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A Stereo Image Matching Method on Images with Varying Light Conditions

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Abstract— **In the process of 3D regeneration from stereo images, a disparity map can be determined by matching the same objects on the stereo image pair. However, different light conditions of an image pair, such as exposure, illumination, and illuminant color, usually compromise the accuracy of matching. This usually occurs when taking outdoor images. In this paper, we propose a preprocessing method to improve condition of image to build disparity map with less effect from varying light conditions. Stereo images from the Middlebury dataset is used to test our method. We used LogRGB algorithm as a baseline. Compared to the ground truth, experimental results show that our method performs the 3.02% RMS error and 4.0% percentage of bad matching while 3.47% RMS error and 6.9% bad matching for LogRGB.**

Keywords— Stereo vision, Exposure, Disparity map, Histogram Processing, YCbCr

I. INTRODUCTION

3D image reconstruction can be calculated by finding differences between each of stereo image pair [1-3], which are two images of the same objects taken at different positions. Generally, to take a pair of stereo images, we should take those two pictures at the same time in order to preserve the same light conditions. However, it is very normal that images at the same location in the same photo stock may have different light conditions.

When a camera is fixed at a location to take a photograph, all images must have the same composition; however, if it is taken at different time, light exposure would be different. Light exposure is about amount of light on a specific area of image that percepted by a capturing device. For the image taken at a fixed location, if light condition is high exposure, the image will be bright, otherwise the image will be dim.

To solve this condition, George, M. [4] and Gaojian, L. [5] used the normalized cross correlation (NCC) as a pre-processing method in order to create a disparity map. However, the accuracy of the disparity map is acceptable except when the both of the stereo images has low intensity. Baydoun, M. [6] and Il-Lyong [7] used correlation of the envelopes of pixel intensity histogram of each image. This method also provide. However, the result is different in extreme cases; i.e. intensity of reference histogram is either very high or very low.

In this paper, we propose a preprocess method by amplifying intensity of image and then using histogram equalization to reduce effect of imbalanced intensity distribution. The stereo image dataset of Middlebury is used to test for our algorithms. LogRGB algorithm [4] is used as a baseline in the experiment. The result shows that accuracy our algorithm is 3.02% root-mean-square (RMS) error and 4.0% percentage of bad matching, respectively.

The rest of this paper is organized as follows. Sections II describe related work. Proposed method is presented in sections III. Section IV has details of the experiment and section V shows their results. Finally, conclusion and future work is presented in Section VI.

II. Related works

There are many techniques to solve problem from effect of exposure such as George, M. [4], Gaojian, L. [5], and Baydoun, M. [6]. George, M. [4] proposed a pre-process of amplify dark area of image using logarithm function onto each channel of RGB image. However, this model is not tolerant to light intensity and direction. Gaojian, L. [5] used a post-process by cross-checking on matching results. Usually, to match object to determine a disparity map is about to match parts of image on left image plane onto ones on right image plane. Cross-checking is about re-check by match parts of image on the right image plane back on to the left image plane. Both method can reduce problems of unequal light conditions in the stereo images; however, it produces lowly accurate results on low-intensity images. Baydoun, M. [6] proposed a low-pass-filter-like method on histogram envelope as a feature to match the objects in left and right image plane. They separated histogram into five parts. Histogram elements that has the highest frequency in each part is considered as a representative of that part. Therefore, it can reduce dimension of histogram and preserve enough histogram distribution for object matching. However, statistic mode values in parts of histogram could be random noises. The envelope would contain very noisy data and then produce a low-quality disparity map.

In this paper, we present a pre-processing algorithm to build a more accurate disparity map. The concept of algorithm is to 1) amplify the dim area since it has more information to match; 2) use histogram envelope to match the object; and 3) use histogram equalization on light intensity channel in YCbCr color model to eliminate effect of imbalanced light condition between left and right image planes.

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III. Proposed Method

There are following steps to generate a disparity map: converting color model of images from RGB to YCbCr, using our algorithm to adjusting light condition, and calculating the disparity map by using Normalized Cross Correlation (NCC). As shown in Fig. 1.

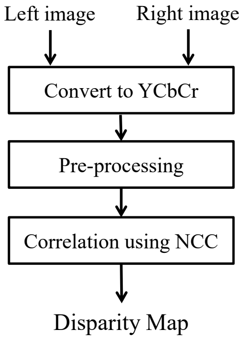


Fig. 1 Model to generate disparity map.

First, to solve the problem of intensity, we should use a model that is easy to deal with intensity. RGB color model is not appropriate to deal with intensity because information of intensity is mixed from all three channels. HSV and YCrCr are two widely-used color models that separate light intensity to be a channel [8]. However, by preliminary experiment and result in [9], effect of intensity representation of V of HSV to the dim area is less efficient than Y of YCbCr.

Second, Intensity in a low-contrast area is improved by stretching data which may be ranged in dim area onto the all possible range of intensity; therefore, object would be more contrast and easier to detect the difference between left and right image planes.

Third, we equalize intensity histogram in two steps. Normal histogram equalization is used to equalize the whole image globally and Contrast Limited Adaptive Histogram Equalization (CLAHE) [10] is used further to improve dim parts of image locally. The CLAHE process is a type of adaptive histogram equalization [11]. It is can improve the local contrast of an image and bringing out more details and reduces a tendency to over amplify noise in relatively homogeneous regions of an image [12].

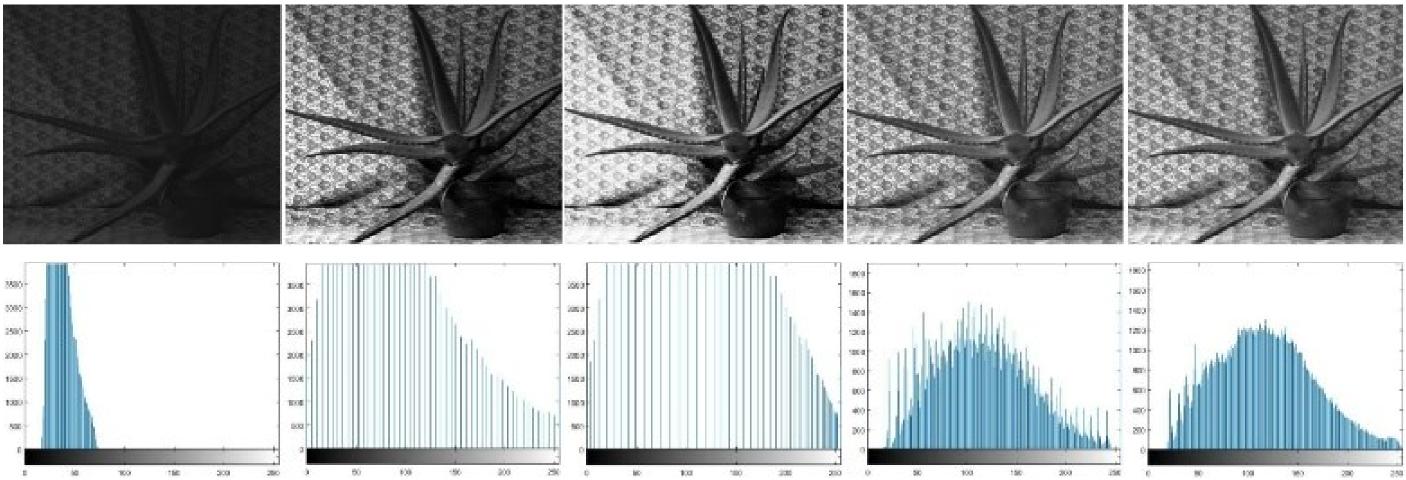
Forth, we adjust an image to smooth with a Gaussian filter to reduce the detail of an image after histogram processing to help the intensity of pixel have a similarity.

Fig. 2 demonstrates step-by-step results in both image and its histogram. Fig.2 (a) shows an original image. Fig. 2(b) shows result after adjusting image contrast. Fig. 2(c) shows a result after histogram equalization process. Fig. 2(d) show a result after CLAHE process. Finally, Fig. 2(e) shows a result of Gaussian filter.

Fifth, image is normalized by Normalized cross-correlation (NCC), which is a standard statistical method for determining similarity. Its normalization, both in mean and the variance, makes it relatively insensitive to radiometric gain and bias [13]. NCC is defined by the Eq.1. Let $D_{L,R}[x,y]$ be a part of disparity map of a stereo pair (L,R) for an object at coordinate (x,y) on the image L. d is the search models, where it theoretically is infinity. $D_{L,R}[x,y]$ is determined by finding d the produce the maximum $NCC_{L,R}$. The $NCC_{L,R}(x,y,d)$ is defined by Eq.2 [14], where I_L and I_R are intensity of the images L and R, respectively; μ_L and μ_R are the mean, and $N(x,y)$ is selectable window size of area of interest at coordinate (x,y).

$$D_{L,R}[x,y] = \underset{d\in[0,\infty]}{\operatorname{argmax}} NCC_{L,R}(x,y,d) \tag{1}$$

$$NCC_{L,R}(x,y,d) = \frac{\sum_{(i,j)\in N(x,y)}(I_L(i,j)-\mu_L)\times(I_R(i+d,j)-\mu_R)}{\sqrt{\sum_{(i,j)\in N(x,y)}|I_L(i,j)-\mu_L|^2}\times\sqrt{\sum_{(i,j)\in N(x,y)}|I_R(i+d,j)-\mu_R|^2}} \tag{2}$$



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

Fig. 2 Results of each preprocessing steps. The top row shows the left images Illumination 1 Exposure 0 and the bottom row shows histogram of left image : (a) Y component ; (b) image adjustment; (c) Histogram Equalization; (d) Contrast-Limited Adaptive Histogram Equalization; and (e) Gaussian filter;

A. The proposed algorithm

The proposed algorithm is described as a pseudo code in Algorithm 1.

```
Algorithm 1: Disparity map by using Histogram Processing and YCbCr Color Model
Input: Left images (ImgL_RGB), Right image (ImgR_RGB), Disparity range (∞)
Output: Disparity map (D_L,R)
// Pre-Process Algorithm
ImgL_YCbCr ← RGBtoYcbcr (ImgL_RGB).
ImgR_YCbCr ← RGBtoYcbcr (ImgR_RGB).
ImgL_Y ← Select_Y_component (ImgL_YCbCr).
ImgR_Y ← Select_Y_component (ImgR_YCbCr).
ImgL_Adj ← Adjust_Contrast (ImgL_Y).
ImgR_Adj ← Adjust_Contrast (ImgR_Y).
ImgL_HE ← Histogram_Equlization (ImgL_Adj).
ImgR_HE ← Histogram_Equlization (ImgR_Adj).
ImgL_CLAHE ← CLAHE
(ImgL_HE, distribute are bell shaped).
// Contrast-Limited Adaptive Histogram Equalization.
ImgR_CLAHE ←CLAHE
(ImgR_HE, distribute are bell shaped).
// Contrast-Limited Adaptive Histogram Equalization.
ImgL_GF ← Gaussian_filtering (ImgL_CLAHE).
ImgR_GF ← Gaussian_filtering (ImgR_CLAHE).
// Compute disparity map
for each [x_L, y_L] in IL_GF
  for each [x_R, y_R] in ImgR_GF
      D_L,R[x_L, y_L] = argmax_{d∈[0,∞]} NCC_L,R(x_L, y_L, ∞[x_R, y_R])
  end for
end for
D_L,R = D_L,R[x_L, y_L]
end
```

IV. EXPERMENTS

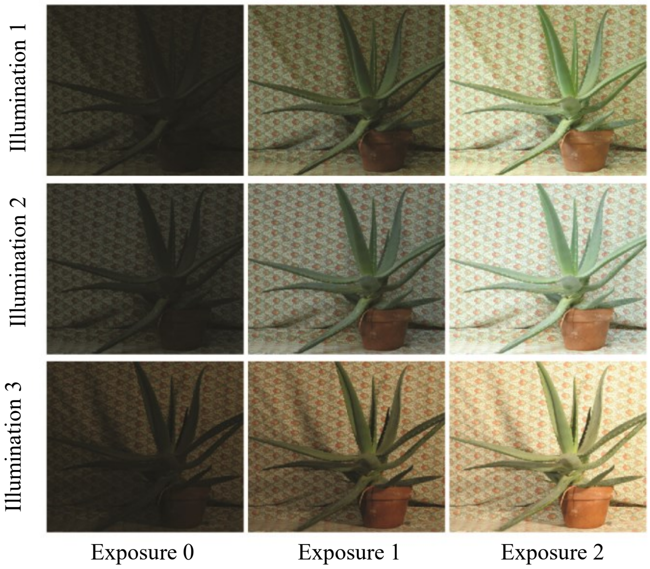
The experiments are to prove that our proposed algorithm can produce more accurate disparity map from stereo pair images that have different exposures. We divide the experiment into two parts: 1) accuracy of the disparity map of images with varying exposure; and 2) accuracy of the disparity map of images from Middlebury standard dataset. The LogRGB algorithm is used as a baseline. Results of these experiments are comparisons among quality of disparity map using 1) original NCC; 2) LogRGB; and 3) the proposed algorithm. All codes are run on MATLAB 2015a on a Windows PC.

A. Middlebury dataset

The Middlebury stereo image dataset [15] is used in our experiments. Ground truths of depths of images are available in the dataset's metadata. All images are rectified and radial distortion has been removed. Only images whose size are 427x370 pixels are used in the experiments. We use five image sets, Aloe, Tsukuba, Venus, Cone, and Teddy.

Only the Aloe set contains the same image shots that have different illumination direction and different exposure [16, 17]. The characteristic of Aloe can be described as: "80 disparity range, Repeat texture, Texture-less, Occlusion." Examples of Aloe are shown in Fig. 3.

Other images in the test set are shown in Fig. 4. Properties of images are listed in Table I.



(a) (b) (c)

Fig. 3 Left image of Aloe. The top row shows the left images of illumination 1, the middle row shows the left images of illumination 2 and the bottom row shows the left images of illumination 3: (a) Exposures 0; (b) Exposures 1; and (c) Exposures 2;

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

Fig. 4 Data set. The top row shows the left images and the bottom row shows their disparity ground truth: (a) Tsukuba; (b) Venus; (c) Cone; and (d) Teddy;

TABLE I. CHARACTERISTICS OF IMAGES

Name of images	Disparity range	Description
Tsukuba	0-15	Uniform and repetitive areas
Venus	0-19	Less texture and the shape of a plane stacked
Cone	0-59	Complex geometry
Teddy	0-59	Complex geometry and less texture

The accuracy of disparity map is measured by the differences between the disparity map from algorithms $D_E(x,y)$ and ground-truth disparity maps $D_G(x,y)$. The differences are determined by using root mean square (RMS) error and the percentage of badly matching pixels (B) in all non-occluded regions. The RMS error is defined in Eq.3 and Percentage of bad matching defined in Eq.4, where N_{nocc} is a number of all non-occluded pixels and δ_d is a disparity error tolerance (δ_d =1.0 in this research) [18, 19].

$$RMSE = \left(\frac{1}{N_{nocc}}\sum_{(x,y)} |D_E(x,y) - D_G(x,y)|^2\right)^{1/2} \quad (3)$$

$$B(\%) = 100\left(\frac{1}{N_{nocc}}\sum_{(x,y)}(|D_E(x,y) - D_G(x,y)|) \geq \delta_d\right) \quad (4)$$

V. Experimental Results

A. Results on images with varying exposures

In this experiment, we compare errors of our algorithms with the baseline (LogRGB), ordinary NCC and ground-truth. Qualitative results of disparity maps from Aloe with the light directions Illum 1, Illum 2, and Illum 3 are shown in Figs. 5, 6, and 7, respectively. Quantitative results, which are error and bad matching pixel from the experiments, are shown in Figs. 8 and 9, respectively.

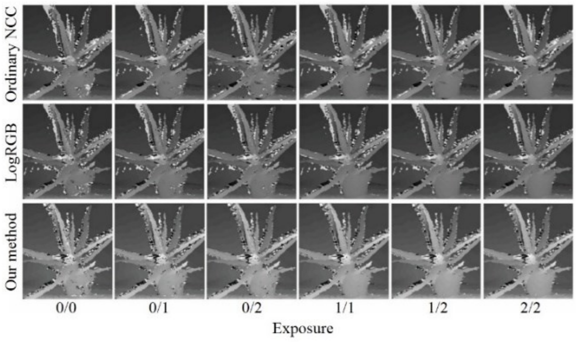


Fig. 5 Results on Aloe with Illumination 1.

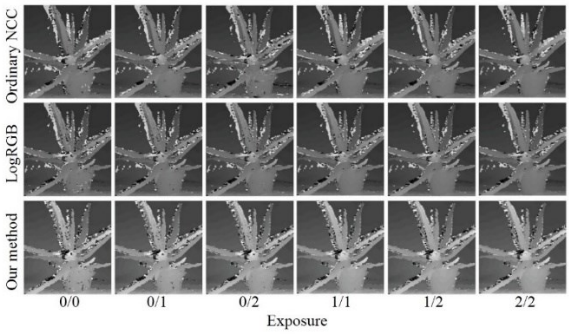


Fig. 6 Results on Aloe with Illumination 2.

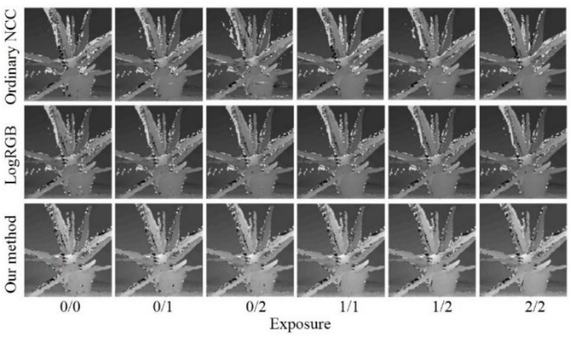


Fig. 7 Results on Aloe with Illumination 3.

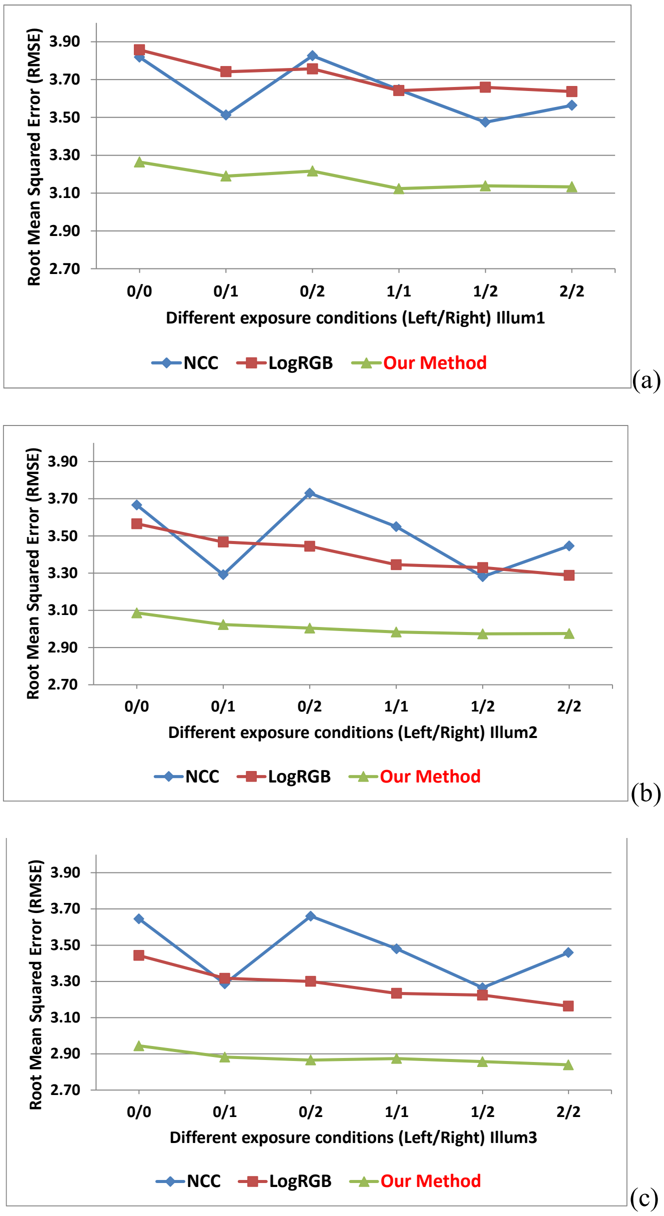


Fig. 8 RMS error of disparity map with different exposures: (a) illumination 1; (b) illumination 2; and (c) illumination 3;

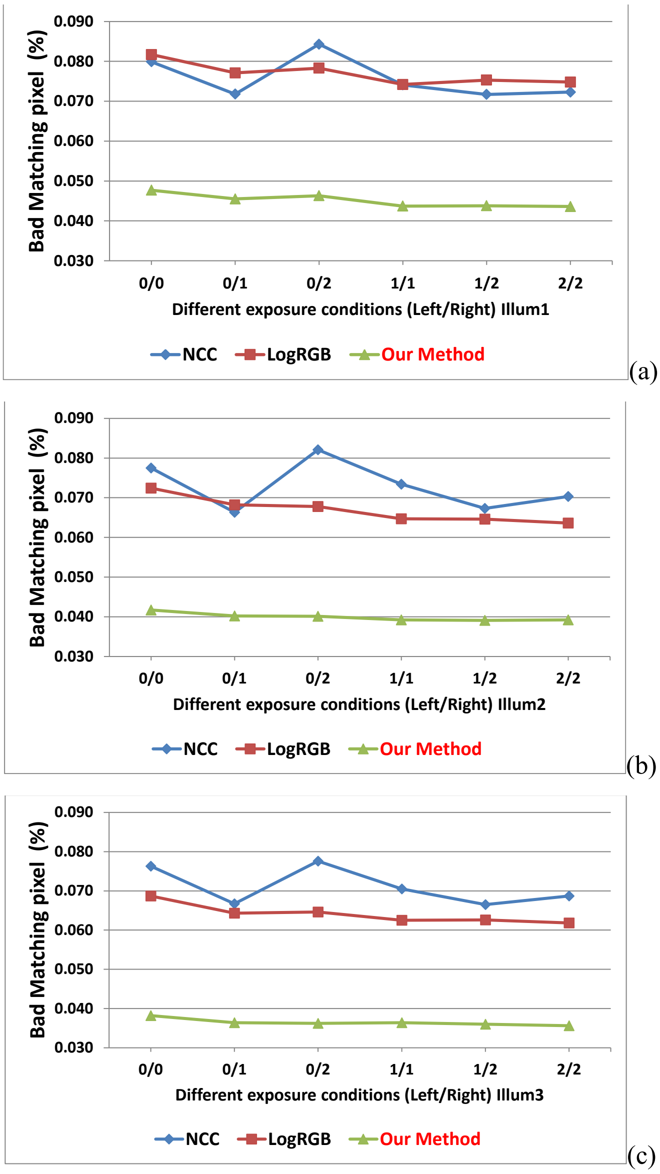


Fig. 9 Bad matching pixel of disparity map with different exposures: (a) illumination 1; (b) illumination 2; and (c) illumination 3;

B. *Results on benchmark dataset*

Beside effect of the varying exposures, the regular situation is tested by other image in the Middlebury dataset. The experiments are conducted the same method as explained in the above section. Fig. 12 shows disparity maps of test images. The error and bad matching from the experiments are shown in Figs. 13 and, respectively. Our results perform better than LogRGB on Venus and Teddy, comparably equal on Cone, and worse on Tsukuba. This is because large area of Tsukuba is dark and when it is amplified. The white area becomes too bright and then it is hard to match objects accurately.

Fig. show the result of disparity map of standard dataset where 4 images. The error and bad matching from the experiments are shown in Fig. and Fig. 12, respectively. From the result of the experiment where compare baseline (LogRGB), ours algorithms better than baseline two images (Venus, Teddy), equal basedline one image (Cone) and worse than baseline one image (Tdukuba). Because that is so, Tsukuba has mostly dark tone and white object when using our algorithm white object were reduced the details leads to the error, in calculating the disparity map. The result shows that our algorithms can be worked on standard dataset.

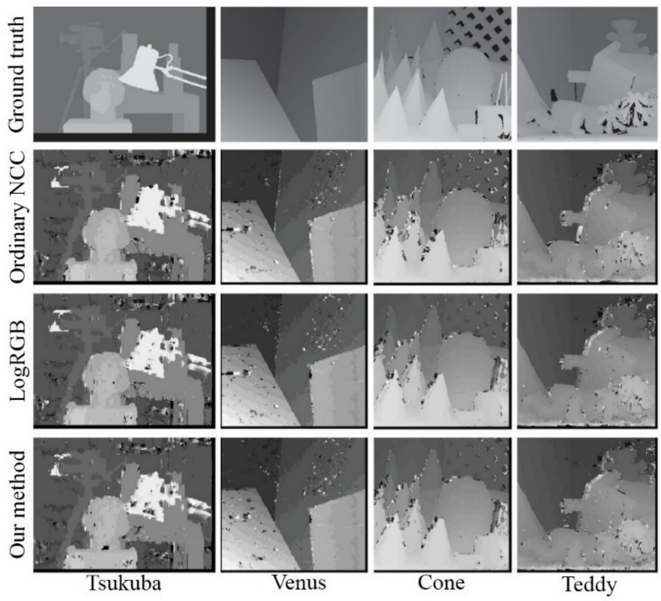


Fig. 10 Disparity map of test images.

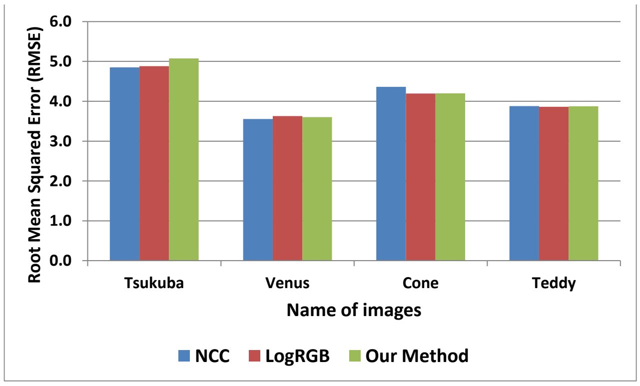


Fig. 11 Comparison of root mean square error of standard dataset.

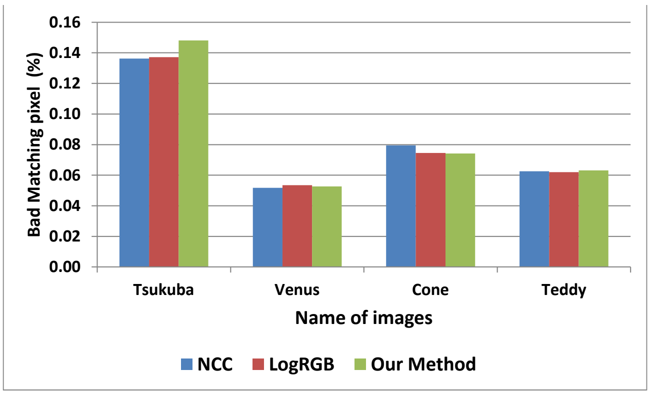


Fig. 12 Comparison of bad matching pixel of standard dataset.

VI. CONCLUSION

In this paper, we present an algorithm for preprocessing for disparity map generation from stereo images, where the image exposures are varying. Our algorithm is to amplify contrast, transform image into YCbCr model, eliminate effect of intensity differences by two histogram equalization algorithms, and then use normalized cross correlation to match objects to create its disparity map. Middlebury dataset is used as benchmark data. LogRGB algorithm is used as a base line. Accuracy is computed from ground truth. The results show that our algorithm produces more accurate disparity map than the baseline.

For future work, we will improve the case when large part of image is dark and some small parts are very bright, matching on that bright area may be less accurate. We will investigate this issue further.

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