A Histogram Modification Framework and Its Application for Image Contrast Enhancement

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Abstract—**A general framework based on histogram equalization for image contrast enhancement is presented. In this framework, contrast enhancement is posed as an optimization problem that minimizes a cost function. Histogram equalization is an effective technique for contrast enhancement. However, a conventional histogram equalization (HE) usually results in excessive contrast enhancement, which in turn gives the processed image an unnatural look and creates visual artifacts. By introducing specifically designed penalty terms, the level of contrast enhancement can be adjusted; noise robustness, white/black stretching and mean-brightness preservation may easily be incorporated into the optimization. Analytic solutions for some of the important criteria are presented. Finally, a low-complexity algorithm for contrast enhancement is presented, and its performance is demonstrated against a recently proposed method.**

Index Terms—**Histogram equalization, histogram modification, image/video quality enhancement.**

I. INTRODUCTION

CONTRAST enhancement plays a crucial role in image processing applications, such as digital photography, medical image analysis, remote sensing, LCD display processing, and scientific visualization. There are several reasons for an image/video to have poor contrast: the poor quality of the used imaging device, lack of expertise of the operator, and the adverse external conditions at the time of acquisition. These effects result in under-utilization of the offered dynamic range. As a result, such images and videos may not reveal all the details in the captured scene, and may have a washed-out and unnatural look. Contrast enhancement targets to eliminate these problems, thereby to obtain a more visually-pleasing or informative image or both. Typical viewers describe the enhanced images as if a curtain of fog has been removed from the picture [1].

Several contrast enhancement techniques have been introduced to improve the contrast of an image. These techniques can be broadly categorized into two groups: direct methods [2], [3] and indirect methods [4], [5]. Direct methods define a contrast measure and try to improve it. Indirect methods, on the other hand, improve the contrast through exploiting the under-utilized regions of the dynamic range without defining a specific contrast term. Most methods in the literature fall into the second group. Indirect methods can further be divided into several subgroups: i) techniques that decompose an image into high and low frequency signals for manipulation, e.g., homomorphic filtering [6], ii) histogram modification techniques [7]–[17], and iii) transform-based techniques [18]–[22]. Out of these three subgroups, the second subgroup received the most attention due to its straightforward and intuitive implementation qualities.

Contrast enhancement techniques in the second subgroup modify the image through some pixel mapping such that the histogram of the processed image is more spread than that of the original image. Techniques in this subgroup either enhance the contrast globally or locally. If a single mapping derived from the image is used then it is a global method; if the neighborhood of each pixel is used to obtain a local mapping function then it is a local method. Using a single global mapping cannot (specifically) enhance the local contrast [10], [13]. The method presented in this paper is demonstrated as a global contrast enhancement (GCE) method, and can be extended to local contrast enhancement (LCE) using similar approaches.

One of the most popular GCE techniques is histogram equalization (HE). HE is an effective technique to transform a narrow histogram by spreading the gray-level clusters in the histogram [23], [24], and it is adaptive since it is based on the histogram of a given image. However, HE without any modification can result in an excessively enhanced output image for some applications (e.g., display-processing).

Various methods have been proposed for limiting the level of enhancement, most of which are obtained through modifications on HE. For example, bi-histogram equalization was proposed to reduce the mean brightness change [7]. HE produces images with mean intensity that is approximately in the middle of the dynamic range. To avoid this, two separate histograms from the same image are created and equalized independently. The first is the histogram of intensities that are less than the mean intensity, the second is the histogram of intensities that are greater than the mean intensity. A similar method called equal area dualistic sub-image histogram equalization (DSIHE) was proposed in which the two separate histograms were created using the median intensity instead of the mean intensity [8]. Although they are visually more pleasing than HE, these two techniques cannot adjust the level of enhancement and are not robust to noise, which may become a problem when the histogram has spikes. Also, it should be noted that preserving the brightness does not imply preservation of naturalness. One method to deal with histogram spikes is the histogram low-pass filtering [9]. Another method proposes

modifying the "cumulation function" of the histogram to adjust the level of enhancement [10], but both of these methods are still sensitive to problems created by histogram spikes. These two methods apply gaussian blurring in the spatial domain to obtain a low-pass filtered histogram or a modified cumulation function [9], [10]. The image blurring operation alone may still be insufficient for large spikes in the histogram; modifying the cumulation function alone enables adjustment of enhancement but does not directly handle histogram-spike related problems. In addition, both of these methods are LCE methods, which are known to be more computationally complex than GCE methods and they not only highlight details in the image but also enhance noise. One recent method proposed by Wang and Ward [14] suggests modifying the image histogram by weighting and thresholding before histogram equalization. The weighting and thresholding is performed by clamping the original histogram at an upper threshold P_u and at a lower threshold P_l, and transforming all the values between the upper and lower thresholds using a normalized power law function with index $r > 0$.

There are also unconventional approaches to the histogram-based contrast enhancement problem [11], [12]. Gray-level grouping (GLG) is such an algorithm that groups histogram bins and then redistributes these groups iteratively [11]. Although GLG can adjust the level of enhancement and is robust to histogram spikes, it is mainly designed for still images. Since gray-level grouping makes hard decisions on grouping histogram bins, and redistributing the bins depends on the grouping, mean brightness intensity in an image sequence can abruptly change in the same scene. This causes flickering, which is one of the most annoying problems in video enhancement. Although a fast version of the algorithm is available, GLG's computational complexity is high for most applications.

Contrast enhancement techniques in the first and third subgroups often use multiscale analysis to decompose the image into different bands and enhance desired global and local frequencies [6], [18]–[22], [25]–[27]. These techniques are computationally complex but enable global and local contrast enhancement at the same time by enhancing the appropriate scales.

The aforementioned contrast enhancement techniques perform well on some images but they can create problems when a sequence of images is enhanced, or when the histogram has spikes, or when a natural looking enhanced image is strictly required. In addition, computational complexity and controllability become an important issue when the goal is to design a contrast enhancement algorithm for consumer products. In summary, our goal in this paper is to obtain a visually pleasing enhancement method that has low-computational complexity and can be easily implemented on FPGAs or ASICs and works well with both video and still images. The contributions of this paper in achieving this goal are:

- to describe the necessary properties of the enhancement mapping $T[n]$, and to obtain $T[n]$ via the solution of a bi-criteria optimization problem;
- to incorporate additional penalty terms into the bi-criteria optimization problem in order to handle noise robustness and black/white stretching;

- to present a content-adaptive algorithm with low computational complexity.

In the next section, contrast enhancement is explained. In Section III, the contrast enhancement using the proposed framework is explained in a progressive manner. Then, the proposed low-complexity method is presented in Section IV. Simulation results and discussions are presented in Section V. Finally, the conclusion is provided in Section VI.

II. CONTRAST ENHANCEMENT

Histogram-based contrast enhancement techniques utilize the image histogram to obtain a single-indexed mapping $T[n]$ to modify the pixel values.[1] In HE and other histogram-based methods, mapping function is obtained from the histogram or the modified histogram, respectively [23]. HE finds a mapping to obtain an image with a histogram that is as close as possible to a uniform distribution to fully exploit the dynamic range. A histogram, $h[n]$, can be regarded as an un-normalized discrete probability mass function of the pixel intensities. The normalized histogram $p[n]$ of an image gives the approximate probability density function (PDF) of its pixel intensities. Then, the approximate cumulative distribution function (CDF), $c[n]$, is obtained from $p[n]$. The mapping function is a scaled version of this CDF. HE uses the image histogram to obtain the mapping function; whereas, other histogram-based methods obtain the mapping function via the modified histogram. The mapping function in the discrete form is given as

$$T[n] = \left\lfloor (2^B - 1) \sum_{j=0}^{n} p[j] + 0.5 \right\rfloor \qquad (1)$$

where B is the number of bits used to represent the pixel values, and $n \in [0, 2^B - 1]$. Although the histogram of the processed image will be as uniform as possible, it may not be exactly uniform because of the discrete nature of the pixel intensities.

It is also possible to enhance the contrast without using the histogram. Black stretching and white stretching are simple but effective techniques used in consumer-grade TV sets [1]. Black stretching makes dark pixels darker, while white stretching makes bright pixels brighter. This produces more natural looking black and white regions; hence, it enhances the contrast of the image. Linear black and white stretching can be achieved by the mapping

$$T[n] = \begin{cases} n \times s_b, & n \le b \\ n \times g[n], & b < n < w \\ w + (n - w) \times s_w, & w \le n \end{cases} \qquad (2)$$

where b is the maximum gray-level to be stretched to black and w is the minimum gray-level to be stretched to white, $g[n]$ is any function mapping the intensities in between, and s_b, s_w are black and white stretching factors both of which are less than one.

III. HISTOGRAM MODIFICATION

To fully exploit the available dynamic range, HE tries to create a uniformly distributed output histogram by using a

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[1]The term "pixel intensity" will sometimes be used to refer to the pixel values in single-channel images.
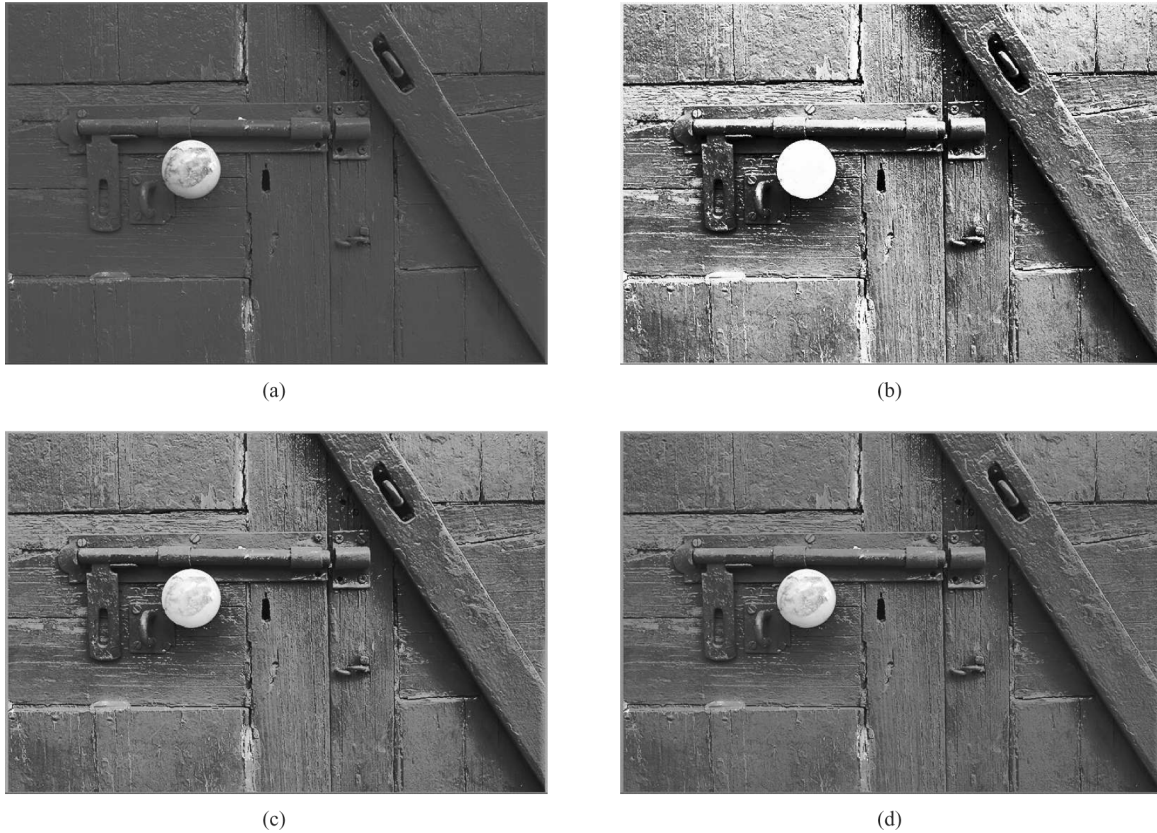
Fig. 1. Modified histogram equalization results using (6) for image *Door*. (a) Original image, (b) enhanced image using (6) with $\lambda = 0$, (c) enhanced image using (6) with $\lambda = 1$, (d) enhanced image using (6) with $\lambda = 2$.

cumulated histogram as its mapping function. However, HE often produces overly enhanced unnatural looking images. One problem with HE rises from large backward-difference values of $T[n]$, i.e., $T[n] - T[n-1]$ may be unusually large. To deal with this, the input histogram can be modified without compromising its contrast enhancement potential. The modified histogram can then be accumulated to map input pixels to output pixels, similar to HE.

It is important to note that when the input distribution is already uniform, the mapping obtained from cumulating the input distribution is $T[n] = n$, which identically maps input to output. Hence, to lessen the level of enhancement that would be obtained by HE, the input histogram $\mathbf{h_i}$ can be altered so that the modified histogram $\tilde{\mathbf{h}}$ is *closer* to a uniformly distributed histogram $\mathbf{u}$, according to a suitably chosen distance metric.

The modified histogram can be seen as a solution of a bi-criteria optimization problem. The goal is to find a modified histogram $\tilde{\mathbf{h}}$ that is closer to $\mathbf{u}$ as desired, but also make the residual $\tilde{\mathbf{h}} - \mathbf{h_i}$ small. This modified histogram would then be used to obtain the mapping function via (1). This is a bi-criteria optimization problem, and can be formulated as a weighted sum of the two objectives as

$$\min \|\mathbf{h} - \mathbf{h_i}\| + \lambda \|\mathbf{h} - \mathbf{u}\| \tag{3}$$

where $\mathbf{h}, \mathbf{h_i}, \tilde{\mathbf{h}}$, and $\mathbf{u} \in R^{256 \times 1}$, and λ is a problem parameter.[2] As λ varies over $[0, \infty)$, the solution of (3) traces the optimal

[2] $R^{256 \times 1}$ assumes 8-bit/channel bit-precision for simplicity.

trade-off curve between the two objectives. HE obtained by $\lambda = 0$ corresponds to the standard HE, and as λ goes to infinity it converges to preserving the original image. Therefore, various levels of contrast enhancement can be achieved by varying λ.

A. Adjustable Histogram Equalization

An analytical solution to (3) can be obtained when the squared sum of the Euclidean norm is used, i.e.,

$$\tilde{\mathbf{h}} = \underset{\mathbf{h}}{\operatorname{argmin}} \|\mathbf{h} - \mathbf{h_i}\|_2^2 + \lambda \|\mathbf{h} - \mathbf{u}\|_2^2 \tag{4}$$

which results in the quadratic optimization problem

$$\tilde{\mathbf{h}} = \underset{\mathbf{h}}{\operatorname{argmin}}[(\mathbf{h} - \mathbf{h_i})^T(\mathbf{h} - \mathbf{h_i}) + \lambda(\mathbf{h} - \mathbf{u})^T(\mathbf{h} - \mathbf{u})]. \tag{5}$$

The solution of (5) is

$$\tilde{\mathbf{h}} = \frac{\mathbf{h_i} + \lambda \mathbf{u}}{1 + \lambda} = \left(\frac{1}{1 + \lambda}\right)\mathbf{h_i} + \left(\frac{\lambda}{1 + \lambda}\right)\mathbf{u}. \tag{6}$$

The modified histogram $\tilde{\mathbf{h}}$, therefore, turns out to be a weighted average of $\mathbf{h_i}$ and $\mathbf{u}$. Simply by changing λ, the level of enhancement can be adjusted instead of the more complex nonlinear technique given by Stark [10].

An example image and enhanced images using modified histogram equalization with three different λ values (0, 1, 2) are shown in Fig. 1. When λ is zero, the modified histogram is equal to the input histogram; hence, the standard HE is applied.
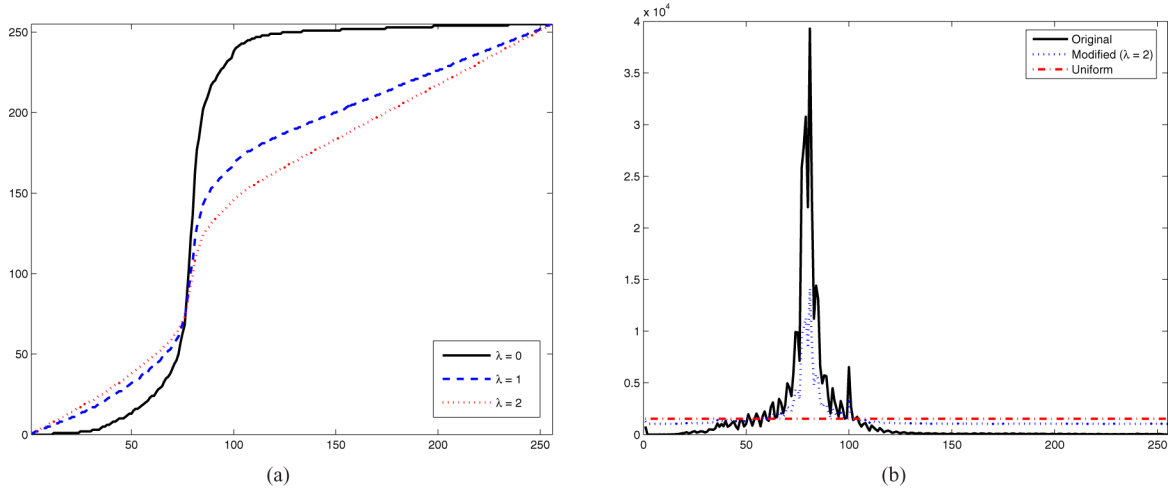
Fig. 2.   The mappings and histograms for Fig. 1. (a) Mappings for three different λ values used in Fig. 1, (b) original histogram, modified histogram with $\lambda = 2$ and the uniform histogram.

The resulting image is over-enhanced, with many unnatural details on the door and loss of details on the doorknob. When λ is increased to one, the penalty term comes into play and the enhanced image looks more like the original image. For $\lambda = 2$, the level of enhancement is further decreased and the details on the doorknob are mostly preserved. In Fig. 2(a), the mappings for the three λ values are given. As λ increases, the mapping becomes more similar to $T[n] = n$ line. The fixed point observed around gray-level value of 76 is a repelling fixed point.[3] Although the level of enhancement is decreased with increasing λ, the slope[4] of the mapping at the fixed point, n^*, is still rather large. The slope at n^* determines how fast the intensities in the enhanced image move away from the fixed point [28]. This may become especially important for images with smooth background in which gray-level differences in neighboring pixels look like noise. An example for this situation is shown in Fig. 9(b) and (c).

The problem of $\dot{T}[n^*]$ having a large slope arises from spikes in the input histogram. The original histogram given in Fig. 2(b) exhibits spikes and the modified histogram has also spikes at the corresponding intensities. This sensitivity to spikes is observed because ℓ_2 norm heavily penalizes large residuals, therefore, is not robust to spikes. One way to deal with histogram spikes is to use ℓ_1 norm for the histogram approximation term in the objective while using ℓ_2 norm for the penalty term. Hence, the problem in (4) is changed to

$$\tilde{\mathbf{h}} = \underset{\mathbf{h}}{\operatorname{argmin}} \|\mathbf{h} - \mathbf{h_i}\|_1 + \lambda \|\mathbf{h} - \mathbf{u}\|_2^2. \qquad (7)$$

To transform this mixed norm problem into a constrained quadratic programming problem, the first term can be expressed as a sum of auxiliary variables

$$\tilde{\mathbf{h}} = \underset{\mathbf{h}}{\operatorname{argmin}} [\mathbf{t}^T \mathbf{1} + \lambda (\mathbf{h} - \mathbf{u})^T (\mathbf{h} - \mathbf{u})]$$

[3]Please see chapter 14 of "Mathematical Methods and Algorithms for Signal Processing" by Moon and Stirling [28] for a detailed discussion of repelling/attractive fixed points.

[4]The term "slope" is used to refer to the slope of the $T(x)$, interpolated (i.e., continuous) version of $T[n]$.

subject to

$$-\mathbf{t} \preceq (\mathbf{h} - \mathbf{h_i}) \preceq \mathbf{t}$$

where $\mathbf{t} \in R^{256 \times 1}$ and represents the auxiliary variables,[5] and $\mathbf{1} \in R^{256 \times 1}$ is a vector of ones. However, this constrained quadratic programming problem has high computational complexity since there are 512 optimization variables. Hence, this approach will not be pursued and is presented here for completeness.

Another way to deal with the histogram spikes in the input histogram is to use one more penalty term to measure the smoothness of $\tilde{\mathbf{h}}$, which reduces the modified histogram's sensitivity to spikes.

B. Histogram Smoothing

To avoid spikes that lead to strong repelling fixed points, a smoothness constraint can be added to the objective. The backward-difference of the histogram, i.e., $h[i] - h[i - 1]$, can be used to measure its smoothness. A smooth modified histogram will tend to have less spikes since they are essentially abrupt changes in the histogram.

The difference matrix $D \in R^{255 \times 256}$ is bi-diagonal

$$D = \begin{bmatrix} -1 & 1 & 0 & \cdots & 0 & 0 & 0 \\ 0 & -1 & 1 & \cdots & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & -1 & 1 & 0 \\ 0 & 0 & 0 & \cdots & 0 & -1 & 1 \end{bmatrix}$$

with the additional penalty term for smoothness, the optimal trade-off is obtained by

$$\min \|\mathbf{h} - \mathbf{h_i}\|_2^2 + \lambda \|\mathbf{h} - \mathbf{u}\|_2^2 + \gamma \|\mathbf{D}\mathbf{h}\|_2^2. \qquad (8)$$

The solution of this three-criterion problem is

$$\tilde{\mathbf{h}} = ((1 + \lambda)\mathbf{I} + \gamma \mathbf{D}^T \mathbf{D})^{-1}(\mathbf{h_i} + \lambda \mathbf{u}). \qquad (9)$$

[5]$\preceq$ symbol denotes vector/componentwise inequality.

Fig. 3. Histogram smoothing results using (9) for image *Palermo*. (a) Original image, (b) enhanced image using (9) with $\gamma = 0$ and $\lambda = 1$, (c) enhanced image using (9) with $\gamma = 0$ and $\lambda = 3$, (d) enhanced image using (9) with $\gamma = 1000$ and $\lambda = 1$.

While (6) results in a weighted average of $\mathbf{h_i}$ and $\mathbf{u}$, (9) further smoothes this weighted average to avoid spikes. The first term in (9), that is, $S^{-1} = ((1+\lambda)\mathbf{I} + \gamma \mathbf{D}^T\mathbf{D})^{-1}$ in fact corresponds to a low-pass filtering operation on the averaged histogram. This can be seen by expressing $S = ((1+\lambda)\mathbf{I} + \gamma \mathbf{D}^T\mathbf{D})$ explicitly as (10), shown at the bottom of the page, where S is a tridiagonal matrix. Each row of its inverse can be shown to be a zero-phase low-pass filter by using a theorem of Fischer and Usmani [29]. Hence, a penalty term for smoothness corresponds to low-pass filtering the averaged histogram. This shows that the proposed framework provides an explanation for the histogram low-pass filtering approaches investigated in the literature, as in Gauch's work [9], from a different perspective.

To illustrate the performance of histogram smoothing, the image given in Fig. 3(a), which is captured from a compressed video stream, is enhanced using adjustable histogram equalization with and without histogram smoothing. Fig. 3(b) and (c) adjusts the level of enhancement with $\gamma = 0$, $\lambda = 1$ and $\gamma = 0$, $\lambda = 3$, respectively. After enhancement, both exhibit artifacts, which are observed as black grain noise around the text. These artifacts arise from the strong repelling fixed-point in the mapping created by the spikes of the original histogram. The ringing-artifact pixels that have intensities less than the background pixels are mapped to even darker intensities. Histogram smoothing with $\gamma = 1000$ solves this problem as can be seen in Fig. 3(d). The mappings for the corresponding enhanced images are given in Fig. 4. The slope, $\dot{T}(x)$, at the spike bin gray-level has been successfully reduced with histogram smoothing.

Although histogram smoothing is successful in avoiding histogram spikes, it has a shortcoming. For a real-time implementation S^{-1} has to be computed for each image as γ needs to be adjusted based on the magnitude of the histogram spikes. Even though there are fast algorithms for inverting tridiagonal matrices that require only $\mathcal{O}(7n)$ arithmetic operations [30] as opposed to $\mathcal{O}(n^3/3)$, it is still unacceptable because of the application at hand (i.e., LCD display processing). This renders
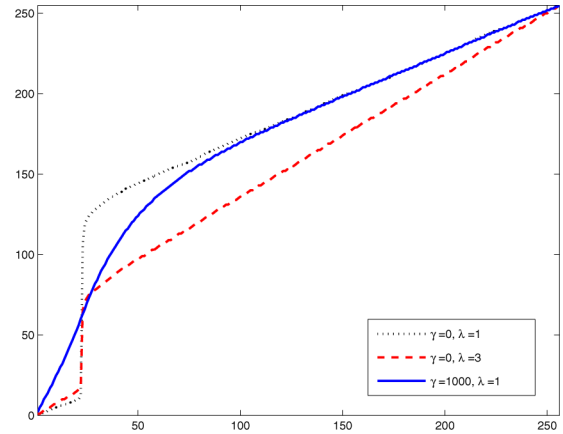

Fig. 4. Mappings for the enhanced images given in Fig. 3.

the algorithm not easily implementable on FPGAs. Instead of using (9), a low-pass filtering on the histogram can also be performed. But the number of taps and the transfer function must also be adaptive. Another approach that is less computationally complex is to use a weighted error norm for the approximation error $\mathbf{h} - \mathbf{h_i}$, which is to be described next.

C. Weighted Histogram Approximation

Histogram spikes occur because of the existence of large number of pixels with exactly the same gray-level values as their neighbors. Histogram spikes cause the forward/backward difference of the mapping at that gray-level to be large. This results in an input-output transformation that maps a narrow range of pixel values to a much wider range of pixel values. Hence, it causes contouring and grainy noise type artifacts in uniform regions. A large number of pixels having exactly the same gray-levels are often due to large smooth areas in the image. Hence, the average local variance of all the pixels

$$S = \begin{bmatrix} 2\gamma + (1+\lambda) & -2\gamma & 0 & 0 & \cdots \\ -2\gamma & 4\gamma + (1+\lambda) & -2\gamma & 0 & \cdots \\ 0 & -2\gamma & 4\gamma + (1+\lambda) & -2\gamma & \cdots \\ \vdots & \vdots & \vdots & \vdots & \ddots \end{bmatrix} \tag{10}$$

(a) (b)

Fig. 5. Comparison results of histogram smoothing and weighted histogram approximation for image *Palermo*. (a) Histogram smoothing using (9) with $\gamma = 1000$ and $\lambda = 1$, (b) weighted approximation using(12) with $\lambda = 1000$.
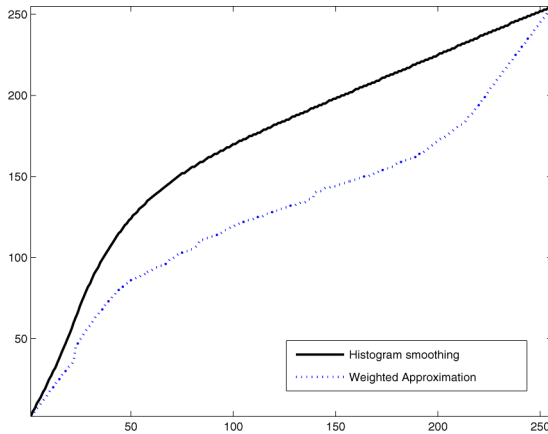

Fig. 6. Mappings for the enhanced images given in Fig. 5.

with the same gray-level can be used to weight the approximation error, $\mathbf{h} - \mathbf{h_i}$. Histogram approximation error at the corresponding bin will be weighted with a smaller weight. Therefore, the modified histogram bin will not closely follow the input histogram's spike bin to minimize the approximation error. The objective function with the weighted approximation error is

$$\min(\mathbf{h} - \mathbf{h_i})^T \mathbf{W}(\mathbf{h} - \mathbf{h_i}) + \lambda(\mathbf{h} - \mathbf{u})^T(\mathbf{h} - \mathbf{u}). \quad (11)$$

where $\mathbf{W} \in R^{256 \times 256}$ is the diagonal error weight matrix, and $W(i,i)$ measures the average local variance of pixels with gray-level i. The solution of (11) is

$$\tilde{\mathbf{h}} = (\mathbf{W} + \lambda \mathbf{I})^{-1}(\mathbf{W}\mathbf{h_i} + \lambda \mathbf{u}). \quad (12)$$

This is computationally simpler than (9). Since the first term is a diagonal matrix, taking matrix inverse is avoided, i.e., only simple division operations for the diagonal elements are needed to compute its inverse.

Fig. 5 shows the weighted histogram approximation and histogram smoothing for comparison. The grain-noise-type artifacts around the text are avoided in both methods. The mappings for the two methods is given in Fig. 6. The difference of the mapping corresponding to smooth background pixels has further been reduced. However, the mapping is not as smooth as histogram smoothing since no explicit smoothing is performed on the modified histogram.

D. Black and White Stretching

Black and white (B&W) stretching is one of the oldest image enhancement techniques used in television sets. B&W stretching maps predetermined dark and bright intensities to darker and brighter intensities, respectively. To incorporate B&W stretching into histogram modification, where the gray-level range for B&W stretching is $[0, b]$ and $[w, 255]$, respectively, the modified histogram $\tilde{\mathbf{h}}$ must have small bin values for the corresponding gray-level ranges. Since the length of the histogram bins determines the contrast between the mapped intensities, by decreasing the histogram bin length for $[0, b]$ and $[w, 255]$, the mapping obtained by accumulating the modified histogram will have a smaller forward/backward difference for these two gray-level ranges.

An additional penalty term for B&W stretching can be added to one of the objective functions presented in previous subsections [e.g., adjustable histogram equalization equation given in (5)]

$$\min(\mathbf{h} - \mathbf{h_i})^T(\mathbf{h} - \mathbf{h_i}) + \lambda(\mathbf{h} - \mathbf{u})^T(\mathbf{h} - \mathbf{u}) + \alpha \mathbf{h}^T \mathbf{I}^B \mathbf{h} \quad (13)$$

where $\mathbf{I}^B$ is a diagonal matrix. $\mathbf{I}^B(i,i) = 1$ for $i \in \{[0, b] \cup [w, 255]\}$, and the remaining diagonal elements are zero. The solution to this minimization problem is

$$\tilde{\mathbf{h}} = ((1 + \lambda)\mathbf{I} + \alpha \mathbf{I}^B)^{-1}(\mathbf{h_i} + \lambda \mathbf{u}). \quad (14)$$

In Fig. 7, histogram smoothing with and without B&W stretching is illustrated. In this experiment, black stretch gray-level range is $[0, 20]$ and white stretch gray-level range is $[200, 255]$ with α set to 5. With the more natural look of the black and white in the image, the contrast has greatly improved. The mapping as given in Fig. 7(d) clearly shows B&W stretching and the smooth transition to nonstretching region.

IV. LOW-COMPLEXITY HISTOGRAM MODIFICATION ALGORITHM

In this section, a low-complexity histogram modification algorithm is presented. The pseudo-code of the algorithm is given in Algorithm 1. It deals with histogram spikes, performs B&W stretching, and adjusts the level of enhancement adaptively so that the dynamic range is better utilized while handling the noise visibility and the natural look requirements. Also, the proposed algorithm does not require any division operation.

Using histogram smoothing or weighted histogram approximation is computationally complex when considering the scarce memory and gate-count/area resources in an hardware implementation. Histogram smoothing requires either solving (9) or explicit low-pass filtering with adaptive filter length and transfer function. On the other hand, weighted approximation with solution given in(12) requires division operation.

A. Histogram Computation

To deal with histogram spikes in a simple way, instead of smoothing or weighting the input histogram, one can change the way a histogram is computed. Histogram spikes are created because of a large number of pixels that have the same gray-level and these pixels almost always come from smooth areas in the

Fig. 7. Comparison results of histogram smoothing with and without B&W stretching for image *Palermo*. (a) Original image, (b) enhanced image using (9) with $\gamma = 1000$ and $\lambda = 1$, (c) enhanced image using (14) with $\gamma = 100$, $\lambda = 1$, and $\alpha = 5$, (d) mappings for the two enhanced images in (b) and (c).

input image *when* they create artifacts/noise in the enhanced image. Hence, histogram computation can be modified so as to take pixels that have some level of contrast with their neighbors into account, which will solve the histogram spike problem at the very beginning. It is also possible to relate this practical approach with optimization based solutions discussed in the previous section as follows: For a successful contrast enhancement, the histogram should be modified in such a way that the modified histogram, $\tilde{\mathbf{h}}$, represents the conditional probability of a pixel, *given that it has a contrast with its neighbors (denoted by* $\mathbf{C}$). That is, $\tilde{h}[i] = p[i|\mathbf{C}]$, where $p[i|\mathbf{C}]$ denotes the probability of a pixel having gray-level i given the event $\mathbf{C}$. Performing histogram equalization on $\tilde{\mathbf{h}}$ rather than h will enhance the contrast but not the noise, since the former will only utilize the dynamic range for pixels that have some level of contrast with their neighbors. Noting that the histogram modification methods presented in the previous section (e.g., weighting) also aim to increase contrast but not the noise visibility, they must modify the histogram in such a way that the the modified histogram resembles $p[i|\mathbf{C}]$ rather than $p[i]$. However, one can simply obtain $p[i|\mathbf{C}]$ by counting only those pixels that have contrast, rather than solving complex optimization problems, which in essence corresponds to dealing with histogram spikes resulting from smooth area (*noncontrast*) pixels after computing the histogram in the conventional way.

To obtain the histogram, the local variation of each pixel can be used to decide if a pixel has sufficient contrast with its neighbors. One efficient way of achieving this for hardware simplicity is to use a horizontal variation measure by taking advantage of the row-wise pixel processing architecture, which is available in common video processing hardware platforms. A horizontal one-lagged difference operation is a high-pass filter, which will also measure noise. On the other hand, a horizontal two-lagged difference operation is a band-pass filter which will attenuate high-frequency noise signals. Histogram is created using pixels with a two-lagged difference that has a magnitude larger than a given threshold (*steps 5, 6, 7*). The number of pixels included in the histogram is also counted for proper normalization.

B. Adjusting the Level of Enhancement

As described in Section III-A, it is possible to adjust the level of histogram equalization to achieve natural looking enhanced images. The modified histogram is a weighted average of the input histogram $\mathbf{h_i}$ and the uniform histogram $\mathbf{u}$, as given in

(6). The contribution of the input histogram in the modified histogram is $\kappa^* = 1/(1 + \lambda)$. The level of histogram equalization should be adjusted depending on the input image's contrast. Low contrast images have narrow histograms and with histogram equalization, contouring and noise can be created. Therefore, κ is computed to measure the input contrast using the aggregated outputs of horizontal two-lagged difference operation (*step 4*). Afterwards, κ is multiplied by a user-controlled parameter g, then $g\kappa$ is normalized to the range $[0, 1]$ (*step 11*) to get κ^*. It is a good practice to limit the maximum contribution of a histogram, since this will help with the worst-case artifacts created due to histogram equalization. By choosing the maximum value that $g\kappa$ can take on as a power of two, the normalization step can be done using a bit-shift operation rather than a costly division. To ensure that $\mathbf{h_i}$ and $\mathbf{u}$ have the same normalization, $\mathbf{u}$ is obtained using the number of pixels that are included in the histogram (*step 12*). $u_{\min}$ is used to ensure that very low bin regions of the histogram will not result in very low slope in the mapping function; it will increase the slope in these regions, resulting in increased-utilization of dynamic range.

B&W stretching is performed using (14) (*step 17*). Parameters b, w, and α can be adapted with the image content. b and w is usually derived from the histogram as the minimum and maximum intensities. For noise robustness, b should be chosen as the minimum gray-level that is bigger than some predefined number of pixels' intensities, w can be chosen similarly. It is a good practice to impose limits on b and w. The stretching parameter should also be adapted with image content. For dark images white stretching can be favored, while for bright images black stretching can be favored. α may also depend on the input image's contrast.

V. RESULTS AND DISCUSSION

Assessment of image enhancement is not an easy task. Although it is desirable to have an objective assessment approach to compare contrast enhancement techniques, unfortunately there is not any accepted objective criterion in the literature that gives meaningful results for every image. There are some metrics used in the literature that approximate an average contrast in the image based on entropy or other measures. If these metrics are used, HE can achieve the best performance even though it may not produce the visually pleasing image, and possibly may produce an un-realistic look. However, it is usually desired to have some quantitative measures in

Fig. 8. Results for image *Beach*. (a) Original image, (b) enhanced image obtained using HE, (c) enhanced image obtained using WTHE, (d) enhanced image obtained using the proposed algorithm.

addition to subjective assessment. Hence, we will use the following quantitative measures: Absolute Mean Brightness Error (AMBE), the discrete entropy (H), and the measure of enhancement (EME) [3], [16], [18]. AMBE is the absolute difference between input and output mean [16]. The discrete entropy is used to measure the content of an image [3], where a higher value indicates an image with richer details. The measure of enhancement (EME) approximates an average contrast in the image by dividing image into nonoverlapping blocks, finding a measure based on minimum and maximum intensity values in each block, and averaging them. In addition, a time complexity comparison of HE, weighted thresholded HE (WTHE), and the proposed method is included. The proposed algorithm has been successfully tested on a variety of test images and video sequences. Only, a few of the results are shown in this paper.

A. Subjective Assessment

1) Gray-Scale Images: Figs. 8–10 show the original test images and their corresponding contrast enhanced versions. Their mapping functions are shown in Fig. 12(a)–(c), respectively. The proposed algorithm is compared with a recently proposed contrast enhancement algorithm, (WTHE), presented by Wang and Ward [14]; they compare WTHE against the algorithms proposed by Kim [7], Yang *et al.* [15], Chen and Ramli [16] and show their algorithm's superiority. Both WTHE and our pro-

posed method show similar visual quality on many of the images we tested. However, that is not always the case. Hence, images included in this paper are selected among the ones that cause different visual quality.

Usually, histogram equalized images result in the best utilization of the dynamic range of the pixel values for maximum contrast. However, this often does not mean that the resulting image is better in terms of visual quality. This situation is also observed with images in Figs. 8(b), 9(b), and 10(b). Undesired artifacts become more prominent, and amplified nature of noise degrades the quality of the image resulting in an unnatural look. WTHE and the proposed algorithm on the other hand offers a controllability of the contrast enhancement. Since the histogram of the proposed algorithm is formed from the conditional probability, it does not have histogram spikes resulting from uniform regions; hence, the proposed method does not produce artifacts as HE and WTHE, which are caused by having histogram spikes that cause high slope in the mapping function. Even though WTHE thresholds high and low bin values to prevent its undesired effect, it does not produce as pleasing results as the proposed algorithm does. One other situation HE and WTHE introduces artifacts is when the dynamic range of the original image is shrunk from either one or both ends. In either case, the resulting image is either darkened and/or brightened more than necessary. The proposed algorithm, on the other
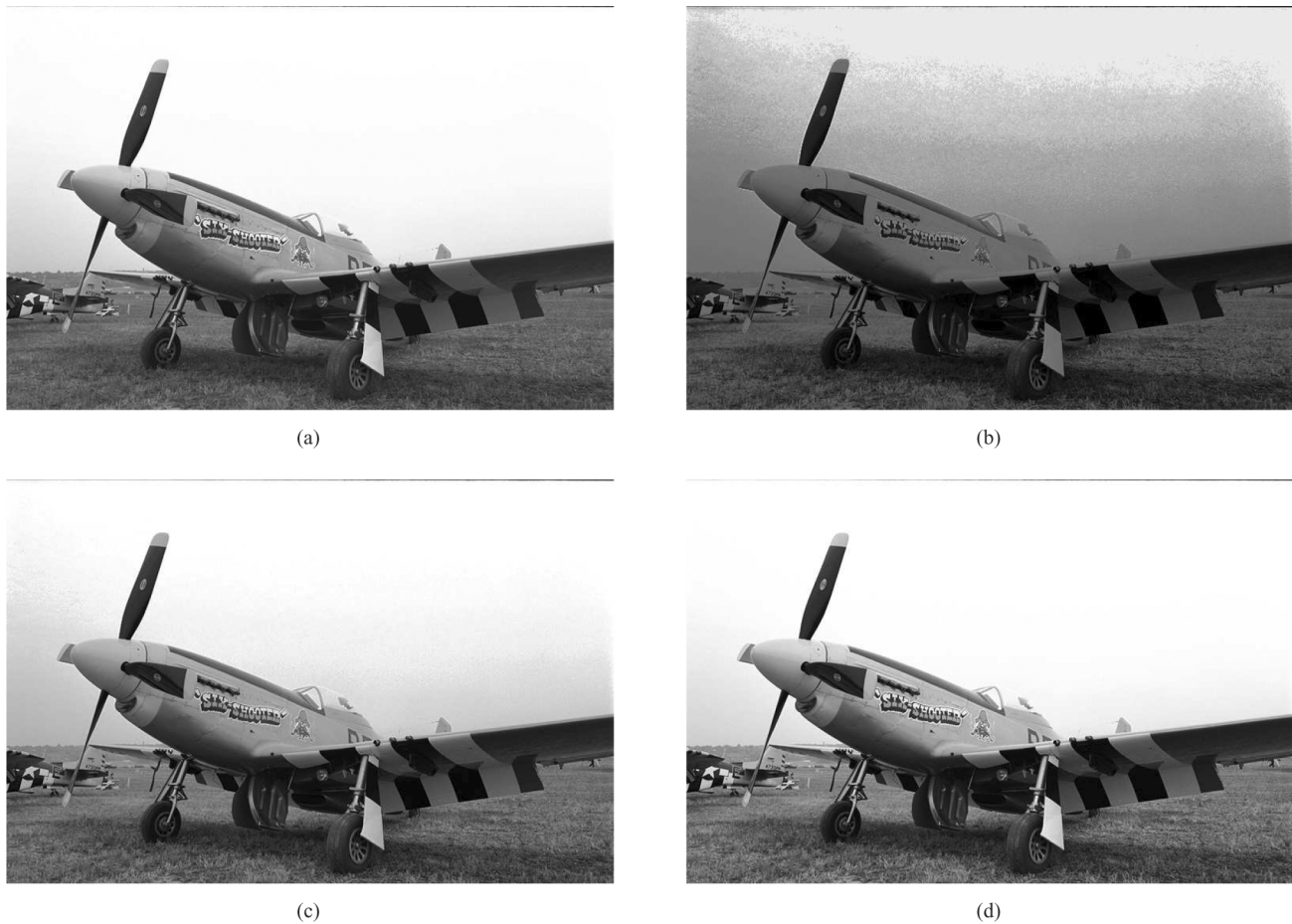
Fig. 9. Results for image *Plane*. (a) Original image, (b) enhanced image obtained using HE, (c) enhanced image obtained using WTHE, (d) enhanced image obtained using the proposed algorithm.
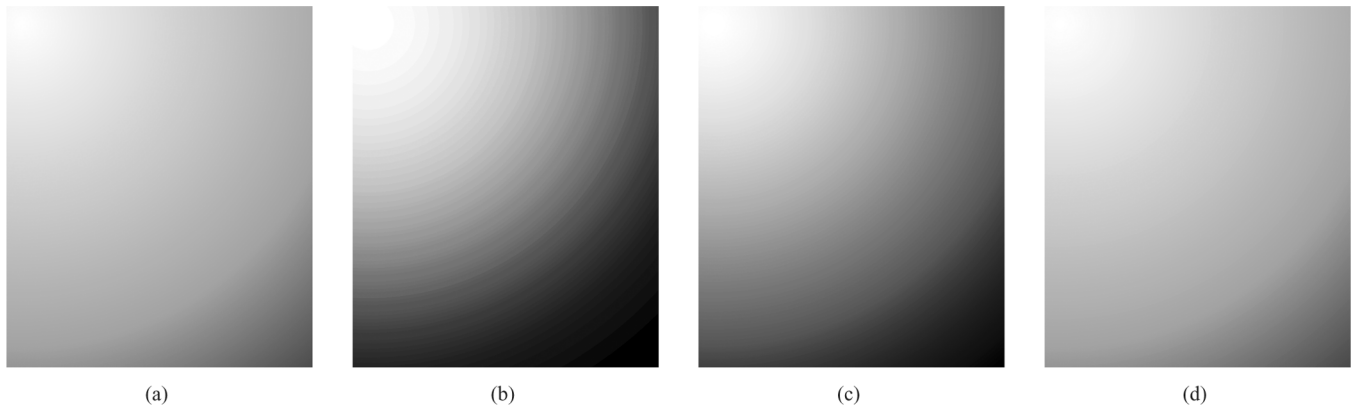

Fig. 10. Results for image *nonuniform illumination*. (a) Original image, (b) enhanced image obtained using HE, (c) enhanced image obtained using WTHE, (d) enhanced image obtained using the proposed algorithm.

hand, avoids this situation through the use of mixing of conditional histogram and $u_{\min}$ as explained on lines 14–18 of the Algorithm 1. By modifying the histogram, the proposed method improves the natural-look of the image substantially compared to HE and WTHE.

Fig. 8(b) is the histogram equalized image of Fig. 8(a). The contrast of the image is maximized at the expense of the amplified noise, and image artifacts. The resulting artifacts

are mostly in the darker regions, which is also evident from Fig. 12(a). Darker regions become even darker, and very bright region gets even brighter. WTHE reduces the effect of HE. However, the resulting image still has some flavor of HE: bodies of two people, and the trees are still darker and the resulting image Fig. 8(c) is not as visually pleasing as Fig. 8(d). As can be clearly seen, the mapping function in the region around 175 has a very steep curve resulting in a stretching of

Fig. 11. Results for image *clouds*. (a) Original image, (b) enhanced image obtained using HE, (c) enhanced image obtained using WTHE, (d) enhanced image obtained using the proposed algorithm.
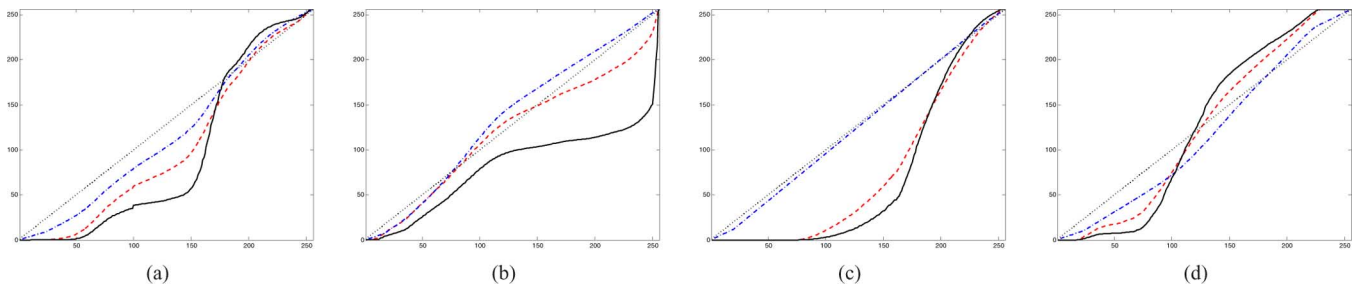

Fig. 12. Mappings for enhanced images in Figs. 8, 9, 10, and 11. (a) mappings of Fig. 8, (b) mappings of Fig. 9, (c) mappings of Fig. 10, and (d) mappings of Fig. 11. Solid line indicates the HE mapping, red dashed line indicates the WTHE mapping, blue dash-dotted line indicates the proposed method, and the dotted line indicates the no change mapping.

a very narrow region into a wider region; range of [150, 180] is getting mapped to [60, 180]. These pixel values are mostly due to the sand and some part of the sea. The pixel values of the two bodies are around 60 and the pixel values of the trees are around 40. The mapping functions for both HE and WTHE are mapping these values into darker pixel values. This is caused by the histogram of the original image having very few pixel values below 40. However, in the proposed algorithm this situation is prevented by filling bins with very low values with $u_{\min}$ as illustrated in Algorithm 1. Hence, the contrast enhanced image obtained by the proposed method is visually more pleasing than HE and WTHE.

Fig. 9(b) is the histogram equalized image of 9(a). HE image, again, looks very unnatural. Especially, the dominance of the sky region results in a very big slope in the mapping function around the pixel value of 250, which results in mapping of range [250, 256] into [150, 256]. Unnatural look of the histogram equalized image is lessened using WTHE. However, it is not alleviated completely. Graininess in the sky still exist in the regions close to the plane. The proposed algorithm, on the other hand, produces a good visual quality result; there is no graininess in the sky and the contrast of the grass is improved compared to HE and WTHE result. The success of the proposed method in this type of images is, again, due to the use of the conditional histogram. Big uniform regions in an image cause corresponding bins in the histogram to be very high compared to other bins. However, conditional histogram avoids having very high bin values. This feature is controlled adaptively by the variable κ in the algorithm. If an image contains large smooth regions, then the effect of histogram is lessened so that the resulting image preserves the smoothness and does not introduce visual artifacts. On the other hand, if there is no domi-

nant smooth region in an image, then the effect of κ is increased to increase the contrast.

Fig. 10(b) is the histogram equalized image of Fig. 10(a). The histogram of the original image occupies bins [75, 255]; as a result, HE results in a darkened image since it stretches the histogram to increase the dynamic range. A lack of pixel values in the range [0, 74] results in mapping [75, 255] range into [0, 255] range; more specifically [75, 165] range is mapped into [0, 50] and [165, 220] range is mapped into [50, 220]. As can be seen from the mapping function in Fig. 12(c), mapping also makes bright regions brighter. One can also observe that HE results in banding. Although the effect of WTHE is not as severe as HE, it also results in darkened image and has slight banding. The proposed algorithm on the other hand, does not darken the image and produces a good visual quality result. The proposed algorithm prevents stretching of the histogram due to the use of mixing of conditional histogram and $u_{\min}$. The conditional histogram only counts a small number pixels since the input image pixels do not have sufficient contrast. Therefore, the uniform histogram dominates the conditional histogram to a good extent with the help of κ.

2) Color Images: Contrast enhancement can be easily extended to color images. The most obvious way to extend the gray-scale contrast enhancement to color images is to apply the method to luminance component only and to preserve the chrominance components. One can also multiply the chrominance values with the ratio of their input and output luminance values to preserve the hue. Some examples using color images are given in Figs. 11, 13, 14, 15, and 16.

Fig. 11(b) is the histogram equalized image of Fig. 11(a). This image has nonuniform illumination. This becomes more apparent with HE as it stretches the histogram to increase the
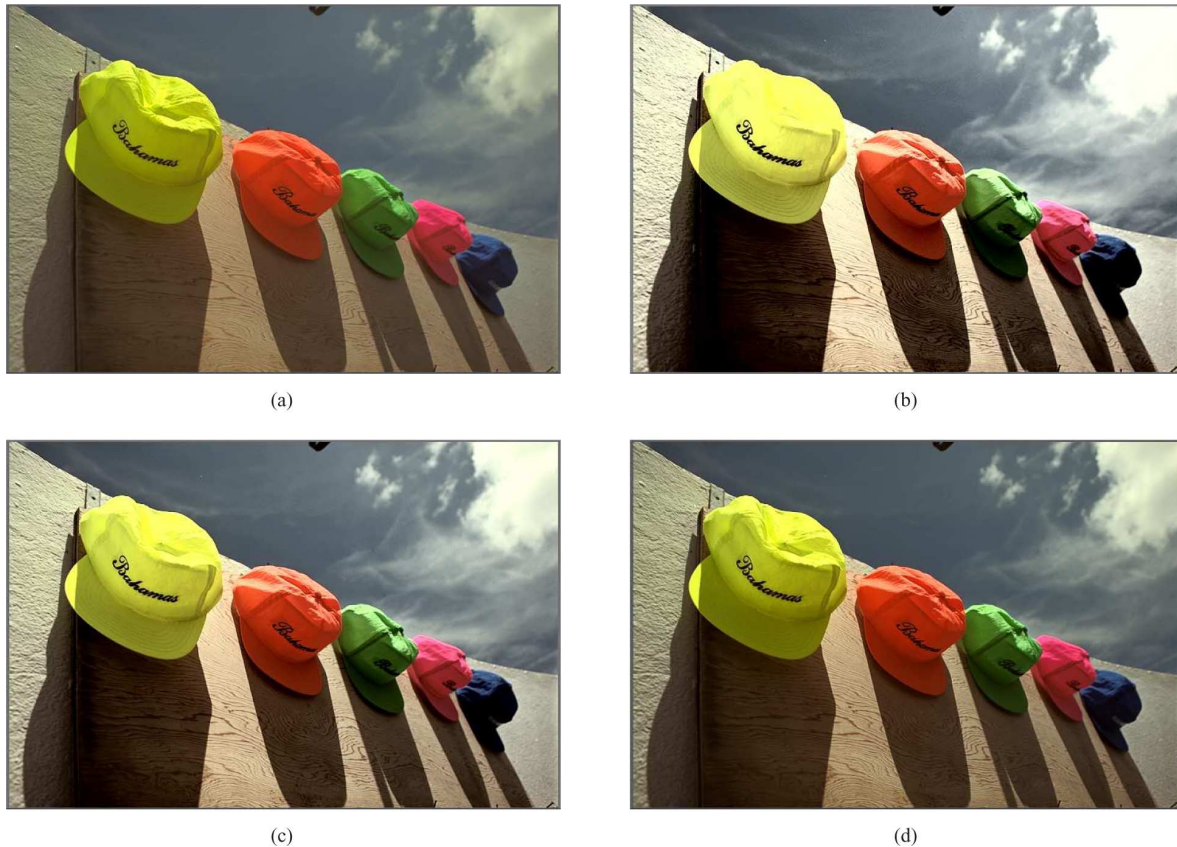
Fig. 13.   Results for image *Hats*. (a) Original image, (b) Enhanced image obtained using HE, (c) Enhanced image obtained using WTHE, (d) Enhanced image obtained using the proposed algorithm.

contrast. The histogram of the original image occupies bins [17, 233]. A lack of pixel values in the range [0, 16] and [234, 255] results in mapping [17, 233] range into [0, 255] range; more specifically it darkens the pixels in the range [17, 118] and brightens the pixels in the range [119, 233], which can be seen from the mapping function in Fig. 12(d). One can easily see that the darker clouds become even darker, and clouds in front of the sun become even brighter resulting in loss of details. Although the effect of WTHE is not as severe as HE, it also results in similar artifacts. The proposed algorithm on the other hand, does not darken the image as much as HE and WTHE, and preserves bright regions and as a result produces a better visual quality result.

In Fig. 13, both HE and WTHE result in loss of details in the clouds and on top of the yellow hat, whereas the proposed algorithm keeps the details while increasing the contrast. In Fig. 14, HE makes the stones around the window and the pink flower very bright; hence, it has an unnatural look. Although WTHE performs better than HE, it still does not remove this effect completely. In Fig. 15, HE makes the sea darker and clouds brighter resulting in an unnatural look. WTHE decreases the effect of HE, however, the resulting image is not as pleasing as the one obtained with the proposed method. Finally, in Fig. 16, WTHE decreases the brighter look of the image obtained by HE. However, some portions of her skin still look brighter. Again, the proposed method gives a more natural looking skin tone on both the face and shoulders.

B. Objective Assessment

Computed quantitative measures AMBE, H, and EME listed in Table I supplement the visual assessment presented earlier. Comparison of AMBE values shows that the proposed method outperforms both HE and WTHE in all images except the clouds image. Although HE and WTHE give a smaller AMBE value than the proposed algorithm in the clouds image, it does not necessarily mean they are more faithful to the original image. Preserving the mean brightness does not always mean preserving the natural look of an image. HE results in a small AMBE value because HE has an S shaped mapping function. An S shaped mapping function causes the bright pixels to be even brighter, and dark pixels to be even darker, eventually resulting in a small change in AMBE, although the resulting image has an unnatural look. The same reasoning applies to the image obtained by WTHE. Visual comparison, on the other hand, shows that the visually closest equalized image to the original clouds image is obtained through the proposed method. The mapping function in Fig. 12(d) also demonstrates this. Comparison of H values show that the proposed method performs similar to WTHE and both of them outperform HE. Normally, one would expect HE to give higher discrete entropy value as HE results in more uniform histogram distribution. However, HE results in bin grouping and this decreases the H value. Comparison of EME values show that HE outperforms both WTHE and the proposed method; WTHE gives

Fig. 14. Results for image *Window*. (a) Original image, (b) enhanced image obtained using HE, (c) enhanced image obtained using WTHE, (d) enhanced image obtained using the proposed algorithm.

higher EME values than the proposed method. Since EME measures a form of contrast, it is no surprise that HE gives the highest value even though it does not produce the most visually pleasing image.

C. Complexity Comparison

We analyze the time complexities of HE, WTHE, and the proposed algorithm for an $M \times N$ image. For comparison, we calculate the total time complexity of obtaining the enhanced image using each contrast enhancement algorithm.

For HE, computation of the histogram requires $\mathcal{O}(MN)$ time. Calculating the mapping function from the histogram requires $\mathcal{O}(2^B)$ time, and finally obtaining the enhanced image using the mapping function requires $\mathcal{O}(MN)$ time. Hence, the total time complexity of HE is $\mathcal{O}(2MN + 2^B)$.

For WTHE, computation of the histogram requires $\mathcal{O}(MN)$ time. Calculating the modified histogram requires $\mathcal{O}(2^B)$ time, and the computation of the mapping function requires $\mathcal{O}(2^B)$ time, and, finally, obtaining the enhanced image using the mapping function requires $\mathcal{O}(MN)$ time. Hence, the total time complexity of WTHE is $\mathcal{O}(2MN + 2^{B+1})$.

For the proposed algorithm, computation of the histogram and κ requires $\mathcal{O}(MN)$ time. Computation of the modified histogram for each bin requires $\mathcal{O}(2^B)$ time, and the computation of the mapping function requires $\mathcal{O}(2^B)$ time. And finally obtaining the enhanced image using the mapping function requires

$\mathcal{O}(MN)$ time. Hence, the total time complexity of the proposed algorithm is $\mathcal{O}(2MN + 2^{B+1})$.

As a result, the time complexity of WTHE and the proposed algorithm is the same and it is slightly worse than HE as HE does not require the modification of the histogram before equalization. Although WTHE and the proposed algorithm has the same time complexity, the computational complexity of the proposed algorithm is simpler than that of WTHE as WTHE requires using a power law function with index $r > 0$.

VI. CONCLUSION

A general framework for image contrast enhancement is presented. A low-complexity algorithm suitable for video display applications is proposed as well. The presented framework employs carefully designed penalty terms to adjust the various aspects of contrast enhancement. Hence, the contrast of the image/video can be improved without introducing visual artifacts that decrease the visual quality of an image and cause it to have an unnatural look.

To obtain a real-time implementable algorithm, the proposed method avoids cumbersome calculations and memory-bandwidth consuming operations. The experimental results show the effectiveness of the algorithm in comparison to other contrast enhancement algorithms. Obtained images are visually pleasing, artifact free, and natural looking. A desirable feature
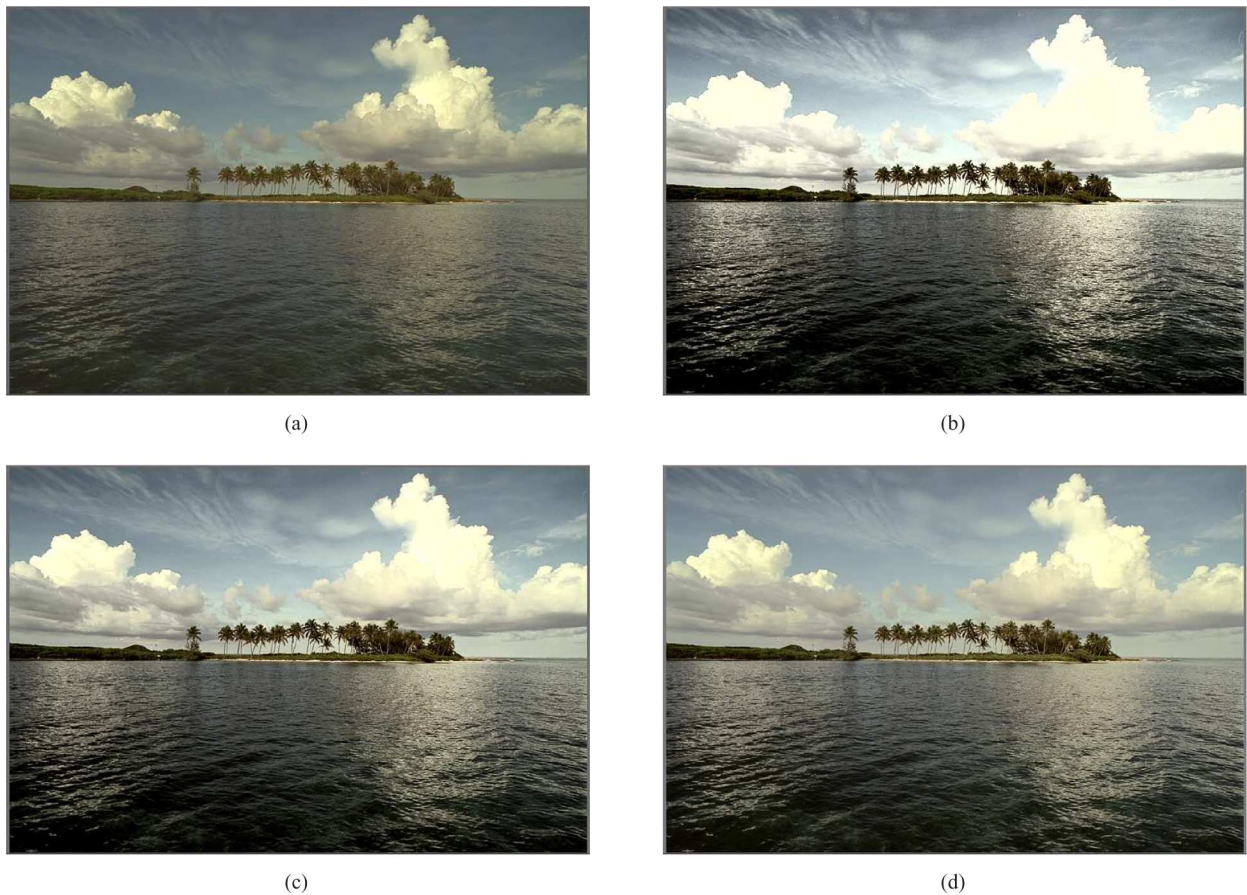
Fig. 15. Results for image *Island*. (a) Original image, (b) enhanced image obtained using HE, (c) enhanced image obtained using WTHE, (d) enhanced image obtained using the proposed algorithm.

Fig. 16. Results for image *Face*. (a) Original image, (b) enhanced image obtained using HE, (c) enhanced image obtained using WTHE, (d) enhanced image obtained using the proposed algorithm.

of the proposed algorithm is that it does not introduce flickering, which is crucial for video applications. This is mainly due to the fact that the proposed method uses the input (conditional) histogram, which does not change significantly within the same scene, as the primary source of information. Then, the proposed method modifies it using linear operations resulting from different cost terms in the objective rather than making algorithmic hard decisions.

The proposed method is applicable to a wide variety of images and video sequences. It also offers a level of controlla-

TABLE I
QUANTITATIVE MEASUREMENT RESULTS. AMBE DENOTES THE ABSOLUTE MEAN BRIGHTNESS ERROR, H DENOTES THE DISCRETE ENTROPY,
AND EME DENOTES THE MEASURE OF ENHANCEMENT

Image	AMBE			H				EME			
	HE	WTHE	Prop.	Orig.	HE	WTHE	Prop.	Orig.	HE	WTHE	Prop.
Beach	34.88	24.88	9.65	6.96	5.80	6.90	6.89	5.32	32.09	12.29	7.76
Plane	48.23	5.16	3.34	6.32	4.96	6.03	6.08	9.06	24.75	12.96	11.72
Nonuni. Illum.	58.61	48.23	1.12	6.92	5.93	6.90	6.91	0.16	1.44	0.58	0.16
Clouds	2.11	3.55	15.54	7.29	5.97	7.27	7.20	4.76	16.93	9.12	6.76
Hats	23.84	12.60	3.13	6.89	5.91	6.87	6.89	5.50	27.15	11.88	8.13
Window	17.11	20.84	14.49	6.80	5.79	6.82	6.83	9.11	52.32	21.01	14.04
Island	22.18	9.88	14.13	7.01	5.96	6.97	6.98	8.02	51.69	20.68	13.68
Face	27.58	16.34	18.79	6.93	5.95	6.90	6.91	7.78	40.62	17.57	14.05
Average	29.32	17.68	10.02	6.89	5.78	6.83	6.84	6.21	30.87	13.26	9.54

bility and adaptivity through which different levels of contrast enhancement, from histogram equalization to no contrast enhancement, can be achieved.

Algorithm 1: GCE Histogram Modification Algorithm

Input: Input image: f,
B&W stretch parameters: b, w, and $1/(1 + \alpha)$
Level of enhancement: g

Output: Modified histogram: $\tilde{\mathbf{h}}$
1   Initialize κ;
2   **foreach** *row m* **do**
3   **foreach** *column n* **do**
4     $\kappa = \kappa + |f[m,n] - f[m, n-2]|$;
5   **if** $|f[m,n] - f[m, n-2]| > $ *Threshold* **then**
6      $++ h_i[f[m,n]]$;
7      $++ count$;
8   **end**
9   **end**
10   **end**
11   Normalize $g\kappa$ to get κ^*;
12   $u = \min\{count/256, u_{\min}\}$;
13   **foreach** *bin n* **do**
14   **if** $b < n < w$ **then**
15     $\tilde{h}[n] = (1 - \kappa^*)u + \kappa^* h_i[n]$;
16   **else**
17     $\tilde{h}[n] = 1/(1 + \alpha)[(1 - \kappa^*)u + \kappa^* h_i[n]]$;
18   **end**
19   end

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