Perceptually Optimized Enhancement of Contrast and Color in Images

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ABSTRACT In this paper, we propose perceptually optimized enhancement of contrast and color in images using just-noticeable-difference (JND) transform and color constancy. We adopt JND transform to get JND map that represents the perceptual response of the human visual system (HVS). We utilize color constancy to estimate the light source color and be robust to color bias. First, we use a perceptual generalized equalization model for the optimization of both color and contrast based on color constancy and contrast enhancement, i.e. base image. Second, we generate JND map based on HVS response model from foreground and background luminance, called JND transform. Next, we update the JND map based on Weber’s law to boost perceptual response. Finally, we perform inverse JND transform from the base image and its JND map to produce the enhanced image highly correlated with the human visual perception. Experimental results show that the proposed method achieves good performance in contrast enhancement, color reproduction, and detail enhancement.

INDEX TERMS Contrast enhancement, color constancy, image enhancement, just-noticeable-difference, JND transform, HVS response model.

I. INTRODUCTION
With the fast development of the digital imaging technology, billions of digital photos are created by smart phones, cameras, scanners and computers every day. During the capturing process, their contrast is often degraded by undesirable light source, bad weathers and failure of the imaging device itself. Moreover, old images contain historical events among the years, but are of low perceptual contrast and color bias. Thus, contrast enhancement and color constancy are required for better visual perception and interpretation of the scene in many cases. In general, contrast enhancement methods are classified into two groups from the viewpoint of methodology. The first group is spatial filtering-based methods. By preserving the low-frequency component with amplifying the high-frequency part, they achieve local contrast enhancement and make the details obvious [1]–[4]. The second group is histogram-based methods. Compared with filtering-based methods, histogram-based ones have been more widely used in global contrast enhancement due to the low computational complexity. Histogram equalization (HE) is the most popular and classical one. Based on HE, many variant methods have been proposed [5]–[8]. Their main issue is how to preserve a good tone while achieving contrast enhancement. OCTM [8] solved the contrast enhancement problem by maximizing the contrast gain subject to an upper limit on tone distortion. It achieved outstanding performance in contrast enhancement of the intensity channel. However, it has a limit to consider the relationship between contrast and tone on three color channels. Thus, Xu et al. [9] proposed a generalized equalization model (GEM) that integrated contrast enhancement and white balancing into a unified framework based on the relationship between image histogram and contrast enhancement/white balancing. GEM achieved good performance in enhancing both contrast and color while preserving the image tone. However, GEM often allocates a large dynamic range in a dark smooth region with over-enhancement as well as produces unnatural-looking results with tone discontinuity.

In this paper, we propose perceptually optimized enhancement of contrast and color in images using JND transform and color constancy. We perform JND transform to estimate JND map that represents perceptual response of HVS from an image. That is, JND map is mainly composed
of HVS response model that simulates HVS perception. Color constancy estimates the scene illuminant and then utilizes it to map the color-biased image to the canonical image under white light source. First, we perform perceptual GEM to adjust the image tone while preventing over-enhancement. Perceptual GEM effectively selects the pixels of high contrast and sensitivity in human eyes and constructs the image histogram based on Weber’s law [10] and JND model, i.e. luminance adaptation that indicates the minimum threshold perceived by HVS [11]. Second, we perform JND transform to obtain JND map from foreground and background luminance, and update it using the ratio between the enhanced and original base grayscale images. Next, we obtain the final gray scale image with fine details by inverse JND transform. Finally, we produce the perceptually optimized enhancement result by color restoration from the final grayscale image. Fig. 1 illustrates the entire framework of the proposed method. Compared with exiting methods, main contributions of the proposed method are as follows:

- We propose JND transform for contrast enhancement to effectively extract detail information with much attention by HVS.
- We provide JND-based perceptual GEM to effectively allocate a dynamic range while preventing over-enhancement.

The rest of this paper is organized as follows: In Section 2, we illustrate the related work of our work. In Section 3, we introduce the human visual perception model. The details of the proposed method are described in section 4. In Section 5, we provide experimental results and their corresponding analysis, while we draw conclusions of this paper in Section 6.

II. RELATED WORK

Wu [8] proposed Optimal Contrast-Tone Mapping (OCTM) to solve image enhancement by maximizing the expected contrast gain subject to an upper limit on tone distortion. We consider the histogram of a grayscale image and its probability denoted as \( \{h, p\} \). In [8], context-free contrast of an image \( C \) is defined as follows:

\[
C = p^T s
\]

where \( s \) is the intensity difference. The relationship between image histogram and contrast enhancement is represented as follows:

\[
\max_s \sum_{0 \leq j < L} p_j s_j \\
\text{s.t. } \sum_{0 \leq j < L} s_j < L' \\
\quad s_j \geq d, \quad 0 \leq j < L
\]

where \( p \) is the probability of gray level \( h \); \( s \) is the distance of adjacent intensity levels; \( L \) and \( L' \) are the input and output upper bound dynamic range, respectively; \( d \) is an upper bound which is set to 1/2 or 1/3. In (2), the first constraint confines the output intensity level to the available dynamic range, while the second constraint specifies the maximum tone distortion allowed. Thus, the contrast enhancement is achieved by maximizing (2). OCTM is effective for intensity channel, but does not describe the relationship between contrast and tone on color channels [8]. Based on OCTM, Xu et al. [9] have analyzed the relationships between image histogram and tone/contrast of image, and established a generalized equalization model (GEM). The histogram of an color image and its probability are denoted as \( \{h_c, p_c\} \).
First, we get the relationship between image histogram and color constancy as follows:

\[ e_c (\alpha) = \frac{(p_c^T h_c) \frac{1}{2}}{\sqrt{\sum_{c=r,g,b} (p_c^T h_c)^2}^\frac{1}{2}} \]  

where \( c = r, g, b \) and the available dynamic range of each channel is \([0, L_c]\); \( h_c \) represents the total \( K \) intensity levels corresponding to probability vector \( p_c \); \( K \) is the number of intensity levels whose probability is non-zero; \( e_c \) is the normalized estimation of a light source; and \( \alpha \) is a parameter that reflects the hypothesis for color constancy [12]. Then, white balancing is achieved by multiplying the element of \( e_c \) to the corresponding channel. Because \([1/\sqrt{3}, 1/\sqrt{3}, 1/\sqrt{3}]^T\) is the normalized form of white light, the multiplication factor of \( c \) is \( 1/(e_c \cdot \sqrt{3}) \). As a result, the histogram of the white balancing result is computed as follows:

\[ \hat{h}_c = \frac{1}{e_c (\alpha) \sqrt{3}} h_c \]

GEM is inspired by (2),(4) and histogram equalization [13], which formulated as follows:

\[ s_c = \arg \min_{s_c} \sum_{c=r,g,b} \| p_c^T s_c \|_n \]

s.t. \[ \sum_{i=1}^{K} s_{ci} = \frac{1}{e_c (\alpha) \sqrt{3}} \sum_{i=1}^{K} \hat{s}_{ci}, \ s_{ci} \geq d \]

where \( p_c = \text{diag}(p_{c1}, \ldots, p_{cK}) \), \( \hat{s}_{ci} \) is the original distance of adjacent intensity levels of the channel \( c \), and \( \alpha = \infty \), \( d = 0 \), \( \beta \) and \( n \) have different values in different situations [9]. Xu et al. [9] set the output upper bound \( L_c \) as the result of white balancing \( 1/e_c (\alpha) \sqrt{3} \sum_{i=1}^{K} \hat{s}_{ci} \). They effectively combined contrast enhancement and color constancy in a unified framework to achieve contrast enhancement while preserving a good tone.

III. HUMAN VISUAL PERCEPTION MODEL

We describe the local contrast property of HVS, which is the basis of the proposed method. The photoreceptors of human eyes on the retina (rods and cones) perceive the light to hit the eye and act as the sensors for HVS [14]. Cones are divided into three types of red, green and blue, which are responsible for color vision at photonic levels of illumination \((10^{-2}.10^6 \text{ cd}/\text{m}^2)\) and are less sensitive than rods. Rods, which are sensitive to light, are responsible for visual perception in dim light \((10^{-6}.10 \text{ cd}/\text{m}^2)\) and do not contain color vision. The neurons transfer a signal with a range of only around three orders of magnitude, and the range that the human eye can adapt is enormous about the order of \(10^0.10^{12}\). Therefore, we need a mechanism that enables HVS to adapt to a certain luminance value and perceive images in a rather small dynamic range around this luminance value. Several HVS models have been proposed such as JND model [11] (luminance adaptation and visual masking [15]) and HVS response model [16] as follows:

A. JND MODEL

JND was first proposed in [17], which shows the minimum brightness difference that HVS can distinguish. However, since the visual mechanism is too complex and related to visual psychology, there is no precise mathematical model to be consistent with the visual characteristics [18]. Therefore, the visibility threshold of the JND model is determined by experiments [11] as follows:

\[ \text{JND}(x) = \begin{cases} 17 \times \left(1 - \sqrt{\frac{x}{127}} \right) + 3, & \text{if } x \leq 127 \\ \frac{3}{128} \times (x - 127) + 3, & \text{others} \end{cases} \]

where \( x \) is the luminance value within \((0, 255)\). Fig. 2 shows the visibility threshold for different gray levels. As shown in the figure, HVS is more sensitive to the luminance change at the middle gray levels compared with the luminance in dark or bright regions.

B. HUMAN VISUAL RESPONSE MODEL

Huang et al. [16] have addressed that the human perceptual response to an image follows a nonlinear function of the luminance. An HVS model characterizes the nonlinear behavior by taking luminance as the input and converting it to a nonnegative integer as the output such that a difference of 1 in the output corresponds to a just noticeable difference in luminance. To practically use the HVS model, we get \( L_i \) as follows:

\[ L_i = L_{i-1} + \text{JND}(L_{i-1}), \quad i > 0 \]

where \( i \) is an integer; \( \text{JND}() \) is defined in (6); and \( L_i \) reaches the upper bound of the luminance range. We construct an HVS response function based on the HVS response model to get the HVS response curve.

IV. PROPOSED METHOD

We use base image and JND map for perceptually optimized contrast/color enhancement as follows:

A. BASE IMAGE

As shown in Fig. 1, we perform perceptual GEM, color space conversion (RGB to YCbCr), and adaptive smoothing
Weber’s law and JND model as follows: $JND(x) = \frac{c(x) - \bar{c}(x)}{\bar{c}(x)}$ where $JND(\cdot)$ is defined in (6). Then, we obtain a new local contrast as follows:

$$C_c(x) = \frac{L_c(x) - \bar{L}_c(x)}{\bar{L}_c(x)}$$

(8)

where $x$ is the intensity within $(0, 255)$, $L_c$ is the original pixel value, $\bar{L}_c$ is the average pixel value use a $5 \times 5$ filter. Moreover, we utilize a JND model to define the local perceptual contrast threshold as follows:

$$J_c(x) = JND(x) / \bar{L}_c(x)$$

(9)

where $JND(\cdot)$ is defined in (6). Then, we obtain a new histogram for perceptual contrast enhancement based on Weber’s law and JND model as follows:

$$p(k) = \frac{\sum_{(i,j) \in B_k} l(i,j)}{\sum_{(i,j) \in S} l(i,j)}$$

(10)

where

$$S = \{(i,j) : C_c(i,j) > J_c(i,j)\}$$

(11)

$$B_k = \{(i,j) \in S : k = 0, 1, \ldots, 255\}$$

(12)

where $S$ is the set of high contrast pixels whose local contrast is higher than the perceptual local contrast threshold; $B_k$ is the subset of $S$ which contains pixels whose intensity is $k$. Then, we get a high contrast map (Fig. 3(b)) that is composed of pixels with high contrast. If the local contrast of the pixel is greater than JND value, human eyes are more sensitive to the luminance by (11) while preventing flat regions from over-enhanced. Thus, we construct a new perceptual histogram for contrast enhancement using the selected pixels. We perform perceptual GEM as follows:

$$\hat{s}_c = \arg \min_{s_c} \sum_{c=r,g,b} p^{\beta}_{new}(s_c) \| n $$

s.t. $\sum_{i=1}^K s_{ci} = \frac{1}{e_c(\alpha) \sqrt{2}} \sum_{i=1}^K \hat{s}_{ci}, \quad s_{ci} \geq d$ (13)

where $p_{new} = \text{diag}(p_{new1}, \ldots, p_{newK})$, and the original image processed by perceptual GEM as shown in Fig. 3(d). Compared with Fig. 3(c), perceptual GEM deals with over-enhancement in dark areas, which looks more natural in both brightness and color. Fig. 3(e) shows the histogram of the enhanced image by GEM (red) and enhanced image by perceptual GEM (black). It can be observed that the magnitude of spikes for perceptual GEM is smaller than original GEM, which effectively suppresses over-enhancement. In the base image part, we first perform perceptual GEM to enhance the original image, and then convert RGB color space to YCbCr one to select the enhanced grayscale image $Y_b$. Finally, we conduct bilateral filtering on the enhanced grayscale image to achieve edge preserving smoothing and get the enhanced base grayscale image $Y_{b'}$.

B. JND MAP

1) JND TRANSFORM

As shown in Fig. 1, we get $Y$ based on the conversion of the original RGB color space into YCbCr color space. Then, we perform bilateral filtering to get the base grayscale image $Y_b$ from $Y$. Assume $Y$ as foreground luminance $L_F$ and $Y_b$ as background luminance $L_B$. Based on the human visual response model, we model the HVS response to $L_F$, given $L_B$. Denote the HVS response function by $f(L_F, L_B)$. When both $L_F$ and $L_B$ are equal to $L_0$, we have $f(L_0, L_0) = 0$, i.e. HVS cannot perceive the foreground when it has the same luminance as the background. We also have $f(L_1, L_0) = 1$, $f(L_2, L_0) = 2$, due to the increase or decrease of the HVS response by one unit, resulting in a just noticeable change of luminance [19]. We have the HVS response for some discrete
where $\kappa$ is the boosting ratio. We obtain the optimal ratio $\hat{\kappa}$ to minimize the approximation error in (15) as follows:

$$\hat{\kappa} = \arg \min_k \left\| b'_p - \kappa b_p \right\| = (b'_p, b_p) \left( b'_p, b_p \right)$$

According to Weber’s law, base image and JND map should be boosted with the same ratio to preserve the perceptual response. Thus, let $r_p$ and $r'_p$ denote the vectorized $m \times m$ blocks centered at $p$ in $R$ and $R'$, respectively. We obtain their relationship by

$$r'_p = \hat{\kappa} r_p$$

It is well-known that in addition to Weber’s law spatial characteristics in the input image also affect the HVS response, i.e. HVS is more sensitive to textureless regions than to textured regions, given a lighting condition [21]. Thus, we add a parameter $\beta_p$ to control the amount of detail enhancement and increase the perceptual response as follows:

$$r'_p = \beta_p \frac{b_p}{b_p} r_p$$

Therefore, to achieve perceptually uniform enhancement on the entire image, we set the boosting parameter $\beta_p$ in (15) to be proportional to the amount of textures in $r_p$ as follows:

$$\beta_p = 1 + \frac{1}{2m^2} \sum_{i=1}^{m^2} \left( 1 - \exp \left( -\frac{r_p(i)^2}{2\sigma^2} \right) \right)$$

where $r_p(i)$ denotes the $i$-th element of $r_p$. The parameter $\sigma$ controls the amount of texture enhancement and is empirically set to 0.03 in this work. Finally, we obtain the updated JND map $R'$ as shown in Fig. 5(b). After boosting, we perform inverse JND transform as illustrated in Fig. 4(b), which takes $R'$ and $Y_{B'}$ as the input and generates the final image $Y_e$ as the output.

### C. Color Restoration

The final step of the proposed method restores the color component by maintaining the ratio between the three color components. We produce the final output $[R_{out}, G_{out}, B_{out}]^T$ from the original RGB components $[R, G, B]^T$ as follows:

$$\begin{bmatrix} R_{out} \\ G_{out} \\ B_{out} \end{bmatrix} = \begin{bmatrix} Y_e/\bar{Y}_B \\ 0 \\ Y_e/\bar{Y}_B \end{bmatrix} \cdot \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$

### V. EXPERIMENTAL RESULTS

We perform experiments on a PC with Core Duo 3.60 GHz CPU and 4G RAM using Matlab R2015b and Windows 7 operation system. In (13), we set $\beta, n, \alpha$ and $d$ to 0.32, 2, $\infty$, 0, respectively, i.e. the same as the default configuration of the original GEM. In (19), we set $\sigma$ to 0.03 and the block size $m$ to 9. In our experiments,
we perform three groups of experiments: 1) optimal contrast enhancement, 2) post-processing for image de-hazing, and 3) global tone mapping for high dynamic range (HDR) images. We select 6 test image for each group, i.e. total 18 images, as shown in Figs. 6-8. Some images are obtained by the Nagasaki University library, while others are taken by our own digital still camera (Canon EOS 60D) or through internet (http://www.cs.huji.ac.il/~raananf/projects/defog/, http://www.cs.sfu.ca/~colour/data/funt_hdr/). The test images of the first group suffer from low contrast and serious tone distortion. Those of the second group are contaminated by fog and haze, while those of the third group are HDR images with a very dark tone and we perform tone mapping for them.

A. OPTIMAL CONTRAST ENHANCEMENT

We compare the performance of the proposed method with those of OCTM [8] and GEM [9] to demonstrate its superiority. Our perceptual GEM achieves better contrast enhancement with color and detail preservation than the others. Figs. 9-12 show experimental results on four test images. The first two images have low contrast with a color bias, while the others have low contrast with a dark tone. Figs. 9-10(b) provide white balancing results in OCTM [8] for color correction, while Figs. 11-12(b) present high contrast maps for contrast enhancement. OCTM achieves good contrast enhancement but fails to keep color as shown in Figs. 9-12(c). GEM produces good contrast enhancement and color reproduction, but causes over-enhancement especially in dark smooth regions as shown in Figs. 9-12(d). Perceptual GEM deals with the over-enhancement problem effectively by constructing a new histogram using the high contrast map (Figs. 11-12(b)) as shown in Figs. 9-12(e). Figs. 9-12(f) show the enhancement results by the proposed method, and it can be observed that the details are more abundant than the perceptual GEM, OCTM and GEM due to the JND map based on HVS response model. Figs. 9-12(g)(h) show the zoomed results of the perceptual GEM (Fig. 9-12(e)) and proposed method (Fig. 9-12(f)), and it can be observed that the proposed method achieves perceptually better contrast enhancement with rich details than the perceptual GEM. For quantitative measurements, we evaluate the results in terms of three measures: Feature similarity index (FSIM) [25], local tuned global (LTG) [26], and color quality enhancement (CQE) [27].

(1) FSIM reflects the overall similarity between the output image and reference image as follows:

\[
FSIM = \frac{\sum_{x \in \Omega} S_1(x) PC_m(x)}{\sum_{x \in \Omega} PC_m(x)}
\]

where \( \Omega \) means the whole image spatial domain and \( PC \) is perceived with a maximizing Fourier component in phase and is used to weight the importance of \( S_1(x) \) in the overall similarity between the output and reference images.

(2) LTG approaches the process of human visual perception to image quality, which is an effective color image quality assessment (IQA) algorithm as follows:

\[
LTG(x, y) = \frac{\Phi(G_s^\theta_1)}{\Phi(G_m^\theta_3)} \cdot \Phi(I_m^\theta_2, Q_m^\theta_3)
\]

where \( G_m \) the difference of gradient magnitude (GM) maps of the original image \( x \) and its contaminated version \( y \), \( G_s \) indicates the highest \( k\% \) values in \( G_m \); \( I_m \) and \( Q_m \) to measure the distinction of chrominance between the original and distorted images, \( \theta_1, \theta_2, \) and \( \theta_3 \) are model parameters.

(3) CQE is composed of sharpness, colorfulness and contrast attributes, and has the advantage of being applicable to a wider variety of distorted images. After the colorfulness, sharpness and contrast metrics are obtained, multiple linear regression (MLR) is applied to obtain the three coefficients as follows:

\[
CQE = c_1 \times colorfulness + c_2 \times sharpness + c_3 \times contrast
\]

where \( c_1, c_2 \) and \( c_3 \) are constants.
Table 1 shows the quantitative measurement of three methods on six test images. It can be observed that LTG and CQE evaluations verify the superiority of the proposed method. FSIM of the proposed method is a bit smaller than that of OCTM. The experimental results indicate that the proposed method successfully enhances color and details in images.

### B. POST-PROCESSING FOR IMAGE DE-HAZING

The proposed method is also applicable to image de-hazing as post-processing. Although the existing de-hazing methods successfully remove the component of white light in the background of the images, they may cause tonal distortion in the foreground. Thus, we use the proposed method as the post-processing step of the image de-hazing to rectify the tonal distortion. To evaluate the performance of the proposed method, we apply it to the image de-hazing results. First, we use different de-hazing methods to process the original image, then use the proposed method as the post-processing. Finally, we compare the results of image de-hazing and post-processing. In our experiments, we use three de-hazing methods of [22], [23], [24]. We provide some results in Figs. 12-13. After applying the proposed method to the de-hazing results, we achieve better performance in brightness and color than them. For more quantitative
measurements, we evaluate the results in terms of two measures: Discrete entropy (DE) [28] and blind image quality assessment (BIQA) [29] as follows:

(1) DE estimates image details according to the probability histogram distribution, which measures the degree of randomness by the average amount of information.
The enhanced result with high contrast or uniform histogram distribution has a high entropy value as follows:

$$H(p) = - \sum_{i=0}^{L-1} p(i) \log_2 p(i)$$  \hspace{1cm} (24)

(2) BIQA uses a variety of existing and new natural scene statistics (NSS) features computed from a collection of clean natural image patches that fits the extracted NSS features to a multivariate Gaussian (MVG) model. Therefore, this MVG model is deployed as a reference model to measure the quality of a given test image.

We provide the objective evaluation results in Table 2. Except for DE, the higher the objective evaluation metrics are, the better the image quality is. As listed in Table 2, the post-processing results reveal more details than de-hazing results. The scores of the blind image quality assessment (BIQA) for different methods are provided for a comparison in Table 2. BIQA models the natural statistics of the local structures, contrast, multiscale decomposition, and colors, and then measures the deviation of the distorted images from the reference statistics. The lower the score is, the better the image quality is. Table 2 shows that the proposed method obtains the smallest average BIQA score, which indicates the best visual quality among those methods.

**C. GLOBAL TONE MAPPING FOR HDR IMAGES**

Based on GEM [9], the proposed method is applied to the tone mapping of HDR images. It is well-known that the bit-depth of most HDR images are bigger than 8-bit. If some HDR images are mapped into 8-bit, then they become very dark. Thus, we need to use tone mapping to perform image enhancement. Many tone mapping methods have been proposed over the past decades, e.g. [2], [3], [30], [31]. Although these methods based on local adaptive filtering achieve encouraging results, the global method, such as gamma correction, is still the most popular choice because of its robustness and low complexity.

In our experiments, we obtain the HDR image dataset from http://www.cs.sfu.ca/colour/data/funt_hdr/, and map them into 8-bit. We compare the tone mapping results with those of Matlab tone mapping, i.e. tonemap(x), and gamma correction as shown in Fig. 15. As shown in Fig. 15(b), Matlab tone mapping produces image details without recovering the color.
TABLE 3. Performance Comparison between Matlab tone mapping, gamma correction and proposed method.

<table>
<thead>
<tr>
<th>Index</th>
<th>Algorithm</th>
<th>HDR1</th>
<th>HDR2</th>
<th>HDR3</th>
<th>HDR4</th>
<th>HDR5</th>
<th>HDR6</th>
<th>Average</th>
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<td>DE</td>
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<tr>
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<td>24.8387</td>
<td><strong>23.0223</strong></td>
</tr>
</tbody>
</table>

Bold numbers represent the best or equally best performance in each metric.

FIGURE 14. De-hazing results by [22], [23], [24], and their post-processing results. (a) Original image. (b) De-hazing result by [22]. (c) Its post-processing result [22]. (d) Dehazing result by [23]. (e) Its post-processing result [23]. (f) De-hazing result by [24]. (g) Its post-processing result [24].

FIGURE 15. Experimental results. (a) Original image. (b) Matlab tone mapping. (c) Gamma correction ($\gamma=0.4$). (d) Proposed method.

of images correctly. That is, the contrast is enhanced but its tone is biased more. On the other hand, gamma correction avoids obvious tone bias with protecting the color of image, but suffers from low contrast as shown in Fig. 15(c). The proposed method achieves good contrast enhancement while producing vivid color and rich details of images as shown in Fig. 15(d). For quantitative measurements, we also evaluate the results in terms of two measures: Discrete entropy (DE) [28] and blind image quality assessment (BIQA) [29]. We provide the objective evaluation results in Table 3. As listed in Table 3, the proposed method outperforms the others in terms of DE. Table 3 shows that the proposed method obtains the smallest average BIQA score, which indicates the best visual quality among those methods.
In this paper, we have proposed perceptually optimized enhancement of contrast and color in images using JND transform and color constancy. We have performed JND transform to get a JND map that represents the perceptual response of HVS. We have conducted perceptual GEM to adjust the image tone while preventing over-enhancement. We have combined perceptual GEM with JND transform to achieve contrast enhancement, color reproduction and detail enhancement in images. Experimental results demonstrate that the proposed method successfully enhances low contrast images with color bias and dark tone. Our future work includes investigating noise reduction in contrast enhancement of images.

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