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Color Barycenter Model based Multi-Histogram Mapping and Merging for Image Enhancement

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Abstract

In this paper, the color barycenter model (CBM) based image enhancement method using multi-histogram mapping and merging is presented. Generally, histogram analysis based methods are effective for contrast enhancement, but this kind of method is hard to enhance the dark and bright regions efficiently simultaneously, such as the back-light image. To solve this problem, a mapping function is studied for multi-histogram mapping to obtain several images with different contrast, and merging them by the best patch selecting of every position. Firstly, using the CBM to calculate the gray component as the input data. Secondly, obtaining several image with different contrast by our mapping function. Thirdly, calculating the gradient feature of the separated patches and selecting the best ones for merging. Finally, using the mix Gaussian filter to smooth the merged image. Based on the proposed approach, enhancement can be achieved for global/local regions under different light conditions. The experimental results show better effectiveness than other methods.

1 Introduction

Image contrast enhancement plays a crucial role in image processing which makes image can be easily observed. However, the images with poor contrast often exist in practice because of poor quality of imaging device, adverse conditions of acquisition, and so on. So many methods have been proposed for contrast enhancement to obtain more visually pleasing and informative image.

Histogram analysis is one of the popular technique. Among them, histogram equalization (HE) is considered as the classical method. However, HE is not effective when the contrast characteristics vary across the image. To overcome this drawback, the adaptive HE [1] is proposed to generate a mapping of each pixel in the surrounding partition of histogram, and many researchers improve this approach in their studies. As well as HE based methods, histogram specification (HS) based methods and transform based methods were also studied.

The purpose of HE based approach is to make the histogram become to flat in local or global region with some strategies [2, 3, 4]. It is different from HE and HS, which 'knows' the new histogram and try to 'close' it to merge the characteristics of both histograms [5, 6, 7]. The transform based approaches are try to transfer the image into frequency space for analyzing and modifying the image more easier [8, 9, 10].

The methods for image enhancement are widely studied and they can also work well for some certain images. But if the image includes too bright or too dark regions locally, these methods will lose effectiveness. By analyzing the shortage of these methods, we find that they didn't consider all different regions in one step. So for overcoming the deficiency of existing methods and remedy the one scene only has one image's problem, the multi-histogram mapping and merging method is proposed.

For color image enhancement, the researchers usually select one component, which can reflect the main information of an image, from different color space. However, no one can say the selected component of different color space is best and suitable for different kinds of images. In this paper, our color barycenter model (CBM) is used to convert color images to gray ones, which can preserve more details and color characteristic.

2 Proposed Method

2.1 The framework of proposed method

To overcome the shortage of signal image based method, an effective framework is presented as shown in Fig. 1. The procedure is introduced as follows:

1. Calculate the new gray component G_{BC} by CBM.
2. Map the gray image G_{BC} to several images with different contrast by mapping function.
3. Separate the image into several patche and calculate the feature vector to select the best ones in same position.
4. Combine all the selected patches as the mergence mask and used for merging image.
5. Remove the sharp transitions of the merged image using mix Gaussian filter.

In following sections, these five steps will be discussed in detail.

2.2 Gray Image Acquisition

In our previous work [11], the CBM is proposed. The main idea of it is to convert one pixel in RGB color space (one 3D point) into 2D color triangle with three 2D points, and then use them to calculate the color barycenter (one 2D point),which can be used to reflect the color characteristic easier than other color space. More details and definitions are introduced in [11].

In this paper, the CBM is used to calculate the distance from the color barycenter to the three color apexes as the weight. And then normalize the weight

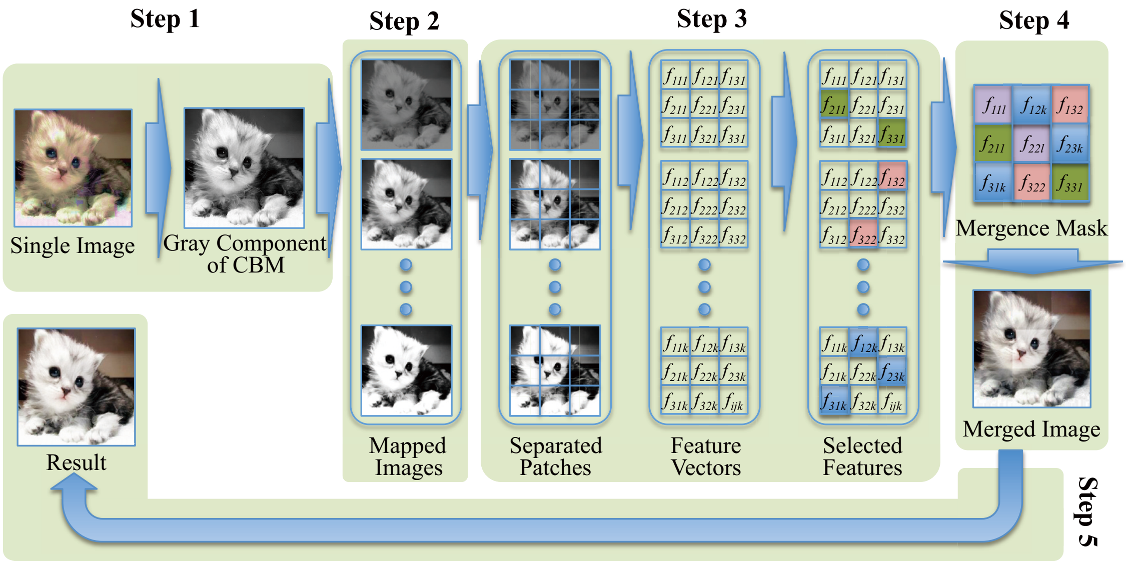


Figure 1. Framework of multi-histogram mapping and merging

of R, G, and B by following equation to obtain the gray like component G_{BC} (step 1 of Fig. 1).

$$G_{CB} = W_{CR}R + W_{CG}G + W_{CB}B, \tag{1}$$

where

$$\begin{cases} W_{CR} = \frac{d_{CR}}{d_{CR}+d_{CG}+d_{CB}}, \\ W_{CG} = \frac{d_{CG}}{d_{CR}+d_{CG}+d_{CB}}, \\ W_{CB} = \frac{d_{CB}}{d_{CR}+d_{CG}+d_{CB}}. \end{cases} \tag{2}$$

The d_{CR}, d_{CG}, and d_{CB} are the distance from color barycenter to three color apexes.

2.3 Multi-Histogram Mapping

Usually, when we capture an image for revealing the real scene, some regions of the image may too bright or too dark. The existing methods can enhance the whole image globally, but it is hard to enhance the dark regions enough. So here the multiple histogram mapping based method is used to enhance different regions, respectively (step 2 of Fig. 1). Here we present a mapping function to map the histogram to obtain several image with different contrasts. Through abundant analysis and test, we find that the curve as shown in Fig. 2 can be used to map the histogram easily and enhance or reduce different region with luminance. So the modified parabola function is defined as the mapping function:

$$MF(g) = mf \times g + (1 - mf) \times g^2, \tag{3}$$

where g is the value of current histogram which normalize to $[0, 1]$ and mf is the mapping factor which can affect the contrast of image. Considering the normalized gray value must be in [0, 1], so if $MF(g) > 1$, let $MF(g) = 1$; and if $MF(g) < 0$, let $MF(g) = 0$.

Fig. 2 gives the illustrator and a real landscape image with different contrast to show the influence of mf. In our experiment, we set the total number N of mapped images as 4 and $mf = \{-0.5, 1.0, 2.0, 3.0\}$. After this operation, the new images with different contrasts can be obtained. The next step is to separate the images as several regions for selecting the best ones.

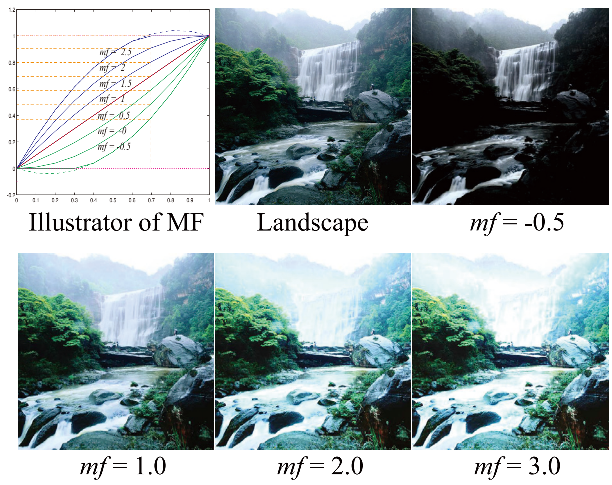


Figure 2. Illustrator of mapping function and example of mapping factor selection

2.4 Patch Separating and Selecting

After the color images mapping, the G_{CB} components are selected for processing. And for image merging, the key step is to select the ideal regions. In theory, any shape of region can be selected for merging. For simplicity, in our study, we set the patch as the local region (step 3 of Fig. 1). Hence, all images are divided into $n \times m$ non-overlapped patches with same size as width pw and height ph.

In this section, we will address the issue of feature representation of all patches. For all images, one possible scheme is to define the feature vector as a concatenation of the luminance values of all pixels. However, this simple scheme is not satisfactory, only values cannot select the ideal patch.

An alternative scheme we use in this paper is to consider the relative luminance changes within a patch. For describing the changes of luminance, the gradient is selected. The more detailed the information is, the higher the sum of gradient values will be. More specifically, we use the first-order and second-order gradients of gray component as the features to reflect the intensity of detail. The horizontal and vertical directions of first-order and second-order gradients are set as:

$$\begin{aligned} &\nabla H1 = [-1, 0, 1], \qquad \nabla V1 = [-1, 0, 1]^T, \\ &\nabla H2 = [1, 0, -2, 0, 1], \nabla V2 = [1, 0, -2, 0, 1]^T. \end{aligned} \tag{4}$$

Then let $\mathcal{P}^{H1}(x, y)$, $\mathcal{P}^{V1}(x, y)$, $\mathcal{P}^{H2}(x, y)$, and $\mathcal{P}^{V2}(x, y)$ as the four gradient components of the pixel at location $[x, y]$ in the image to be processed. $\mathcal{P}$ is the patch region with size pw and ph, and the upper left corner at position $[x_p, y_p]$. The G_{CB} component level of the detail inside of patch $\mathcal{P}$ is defined as:

$$\begin{aligned} \mathcal{F}^{H1}(\mathcal{P}) &= \textstyle\sum_{i=0}^{pw} \sum_{j=0}^{ph} \mathcal{P}^{H1}(x_p + i, y_p + j), \\ \mathcal{F}^{V1}(\mathcal{P}) &= \textstyle\sum_{i=0}^{pw} \sum_{j=0}^{ph} \mathcal{P}^{V1}(x_p + i, y_p + j), \\ \mathcal{F}^{H2}(\mathcal{P}) &= \textstyle\sum_{i=0}^{pw} \sum_{j=0}^{ph} \mathcal{P}^{H2}(x_p + i, y_p + j), \\ \mathcal{F}^{V2}(\mathcal{P}) &= \textstyle\sum_{i=0}^{pw} \sum_{j=0}^{ph} \mathcal{P}^{V2}(x_p + i, y_p + j). \end{aligned} \tag{5}$$

The feature vector with the four gradient component levels of detail gives the level of detail in region $\mathcal{P}$, i.e.,

$$\mathcal{F}(\mathcal{P}) = \left\{\mathcal{F}^{H1}(\mathcal{P}), \mathcal{F}^{V1}(\mathcal{P}), \mathcal{F}^{H2}(\mathcal{P}), \mathcal{F}^{V2}(\mathcal{P})\right\}. \tag{6}$$

The higher the calculated $\mathcal{F}(\mathcal{P})$ value is, the better enhanced region becomes. In the following, we will use this feature vector to measure the patches.

When the feature of every patch be selected, the next step is to calculate the best patch of same position for all mapped images. Here let $\mathcal{P}_{ijk}$ denotes the patch in the ith row and the jth column of the image with index k, where $k = 1, \cdots, N$, and N stands for the number of images to be processed, each of them mapped with different contrast. Our goal is to produce an image that is the combination of the N input images and contains all details that are involved in all of the images without producing noise. For each image, the level of detail has to be estimated inside every patch $\mathcal{P}_{ijk}$. This information helps us to select the best enhanced regions among the corresponding image patches (indexed by the same i and j values). To select the best one, let l be the index in the ith row and jth column of patch $\mathcal{P}$, which calculated by maximum Mean-Square Error (MSE) as

$$\begin{aligned} &MSE = \underset{l \in [1, N]}{\arg\max} \, ||\mathcal{F}(\mathcal{P}_{ijl}) - \mathcal{F}(\mathcal{P}_{ijk})||^2, \\ &k = 1, \cdots, l-1, l+1, \cdots, N. \end{aligned} \tag{7}$$

After this calculation, the most detail included patches $\mathcal{P}_{ijl}$ will be selected.

2.5 Mask Creating and Merging

When the best patches be selected, the following step is merge the selected patches $\mathcal{P}_{ijl}$ as the mask, where $i = 1, \cdots, n$, and $j = 1, \cdots, m$. After this, a merging mask can be created with the position $[i, j]$ and index l of patches as the above part of step 4 in Fig. 1 shown.

Then apply the mask $\mathcal{P}_{ijl}$ to all components of RGB color space, respectively, to obtain the merging result as the below part of step 4 in Fig. 1 shown. Unfortunately, the result image usually contains sharp transitions along the borders of the regions. To solve the problem, the elimination method is studied in next section.

2.6 Sharp Transitions Removing

For removing the sharp transitions between the patches, the mix Gaussian filter is applied. Through observing the image with sharp transitions, the effective way is weaken the boundary information of each patch. Find that the relation between patches which can be used to make the transitions become to smooth. So we use the local filter to weaken the boundary and global filter to smooth the transition. Then combine the local and global filters into the mix Gaussian filter:

$$G_{ij}(x, y) \quad = \quad \frac{e^{-\left[\frac{(x - lx_{ij})^2}{2\sigma_x^2} + \frac{(y - ly_{ij})^2}{2\sigma_y^2}\right]}}{\sum_{p=1}^{m} \sum_{q=1}^{n} e^{-\left[\frac{(x - gx_{pq})^2}{2\sigma_x^2} + \frac{(y - gy_{pq})^2}{2\sigma_y^2}\right]}}, \tag{8}$$

where (lx_{ij}, ly_{ij}) is the center of current (ith, jth) patch, (gx_{pq}, gy_{pq}) is the center of (pth, qth) patch, m and n denote the total number of column and row, and σ_x and σ_y are the standard deviation of horizontal and vertical direction.

Then using the mix Gaussian filter $G_{ij}(x, y)$ to smoothing the sharp transitions of R, G, and B components respectively as follows:

$$I(x, y) = \sum_{i=1}^{n} \sum_{j=1}^{m} G_{i,j}(x, y) I_{p_{ij}}^{<R,\,G,\,B>}(x, y), \tag{9}$$

where the $I_{p_{ij}}^{<R,G,B>}$ means the different region p_{ij} in $< R,\ G,\ B >$ component, respectively. In addition, changing the size of the patches and the standard deviations of the mix Gaussian filter can change the output color and intensity. The smaller the standard deviation of the Gaussian filter, the lower detail level as the result.

3 Experimental Results Discussion

In this section, the performance of proposed method and the comparison are discussed. All testing sample images are got from NASA Langley Research Center and Internet. In the proposed method, only two parameters need be set. One is the patch size which defined as pw and ph is set as 40×40, and the other one is the deviation of mix Gaussion filter which defined as (σ_x, σ_y) is set as (60, 60).

For comparison, some methods are selected: HE, Dynamic Histogram Equalization (DHE) [4], Alpha Rooting (AR) [8], RMSHE [2], GLG [3], EHS [6], Color Enhancement by Scaling (CES) [10], Multi-Contrast Enhancement (MCE) [9], Contrast Normalization (CN) [5], and Adaptive Histogram Separation and Mapping Framework (AHSMF) [7].

Fig. 3 shows the comparison of NASA image $18^\sharp$ with the mentioned methods. In this figure, the effect of proposed method, AHSMF, GLG, EHS, and CES show the acceptable effect. And other methods, such as HE, DHE, AR, RMSHE, MCE, and CN only enhance some local region, the effect of whole images are hard to observed. Except the comparison of Fig. 3, Fig. 4 shows the result of proposed method with back-light image from Internet. From these results, we can see that the proposed method is effective.


(a) Original image


(b) Proposed


(c) AHSMF [7]


(d) HE

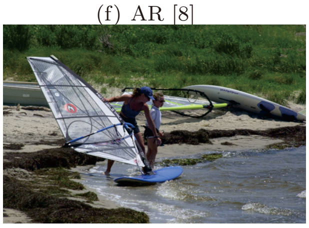

(e) DHE [4]


(f) AR [8]


(g) RMSHE [2]


(h) GLG [3]


(i) EHS [6]


(j) CES [10]


(k) MCE [9]


(l) CN [5]

Figure 3. Result comparison of NASA image 18$^\sharp$


Figure 4. Other result of proposed method with Internet images

4 Conclusion

This paper presents a multi-histogram mapping, patch feature selection and merging strategy in CBM for color image enhancement. The proposed method can obtain good results both in dark and light region of all kinds of images. The experimental results also show the effectiveness of the proposed method by comparing it with other contrast enhancement methods.

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