Color Image Enhancement through 2D Histogram Equalization

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Abstract - In this paper we introduce a novel approach for color image enhancement by using equalization of three $2D$ histograms. These histograms are built through the combination of two at two of three well known color channels, i.e. R - Red, G - Green, and B - Blue, namely RGB system. These histograms allow us to perform an equalization taking into account the correlation of color channels two at two. Our approach has square complexity of time and space, i.e. $O(L^2)$, regarding the number L of levels in each channel. A comparison of our histogram equalization method with other two color image enhancement techniques is performed. Experiments show that our approach outperforms $1D$ and $3D$ histogram equalization techniques in some situations.

1. INTRODUCTION

Image Enhancement (IE) techniques have been often applied as preprocessing to several Image Processing and Computer Vision applications in order to increase the probability of success in the image analysis task [2]. IE increases the image quality so that the image resulted may be more suitable than the original for an application. Besides, the scope of IE includes contrast manipulation, noise reduction, edge crispening and sharpening, filtering, interpolation, magnification and pseudo-coloring.

The histogram of a monochrome (e.g. gray scale) image presents the frequency of occurrence of levels in the image. By its analysis it is possible to know some interesting image global features, such as the mode (i.e. the most frequent level) and the distribution of levels. A well known technique for IE is Histogram Equalization (HE). The main idea behind HE is to uniformly distribute the image pixels over the entire gray level range such that a better quality may be reached. This seems to be a reasonable supposition. HE is a spatial-domain enhancement technique and was proposed as an efficient technique for the enhancement of gray level images in real time applications [9]. Histogram modification and histogram specification are variations of this technique, proposed in [4] and [3], that yield histograms with a desired shape.

A great number of approaches are found in literature for the purpose of IE. Here, however, we focus our attention on Color IE through HE. In [1], it is proposed a HE approach based on brightness, saturation, and hue (HSI) color space. This technique yields an image with uniform brightness and saturation histograms, letting the hue channel unchanged. A technique similar to this one was proposed in [6]. A special attention is given to saturation, where high frequency components are present. In [8], a modified cosine function and semi-histogram equalization are proposed for gray level images and an extension of this methodology is suggested to color images by equalizing the three channels (R, G and B) separately. All these techniques only use marginal color histograms. Therefore, they do not take into account the correlation between the different channels. In [5], Pichon *et al.* propose an algorithm for HE taking into account color channels correlation through mesh deformation, which always generates almost (i.e. discrete) uniform color histograms. Thus, making an optimal use of the color space. This algorithm is indicated for scientific visualization purposes, but not for IE, since it does not preserve the image natural features.

In this paper, we present an algorithm for IE through HE by using three $2D$ histograms, built through the combination of RGB channels, namely, we use RG, RB and GB histograms. The rationale for this is to use the correlation of the channels two at two, instead of performing equalization separately or by using the three channels simultaneously. The time and space complexity of our approach is bounded by $2D$ histograms construction, namely $O(L^2)$ regarding L levels of discretization. Although, the histogram construction takes $O(L^2)$ in time, the transform/equalization step takes only $O(L)$ for each image pixel. This approach is different of that one introduced in [7], where only one $3D$ histogram is created through the three channels R, G, and B and time and space complexity is $O(L^3)$.

The rest of this paper is organized as follows. In Section 2, the well known HE technique for monochrome image is explained, and HE for Color IE by using a $3D$ histogram [7] is also presented. In Section 3, our approach for $2D$ HE for Color IE is introduced. In Section 4, experiments are performed in order to evaluate and to compare our approach. And, finally, in Section 5, conclusions are pointed out and further investigations are exposed.

2. HISTOGRAM EQUALIZATION

The HE process consists of generating a uniform histogram (i.e. uniform distribution) for the output image through original histogram of the input image, by using the entire range of discrete levels. Therefore, this redistribution of levels is the supposition for IE through HE, what seems to be reasonable.

2.1 $1D$ *Histogram*

The HE technique for monochrome (e.g. gray scale) images is mentioned here. Consider the variable I, discretized in L levels, and H^I the distribution function (i.e. histogram) of I. Therefore, $H^I_{L_i}$ represents the occurrence (i.e. absolute frequency) of L_i level, where $0 \leq L_i \leq L-1$. Let C^I be the cumulative density function of I, and $C^I_{L_i}$ the cumulative density of L_i level, i.e. $C^I_{L_i} = \sum_{l_i=0}^{L_i} H^I_{l_i}$.

The goal of HE is to uniformly distribute H^I over the entire range of levels or generate a cumulative density function which increases monotonically as a straight line. For such aim, let I and O be the input and output (i.e. original and equalized images) variables that take the values L_i and L_o, with $L_i, L_o = 0, 1, 2, \ldots, L-1$, with histogram H^I, and cumulative density function C^I, as said above. Let H^O be the desired uniform histogram, where each bin has the same density (i.e. amount of pixels), i.e. $H^O_{L_o} = \frac{1}{L}(N \times M)$, where N and M represent the image width and height. Thus, the cumulative density function C^O is defined as $C^O_{L_o} = \sum_{l_o=0}^{L_o} H^O_{l_o} = \frac{(L_o+1)}{L}(N \times M)$.

Let the value L_o be the smallest value of C^O for which $C^O_{L_o} - C^I_{L_i} \geq 0$. Then L_o is the output equalized level corresponding to the input level L_i. In other words, the output level L_o can be computed as being the transformation function $T^I[L_i]$, i.e. $L_o = T^I[L_i] = round(\frac{L*H^I_{L_i}-1}{N \times M})$, where $round(\bullet)$ is a function which returns the nearest integer.

This technique can easily be extended for Color IE, by applying separately the equalization process described here to each one of the three channels of RGB system. Here, we will call this technique as being $1D$ HE for Color IE, because it uses only one-dimensional histograms.

2.2 $3D$ *Histogram*

As shown in [7], the joint probability density function, which takes into account the three channels simultaneously, guaranties the uniform distribution for HE only when the independence assumption is not taken. And it is well know that the independence assumption is not valid in cases of correlation among channels.

The approach proposed by Trahanias and Venetsanopoulos in [7] takes into account the correlation of the three channels, R, G, and B, simultaneously. Let I and O be the input and output variables, which assume as values triplets (R_i, G_i, B_i) and (R_o, G_o, B_o), with $R_i, G_i, B_i, R_o, G_o, B_o = 0, 1, 2, \ldots, L-1$. Let $H^{I(R,G,B)}$ and $H^{O(R,G,B)}$ be the $3D$ density functions of the input and output images, respectively, where $H^{I(R,G,B)}$ is computed from the original image, and $H^{O(R,G,B)}$ is set to $1/L^3$ for each entry, such that the $3D$ uniform histogram can be achieved. $C^{I(R,G,B)}$ and $C^{O(R,G,B)}$ are computed from $H^{I(R,G,B)}$ and $H^{O(R,G,B)}$, respectively, i.e. $C^{I(R,G,B)}_{R_i,G_i,B_i} = \sum_{r_i=0}^{R_i} \sum_{g_i=0}^{G_i} \sum_{b_i=0}^{B_i} H^{I(R,G,B)}_{r_i,g_i,b_i}$,

$$C^{O(R,G,B)}_{R_o,G_o,B_o} = \frac{(R_o+1)(G_o+1)(B_o+1)}{L^3}. \qquad (1)$$

3. APPROACH - $2D$ HISTOGRAM

Unlike [7], here we will use the correlation of channels two at two for HE of Color IE. For such aim, we will use three $2D$ histograms. Our approach is divided in three main steps. Thus, let I and O be the image input and output variables, and $H^{I(R,G)}$, $H^{I(R,B)}$, and $H^{I(G,B)}$ the three $2D$ histograms two at two of the R, G, and B channels of the input image, computed in the first step with time and space complexity $O(L^2)$. Then, the second step of our approach consists of computing the cumulative distribution functions through these three histograms, i.e.

$$C^{I(R,G)}_{R_i,G_i} = \sum_{r_i=0}^{R_i} \sum_{g_i=0}^{G_i} H^{I(R,G)}_{r_i,g_i}. \qquad (2)$$

$C^{I(R,B)}_{R_i,B_i}$, and $C^{I(G,B)}_{G_i,B_i}$ can be computed similarly. This computation for the $2D$ histograms has complexity $O(L^4)$, and can make this step very expensive. However, by using dynamic programming principles we can compute $C^{I(R,G)}$ in $O(L^2)$, i.e.

$$C^{I(R,G)}_{R_i,G_i} = C^{I(R,G)}_{R_i-1,G_i} + C^{I(R,G)}_{R_i,G_i-1} - C^{I(R,G)}_{R_i-1,G_i-1}, \qquad (3)$$

Similarly, $C^{I(R,B)}$, and $C^{I(G,B)}$ can be computed. Finally, $C^{I(R,G,B)}_{R_i,G_i,B_i}$ is computed as being the product of three cumulative functions, i.e.

$$C^{I(R,G,B)}_{R_i,G_i,B_i} = C^{I(R,G)}_{R_i,G_i} \times C^{I(R,B)}_{R_i,B_i} \times C^{I(G,B)}_{G_i,B_i}, \qquad (4)$$

In our approach, $C^{O(R,G,B)}$ is computed as in the $3D$ approach (Equation 1) and used in the third step. In fact, we will not equalize the three $2D$ histogram, but we will equalize a $3D$ pseudo-histogram through $C^{I(R,G,B)}$ and $C^{O(R,G,B)}$. Although we are performing a $3D$ pseudo-histogram equalization, we are taking into account the correlation of the three channels two-at-a-time, with lower complexity cost, i.e. $O(L^2)$. The main rationale for such is that in an image the three channels are usually not simultaneously correlated.

The third step consists of an iterative process and is performed in $O(L)$ for each image pixel, as follows. Initially, R_o, G_o, and B_o (the output triplet) are set up as R_i, G_i, and B_i (the input triplet), respectively, i.e.

$$(R_o, G_o, B_o) \leftarrow (R_i, G_i, B_i). \qquad (5)$$

Then an initial $C^{O(R,G,B)}_{R_o,G_o,B_o}$ is computed by Equation 1, and an error represented by Equation 6 is generated.

$$C^{I(R,G,B)}_{R_i,G_i,B_i} - C^{O(R,G,B)}_{R_o,G_o,B_o}. \qquad (6)$$

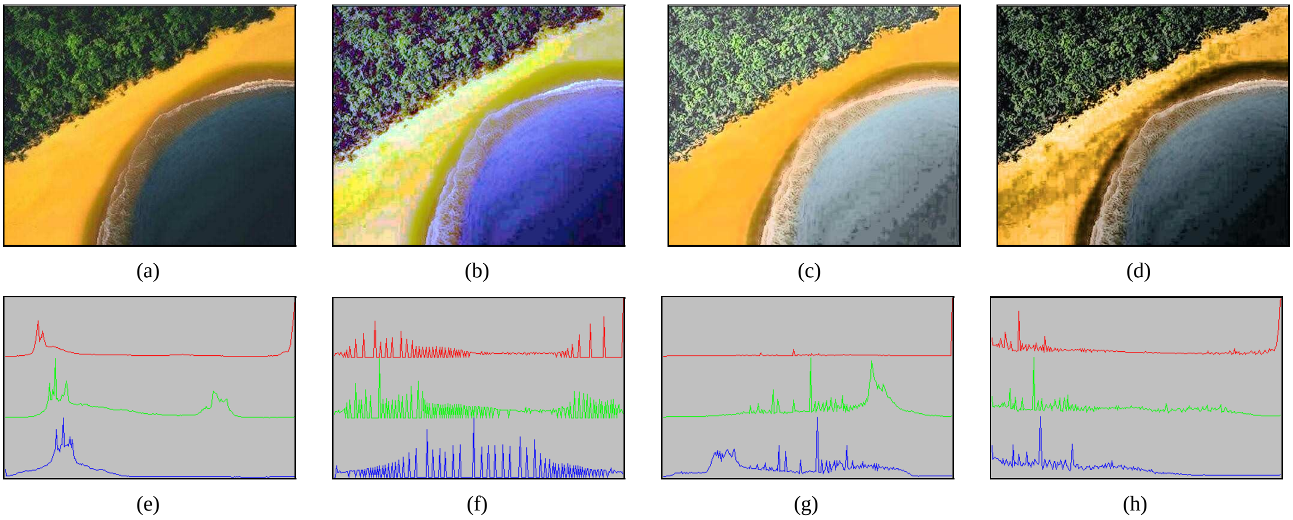

Fig. 1. Results for Partial Brazil Flag/Beach image: (a) original image; (b) $1D$ HE; (c) $3D$ HE; (d) $2D$ HE. R̃espectively, their histograms are shown bellow of each image.

This error will be used to guide the iterative process increasing or decreasing the values of R_o, G_o, and B_o. The output triplet is increased if the computed error (Equation 1) is positive, and decreased if it is negative. However, a minimum increase/decrease of 1 in R_o, G_o and B_o is required. Hence, for each channel, we calculate increasing or decreasing factors according to Equation 1. The increasing factor is given by

$$T_R = ((L-1) - R_o)/T, \tag{7}$$

$$T_G = ((L-1) - G_o)/T, \tag{8}$$

and

$$T_B = ((L-1) - B_o)/T, \tag{9}$$

where $T = max(L - R_o, L - G_o, B_o)$. The decreasing factor is described as

$$T_R = R_o/T, \tag{10}$$

$$T_G = G_o/T, \tag{11}$$

and

$$T_B = B_o/T, \tag{12}$$

where $T = max(1 + R_o, 1 + G_o, 1 + B_o)$.

After these factors are computed and a direction is taken (i.e. increasing or decreasing the triplet), the iterative process starts. If the increasing direction is taken, the output triplet is updated by:

$$R_o = \begin{cases} R_o + T_R & \text{if } R_o < (L-1), \\ L-1 & \text{otherwise.} \end{cases} \tag{13}$$

$$G_o = \begin{cases} G_o + T_G & \text{if } G_o < (L-1), \\ L-1 & \text{otherwise.} \end{cases} \tag{14}$$

$$B_o = \begin{cases} B_o + T_B & \text{if } B_o < (L-1), \\ L-1 & \text{otherwise.} \end{cases} \tag{15}$$

In contrast, for the decreasing direction, the output triplet is updated as follow:

$$R_o = \begin{cases} R_o - T_R & \text{if } R_o > 0, \\ 0 & \text{otherwise.} \end{cases} \tag{16}$$

$$G_o = \begin{cases} G_o - T_G & \text{if } G_o > 0, \\ 0 & \text{otherwise.} \end{cases} \tag{17}$$

$$B_o = \begin{cases} B_o - T_B & \text{if } B_o > 0, \\ 0 & \text{otherwise.} \end{cases} \tag{18}$$

After the output triplet is updated, Equation 6 is recomputed, and the iteration process repeated until a triplet (R_o, G_o, B_o) which minimizes Equation 6 is found. The output triplet (R_o, G_o, B_o) is the nearest triplet which approximates to zero the difference between the cumulative density functions $C^{I(R,G,B)}$ and $C^{O(R,G,B)}$.

4. EXPERIMENTS

The proposed approach was implemented and tested in a set of color images. A comparison with $1D$ [2] and $3D$ [7] HE methods was performed. A qualitative (i.e. visual) evaluation was performed, since for this kind of task (i.e. enhancement) it is difficult to establish a measure of performance. We present two results: Figure 1 shows an example where our approach outperforms $3D$ HE, and $1D$ HE approach fails; An example where $3D$ HE performs well and $1D$ HE and our approach fail is shown in Figure 2. In the first example (Figure 1), the colors produced by $1D$ HE (Figure 1(b)) approach do not correspond to real ones, and the image produced by our approach (Figure 1(d)) is more realistic and more enhanced than that one produced by

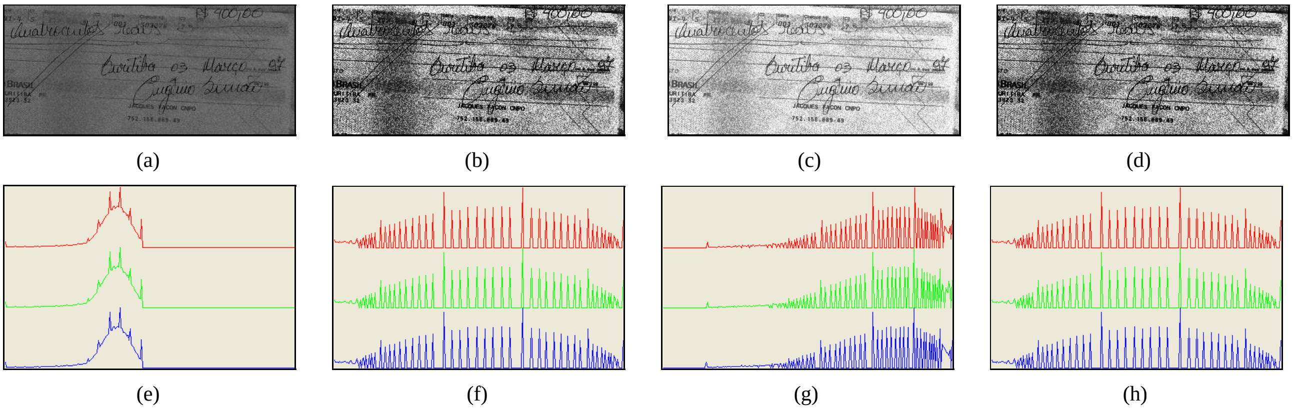

Fig. 2. A gray scale brazilian cheque: (a) original Image; (b) $1D$ HE ; (c) $3D$ HE; (d) $2D$ HE. Respectively, their histograms are shown bellow of each image.

$3D$ HE (Figure 1(c)). Besides, with our approach the image presents some details in the beach that were not visually perceived in the original image (Figure 1(a)). But, why does our approach work better than $3D$ HE? Our supposition is that in this image the channels are correlated two at two, and not simultaneously correlated. On the other hand, in the second example (Figure 2), $3D$ HE performed well the task of enhancement while our approach and the $1D$ one did not work well, and obtained the same results. The image on Figure 2(a), is a gray scale image. This is exactly the case where the channels R, G, and B are fully correlated. Therefore, $3D$ HE approach is the most indicated for gray scale images among the approaches tested here, since gray scale images has the three channels totally correlated. Nonetheless, $3D$ HE approach has time and space complexity $O(L^3)$. This result of $3D$ one approach for gray scale images was verified in several other gray scale images. As a conclusion, we can say that a color correlation measure has to be established in order to decide which approach is the best one for each image.

5. Conclusion

In this paper, we introduced and implemented a new approach for image enhancement through histogram equalization. Our experiments show that our approach outperforms $3D$ HE [7] for images where the color information is not fully correlated. However, our approach and $1D$ one fails when color channels are quite correlated.

The complexity of our approach is $O(L^2)$ in the steps of $2D$ histograms and cumulative functions computation, but $O(L)$ in the output histogram equalization step. In future works, in order to apply the proposed approach to real time tasks, the use of a dynamic hash table will be considered to make the third step near to $O(1)$ (for each image pixel). All the focus now has to be in the third step. This is because the first step can be computed in one pass throughout the input image, the second step is performed only once, but the third step is computed for each image pixel.

The main drawback of IE based on HE is the global treatment received through the image content. Nonetheless, global approaches usually have the advantage of being parameter-free. A comparison between the use of color IE through HE based on RGB and HSI system is also needed. In future work, we plan to adopt a color correlation measure for images, aiming to establish which channels are correlated and therefore indicate which of the approaches considered in this paper (i.e. $1D$, $2D$, or $3D$ HE) is more suitable for each image.

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