Perceiving Unknown in Dark from Perspective of Cell Vibration

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Abstract—Low light very likely leads to the degradation of image quality and even causes visual tasks’ failure. Existing image enhancement technologies are prone to over-enhancement or color distortion, and their adaptability is fairly limited. In order to deal with these problems, we utilise the mechanism of biological cell vibration to interpret the formation of color images. In particular, we here propose a simple yet effective cell vibration energy (CVE) mapping method for image enhancement. Based on a hypothetical color-formation mechanism, our proposed method first uses cell vibration and photoreceptor correction to determine the photon flow energy for each color channel, and then reconstructs the color image with the maximum energy constraint of the visual system. Photoreceptor cells can adaptively adjust the feedback from the light intensity of the perceived environment. Based on this understanding, we here propose a new Gamma auto-adjustment method to modify Gamma values according to individual images. Finally, a fusion algorithm, combining CVE and Gamma auto-adjustment (CVE-G), is proposed to reconstruct the color image under the constraint of lightness. Experimental results show that the proposed algorithm is superior to six state of the art methods in avoiding over-enhancement and color distortion, restoring the textures of dark areas and reproducing natural colors. The source code will be released at https://github.com/leixiaozhou/CVE-G-Resource-Base.

Index Terms—Low light, Cell vibration, Energy model, Gamma adjustment, Tone mapping.

I. INTRODUCTION

WITH increasing demands for video recordings collected in night scenes, where images are acquired without sufficient exposure, people must deal with the problems such as low lightness, low contrast and increasing image noise. Image contents may be missing or obscured due to darkness, and to make these low quality images re-usable, suitable image enhancement technologies are being developed in order to reveal the image information hidden in the dark [1], [2].

In the field of low light image enhancement, one of the classical and extensively utilised methods is histogram-based techniques. Histogram equalisation (HE) [3] is a simple yet fast method, which adjusts corresponding distributions of individual RGB channels in a color image. Problems such as over-enhancement, color distortion, and evident noise in dark areas cannot be avoided due to lack of the constraints of color correlation across channels. In order to cope with these shortcomings, several HE based methods have been proposed, such as CLAHE [4], CVC [5], MLHE [6], [7], etc. Celik and Tjahjadi [5] reported that the input image contrast can be enhanced by constructing a two-dimensional histogram based on the neighborhood relationship of image pixels. The disadvantage of the method is that color restoration still needs to be improved [8]–[10]. Caselles et al. [6] proposed a local contrast enhancement algorithm for shape preservation. The disadvantage is that the image noise is also amplified [7].

Another widely influential method is model-based approaches, such as Retinex model [2], [11]–[17], tone mapping method [18], [22], and physical lighting model [10], [23]–[26]. For the Retinex model, Frankle and McCann [13] proposed a Retinex approach which uses the path of spiral structures to evaluate the pixel correlation. This approach runs a number of iterations to search for local information with increasing computational efforts as the iterations carry on. The LIME algorithm proposed by Guo [2] has attracted much attention. By building a smooth structure perception model, the illumination consistency can be improved, and finally a well structured illumination map is obtained. Recently, Gu et al. [17] proposed a fractional-order variational model based on Retinex to obtain appropriate illumination estimation results. Both [2] and [17] used Gamma transformations to improve illumination estimation results.

For tone mapping methods, Moroney [18] proposed a scheme that uses a non-linear template for color correction. This scheme is a global HUE mapping scheme with a fast computation speed. Empirical results show that the improvement of this method is very limited. Ahn and Keum [19] proposed to enhance dark images using a two-step method including global mapping and local color adjustment. This method can retrieve image details and has less computational cost. For physical lighting models, Jiang and Yao [23] constructed a foggy image by reversing the pixels of the dark image, and then used the dark channel algorithm to remove the noise so as to improve the contrast of the dark image. Recently, Yu and Zhu [26] proposed a physical illumination model to describe the degradation of the illuminated images. Their method adjusts the estimation result of the ambient light by using the constraints on information loss to restore the color of the low illumination images. Based on the illumination-
reflection methods in both qualitative and quantitative evaluation. Our Section III shows the experimental results of seven state of the then introduce a new Gamma auto-adjustment method with Section II, we first construct the cell vibration model with 

contributions are summarised as follows. In summary, our dark image. 

encoder-decoder network to output the color version of the full convolution network. Ren and Liu [29] proposed a new exposure reference image. Using this dataset, they developed a dark image enhancement method, based on the end-to-end 

image restoration in different circumstances. In summary, our contributions are summarised as follows.

1) A color-forming hypothesis based on the description of photon energy is presented, which considers the color sensed by retinal cells as the accumulation of photon flow energy. Based on this mechanism, a color image is decomposed into two components that need to be estimated, where component estimation is an ill-posed problem to be solved here.

2) We establish a cell vibration model to estimate photon energy from the image. This photon energy function shows its strong sensitivity to image pixels, which are particularly supportive to low-light image enhancement. It is understood that photon flow energy can be adjusted using the photoreceptor correction function of cells. This physical analysis helps improving the ability to deal with the ill-posed problem shown in Eq. (1).

3) To implement the function where photoreceptor cells automatically adjust with respect to image lightness, a new Gamma auto-adjustment method is proposed in this paper. This method establishes a smoothness constraint for the reconstructed image’s lightness and the Gamma values in order to deliver high quality illumination.

4) To improve the adaptability of the algorithm, a fusion method (CVE-G) combining cell vibration energy (CVE) mapping method and the Gamma auto-adjustment method is proposed to reconstruct the image under the constraint of illuminance.

The remainder of the paper is organised as follows: In Section II we first construct the cell vibration model with the analysis to the impact of the engaged parameters. We then introduce a new Gamma auto-adjustment method with curve fitting for maintaining quality illumination over images. Section III shows the experimental results of seven state of the art methods in both qualitative and quantitative evaluation. Our conclusions are given in Section IV.

II. METHODOLOGY

Our proposed method is based on the following physical hypothesis, which describes the mechanism of color generation.

Postulate 1: Color is the sensory expression of energy, which is the result of periodic accumulation of photon flows. The mathematical description of this formation is:

\[ C = DE \] (1)

where \( C \) represents the color image generated by accumulating the energy to stimulate retinal cells. \( D \) is a scalar, called the period doubling index of photon energy flows on retinal cells. \( E \) is the photon flow energy in a single period. In a 2D RGB image, the size is \( m \times n \), with three color channels, i.e. red, green and blue. For better mathematical analysis, we assume that \( C \) and \( E \) have the same size and channels. To avoid the influence of image bytes, we normalise the image target so that its intensity value falls in the range of [0,1]. For the pixel value \( I(x,y) \) of the \( i \)th color channel \( C_i \) at coordinate \((x,y)\) of color image \( C \), we have: \( I(x,y) \in [0,1] \). As for the photon flow energy \( E \), it is part of the energy absorbed by the visual system in the photon flow from the external environment. Its value is usually very small, close to 0. Naturally, period doubling index \( D \) represents the multiplication used to stretch the maximum \( E_{max} \) in the photon flow energy to its constraint \( E \). For each color channel, there is a corresponding linear magnification \( D_{i} \), so the size of \( D \) is \( 1 \times 3 \). More specifically, \( D = [D_R, D_G, D_B] \). For the \( i \)th color channel, there are

\[ C_i = D_i E_i \] (2)

Our model attempts to decompose each color channel \( C_i \) into two components, including period doubling index \( D_i \) and photon flow energy \( E_i \). In this case, \( E \) is a color related component. Since the amplification coefficient \( D \) is determined by \( E \), the key problem of the modeling is to estimate photon flow energy \( E \) acting on the retinal cells from image \( X \), that is, the mathematical description between \( E \) and \( X \).

The gray scale range of pixels in a low light image is usually narrow, and low-light image enhancement enables us to expand the gray scale of image pixels, where a non-linear mapping function is used to project the image pixels in the original image space onto those in a defined image space. Fig. 1 shows an example of our application in the field of low-light image enhancement using the proposed model. Our model first determines the color related component \( E \) from the image, and then extends the pixel range of each color channel to the pixel range of the entire image through period doubling index \( D \). Fig. (d) and (e) shows the histograms of the images in gray scale. The pixel extension of the proposed method is selectively controlled rather than being uniformly distributed across the entire image. This avoids excessive pixel re-mapping and reduces the probability of color distortion. In the next two subsections, we will construct the relationship between image \( X \) and photon flow energy \( E \) from the perspective of cell vibration.
A. Single Photon Energy Estimation

Before studying photon flow energy, we first investigate possible influence of a single photon on retinal cells. Afterwards, we study the magnitude of the energy of a single photon perceived by retinal cells after the photon has been captured. When light is applied to the material, there is a photothermal effect in which part of the light energy is converted to heat. Considering the energy transfer, we have the following assumptions.

**Postulate 2:** When photon energy is captured by cells, the cytoplasm undergoes slight expansion after heat absorption, which makes the cell membrane expand. Afterwards, heat is transferred from the cell to its neighbors, leading to a decrease of the temperature of the cytoplasm and subsequent contraction of the cytoplasm and the cell membrane.

This process is demonstrated in Fig. 2(a). According to **Postulate 2**, we attempt to establish a physical vibration model to describe the expansion-contraction process of cell membranes. The model is shown in Fig. 2(b). The cell membrane can expand and contract dynamically as an elastic element, which has a stiffness value of $k$. The cytoplasm with energy and shock absorption can be treated as a damper, which has a viscous damping coefficient of $c$. At the same time, the stimulus given by photons are defined as the imaginary mass, which has a weight of $m$ equivalent to the stimulus intensity. According to the theory of mechanical vibrations, we assume that the physical vibration model is a free vibration model of a damped system. Therefore, the vibration displacement $s(t)$ of the model can be used to describe the extent of expansion and contraction of cell membrane.

**Definition 1 (Differential of Displacement):** The differential of displacement $s(t)$ for the cell membrane under a single vibration is

$$m\ddot{s}(t) + c\dot{s}(t) + ks(t) = 0$$

(3)

By definition 1, there are:

$$\ddot{s}(t) + 2\beta\dot{s}(t) + \omega_0^2s(t) = 0$$

(4)

where $\omega_0^2 = \frac{k}{m}$, $\beta = \frac{c}{2m}$. $\beta$ is a viscous damping factor or damping rate, which is a dimensionless parameter. $\omega_0$ is the natural frequency of the system. The mass $m$ is determined by the parameters of the system itself, independent of the external excitation, initial conditions, etc., in addition to the current stimulus intensity.

For the selection of a general solution, we consider the case of critical damping. This is because if there is no follow-up energy supplementary, and the cells will return to the initial stability due to energy dissipation. In this case, the system returns to the static balance position in a short time.

**Definition 2 (Motion Displacement):** The motion displacement $s(t)$ of the cell membrane from a single vibration to its static equilibrium is

$$s(t) = e^{-\beta t}(c_1 + c_2t)$$

(5)

where $c_1$ and $c_2$ are two integral constants determined by the starting condition of motion. Fig. 2(c) shows that cell membrane movement tends to reach a balanced position over time. This is consistent with the setting where cells return to their original states after the stimulus has been removed.

After having obtained the expression of the motion displacement $s(t)$, we derive the energy ($E_p$) of a photon from the motion displacement $s(t)$. For this purpose, we set up three preconditions:

**Postulate 3:** Light transfers energy by independent photons.

**Postulate 4:** The energy that light acts on cells is absorbed without any loss.

**Postulate 5:** Cells absorb only one photon of energy at a time. When a photon is captured and absorbed by the cell, this is equivalent to a stimulus to the cell. After that, the cell returns to the stable state instantly.

The differential form of energy($E_p$) is as follows:

$$\frac{dE_p}{dt} = v\frac{dm}{dt} + mv\frac{dv}{dt}$$

(6)

According to the definition of mass and *Postulate 3 - 5*, there are

$$\frac{dm}{dt} = 0$$

(7)

The total energy consumed by cell movement during the period starting from cell vibration to the recovery of the steady
state is as follows:

\[ E_p = \int_0^{+\infty} \frac{dE_p}{dt} dt = \int_0^{+\infty} mv dv = \frac{1}{2}mv^2 \bigg|_0^{+\infty} \]  

(8)

There is a differential relationship between the velocity and the displacement, i.e.

\[ v = \frac{ds}{dt} \]  

(9)

Therefore, given the stimulation intensity \( m \), the energy \( E_p \) is described as

\[ E_p = c_1c_2\sqrt{km} - \frac{1}{2}c_2^2m - \frac{1}{2}kc_2^2 \]  

(10)

(10) indicates that if there is no light stimulation, i.e. \( m = 0 \), there is still a negative energy term related to the membrane stiffness \( k \). Disassembling (10) into a combination of two items, we have the following equation:

\[ E_p = E_s - E_r \]  

(11)

**Definition 3 (Repulsive Energy):** During cell vibration, the energy used by the cell system to reject the stimulus is

\[ E_r = \frac{1}{2}kc_2^2 \]  

(12)

where the minus sign indicates that the cell exhibits spontaneous resistance or repulsion during the energy absorption and vibration. This is consistent with the observation that live cells are able to dynamically respond to external stimuli.

**Definition 4 (Stimulation Energy):** The energy of the external stimulus that causes the vibration of the cell membrane is

\[ E_s = c_1c_2\sqrt{km} - \frac{1}{2}c_2^2m \]  

(13)

Based on the cell membrane vibration model (CMV) established under **Postulate 2**, with the support of **Postulates 3 - 5**, we have an estimated solution \( E_s \) describing the energy of a single photon. This means that, given the stimulus intensity \( m \) of a single photon, we can obtain the magnitude of the photon energy of a cell. In order to establish the connection between image \( X \) and the energy \( E_s \) of a single photon, we further assume,

**Postulate 6:** The value of each pixel in image \( X \) depicts the stimulus intensity under the action of a single photon.

Based on **Postulate 6**, for each color channel \( X_i \), the energy \( E_s \) of a single photon can be estimated as:

\[ E_s = \lambda \sqrt{I(x,y)} + (1 - \lambda)I(x,y) \]  

(14)

where \( I(x,y) \) is the pixel value of layer \( X_i \) at coordinate \( (x,y) \), and we have \( I(x,y) \in [0,1], \lambda \in (1,2). \) (14) is a simplified form of (13), which ensures that the maximum value of \( E_s \) is 1.

The energy \( E_s \) of an image changing with \( \lambda \) is illustrated in Fig. 3. We understand that the change of \( E_s \) is sensitive to dark tones. This characteristic makes it possible to enhance the low light image using Eq. (14). In addition, this observation is consistent with the recognised Weber-Fechner law, that is, the human perception of natural stimuli is nonlinear. We treat the \( E_s \) curve as a tone mapping example, which helps enhance the low-light image, but the color restoration is not satisfactory as \( \lambda \) limits the mapping range of the gray image as shown in Fig. 4. Using a physical model of cell vibration, we wish to estimate the photons energy that perceives, captured by the retinal cells. Unfortunately, no easy way exists to measure the estimation accuracy.

**B. Photon Flow Energy Estimation**

For the estimation of photon flow energy, it is agreed that photon flow energy is equal to the product of the energy of a single photon and the photon frequency, i.e.

\[ E = f \varepsilon \]  

(15)

In order to calculate the photon flow energy of each layer, we replace the photon frequency with the cell membrane vibration frequency. Cell absorbs \( N \) photons which enable the cell membrane to be of frequency \( f \) in a unit cycle. Using **Postulate 5**, a single photon only makes the cell vibrate once at a time. Therefore, the vibration frequency of the cell...
membrane characterises the number of photo-quanta absorbed by the cell in a unit cycle.

In the CMV model, the angular frequency of cell membrane vibration is \( w_0 \), and the relationship between the angular frequency and the frequency is as follows:

\[
    w_0 = 2\pi f
\]

Therefore, frequency \( f \) is described as follows:

\[
    f = \frac{\lambda}{2\sqrt{2\pi c_1}\sqrt{I(x,y)(\lambda - 1)}}
\]

The photon flow energy \( E \) can be written as

\[
    E = fE_s = \frac{1}{2\sqrt{2\pi c_1}} \left[ \frac{\lambda^2}{\sqrt{\lambda - 1}} - \lambda\sqrt{I(x,y)(\lambda - 1)} \right]
\]

Taking into account the property of \( c_1 \), \( \lambda \) can be simplified as follows

\[
    E = \frac{\lambda^2}{\sqrt{\lambda - 1}} - \lambda\sqrt{I(x,y)(\lambda - 1)}
\]

On the one hand, photon flow energy may be small. On the other hand, photoreceptors can flexibly regulate the retinal imaging outcome using the light intensity of the ambient environment. It is true that \( \lambda \) cannot meet these physical requirements at the same time. Furthermore, the negative correlation between \( E \) and \( I(x,y) \) does not physically sound so we introduce a photosensitive correction to re-calibrate the photon flow energy.

**Definition 5 (Corrected Photon Flow Energy):** Photoreceptor cells correct the received photon flow energy using a photoreceptor correction function. Corrected photon flow energy is the product of the correction function and the photon flow energy, i.e.

\[
    E_c = \alpha E
\]

where \( E_c \) is the corrected photon flow energy, and \( \alpha \) is the photoreceptor correction function. We here use,

\[
    \alpha = \frac{I(x,y)^\Gamma}{\|X_i\|_F}
\]

The photoreceptor correction function \( \alpha \) consists of the Gamma transformation of the stimulus intensity and a F-norm of the color channel. The Gamma transformation ensures that the energy of the photon flow is positively correlated with the stimulus intensity. In the subsequent analyses, we utilise the definite relationship between Gamma values and lightness to simulate the feedback correction of the photoreceptor cells. The F-norm of each color channel ensures that the stimulus energy caused by photons is of a small value, making it close to the realistic one. In later analyses, we recognise that this item may be omitted. The changes before and after the correction are shown in Fig. 5.

Therefore, the photon flow energy within a short period is estimated as follows:

\[
    E_c = \frac{I(x,y)^\Gamma}{\|X_i\|_F} \left( \frac{\lambda^2}{\sqrt{\lambda - 1}} - \lambda\sqrt{I(x,y)(\lambda - 1)} \right)
\]

**C. Period Doubling Index Determination**

In this subsection, we will describe the method for determining the doubling period index in Postulate 1.

**Definition 6 (Period Doubling Index):** Period doubling index \( D \) is a factor used to maximise \( E_{\text{max}} \) to the constraint value \( \tilde{E} \). Here, \( \tilde{E} \) stands for the final state that the physical sensory organ can tolerate. The entire mathematical description is:

\[
    D = \frac{\tilde{E}}{E_{\text{ci max}}}
\]

For each color channel of the RGB image, there is a corresponding linear magnification \( D_i \). Hence, there are \( D_i = \tilde{E}_i/E_{\text{ci max}} \). \( \tilde{E}_i \) and \( E_{\text{ci max}} \) are the constraints of the \( i \)th color channel and the maximum photon flow energy value, respectively. \( \tilde{E} \) can be regarded as the normalised color signal. For a 8-bit image, when \( \tilde{E} = [255, 255, 255] \), this refers to a
pure white image. The following lemmas are given in order to derive $E_{ci \text{ max}}$.

**Lemma 1:** The maximum photon flow energy is equal to the photon flow energy obtained at the maximum pixel value, i.e.

$$E_{ci \text{ max}} = E_{ci}(I_{\text{max}}) \quad (24)$$

where $I_{\text{max}}$ is the maximum pixel value of the $i$th color channel.

**Proof:** It is straightforward to know from (22) that $E_c$ is positively correlated with $I(x,y)$ for all $I(x,y) \in [0,1]$. This completes the proof.

**D. Color Image Reconstruction**

In the first three subsections, based on the hypothetical cell membrane vibration model, we describe $D$ and $E$ components in the Postulate 1 in detail and present the corresponding representations. For input image $X$, the definition of the perception domain is then produced.

**Definition 7 (Perception Domain):** Perception domain is the sum of all possible situations in which retinal cells perceive the input image information, relying on the product of cell membrane vibration and photoreceptor correction. The symbol is represented as $G(X, E, \lambda, \Gamma)$, and the element in the perception domain is color image $C$.

According to the mathematical description shown in Eq. (1), for the $i$th color channel, there are

$$C_i = \frac{\tilde{E}_i}{E_{ci \text{ max}}} \frac{I(x,y)\Gamma}{\|X_i\|_F} \left[ \frac{\lambda^2}{\sqrt{\lambda-1}} - \lambda \sqrt{I(x,y)(\lambda-1)} \right] \quad (25)$$

Using Lemma 1, we have:

$$C_i = \frac{\tilde{E}_i}{E'_{ci \text{ max}}} \frac{I(x,y)\Gamma}{\|X_i\|_F} \left[ \frac{\lambda^2}{\sqrt{\lambda-1}} - \lambda \sqrt{I(x,y)(\lambda-1)} \right] \quad (26)$$

From the mathematical description of $C_i$, we use the molecular part as the calculation of the photon flow energy. The advantage of this way is that it does not need to calculate $\|X_i\|_F$, so reduce the computational efforts. Therefore, the new mathematical form of $E_c$ is defined as

$$E'_c = I(x,y)\Gamma \left[ \frac{\lambda^2}{\sqrt{\lambda-1}} - \lambda \sqrt{I(x,y)(\lambda-1)} \right] \quad (27)$$

In summary, for the $i$th color channel,

$$C_i = \frac{\tilde{E}_i}{E'_{ci \text{ max}}} I(x,y)\Gamma \left[ \frac{\lambda^2}{\sqrt{\lambda-1}} - \lambda \sqrt{I(x,y)(\lambda-1)} \right] \quad (28)$$

where $E'_{ci \text{ max}}$ is solved jointly using Eqs. (24) and (27).

So far, we have established a global tone mapping method for mapping from input image $X$ to a new color image $C$. This new method evolves from the color formation mechanism and the cell membrane vibration model with rich physical implications. We apply this method for enhancing low light images in order to perceive the information in the dark. This new method only needs two steps of calculation to achieve the mapping practice, and operates on image pixels without any additional neighborhood operation. Therefore, its implementation is efficient.

**E. Gamma Auto-adjustment**

The photoreceptor correction function Eq. (21) contains a core parameter, i.e. $\Gamma$. The major challenge in this work is to automatically adjust the Gamma value according to the change of lightness. The difference between the means of the $V$ channel in the HSV space is used to describe the
enhancement outcome of Algorithm 1. The mean lightness of the initial image and the enhanced image are \( x_{e0} \) and \( x_{e1} \) respectively. The degree of enhancement(\( dv \)) is defined as

\[
dv = x_{e1} - x_{e0}
\]  

(29)

In order to make our proposed method adaptive to different image environments, a method of automatically adjusting \( \Gamma \) under the lightness constraints is proposed. The method of automating \( \Gamma \) adjustment is as follows:

(a) Generating a smaller version of the initial image. The scale ratio is \( K \), and we set \( K \) as

\[
K = \begin{cases} 
\frac{\max(m,n)}{r}, & \text{if } \max(m,n) > r \\
1, & \text{if } \max(m,n) \leq r 
\end{cases}
\]  

(30)

(b) Using the above CVE mapping method to obtain the color reconstruction map under a set of \( \Gamma \) values. Afterwards, the color space of the reconstructed image is converted from the RGB space to the HSV space, and the value of \( dv \) is calculated and recorded.

(c) Combining \( \Gamma \) and \( dv \) into coordinates \((\Gamma, dv)\), and using the following curve model to fit the \( \Gamma - dv \) curve.

\[
dv = c + \frac{1}{a\Gamma + b}
\]  

(31)

(d) Inputting the desired lightness constraint \( dv^* \) and obtaining \( \Gamma^* \) for initial image calculation from Eq. (32).

\[
\Gamma^* = a^{-1} \left( \frac{1}{dv^* - c} - b \right)
\]  

(32)

In step (a), \( r \) is defined as the threshold to determine whether or not we should conduct down sampling. If the maximum size of the initial image is larger than \( r \), then the initial image is reduced. The advantages of down sampling are to reduce resource consumption and computational time, but this will result in the loss of image information, which indirectly changes the value of \( dv \). We do not recommend setting too small. By default, \( r = 1000 \).

In step (c), the fitting model contains three parameters, i.e. \( a, b, c \). Therefore, three or more Gamma values are demanded to generate the fitting model. We prefer to use a nonlinear least square method called the trust region reflection algorithm due to its efficiency [40], [41] (this method is encapsulated in the MATLAB computing library). By default, \( \Gamma = [0.3, 1.8] \) with an interval of 0.5.

In step (d), \( dv^* \) represents the needs of individuals for global lightness.

Compared with other algorithms such as LIME that also use Gamma correction, our proposed algorithm has the advantage of efficiently and effectively constructing the adjustment function that has a definite relationship between Gamma and the mean of the \( V \)-channel. Using this determined association rule, we can improve the quality of the reconstructed color images. Except for constraining the value of \( dv \), we can manipulate the \( x_{e1} \) value of the reconstructed image to balance the lightness of each color image.

When the constrained variable is \( dv^* \), our Gamma auto-adjustment method is shown below. If the constrained variable is \( x_{e1} \), we replace \( dv^* \) with \( x_{e1} \) in Algorithm 2.

### Algorithm 1 CVE mapping method

1. Input a low illumination image \( x \), and initialize \( E, \lambda, \Gamma \).
2. Normalize the image scale to \( \{x|0 \leq x \leq 1\} \), collect the maximum value \( I_{\text{max}} \) of each color channel.
3. Solve \( E'_{\text{cl}_{\text{max}}} \) using Eq. (27).
4. Solve \( C_i \) using Eq. (28).
5. Output the reconstruction color image \( C \).

### Algorithm 2 Proposed Gamma auto-adjustment method

1. Input a low illumination image.
2. Initialize \( E, \lambda, \Gamma, dv^*, r \).
3. Resize the image using Eq. (30).
4. Call the CVE mapping method for each \( \Gamma \) to calculate the reconstructed color image \( x^* \).
5. RGB \( \rightarrow \) HSV for \( x \) and \( x^* \), and solve \( dv \) using Eq. (29).
6. Derive \( (a, b, c) \) using a nonlinear least squares method for sequence \((\Gamma, dv))\).
7. Derive \( \Gamma^* \) using Eq. (32) and output.

### Algorithm 3 Proposed fusion method: CVE-G

1. Input a low illumination image.
2. Initialize \( E, \lambda, \Gamma, r, dv^* \) or \( x_{e1} \).
3. Call the Gamma auto-adjustment method to derive the final \( \Gamma^* \).
4. Call the CVE model using \( \Gamma^* \), and output the reconstructed color image \( C \), and its average lightness is increased to \( x_{e1} \).

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**Fig. 9.** Some Low-light images used in the experiment. Image A1 was obtained in an extremely low light environment. Image A2 is from the LIME dataset. Image A3 is from the Internet. Images B1, B2 and B3 come from the open dataset SIDD. Images C1, C2 and C3 are from the HDR dataset.

**Fig. 10.** Reference images under normal lighting for row C of Fig. 9.
F. Fusion Method Determination

To work with complex lighting environments, a fusion method (CVE-G) is here proposed, which combines the CVE mapping and Gamma auto-adjustment methods. From the previous analyses, we have two algorithms to help achieve low light image enhancement. Using very few parameters, such as Gamma intensity, the CVE mapping method can present several versions of the reconstructed image. To automate the optimisation of the rendering of the reconstructed image, we here consider the use of a Gamma auto-adjustment method. The fusion method (CVE-G) is shown in Algorithm 3.

III. EXPERIMENTAL WORK

In this section, we first examine the effects of the involved parameters. Next, the reasons for using Eq. (31) as a curve fitting model are discussed. Afterwards, we compare our CVE-G with several state of art methods from the perspective of subjective qualitative and objective quantitative evaluation. The comparison methods include: HE [3], NLM [18], McCann [13], [14], ALTM [20], LIME [2] and AIEMC [10]. A test platform based on the Notebook (Intel Core i5-3230m @2.6GHz, 16gram and windows 7 operating system) is established. The software has been developed with Matlab 2016b. The images used in the experiment comes from the publicly accessible datasets and self-collections of the authors of this paper. Image data has been acquired in various complex lighting environments, such as extremely low and natural lighting. The majority of our experimental images are from four databases, i.e. LIME [2], SIDD [31], [33], the ESPL-LIVE HDR Image Quality Database (HDR) [34], [35] and ExDark [38], [39]. The numbers of the images pulled from these datasets are 10, 70, 292 and 600, respectively. Fig. 9 and Fig. 16 show some examples of the experimental images.

A. Parameters’ impact

Algorithms 1-3 contains three indeterminate parameters, $\tilde{E}$, $\lambda$ and $\Gamma$. To understand the role of each parameter, we analyse each parameter individually. The CVE-G method is used to analyse parameter $\tilde{E}$, and the remaining parameters are analysed by using the CVE method.

1) Effect of parameter $\tilde{E}$: We can adjust the molecular parts of each component in $\tilde{E}$ to have different color shading outcomes. Fig. 6 shows different image outcomes when setting different $\tilde{E}$. In the process, $dv^* = 0.0$ or 0.3, $\lambda = 2$. In subsequent analyses, we set $\tilde{E} = [255, 255, 255]$.

2) Effect of parameter $\lambda$: In Section II, the value of parameter $\lambda$ has the range of [1, 2]. The reconstructed image B2 from Fig. 9 are shown in Fig. 7. In this process, $\lambda = [1.05, 2]$ with an interval of 0.05, and $\Gamma = 1$. After having been sorted, the image $dv$ changing with $\lambda$ is shown in Fig. 7(d).

With increasing $\lambda$, $dv$ increases gradually, suggesting that image enhancement becomes stronger. The difference of $dv$ for $\lambda = 1.05$ and $\lambda = 2$ is 0.0481. From the subjective point of view, the difference between the two reconstructed color images is subtle. Therefore, in the subsequent analysis, we set $\lambda = 2$.

Fig. 11. The $\Gamma$ – $dv$ scatter diagrams from the experiments.

Fig. 12. Curve fitting diagrams for different images.

| A1 | A2 | A3 | C1 | C2 | C3 | E1 | E2 | E3 |
|----|----|----|----|----|----|----|----|----|
| $e_m$ | 0.0341 | 0.0194 | 0.0521 | 0.0023 | 0.0001 | 0.0156 | 0.0328 | 0.0178 |
| $S_e$ | 0.3143 | 0.2312 | 0.0745 | 0.0382 | 0.0013 | 0.0463 | 0.2051 | 0.2736 | 0.2257 |

3) Effect of parameter $\Gamma$: Similarly, using the color checker image, the reconstruction results are shown in Figure 8. In this process, $\Gamma = [0.4, 2.2]$ with an interval of 0.2. After having been sorted, the image $dv$ changing with $\Gamma$ is shown in Fig. 8(d).

The results show that the reconstructed image is foggy when the Gamma value is small. With the increasing $\Gamma$, the foggy scene gradually disappears. For different images, how to select a suitable Gamma value to obtain a satisfactory reconstructed image is a difficult problem. In this paper, this problem can be solved by the proposed Gamma auto-adjustment method.
B. Curve Model

The reasons for us to choose Eq. (31) as the curve fitting model are explained here. The CVE method is used in this part of experimental analysis. We have carried out comprehensive experiments in order to explore the characteristics of the proposed model. The $\Gamma - dv$ scatter diagrams collected in the experiments are shown in Fig. 11 where the scattered points with the Gamma values sitting between 0 and 2.2 and the interval of 0.05 are recorded.

Looking at the data plot, we believe that the trend of these scatters is close to the curve of $1/\Gamma$, i.e. $dv \sim 1/\Gamma$. Therefore, taking into account this data distribution, we establish a fitting model as shown in Eq. (31). This smoothness constraint for the relationship of Gamma values and lightness helps solve the problem of Gamma selection for different images.

The error of the model fitting ($e$) is defined as:

$$ e = dv' - dv $$

where $dv$ is the actual value, $dv'$ is the data to be fitted. Moreover, the maximum error of the curve fitting is defined as $e_m = \max\{|e|\}$. The sum of the errors is defined as $S_e = \sum |e|$. Considering the error of Gamma falls in the range of $[0.3, 1.8]$, as an example, the curve fitting of the image from Fig. 9 is shown in Fig. 12 where the blue solid line is a fitted curve, and the red point is part of the scatter-plot shown in Fig. 11. The fitting errors and related statistics are reported in Table I. Image A1 has the maximum error index, $e_m = 0.0341$, which is very small and hardly changes the reconstruction quality of the image. In addition, given $S_e = 0.3143$, the percentage between $S_e$ and the real value is 0.1128%, which is also very small. From the experiments, we conclude that the selected $\Gamma - dv$ curve fitting model has satisfactory outcomes with minor discrepancy.

C. Subjective and Qualitative Evaluations

In terms of algorithmic parameter settings, there is no parameter to set up for HE and NLM methods, the number of the iterations used in the McCann method is 6, and the parameters provided in their published papers are used in ALTM, LIME, and AIEMC methods. The proposed algorithm in the experiments deploys $dv' = 0.3 \ or \ x_{v1} = 0.55$, and the other parameters are the default ones mentioned previously in this paper.

From Figs. 13-15, we notice that the color recovery capability of the NLM method is relatively weak, the lightness of the reconstructed color image is still dim, and the image details cannot be distinguished. Although the lightness has been significantly improved using HE, McCann, ALTM, LIME, and AIEMC methods, they also accompany significant overexposure or color distortions. For example, for the HE method, only image B1 shows excellent overall color performance. For the McCann method, some areas in the images of rows A and C have significant color distortions, whilst the reconstructed images of row B are bright and natural. The color checker image shown in Fig. 14(d) shows slight color distortion.

For the ALTM, LIME, and AIEMC methods, the reconstructed color images look very similar, e.g. the background color tends to be red for the reconstructed images A1, B2, B3 and C1. The results of image C2 show that the details of the reconstructed images are still unclear. The results of image C3 are much positive. For the proposed method, the systematic performance is maintained in various complex image environments. For the Chinese man shown in image A1, the facial skin remains pale yellow in the reconstructed image. For the images of row B, the color of the reconstructed image is clean, bright and natural with no color distortion. The image details have been properly restored, and similar observations can be obtained for the outcomes of images C1 and C2. For images A2, A3, and C3, texture features have been largely restored, but color saturation of the sky is slightly reduced. The reason for this defect is that the blue component of the sky does not dominate the image anymore, leading to a transition from blue to white, and a decrease in the saturation of the blue color. Adjusting the saturation of the reconstructed image may improve this situation.

D. Objective Quantitative Examination

The images used in the objective quantitative experiments consist of two parts: (1) Only low-light images, and no corresponding normal light reference images, e.g. the images of row A and B shown in Figs. 9 (2) Including low-light images and normal-light reference images, e.g. the images of row C shown in Figs. 9. In this section, we design two different experiments, namely (I) indirect comparison experiment and (II) direct comparison experiment.

1) Indirect Comparison: PSNR index can be used to describe the similarity between two images. If a PSNR value is large, it means that the compared image is similar to the reference image. The images of LIME (SIDD and ExDark) lack reference images under the normal light state, and the initial low light image is used as the reference. In this case, a higher image quality score means that the compared image is similar to the original low light image, inferring that the enhancement of this particular algorithm is worse. Therefore, this is an indirect way to evaluate the degree of the algorithmic enhancement. The images of HDR are also processed in this way.

The PSNR index of the experimental images are shown in Tables II. Bold fonts are used to highlight the top three algorithms in the tables. To fully describe the quantitative background, we also use the mean of the test results to show the overall performance of each algorithm.

The results shown in Tables II show that the NLM algorithm obtains the largest value in the experiment, which demonstrates the rationality of the indirect comparison experiment. The top three algorithms shown in Fig. 9 are HE, the proposed method and McCann. Regarding the PSNR average statistic indexes for each database, performance of these algorithms is different. With the increasing number of the images, the statistical index shows the superiority of HE and the proposed method. Combining with the subjective comparison experiment, we
recognise that the HE algorithm is top-ranking in the case of over-enhancement. The proposed method is the 2nd top-ranking with a strong enhancement ability to preserve the natural color of the images.

2) Direct comparison: PSNR, MSSIM [36] and VIF [37] are used to measure the evaluation indexes of the direct comparison experiments. MSSIM is usually used to describe the detail reconstruction intensity of an image. VIF is the abbreviation of visual information fidelity, which depicts the degree of information fidelity. Direct comparison experiment only focuses on the images of HDR, and uses the images under normal light as the reference images. In this case, a higher index score means that the quality of the reconstructed image is better. Fig. [10] shows three examples in the HDR database under normal light. The PSNR, MSSIM, and VIF indexes of the experimental images are shown in Table [III].

Table [III] shows that, for the images of row C, the proposed method achieves the highest index scores in most of the three
TABLE II
PSNR evaluation index statistics (low illumination image as the reference). For four databases, the mean score of each algorithm is displayed below the double horizontal line.

| Image   | HE    | NLM   | McCann | ALTM  | LIME | AIEMC | Proposed ($dv^* = 0.3$) | Proposed ($x_{11} = 0.55$) |
|---------|-------|-------|--------|-------|------|-------|------------------------|----------------------------|
| A1      | 4.7889| 19.5784| 4.7818 | 14.4643| 13.3672| 16.4039| 9.5333                  | 5.0764                      |
| A2      | 7.0934| 17.5786| 9.5684 | 13.4915| 10.0318| 10.7430| 10.0398                  | 6.5994                      |
| A3      | 10.6890| 18.4600| 9.2992 | 13.7299| 12.2752| 12.5830| 10.4827                  | 11.2365                     |
| B1      | -7.9432| 2.4983 | -9.0113|-7.8221 | -3.3997|-3.2475 | -3.8191                  | -7.2859                     |
| B2      | 1.5704| 10.1558| 1.2789 | -0.6616| 1.6893 | 0.3310 | 2.4566                   | 2.8326                      |
| B3      | 4.1132| 12.3808| 4.0744 | 5.6512 | 5.2276 | 5.2550 | 6.3140                   | 7.4226                      |
| C1      | 7.5914| 17.7346| 12.9475| 13.6332| 13.7239| 17.2348| 12.4106                  | 9.5803                      |
| C2      | -7.9432| 2.4983 | -9.0113|-7.8221 | -3.3997|-3.2475 | -3.8191                  | -7.2859                     |
| C3      | 8.2331| 17.1114| 12.6847| 13.3401| 13.3487| 12.5480| 9.4600                   | 8.2192                      |
| mean    | 4.3842| 15.0244| 6.1541 | 9.0436 | 8.1501 | 9.4678 | 7.4181                   | 5.3051                      |
| LIME    | 8.2331| 17.1114| 12.6847| 13.3401| 13.3487| 12.5480| 9.4600                   | 8.2192                      |
| SIDD    | 1.7745| 10.8946| 1.0630 | 2.7159 | 2.4422 | 4.0581 | 3.5341                   | 3.8751                      |
| HDR     | 9.7502| 17.3994| 14.4295| 11.5738| 9.0658 | 9.0658 | 9.0658                   | 9.0658                      |
| ExDark  | 7.3095| 17.0897| 13.3487| 12.4106| 12.5480| 9.4600 | 8.2192                   | 8.2192                      |

TABLE III
PSNR, MSSIM, and VIF evaluation statistics (a normal light image as the reference). For the HDR database, the mean score of each algorithm is displayed below the double horizontal line.

| Image   | Metric | HE    | NLM   | McCann | ALTM  | LIME | AIEMC | Proposed ($dv^* = 0.3$) | Proposed ($x_{11} = 0.55$) |
|---------|--------|-------|-------|--------|-------|------|-------|------------------------|----------------------------|
| C1      | PSNR   | 13.4886| 17.7862| 19.8325| 22.1085| 21.3450| 22.5969| 17.4958                 | 22.5969                    |
|         | MSSIM  | 0.6698 | 0.8082 | 0.7964 | 0.8672 | 0.8545 | 0.8322 | 0.8918                  | 0.8322                     |
|         | VIF    | 0.2721 | 0.2772 | 0.2926 | 0.3136 | 0.3247 | 0.3002 | 0.3129                  | 0.3086                     |
| C2      | PSNR   | 12.7370| 10.9881| 13.3887| 15.3269| 13.7837| 20.6170| 14.8234                 | 20.6170                    |
|         | MSSIM  | 0.6846 | 0.4539 | 0.6876 | 0.7170 | 0.7676 | 0.9296 | 0.8291                  | 0.8291                     |
|         | VIF    | 0.4086 | 0.3984 | 0.4098 | 0.5116 | 0.4443 | 0.5081 | 0.5145                  | 0.4651                     |
| C3      | PSNR   | 13.6261| 11.3972| 14.4155| 17.0809| 16.5325| 18.1321| 18.5240                 | 18.5240                    |
|         | MSSIM  | 0.7150 | 0.6500 | 0.7755 | 0.7516 | 0.8385 | 0.8807 | 0.9392                  | 0.9058                     |
|         | VIF    | 0.3412 | 0.4213 | 0.3591 | 0.3010 | 0.4849 | 0.5175 | 0.5229                  | 0.5250                     |
| HDR     | PSNR   | 14.9971| 13.9711| 16.1217| 18.1442| 16.5887| 17.0097| 16.6813                 | 16.2863                    |
|         | MSSIM  | 0.7548 | 0.7580 | 0.7963 | 0.8581 | 0.8477 | 0.8298 | 0.8476                  | 0.8283                     |
|         | VIF    | 0.5350 | 0.4495 | 0.5896 | 0.5794 | 0.6222 | 0.5253 | 0.5602                  | 0.5668                     |

Fig. 16. Some examples in the ExDark database and the corresponding reconstruction results are obtained using the proposed method under the setting of $dv = 0.3$.

evaluation experiments, where the quality of the reconstructed image is very close to the reference image. Combining with the subjective comparison experiment, we also know that the color of the reconstructed image is close to that of the reference image, e.g. image C1. The index scores of the NLM and HE algorithms are relatively low, which shows that the quality of the reconstructed image is poor by these algorithms individually. For the VIF index score of image C1, although LIME is the highest, the background color is close to red.

Fig. 17. Illustration of the relationship between the index score and $dv$ with the reconstructed image at the maximum index score. The maximum value is marked with a red circle. PSNR$_{max} = 31.7656$, MSSIM$_{max} = 0.9721$, VIF$_{max} = 0.6902$. (a) Input low illumination image. (b) Reference image under normal illumination. (c) The curve for the index scores (PSNR, MSSIM and VIF) and $dv$. The PSNR index scores are normalised. (d) Image at the highest score of PSNR and MSSIM with $dv = 0.22$. (e) Image at the highest score of VIF with $dv = 0.27$. Note that the data in (c) is obtained in this range: $dv = [0, 0.6]$, and the interval is 0.01. It is clear that the setting of $dv = 0.3$ in the direct comparison test is not optimal for image (a).
rather than orange. For those 292 images in HDR, both ALTM and LIME show good performance as a whole. The proposed method is slightly inferior to these two methods in this case.

We use an image in HDR to plot the curve describing the relationship between the three indexes and $dv$ as shown in Fig.[7] which also shows the image with the maximum index score. This suggests that we can take a simple parameter selection strategy to adjust the value of $dv$ to generate an image with the maximum index score. For the HDR datasets, we use this strategy to obtain the mean of the maximum values of the three metrics. $dv = [0.0, 0.6]$, and the interval is 0.01. For PSNR, MSSIM and VIF indexes, the average of the maximum index scores with optimal $dv$ are $20.7563$, $0.9002$ and $0.5931$, respectively. Compared against the results of Table III we can see that the proposed method achieves the best performance in PSNR and MSSIM, whilst only the VIF index value is slightly worse than LIME. For low light images without any reference, research work will be undertaken in the future to explore an optimal $dv$ value.

IV. CONCLUSIONS

In this paper, we have proposed a simple yet effective tone mapping method to enhance low-light images and perceive the unknown information in the dark. Based on the mechanism of color formation, the mathematical description between an image and its photon flow energy was constructed using cell vibration and photoreceptor correction, and the color reconstruction of the low illumination image was satisfactorily achieved. Comprehensive experiments have been undertaken and the results show that our algorithm well recovered image details, and effectively handles over-enhancement and color distortion, where the color representation of the reconstructed image is natural. Compared with several state of the art methods, our method has achieved a step forward in image enhancement tasks. The limitation of our proposed algorithm is that it reduces the color saturation in very few cases, thus losing some textures. In the future work, we will extend the proposed algorithm and further explore the mechanism of retinal cells to deal with the challenge.

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