Histogram Learning in Image Contrast Enhancement

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Abstract

In this paper, we propose a novel contrast enhancement method utilizing a fully convolutional network (FCN) to learn the weighted histograms from input images. In this method, the enhanced image references are not required. The training images are synthesized by randomly adding illumination on different regions in the source images to simulate the input images with poor contrast in different regions, and to enlarge the scale of training image set. And with this data-driven strategy for learning the underlying ill-posed illumination information of each pixel, a novel weighted image histogram is developed. It not only describes the distribution of pixel intensity, but also contains the illumination information of input images. Consequently, the proposed method can fast and efficiently enhance the regions with poor contrast and have the regions with acceptable contrast preserved, which keeps vivid color and rich details of the enhanced images. Experimental results demonstrate the effectiveness of our proposed method in comparison with some state-of-the-art methods.

1. Introduction

Capturing entire dynamic range of a real scene is typically impossible for off-the-shelf digital cameras. However, images with low contrast not only degrade the visual aesthetics for photography, but also degenerate the performance of many machine vision tasks [11]. To address this issue, many contrast enhancement algorithms have been proposed to increase the contrast of input images with low dynamic range and obtain enhanced images with higher visual quality or with more useful information. In general, recent works can be categorized into three major groups: histogram-based, Retinex-based and deep learning-based methods. Three different types of approaches attempt to deal with the issue from different and independent aspects. And how to make use of their advantages appropriately remains an opening question.

Because of the simplicity and fast implementation, histogram-based methods have been widely used. The global histogram equalization (GHE) [20] is one of the most popular techniques. However, GHE usually results in excessively enhanced images, such as saturation, halo artifacts, *etc*. Various methods [25, 15, 31, 3, 21, 34] have been proposed to overcome the drawbacks of GHE, and most of these methods focus on changing the generation of image histogram. The histograms in these methods are constructed according to the distribution of pixel intensity of the input images. When the histogram has spikes, which is very common, these methods will lead image's details losing [5]. More recently, some histogram-based methods [10, 26, 13, 11, 12] leveraged context information of each pixel to construct the histogram, and many spikes can be efficiency reduced. Although the histogram-based methods typically have low computation complexity and can provide acceptable results, the intrinsic properties of input images (*e.g*., color, texture, illumination conditions) which relevant to human preference, have been ignored in these methods.

Retinex-based image contrast enhancement methods assume that the scene in human's eyes is the product of reflectance and illumination layers. And by applying illumination adjustment on reflectance layer, the enhanced images will be obtained [33]. Although Retinex-based methods enable both global and local contrast enhancement, recovering reflectance and illumination layers from a single image seems almost impossible [24]. Especially for the contrast enhancement task, it usually contains complex scenes and illumination in the input images. Many methods introduced the constraints on both reflectance and illumination layers to convert the image decomposition into an optimization problem. Centre-surround Retinex [24] algorithm was developed to obtain the enhanced image that is invariant to spatial and spectral illumination variations. Intrinsic image decomposition based contrast enhancement [33] introduced a constraint on neighboring pixels according to the color similarity, so that the decomposed reflectance would not be affected much by the illumination information. Although many Retinex-based methods have been proposed, and can obtain the promising results, the computation complexity

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is still the main restriction. Furthermore, the constraints for image decomposition are specified by the scene of input images, *i.e.*, there are no commonly acceptable constraints for image decomposition.

Deep learning methods, especially convolutional neural networks (CNNs), have become a major workhorse for variety of image processing tasks, including image enhancement [30, 14, 9, 22, 23, 17]. [14] and [9] collected their datasets and used CNN-based methods especially for low-light image and multi-exposure image enhancement, respectively. Recently, Ignatov *et al*. [22] collected the DPED dataset consisting of images of the same scene taken by mobile devices and a DSLR camera, and trained generative adversarial networks to learn the mapping between photos from different cameras to improve image quality. Although some promising results can be achieved by state-of-the-art deep learning-based methods, enhanced image references are required for training models. The process of collecting them is time-consuming, *e.g*., they are retouched by well-trained photographers [8] or generated by high dynamic range (HDR) algorithms and multi-exposure images [9].

As mentioned above, histogram-based methods have the superiority of satisfying the real-time application requirement, but the human preference is not taken into consideration. On the other hand, the deep learning-based and Retinex-based methods can achieve promising results, while the human preference is considered. However, the implementation time of them is usually unsatisfactory and the image decomposition is usually hard to estimate. Is it possible to combine the advantages of these three types of methods together, and develop a novel image contrast enhancement method for simultaneously satisfying the computation time requirement, achieving the promising enhanced results and taking human preference into consideration?

In this paper, we take a first attempt to combine the superiorities of histogram-based and Retinex-based image contrast enhancement methods using advanced deep learning techniques, illustrated in Figure 1. In contrast to estimating the illumination information of input images by image decomposition used in Retinex-based image contrast enhancement methods, our proposed method leverages the FCN to learn the illumination feature of pixels. We first synthesize images with different illumination conditions to construct an image set for FCN training. Then, input images can be fed into the well-trained FCN to obtain the illumination features which contain predictions of illumination condition of each pixel. On this basis, by weighting the illumination feature of each pixel, a novel weighted histogram for each input image can be developed, which contains both the distribution of pixel intensity and the illumination condition of each pixel. At last, histogram equalization is adopted to achieve the final enhanced results. Several advantages of our proposed method are highlighted as follows:

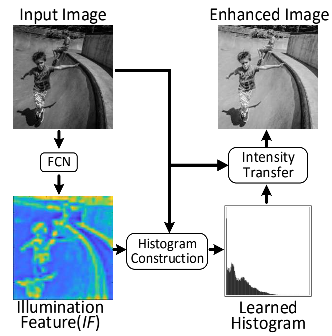


Figure 1: The framework of the proposed method.

- All pixels in input images are weighted the by illumination information. It is learned from the synthetical images, rather than enhanced image references that are required in state-of-the-art deep learning-based image enhancement methods;
- Since the developed histogram is weighted by illumination information, the contrast enhancement mainly performs on poor contrast regions, and the regions with acceptable contrast can be preserved in the enhanced image comparing to conventional histogram-based methods;
- The proposed method is histogram-based that can satisfy the real-time application requirement.

2. FCN for histogram learning

Since objects in a real scene might be illuminated from every visible direction and real objects vary greatly in reflectance behavior, recovering reflectance and illumination from a single image in the real world remains a challenging task. The ambiguity image formation process makes reversing the process ill-posed [27]. In [18], Georgoulis *et al*. introduced a CNN that directly predicts a reflectance map from a single image depicting a single-material specular object. However, training a deep learning model for reconstructing illumination map accurately is very complicated, and difficult to be achieved (each pixel should be labeled to 256 classes due to it has 256 levels for depicting the illumination information). To reconstruct a robust illumination map (we called this as illumination feature for each pixel) for image contrast enhancement, we consider that utilizing deep learning models with coarse labels (will be introduced in Section 2.1) to estimate illumination feature of input image. In this paper, we utilize a FCN architecture to estimate the illumination feature for image contrast enhancement.

2.1. Training image set generation

In practice, most of realistic images can be utilized as the training images. To label the illumination feature of

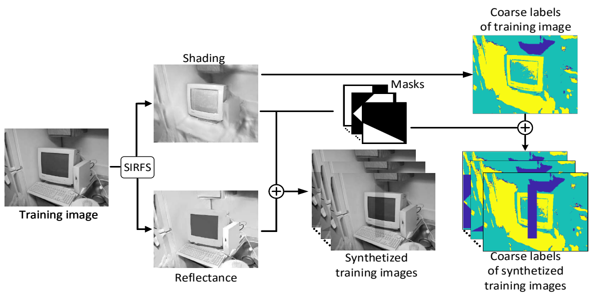


Figure 2: Synthesize training image by SIRFS.

each pixel in realistic images, the simplest way is recovering the reflectance and illumination layers, and setting the reconstructed illumination map as the label of pixels. Since the complexity of scene and illumination in realistic images, the reconstruction of illumination and reflectance layers is an ill-posed problem, and the accurate reconstruction of illumination map is difficult to be achieved. It means that there are not accurate labels for training FCN to learn the illumination feature of each pixel. Moreover, the reconstructed illumination map is not well-performed for the regions with nonuniform illumination (or low-light regions). Therefore, on the basis of reconstructed illumination map, we introduce the concept of coarse labels that set a range of reconstructed illumination values as one label to mark the pixels of input images. In this paper, we define three coarse labels for representing low-light, normal-light and acceptable-light. Through the coarse labels, the FCN can learn the illumination information of input images and output three illumination maps corresponding to three different illumination conditions, and the input images can be segmented into three kinds of regions based on the learned illumination conditions.

Additionally, nonuniform illumination can also cause poor contrast regions in the input images, and the low-light label may not cover this condition. Thus, we synthesize the nonuniform illuminated regions on realistic images to avoid this problem and enlarge the scale of training image set. As shown in Figure 2, the training image set generation consists of three steps: 1) Decomposition training images into reflectance and illumination layers; 2) Utilizing three coarse labels to mark pixels in training images by the reconstructed illumination maps; 3) Adding nonuniform illumination regions on the training images by artificial synthesis.

We use the images from PASCAL VOC-2012 (VOC-2012) [1] to synthesise the training images in this paper because: 1) These images that are originally used for realistic scene classification, detection, and segmentation can satisfy the complex scene and illumination requirements in image contrast enhancement; 2) The decomposition method used in this paper can recover reflectance and illumination layers more accurately on this dataset since VOC-2012 has the shapes segmented; 3) FCN has overwhelming segmentation performance on this image set, thus, it is available to learn the illumination feature of pixels in the input image by performing a fine-tuning on the FCN trained by VOC-2012.

Decomposition: Barron and Malik [6] proposed an optimization strategy to recover the shape, illumination, and reflectance from the shading in input image (SIRFS), which produces more accurate reconstructed results compared with recently proposed methods [33]. The values of reconstructed reflectance and illumination layer are from 0 to 255.

Coarse labels: We empirically set two thresholds (100 and 200) to mark the training images with three labels on the reconstructed illumination map, *i.e.*, the first label (low-light) corresponds to the illumination values from 0 to 100, the second label (normal-light) from 101 to 200, and the third label (acceptable-light) from 201 to 255.

Adding nonuniform illumination: The photometric reflectance model resulting from the Kubelka-Munk theory is given by [19]:

$$\begin{aligned} E(\lambda,\vec{x}) = e(\lambda,\vec{x})(1-\rho_f(\vec{x}))^2 R_\infty(\lambda,\vec{x}) \\ + e(\lambda,\vec{x})\rho_f(\vec{x}), \end{aligned} \tag{1}$$

where $E(\lambda,\vec{x})$ represents the reflected spectrum in the viewing direction, x denotes the position at the imaging plane and λ is the wavelength. $e(\lambda,\vec{x})$ denotes the illumination spectrum and $\rho_f(\vec{x})$ is the Fresnel reflectance at $\vec{x}$. The material reflectivity is denoted by $R_\infty(\lambda,\vec{x})$. Concerning the Fresnel reflectance, the photometric model assumes a neutral interface at the surface patch. The deviations of ρ_f over the visible spectrum are small for commonly used materials, thus, the Fresnel reflectance coefficient may be considered as a constant [19]. The definition of $E(\lambda,\vec{x})$ in Eq. 1 reduces to the Lambertian model:

$$E(\lambda,\vec{x}) = e(\lambda,\vec{x})R_\infty(\lambda,\vec{x}). \tag{2}$$

Therefore, by performing a minus operation on the illumination layer, the nonuniform illuminated regions can be generated.

$$E_{train}(\lambda,\vec{x}) = (e(\lambda,\vec{x})-\beta)R_\infty(\lambda,\vec{x}) \tag{3}$$

Similar to [32], we simply create 12 kinds of masks, shown in Figure 3, to manually add nonuniform illuminated regions on the training images. Since the size of images in VOC-2012 is varying from 500×330 to 500×375, in this paper, we set 8 different size of square masks (32, 64, 96, 128, 160, 192, 224 and 256), thus, totally 96 masks are created. For every image in VOC-2012, we randomly sample 6 masks (with 2 different sizes and 3 different masks) and 3 different illuminations for nonuniform illuminated regions generation. Furthermore, we randomly add the nonuniform illuminated regions on 3 different positions. Therefore,

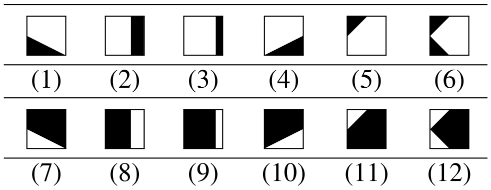


Figure 3: 12 masks used for adding nonuniform illumination regions on one input image.

we have 80,520 images (1464 VOC-2012 source images and 1464×2×3×3×3 nonuniform illuminated images) for training the FCN.

2.2. Fully convolutional network architecture

In our proposed method, the implementation of FCN is mainly following FCN VGG-16 [28]. It has 13 convolutional layers, each of which is equipped with a ReLU. In addition, some layers are followed by the max pooling layers, as shown in Figure 4. We also use the skip architecture which combines the predictions from the final layer, the pool 4 and pool 3 layer, at stride 8, to provide further precision. The first 13 layers of FCN are initialized from the ”FCN-8s” for PASCAL segment model , which achieves a discriminative power for semantic object classification. Our FCN is fine-tuned 200 epochs using SGD with momentum of 0.9. Minibatch size of 10, learning rate of 10^{-4} and weight decay of 5^{-4} are utilized for fine-tuning training.

For a single input image, through the FCN illustrated in Figure 4, three illumination features of each pixel are obtained. By selecting the max value from the three illumination features, the segmentation of low-light, normal-light and acceptable light regions in the input image is obtained (*e.g.*, in Figure 4, the yellow, green and blue regions describe the regions with acceptable, normal and low-light, respectively).

3. The proposed method

As depicted in Figure 1, there are two steps in our proposed method: 1) Developing image histogram based on the prediction results for low-light regions by FCN to get the cumulative distribution function; 2) Using the intensity transfer function to obtain the enhanced image. The intensity transfer function $T(n)$ is defined as:

$$T(n) = (2^B - 1)c(n) + 0.5, \tag{4}$$

where $c(n) = \sum_{i=0}^{n} h(i)$ is the cumulative distribution function, $h(n)$ is the histogram of input image, B is the number of bits (for an 8-bit image, $B = 8$). As mentioned in Section 1, since $h(n)$ in GHE is generated by accounting the frequency of pixel intensity, when $h(n)$ has spikes, the difference of $T(n) - T(n-1)$ is unusually large, GHE introduces unnatural looking and brings visual artifacts easily.

In Section 2, we have introduced the learned illumination features of each pixel in the input image using FCN. It is considered that the pixels with high illumination feature (or in the acceptable-light and normal-light regions) in the input image should be less enhanced or even not be enhanced, while the pixels with low illumination feature (or in the low-light regions) should be more strongly enhanced. In this way, the enhanced image can have higher contrast than the input image and also have the details preserved. Since the illumination features for low-light label are the description for the regions with poor contrast. Therefore, illumination features for low label are more suitable for developing the learned histogram.

Considering an input image f with size $M \times N$, a pixel intensity at location (x, y) is denoted as n, the illumination based histogram ($\mathbf{H}_f$) is defined as:

$$\mathbf{H}_f = \{h_f(n) | 0 \leq n \leq 2^B - 1\} \tag{5}$$

with

$$h_f(n) = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} \varphi_n(x, y) \tag{6}$$

where

$$\varphi_n(x, y) = \begin{cases} IF(x, y), & if\ f(x, y) = n \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

and $IF(x, y)$ is the predicted illumination features correspond to the low-light label shown in Figure 1.

We believe that the learned histogram that weighted by the illumination features of pixels, can weak or even avoid the unnatural looking and image details loss that introduced by the spikes in conventional image histogram. In addition, the learned histogram not only includes the contextual information by associating neighborhood pixels, but also describes the illumination condition of each pixel. On the contrary, the conventional histogram only describes the frequency of each intensity and ignores the neighboring information and illumination features, which usually brings over-enhanced artifacts.

4. Experiment results

We use two publicly available datasets to evaluate the performance of the proposed method: the Berkeley image dataset (bsd) [4] and Kodak dataset (kodak) [2]. The proposed method is compared with the traditional histogram-based method CLAHE [34], the state-of-the-art histogram-based method FCCE [29], the Retinex-based method IID [33] and the state-of-the-art deep learning-based method DPED [22]. The experiment results of IID are provided

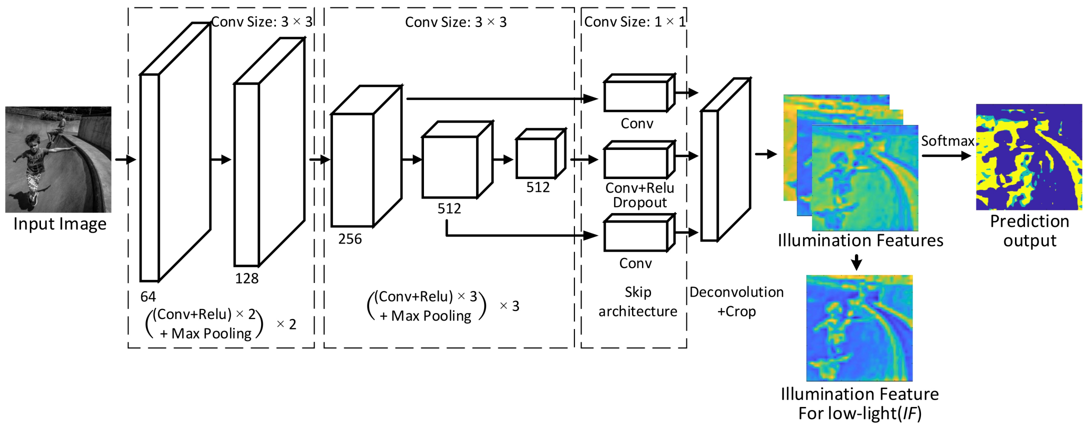
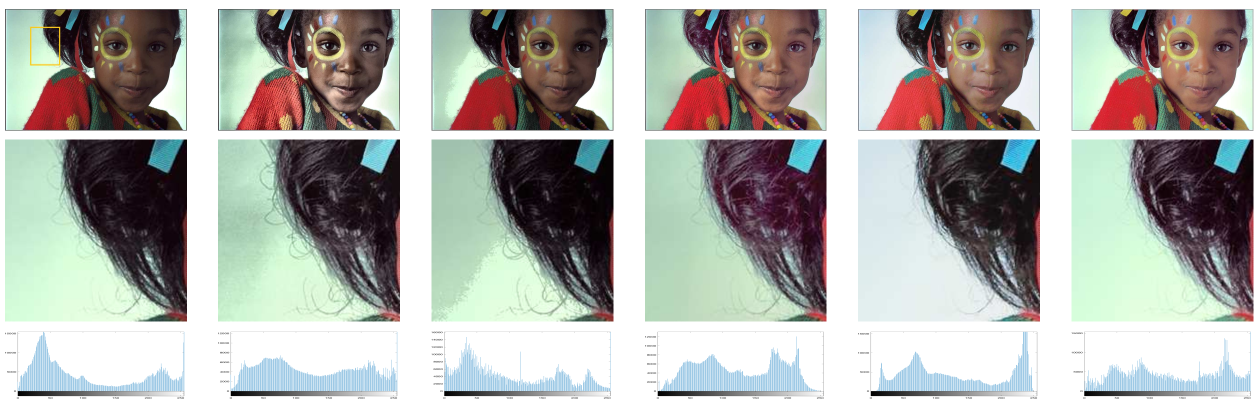


Figure 4: The structure of FCN.



(a)Input (b)CLAHE (c)FCCE (d)IID (e)DPED (f)Ours

Figure 5: The input and enhanced "Shy" images by different methods.

by the corresponding authors. Since the corresponding enhanced image labels are absent in the datasets, some commonly used quality evaluation metrics using enhanced image label as reference might be unsuitable, *e.g.*, MSE, PSNR, SSIM. We select another two quantitative measures: the Absolute Mean Brightness Error (AMBE) [16] and the Discrete Entropy (DE) [7] to assess the enhanced results. AMBE is the measure with reference image, whereas DE is the measure with no-refers. AMBE measure the difference between inputs and output enhanced images. The higher the AMBE value is, the larger difference between input image and enhanced image produced. DE measures the degree of enhancement in image content only from enhanced image, where a higher value indicates an image with richer details.

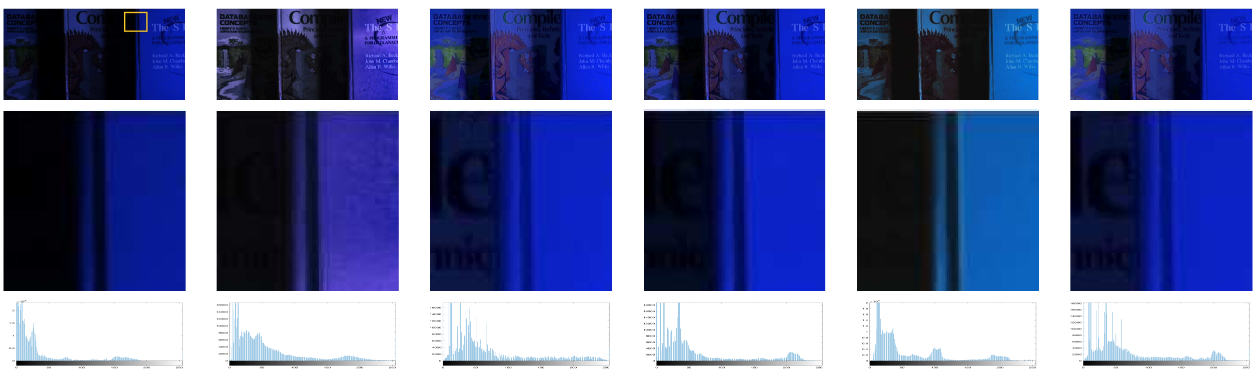
4.1. Visual assessment

To evaluate the performance of different contrast enhancement methods, we design two groups of testing images. Images in the first group have explicit focus and contain one or more characters, and the second group has no explicit focus on input images. All testing images in two groups have the low-light, nonuniform and and normal-light illuminated conditions. Besides, these testing images contain either complicate or simple background that can test the robustness of contrast enhancement methods.

First Group: The first group is the personal profile group. The input and the enhanced "Shy" images by different methods are shown in the first row of Figure 5. The second row of Figure 5 shows the magnified regions taken from the first row. The input "Shy" image is a low-light image, and contains simple background. Since pixel intensities in such simple background are smooth, a spike in histogram is formed, conventional histogram based methods can easily lead halo artifacts. From this figure, we can see that, the images enhanced by CLAHE and FCCE have obviously halo artifacts in the background region, and the CLAHE fails in performing contrast enhancement on the "face" region. The IID method produces over-enhanced artifacts in the "hair" region, and the color of "hair" turns a little red. Similarly,

(a)Input (b)CLAHE (c)FCCE (d)IID (e)DPED (f)Ours

Figure 6: The input and enhanced "Beach" images by different methods.



(a)Input (b)CLAHE (c)FCCE (d)IID (e)DPED (f)Ours

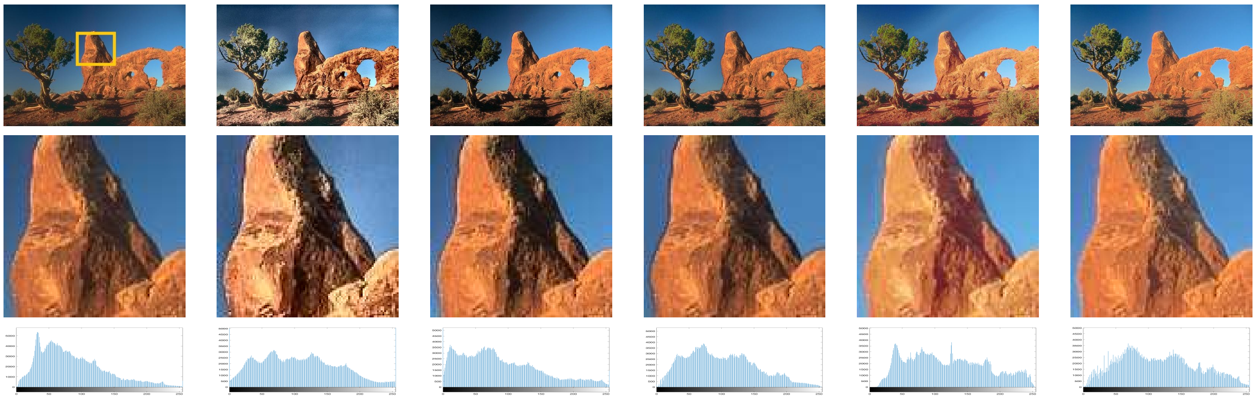
Figure 7: The input and enhanced "Books" images by different methods.

the DPED also produces color distortion in the background region, which is not consistent with the input image. From Figure 5 (f), we can see that, our proposed method produces the best result both in background and character regions.

Figure 6 shows the input and enhanced "Beach" images. The input "Beach" image is a normal-light image and contains complex background. As shown in Figure 6 (b) and (c), by CLAHE and FCCE, the pixels intensities in most regions are transferring into darker, which is failed in performing contrast enhancement. In Figure 6 (d), there is an uneven illumination condition on the "sky" region which causes detail loss. In Figure 6 (e), there is obviously contour line around "character" region, causing unnatural looking in the enhanced image. In Figure 6 (e), the color distortion is found and even some pseudo-color is produced in the "cloth" and "skin" region. Moreover, some details such as the logo on the man's cloth, man's body hair, the man and woman's face are also lost in Figure 6 (e). From Figure 6 (f), it can be found that, our proposed method produces the most natural looking result among those methods.

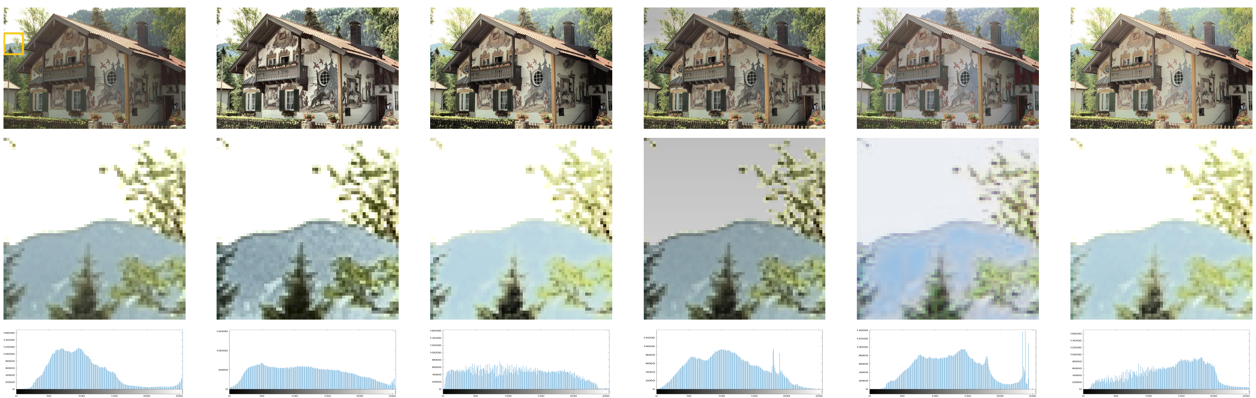
Second Group: The second group is a none explicit focused group. Similar with the first group, all images are under different illumination conditions. Figure 7 shows the input and enhanced "Books" images. The input "Books" image is with low-light, and contains complex background. From Figure 7 (c) and (f), it can be found that our method and FCCE produce almost the same enhanced results under the extremely low-light conditions. The enhanced results of ours and FCCE are acceptable and natural looking. As shown in Figure 7 (b), (d) and (e), CLAHE, IID and DPED have obvious detail losing.

Figure 8 shows the input and enhanced "Rock" images. The input "Rock" image is a nonuniform illuminated image, and the regions with low-light (*e.g.*, the one behind the rock) mainly need contrast enhancement. Since the "rock" region is with irregular shape, it is difficult to reconstruct the reflectance layer and illumination layer of this region by IID. As shown in Figure 8 (b)-(e), all the enhanced results by existing methods are still in low contrast and with obvious contour line. It can be observed from Figure 8 (f) that,



(a)Input (b)CLAHE (c)FCCE (d)IID (e)DPED (f)Ours

Figure 8: The input and enhanced “Rock” images by different methods.



(a)Input (b)CLAHE (c)FCCE (d)IID (e)DPED (f)Ours

Figure 9: The input and enhanced “Country” images by different methods.

our proposed method produces the best enhanced result.

In Figure 9, the input “Country” image is a normal-light image. As shown in Figure 9 (b), CLAHE over-enhances the input image that makes the contour of “mountain” region is too obvious. In Figure 9 (d), the enhanced result of IID is darker than the input image, and the contour of “mountain” region is too obvious to cause unnatural looking. From Figure 9 (e), we can see that DPED still produces some pseudo-color in the “mountain” region. FCCE and our proposed methods produce acceptable enhanced result, but our result is more suitable for human vision since FCCE transfers the “windows” region to darker intensities.

4.2. Qualitative assessment

The qualitative measures of enhanced results by different methods that illustrated in Figure 5–9 are listed in Tables 1 and 2. Table 1 shows that ours has higher AMBE value than other methods in most cases. It means that the ours achieves larger difference between the enhanced and input images than other methods. Moreover, compared with the enhanced results of ours and other methods from Figure 5–9, ours have no over-enhanced artifacts. IID has second low AMBE value, as compared with these input and enhanced

	Shy	Beach	Books	Rock	Coun.	Aver.
CLAHE	18.362	13.479	23.059	22.207	17.235	18.302
FCCE	0.829	36.128	23.316	2.527	14.253	18.955
IID	16.329	10.782	14.948	14.365	3.821	14.177
DPED	27.118	30.641	26.415	33.505	20.943	27.803
Ours	31.922	31.541	21.597	29.326	35.629	32.869

Table 1: AMBE values of Figure 5–9.

	Shy	Beach	Books	Rock	Coun.	Aver.
Input	7.416	6.979	5.238	7.131	7.115	6.883
CLAHE	7.880	7.395	6.077	7.693	7.759	7.406
FCCE	7.531	7.797	5.991	7.513	7.744	7.419
IID	7.519	6.570	5.903	7.134	7.575	7.017
DPED	7.440	6.561	5.890	7.343	7.464	7.034
Ours	7.626	6.533	5.892	7.199	7.503	7.094

Table 2: DE values of Figure 5–9.

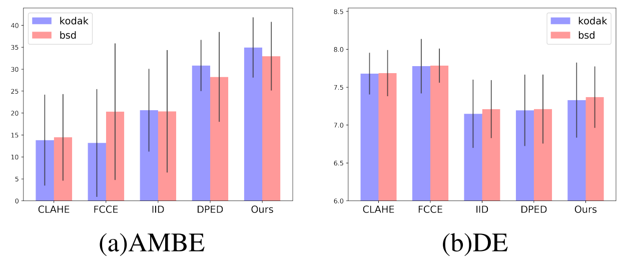


Figure 10: Average and variance values of AMBE and DE on two image sets.

images, it can be found that, in the background regions, the pixel intensity in IID results is darker than input image, which cause unnatural looking. This may indicate that the IID still has space for performing contrast enhancement on these background regions.

Table 2 shows the DE measure of each method. Since this measure is a no-refers measure, the DE values of input images are also listed in this table. From this table, we can find that, FCCE obtains the highest value in most cases. Although higher DE value indicates richer details are existed in the enhanced image, DE with too high value may lead image details over-enhanced or even unnatural looking generated. For example, for the “Beach” image shown in Figure 6, FCCE obtains the highest DE value, whereas the unnatural looking of enhanced image is obvious. But from the visual effect, we can find that, our result is brighter and more suitable for human vision than FCCE.

4.3. Assessment on two image sets

We also perform more objective assessment on two image sets described above to demonstrate the efficiency of the proposed method. “kodak” image set includes most testing images with acceptable contrast, “bsd” image set includes testing images with all kinds of illumination conditions. The variance and average values of AMBE and DE are depicted in Figure 10. From Figure 10 (a), we can see that, the average values of AMBE by our method and DPED are obviously higher than other methods. It indicates that our method and DPED achieve larger image enhancement than other methods. Moreover, the variance values of AMBE by our method and DPED are smaller than other methods, which indicates that these two methods have the most stable image enhanced results. More assessment results of DE on two image sets depicted in Figure 10 (b) also verify the discussion we provided in Section 4.2.

4.4. Computation time analysis

The experiments are performed on a PC with 32G RAM, 1.7 GHz CPU and one NVIDIA TITAN X GPU. 20 color images of the size 399×600 in kodak dataset are used, and the average computation time per image is recorded in Table 3. From this table, it can be found that, IID is the slowest method due to the reconstruction of illumination and reflectance layer is very high in time consumption. FCCE takes the least time since it only develops the image histogram by using the fuzzy theory and followed by a calculation of the intensity transform function. DPED takes obviously higher time consumption than our method due to the much deep CNN-based image generation model is introduced. Since performing deep learning models on GPUs is a common way, the computation time of illumination features estimation by our method can be significantly reduced. The proposed method is only 0.05s slower than FCCE. It can meet the requirements in real-time applications.

CLAHE	FCCE	IID	DPED	Ours
0.82	0.46	12	3.62	0.51

Table 3: Average computation time per image (in seconds).

5. Conclusion

In this paper, a deep learning model is first introduced to learn the image histogram for image contrast enhancement. Since the lacking of public image set for illumination map learning in contrast enhancement, we synthesize training images with realistic images, and use coarse labels to help FCN learning illumination features. We also introduce image masks to add different nonuniform illuminated regions on input images for enlarge the scale of training image set and simulate realistic illumination conditions. On this basis, a novel weighted histogram is developed by the learned illumination features. The developed histogram is constructed on the illumination feature of each pixel rather than the distribution of pixel intensity, and it not only includes the contextual information, but also describes the weighted frequency of each intensity in the input image. Therefore, the proposed algorithm has the capability of performing contrast enhancement both locally and globally, and guarantees the natural looking of the enhanced images.

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