Globus: An International Journal of Medical Science, Engineering and Technology
A Refereed Research Journal
Vol 3 / No 2 / Jul - Dec 2014 ISSN: 2319-8958

# MULTIHISTOGRAM EQUALIZATION METHODS

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**Abstract**

The present paper explains about the intensity value that divides the image in to sub images is the optimal threshold set. The optimal threshold can be calculated using different methods but here we use two methods to calculate the threshold set. The first algorithm calculates the optimal threshold set based on the within class variance and divides the input image in to different sub images based on the threshold set. The second algorithm divides the input image in to several sub images based on the optimal threshold set generated using Otsu method.

**Keywords: Histogram, technique.**

## INTRODUCTION

Multi Histogram Equalization is a technique in which the input image is divided in to multiple sub images and then Histogram Equalization technique is applied for each sub image.

The intensity value that divides the image in to sub images is the optimal threshold set. The optimal threshold can be calculated using different methods but here we use two methods to calculate the threshold set. The first algorithm calculates the optimal threshold set based on the within class variance and divides the input image in to different sub images based on the threshold set. The second algorithm divides the input image in to several sub images based on the optimal threshold set generated using Otsu method. The image is divided up to a scale r, so that $2^r$ sub images are generated. Where r can any predefined value.

The main idea behind the Multi Histogram Equalization Methods is to find an optimal threshold set $T^k = \{ t^1_k , t^2_k, .......,t^k_{k-1} \}$. The given input image is divided in to two sub images based on the mean value. The optimal threshold set is then calculated for each sub image and the original image is then divided in to K sub images $I[ l_s^1, l_e^1],.....,I[l_s^k, l_e^k]$, where $l_s^1$ referred to the minimum threshold value in the first sub image and $l_e^1$ referred to the maximum threshold in the first sub image. After dividing the image in to sub images apply Histogram Equalization Method for all the sub images and combine the equalized images to obtain the desired result.

### Minimum Variance Multi Histogram Equalization

**Step 1:** Calculate the histogram of the image.

**Step 2:** Based on the mean Brightness value**,** divide the histogram in to two classes.

**Step 3:** Calculate the within class variance for both the classes. Within class variance is calculated as shown in equation (4)

$Disc(i)=(i-Im)^2 * p(i)$ (4)

Where $I_m$ is the average of all the intensity values within each class.

p(i) is the probability density function and ‘i’ is the intensity value.

**Step 4:** Consider the intensity value that yeilds Minimum Within Class variance and divide each class in to different sub images.

**Step 5:** Apply Histogram Equalization technique for all the sub images.

Otsu method is used to perform histogram shape-based image thresholding. The method assumes that the input image contains two classes of pixels or bi-modal histogram i.e., foreground and background, and then calculate the threshold separating these two classes.

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The extension of multi-level thresholding is referred to as the Multi Otsu method, in which multiple threshold values are identified to divide the image in to multiple sub images.

### Optimal Thresholding Multi Histogram Equalization

**Step 1**: Calculate the histogram of the image.

**Step 2:** Based on the mean Brightness value**,** divide the histogram in to two classes.

**Step 3:** Calculate the optimal threshold set using otsu method.

**Step 4:** Based on the optimal threshold set divide the image in to different sub images.

**Step 5:** Apply Histogram Equalization technique for all the sub images.

### Global Histogram Equalization

Histogram equalization is a technique used to enhance the contrast of an image. The statistics of the image are collected and represented in a graphical representation showing the distribution of image data. Color images are frequently delivered from cameras in red green blue (RGB) signals or spaces. It is also a common strategy to enhance a color image by first converting the image to its intensity-related space, where enhancement operations are applied. The intermediate results are then converted to eventually give an enhanced color image.

Let the input or original color image be represented by

$$\mathscr{I} = \{\mathbf{I}_{uv}\}, \quad \mathbf{I}_{uv} = \left[R_{uv} G_{uv} B_{uv}\right]^T ,$$

where $u$, $v$ are pixel coordinates in the width and height dimensions, respectively.

Since the RGB space contains three color-related signals, it is intuitive to operate on the three signal spaces simultaneously for image enhancement. Furthermore, since the human visual system is sensitive to intensity variation when accessing image contrast, the image is converted before applying enhancement. For example, the image is commonly converted to the hue saturation value (HSV) format:

$$\begin{bmatrix} H \\ S \\ V \end{bmatrix}_{uv} = \mathbf{T}\left(\begin{bmatrix} R \\ G \\ B \end{bmatrix}_{uv}\right) = \begin{bmatrix} \arctan(\sqrt{3}(G-B)/(2R-G-B)) \\ 1 - 3 \times \min(R,G,B)/(R+G+B) \\ \max(R,G,B) \end{bmatrix},$$

where the $H$ component represents the color tone, $S$ denotes saturation and $V$ corresponds to the image intensity. The restoration from HSV to RGB space is conducted using $\mathbf{T}^{-1}()$, the inverse transform of $\mathbf{T}()$.

A histogram is obtained from intensities $V_{uv}$, giving

$$\mathscr{H} = \{h_i\}, \quad \sum_{i=1}^{L} h_i = N,$$

where $h_i$ is the number of pixels having the $i^{th}$ intensity level and $N$ is the total number of pixels. The number of levels is taken as $L = 256$, corresponding to 8-bit ($2^8 = 256$) electronic display.

In principle, image contrast will be enhanced as long as one can make use of the whole available intensity range. A uniform histogram is therefore used, where the numbers of pixels that fall inside each intensity level are equal. That is, the desired histogram is

$$\mathscr{H}^d = \{h_j^d\}, \quad h_j^d = NL^{-1}, \quad j = 1, \ldots, L.$$

To perform enhancement, two cumulative histograms are constructed from the input and desired histograms, respectively. We have

$$\mathscr{C} = \{c_i\}, \ c_i = \sum_{k=1}^{i} h_k; \ \text{ and } \mathscr{C}^d = \{c_j^d\}, \ c_j^d = \sum_{k=1}^{j} h_k^d.$$

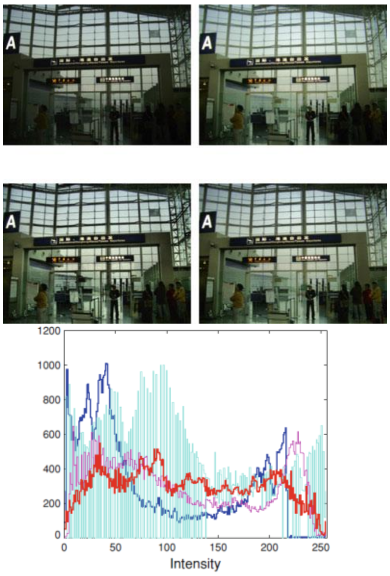
For a pixel with original intensity $i$ in the cumulative histogram $C$ at the $c_i th$ position, its equalized intensity value is obtained by referring to the $c^d_j th$ element in the cumulative desired histogram $C^d$ and overriding. That is,

$$j = \{i : c_i = c_j^d\}.$$

The aforementioned process is referred to as global histogram equalization because all pixels in the image are used in constructing the histograms. This method is easy to implement but there are also limitations in its performance, particularly in viewing. To illustrate this remark, an image is taken for an indoor scene where the camera is being saturated from the background high-level illumination magnitude (Fig. a). The result from global histogram equalization is given in Fig. b. It is observed that some degree of enhancement is obtained for the people sighted at the bottom-right corner. Further comparison can be made with results from a canonical implementation of a local equalization scheme as well as the proposed approach, discussed in what follows, for which the results are shown respectively in Figs. c and d. It is noted that further contrast enhancements can be obtained, also illustrated by the bottom-right corner portion of the image, via the sectorized approach, while a better result is obtained from the proposed method. Histograms of the intensities of these images are plotted in Fig. e For the global equalization process, the histogram shown in cyan illustrates that there are occasions where some of the intensity ranges, with zero counts of pixel intensity, have not been utilized for conveying scene information. On the other hand, intensity ranges are more utilized in the two other sector-based equalization methods, as can be seen in Figs. c and d.

### Local Histogram Equalization

In order to enhance the contrast of a color image and to extract details not deliverable by global histogram equalization, a local equalization method is developed and reported in the remainder of this chapter. In brief, the proposed method consists of three major steps: (i) to independently equalize image sectors or blocks, (ii) to reduce intensity discontinuity along sector boundaries, and (iii) to aggregate an enhanced image using a weighted-sum scheme.




(e)

**Figure:** Performance of global against local/sectorized histogram equalization: **a** original image, **b** globally equalized image by a uniform target distribution, **c** canonical sectorized equalization result, **d** proposed sectorized equalization result, **e** resulting histograms, *blue*: original **a**; *cyan*: globally equalized image **b**; *magenta*: canonical sectorized equalization **c**; *red*: proposed sectorized equalization **d**, to be discussed.

## Sectorized Equalization

Given an image to be enhanced, the process starts first with its conversion from the RGB space to the HSV space, where the intensity component is denoted as *Vuv*.

Four sectors are then generated. The center point *(p, q)* of dividing the sectors is determined by randomly drawing a sample in the image. That is,

**Fig.** An intermediate image showing independently equalized sectors. Note intensity differences along the sector boundaries

$$p \sim \mathscr{U}(1, u_{max}), \quad q \sim \mathscr{U}(1, v_{max}),$$

Four sectors that are formed using the point *(p, q)* as the center, indexed by superscript $s = 1, \ldots, 4$, are given by

$$\mathscr{S}^{s}_{pq} = \begin{cases} \mathscr{I}_{1:p,1:q} \\ \mathscr{I}_{p+1:u_{max},1:q} \\ \mathscr{I}_{1:p,q+1:v_{max}} \\ \mathscr{I}_{p+1:u_{max},q+1:v_{max}} \end{cases}$$

Each sector $\mathscr{S}^{s}_{pq}$ is then equalized to the desired uniform distribution using the procedure described, giving equalized sectors as

$$\mathscr{E}^{sd}_{pq} = \{\mathscr{S}^{s}_{pq} : \mathscr{S}^{s}_{pq}(c_i) = \mathscr{E}^{sd}_{pq}(c_j)\}.$$

The result is depicted in Fig. where it can be seen that for each individual sector, the contrast is increased. However, it is also observed that along the sector boundaries, intensity differences or discontinuities are noticeable and need to be mitigated.

## Mitigation of Sector Discontinuities

In order to reduce the difference of intensities along sector boundaries, an arithmetic mean aggregation approach is adopted in order to combine the locally equalized

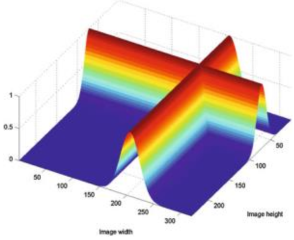


**Fig.** The Gaussian weighting kernel to remove boundary discontinuities corresponding to the sectors.

sectors. In addition, enhancements in each sector should be retained as much as possible. Here, these requirements are satisfied by weighting the sectors with a Gaussian kernel and then integrating with the original image.

Let a normalized one-dimensional Gaussian for each boundary be given by

$$\mathbf{G}^{b}(\delta, \sigma) = \exp\left(\frac{-\delta^{b2}}{2\sigma^{b2}}\right),$$

where superscript $b \in \{u, v\}$ denotes if the Gaussian is for the height *(v)* or width *(u)* for the image dimension, $\delta$ is the distance from the boundary along the associated dimension, and $\sigma$ is the Gaussian standard deviation. The overall Gaussian used to remove the boundary discontinuities is obtained from an element-wise maximization operation, that is,

$$\mathbf{G}_{uv} = \max\{\mathbf{G}^{u}(\delta, \sigma), \ \mathbf{G}^{v}(\delta, \sigma)\}.$$

The resultant Gaussian weighting kernel is shown in Fig.

The original image *I* and the complete image *E*, formed by aggregating the independently equalized sectors $E^{s}_{pq}$, are then fused to obtain a smoothed image $S_{sm}$. For this, the Gaussian weights and an element-wise operator $\odot$ defined by

$$\mathscr{S}_{sm} = \mathbf{G} \odot \mathscr{I} + (\mathbf{I} - \mathbf{G}) \odot \mathscr{E},$$

are used, where I is a matrix having dimension u ×v for all elements equal to unity. The smoothed image is depicted in Fig.

**Fig.** The boundary smoothed image is obtained by fusing the equalized and original images via the Gaussian weighting kernel

## Iterated Enhancement

The smoothed image in Fig. is obtained from a randomly selected center point *(p, q)*. A further improvement can therefore be expected from deliberate determination of a proper center point. For the purpose of ensuring enhancement across all possible cases of scene variations, a number of center points and sectors have to be generated and their enhancement conducted iteratively using histogram equalization.

To this end, a collection of smoothed images is created. Moreover, in order to produce an enhanced image from the smoothed images, a strategy for their combination using an information-based weighted-sum technique is adopted.

The quality of the smoothed intermediate image $S_{sm}$ is taken as information entropy. That is,

$$H_t = -\sum_{i=0}^{L} \log(p_i) p_i,$$

where subscript $t$ stands for the iteration count, $L$ = 255 is the maximum intensity, *pi* is the probability of pixel that takes on the *i*th intensity. The values of *pi* are obtained as normalized histogram elements *hi*.

In local and sectorized equalization, through the selection of a certain enter point to sector the original image as well as repeated calculation of the quality metric for, say, $\tau$ iterations, the final output can be obtained by first normalizing the information contents as

$$\bar{H}_t = \frac{H_t}{\sum_{t=1}^{\tau} H_t},$$

and then by combining this with a weighted-sum average of the intermediate resultant images, yielding

$$\bar{\mathscr{I}} = \sum_{t=1}^{\tau} \bar{H}_t \mathscr{S}_{sm,t}.$$

The result is depicted in figure. It can be seen that intensity discontinues are removed and contrast is increased in local sectors. This image then replaces the

**Figure:** Resultant image obtained from fusion of sectorized equalization and smoothing V-component in the HSV domain and is finally converted back to the RGB space as a color image.

## PSO-Based Parameter Optimization

In the above development and illustration, it is observed that effective results are obtained by incorporating an iterative smoothing operation into the sectorized local equalization approach. A nontrivial question can then be raised as to what should be the proper sector that divides the image and how should smoothing weighting be assigned. To this end, we solve these unknowns by the use of a multi objective optimization algorithm for which the computational effectiveness remains a requirement.

For this, particle-swarm optimization (PSO) is used as described in the following.

The PSO algorithm can be viewed as a stochastic search method for solving nondeterministic optimization problems. For example, in the problem at hand, the sector center point *(p, q)* and the standard deviation $\sigma$ of the smoothing Gaussian are coded as particles:

$\mathbf{x} = [p_1, q_1, \sigma_1, \ldots, p_\tau, q_\tau, \sigma_\tau]T$ ,

where each set of parameters or part of the particles $\{p, q, \sigma\}$ gives one smoothed image from the sectorized histogram equalization approach.

At the start of the algorithm, the particle positions are generated to cover the solution space. These positions may be deterministically or randomly distributed and the number of particles is predefined. In general, a small number reduces the computational load but at the expense of extended iterations required to obtain the optimum (but the optimal solution is not known *a priori*). The velocities **v***i*0 can also be set randomly or simply assigned as zeros. A problem-dependent fitness function is evaluated, and a fitness value is assigned to each particle. Here, the fitness function is taken from the entropy of the image given in Eq. For the set of fitness values, the one with the highest value is taken as the global best **g***best* (for a maximization problem). This set of initial fitness values is denoted as

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