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Image Enhancement Using Patch-Based Principal Energy Analysis

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ABSTRACT The visual quality of a captured image is often degraded by complicated lighting conditions in various real-world environments. This quality deterioration probably leads to the significant performance drop in many algorithms of computer vision, which require high-visibility inputs for precise results. In this paper, a novel method for image enhancement is proposed with the principal energy analysis. Specifically, based on the key observation that the illumination component is dominant over a small local region, the corresponding energy is efficiently separated from the scene reflectance by exploiting the subspace analysis. Owing to this clear separation, the illumination component can be easily adjusted independent of the reflectance layer for better visual aesthetics. In contrast to previous methods that still suffer from the exaggerated or conservative restoration yielding the loss of details and defects of halo artifacts, the proposed scheme has a good ability to enhance the image contrast while successfully preserving the color attribute of the original scene. Moreover, the proposed method is conceptually simple and easy to implement. Experimental results demonstrate the effectiveness of the proposed method even under diverse lighting conditions, e.g., low light, casting shadow, uneven illuminations, and so on, and the superiority of the proposed method over previous approaches introduced in the literature.

INDEX TERMS Quality deterioration, image enhancement, principal energy analysis, subspace analysis, illumination component.

I. INTRODUCTION

As camera-mounted mobile devices, e.g., smartphones, tablets, etc., become more widespread, a vast amount of photos are produced in our daily life. In keeping with this trend, technologies related to the camera sensor have been rapidly developed for user satisfaction on the image quality, however, the high visibility of a captured image is hard to be guaranteed all the times under complicated lighting conditions of diverse real-world scenarios as shown in Fig. 1. Such deteriorated images not only degrade the viewing experience but also adversely affect the performance of the computer vision algorithms, e.g., object detection [1], tracking [2], and recognition [3], which require high-quality inputs.

To resolve this problem, many approaches have been developed for image enhancement and the mainstream can be categorized into two groups: statistical information-based and decomposition model-based methods. In the former, the distribution of intensity (or color) values in input images is allowed for exploring both the desirable dynamic range and the density for each value to enhance the contrast while the latter focuses on the physical model of the capturing process and attempts to apply it for completely separating the illumination layer from a given scene. Due to the data-driven nature, statistical-based methods, e.g., histogram equalization and its variants, have been actively studied in the beginning and those are easily combined with several optimization techniques for efficiently adjusting the intensity distribution of the

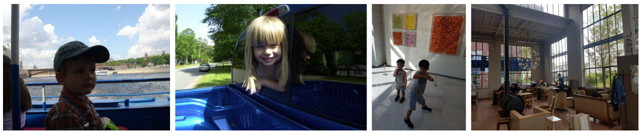

FIGURE 1. Some examples of photos taken under complicated lighting conditions including backlight, casting shadows, and uneven illuminations. Note that samples are selected from NASA database [4] and Google images.

original image. Even though such methods are quite effective for contrast enhancement, restored results are still exaggerated (i.e., over-enhanced) under uneven illuminations. On the other hand, researchers have started to a little more concentrate on decomposition model-based approaches. Most algorithms belonging to this category are based on the Retinex theory [5] that the pixel intensity is determined by a product of illumination and reflectance components. Therefore, they are devised to precisely separate the illumination layer from a given scene and regard the estimated reflectance component as the illumination-invariant enhancement result. However, the unclear decomposition between illumination and reflectance layers frequently yields unnatural outputs, which give the visual discomfort to users.

In this paper, a simple yet powerful method for image enhancement is proposed. The heart of the proposed method is to accurately separate the illumination layer by utilizing the principal energy of the local patch, which is computed based on the subspace decomposition. Specifically, since the illumination component is dominant compared to the textural one over a small local patch (e.g., 3×3 pixels), it is naturally thought that the principal component in a given patch, which is efficiently separated by a simple orthogonal transform, can be employed to formulate such illumination effect. The separated illumination layer based on the Retinex theory is subsequently adjusted in a similar way of [6]. Note that the proposed decomposition scheme is conducted only on the intensity channel to avoid color artifacts during the adjustment process. The main contributions of this paper are two-fold:

- The proposed method represents the patch-based principal energy, which can be clearly isolated from others in the subspace, as an illumination component at each pixel position. This is fairly desirable to reduce the ambiguity occurring in the decomposition process as well as the halo artifacts shown in previous methods.
- Instead of employing the complicated physical model and the optimization framework, the proposed method simply adopts the conventional orthogonal transform, which efficiently reveals the principal energy on the subspaces, for resolving the problem of the illumination-reflectance decomposition. This scheme is conceptually simple and easy to implement, and thus can be easily applied to a wide range of real-world applications.

The remainder of this paper is organized as follows. A comparative review of related works is presented in Section II. The proposed image enhancement is introduced in detail in Section III. Experimental results on images taken under various lighting conditions are demonstrated with the performance comparison by other approaches in Section IV. The conclusions follow Section V.

II. RELATED WORK

In this section, we give a brief review of image enhancement methods presented in the field of computer vision. Since the high quality of the input image is a key prerequisite for guaranteeing the reliability of applications such as object recognition and scene understanding, many researchers have actively studied to enhance the visibility of input images taken in diverse lighting conditions.

Initially, the statistical information, e.g., histogram, has been popularly adopted for this task. As a baseline, the histogram equalization (HE) forces the distribution of intensity or color values to be flat for widening the dynamic range, which successfully improves the image contrast. Inspired by the simplicity and the effectiveness of HE, its variants have been constantly developed until recently [7]–[12]. In [7], the clipping strategy is applied to the histogram equalization of each local patch for suppressing over-saturated areas that are sufficiently bright in an original input image. Dynamic histogram specification [8] utilized the derivatives of the histogram for image enhancement while keeping the characteristics of the input image. On the other hand, Lee *et al.* [11] extracted a 2-D histogram, which counts pairs of adjacent pixels whose values are specified with a fixed bias (e.g., k and $k + l$ in the intensity space), and attempted to seek a layered difference in this 2-D histogram for contrast enhancement. Furthermore, Gu *et al.* [12] combined the subjective and objective quality assessments to derive the optimal histogram mapping for the automatic contrast enhancement.

Based on the Retinex theory that the image can be decomposed into two layers, i.e., illumination and reflectance, a variety of techniques for layer decomposition also have been actively explored. In the early stage, the single-scale Retinex (SSR) [13] and its multi-scale version (MSR) [14] were widely employed to extract the reflectance component as the enhanced result by using the Gaussian filter and logarithmic operations. Although such algorithms efficiently highlight the details of the input image even under various lighting conditions, they often yield unnatural results, which are visually inconsistent with real scenes [15]–[19]. To cope with this limitation, some approaches have started to pay attention on adjusting the decomposed illumination layer for image enhancement. Wang *et al.* [20] devised the bright-pass filter to estimate the illumination component in the non-uniformly illuminated images and the corresponding result is subsequently fed into the bi-log transformation for enhancement. Liang *et al.* [21] tried to estimate the illumination layer by iteratively solving a nonlinear diffusion equation, which embeds the effect of the noise suppression into the conductance function during the diffusion procedure, and adjusted the decomposed illumination layer via the conventional Gamma correction. Fu *et al.* [22] proposed a weighted variational model to simultaneously estimate illumination and reflectance components while complementing the performance of the logarithmic transformation with the better prior representation. Guo *et al.* [23] simply selected the maximum value among the RGB color channel at each pixel position as the illumination component and refine this initial illumination map by imposing a structure prior. Yue *et al.* [6] conducted the intrinsic image decomposition

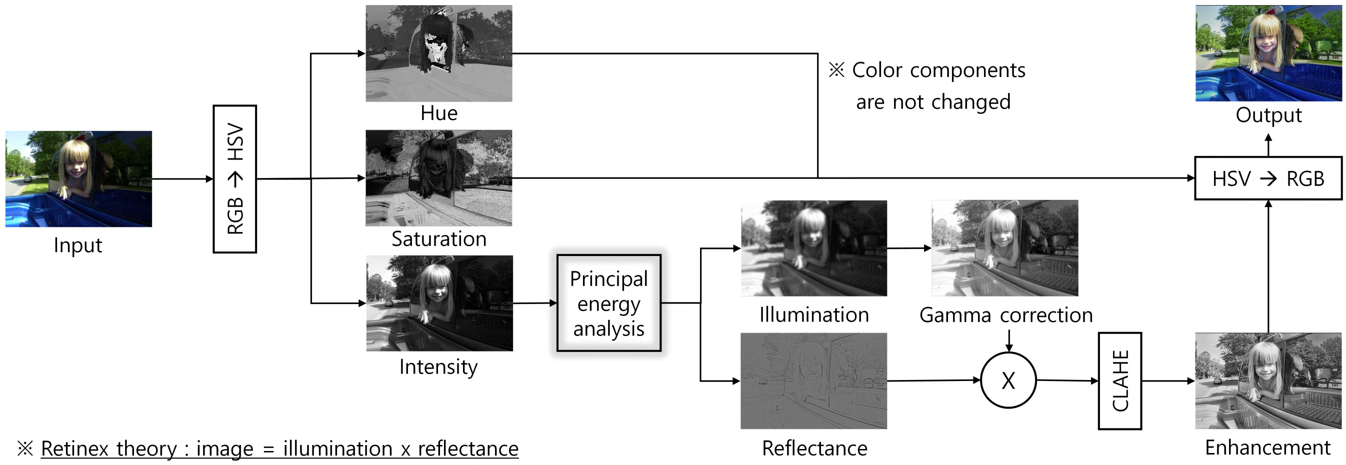

FIGURE 2. Overall procedure of the proposed method. The heart of the workflow is to decompose a given image into illumination and reflectance components with the principal energy analysis. Note that the proposed algorithm is only applied to the intensity channel for avoiding potential color artifacts.

with regularization of the color similarity and the intensity smoothness for reflectance and illumination layers, respectively. Note that several approaches have adopted partial differential equations with the fast Fourier transform for solving the enhancement problem more efficiently [24], [25]. Such decomposition-based approaches are mostly applied to the only intensity channel to avoid the potential color artifacts. Even though diverse approaches have been studied for image enhancement as introduced, they still suffer from exaggerated colors and relatively conservative restoration, which are not enough for providing the better viewing experience to users as well as giving the underlying structure clearly to further applications. Moreover, some previous methods require the high-computational modeling procedure, which is hardly applied to mobile devices. In this paper, a simple yet powerful method for image enhancement is proposed. Rather than relying on the complicated physical model, the proposed method focuses on the clear observation regarding the effect of illuminations in the small local region. Technical details of the proposed method will be explained in detail in the following section.

III. PROPOSED METHOD

The key idea of our new approach lies on the observation that the illumination component is dominant over a small region defined at each pixel position. It follows that a measure of the principal energy in the local patch provides a good approximation of the illumination component, which can be efficiently achieved with the subspace analysis based on the orthogonal transform. The estimated illumination is subsequently adjusted by a conventional Gamma function and combined with the reflectance layer, which is separated from a given image according to the Retinex theory, for generating the enhanced image. Note that the input image is converted from RGB to HSV color space for the enhancement algorithm to be applied to the intensity channel only. The overall procedure of the proposed method is shown in Fig. 2.

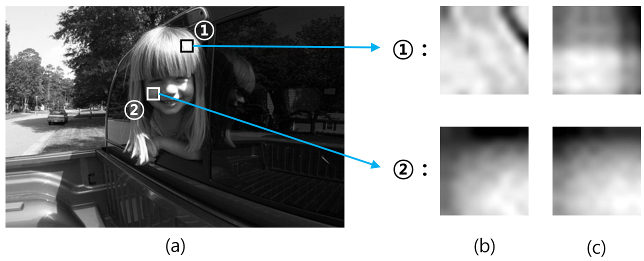

FIGURE 3. (a) Intensity channel of the original input image. (b) Selected local patches (11 × 11 pixels). (c) Reconstructed local patches only with the s_1 value estimated in the corresponding blocks.

A. ILLUMINATION ESTIMATION VIA PRINCIPAL ENERGY ANALYSIS

The first task for estimating the illumination component is to define the small local patch at each pixel position and conduct the orthogonal transform for the corresponding region. To do this, the singular value decomposition (SVD) is adopted in the proposed method, which is known to be useful for factorizing given data and revealing the underlying structure of their distribution [26], [27]. More concretely, let the small local patch be $B(x, y)$ whose size is $N \times N$ pixels, which is centered at (x, y) pixel position. Then, the computational procedure of SVD can be represented as follows:

$$B(x, y) = USV^T, \tag{1}$$

where S includes the singular values as its diagonal term, i.e., $S = diag(s_1, s_2, \cdots, s_N)$, which represent the power of the independent components estimated from the given intensity lattice in an ordered manner (i.e., $s_1 > s_2 > \cdots > s_N$). V denotes singular vectors indicating the direction of corresponding independent components. Note that U and V are orthogonal matrices while satisfying $U^TU = I$ and $V^TV = I$. Therefore, it is thought that s_1 can be regarded as the principal energy related to the illumination component in the current pixel position. Figure 3 shows the restoration result by only using the s_1 value of several local patches. As can be seen, the principal energy, i.e., s_1, greatly represents the illumination component of each local patch.

According to the Retinex theory, the reflectance component at each pixel position can be subsequently extracted as follows:

$$R(x, y) = \frac{f(x, y)}{s_1(x, y) + \tau}, \tag{2}$$

where $f(x, y)$ denotes the intensity value at the (x, y) position. τ is a small positive number to prevent the zero-division problem. As described above, $s_1(x, y)$ is employed as the illumination component. Some examples of decomposition results by the proposed method are shown in Fig. 4. It is noteworthy that edges and textures, i.e., reflectance components, are well revealed even under unevenly lighted regions, for example, the dark window of the right side (see Fig. 4(c)).

FIGURE 4. **(a) Intensity channel of the original input image. (b) Estimated illumination map (i.e., $s_1(x, y)$). (c) Estimated reflectance map. Note that decomposed layers are normalized from 0 to 255 for the gray-scale representation.**

B. IMAGE ENHANCEMENT

In this subsection, the estimated illumination, i.e., s_1, is now adjusted to enhance the visual quality of a given image in a similar way of previous methods. To this end, several mapping functions, e.g., logarithmic, sigmoid, and Gamma functions, have been popularly employed and we adopt the Gamma function for the proposed method to efficiently minimize the loss in the bright area, which is formulated as follows:

$$\tilde{I}(x, y) = 255 \times \left(\frac{s_1(x, y)}{Z}\right)^{1/\gamma}, \tag{3}$$

where $s_1(x, y)$ denotes the estimated illumination component as mentioned and γ is set to 2.2 in our experiments. Z is a scaling factor. In the following, the initial enhanced image is generated by multiplying $R(x, y)$ and $\tilde{I}(x, y)$ at each pixel position. Since the Gamma function only allows for the global contrast, the CLAHE [7] technique is further employed to supplement the local enhancement [6]. Therefore, the result of the enhanced intensity f_e can be represented as follows:

$$f_e(x, y) = \sigma\left(\tilde{I}(x, y) \times R(x, y)\right), \tag{4}$$

where $\sigma(\cdot)$ denotes the CLAHE operator. Note that the clip-limit value is set to 2.0 in our implementation. Finally, the color enhanced image is produced by utilizing the HSV→RGB transformation with the enhanced intensity f_e. The example of image enhancement by the proposed method is shown in Fig. 5. The comparison between the original input and the enhanced result is also shown in Fig. 6. In particular, the shadow on the face is well suppressed while the contrast of dark regions is successfully improved without severe distortions of textures and color attributes.

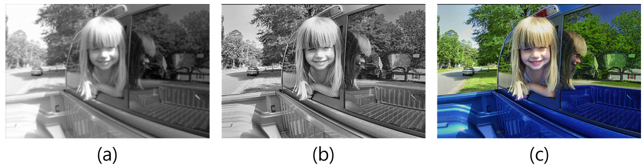

FIGURE 5. **(a) Adjustment result by the Gamma function. (b) Enhanced intensity map by the CLAHE operator, i.e., f_e map. (c) Final result of image enhancement with the color information.**

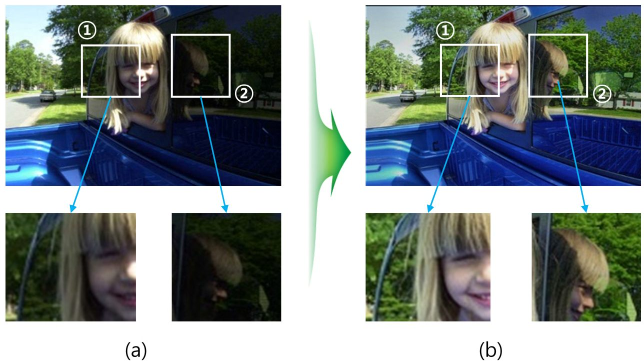

FIGURE 6. **(a) Original input image with some cropped local patches. (b) Enhanced result by the proposed method with some cropped local patches. Note that the effect of uneven lighting is well suppressed in the enhanced result without distortions of textures and color attributes.**

For the sake of completeness, the overall procedure of the proposed method is summarized in Algorithm 1.

Algorithm 1 Image Enhancement via Principal Energy Analysis

Data: f: intensity channel of the input color image
H: height of input, W: width of input
Result: Enhanced color image
while $1 \leq x \leq W$ *and* $1 \leq y \leq H$ **do**
1. Illumination estimation
i) Define a small local patch $B(x, y)$ (e.g., 3×3) at each pixel position
ii) Conduct SVD on $B(x, y)$ and compute $s_1(x, y)$
iii) Compute the reflectance value $R(x, y)$ using (2)
: $R(x, y) = \frac{f(x,y)}{s_1(x,y)+\tau}$
2. Illumination adjustment
iv) Apply the Gamma mapping to $s_1(x, y)$
: $\tilde{I}(x, y) = 255 \times \left(\frac{s_1(x,y)}{Z}\right)^{1/\gamma}$
v) Restore the intensity $\tilde{f}(x, y) = \tilde{I}(x, y) \times R(x, y)$
x and y increase in a raster scanning manner
end
⋆ For local adjustment, CLAHE is applied to $\tilde{f}$
⋆ Finally, conduct HSV→RGB with $\tilde{f}_e$ defined in (4)

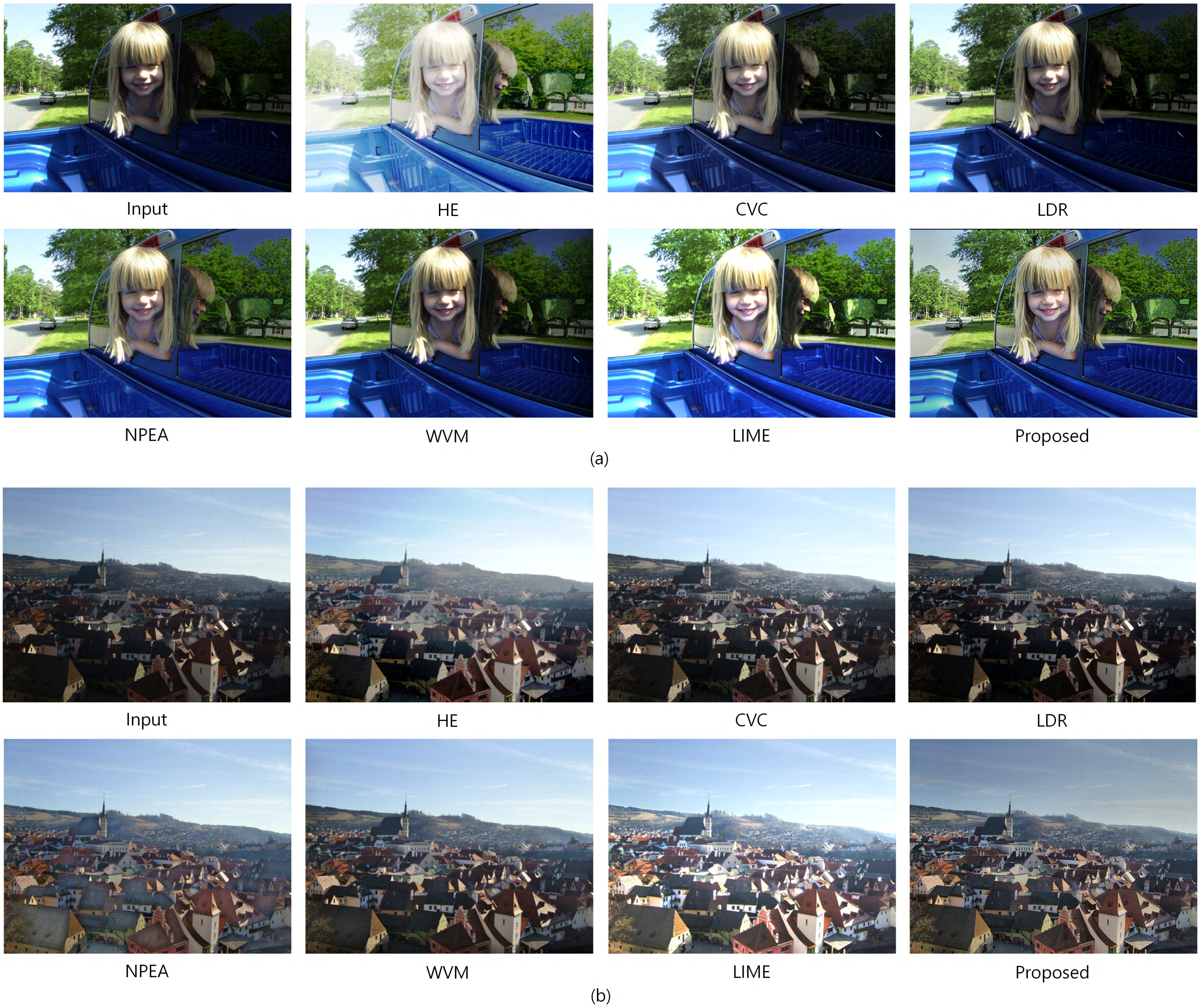

FIGURE 7. Results of image enhancement under complicated lighting conditions. Note that the proposed method yields visually acceptable results compared to other approaches by successfully maintaining the color attribute of the input image while increasing the contrast.

C. IMPLEMENTATION DETAILS

In this subsection, the procedure of implementation for the proposed method is provided in detail. First of all, the RGB color space of the input image is converted into the HSV one [28] to separately handle the intensity channel. Note that only this intensity channel is employed for all subsequent operations in this work. Specifically, we have one major parameter, i.e., the size of the local patch $N \times N$ pixels. To comply with the key observation that the illumination component is dominant over a *sufficiently small* region, N is set to three (i.e., 3×3 pixels) in the proposed method. In the procedure of illumination adjustment, we adopt the specific scaling factor Z instead of using 255 since the estimated illumination space s_1 is not normalized as the gray scale. Based on extensive experiments, the scaling factor Z is set to 5.0 for the best performance. As explained, $\gamma = 2.2$ is adopted as the mapping parameter in (3). It should be emphasized that those two parameters are strongly coupled each other since their combination actually determines the strength of the nonlinear mapping. In regard to the calculation precision, the float-type data is enough since the main operation of the proposed method is to compute the first singular value from the local patch defined at each pixel position.

IV. EXPERIMENTAL RESULTS

In this section, the proposed method for image enhancement is evaluated based on total 40 images obtained in various lighting conditions. The test samples are collected from Google image search and NASA database [4], which contain backlight, casting shadows, uneven illuminations, low-light, etc. The size of test images varies from 360×236 pixels to 656×1000 pixels. Details of experimental results are explained in the following subsections.

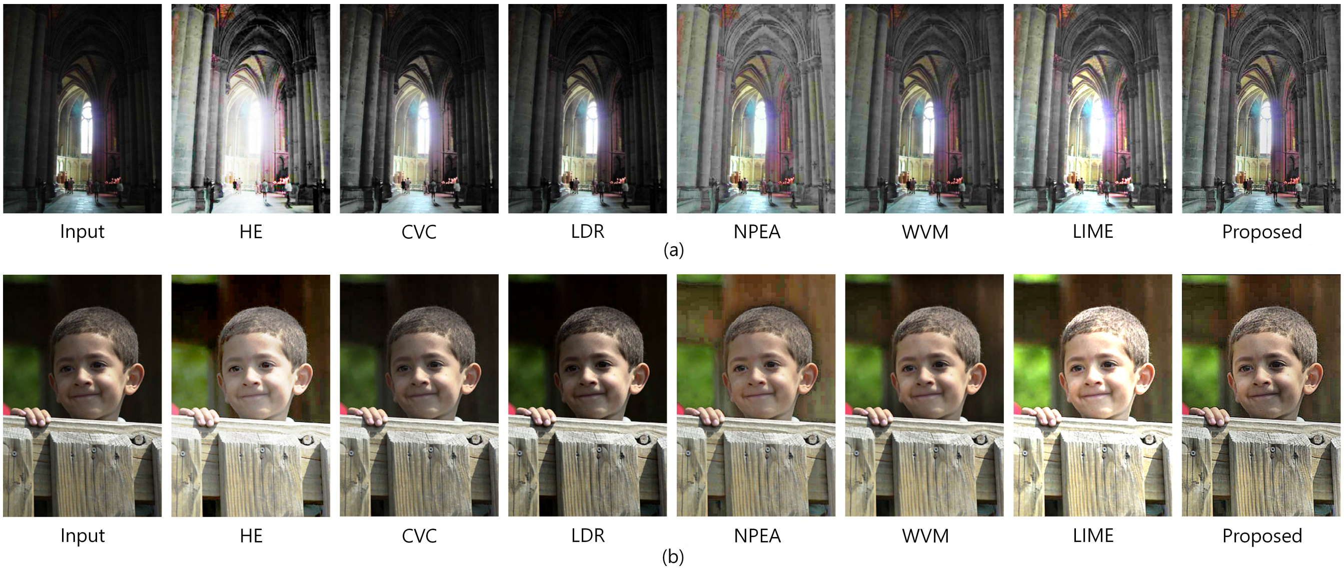

FIGURE 8. **Results of image enhancement under complicated lighting conditions. (a) Enhancement results obtained under the backlighting condition. Note that the input image is from [21]. (b) Enhancement results obtained under the quite cloudy outdoor environment.**

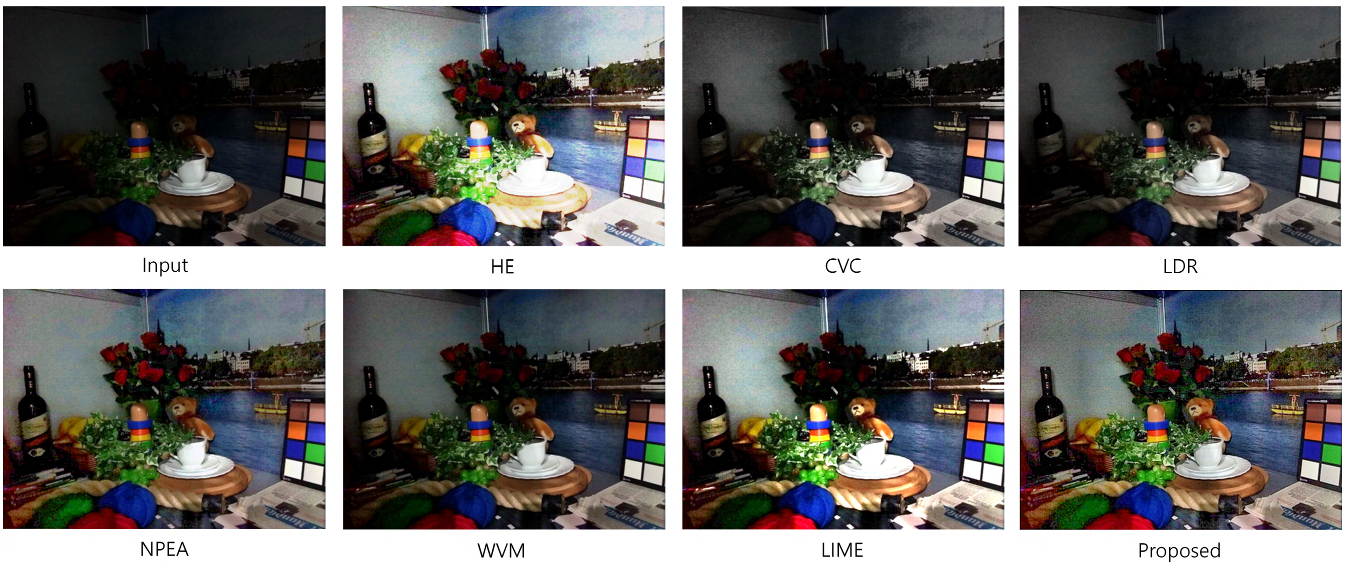

FIGURE 9. **Results of image enhancement under the low-lighting condition. The performance of image enhancement for this case is strongly dependent on three specific points : colors of roses and the checkboard, edges and textures of objects on the table, and details in the paint.**

A. QUALITATIVE EVALUATION

To show the effectiveness of the proposed method, we compare ours with the baseline histogram equalization (HE) and five representative methods as well, which are CVC [10], LDR [11], NPEA [20], WVM [22], and LIME [23]. Some results of image enhancement are shown in Figs. 7, 8, 9, and 10. Specifically, there is very complicated light on a given scene in Fig. 7(a) and such uneven illuminations thus lead to the unbalanced enhancement for previous models. Histogram-based methods, e.g., CVC and LDR, fail to accurately enhance the sharpness of contents belonging to the dark region due to the conservative restoration. NPEA and WVM get better results in the dark region, however, they still suffer from the low contrast. Even though LIME successfully reveals the underlying structure reflected onto the window, other regions in the bright area are over-enhanced with the loss of details. In contrast, the proposed method greatly restores edges and textures in the dark region while maintaining the color attribute of the original input without severely exaggerating the contrast. Figure 7(b) shows another example of the uneven lighting condition. Most previous methods hardly restore contents in the shadowed region of the bottom part. NPEA and LIME improve the low contrast shown in the corresponding region, however, the color attribute of the shadow is adversely changed from black to white on the roof (NPEA) and the bright side of buildings is over saturated (LIME). Unlike previous approaches, the well-balanced improvement can be achieved by the proposed method as shown in the last image of Fig. 7(b).

In regard to the backlighting condition, the proposed method also provides the reliable enhancement results compared to other methods as shown in Fig. 8(a). In particular, details of boundaries in the architectural structures, e.g., arch-typed ceiling and pillars, are effectively revealed in the enhancement result by the proposed method. Even though NPEA and LIME also successfully restore the sharpness of shaded objects in the dark region, structured bars in the glass window are suppressed due to saturation of the brightness. Figure 8(b) shows an example of images that can be easily acquired in everyday life. Even though such images do not contain severely uneven illuminations, the visual quality is often degraded due to the weather effects, for example, cloudy outdoor environments. From enhancement results shown in Fig. 8(b), it is easy to see that the proposed method has a good ability to preserve the naturalness of a given image while efficiently improving the contrast even for the slightly shaded region.

The enhancement results under the low-lighting condition are shown in Fig. 9. In this case, the performance can be evaluated by focusing on three specific points, which are colors of roses and the checkboard, the sharpness of objects on the table, and details of the paint on the wall. Specifically, CVC and LDR hardly maintain the color attribute in most parts of the original input image and their performance for contrast enhancement is also limited in low-lighting environments. In results of WVM and LIME, contents in the background are quite a successfully restored, however, the color of roses is still dark. It is noteworthy that roses positioned in the middle of a given image need to be sufficiently reddish in the enhancement result for better viewing experience. In addition, attributes of different colors in the checkboard should be preserved, however, HE, CVC, and LDR make some changes in their results. In contrast, the proposed method successfully removes the effect of the low-light without the locally over-enhanced phenomenon as shown in the teacup of the LIME's result. Moreover, underlying structures contained in the paint are well revealed by the proposed method whereas most other approaches still leave corresponding areas dark with the loss of details. More additional enhancement results by the proposed method are shown in Fig. 10. As can be seen, it is thought that the proposed method is effective for image enhancement under various lighting conditions of both indoor and outdoor environments.

B. QUANTITATIVE EVALUATION

For the quantitative evaluation, two objective metrics widely used in visual quality assessment are employed, which are NFERM [30] and C-PCQI [29]. The first metric is designed as a no-reference metric (i.e., it does not require the deterioration-free original image) and considers the natural scene statistics as well as visual features, which are inspired by the human vision system, to predict the quality of a given image. The second metric allows for mean intensity, contrast change, and structural distortion to estimate the degree of the distortion driven by the enhancement process. It is noteworthy that NFERM takes into account the naturalness of enhancement results while C-PCQI measures the color distortion compared to the original input image (i.e., full-reference based metric). Therefore, such two metrics are useful to interpret and evaluate the performance of each enhancement scheme in a quantitative manner. The performance comparison according to NFERM and C-PCQI for total 40 images are shown in Table 1. Note that the lower value is more desirable for NFERM while the higher one indicates the better performance in the C-PCQI metric. As shown in Table 1, it is thought that the proposed method provides the visually acceptable enhancement results even under diverse lighting conditions.

TABLE 1. Performance comparison based on NFERM and C-PCQI metrics.

Methods	NFERM ↓	C-PCQI ↑
Original input	22.21	-
HE (baseline)	23.63	0.97
CVC [10]	20.17	1.05
LDR [11]	20.67	1.07
NPEA [20]	21.18	0.97
WVM [22]	23.63	1.01
LIME [23]	24.30	0.97
Proposed method	14.28	1.07

TABLE 2. Performance comparison by the processing time.

Methods	Processing time	Implementation
HE (baseline)	0.04 sec	Matlab
CVC [10]	0.39 sec	Matlab
LDR [11]	0.11 sec	Matlab
NPEA [20]	7.87 sec	Matlab
WVM [22]	8.21 sec	Matlab
LIME [23]	0.15 sec	Matlab
Proposed method	2.11 sec	Matlab

The average of the processing time for all the methods is also evaluated and shown in Table 2. The enhancement framework is implemented on a single PC whose specifications are given as follows: Intel Xeon 2.2GHz CPU and 64 GB of RAM. Source codes for previous methods are available in authors' websites (provided as Matlab codes) and directly used for the performance comparison without any modification. The proposed method is implemented by using both C and Matlab, and the Matlab version is employed for evaluating the processing time to be fair for the performance comparison. Since the proposed method requires the SVD computation at every pixel position, it takes more processing time compared to CVC, LDR, and LIME. To improve the operating speed of the proposed algorithm, more advanced techniques [31], [32] for computing SVD can be efficiently applied to the proposed method. Note that the

FIGURE 10. Odd rows : original input images. Even rows (with the blue rectangle): enhancement results by the proposed method. Note that the proposed method works well under both indoor and outdoor environments with various lighting conditions.

C language-based implementation of the proposed method operates at the average speed of 0.45 seconds, which can be sufficiently employed for applications working on mobile devices while providing the visually convincing results compared to other approaches.

V. CONCLUSION

In this paper, a novel and powerful method for image enhancement is proposed. The key idea is simple, that is, the illumination component becomes dominant over the textural one in a small region of a given scene and it can be efficiently decomposed from the reflectance layer by exploiting the SVD-based principal energy analysis. After simply adjusting the separated illumination component, e.g., by using Gamma correction, and conducting restoration with color channels, the visual quality of the input image is successfully enhanced. Based on various experimental results, it is confirmed that the proposed method is effective for image enhancement under a wide range of lighting conditions including backlight, low-light, bad weather, uneven illumination, etc.

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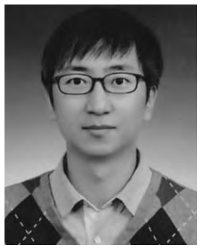

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