IEIE Transactions on Smart Processing and Computing, vol. 4, no. 5, October 2015
http://dx.doi.org/10.5573/IEIESPC.2015.4.5.349

IEIE Transactions on Smart Processing and Computing

Image Contrast Enhancement Based on a Multi-Cue Histogram

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Received July 15, 2015; Revised August 6, 2015; Accepted August 9, 2015; Published October 31, 2015

** Regular Paper*

Abstract: The conventional intensity histogram does not indicate edge information, which is important in the perception of image contrast. In this paper, we propose a multi-cue histogram (MCH) to represent a collaborative distribution of both the intensity and the edges of an image. Based on the MCH, if the intensity values have high frequency and a large gradient magnitude, they are spread into a larger dynamic range. Otherwise, the intensity values are not strongly stretched. As a result, image details, such as edges and textures, can be enhanced while artifacts and noise can be prevented, as demonstrated in the experimental results.

Keywords: Image contrast enhancement, Histogram equalization, Multi-cue histogram

1. Introduction

Since the human visual system (HVS) perceives contrast in an image very well, rather than the absolute intensity value, changes at or near edges have a profound impact on human perception [1]. Therefore, many conventional contrast enhancement methods [2-4] based on the intensity histogram tend to not only weaken the edge strength, especially in the bright regions, but to also produce artifacts in the homogenous regions.

In recent years, approaches that consider the edges or context as well as the intensity values have been presented [5-8]. The contrast enhancement method [5] enforces a strict order of pixels in the image based on intensity values as well as the averages in the local neighborhood. Then, new intensity values are assigned uniformly to the pixels, according to a strict order. Wan et al. [6] employed a similar approach [5] except that the pixels are ordered using wavelet coefficients instead of local average inten-sity values. Hashemi et al. [7] adopted a genetic algorithm to obtain a target histogram by maximizing a contrast measure based on the image edges. Then, a histogram specification is performed using this target histogram. Celik and Tjahjadi [8] constructed a 2D histogram for the input image using the mutual relationship between each pixel and its neighboring pixels. Then, a 2D target histo-gram is obtained by minimizing the difference between the input histogram and the uniform histogram. Image contrast is enhanced through mapping the diagonal elements of the input histogram to those of the target histogram.

In this paper, we propose a contrast enhancement method based on a novel multi-cue histogram (MCH). As the conventional histogram counts the number of pixels with each intensity value in the image, the MCH replaces the intensity value with a feature vector consisting of both the intensity value and edge magnitude. By counting the number of pixels corresponding to each feature vector, the MCH can represent a collaborative distribution of the intensity and edge information of the image. Thus, the MCH enables the transformation function to adapt to not only the pixel frequency but also the image edges. The proposed method can improve the contrast of the image details, as well as avoid magnifying noise and artifacts in the smooth regions.

The rest of the paper is organized as follows. In Section 2, the proposed MCH is defined and the derivation of the transformation function is presented. The experimental results and parameters are given in Section 3. Section 4 concludes the paper.

2. Proposed Method

2.1 Multi-cue Histogram

The conventional intensity histogram represents the frequency of each intensity value of the image. Figs. 1 (a)-(b) present two different images, which have the same intensity histogram as shown in Fig. 1(c). Applying histogram equalization (HE) to these two images produces different enhanced results, as shown in Figs. (d) and (e). Note that the noise is magnified in Fig. 1(d), whereas the patterns are more visible in Fig. 1(e).

To solve this problem, we introduce the MCH, which considers edge magnitude as well as the intensity value. Let V = (r, g) denote the feature vector, where r and g are the intensity and edge magnitude, respectively. The gradient magnitude can be calculated using any edge detector, such as the Sobel operator. Each bin of the MCH is indicated by a feature vector, Vi = (ri, gi), i = 1,□, K, where K is the number of bins in the MCH. The representative feature vectors, Vi's, are defined in advance and fixed for any input image. Since the gradient magnitude has a great variety of values in natural images, a large number of feature vectors can be generated. Therefore, we select the K representative feature vectors through quantizing the feature vectors. Specifically, the feature vectors from an image dataset are collected into a 2D feature space, and a clustering algorithm is applied to categorize these feature vectors into K groups. The group centers are used as the representative feature vectors. The bins are sorted in the order of their intensity values. The gradient magnitudes are normalized into [0, 1] by dividing the highest value in the dataset. The implementation details are given in Section 3.1.

To construct the MCH for an input image using the pre-defined $\mathbf{V}_i$'s, the feature vector $\mathbf{V}(x, y)$ for each pixel at position (x, y) is calculated and assigned to one of the $\mathbf{V}_i$'s based on the Euclidean distance. The i-th bin of the MCH represents the frequency of the assignments to the i-th representative feature vector $\mathbf{V}_i$. The MCHs of the images in Figs. 1(a)-(b) are shown in Fig. 2, where the representative feature vectors of the three highest bins are displayed. From the images with the same intensity histogram in Figs. 1(a)-(b), the resultant MCHs look totally different, as seen in Fig. 2.

It is worthwhile to state that, although the intensity and edge magnitude are used in the proposed method, the MCH can be extended by utilizing different kinds of low-level features, such as chrominance values, the local binary pattern (LBP), and Gabor filter responses.

2.2 Transformation Function

In most HE-based contrast enhancement methods, the transformation function is steep at the intensity values, with high frequencies in order to redistribute these values into a wider range. As a result, when these frequent intensity values are with high gradient magnitudes, the strong stretching can enhance the contrast of the edges. However, a strong stretching in the homogenous region consisting of pixels with low gradient magnitudes results

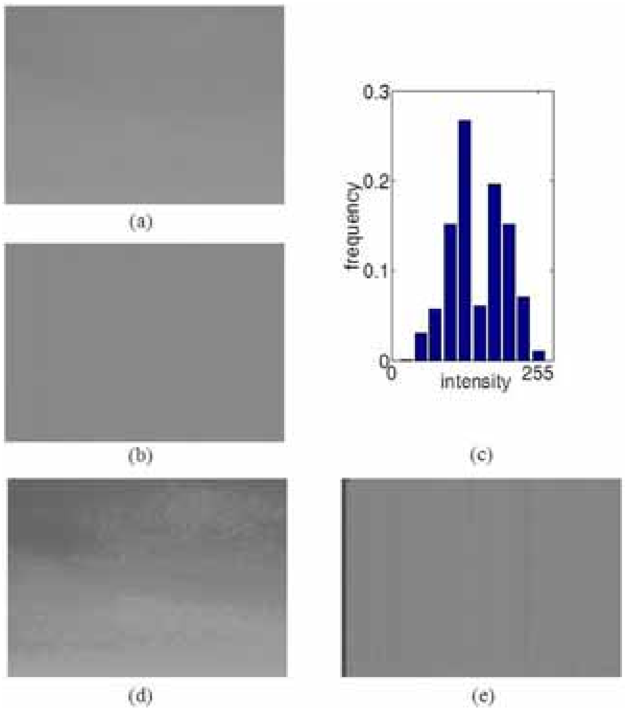


Fig. 1. (a) An image with low noise, (b) an image with a vertical pattern, (c) an intensity histogram of the two images, (d) the HE result of (a), and (e) the HE result of (b).

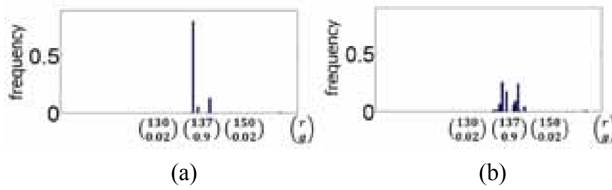


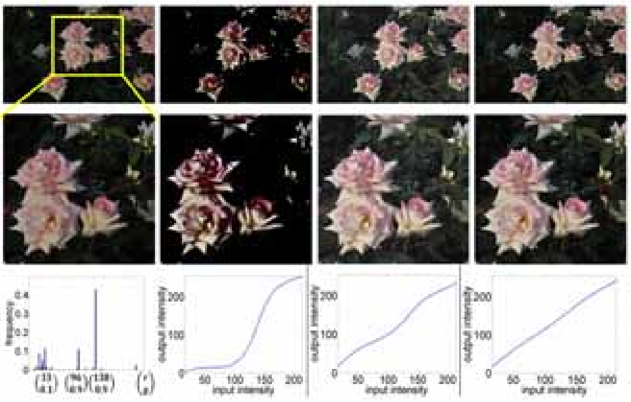
Fig. 2. (a) MCH of Fig. 1(a), and (b) MCH of Fig. 1 (b).

in artifacts. To solve this problem, we introduce a contrast enhancement method based on the MCH. The MCH, which represents the frequency as well as the gradient magnitude, enables the transformation function to adapt to both the frequency and gradient. We design the transformation function to be steep at high gradient values (to enhance the image edges) and to be gentle at the low gradient values (to avoid artifacts). Thus, the slope of the transformation function should be proportional to the pixel frequency as well as the gradient magnitude, as follows:

$$a_i = C \cdot (f_i \cdot g_i)^{\beta} \quad (1)$$

where a_i, f_i and g_i represent the slope, the frequency and the representative gradient magnitude of the i-th bin, respectively, and C is a constant. Let Δr_i denote the intensity range of the i-th bin, where the boundary between two bins is a medium value of the two representative intensity values. Then the output intensity increment Δs_i for the i-th bin can be calculated as $\Delta s_i = \Delta r_i \cdot a_i$. Normalizing the intensity values into [0, 1] using

$$\sum_i \Delta s_i = \sum_i \Delta r_i \cdot a_i = 1 \quad (2)$$



(a) (b) (c) (d)

Fig. 3. (a) Test image flower and its MCH. Resultant images and the corresponding transformation functions using (b) β=1, (c) β=1/3, and (d) β=1/10.

the constant C can be calculated by

$$C = 1 \Big/ \sum_i \Delta r_i \cdot (f_i \cdot g_i)^{\beta} \tag{3}$$

The power β, which is experimentally selected from the range [0, 1], adjusts the degree of image dependency in the contrast enhancement.

Fig. 3 illustrates the results for different β's. In Fig. 3(a), the representative feature vectors of the three highest bins are displayed. The bin with the highest frequency is obtained at an intensity value of about 138 and a normalized gradient magnitude of 0.9. For β = 1, the transformation function in Fig. 3(b) is very steep around intensity 138 because of the high frequency and gradient value of the corresponding bin. As a result, the contrast of the bright regions in the image is over-enhanced, while the details in the dark region are ignored. For $\beta = 0$, the slope a is always 1; thus, the transformation function does not change the intensity value after mapping. For $0 < \beta < 1$, the transformation function can be seen as a trade-off between the preservation of the original appearance (β = 0) and adaptation to the MCH (β = 1). As shown in Figs. 3(c) and (d), the transformation function with a higher β adapts more to the image characteristics.

Besides the pixel frequency and gradient magnitude, we also consider the property of the HVS. According to Weber's law [9], the HVS is more sensitive to contrast at low intensities than to that at high intensities. Therefore, we use a weighting factor to stretch the distribution of low intensity values and compress the distribution of high intensity values [10]:

$$w_i = \frac{\log(r_i + \alpha) - \log(\alpha)}{r_i \cdot (\log(1+\alpha) - \log(\alpha))} \tag{4}$$

where $\alpha \in (0,1]$. A higher α provides stronger stretching to the distribution of low intensity values. (1) and (3) are modified as

$$a_i = C \cdot w_i \cdot (f_i \cdot g_i)^{\beta} \tag{5}$$

$$C = 1 \Big/ \sum_i \Delta r_i \cdot w_i \cdot (f_i \cdot g_i)^{\beta} \tag{6}$$

Then, the output intensity s_i for r_i can be calculated as

$$\begin{cases} s_i = \dfrac{r_i}{\Delta r_i} \cdot \Delta s_i, & i = 1 \\ s_i = \displaystyle\sum_{l=1}^{i-1} \Delta s_l + \frac{r_i - \sum_{l=1}^{i-1} \Delta r_l}{\Delta r_i} \cdot \Delta s_i, & i = 2, 3, \cdots K \end{cases} \tag{7}$$

Finally, a spline function that satisfies all K pairs of (r_i, s_i) is calculated and used as a transformation function. The contrast-enhanced image is obtained by mapping intensities of the input image according to the transformation function.

3. Experimental Results and Evaluations

Color images are converted into the *YCbCr* color space and only the luminance component *Y* is processed. The edge magnitude is calculated using the Sobel operator and normalized by the largest value in the image dataset [12]. $\alpha = 0.8$ in (4) and $\beta = 1/3$ in (5) are used for our simulation.

3.1 Selection of the Representative Feature Vectors

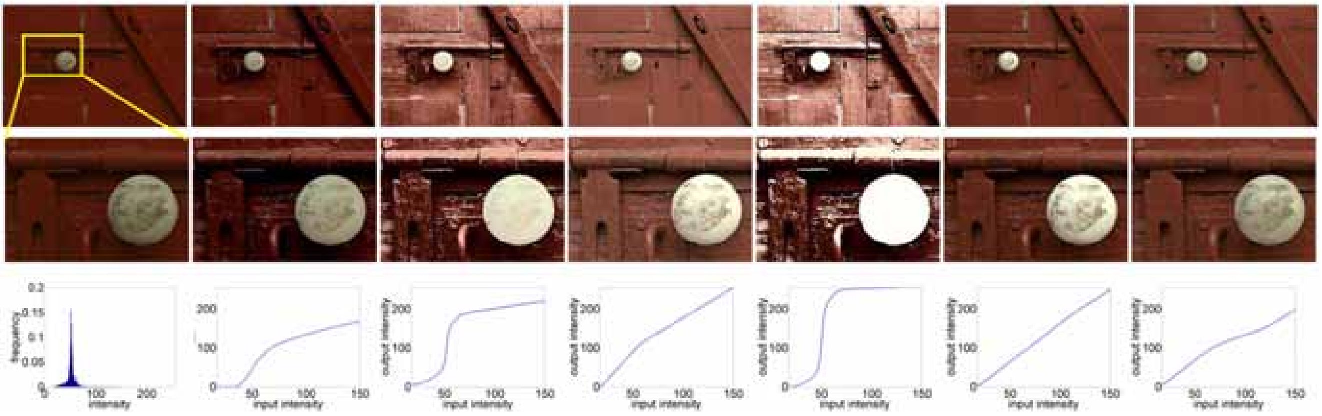
To select appropriate representative feature vectors for MCH bins, we first collect the feature vectors from the image dataset [11] into a two-dimensional space. Then starting from uniform initial seeds, the k-means clustering algorithm is applied to these feature vectors to obtain K representative groups. Let $\mathbf{U}_i$ denote the i-th group and $\mathbf{V}_i = (r_i, g_i)$ denote the center of $\mathbf{U}_i$. $\mathbf{V}_i$ is used as the representative feature vector for the i-th bin of the MCH. We calculate the Euclidean distance between the feature vectors and their corresponding group centers as

$$d_k = \sum_{i=1}^{K} \sum_{\mathbf{V}^i \in \mathbf{U}_i} \| \mathbf{V}^i - \mathbf{V}_i \| \tag{8}$$

where Vi represents the feature vector in the group Ui. A smaller distance indicates that the feature vectors can be represented more accurately by the corresponding group centers. As expected, our experiments show that dk decreases as K increases. But the decreasing rate Δdk/ΔK tends to be insignificant for a large K. Considering both dk and its decreasing rate, we select K = 100 as the group number for our simulation.

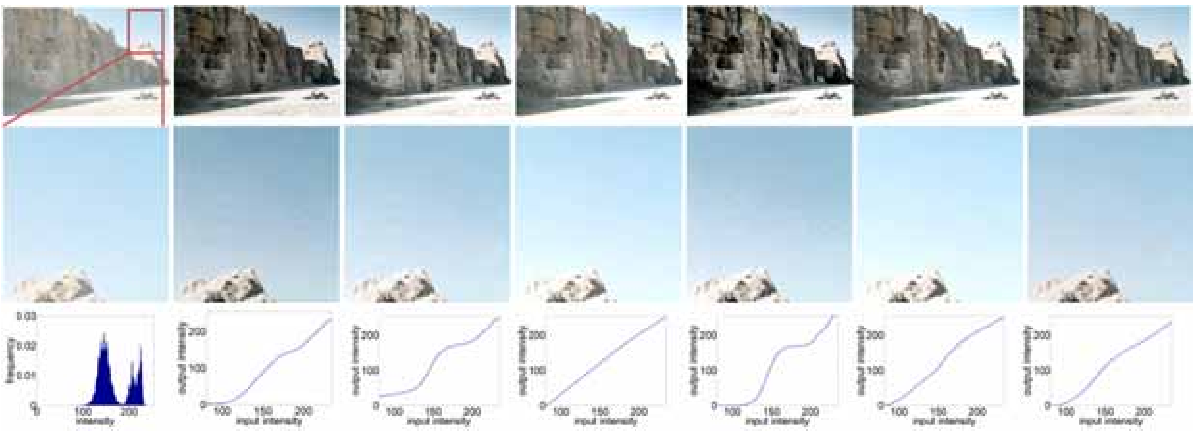
3.2 Result Assessment

The proposed method is compared with the weighted thresholded histogram (WTH) [2], the histogram modification framework (HMF) [3], the Gaussian Mixture Model (GMM)–based method [4], the exact histogram specification (EHS) [5], and the joint exact histogram specification



(a) (b) (c) (d) (e) (f) (g)

Fig. 4. (a) Test image door and its MCH. Contrast enhancement results and the corresponding transformation functions using, (b) WTH, (c) HMF, (d) GMM, (e) EHS, (f) JEHS, and (g) the proposed method.



(a) (b) (c) (d) (e) (f) (g)

Fig. 5. (a) Test image mountain and its MCH. Contrast enhancement results and the corresponding transformation functions using, (b) WTH, (c) HMF, (d) GMM, (e) EHS, (f) JEHS, and (g) the proposed method.

Table 1. AMBE, DE and EME of Test Image Door.

	WTH	HMF	GMM-based	EHS	JEHS	Proposed
AMBE	0.78	44.55	44.54	74.01	16.51	**21.81**
DE	4.33	5.19	4.23	5.35	3.95	3.92
EME	13.47	22.45	7.05	23.07	6.87	6.57

Table 2. AMBE, DE and EME of Test Image Mountain.

	WTH	HMF	GMM-based	EHS	JEHS	Proposed
AMBE	53.44	29.74	18.71	41.68	27.84	**36.57**
DE	5.20	5.24	4.74	5.15	4.84	5.12
EME	11.16	10.47	6.11	16.84	7.12	9.26

(JEHS) [6]. For objective assessment, we measure the average mean brightness error (AMBE), the discrete entropy (DE), and the measure of enhancement by entropy (EME).

Fig. 4 presents the test image door and its results, with the objective assessments in Table 1. The WTH does not brighten the overall luminance while improving the image contrast. The HMF and the EHS tend to over-enhance the images and produce an unnatural appearance. Among the GMM-based method, the JEHS, and the proposed method, the proposed method best preserves the details of the knob. The proposed method produces a medium AMBE by properly brightening the dark original image. Although the proposed method exhibits low DE and EME, the methods with high DE and EME values produce obvious over-enhanced results.

In Fig. 5, the test image mountain presents a washed out appearance. All the aforementioned methods produce similar overall brightness, except WTH, which produces the highest AMBE and tends to darken the image. Since DE and EME measure the contrast, WTH, HMF, and EHS (which produce high DE and EME) tend to increase the noise in the sky region. The hilltop in the results of GMM and JEHS are too bright to be distinguished from the sky. The proposed method enhances the overall contrast without magnifying noise in the sky region.

4. Conclusion

This paper presents an image contrast enhancement method based on the MCH. Using the MCH representing the collaborative distribution of the edge information as well as the intensity value, the transformation function for contrast enhancement is derived. We found that the transformation function can enhance the image edges and avoid artifacts by redistributing the pixel intensity values in proportion to not only the pixel frequencies but also the gradient magnitudes. Experimental results indicate that the proposed method improves image contrast while preserving image details, as well as the smoothness of the homogeneous regions. The proposed MCH can easily be extended by adopting various image features. Furthermore, it can be applied to other image processing areas, such as image retrieval and image segmentation.

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