



# Improved Contrast Enhancement Feature Map Technique for Stereoscopic Images

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## ABSTRACT

Recently, technical breakthroughs of the color image enhancement have been found using depth or stereo as side information. Stereo matching algorithms and depth sensors are now providing highly accurate depth images, and thus the use of the depth image for the color image enhancement becomes an important research issue. Many saliency detection models for 2D images have been proposed for various multimedia processing applications during the past decades. Currently, the emerging applications of stereoscopic display require new saliency detection models for salient region extraction. Different from saliency detection for 2D images, the depth feature has to be taken into account in saliency detection for stereoscopic images.

In this a new global contrast enhancement algorithm using the histograms of color and depth images. On the basis of the histogram-modification framework, the color and depth image histograms are first partitioned into subintervals using the Gaussian mixture model. The positions partitioning the color histogram are then adjusted such that spatially neighboring pixels with the similar intensity and depth values can be grouped into the same sub-interval. By estimating the mapping curve of the contrast enhancement for each sub-interval, the global image contrast can be improved without over-enhancing the local image contrast. Experimental results demonstrate the effectiveness of the proposed algorithm.

**Index Terms:** Contrast enhancement, depth image, histogram modification, and histogram partitioning.

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## I. INTRODUCTION

Image contrast enhancement techniques have been studied in the past decades. There are various contrast enhancement methods are there, among those, histogram modification methods have received the greatest attention because of their simplicity and effectiveness. , since global histogram equalization over-enhance the image details, an alternative to this, the approaches of dividing an image histogram into several sub-intervals and modifying each sub-interval separately. The effectiveness of these sub histogram based methods is dependent on how the

image histogram is divided. The histogram of a image is obtained by using the Gaussian mixture model (GMM) and divides the histogram using the intersection points of the Gaussian components. The divided sub- histograms are then separately stretched using the estimated Gaussian parameters. Now a days technique of the color image enhancement have been found using depth [4]–[6] or stereo [7]–[9] as side information. Stereo matching algorithms and depth sensors are providing accurate depth images, and thus the use of the depth image for the color image enhancement becomes an important issue. So In this project, we propose a new contrast

enhancement algorithm that exploits the histograms of both color and depth images.

The histograms of color and depth histograms are first divided into subintervals by using Gaussian mixture model. Then the histograms of color histograms are adjusted with the similar intensity and depth values of depth image. Image obtained by [10].

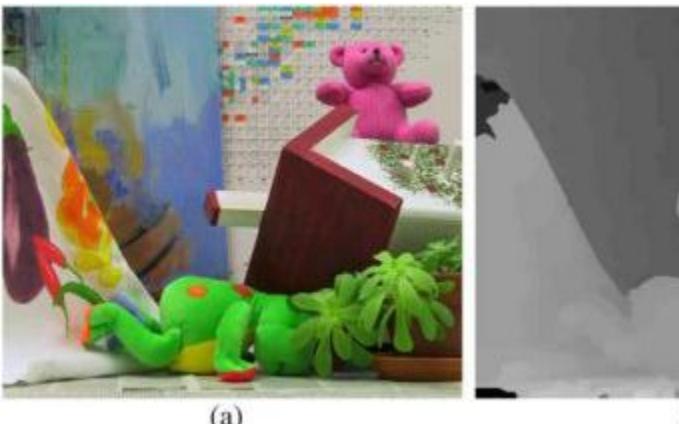


Fig. 1. (a) The color image *Teddy* and (b) its depth image obtained by [10]

## II. PROPOSED ALGORITHM 1

A pair of color and depth images is given as input, as shown in Fig. 1. By using Gaussian mixture model we obtain the histograms of input images. Then the algorithm modifies the histogram of the color image using the histogram of the depth image as side information. The histogram of the color image is transformed from the RGB space to the hi-saturation-intensity space. Histogram modification is then applied to the intensity channel, and then result ant color image is obtained by transforming the HIS to RGB. Figure. 2(a) and (b) show the histograms of the color and depth images with their Gaussian mixture models. Figs. 2(a) and (b)) are used to divide the histogram into subintervals.

Let  $c$  and  $d$  represent the color image and the depth image, respectively. The histograms of  $c$  and  $d$  are assumed to be divided into  $N$  and  $M$  sub-intervals, respectively, and the intersection points between the  $i^{\text{th}}$  and  $(i+1)^{\text{th}}$  sub-intervals of  $c$  and  $d$  Layer labeling results of Figs. 1(a) and (b), are denoted as  $l_0$  and  $m_0$ , respectively. Using the intersection points,  $c$  and  $d$  can be decomposed into multiple layers. In histogram based contrast enhancement algorithms, the mapping function for each layer is estimated such that image details in each layer can be effectively enhanced. However, histogram partitioning using only the intensity channel can assign different labels to

the neighboring pixels that have similar intensity and depth values the background region inside the dotted circle as shown in Fig. 2(c) has similar intensity and depth values as input image but different labels are cluttered in the region. Thus, if we use contrast enhancement on this background region which results unnatural images. So we propose an algorithm that adjusts the histogram partitioning such that a same label is enforced for the pixels with the similar intensity and depth values.

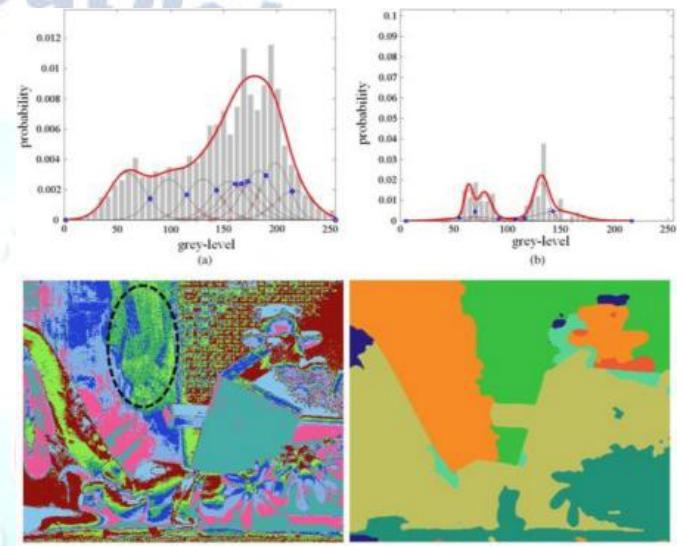


Figure 2: (a)-(b) Histogram and layer partitioning results of Figures. 1(a) and (b), respectively. (c) - (d) Layer labeling results of Figs. 1(a) and (b),.

## III. EXPERIMENTAL RESULTS FOR ALGORITHM 1

In order to evaluate the performance of the proposed algorithm, the Middlebury stereo test images [14] were used in our experiment. The depth images were obtained using the stereo matching algorithm [10] as shown in Fig. 3. The pixel values of the color images were then divided by 4 to simulate low-contrast input images.



Figure 3: Fig. 3. Experimental results corresponding to the input images in Fig. 2s. (a)-(c) the resultant image obtained by [2], (d)-(f) the resultant image obtained by the proposed algorithm, (g), (i), (k): the magnified sub regions corresponding to (a)-(c), respectively, (h), (j), (l) the magnified sub regions corresponding to (d)-(f), respectively.

Using the same histogram partitioning and mapping curve generation methods in [2], the effectiveness of the proposed algorithm can be evaluated by comparing the results obtained with and without modifying the histogram sub-intervals, respectively. Figure 4 shows that the layer labeling result  $s_i$  became more spatially uniform as  $\lambda$  increased. We empirically found that  $\lambda=1000$  performed well in enhancing the contrast of images. The results given here after were obtained using  $\lambda=1$ .

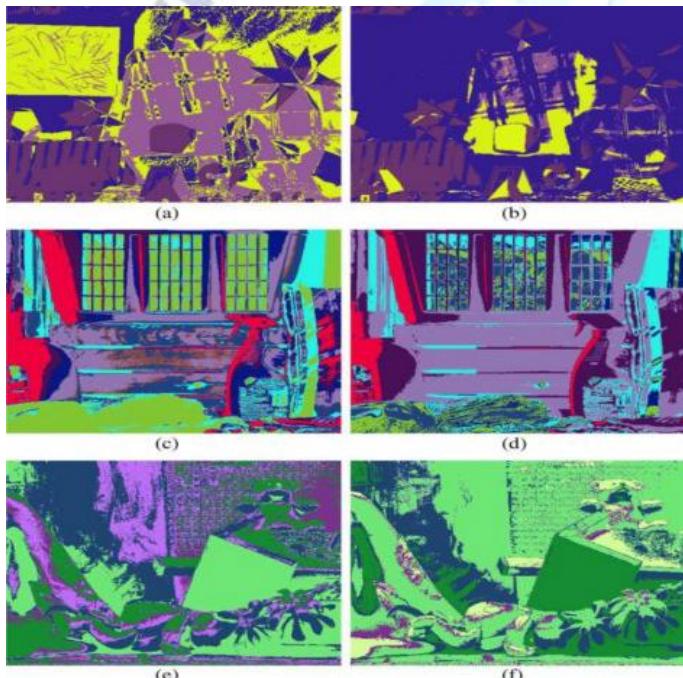
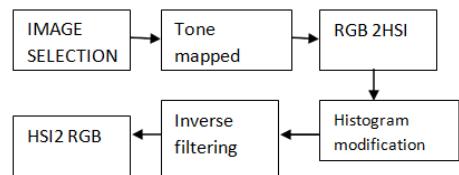


Figure 4: Layer labeling results for the conventional method (first column) and the proposed method (second column)

Figure 3 shows the experimental results obtained using the conventional [2] and proposed algorithms. Both algorithms successfully enhanced the global contrast of the input images shown in Fig. 3. However, the conventional method produced artifacts at some image regions as shown in Figs. 3(g), (i), and (k). This is because the image regions with the similar intensity and depth values were decomposed into different groups as shown in Figs. 4(a), (c), and (e). By using the proposed algorithm, such regions were merged into the same layer as shown Figs. 4(b), (d), and (f), and thus the over-enhancement was prevented.

#### IV. PROPOSED ALGORITHM 2

##### Tone mapped Operator



**Tone mapping** is a technique used in image processing and computer graphics to map one set of colours to another to approximate the appearance of high dynamic range images in a medium that has a more limited dynamic range. Print-outs, CRT or LCD monitors, and projectors all have a limited dynamic range that is inadequate to reproduce the full range of light intensities present in natural scenes. Tone mapping addresses the problem of strong contrast reduction from the scene radiance to the displayable range while preserving the image details and color appearance important to appreciate the original scene content.

##### PURPOSE AND METHODS

The goals of tone mapping can be differently stated depending on the particular application. In some cases producing just aesthetically pleasing images is the main goal, while other applications might emphasize reproducing as many image details as possible, or maximizing the image contrast. The goal in realistic rendering applications might be to obtain a perceptual match between a real scene and a displayed image even though the display device is not able to reproduce the full range of luminance values.

Various tone mapping operators have been developed in the recent years.<sup>[5]</sup> They all can be divided in two main types:

- *global* (or *spatially uniform*) operators: These are non-linear functions based on the luminance and other global variables of the image. Once the optimal function has been estimated according to the particular image, every pixel in the image is mapped in the same way, independent of the value of surrounding pixels in the image. Those techniques are simple and fast<sup>[1]</sup> (since they can be implemented using look-up tables), but they can cause a loss of contrast. Examples of

common global tone mapping methods are contrast reduction and colour inversion.

- *local* (or *spatially varying*) operators: The parameters of the non-linear function change in each pixel, according to features extracted from the surrounding parameters. In other words, the effect of the algorithm changes in each pixel according to the local features of the image. Those algorithms are more complicated than the global ones; they can show artefacts vision is mainly sensitive to local contrast.

#### VISUAL EFFECT

Local tone mapping method produces a number of characteristic effects in images. These include halos around dark objects, a "painting-like" or "cartoon-like" appearance due to a lack of large global contrasts, and highly saturated colours. Many people find the resulting images attractive and these effects to add an interesting new set of choices for post-processing in digital photography. Some people believe that the results stray too far from realism, or find them unattractive, but these are aesthetic judgements, and often concern the choices made by the photographer during the tone mapping process, rather than being a necessary consequence of using tone mapping.

Not all tone mapped images are visually distinctive. Reducing dynamic range with tone mapping is often useful in bright sunlit scenes, where the difference in intensity between direct illumination and shadow is great. In these cases the global contrast of the scene is reduced, but the local contrast maintained, while the image as a whole continues to look natural. Use of tone mapping in this context may not be apparent from the final image:

#### CORRELATION COEFFICIENT:

Where  $x$  represents a reference image and  $y$  denotes a degraded image.  $\mu$  and  $\sigma$  indicate Gaussian weighted filtered average and standard deviation, respectively, and  $x y$  signifies covariance of  $x$  and  $y$ .  $C_1$ ,  $C_2$ , and  $C_3$  are non-zero constants to avoid instability. Luminance (first term) measures the similarity of local

averaged luminance value. Contrast (second term) measures the similarity of local variation whereas structure (third term) measures the cross correlation

$$S_{local}(x, y) = \frac{2\sigma'_x\sigma'_y + C_1}{\sigma'_{x^2 + \sigma'^2_y} + C_1} \cdot \frac{\sigma_{xy} + C_2}{\sigma_x\sigma_y + C_2} \dots (1)$$

The original image SSIM algorithm is applied locally and it contains structure and contrast. here we have three parameter function to scalarize the joint measure ,resulting in tone mapped image quality index (TMQI)

$$Q = aS^\alpha + (1 - a)N^\beta \quad (2)$$

Where  $0 \leq a \leq 1$  adjusts the relative importance of the two components, and  $\alpha$  and  $\beta$  determine their sensitivities, respectively . since both S and N are upper – bounded by 1, the overall quality measure is also upper bounded by 1.

The parameters in (2) are left to be determined. In our implementation, they are tuned to best fit the subjective evaluation data provided. in their experiments, the subjects were instructed to look simultaneously at two LDR images created by two different TMOs applied upon the same HDR images, and then pick the one with better overall quality the data base includes 6 data sets, each of which contains images generated by 5 well-known TMOs, introduced by dragon et.al this iterative learning process further more to ensure the process if the model generates the objective score that given the same order of the pair as the subjective rank order we conducted a leave -one -out cross validation procedure, where the database (of 6 data sets was divided in to 5 training sets and 1 testing set, and the same process was repeated 6 times, each with a different division between training sets. Although each time ends up with a different set of parameters, the are fairly close to each other and result in the same ranking orders for all the training and testing sets.in the end we select  $b=0.1012$ ,  $a =0.8026$  and  $\beta = 0.7088$  . and final  $b=0.1$  as our final model image generated ., parameter  $A = \pi r^2$  coecoe=0.1677 output value.

1)spear man's rank -order correlation (SRCC)

$$SRCC = 1 - \frac{6 \sum_{i=1}^N d_i^2}{N(N^2 - 1)} \quad (3)$$

2)Kendall's rank-order correlation coefficient (KRCC) is another non-parametric rank correlation metric computed as

$$KRCC = \frac{N_C - N_d}{1/2N(N-1)} \quad (4)$$

**Standard Deviation:** the SSIM approach provides a useful design for measuring structural fidelities between images . comparison of three components

- luminance , and contrast structure , TMO are mean to change the local intensity and contrast , direct comparisons to local and contrast are in appropriated . let  $x$  and  $y$  be two local images patches extract ed from the HDR and the tone mapped LDR images respectively. Local structural fidelity measure as

$$S_{local}(x, y) = \frac{2\sigma'_x \sigma'_y + C_1}{\sigma'_{x^2 + \sigma'^2 y^2} + C_1} \cdot \frac{\sigma_{xy} + C_2}{\sigma_x \sigma_y + C_2} \dots (5)$$

stranded deviation is a measure structural fidelities between images. how spread out numbers are. Its symbol is  $\sigma$  (the greek letter  $\lambda\sigma$ ) The formula is easy: it is the square root of the Variance between  $x$  and  $y$ .

## V. EXPERIMENTAL RESULTS FOR ALGORITHM 2 VALUE TABLE PERFORMENCE EVALUTION S USING 4 IMAGE SETS AND 4 TMOS

	IMAGE SETS	1	2	3	4
EXISTING SCHEME	STANDAR D DEVIATO	0	0.025	0.0098	0.019
	COORELATI O N COEFFICIENT	0	0.80	0.78	0.90
PROPOSED SCHEME	STANDAR D DEVIATO	0.	0.0083	0.0072	0.0069
	COORELATI O N COEFFICIENT	0	0.83	0.85	0.92

$$\sigma' = \frac{1}{\sqrt{2\pi}\theta} \int_{-\infty}^{\sigma} \exp \left[ -\frac{(x-\lambda_\sigma)^2}{2\theta_\sigma^2} \right] \dots (5),$$

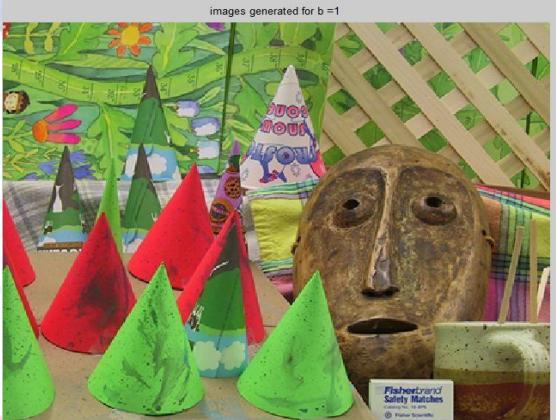
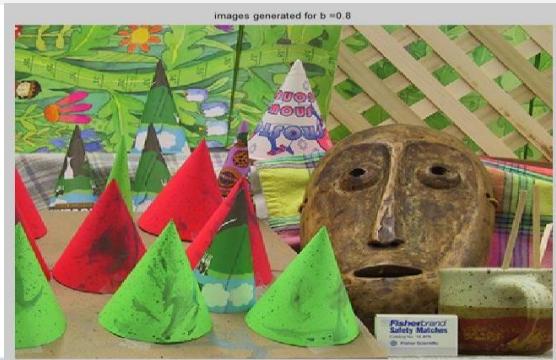
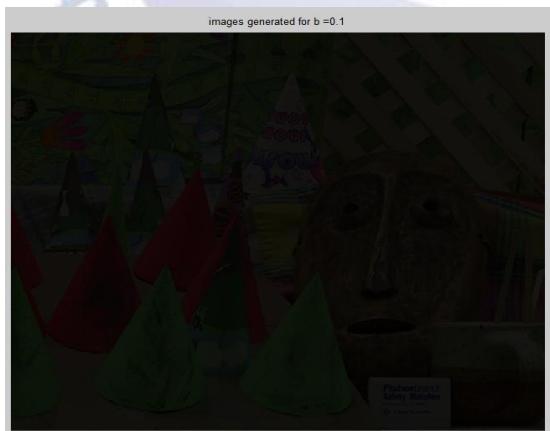
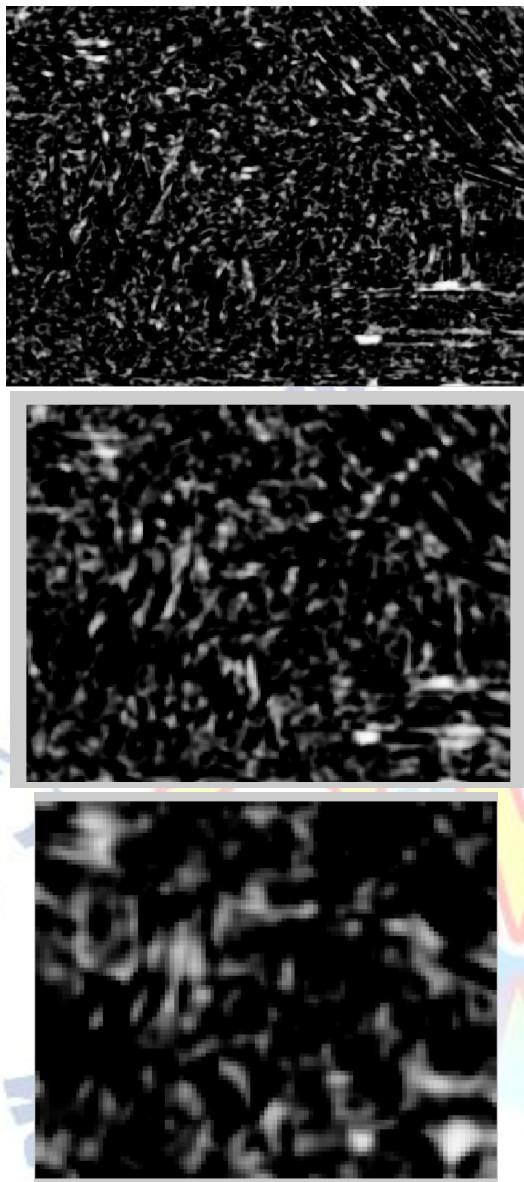


Fig:5 LDR images generated with different parameter  $b = 0.1, S=0.8, N= 0.7$

**STANDED DEVIATION OUTPUT IMAGES**

*Fig:6 Tone mapped LDR image and structural fidelity maps in scale the images "highlightcompressiond" exposure and gamma" s=0.8,b=0.1,b=0.9.*

**VI. CONCLUSION**

In this project, we proposed a new histogram-based image contrast enhancement algorithm using the histograms of color and depth images. The histograms of the color and depth images are first partitioned into subintervals using the Gaussian mixture model. The partitioned histograms are then used to obtain the layer labeling results of the color and depth images. The sub intervals of the color histogram are adjusted such that the pixels with the similar intensity and depth values can belong to the same layer. Therefore, while a global image contrast is stretched, a local image contrast is also consistently improved without the over

enhancement. We plan to extend our layer -based algorithm to a segment based algorithm by using a joint color-depth segmentation method. In the proposed technique the tone mapped operator is used. By using the we can obtain the missed out regions of an image on compression with the other image. Resolution can also be decreased for further time reduction. So, both resolution and image size reduction can yields the performance degradation of original image. The histograms of the color and depth images are first partitioned into sub-intervals using the Gaussian mixture model. The sub-intervals of the color histogram are adjusted such that the pixels with the similar intensity and depth values can belong to the same layer. Therefore, while a global image contrast is stretched, a local image contrast is also consistently improved without the over-enhancement.

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