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An Efficient Sparse Code Fusion Method for Image Enhancement

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Abstract

Image enhancement can improve the perception of information for human viewers, which is also a basic and pretty significant role in image processing. However, there also exist some limitations in most image enhancement algorithms. In this paper discuss the limitations of existing techniques of image enhancement. In order to solve the limitations well, a novel sparse code fusion (SCF) method is proposed, in which combine piecewise dictionaries strategy. The proposed method firstly is that color space conversion from RGB to Ycbcr color space, secondly enhanced Y component using piecewise sparse code fusion strategy, finally color image reconstruction. Experimental results show that our method can obtain more appealing perceptual quality than the state-of-the-art usual algorithms.

Keywords: *Image enhancement; Ycbcr color space; Sparse code; Image fusion*

1. Introduction

Image enhancement is an active topic in computer vision aims at taking a good understanding of low illumination images to provide a better representation for further processing, such as image segmentation, detection, analysis and recognition, entertainment, healthcare, system performance evaluation, *etc.* [1].

Traditional image enhancement techniques can be broadly categorized into two groups: spatial-based domain and frequency-based domain. Spatial-based domain refers to the image plane itself, and approaches in this category are based on direct manipulation of pixels in an image [2]. It is denoted by the expression: $g(x, y) = T[f(x, y)]$, where $f(x, y)$ is the input image, $g(x, y)$ is the processed image, and T is an operator on f , defined over some neighborhood of (x, y). Frequency-based domain processing techniques are the spatial frequency spectrum modified of the image as obtained by transform [2]. The traditional method is based on 2D discrete Fourier transform to deal with enhanced images.

Most existing techniques usually have some limitations. Histogram equalization (HE) is a widely used approach in image contrast enhancement, which utilizes the image histogram to obtain a single-indexed mapping to modify the pixel values. Due to stretching intensities excessively, HE tends to make images unnatural and produces flickering effect, such as over enhancement. Meanwhile, HE does not achieve a well-balanced enhancement effect over different parts of an image [3]. For improve these limitations, some researchers [4,5] had improved HE-based enhancement techniques, for example, a global HE-based enhancement algorithm, however, these methods have to adjust parameters value by manipulating to control over the degree of enhancement. T. Arici *et al*. [6] proposed a histogram modification framework, which is based on mapping way. The detailed description as follows.

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$$T[n] = \begin{cases} n \times s_b & n \le b \\ n \times g[n] & b < n < w \\ w + (n - w) \times s_w & w \le n \end{cases} \quad (1)$$

Where T[n] is mapping function, b is the maximum illumination level to be stretched to black, and w is the minimum illumination level to be stretched to white, g[n] is any function mapping the intensities in between, and s_b, s_w are black and white stretching factors both of which are less than one. The drawback is to make the residual between modified histogram and input histogram is small. And make enhanced image unnatural. N. Mitianoudis *et al*.[7] proposed a image enhancement method, which combine the pyramid decomposition and the Dual-Tree Wavelet (DTW) transform method. The fusion stage also use the Independent Component Analysis (ICA) and Topographic Independent Component Analysis (TICA) bases. However, this method has complex coefficients and need set by hand. He *et al*. [8] presented an image enhancement method based on singular value decomposition to improve the performance of face recognition with a single training sample. However, complex combination parameters don't accurate and only based on face images.

Based on analysis above algorithms, in order to overcome these limitations of researcher's mentions, we propose a novel approach for low illumination images with complicated background scenes. The proposed method include three components: sparse coding stage, dictionary update stage, and sparse codes fusion stage. Experimental results show that our method can obtain more appealing perceptual quality than the state-of-the-art usual algorithms.

The remainder of the paper is organized as follows. Section 2 describes the proposed methodology. Experimental results are presented in Section 3. Finally, the conclusion is given in Section 4.

2. Methodology

The detailed procedures of the proposed method can be described as in Figure1. The proposed method is composed of the following steps: (1)conversion of RGB to Ycbcr and extract L component, (2)sparse coding stage, (3)dictionary update stage, (4)sparse code fusion stage, (5)enhanced Y component using sparse code fusion method, and (6)color image reconstruction. These steps are described in details in the following.

The basic idea of our method is that input low illumination images firstly are conversion of RGB color space to Ycbcr color space, then extract L component is enhanced using sparse code fusion. The enhanced images are reconstructed from the enhanced L illumination component and cbcr color component.

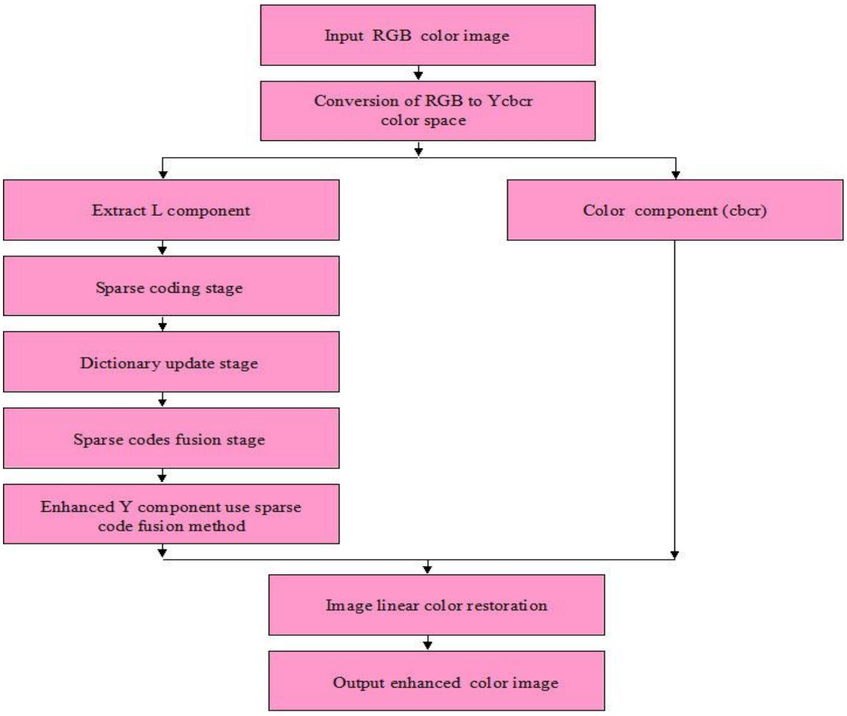


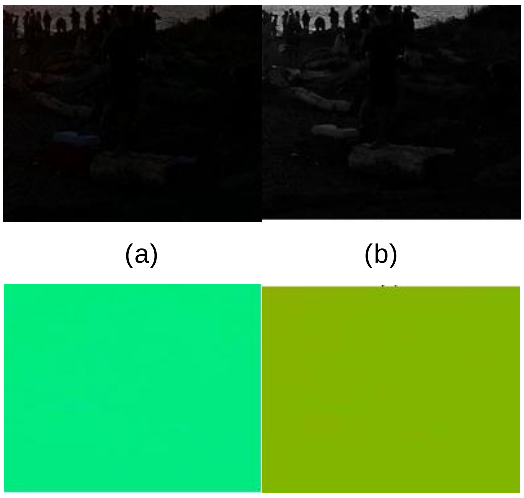
Figure 1. A Block Diagram of the Proposed Sparse Code Fusion Method

2.1 Conversion of RGB to Ycbcr Color Space

Input low illumination images are in the RGB format which consists of three additive primaries: red, green, and blue. Since we perform enhancement method based on the illumination layer, a conversion is needed to convert input low illumination images from RGB to intensity+color components for achieving the intensity component. Ycbcr is the most complete color model used conventionally to describe all the colors visible to the human eye, RGB color space is converted into Ycbcr color space where color information is not affected while modifying intensity values Y [2,9]. The Y component is taken as the intensity. The next processes are carried on the intensity component only. The Ycbcr color components are given by the following equations [3,5].

$$\begin{bmatrix} X \\ Cb \\ Cr \end{bmatrix} = \begin{bmatrix} 16 \\ 128 \\ 128 \end{bmatrix} + \begin{bmatrix} 65.481 & 128.553 & 24.966 \\ -37.797 & -74.203 & 112.00 \\ 112.00 & -93.786 & -18.214 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{2}$$

Where cb and cr are color components,respectively, Y is intensity component. Some examples of converted Ycbcr component are shown in Figure2.



(a) (b)

(c) (d)

Figure 2. Conversion RGB to Ycbcr Color Space (a) Original Image, (b) Y Component, (c) Colored CB Component, (d) Colored CR Component

2.2 The Proposed SCF Method

In this Section, after conversion from RGB to Y+Cb+Cr components for achieving the intensity component. We firstly use piecewise strategy based on Y components, in which decompose Y component of the low illumination images f(L(x, y)) into two sub-piecewise f_A(L(x, y)) (low illumination part) and f_B(L(x, y))(high illumination part). The detailed description is defined as follows.

$$f(L(x,y))\begin{cases} f_A(L(x,y)) & if \quad L\in[0,T] \\ f_B(L(x,y)) & if \ L\in[T,255] \end{cases} \tag{3}$$

Here, L is illumination value of the low illumination images. T is a threshold, which is used the conjunctive the two parts.

Based on analysis above sub-piecewise f_A(L(x, y)) and f_B(L(x, y)) of L component, we propose a new sparse coding fusion method to enhance low illumination images.

Given a data matrix as follows:

$$Y=[y_1,...,y_i,...,y_m]\in IR^{n\times m},(m>>k) \tag{4}$$

Here, it represents n images patches sampled in the m-dimensional feature space. In this paper, the adaptive objective function is listed as follow:

$$\min_{D.X}(\|Y-DX\|_F^2+\alpha\sum_{i=1,j=1}^{k}\sum_{j\neq i}^{k}|(d_i^T d_j)^{-1}|) \qquad s.t\forall_i,\|x_i\|\leq K,\alpha>0 \tag{5}$$

Where α is a tradeoff parameter, which is chosen by performing five-fold cross validation on the training dataset. The mutual coherence $\alpha\sum_{i=1,j=1}^{k}\sum_{j\neq i}^{k}|(d_i^T d_j)^{-1}|$ included in the objective function is set to increase the contestability of the atoms in dictionary D. $D=[d_1,...,d_i,...,d_k]\in IR^{n\times k}$ is the piecewise dictionary of the sparse coding. $X=[x_1,...,x_i,...,x_m]\in IR^{k\times m}$ is minimizing the reconstructed error [10].

We propose sparse codes fusion method, which include three components: **sparse coding stage**, dictionary update stage, and sparse code fusion stage.

Sparse coding stage: It needs to solve the encoding problem to find the sparse codes x, giving the dictionary D (In this paper, it represent $f_A(L(x,y))$ or $f_B(L(x,y))$. This is an optimization problem having no mutual coherence penalty term for each y_i in Y.

$$\min_{x_i} \| y_i - D_{x_i} \|^2 \qquad s.t \| x_i \|_0 \le K \tag{6}$$

Note: the coefficient x_i has less than K non-zero entries.

Dictionary update stage: With the sparse code matrix X from the sparse coding stage, the atom d_i in dictionary D is optimized with the mutual coherence penalty term, for each d_i is defined as follow:

$$\min_{d_i}(\| Y - DX \|_F^2 + \alpha \sum_{i=1,j=1}^{k} \sum_{j\neq i}^{k} | (d_i^T d_j)^{-1} |) \qquad \alpha > 0 \tag{7}$$

If there is no penalty term in the objective function, the optimization problem will be easy to solve, and the optimization result will be used as follows Eq.

$$d_i^* = \frac{C_1 x_i}{C_0} \tag{8}$$

Here the C_0 and C_1 are constant parameters:

$$C_0 = x_i^T x_i, \qquad C_1 = Y - \sum_{j=1, j\neq i}^{k} d_i x_j^T \tag{9}$$

Sparse code fusion stage: We use sparse code fusion to compute the low illumination dictionary of sub-piecewise $D_{f_A(L(x,y))}$, $D_{f_B(L(x,y))}$ and sparse codes X_d, X_n.

As shown in Figure3, the patches sampled from low illumination part images and high illumination part images have their own serial number that records the coordinate position. If the dictionary size equals to or be more than the quantity of patches in a whole image, the atoms will be reconstructed into scene with the help of serial number [11].

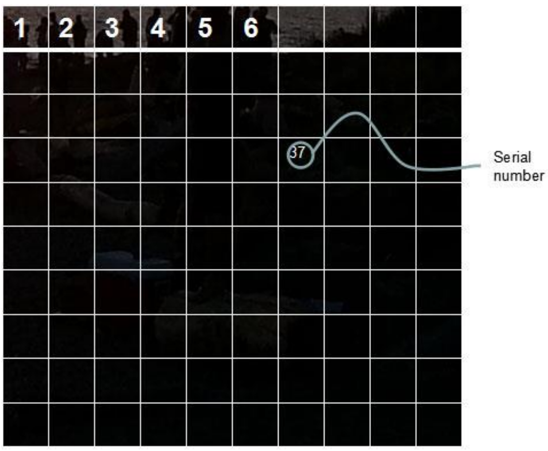


Figure 3. The Images of Training Data-Set are Divided into Patches which have their Own Serial Number to Record the Coordinate Position

Based on analysis above sparse coding stage and dictionary update stage, the learned dictionary $D_{f_A(L(x,y))}$, $D_{f_B(L(x,y))}$ and sparse codes X_d, X_n. The proposed fusion method is described as follows:

$$F_{fusion}(x,y) = \beta D_{f_A(L(x,y))} X_{f_A(L(x,y))} + \lambda D_{f_B(L(x,y))} X_{f_B(L(x,y))} \quad (10)$$

Where $F_{fusion}(x,y)$ is the ith patch after sparse code fusion processing, $D_{f_A(L(x,y))}$ and $D_{f_B(L(x,y))}$ are the ith column vector in $X_{f_A(L(x,y))}$ and $X_{f_B(L(x,y))}$, respectively. β and γ are fusion parameters. Experiments demonstrate that when β is near 0.62 and γ is about 9.91, the fusion result is better than other parameters setting.

2.3 Color Image Reconstruction

After using the sparse code fusion $F_{fusion}(x,y)$ of based on L component to enhance low illumination images, the images in Ycbcr color space is converted back to R'G'B' color space. Color space conversion routines are used for converting between color spaces. In this paper, to restore the color information, we use a linear color restoration process based on the chromatic information of the original image to converting the enhanced intensity image to RGB color image. The RGB values $G^{'} = \frac{I^{'}}{I} G$ of the restored color image are obtained as following:

$$R^{'} = \frac{I^{'}}{I} R, G^{'} = \frac{I^{'}}{I} G, B^{'} = \frac{I^{'}}{I} B \quad (11)$$

The color consistency between the original color image and the enhanced color can be achieved.

3. Experimental Results

In this section, in order to demonstrate the performance of the proposed method, all experiments are performed in Pentium (R) Dual-Core 3.06 GHz computer with 4GB memory, and all the methods used for comparison are implemented with the same programming language setting. And the proposed method is implemented by MATLAB (R2010a) for data training and learning. We collect 1000 low illumination images from various datasets and perform experiments on them.

Due to limited space, only some of the samples (8 images) are chosen to be shown in this paper. In order to demonstrate the performance of the proposed method well, different low illumination images are used in our experiments. Figure 4 shows a complete experimental processing and the results of sparse code fusion. From Figure 4, it show robustness of the proposed method well and overcomes the drawback of the traditional methods.

Some other related methods have been implemented and their results are compared with our method. Figure 5-6 shows the results of our method, HE, method in [4], method in [6], method in [8]. Compared to these methods, Figure 5-6(b) show that the proposed method produce natural looking images and it is clear from figure that proposed method achieves the detail content. Figure 5 also shows that the relations between histogram. From Figure 5-6, we find that output intensity are effective enhanced by our method.

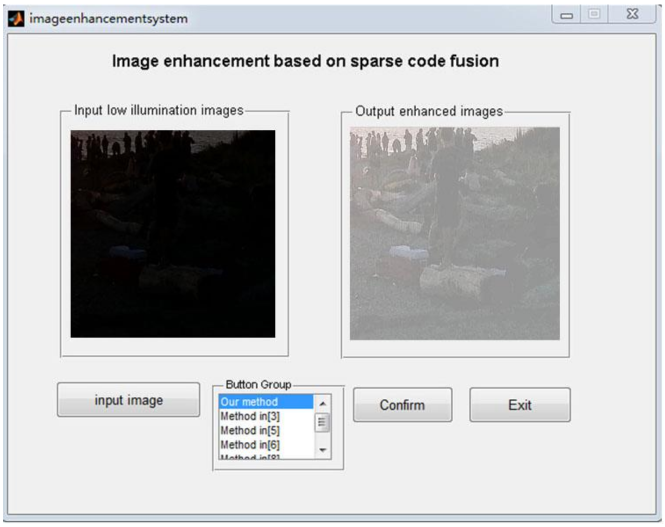


Figure 4. The Image Enhancement System Developed Based on our Proposed Method

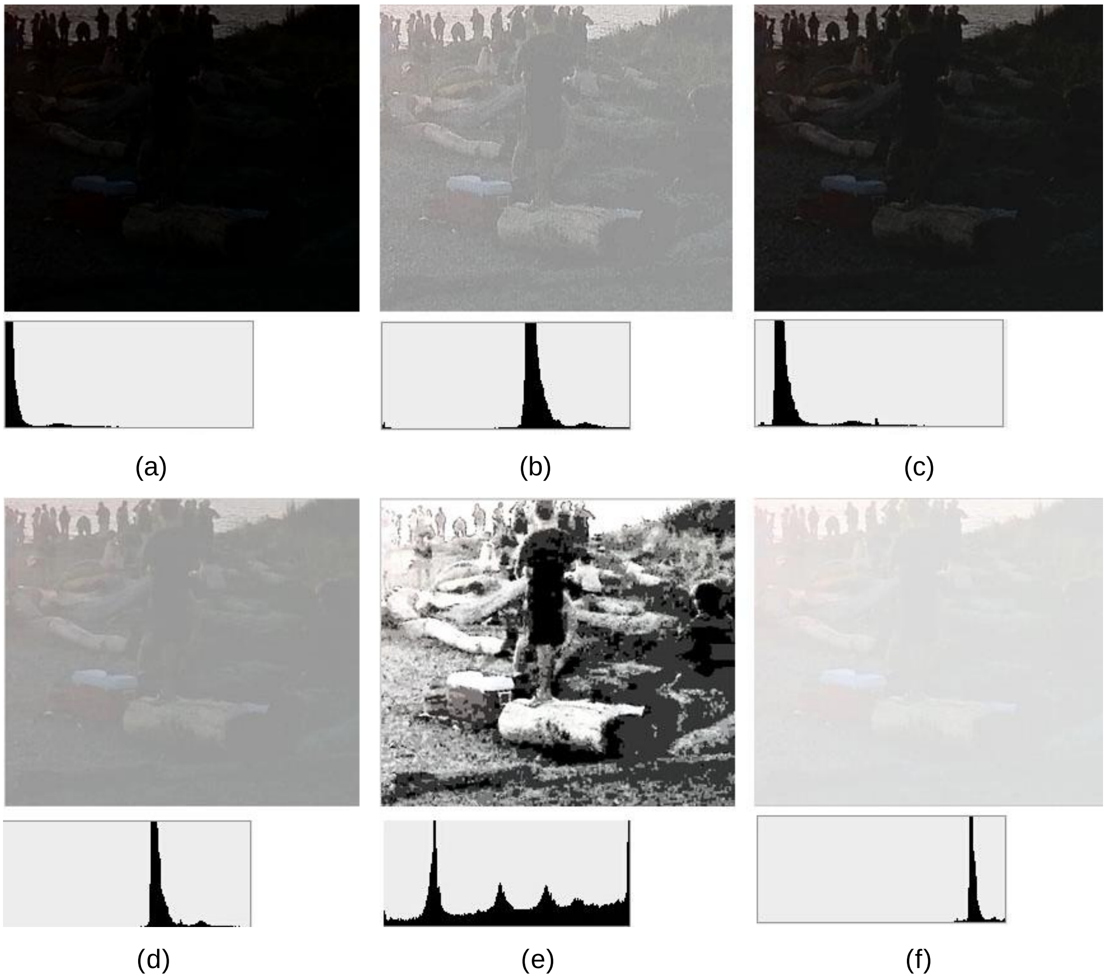


Figure 5. Results Comparison of Different Methods Operated on "Beach" Image. (a) Original Low Illumination Image, (b) The Enhanced Result Using our Method, (c) The Enhanced Result Using Method in [4]. (d) The Enhanced Result Using Method in [8], (e) The Enhanced Result Using HE, (f) The Enhanced Result Using Method in [6]

Figure 6. Results Comparison of Different Methods Operated on "Door" Image. (a) Original Low Illumination Image, (b) The Enhanced Result Using our Method, (c) The Enhanced Result Using Method in [4]. (d) The Enhanced Result Using Method in [8], (e) The Enhanced Result Using HE, (f) The Enhanced Result Using Method in [6]

We adopt some quantitative measurement to evaluate the performance of our method. Table 1 compares the pixels illumination value measure results for different methods. From Table 1, we find that the proposed method can achieve bigger illumination value than the conventional methods. It's only smaller than HE method, however, HE make images unnatural and over enhancement.

Table 1. Pixels Illumination Value Measure Results Comparison

Name	original value	HE	Method [4]	Method [6]	Method [8]	Our method
Beach	56	220	180	208	192	210
campus	45	210	171	190	181	205
door	78	230	189	187	202	227
highway	88	232	191	212	203	229
leaf	90	235	194	215	204	230
park	70	227	186	206	198	225
city	75	228	187	207	198	223
parking lots	50	215	174	194	180	212

Peak signal-to-noise ratio (PSNR) method, which is most commonly used as a measure of quality of reconstruction in image compression and images/videos enhancement, is adopted to evaluate objectively the enhanced images [12]. PSNR can be computed by as follows Eq:

$$PNSR = 10 \times \log_{10}\left(\frac{(2^n - 1)^2}{MSE}\right) \qquad (12)$$

Where MSE is mean square error between the original images and enhanced images. If PSNR value is the greater, the enhanced result is the better. As shown in Table 2, our method achieves higher level of enhancement compared to other methods. The reason why we select these methods as comparison object is that they outperform others in pixels illumination value measurement and PSNR evaluation of image enhancement.

Table 2. PSNR Evaluation Results Comparison

Name	HE	Method [4]	Method [6]	Method [8]	Our method
Beach	29.90	33.61	30.52	34.81	**38.41**
campus	31.80	34.62	32.78	33.40	**39.80**
door	30.42	33.75	34.20	32.81	**40.02**
highway	32.81	34.70	33.91	36.50	**38.51**
leaf	30.90	32.81	33.80	34.82	**39.45**
park	31.82	33.90	32.81	33.02	**38.90**
city	32.50	35.95	36.91	37.23	**40.23**
parking lots	32.02	34.68	36.02	35.18	**38.80**

For the sake of objective evaluation of the enhanced results, all the low illumination images datasets are measured by detail variances (DV) and background variances (BV) of the gray images. When DV value of the enhanced result increases but BV is not change much compared to original gray frame, it is supposed that efficient contrast enhancement has been achieved [13]. DV and BV are obtained by using the neighboring pixels, which the neighboring window is set as the size of 5*5. If the variance is more than the threshold, the pixel will be classified into foreground, if not, it will be classified as background (Herem the threshold is set 0.04). The averaged variance of all pixels included in the foreground class is DV, and those included in the background class is BV. From the comparison shown in Table 3, our method results in the largest DV value and the nearest BV value to original image gray.

Table 3. The Measured Results of DV and BV

image name	original image	HE	method in[4]	method in[6]	method in[8]	our method
	DV/BV	DV/BV	DV/BV	DV/BV	DV/BV	DV/BV
Beach	420.3/12.5	1137.6/28.5	982.6/27.1	1574.7/24.8	1134.7/23.5	**1726.8/14.0**
campus	210.4/17.5	1070.8/22.8	890.3/26.2	1371.5/20.9	1272.4/24.2	**1368.2/16.3**
door	109.2/8.7	1204.0/25.2	902.4/31.0	1400.8/29.7	1410.4/31.3	**1810.3/24.1**
highway	330.4/14.6	1182.7/24.7	1004.5/20.7	1207.2/24.8	1238.7/25.6	**1682.7/18.4**
leaf	280.2/15.0	1270.6/23.8	1102.3/21.8	1572.3/23.9	1640.0/24.7	**1759.3/17.4**
park	230.7/20.1	1090.5/29.3	1028.4/30.0	1430.7/31.7	1512.5/32.6	**1842.4/21.8**
city	145.1/12.8	1300.4/32.5	970.5/30.2	1427.9/31.7	1627.8/29.8	**1941.6/22.9**
parking lots	170.8/10.5	1275.6/28.4	901.4/29.6	1372.8/30.5	1458.9/31.6	**1847.5/28.3**

4. Conclusions

In this paper, we propose an effective image enhancement method, in which is combine piecewise dictionaries strategy. Our method has as follows merits: (1) the proposed method has low computational complexity and is suitable for real-time image enhancement. (2) It can be directly applied in diverse low illumination images without any pre-processing and conditions. Experimental results show that the proposed algorithm is robust and effective.

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