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# Image Enhancement Based on Light-Curve and Color Decoupling Techniques

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## ABSTRACT

This paper presents a lightweight, unsupervised image enhancement method based on existing models, termed LCCDnet (Light-curve and Color-decoupled). The method separates the enhancement task into light enhancement and detail optimization. Images are decomposed into HSV channels: HS channels manage image details, while the V channel controls brightness. A light curve is applied to estimate brightness enhancement, with design considerations for pixel value range, monotonicity, and differentiability. For HS channels, a method inspired by the Purkinje effect decomposes the channel into two intrinsic color values, which are then combined into a novel HS channel. LCCDnet does not require paired or unpaired data for training. The method achieves image enhancement through intuitive nonlinear curve mapping, focusing on image details. It is computationally efficient and requires minimal training data, showing promising potential despite some limitations in certain scenarios.

## KEYWORDS

HSV color-model; Luminance curve; Purkinje effect; Color decoupling

## 1. INTRODUCTION

In modern photography and computer vision applications, image quality is crucial for effective information transfer and user experience. However, environmental and technological constraints often result in photos being captured under suboptimal lighting conditions, leading to poor image quality. Common issues include insufficient illumination, uneven lighting, and strong backlighting, which degrade aesthetic appeal and lead to information misrepresentation, such as errors in object and facial recognition. Consequently, developing an effective low-light image enhancement technique holds significant practical importance.

Various methods currently aim to enhance low-light images, often relying on paired or unpaired training data, which poses risks of overfitting. These methods include techniques based on Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs) [3]. Despite some progress, considerable challenges remain in addressing complex and diverse low-light environments.

A novel low-light image enhancement method leveraging deep learning techniques is proposed to improve image quality without relying on paired or unpaired training data. The specific objectives are to enhance brightness and clarity, retain and amplify image details and colors, and achieve real-time processing capabilities to meet practical needs.

To achieve these goals, an iterative luminance curve method combined with color processing adapted to human vision is introduced. This approach features a clear and simple design, separating illumination and color details into two distinct channels for individual processing. The model is lightweight and utilizes unsupervised training, employing taskspecific no-reference loss functions to train a deep image enhancement model without reference images, indirectly evaluating enhancement quality.

The proposed LCCDnet method utilizes image-specific curve estimation, where the V channel of the low-light image serves as input to generate high-order curves for per-pixel dynamic range adjustment, achieving enhancement effects. A lightweight CNN structure iteratively approximates high-order curves to ensure robust and accurate dynamic range adjustment. For the HS channels, a set of convolutional kernels is designed to approximate optimal image parameters based on psychophysical theory. Finally, a suite of specially designed no-reference loss functions, including spatial consistency loss, exposure control loss, and color consistency loss, comprehensively considers illumination enhancement factors to prevent overfitting.

## 2. RELATED WORK

Histogram Equalization (HE) methods enhance illumination by extending the dynamic range of images. Adjustments are made at both global and local levels of the image histogram [8]. Additionally, various methods based on Retinex Theory decompose images into reflectance and illumination components[9]. Typically, reflectance is assumed to be invariant under varying lighting conditions, framing illumination enhancement as an illumination estimation problem. Several Retinex-based approaches have been proposed: Wang et al. developed a natural and information-preserving method for handling nonuniformly illuminated images [10]; Fu et al. introduced a weighted variational model for the simultaneous estimation of reflectance and illumination [11]; Guo et al. estimated a rough illumination map by searching the maximum intensity in RGB channels, which was then refined using structural priors [12]; Li et al. proposed a new Retinex model that accounts for noise effects by solving an optimization problem for illumination estimation [13]. Later, C. Guo et al. proposed a Zero-Reference Curve Iteration (Zero-DCE) method for lightweight unsupervised enhancement, although it had drawbacks such as blurriness [14]. Zhang et al. extended C. Guo’s iterative approach by integrating histogram channel alignment with global feature extraction and related loss functions, addressing some issues of the DCE network but requiring a significantly larger number of parameters and paired training data due to its supervised learning approach [15]. Recently, Feng et al. introduced a new channel, HVI, which trains a novel channel that separately handles intensity and detail, incorporating cross-attention and optical-based color and light processing in intermediate layers, yielding excellent results [16]. However, this approach involves increased parameter computation and requires paired training datasets.

In contrast to traditional methods that either randomly alter histogram distributions or rely on potentially inaccurate physical models, the proposed LCCDnet method combines features from C. Guo and Feng et al. By using HSV images as input (which does not require training and allows partial separation of color and brightness), LCCDnet applies iterative enhancement on the V channel with preprocessing and maximum value constraints. It also incorporates Feng et al.’s method for the HS channels, simplifying the model structure by omitting the cross-attention mechanism. This lightweight, unsupervised approach reduces computational burden and achieves effective image enhancement.

### 2.1. Laplacian Pyramid-Based Curve Iteration.

Recent research in image enhancement reveals that most studies require well-paired datasets and involve substantial computational costs. However, it has been observed that the work by C. Guo et al. utilized a curve iteration method to achieve a lightweight, unsupervised network, although its performance was somewhat unsatisfactory due to significant blurring in practical results. Therefore, a method was developed that combines lightweight luminance enhancement with effective blur control. Initially, integrating a pyramid approach was considered as a promising idea. It was hypothesized that in the Zero-DCE model proposed by C. Guo et al., using the results of multiple convolutions as iteration parameters α might not effectively preserve pixel-level features. To address this, a feature pyramid was employed to retain the features lost during each convolution. However, the results were not as expected. The final output predominantly consisted of image edges and appeared almost entirely white. This issue likely arose because the feature pyramid underwent multiple iterations and was applied simultaneously across the RGB channels, leading to excessive iteration effects.

### 2.2. Self-Attention-Based Curve Iteration.

Inspired by the work of Zhang et al., the concept of focusing solely on the luminance channel for iteration was explored, while other channels primarily address image details. Zhang et al. employed a histogram-based approach for iteration, referencing Zero-DCE. Although promising, this method proved somewhat opaque and reliant on paired data to derive iteration parameters α from images with consistent illumination. With only lowlight images available, obtaining the necessary iteration parameters becomes challenging, indicating high dependence on supervised data.

To address this, the single-channel iteration concept was adapted by replacing the grayscale histogram with the V channel from the HSV (Hue, Saturation, Value) color space, which represents luminance. For unsupervised training, self-attention-derived weights were used as iteration parameters, aiming for greater attention to detail during the iteration process [17]. However, the results were unsatisfactory. Despite multiple down-sampling steps, the computational cost of self-attention remained high. Additionally, the final output exhibited a high-brightness white haze, likely due to excessive attention weights and the amplification of iteration artifacts during up-sampling.

Raw lowlight image with attention

**Figure 1.** The result with attention.

## 3. METHODS

### 3.1. Light-curve Light-Curve

Inspired by the work of C. Guo et al., an iterative luminance curve is employed on the V channel to enhance the image’s brightness [14]. The iterative formula is given by:

$$LE_n(x) = LE_{n-1}(x) + \alpha_n LE_{n-1}(x)(1 - LE_{n-1}(x)) \quad (1)$$

Where $LE_n(x)$ represents the image at each iteration, specifically the V channel in this context. For the iteration parameter α, it was set to 0.5 for the first two iterations. In the third iteration, a learnable parameter ω was introduced to replace α. A total of three iterations were performed to mitigate the risk of exposure issues and overfitting associated with excessive iterations.

### 3.2. Color-decoupled

In processing the HS channels, which correspond to hue and saturation, methods such as cross-attention mechanisms, CNNs, and GNNs present significant challenges. These 4 methods involve substantial parameter counts and computational costs, and frequent down-sampling and up-sampling can lead to image distortion. Consequently, a simpler approach for handling the HS channels was sought.

In psychophysics, the Purkinje effect describes the variation in visual sensitivity to colored light under different adaptation states. Under bright sunlight, red and blue flowers may appear equally bright. However, at night, blue flowers seem brighter, while red flowers appear much dimmer, approaching black. This phenomenon occurs because, as the human eye shifts from daylight to night vision, its peak sensitivity to light shifts toward shorter wavelengths. The figure 2 below illustrates this relationship, showing increased sensitivity to longer wavelengths under bright light and vice versa.

Transformations are applied to the HS channels to mimic the Purkinje effect, steering the image towards regions that align more closely with human visual perception. Given that image enhancement involves increasing brightness, it is logical to shift the hue towards higher frequencies. Consequently, an affine transformation is employed to simulate this process:

$$\overset{\wedge}{H}, \overset{\wedge}{S} = \omega_6(Tanh(+\omega_4\omega_2\omega_1(H)) \odot (Tanh(+\omega_5\omega_3\omega_1(S)) \tag{2}$$

Where $\omega_i$ are all trainable parameters, but the total number is relatively small, approximately 92 parameters.

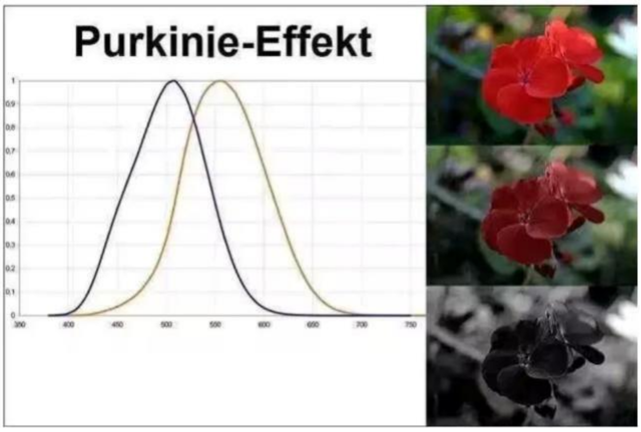

**Figure 2.** Purkinje effect.

### 3.3. Related Function

For the cost function, several effective constraint functions have been proposed in past work[14] . And there are three effective loss functions, and the final cost is the sum of these three losses:

Spatial Consistency Loss: Spatial Consistency Loss: The spatial consistency loss $L_{spa}$ enhances the spatial consistency of the image by preserving the differences between adjacent regions in the input image and its enhanced version. It is defined as:

$$L_{spa} = \frac{1}{K}\sum_{i=1}^{K} \sum_{j\in\Omega(i)} (|(Y_i - Y_j)| - |(I_i - I_j)|)^2 \tag{3}$$

Where $K$ is the number of local regions, and $\Omega(i)$ represents the four adjacent regions (top, bottom, left, right) centered at region $Y_i$ and $I_i$ denote the average intensity values of the local regions in the enhanced image and the input image, respectively.

Exposure Control Loss: To suppress areas of underexposure or overexposure, the exposure control loss $L_{exp}$ manages the exposure levels. It is defined by measuring the distance between the average intensity values of local regions and an optimal exposure level $E$:

$$L_{exp} = \frac{1}{M}\sum_{k=1}^{M} | Y_k - E | \tag{4}$$

Where $M$ denotes the number of non-overlapping local regions of size 16×16, and $Y_k$ represents the average intensity values of local regions in the enhanced image.

Color Constancy Loss: Color Constancy Loss: Based on the gray-world color constancy hypothesis, which assumes that the average color across all channels should be gray, the color constancy loss $L_{col}$ corrects potential color biases in the enhanced image and establishes relationships between the three adjusted channels. It is given by:

$$L_{col} = \sum_{\forall(p,q)\in\varepsilon} (J^p - J^q)^2, \varepsilon = \{(R,G),(R,B),(G,B)\} \tag{5}$$

Where $J^p$, $J^q$ represent the average intensity values of channels in the enhanced image, $p$ and $q$ denotes a pair of channels.

These losses collectively ensure spatial consistency, control exposure levels, and maintain color constancy in the enhanced images.

### 3.4. Network Architecture

The entire network can be represented by the figure 3:

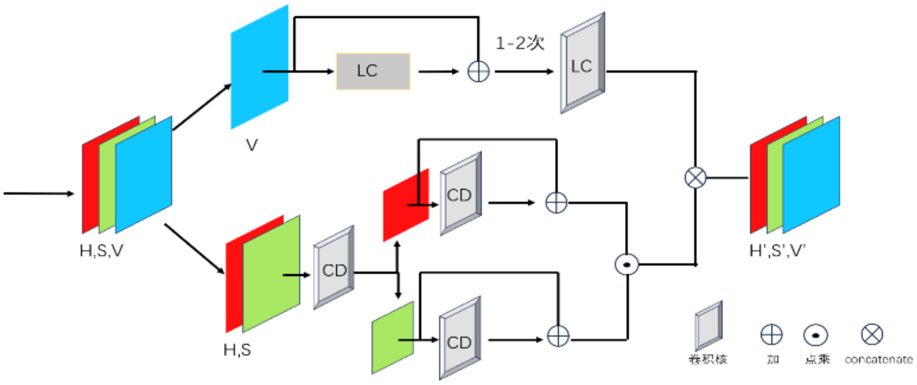

Figure 3. The light-curve and color-decouple net-model.

## 4. EXPERIMENT

The model was trained and tested using the LOL (Low-light datasets), with the results as figure 4:

raw image enhanced image

**Figure 4.** The result with LCCDnet.

The model was set to train for 100 epochs, but it achieved convergence between epochs 70 and 90. The total training time was 12-14 minutes, which is significantly faster compared to the previous most lightweight model, Zero-DCE, which required approximately 30 minutes of training time. The model is notably lightweight and does not require paired training data. However, several issues remain with the results, including significant distortions and color deviations. The potential reasons for these issues are as follows:

- Suboptimal Parameter Configuration: Some model parameters may not be optimally configured.
- Affine Transformation Issues: The affine transformation applied to the HS channels may not be well-designed,
- Affine Transformation Issues: The affine transformation applied to the HS channels may not be well-designed, failing to meet the desired requirements.
- Color Space Conversion Errors: There may be errors in the conversion between RGB and HSV color spaces within the model.
- Library Compatibility Issues: There might be compatibility issues between conversions using the CV2 library and PIL.
- Insufficient Loss Function Constraints: The loss functions used may not effectively constrain the final results.
- Areas for Further Research and Improvement: These issues highlight areas that need further investigation and improvement.

Addressing these points will be crucial for refining the model and achieving better performance.

Although the increasing computational power has made training time less critical in evaluating the quality of a model, there are still many scenarios where simple, low requirement, and lightweight models are necessary. In the field of image enhancement, while many past studies have achieved excellent results, they often involve complex modules with limited practical interpretability and require high-quality paired data. For students or individual enthusiasts who wish to engage in this task based on personal preferences, meeting these implicit requirements can be challenging.

Therefore, there is a significant need for straightforward, transparent networks that demand minimal training data. Additionally, aside from image enhancement, altering the processing of HS channels could lead to valuable research in areas such as style transfer. However, many aspects still require more in-depth investigation.

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