A General Histogram Modification Framework for Efficient Contrast Enhancement

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***Abstract*—In this paper we propose a new general histogram modification framework for contrast enhancement. The proposed model works with a hybrid transformation technique to improve image brightness and contrast based on an optional histogram matching in terms of reassigned probability distribution and S-shaped transfer mapping. Experimental results conducted on natural, dimmed, and tone-mapped images show that the proposed technique creates enhanced images efficiently with equivalent or superior visual quality to those produced by classical and state-of-the-art enhancement approaches.**

***Index Terms*—Contrast enhancement, histogram modification (HM), reassigned probability distribution, histogram matching, S-shaped transfer mapping**

I. Introduction

Contrast enhancement has been playing an important role in the improvement of visual quality for computer vision, pattern recognition and digital image processing. Several conditions may lead to poor contrast in images, including lack of operator expertise and inadequacy of the capture device. Unfavorable environmental conditions in the captured scene, such as the presence of clouds and lack of sunlight or indoor lighting, may also introduce reduced contrast quality [1]. In summary, the details in the input image will be obscured if the overall luminance is insufficient.

We can generally divide existing contrast enhancement technologies into two types: direct methods and indirect methods. Direct enhancement techniques were developed with the help of a simple and specific contrast term defined for the image contrast [2]-[3]. Though simplicity, most of these measures do not work effectively for both simple patterns and complex images simultaneously.

In contrary, indirect enhancement approaches try to improve visual contrast through reassigning the probability density [1]. The histogram modification (HM) technique, due to its easy and fast implementation, is a preferable option for indirect enhancement. Most classical contrast enhancement models are HM methods, which include histogram equalization (HE) [4] and its derivatives brightness preserving bi-histogram equalization (BBHE) [5], dualistic sub-Image histogram equalization (DSIHE) [6], recursive mean-separate histogram equalization (RMSHE) [7], recursive sub-image histogram equalization (RSIHE) [8], and histogram modification framework (HMF) [1]. BBHE and DSIHE work to protect image brightness, but the former BBHE focuses on preserving the mean brightness while the latter DSIHE maintains the median value. RMSHE and RSIHE deploy similar recursive schemes to advance BBHE and DSIHE respectively, in order to better keep the image brightness unchanged. Recently, HMF was developed by searching for an intermediate histogram $\mathbf{h}$ between the input histogram $\mathbf{h}_i$ and the uniform histogram $\mathbf{u}$ via the minimization process of a weighted distance $||\mathbf{h} - \mathbf{h}_i|| + \lambda||\mathbf{h} - \mathbf{u}||$ before performing HE of $\mathbf{h}$.

Another kind of HM techniques, S-shaped transfer based brightness preserving (STBP) [9] and its variant [10], mainly depend on the recent finding concerning the relationship of the third order statistic (skewness) and the surface quality [11]. With a simple and quick histogram mapping operation, enhanced images can be readily generated of suitable luminance, hue and tone as well as without noise injection. Nonetheless, it is usually inefficient to deal with low-contrast images.

In this paper we design a general histogram modification framework (GHMF), which works in a two-stage structure. The first step of GHMF is an optional histogram matching in terms of reassigned probability distribution of image pixels, for highlighting the undiscernible details. This step essentially has a similar target to the traditional HMF method for pursuing the best tradeoff between the histogram of the input image and the uniformly distributed version, but works more effectively in practical. The second step is S-shaped transfer mapping, in order to increase the image gloss and thus the surface quality. Using various kinds of images, including natural, dimmed, and tone-mapped images, as the testing bed, the proposed GHMF shows outstanding enhancement effect.

The remainder of this article is organized as follows. Section II presents the proposed GMHF contrast enhancement method. In Section III, the effectiveness of our algorithm is proved by comparison of its experimental results with those obtained through existing relevant models. Finally, several concluding remarks are presented in Section IV.

II. Proposed Method

The flowchart of the proposed technique is given in Fig. 1. The first component of our GHMF is histogram matching in

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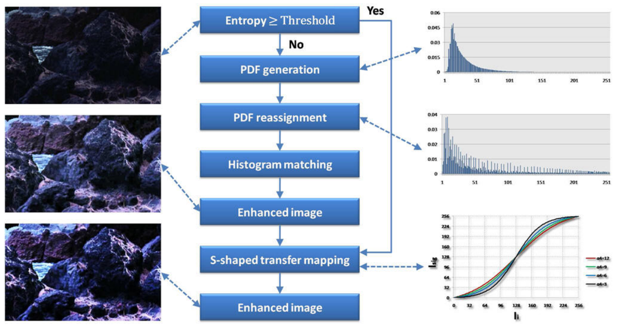


Fig. 1. The flowchart of the proposed enhancement technique.

terms of reassigned probability distribution when the entropy of the input visual signal is beneath the threshold. Histogram matching, as one of the most commonly used method in HM techniques, works to match the input image histogram to the target one. HE is such a classical and popular example with the uniformly distributed histogram as its target. To specify, given an input image I_i, the probability density function (PDF) can be calculated by

$$PDF(l) = \frac{n_l}{MN} \tag{1}$$

where n_l is the number of pixels that have the intensity l. MN is the total number of pixels in the image. The cumulative distribution function (CDF) is formulated based on PDF:

$$CDF(l) = \sum_{i=0}^{l} PDF(i). \tag{2}$$

Then, traditional HE directly utilizes CDF as a transformation curve expressed by

$$T(l) = CDF(l) l_{\max} \tag{3}$$

where $l_{\max}$ is the maximum intensity value of the input image. Owing to the existence of luminance pixels of large PDFs, HE is very likely to induces artifacts. To address the problem, HMF combines the input image histogram and the uniformly distributed one to seek for the best compromising histogram. Nevertheless, HMF will change the PDF value at the intensity level in which the original PDF value is zero, and this may deteriorate image scene and introduce noise. So in this paper a new strategy for finding the tradeoff histogram is explored using a power-law punishment term to reassign the input PDF that is computed by

$$PDF(l) = PDF(l)^{1-\alpha} \tag{4}$$

where α is a constant to control the shape of PDF. Note that the traditional HE is acquired as α goes to one, while Eq. (4) converges to the input image when α is close to zero. It needs to stress that our model can well solve the problem of HMF by avoiding the generation of new non-zero PDFs at intensity levels in the output histogram.

The second part of our GHMF model is the recently proposed S-shaped transfer mapping. More precisely, we compute the mapping $T_s(\cdot)$ and its associated enhanced image I_s using a four-parameter logistic function:

$$I_s = T_s(I_i, \boldsymbol{\phi}) = \frac{\phi_1 - \phi_2}{1 + \exp(-\frac{(I_i - \phi_3)}{\phi_4})} + \phi_2 \tag{5}$$

where $\boldsymbol{\phi} = \{\phi_1, \phi_2, \phi_3, \phi_4\}$ are free parameters required to be solved. We hypothesize that the transfer curve passes four points (b_i, a_i), $i = \{1, 2, 3, 4\}$. In [11], the authors found that an image with a long positive tail in histogram (namely a positively skewed statistics) always tends to appear darker and glossier and has improved surface quality relative to a similar image with lower skewness. Furthermore, the authors provided a possible neural mechanism in human brains which includes on-center and off-center cells and an accelerating nonlinearity to compute the subband skewness. This motivates the usage of the sigmoid mapping for advancing surface quality, which is rolling-symmetry with respect to the straight line $y = x$. We fix seven parameters: $(b_1, a_1) = (0, 0)$, $(b_2, a_2) = (255, 255)$, $(b_3, a_3) = (\frac{l_{\max}}{2}, \frac{l_{\max}}{2})$, $b_4 = 25$, and let a_4 to be the only free parameter. We then search for the optimal control parameters $\boldsymbol{\phi}$ via the minimization of the following objective function:

$$\boldsymbol{\phi}_o = \arg\min_{\boldsymbol{\phi}} \sum_{i=1}^{4} \Big| a_i - T_s(b_i, \boldsymbol{\phi}) \Big|. \tag{6}$$

With the known parameters $\boldsymbol{\phi}_o$, we can finally get the enhanced image:

$$I_s = \max(\min(T_s(I_i, \boldsymbol{\phi}_o), 255), 0) \tag{7}$$

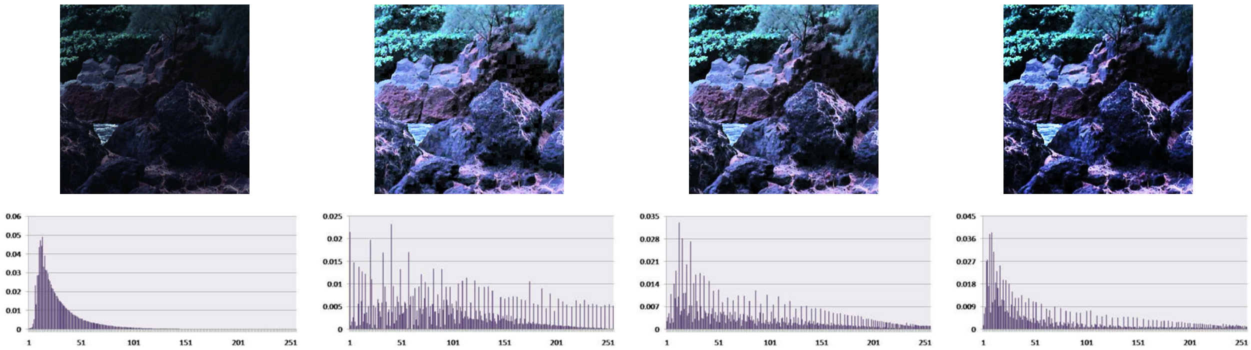
where max and min operations are used to clip I_s's pixel values in the range of 0∼255. Note that a_4 is the only control parameter used to alter curvature of the transfer function. To visualize the sigmoid curve, we plot four curves with different values of a_4 in Fig. 1. The mapping associated to $a_4 = 12$ is first stored and directly used for implementation.

III. Experimental Results

In this section we present some experimental results for the contrast enhancement of dimmed image "rock" and "tree", tone-mapped image "forest", and natural images "lighthouse" and "parrots". The tone-mapped image comes from the tone-mapped image database [12], and the two natural images come from the Kodak database [13]. The classical and popular HM methods (HE and HMF) are used for comparison to confirm the effectiveness of the proposed technique.

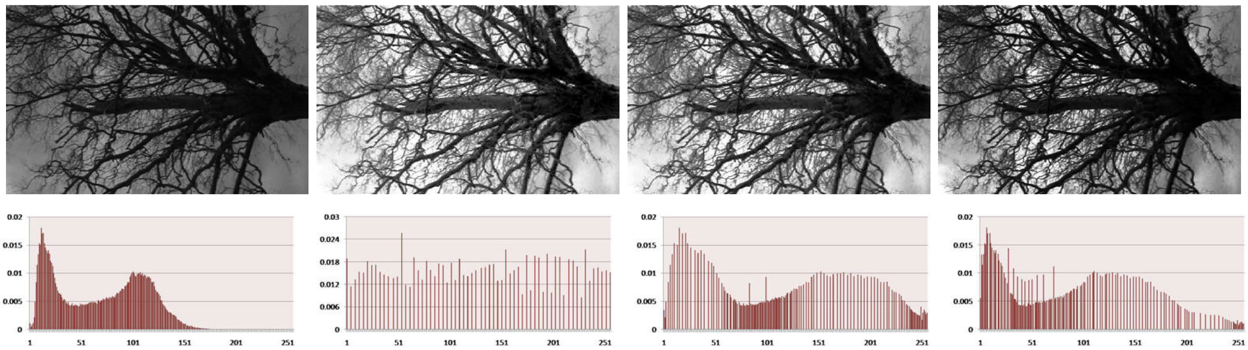
Figs. 2-3 presents the sample dimmed images "rock" and "tree" and the enhancement results of the proposed algorithm compared with other enhancement approaches tested. As given in Figs. 2-3(b)-(c), the enhancement results of HE and HMF show somewhat block artifacts on the rock and tree trunk. In comparison, our model not only well prevents the blockiness introduction but also clearly reveals the luminance variations, e.g. in the "sky" background in Fig. 3(d).

The tone-mapped image "forest" is illustrated in Fig. 4. According to Figs. 4(b)-(d), each of the three testing contrast enhancement technologies show undiscernible details. Besides,



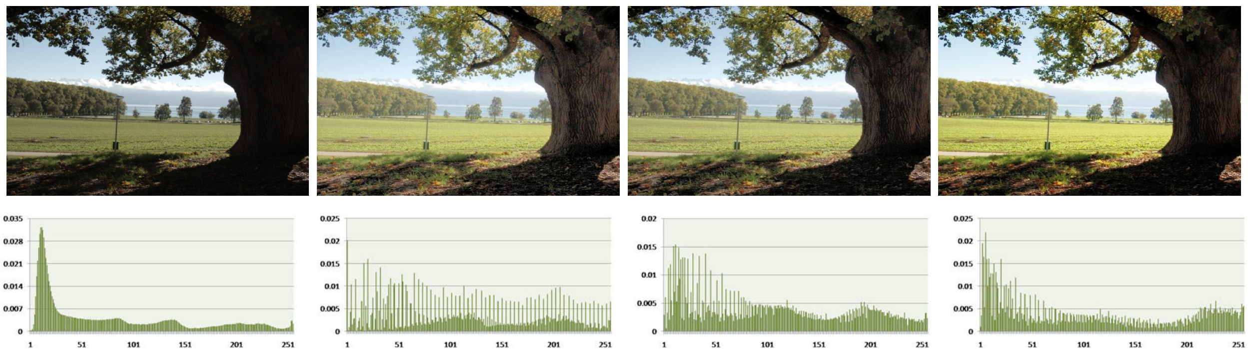
(a) (b) (c) (d)

Fig. 2. Comparison of enhancement results and associated histograms for the dimmed image “rock”: (a) Original image; (b) HE output; (c) HMF output; (d) The proposed GHMF output.



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

Fig. 3. Comparison of enhancement results and associated histograms for the dimmed image “tree”: (a) Original image; (b) HE output; (c) HMF output; (d) The proposed GHMF output.



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

Fig. 4. Comparison of enhancement results and associated histograms for the tone-mapped image “forest”: (a) Original image; (b) HE output; (c) HMF output; (d) The proposed GHMF output.

the enhanced image created by the proposed GHMF is also of much glossier, which is probably caused by the utility of the S-shaped transfer mapping to increase the surface quality, as displayed in Fig. 4(d).

Figs. 5-6 provides the last two natural images “lighthouse” and “parrots”. It is very clear that enhanced images produced by HE and HMF are of visual artifacts, as shown in Figs. 5-6(b)-(c). Conversely, our method succeeds in suppressing noise while improving the visual quality.

In post-processing systems, the efficiency is another crucial index. So the comparison of the computational complexity of the proposed model with other testing ones for an image of size $W \times H$ and B bins will be given based on the analysis in [1]. For HE, the computation of the histogram requires $\mathcal{O}(WH)$ time, calculating the mapping function from the histogram requires $\mathcal{O}(2^B)$ time, obtaining the enhanced image with the mapping function requires $\mathcal{O}(WH)$ time, and thus its total time complexity requires $\mathcal{O}(2WH + 2^B)$ time.

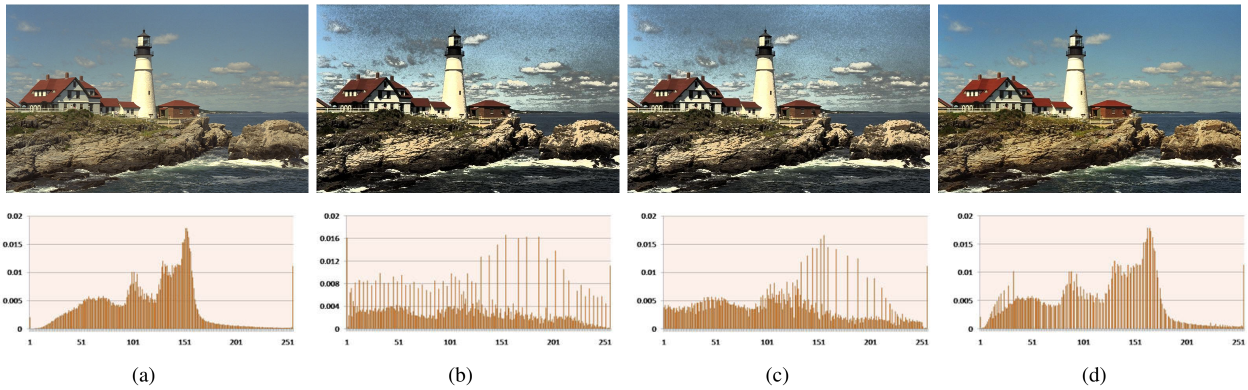


Fig. 5. Comparison of enhancement results and associated histograms for the natural image "lighthouse": (a) Original image; (b) HE output; (c) HMF output; (d) The proposed GHMF output.

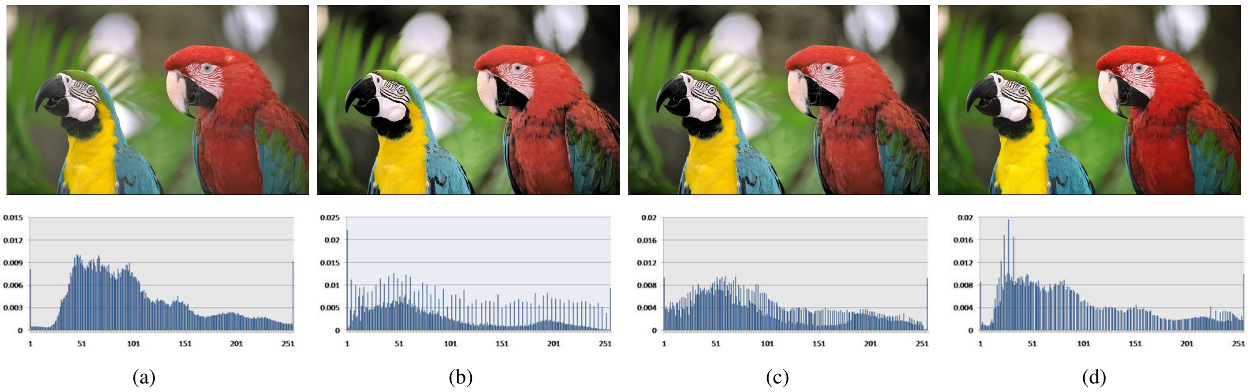


Fig. 6. Comparison of enhancement results and associated histograms for the natural image "parrots": (a) Original image; (b) HE output; (c) HMF output; (d) The proposed GHMF output.

Similarly, HMF requires $\mathcal{O}(2WH + 2^{B+1})$ time since it needs an extra $\mathcal{O}(2^B)$ time for the computation of the modified histogram for each bin. For GHMF, it needs $\mathcal{O}(2WH+2^{B+2})$ time when processing dimmed images while it requires only $\mathcal{O}(2^B)$ time for other conditions. In brief, our algorithm has a low computational load and thereby works efficiently.

IV. Conclusion

In this paper we have proposed a new general histogram modification framework (GHMF) for image enhancement with an optional histogram matching in light of reassigned probability distribution followed by S-shaped transfer mapping. Our approach works effectively for enhancing natural images, dimmed images and ton-mapped images, as compared with the classical/popular histogram modification method HE/HMF. It is noted that enhanced images generated by the proposed GHMF not only reveal undiscernible details but also are much glossier and thus are of improved surface quality. Furthermore, relative to HE and HMF, our technique is also shown to be efficient by the analysis on the computational complexity.

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