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Contrast Enhancement of Color Images with Color Morphing Approach

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***Abstract*—**Low contrast images can result from the wrong setting of image acquisition or poor illumination conditions. Such images may not be visually appealing and can be difficult for feature extraction. Contrast enhancement of color images can be useful in medical area for visual inspection. In this paper, a new technique is proposed to improve the contrast of color images. The RGB (red, green, blue) color image is transformed into normalized RGB color space. Adaptive histogram equalization technique is applied to each of the three channels of normalized RGB color space. The corresponding channels in the original image (low contrast) and that of contrast enhanced image with adaptive histogram equalization (AHE) are morphed together in proper proportions. The proposed technique is tested on seventy color images of acne patients. The results of the proposed technique are analyzed using cumulative variance and contrast improvement factor measures. The results are also compared with decorrelation stretch. Both subjective and quantitative analysis demonstrates that the proposed techniques outperform the other techniques.

***Keywords*—**Contrast enhancement, normalized RGB, adaptive histogram equalization, cumulative variance.

I. Introduction

CONTRAST enhancement is an important step in computer vision and image processing. Low contrast images may result from poor illumination condition during image acquisition or other aberrations of the image capturing and display devices [1]. In low contrast images, the visual relevant details are not vivid. Especially in a medical area where images of the patients of different diseases are examined, and severity of the disease is evaluated.

The histogram is used as a fundament tool for finding the distribution of gray-level values in an image. The histogram of low contrast image spans over a small portion of the range of intensity values [2]. The histogram of well-contrasted image covers the whole dynamic range of intensity. Well-contrasted images are visually appealing and prove effective in subjective evaluation. Along with specular illumination removal, contrast enhancement is also used as an essential step in medical image processing [3]-[5].

The contrast enhancement technique can be divided into two main types; direct enhancement and indirect enhancement techniques. By direct techniques, the intensity values of pixels in an image are modified by directly processing [6]-[8]. While indirect techniques are based on re-distribution of gray level values in an image by calculating cumulative distribution function (CDF) [9]. With the help of CDF, the histogram of gray level values is stretched to the full dynamic range. The contrast in monochrome images is measured by variance or standard deviation of gray level values. These variations in gray level values are attributed to the spatial frequency to which human visual system is very sensitive. The spatial frequency relevant information is captured by edges and usually calculated with the first derivative.

Contrast enhancement of color images is very difficult. If the ratio of the components of RGB color space is changed, the color of the new image may look completely different than the original one. The techniques developed for gray images can be applied to color images in two ways. In the first approach, each channel of RGB color space is treated as a gray image. The method is applied to each of the three channels separately and combined together after processing. In the second approach, the RGB color image is first converted into a color space in which the chrominance and luminance components are separate from each other. The contrast enhancement technique is applied to the luminance component and leaving the chrominance part untouched. It is claimed that the hue is preserved while the contrast of the image is enhanced [10].

The rest of the paper is organized as follows; in Section II, the relevant literature is presented. Section III explains the methodology in detail. In Section IV, the results are presented, and performance of the proposed is evaluated with cumulative variance, peak signal to noise ration and contrast improvement factor. In the last Section V, the conclusion is drawn.

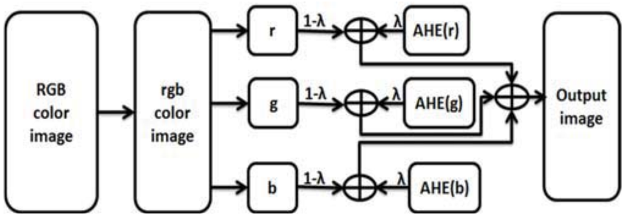

Fig. 1 Proposed technique for color image contrast enhancement

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II. Related Work

Many techniques have been developed for contrast enhancement of digital images, in the spatial domain and transform domain as well.

Edge in images represents contrast relevant activity to which human visual system is very sensitive. In transform domain, edges are characterized by high-frequency contents.

Curvelet transform based approach is adopted in order to emphasize the edges in [11]. The results are compared with the multiscale retinex method and are claimed to be better. Another method for automatic contrast enhancement is developed in [12]. In this method, Gaussian mixture model (GMM) is used to represent the distribution of intensity values in an image [12]. The gray level in the image is divided into different intervals with the help of Gaussian components. The contrast enhanced image is generated by mapping the intensity values in each interval to an output intensity value. The mapping is driven by the dominant Gaussian components of GMM. Shih et al. [13] proposed an efficient method for contrast enhancement of digital images. In this method, the contrast of dimmed image is enhanced with gamma correction and by assigning appropriate weights to the cumulative distribution of the image.

In the spatial domain, histogram equalization (HE) is a primary and basic tool for contrast enhancement of gray level images. The equalization of the histogram can be based on the statistical information of the whole image or the local region. The global histogram equalization does not prove effective in enhancing the local details in some cases. In order to overcome the problem of HE, local histogram equalization approaches are proposed [14]. In local histogram equalization, a small window is selected, and contrast of the central pixel is modified based on the statistical information of that window. The over-enhancement nature of LHE is not visually appealing. Many modifications have been suggested to LHE [15], [16]. In constrained local histogram equalization technique, a balancing parameter is used to prevent LHE over-enhancement of local details. In CLHE, two local histograms are calculated [16]. One histogram is calculated for local window while the pixels outside the local window are treated another window. The balancing parameter is found as the ratio of local window to the background window. According to the value of the balancing parameter, contrast of the local window is modified. In both global and local histogram equalization method, the first histogram of the image is calculated. The histogram can provide useful information about the distribution and can be used in deriving statistical parameters such as mean and variance etc. The histogram of a digital image $I(x,y)$ is defined as in (1):

$$p(r_k) = \frac{n_k}{MN},\ k = 0,1,2,\ldots.L-1 \quad (1)$$

MN is the number of pixels comprising the image, n_k is the number of pixels having intensity value k and L is the intensity levels. The p (r_k) represents the probability of occurring gray level value r_k. The dynamic range for the 8-bit image is [0 255]. The equalization of histogram is obtained through the transformation defined as

$$s_k = f(r_k) = (L-1)\sum_{i=0}^{k} p(r_i) = (L-1)\sum_{i=0}^{k}\frac{n_i}{MN} \quad (2)$$

After equalization, s_k spans the whole dynamic range of gray level values [0 255]. For transformation defined as in (2). The following assumptions must be satisfied.

- f(r) is a monotonically increasing function in the given interval.
- $0 \le f(r) \le L-1$ for $(0 \le r \le L-1)$.

III. Material and Method

As shown in Fig. 1, first the color image is transformed from RGB color space to normalized RGB color space, denoted by small letters, i.e., rgb so that the value of each channel is limited to the range [0 1]. This color space mapping is carried out through (3)-(5).

$$r = \frac{R}{(R+G+B)} \quad (3)$$

$$g = \frac{G}{(R+G+B)} \quad (4)$$

$$b = \frac{B}{(R+G+B)} \quad (5)$$

The effect of non-uniform illumination is removed by normalizing the RGB color space. Adaptive histogram equalization technique is applied to each of the three channels of normalized RGB color space separately. The corresponding channels of the original image (normalized) and that of AHE enhanced image are combined together according to (6)-(8).

$$\bar{R} = (1-\lambda)\times r + \lambda\times\bar{r} \qquad 0 \le \lambda \le 1 \quad (6)$$

$$\bar{G} = (1-\lambda)\times g + \lambda\times\bar{g} \qquad 0 \le \lambda \le 1 \quad (7)$$

$$\bar{B} = (1-\lambda)\times b + \lambda\times\bar{b} \qquad 0 \le \lambda \le 1 \quad (8)$$

The parameter $\lambda \in [0\ 1]$ is used to determine the fusion proportion of the normalized RGB image and the enhanced image. It controls the detail preservation of the image enhanced with AHE. For $\lambda = 0$, only the normalized image is retained, on the other extreme that is case $\lambda = 1$, only the image enhanced with AHE is retained. In this study, $\lambda = 0.6$ is elected. By varying the values of λ, the corresponding channels of the two images can be combined in different proportion; preserving different amount of details. The other variables such as $\bar{r}$, $\bar{g}$, and $\bar{b}$ are the enhanced red, green and blue channels while $\bar{R}$, $\bar{G}$ and $\bar{B}$ are the corresponding channels enhanced with the proposed technique. After enhancing, the three-color channels are concatenated together to form the contrast enhanced color image.

IV. Results and Discussion

In Fig. 2, the 1st column contains the original images while 2nd and 3rd columns contain the images enhanced with proposed technique and decorrelation stretch method respectively. With the proposed method, the results are produced with λ=0.6. By varying the values of λ, one can preserve the different amount of details. A lower value may not enhance the contrast of color image well while the very high value of λ may cause color saturation. The 3rd column in Fig. 2 consists of the images whose contrast is stretched with decorrelation stretch method. The contrast between the skin lesions and skin is increased by assigning completely different between lesion and skin. For subjective analysis of contrast enhancement technique, the original images and the images enhanced with the proposed method were shown to 5 experts in image processing area. All of the five experts were agreed on that the contrast of the images has been increased.

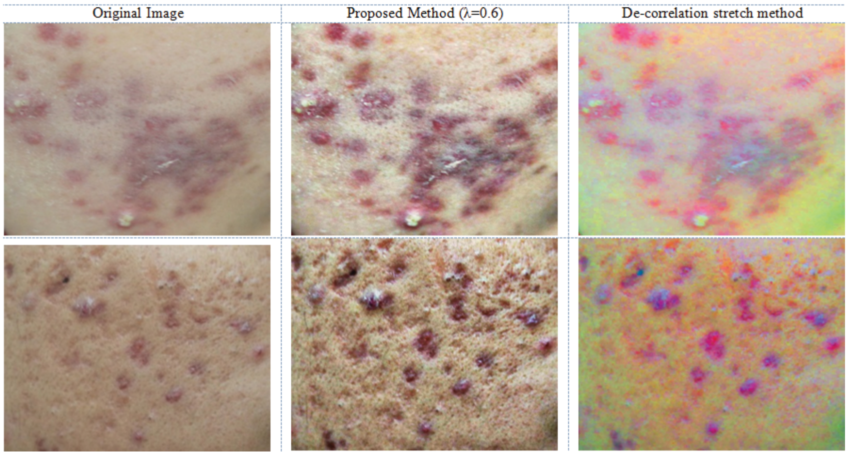

Fig. 2 Visual Comparison of Original images (1st column), enhanced with proposed method (2nd column), decorrelation stretching method (3rd) column

For quantitative analysis of the proposed technique, we have used and computed three metrics; cumulative variance (CV), peak signal to noise ratio (PSNR) and contrast improvement factor (CIR). In gray images, the variance is used to measure the contrast of the given images. Variance or standard deviation indicates variability in values of a color channel. For color images, we have introduced another metric called cumulative variance to measure the contrast of color images. Let I(x, y) be a color image, where x and y are the rows and columns. The image is decomposed into the three channels (red, green and blue) and variance is calculated for each channel according to (9):

$$\sigma_i = \frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N}(I(x,y)-\bar{I})^2 \ , i = R, G, B \tag{9}$$

σ_i represents the variance of a channel i= R, G, B, M and N are the total number of rows and columns in the image. The parameter $\bar{I}$ is the average of a particular channel values. Once the variance is calculated for the three channels, overall contrast of the color image is computed as in (10)

$$\sigma_{overall} = \sum_i \sigma_i \, , \qquad i \in R, G, B \tag{10}$$

Using (9) and (10), cumulative variances are calculated for the original color images, for images enhanced with the proposed technique and for images whose contrast is enhanced with decorrelation stretch method. The cumulative variance of the original images is used as a reference point, whereas the cumulative variances of the images enhanced with the proposed scheme and decorrelation stretch method are compared with the reference CV, in order to see whether the contrast is improved or not. The interpretation of the cumulative variance is easy and straight forward; higher values of CV means improved contrast of the color image. The CV value is high when variances of the individual channels are increased. The cumulative variance measurements are plotted for all the three types of images in Fig. 3; the images are numbered along the horizontal axis while the cumulative variances are shown on the vertical axis. The comparison is shown only for 26 images because of space limitation. In most cases, the curve corresponding to CV values of the images enhanced with the proposed technique is above the reference curve (for original images) and curve corresponding to the CV values of decorrelation stretch method. Based on the CV values plotted in Fig. 3, it can be concluded that the proposed method performs better than decorrelation stretch method in contrast enhancement.

Contrast Improvement Ratio (CIR) is another very useful metric to quantitatively measure the contrast improvement factor for the given images [17]. This measurement is defined by the ratio given in (11):

$$CIR = \frac{\sum[\sigma_I(x,y) - \sigma_{\hat{I}}(x,y)^2]}{\sum \sigma_I(x,y)^2} \tag{11}$$

In (11), $\sigma_I(x, y)$ and $\sigma_{\hat{I}}(x, y)$ are the cumulative variances of the original images and the contrast enhanced images. Originally, this CIR was introduced to evaluate the contrast improvement for a particular region in an image. Here in this paper, the whole image is considered as a region of interest. Higher values of CIR for an image indicate that the contrast of the image has been improved. In Fig. 4, we have plotted the contrast improvement ratio coefficient for our proposed technique.

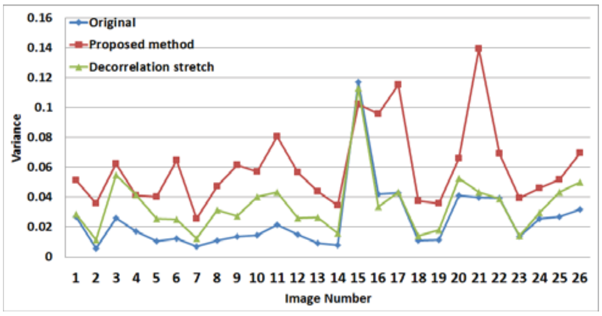

Fig. 3 The cumulative variances for the three types of images

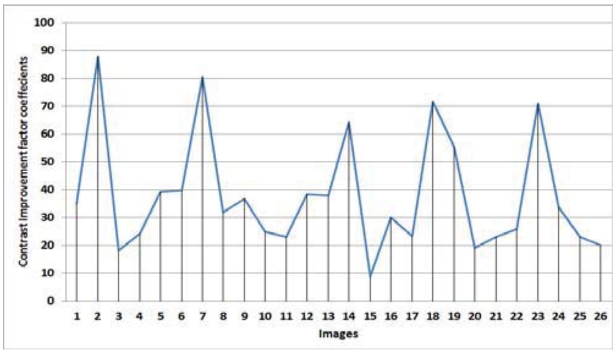

Fig. 4 Contrast improvement ratio for the proposed technique

Fig. 4, the CIR values are shown only for the first 26 images. However, a similar trend was observed for the other images as well. It can be easily observed that the proposed technique shows promising results in improving the contrast of the color images. The variations in the CIR values demonstrate that contrast of different images is improved by different factors; the minimum value of CIR coefficient is 10 while the maximum value is about 88. The variations in CIR coefficients also demonstrate that the images, which are low-contrasted, may need higher improvement in the contrast while the images, which are already well-contrasted, may need less contrast improvement.

V. Conclusion

The contrast enhancement of color images is very critical and import for both visual inspection and image analysis. Based on the subjective and quantitative analysis performed in the results and discussion section, it can be concluded that the proposed technique improves the contrast of color images without introducing color artifacts. The subjective analysis demonstrates that the proposed technique performs better than decorrelation stretch method and adaptive histogram equalization as well. The morphing parameter controls the amount of information retained from both the original image and the image enhanced with AHE. The value of morphing parameter $\lambda = 0.6$ was determined experimentally. In contrast, enhanced images, the boundary of lesions can be easily identified and, therefore, correct ground truth (manually segmented images) can be prepared. Better segmentation and classification results can be obtained for well-contrasted images. The quantitative performance metrics (cumulative variance, and contrast improvement ratio) also indicate the contrast of the images is significantly improved.

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