A GENERALIZED AND AUTOMATIC IMAGE CONTRAST ENHANCEMENT USING GRAY LEVEL GROUPING

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ABSTRACT

Contrast enhancement has an important role in image processing applications. Conventional contrast enhancement techniques either fail to produce satisfactory results for a broad variety of low-contrast images, or cannot be automatically applied to different images, because their parameters must be specified manually to produce a satisfactory result for a given image. This paper describes a new automatic method for contrast enhancement. The basic procedure is to first group the histogram components of a low-contrast image into the proper number of bins according to a selected criterion, then redistribute these bins uniformly over the grayscale, and finally ungroup the previously grouped gray-levels. Accordingly, this new technique is named Gray-Level Grouping (GLG). GLG not only produces results superior to conventional contrast enhancement techniques, but is also fully automatic in most circumstances, and is applicable to a broad variety of images.

1. INTRODUCTION

Contrast enhancement has an important role in image processing applications. Numerous contrast enhancement techniques exist in literature, such as gray-level transformation based techniques (e.g., logarithm transformation, power-law transformation, piecewise-linear transformation, etc.) and histogram processing techniques (e.g., histogram equalization (HE), histogram specification, etc.) [1]. Conventional contrast enhancement techniques generally yield satisfactory results if the proper technique is selected for a given application along with the proper processing parameters. However, conventional contrast enhancement techniques often fail in producing satisfactory results for a broad range of low-contrast images, such as images whose histogram amplitudes are very high at one or several locations on the grayscale, and very small, however, not zero, in the rest of the grayscale. This makes it difficult to increase the image contrast by simply stretching its histogram or by using simple gray-level transformations. The high amplitude of the histogram components corresponding to the image background also often prevents the use of the histogram equalization techniques, which could cause a washed-out effect on the output image and/or amplify the background noise.

Fig. 1(a) shows an original low-contrast subband facial image for multi-spectral face recognition applications, and its histogram. Fig. 1(b) is the result of its histogram equalization (HE), exhibiting the washed-out effect and significantly amplified background noise which are not acceptable for many applications. The cause for the washed-out appearance is that the small histogram components corresponding to the face structure are pushed toward the high end of the grayscale, as shown in the equalized histogram of Fig. 1(b). The cause for the amplified background noise is that the three highest histogram components which correspond to the image background are far apart in the equalized histogram.

Our motivation is to develop a new contrast enhancement technique which not only produces better results, but is also general and can be automatically applied to a broad variety of images. This paper introduces a new histogram-based optimized contrast enhancement technique called Gray-Level Grouping (GLG). The basic procedure of this technique is to first group the histogram components of a low-contrast image into a proper number of groups according to a certain criterion, then redistribute these groups of histogram components uniformly over the grayscale so that each group occupies a grayscale segment of the same size as the other groups, and finally ungroup the previously grouped gray-levels.

2. BASIC GRAY LEVEL GROUPING (GLG)

The algorithm of the basic GLG technique is described as follows:

1) Let $H_n(k)$ denote the histogram of the original image, with k representing the gray levels on the grayscale $[0, M-1]$. To perform gray level grouping, first the n

nonzero histogram components are assigned to gray level bins, or gray level groups, $G_n(i)$.

$$G_n(i) = H_n(k) \quad \text{for } H_n(k) \neq 0, \quad k = 0, 1, 2, ..., M-1; \; i = 1, 2, 3, ..., n. \tag{1}$$

2) The left and right limits, $L_n(i)$ and $R_n(i)$, of the gray level interval represented by $G_n(i)$ also need to be recorded. In this first step, the intervals consist of single values, which are the gray level values, *k*, of the original histogram components, $H_n(k)$.

$$L_n(i) = R_n(i) = k, \text{ for } H_n(k) \neq 0, \quad k = 0, 1, 2, ..., M-1, \; i = 1, 2, 3, ..., n. \tag{2}$$

3) The first occurring smallest $G_n(i)$ is found.

$$a = \min_i G_n(i), \tag{3}$$

and i_a is the group index corresponding to the smallest $G_n(i)$, i.e., *a*.

4) Grouping is performed in this step. Group $G_n(i_a)$ is merged with the smaller of its two adjacent neighbors, and the gray level bins $G_n(i)$ adjusted to create a new set of bins, $G_{n-1}(i)$, as follows.

$$G_{n-1}(i) = \begin{cases} G_n(i) & \text{for } i = 1, 2, ..., i'-1 \\ a+b & \text{for } i = i' \\ G_n(i+1) & \text{for } i = i'+1, i'+2, ..., n-1 \end{cases} \tag{4}$$

where

$$b = \min\{G_n(i_a - 1), G_n(i_a + 1)\} \tag{5}$$

and

$$i' = \begin{cases} i_a - 1 & \text{for } G_n(i_a - 1) \leq G_n(i_a + 1) \\ i_a & \text{otherwise} \end{cases} \tag{6}$$

The left and right limits of the gray level intervals represented by $G_{n-1}(i)$ also need to be adjusted accordingly.

$$L_{n-1}(i) = \begin{cases} L_n(i) & \text{for } i = 1, 2, ..., i' \\ L_n(i+1) & \text{for } i = i'+1, i'+2, ..., n-1 \end{cases} \tag{7}$$

$$R_{n-1}(i) = \begin{cases} R_n(i) & \text{for } i = 1, 2, ..., i'-1 \\ R_n(i+1) & \text{for } i = i', i'+1, ..., n-1 \end{cases} \tag{8}$$

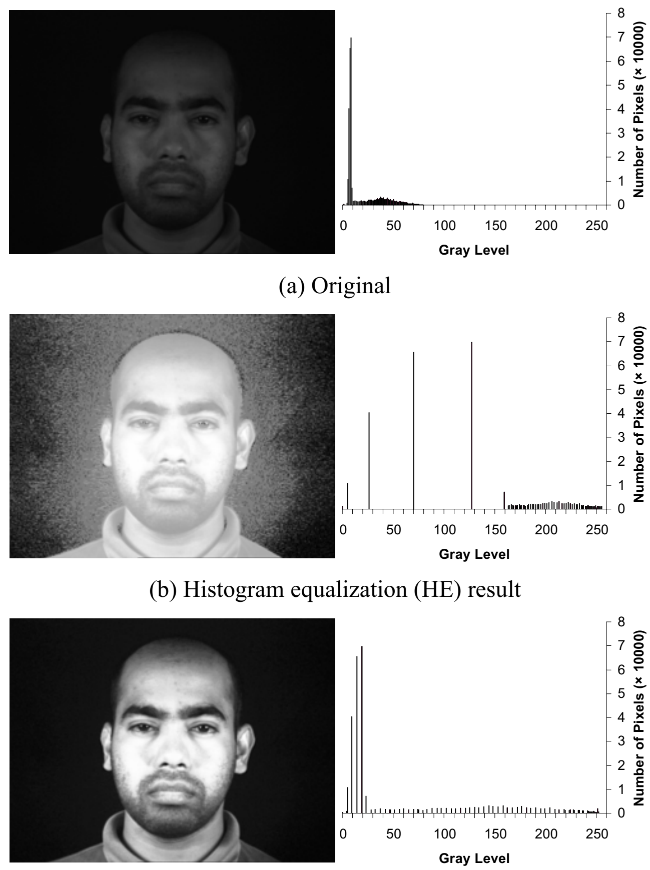
5) Mapping and ungrouping are performed in this step. Now the total number of gray-level bins has been reduced by one. We can start to construct the transformation function $T_{n-1}(k)$, which maps the gray level values of pixels in the input image to the desired values in the output image. In our method, all gray level bins are redistributed uniformly over the entire grayscale, the gray levels are mapped to new values, and the combined histogram components are fully or partially uncombined. We first calculate the number of gray levels, N_{n-1}, that each gray-level bin will occupy in the resulting image. With a total number of bins equal to $n-1$, we have

$$N_{n-1} = \frac{M-1}{n-1}. \tag{9}$$

However, if $L_{n-1}(1) = R_{n-1}(1)$, this indicates that the leftmost gray level bin $G_{n-1}(1)$ contains only one gray level or one histogram component, which usually corresponds to the background, and it will be matched to gray level 0 in the resulting image. To prevent this one histogram component from occupying too many gray levels, we let

$$N_{n-1} = \frac{M-1}{n-1-\alpha}, \tag{10}$$

where α is a constant between 0 and 1, and usually assumes a value of 0.8 in our treatments, found



(a) Original
(b) Histogram equalization (HE) result
(c) GLG result

Fig. 1. A subband facial image from a multi-spectral facial image sequence. (a) Low-contrast original image and its histogram. (b) Result of histogram equalization, has a washed-out appearance and amplified background noise. (c) Result of gray-level grouping, has a crisper look. The result is produced fully automatically. (Original image is from the image database of the Imaging, Robotics and Intelligent Systems (IRIS) Laboratory at the University of Tennessee, Knoxville.)

through multiple trials to work well with a variety of images.

There are four cases to be considered when constructing $T_{n-1}(k)$. For $k = 0, 1, 2, ..., M-1$:

i) If gray level k falls inside gray-level bin $G_{n-1}(i)$, and $L_{n-1}(i) \neq R_{n-1}(i)$, this gray level is first mapped onto the right boundary of the gray level interval assigned to bin $G_{n-1}(i)$, i.e., $[(i-1)N_{n-1}, iN_{N-1}]$, then it is separated from the group by linear rescaling within the assigned gray level interval. Therefore, its transformation function $T_{n-1}(k)$ is

$$T_{n-1}(k) = \begin{cases} \left(i - \alpha - \dfrac{R_{n-1}(i) - k}{R_{n-1}(i) - L_{n-1}(i)}\right) N_{n-1} + 1, \\ \qquad \text{for } L_{n-1}(1) = R_{n-1}(1) \\ \left(i - \dfrac{R_{n-1}(i) - k}{R_{n-1}(i) - L_{n-1}(i)}\right) N_{n-1} + 1, \\ \qquad \text{for } L_{n-1}(1) \neq R_{n-1}(1) \end{cases} \tag{11}$$

If $L_{n-1}(1) = R_{n-1}(1)$, constant α prevents the background histogram from occupying too many gray levels.

If $L_{n-1}(i) = R_{n-1}(i)$, i.e., the bin $G_{n-1}(i)$ contains only one gray level, then the transformation function is

$$T_{n-1}(k) = \begin{cases} (i - \alpha) N_{n-1}, & \text{for } L_{n-1}(1) = R_{n-1}(1) \\ iN_{n-1}, & \text{for } L_{n-1}(1) \neq R_{n-1}(1) \end{cases} \tag{12}$$

ii) If gray level k falls between gray-level bin $G_{n-1}(i)$ and $G_{n-1}(i+1)$, then its transformation function is

$$T_{n-1}(k) = \begin{cases} (i - \alpha) N_{n-1}, & \text{for } L_{n-1}(1) = R_{n-1}(1) \\ iN_{n-1}, & \text{for } L_{n-1}(1) \neq R_{n-1}(1) \end{cases} \tag{13}$$

This ensures that $T_{n-1}(k)$ is monotonically increasing along the grayscale, and the gray level reversal problem will be avoided in the adaptive approach of the GLG method.

iii) If $k \leq L_{n-1}(1)$, then $T_{n-1}(k) = 0$; (14)

iv) If $k \geq R_{n-1}(n-1)$, then $T_{n-1}(k) = M - 1$. (15)

The constructed gray-level transformation function, $T_{n-1}(k)$ for $k = 0, 1, 2, ..., M-1$, is stored in computer memory.

6) By applying the constructed transformation function $T_{n-1}(k)$ to the histogram, $H_n(k)$, of the original image, we obtain the histogram of the processed image, $H_{n-1}(k)$. The average distance, D_{n-1}, between pixels on the grayscale, is used as a criterion to measure the quality of contrast enhancement. This distance is given by the expression below:

$$D_{n-1} = \frac{1}{N_{pix}(N_{pix} - 1)} \sum_{i=0}^{M-2} \sum_{j=i+1}^{M-1} H_{n-1}(i) H_{n-1}(j)(j - i), \quad \text{for } i, j \in [0, M-1] \tag{16}$$

where $[0, M-1]$ is the gray level range of the grayscale, and N_{pix} is the total number of pixels in the image. This criterion generally applies only to the gray-level grouping technique or similar histogram-based techniques, and may not be used to judge the quality of images treated by other enhancement techniques. A counter example is given here — If we set the mean gray level of a low-contrast image as the threshold, and threshold this image into a black-and-white image, the average distance between pixels on the grayscale of the resulting image will be the maximum that could be achieved theoretically, however, the resulting black-and-white image is obviously unacceptable for purposes of enhancement. However, the GLG process tends to spread the histogram components uniformly over the grayscale, preventing the histogram components from concentrating in particular locations on the grayscale. At the same time, a larger D will keep the histogram components further away from each other for better enhancement. Therefore, we consider the average distance between pixels on the grayscale, D, as a sound measure of the quality of images enhanced by GLG technique, and consider that the maximal D corresponds to the optimal contrast enhancement. Visual evaluations of multiple images during our testing also confirmed the validity of this measure. This quality measure is essential in the GLG process to achieve the optimal result. It is worth noting that this image contrast criterion, the average distance between pixels on the grayscale, is not inherent to the GLG algorithm, but could be used in other histogram-based algorithms (especially histogram equalization) as well. However, we suggest that this criterion be used with caution.

In some cases (e.g., the background occupies a large percentage area in the image), in order to achieve the optimal result, the gray levels corresponding to the image background may be excluded when calculating D_{n-1}. For many images, the histogram components corresponding to the background are the highest and distinct in the histogram profile. Therefore, the approximate area of the background can be calculated automatically by summing the amplitudes of the histogram components of the background, given that the algorithm is notified by the user that the input image has a large-area background. If the background occupies a percentage area in the image larger than a user specified threshold (e.g., 40%), the background gray levels are then excluded when calculating D_{n-1}.

7) To determine the optimal number of gray level bins that will lead to the optimal contrast enhancement, we need to repeat the above procedure and group the histogram components into all possible numbers from n to 2 (there is no need to group all histogram components into one bin since the histogram will be the same as the original after it is ungrouped), and calculate the average distance between pixels on the grayscale, D_i, for each set of bins. The maximal D_i will lead to the corresponding optimum number, i_{opt}, for gray-level bins.

$$D_{\max} = \max_i D_i, \quad \text{for } i = n, n-1, n-2, ..., 2. \tag{17}$$

$$i_{opt} = i, \text{ for } D_i = D_{\max}. \tag{18}$$

8) To obtain the final optimally enhanced image, we retrieve the optimal gray-level transformation function $T_{i_{\mathrm{opt}}}(k)$ from computer memory, and then apply it to the original image.

Fig. 1(c) shows the result of applying this technique to the subband facial image and the resulting histogram, respectively. It is obvious that the GLG result is better than that of histogram equalization.

In order to evaluate the competitiveness of the GLG method against existing contrast enhancement techniques, we used the most well-known benchmark image sharpness measure, Tenengrad criterion [2, 3], to compare the results of the GLG and HE method. In order to avoid the influence of the background noise, the noisy background is excluded when calculating the Tenengrad criterion for the HE result. The Tenengrad value of the HE result in Fig. 1(b) is 2.9×10^3, and it's 5.8×10^3 for the GLG result in Fig. 1(c). The Tenengrad criterion indicates that the GLG result is significantly better than the HE result.

3. VARIATIONS OF THE BASIC GLG ALGORITHM

The basic GLG algorithm discussed in the previous section is a general and powerful technique, which can be conveniently applied to a broad variety of low-contrast images and outperforms conventional contrast enhancement techniques. However, the basic GLG method still has limitations and cannot enhance certain classes of low-contrast images well, e.g., images with a large noisy background. The basic GLG also cannot fulfill certain special application purposes, e.g., enhancing only part of an image which corresponds to a certain segment of the image histogram. In order to break through these limitations, we have developed an extension of the basic GLG algorithm, selective gray-level grouping (SGLG), which groups the histogram components in different segments of the grayscale using different criteria and hence is able to enhance different parts of the histogram to various extents, or eliminate image background noise. We have also extended the GLG technique to enhance color images. [4, 5]

4. CONCLUSIONS

We have developed a new automatic contrast enhancement technique. Gray-level grouping (GLG) is a general and powerful technique, which can be conveniently applied to a broad variety of low-contrast images and generates satisfactory results. The benchmark image quality measure, Tenengrad criterion, indicates that the GLG technique is superior to conventional contrast enhancement techniques. The GLG technique can be conducted with full automation at fast speeds and outperforms conventional contrast enhancement techniques. The basic GLG method also provides a platform for various extensions of this technique, such as selective gray-level grouping (SGLG), (S)GLG with preprocessing steps for eliminating image background noises, (S)GLG on color images, and so on. All these variations extend the capability of the basic GLG technique.

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