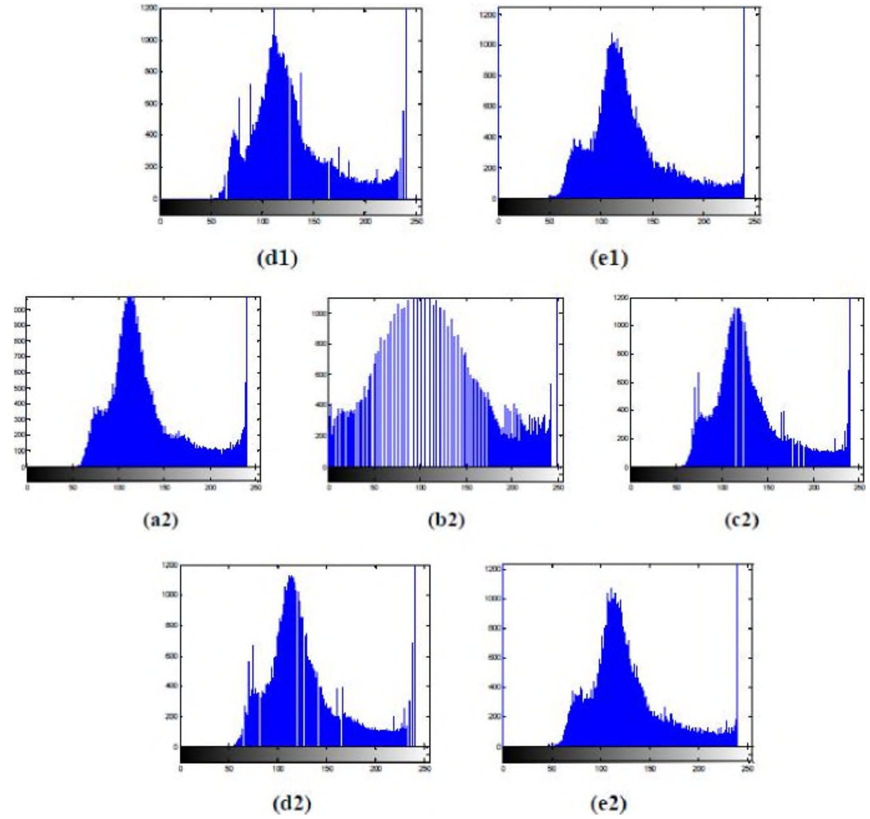


Figure 6: The histogram of the original image-pair and the transformed image-pair by HE, HS, AMIE, BAMIE

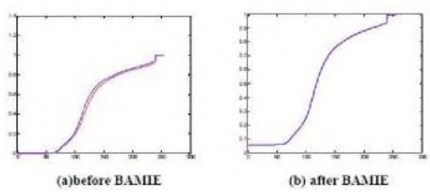


Figure 7: The cumulative histogram of image-pair

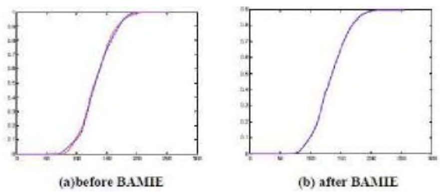


Figure 10: The cumulative histogram of image-pair before and after BAMIE before and after BAMIE

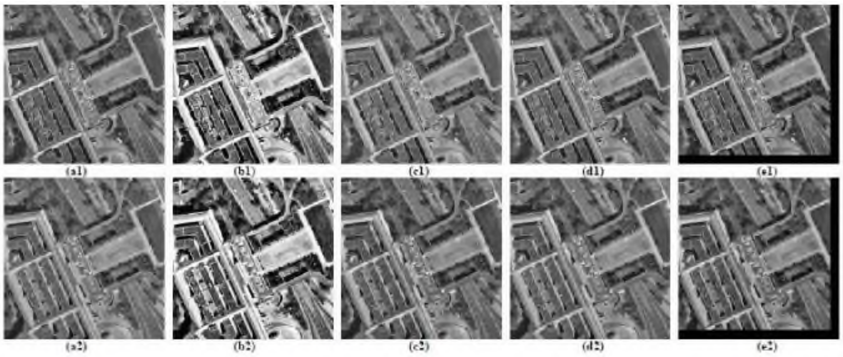


Figure 8: The original image-pair and the transformed image-pair by HE, HS, AMIE, BAMIE

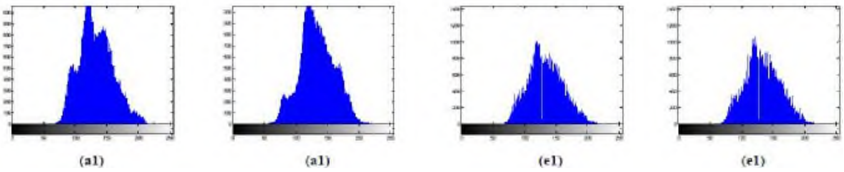


Figure 9: The histogram of the original image-pair and the transformed image-pair by BAMIE

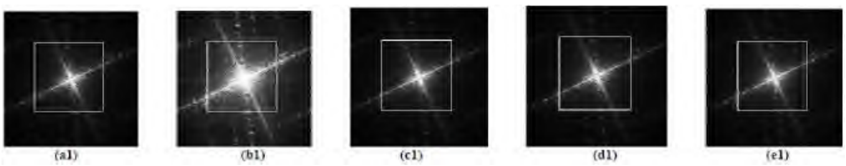


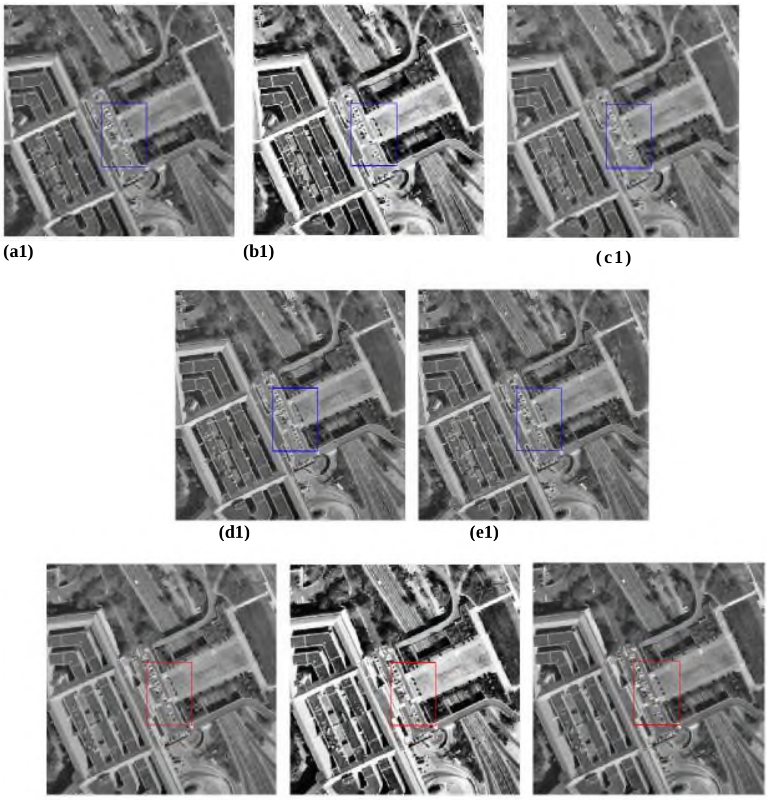
Figure 11: The spectrums of 1***I*** (remote sensing) and after the transformed by HE, HS, AMIE, BAMIE

Table 1 Spectrums energy remained in central square

	original	HE	HS	GMIE	BAMIE
remote image I1	0.2696	0.2807	0.2696	0.2697	0.2706
remote image I2	0.2714	0.2838	0.2715	0.2716	0.2706
stranded image I1	0.2653	0.2687	0.2649	0.2650	0.2882
stranded image I2	0.2660	0.2732	0.2664	0.2662	0.2885

5.3 Effect on matching accuracy

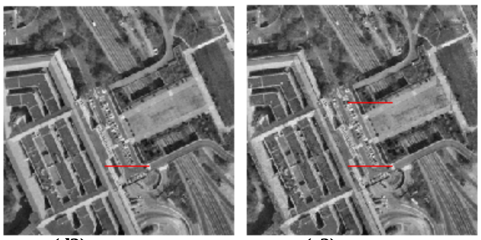
SSD [4]is a commonly used similarity measure method, named the sum of squared disparity. See Fig.12, the right image of remote sensing is the real-time image with the size of 256×256. Take a reference window from the left image at the random point（110,110）with the size of 41×21. The experimental results show that, the matching point from the image transformed by HE, HS, GMIE and BAMIE is（ 113,110）,（113,110）,（113,110）,（113,110）. All the matching points is correct and same, but the matching accuracy is different, see table 2. We take two random experiment results and all the results show that image-pair transformed with the proposed approach can reach the higher matching accuracy.



(a1) (b1) (c1)

(d1) (e1)

(a2) (b2) (c2)



(d2) (e2)

Figure 12: The result of matching based on gray match method

Table 2 Matching accuracy

	original	HE	HS	GMIE	BAMIE
Experiment 1	0.9936	0.9698	0.9930	0.9933	0.9940
Experiment 2	0.9935	0.9708	0.9934	0.9937	0.9940

6 Conclusions

The main contribution of this paper is proposing a new approach noted as BAMIE which combining the advantage of local adaptive and GMIE. BAMIE based approach makes every pixel adapt to its surroundings, better result can be obtained on luminous difference correction and therefore more details can be maintained. Both theoretical analysis and experimental results show that this approach can suppresses luminance difference and improve matching accuracy of stereo image-pair effectively.

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