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Image Contrast Enhancement using Depth Image

Ashish B. Umredkar
Department of Computer Science and Engineering
Priyadarshini Institute of Engg. and Technology
Nagpur, India

Prof. Leena H. Patil
Department of Computer Science and Engineering
Priyadarshini Institute of Engg. and Technology
Nagpur, India

***Abstract*- In this paper, we proposed a newregion based contrast enhancement algorithm for local and global contrast of an image. An image is segmented by detecting all objects in an images using saliency map technique. A depth map is generate using salient object detected image and original image. We generate two depth map, background and foreground depth map. Combining both we get depth image of input image, which is gray image and highlight the foreground objects which is the region of interest. Segmented this depth image about its mean value and consider pixel having high value. The original image is modified according to that. Finally modified Laplacian pyramid framework with detail enhancement is applied on modified image. In this methodology global and local contrast is improved without over enhancement.**

***Index Terms* - Contrast enhancement, saliency map, Depth image, detail enhancement, Laplacian pyramid.**

I. INTRODUCTION

In image processing, image enhancement means improving the quality of image by different techniques likes as contrast stretching, color enhancement, sharpening and smoothing of image and by processing on image histogram. Among various enhancement techniques, histogram equalization and modifications based techniques received great attention. To emphasize more information depth image along with original image is used. Depth image provide more information and also used for segmentation of image in different regions.

Brightness Preserving Histogram Equalization with Maximum Entropy (BPHEME) [3] is used to preserve brightness of image to overcome the drawback of Histogram Equalization which can yield the optimal equalization in the sense of entropy maximization by making histogram flat. But the drawback of this paper is it do not stretched target histogram explicitly but maximize entropy instead which doesn't means contrast enhancement but contrast stretching to some extent.

To overcome the drawback of BPHEME, Flattest histogram specification with accurate brightness preservation (FHSABP) is employed [4], which transform the histogram into a target flattest histogram, subject to a mean brightness constraint. FHSABP tries to find the optimal histogram, which is the flattest one with the mean brightness constraint. But, when the gray level of the input image are equally distributed, FHSABP behave similar as HE.

Adaptive bilateral filter (ABF) used for sharpness enhancement and noise removal. To remove noise, conventional filter are used. Combining the range filter and the domain filter we get a bilateral filter[5]. Previously, un-sharp masking (USM) algorithm is used for sharpening the edges. But the drawback of this method is produces halo around the edges and amplify noise if present in image. To address this problem adaptive bilateral filter is used. ABF outperforms the bilateral filter in noise removal. At the same time, it renders significantly sharper images. Compared with an USM based adaptive sharpening method, ABF stored edges are as sharp as the USM restored edges, but without the halo artifacts as produced by USM.

In the last years, many different solutions have been proposed for the extraction of depth information relative to a real world scene. A depth map is an image or image channel that contains information relating to the distance of the surfaces of scene objects from a viewpoint. Various systems have been proposed in order to solve this task, each one with pros and cons. There are two main groups of methods, passive and active methods. Passive methods use only the information coming from two or more standard cameras to estimate the depth. Among them stereo vision systems[7], that exploit the localization of corresponding locations in the different images are most widely used. Another possible solutions are the active methods such as structured light, laser scanners and Tof

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sensors. By projecting some form of light on the scene such methods can obtain better results than passive stereo vision systems, but they are also usually more expensive.

Binocular Just-Noticeable Difference (BJND) [7] provides a new sharpness enhancement algorithm for stereo images. They introduced a novel application of the BJND model for the sharpness enhancement of stereo images. An efficient solution for reducing the over enhancement problem in the sharpness enhancement of stereo images was proposed. The solution was found within an optimization framework with additional constraint terms to suppress the unnecessary increase in luminance values. The BJND is a threshold related to the inter difference between the left and right views that a human can recognize.

A Gaussian Mixture Model (GMM) [8] is a parametric probability density function represented as a weighted sum of Gaussian component densities which automatically enhances the contrast in an input image. The algorithm uses the Gaussian mixture model to model the image gray-level distribution. The intersection points of the Gaussian components in the model are used to partition the dynamic range of the image into input gray-level intervals. The contrast equalized image is generated by transforming the pixels gray levels in each input interval to the appropriate output gray-level interval according to the dominant Gaussian component and the cumulative distribution function of the input interval.

Adaptive joint trilateral filter (AJTF)[9] is obtain by modifying adaptive Bilateral Filter for which the parameters are determined according to the accuracy of the depth map and image. AJTF consists of domain, range and depth filters which is used for the joint enhancement of images and depth maps, achieved by suppressing the noise and sharpening the edges.AJTF successfully performed joint enhancement when both the image as well as depth map had poor quality. AJTF showed better performance compared to conventional depth enhancement algorithms but the computational complexity of the AJTF is high.

A new method for enhancement of image using color and depth image is introduced in [10]. The input is pair of color and depth images. Depth image is generate using stereo matching algorithm. Proposed algorithm modifies the histogram of the color image using the histogram of the depth image as side information. Histogram modification is applied to the intensity channel of color image only and the resultant image is obtained by transforming the color space back to the RGB space. For partitioning Gaussian Mixture Modeling based portioning method is used. The significant intersection point then used to partition the histogram sub-intervals. The drawback of this method is very time consuming process.

II. PROPOSED METHODOLOGY

In a previous work of enhancement of image using color and depth image, the enhancement is done using layered approach. Here we used region based approach for the enhancement of image. In this letter we take low contrast color image as input. Then finding all objects in an image and enhance them. Finally enhance all image. The proposed technique have three part.

1) Detection of objects in an image using saliency map technique.

2) Generate depth image using color and saliency object detected image.

3) Applying Laplacian pyramid with detail enhancement algorithm.

A. *Object Detection*:-

Saliency object detection is important for adaptive content delivery and image resizing.

Image Signature

The gray-scale images exhibit the following structure:

$$x = f + b \quad x, f, b \in \mathrm{IR}^n$$

Where f represents the foreground or figure signal and is assumed to be sparsely supported in the standard spatial basis. b represents the background and is assumed to be sparsely supported in the basis of the Discrete Cosine Transform. Performing the exact separation between b and f given only x. For the problem of figure-ground separation, we are only interested in the spatial support of f (the set of pixels for which f is nonzero) [12].

a) Generating saliency map of an image

Here we show saliency detection using the image signature. The reconstructed image detects spatially sparse signals embedded in spectrally sparse backgrounds. The exact details of the saliency algorithm are as follows: First, a color image is resized to a coarse 64 × 48 pixel representation. Then, for each color channel x^i, the saliency map is formed from the image reconstructed from the image signature

$$m = g * \sum_i x^{-i} \circ x^{-i}$$

Where g = Gaussian blurring kernel

For the choice of color channels, we use both RGB and CIELAB color spaces. The algorithms associated with these choices will be referred to as RGB-Signature and Lab-Signature respectively. An illustration of this RGB-Signature algorithm is shown in Fig.1 [12].

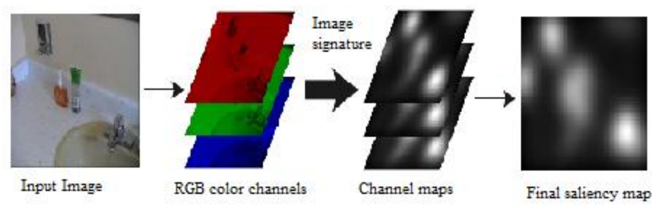

Fig. 1. An illustration of the RGB-Signature algorithm.

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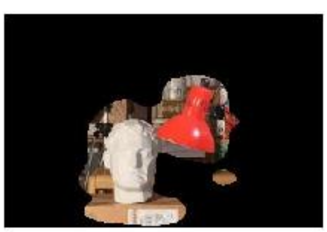
The input color image is decomposed into three channels. A saliency map is computed for each color channel independently, and the final saliency map is simply the sum across three.

b) A simple procedure to detect salient objects in an image

A simple method to find saliency map is given here. The input for this procedure is color image. As all color image are 8 bit image and processing on color image is very time consuming task. Convert RGB image to Gray scale image. Find out the entropy of image. Entropy means energy i.e. information contain in an image. As image consist of background and foreground. The foreground object image consist of maximum information i.e. entropy of foreground object is high as compare to background object. So we can easily segment an input image into image having only objects.

Fig.2.a is the input image. Applying saliency map technique to input image, it converted into hyper-complex representation. In this image white portion shows the entropy of corresponding pixels. As we can see that this is foreground object from input image i.e. this pixel have maximum information indicating objects. The resultant image is smooth 8 times. As we have interested in foreground object, all background pixel value is set to 0 which is shown in fig. 2.b. This image is called saliency map. In final step we impose fig.2.b on input fig.2.a so we get respected pixels and there color (R, G, B) values. Because of we interested in object detection, all background pixels values other than shown in fig.2.b set to be 0 and we get only object. Fig.2.c represent detected object.

a. input image



b. Saliency mapc. Salient object

Fig. 2. Experimental result corresponding to object detection.

B. Generate depth image

The depth map is generate using single color image. For the generation of depth map, saliency detected image is used. The background and foreground depth image is calculated separately using saliency detected image and join then finally to get final depth map. The input for this process is original input image and saliency detected image with same dimension. The stepwise process for generation of depth map is listed as below.

1. Get gray image of original RGB image.
2. Get gray image of final saliency object detected image.

Assign variables values FG=255 and BG=127, quantization=10.

For background image

1) Find indices of all non-zero pixel values using saliency object detected image. As saliency object detected image show only foreground object and value of all background pixel is set as zero.
2) Set pixel values of all indices to zeroin original gray image so we get only background image.
3) Find maximum value of pixel in that image.
4) Divide each pixel by maximum value i.e normalize to 0...1 range.
5) Now multiply each pixel to BG so that it normalize to 0...127 range.
6) Rounding pixel value using formulae – round(map_bg/quantization)*quant, which give nearer value(map_bg is background depth image).

For Foreground image

1) Find indices of all zero pixel values using saliency object detected image, which give only background values.
2) Set pixel values of all indices to zero in original gray image so we get only foreground image.
3) Find maximum value of pixel in that image.
4) Divide each pixel by maximum value i.e normalize to 0...1 range.
5) Now multiply each pixel to FG and add BG value in that. Because we have interest in foreground object.
6) Rounding pixel value using formulae - round(map_fg /quantization)*quant, which give nearer value(map_bg is background depth image).

Finally add both image i.e. foreground and background depth image to get final depth image. The depth image is gray image which highlight foreground object. The reason behind assigning 255 value to variable FG is to highlight foreground object i.e. region of interest and adding value of BG which is 127 to all foreground depth image pixels.

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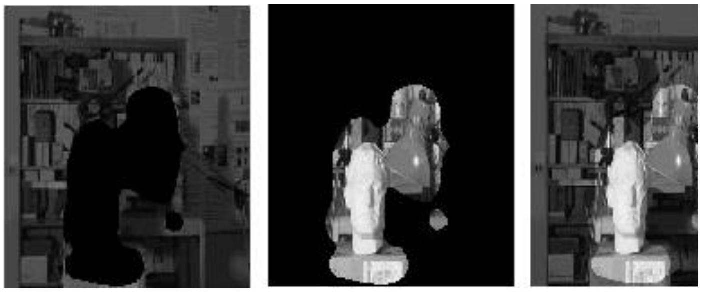

a. Background depth b. foreground depth c. depthimage

Fig 3. Depth Map generation

C. *Enhancement using Laplacian pyramid with detail enhancement*

This enhancement process is applied on color image only. The original low contrast image is being modified by the depth map obtained above. We take only pixels having value greater that it's mean and modify them. The modified image is taken as an input to the Laplacian pyramid method. HE-based algorithms generally paid attention to improve the global contrast of an image and paid little attention to local information such as edges[15]. This issue is considered to be the inherent limitation of HE methods. To overcome the above problem, we chose a Laplacian framework for enhancement. In this method RGB input image is transformed to I_0 luminance and then decomposes I_0 into band-pass images. The RGB input image and I_0 are reused in the final step of the color restoration. Generate the Laplacian pyramid for the given image, for *N*particular levels. So using the equation,

$$I_0 = I_N + \sum_{n=1}^{N} D_n$$

Where *N* is the highest decomposition layer. I_n are Gaussian low-pass filterimages. D_n are Laplacian images by subtracting high level I_{n+1} from a low level. For every intensity (R,G,B) images all enhancement process is applied and finally combine all image to get final enhanced image.

1. *Generate histogram*

In this framework, first contrast is enhanced using HEbased algorithm. To generate the histogram withluminance levels in the range *K* [0, *L*-1] as a discrete functionis described as

$$h(l_k) = n_k$$

Where $l_k$is the kth luminance level in *K* and $n_k$represents thenumber of pixels.

2. *Smooth the histogram using Gaussian filter*

In the histogram, a ridge shape with some consecutive luminance levels can be regarded as the feature area of an image. To globally distinguish between ridges and valleys and remove their ripples, we smooth the histogram [15] like as follows:

$$h_g(l_k) = h(l_k) * g(l_k)$$

Where

$$g(x) = e^{-x^2}$$

Were g(x) is Gaussian function, x is the corresponding location to a bin of the histogram, and coefficients of the Gaussian filter are normalized.

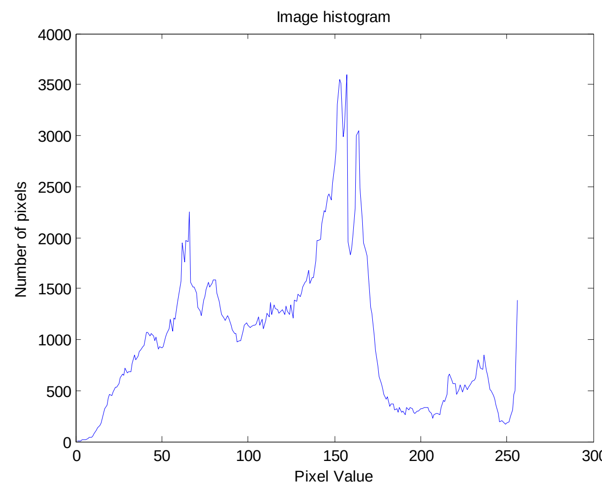

Fig. 4. Histogram of Red intensity image.

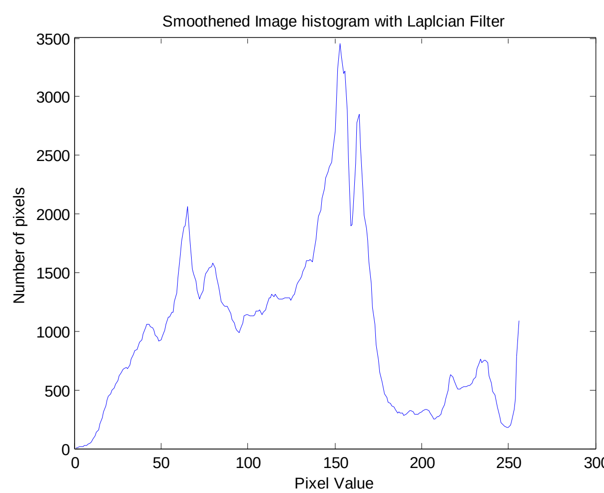

Fig. 5. Smooth histogram of Red intensity image.

3. *Boost minor areas (small ridges).*

Boosting minor areas [15], i.e. small ridges, in the histogram is one of the key strategies of the proposed contrast enhancement to suppress the quantum jump. The peak value in the smoothed histogram $h_g(l_k)$ is found as

$$p(k) = \max_{k \in K}\{h_g(l_k)\}$$

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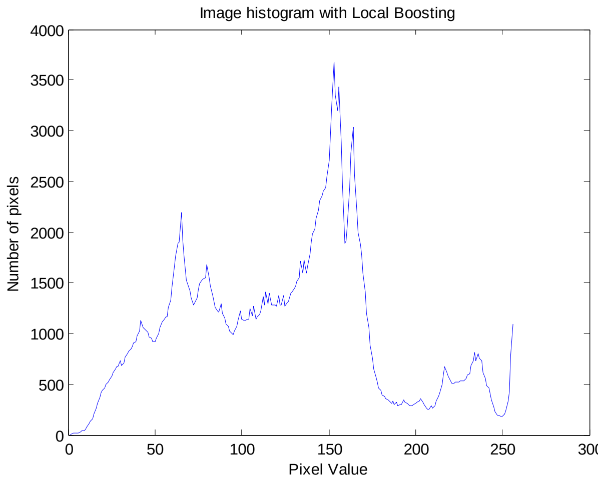

Fig. 6. Histogram of R image with local boosting.

When the previous and next values are less that current values we get peak.The current value is modified as percentage_value = current_value / sum(img smooth hist);
current_value = current_value + (percentage_value * max hist * beta); where beta=5 which is constant.

4. *Slantwise clipping*

The clipping technique[15] is used as it effectively suppresses the quantum jump. We find the mean of newly generated histogram and then find the mid value and then we gather the residual from local and global clipping. Suppose two variable point point (0, y_1) or (I_{max}, y_2) at slant line of the histogram depict the position of y_1, y_2 depending on I_{mean} value. The variable values y_1, y_2 are as fallows.

$$y_1 = -0.5p(K).\left[{}^{I_{mean}}/_{I_{mid}}\right] + p(K)$$
$$y_2 = 0.5p(K).\left[{}^{I_{mean}}/_{I_{mid}}\right] (8)$$

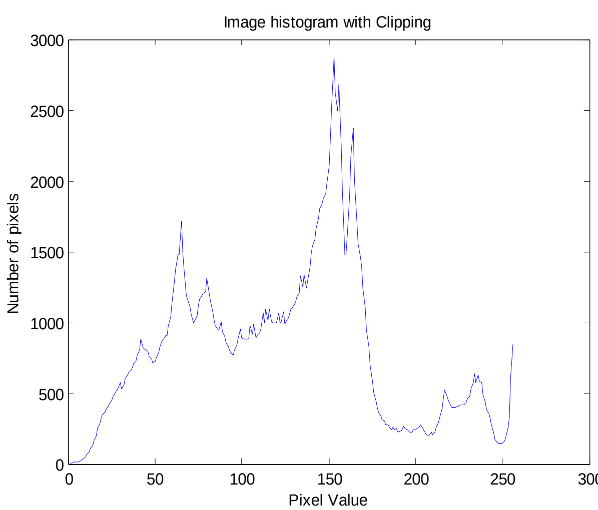

Fig. 7. Histogram of Red intensity image with clipping.

Detail Enhancement

Detail enhancement[15] improve the local information of an image. To solve this problem detail enhancement initially separate an image into band-pass image. It adopt an adaptive gain function mostly used in decomposition-based algorithm. It also used noise reduction function which attenuates estimated noise and prevents them from being amplified due to the adaptive gain function. The detail gain function of an image layer is as follows:

$$f^d(i,j) = [f^1(i,j).f^2(i,j)] * g(i,j)$$

Where f^1 and f^2 are adaptive gain function and noise reduction function respectively and g is Gaussian filter.
The adaptive gain function is as follows.

$$f_n^1(i,j) = {}^1/_{\{q.[I_n(i,j) + 1.0]^p\}}$$

Where p is gain parameter and q depends on p, p=1/ (2^p).

Noise reduction function is as fallows.

$$f_n^2(i,j) = NR_{offset} + \left\{ {}^{NR_{band}}/_{[1 + e^{-(D_n(i,j) - E_n)}]} \right\}$$

Where NR_{offset} is a noise gain offset, NR_{band} is a noise gain band.

Color Restoration

After applying all process to red, green and blue intensity image we get enhanced new red, green and blue image. Add all intensity image we get color enhanced image. Final enhanced image is obtain by combine this image with detail enhanced image, which enhanced local and global information.
The enhanced image is obtained as

$$I' = I'_N + D'$$

By adding Laplacian enhancement and detail enhancement we get final enhanced image.

a. Input Image b. Object enhanced c. final enhanced

Fig. 8. Enhanced Image.

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III. EXPERIMENTAL RESULT

In order to evaluate the performance of the proposed algorithm, following low contrast image were used in our experiment. Depth image is obtain form a single input image which take less time to execute. The table shows the performance details and effectiveness of the proposed method. Peak signal to noise ratio (PSNR) indicates enhancement of an image. This ratio is often used as quality measurement between original and reconstructed image. Higher the PSNR value greater the quality of reconstructed image. Root Mean Square Error (RMSE) is also shown for each image.The total time required for enhancement using this methodology is less as compare to existing methods. Image enhancement using color and depth map using layer labeling approach takes more than 1 minute for enhancement [10]. Our segment based approach takes less than a minute for the process of enhancement which enhanced local and global contrast.

Table 1: Result obtained from different images. PSNR, RMSE and Execution Time for enhancement.

Image	PSNR (dB)	RMSE (dB)	Execution time (sec)
Lamp	15.53	42.67	26.79
Doll	18.34	30.85	25.77
Drumsticks	14.44	48.37	25.77
Laundry	13.17	55.96	25.72
Moebius	13.71	52.61	26.24

IV. CONCLUSION

In this paper we proposed a new image contrast enhancement technique using depth image. The process of detecting salient region and generating depth map is easy to implement and take less time to execute. The proposed system enhance local as well as global contrast without over enhancement. This method is fast, easy to implement and generates high quality enhanced output image.

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