GROUP-BASED SPARSE REPRESENTATION FOR LOW LIGHTING IMAGE ENHANCEMENT

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ABSTRACT

The Group-based Sparse Representation (GSR) is able to sparsely represent natural images in the domain of group, which enforces the intrinsic local sparsity and nonlocal self-similarity of images simultaneously in a unified framework. And the GSR-driven L0 minimization method for image restoration has been proposed. This paper expands the application of GSR from image restoration to low lighting image enhancement. The GSR is not used to represent the natural images anymore, but representing the transmission map of the haze image and recovering it. Because the transmission map is very important for the low lighting image enhancement, the dark channel prior based enhancement method with the enhanced transmission map can get a better enhanced results. Different from other methods, we evaluate the quality of the enhanced images not only by qualitative analysis but also by quantitative results. Extensive experiments on low lighting image show that the GSR-based method gets a better enhancement result than many current state-of-the-art ones.

Index Terms**—**Sparse representation, group-based sparse representation, guided image filter, lowlighting image enhancement, dark channel prior

1. INTRODUCTION

Low lighting image enhancement has wide applications such as surveillance, image inpainting and criminal investigation, etc.. Difficulties arising from extreme low lighting and the effects of noise make image enhancement extremely challenging. Over the past few years, a variety of algorithms, such as histogram equalization, gamma correction and tone-mapping [1], are used to enhance low lighting image have been proposed in the literatures. However, these algorithms are not robust enough to work well in many cases. Due to the successful use of dark channel prior information in single image haze removal [2], Dong et al. [3] utilized it to enhance the inverted version of the low lighting images, and get the enhanced ones.

In the field of haze removal, almost everybody knows He (Kaiming He) et al. proposed haze removal method using dark channel prior [2]. He et al. found the dark channel prior information by analyzing the haze-free outdoor images. With the dark channel prior, He made it easy to get the haze's transmission map t from the atmospheric scattering light physical model, which is widely used to describe the information of a haze image [4, 5]. This method is very simple and effective to recover a high quality haze-free image.

In [3], Dong et al. found the similarity between the haze image and the inverted ones of the low lighting images, and introduced the dark channel prior to deal with the low lighting images for the first time. This method is also very simple and can be used for real time application. However, Dong's method just get a coarse transmission map t leading to unsatisfactory results.

In order to get a better enhancement result, we first try to refine the transmission map by guided image filtering [6], which has been used in the image dehazing, for the reason that the haze imaging equation has a similar form with the image matting equation., which filters the raw transmission map under the guidance of the inverted low lighting image. Experimental results show that by guided image filter the refined transmission t leads to a better enhancement result than the coarse transmission map. However, this may still be a little farfetched in theory in spite that it works well to some degree.

For image restoration, the GSR proposed by Zhang et al. [7] became very popular recently. Comparing with the traditional patch-based sparse representation modeling of natural images, it avoids the large-scale optimization problem in dictionary learning. Instead of using patch as the basic unit of sparse representation, the GSR exploit the concept of group as the basic unit of sparse representation. Inspired by the success of GSR using in image restoration, this paper expends it to low lighting image enhancement.

In this paper, we regard the problem of refining transmission t for the first time as an image restoration problem, and use the Group-based Sparse Representation (GSR) [7] to optimize it. The GSR is able to sparsely represent natural images in the domain of group, which enforces the intrinsic local sparsity and nonlocal self-similarity of images simultaneously in a unified framework. To the best of our knowledge, it is the first time that no reference quality assessment method was introduce to quantitative analyze the performance of low lighting image enhancement algorithms. Extensive experiments manifest that the GSR-based method performs better than guided image filtering-based and Dong's methods.

2. PRELIMINARIES

In [3], Dong et al. have analyzed the similarity between low lighting images and haze ones, and proposed to enhance low lighting images with the advanced methods of dehazing. For the low lighting image I, we invert it to R. It can be formularize as:

$$R^c(x) = 255 - I^c(x), \tag{1}$$

where c is the color channel (RGB) and x is pixel location. Then, we can use the dehazing method to enhance image R, and get the enhanced image I later.

For image R, it can be described by the atmospheric scattering light physical model [8, 9]:

$$R(x) = J(x)t(x) + A(1 - t(x)), \tag{2}$$

where J is the haze-free image to recover, A is the global atmospheric light, x is pixel location, and t is the medium transmission describing the portion of the light that is not scattered and reaches the camera.

Taking the min operation among three color channels in the local patch $\Omega(x)$ and obtaining:

$$\begin{aligned}&\min_c\left(\min_{y\in\Omega(x)}\left(\frac{R^c(y)}{A^c}\right)\right)\\&=\tilde{t}(x)\min_c\left(\min_{y\in\Omega(x)}\left(\frac{J^c(y)}{A^c}\right)\right)+\left(1-\tilde{t}(x)\right)\end{aligned}, \tag{3}$$

where $J^{dark}(x) = \min_c\left(\min_{y\in\Omega(x)}\left(\frac{J^c(y)}{A^c}\right)\right)$ is the dark channel prior of haze-free image J, and it tends to be zero. Therefore, we can estimate the transmission $\tilde{t}$ simply by:

$$\tilde{t}(x) = 1 - \omega\min_c\left(\min_{y\in\Omega(x)}\left(\frac{R^c(y)}{A^c}\right)\right), \tag{4}$$

where ω is a tunable parameter.

To estimate the global atmosphere light A, we first select the top 0.1% brightest pixels in the dark channel. Then, we select the highest intensity pixel as atmospheric light A among these pixels with the same indexes in the image R.

After estimating the t and A, we can get the haze-free image J from the equation (2) as follows:

$$J(x) = \frac{R(x) - A}{t(x)} + A. \tag{5}$$

In the end, we can get the enhanced low lighting image $I_{Enhanced}$:

$$I^c_{Enhanced}(x) = 255 - J^c(x). \tag{6}$$

3. REFINE TRANSMISSION MAP

In this subsection, we will optimize the estimation of transmission $\tilde{t}$ in Eq. (4) by guided image filter and regarding it as an image restoration problem.

3.1 Refine Transmission Map by Guided Image Filter

The guided filter assumes that the filtered t is a linear transform of the guidance image R in a window ω_k centered at the pixel k:

$$t_i = a_k R_i + b_k, \forall i \in \omega_k, \tag{7}$$

where a_k and b_k are some linear coefficients assumed to be constant in ω_k. We can minimize the following cost function to get the linear coefficients:

$$E(a_k, b_k) = \sum_{i\in\omega_k}\left(\left(a_k R_i + b_k - \tilde{t}_i\right)^2 + \lambda a_k^2\right), \tag{8}$$

where λ is a regularization parameter preventing a_k from being too large. The solution to Eq. (8) can be given by linear regression:

$$a_k = \frac{\frac{1}{|\omega|}\sum_{i\in\omega_k} R_i\tilde{t}_i - \mu_k\bar{\tilde{t}}_k}{\sigma_k^2 + \lambda}, \tag{9}$$

$$b_k = \bar{\tilde{t}}_k - a_k\mu_k, \tag{10}$$

where $|\omega|$ is the number of pixels in patch ω_k, $\bar{\tilde{t}}_k$ is the mean of $\tilde{t}$ in patch ω_k, μ_k and σ_k are the mean and variance of R in patch ω_k. We refer the reader to [6] for more detail about guided filter.

3.2 Regard Refining Transmission Map as an Image Restoration Problem

Different from the traditional methods, which recover image from the low lighting one directly, we recover the transmission t from its estimation $\tilde{t}$ to get the enhanced result. The image restoration problem can formulize as:

$$t = \arg\min_t \frac{1}{2}\left\|Ht - \tilde{t}\right\|_2^2 + \lambda\Psi(t), \tag{11}$$

where $\frac{1}{2}\left\|Ht - \tilde{t}\right\|_2^2$ is the ℓ_2 data-fidelity term, and $\Psi(t)$ is the regularization term denoting image prior, H is a matrix representing a non-invertible linear degradation operator and λ is the regularization parameter.

As show in Fig. 1, first, divide the transmission map $t \in \mathbb{R}^N$ into image patch $t_k \in \mathbb{R}^{B_s}$ of size $\sqrt{B_s} \times \sqrt{B_s}$ at location k ($k = 1, 2, \ldots, n$). Second, search the most similar c patches by the Euclidean distance for each patch marked in red box in the training window of size $L \times L$. The set S_{t_k} is composed of all these patches. Then, all the patches in S_{t_k} will be vectorized and stacked into a matrix $G_{t_k} \in \mathbb{R}^{B_s \times c}$,

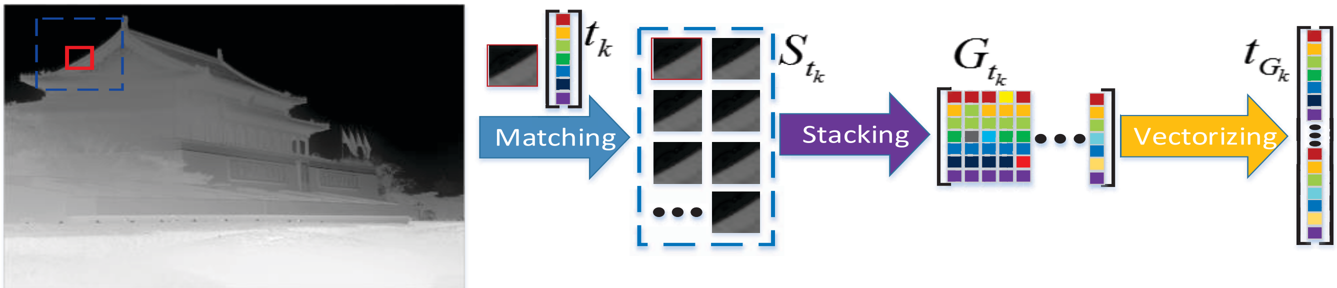

Fig. 1. Illustrations for the group construction. Extract each patch vector t_k from the transmission map *t*. For each t_k, denote S_{t_k} the set composed of its *c* best matched patches. Stack all the patches in S_{t_k} in the form of matrix to construct the group, denoted by t_{G_k}.

which includes every patches in S_{t_k} as its columns, i.e., $G_{t_k} = \{G_{t_k \otimes 1}, G_{t_k \otimes 2}, \ldots, G_{t_k \otimes c}\}$. Last, vectorize G_{t_k} to get t_{G_k}.

We define R_{G_k} the operator that extracts the group t_{G_k} from *t*, and its transpose, denoted by $R_{G_k}^T$, then,

$$t_{G_k} = R_{G_k} t . \quad (12)$$

By averaging all the groups, the transmission map *t* can be formulized as:

$$t = \left(\sum_{k=1}^{n} R_{G_k}^T R_{G_k} \right)^{-1} \sum_{k=1}^{n} \left(R_{G_k}^T t_{G_k} \right). \quad (13)$$

The GSR model assumes that each group t_{G_k} can be accurately represented by a few atoms of a self-adaptive learning dictionary D_{G_k}. The sparse coding process of each group t_{G_k} over D_{G_k} is to seek a sparse vector α_k subject to $t_{G_k} \approx D_{G_k} \alpha_{G_k}$. Then the entire image can be sparsely represented by the set of sparse codes $\{\alpha_k\}$ in the group domain. Reconstructing *t* from the sparse codes $\{\alpha_k\}$ is expressed as:

$$t \approx D_G \circ \alpha_G = \left(\sum_{k=1}^{n} R_{G_k}^T R_{G_k} \right)^{-1} \sum_{k=1}^{n} \left(R_{G_k}^T D_{G_k} \alpha_{G_k} \right), (14)$$

where D_G, α_G denote the concatenation of all D_{G_k}, α_{G_k} respectively.

Accordingly, by considering the image degradation problem, the regularization-based image restoration scheme via GSR is formulated as:

$$\alpha_G = \arg\min_{\alpha_G} \frac{1}{2} \left\| H D_G \circ \alpha_G - \tilde{t} \right\|_2^2 + \lambda \left\| \alpha_G \right\|_0 . \quad (15)$$

With α_G, the reconstructed transmission map can be expressed by:

$$\hat{t} = D_G \circ \alpha_G . \quad (16)$$

4. LOW LIGHTING IMAGE ENHANCEMENT

After inverting the low lighting image *I* to *R*, it can be described by the atmospheric scattering light physical model. Obtaining the atmospheric *A* and transmission map *t* via our GSR method, we can get the enhanced result. Our new low lighting image enhancement method (represent as GSRLLIE) is outlined in algorithm 1.

Algorithm 1: Framework of GSRLLIE

Input: Low lighting image *I*, and parameter ω

$$R^c(x) = 255 - I^c(x)$$

$$R^{dark}(x) = \min_c \left(\min_{y \in \Omega(x)} \left(R^c(y) \right) \right)$$

$$A = \max \left(R \left(\mathrm{Index}_{\max}^{0.1\%} \left(R^{dark} \right) \right) \right)$$

$$\tilde{t}(x) = 1 - \omega \min_c \left(\min_{y \in \Omega(x)} \left(\frac{R^c(y)}{A^c} \right) \right)$$

$$t = \mathrm{GSR}(\tilde{t})$$

$$J(x) = \frac{R(x) - A}{t(x)} + A$$

$$I_{Enhanced}^c(x) = 255 - J^c(x)$$

Output: The enhanced image $I_{Enhanced}$

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5. EXPERIMENTAL RESULTS AND DISCUSSIONS

In order to verify the robustness of our algorithm, we compare it with Dong's method [3] and that refined by He's guided image filter [6]. We implement Dong's algorithm by ourselves based on He's open source code. We share the same parameters with Dong's method and get the similar results the author reported in the paper.

Different from other methods, we evaluate the quality of the enhanced images not only by qualitative analysis but also by quantitative one. For quantitative analysis, we use Fang et al. proposed NR-CDIQA metric [10]. It is a simple but effective method for no-reference quality assessment of contrast distorted images based on the principle of natural scene statistics (NSS). We report four experimental results in this paper. Table 1 gives the objective evaluation score based on NR-CDIQA metric. It shows that our method get highest scores for all four images. Figure 2 to 5 are the results of qualitative analysis. The Fig.2 shows that although Dong's method gets higher brightness image, it always contains too much noise and gets excessive enhancement result in some places. We have highlighted a part in the red box. The words are not clear in Dong's method. Specially, the result of refining by guided image filter is excessive. Our method can recognize the word correctly. It can be more clearly in full size drawing. In fig. 3, it is obvious that Dong's method can't work well in the sky part especially for the moon. In fig. 4, shadow of the trees of Dong's method is very ambiguous. The result after refining transmission using guided image filter still keep some dark region. The biggest advantage of our method in fig. 5 is getting a more beautiful car lamp. All of these show that our method gets a more natural and clear new image.

The good result of our method can be attributed to getting a more accurate transmission map since we regard it as an image restoration problem. Especially the strong ability of describing the nonlocal self-similarity of the GSR make the mistaken transmission correctable.

Table 1. Performance evaluation based on NR-CDIQA metric

Methods	a	b	c	d
Fig. 2	2.0641	2.5131	2.5404	**2.5595**
Fig. 3	2.0690	2.1689	2.2510	**2.5312**
Fig. 4	2.0998	2.3442	2.4436	**2.5595**
Fig. 5	2.2195	2.2548	2.2651	**2.4740**

6. CONCLUSIONS

This paper contributes to optimize the transmission map t using group-based sparse representation (GSR) modeling, which sparsely represents natural images in the domain of group, explicitly and effectively characterizes the intrinsic local sparsity and nonlocal self-similarity of natural images simultaneously in a unified manner. Experimental results show that the method using our refine transmission t gets better enhancement result.

7. ACKNOWLEDGEMENTS

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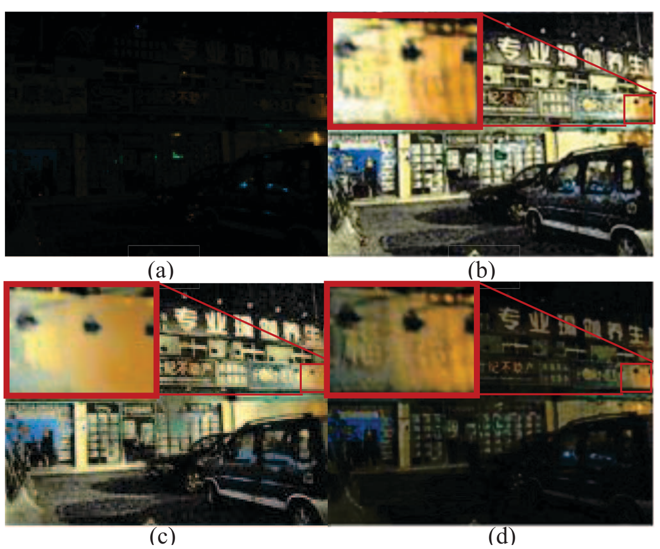

Fig. 2. (a) Input low light image. (b) Enhanced result using Dong's algorithm. (c) Enhanced result after refining t by guided image filter. (d) Enhanced result after refining t by GSR.

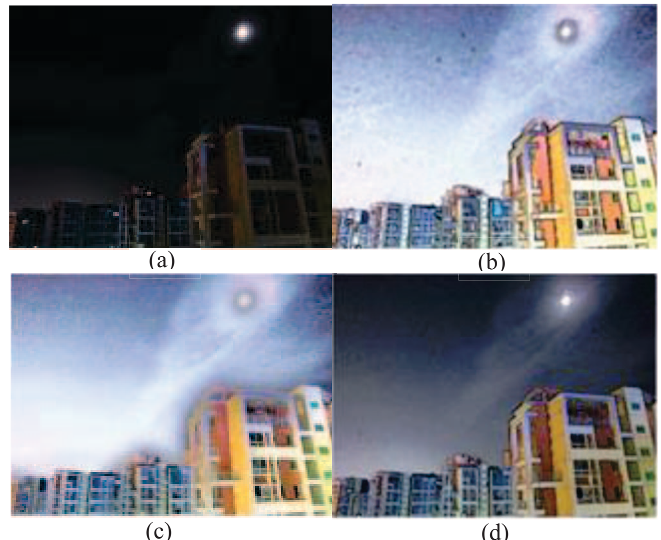

Fig. 3. (a) Input low light image. (b) Enhanced result using Dong's algorithm. (c) Enhanced result after refining t by guided image filter. (d) Enhanced result after refining t by GSR.

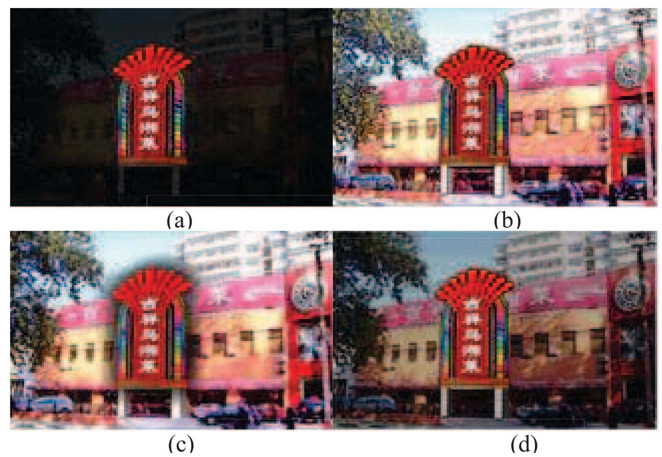

Fig. 4. (a) Input low light image. (b) Enhanced result using Dong's algorithm. (c) Enhanced result after refining t by guided image filter. (d) Enhanced result after refining t by GSR.

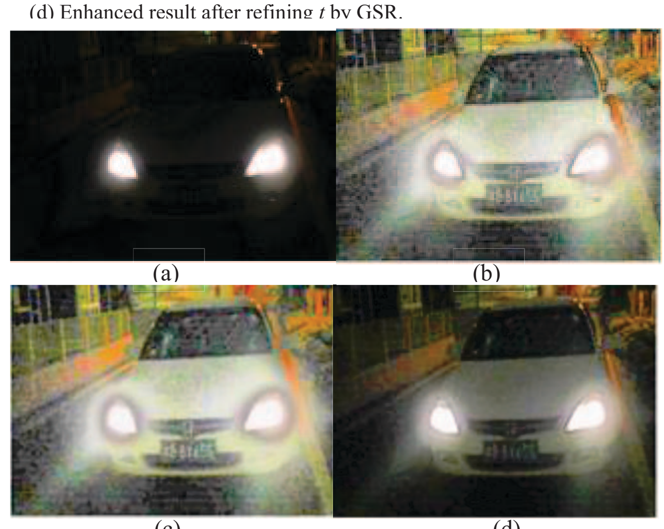

Fig. 5. (a) Input low light image. (b) Enhanced result using Dong's algorithm. (c) Enhanced result after refining t by guided image filter. (d) Enhanced result after refining t by GSR.

8. REFERENCES

[1] Y.B. Rao and L.T. Chen, “A survey of video enhancement techniques,” Journal of Information Hiding and Multimedia Signal Processing, vol. 3, pp. 71–99, January 2012.

[2] K. He, J. Sun, and X. Tang. “Single Image Haze Removal Using Dark Channel Prior,” in Proc. IEEE Conf. Computer Vision and Pattern Recognition. Miami, FL, Jun. 2009, pp. 1956-1963.

[3] X. Dong, G. Wang, Y. Pang, W. Li, J. Wen, W. Meng, and Y. Lu, “Fast efficient algorithm for enhancement of low lighting video,” in Proceedings of International Conference on Multimedia and Expo. IEEE, 2011, pp.1–6.

[4] R. Fattal. Single image dehazing. In SIGGRAPH, pages 1–9, 2008.

[5] R. Tan. “Visibility in bad weather from a single image”. CVPR, 2008.

[6] K. He, J. Sun, and X. Tang. “Guided Image Filtering”. IEEE Transactions on Pattern Analysis and Machine Intelligence, Volume 35, Issue 6, pp. 1397-1409, June 2013

[7] J. Zhang, D. Zhao, W. Gao. “Group-based Sparse Representation for Image Restoration”. IEEE Transations on Image Processing, vol. 23, no. 8, pp. 3336-3351, Aug. 2014.

[8] S. G. Narasimhan, and S. K. Nayar. “Chromatic Framework for Vision in Bad Weather,” in Proc. IEEE Conf. Computer Vision and Pattern Recognition., Hilton Head, SC, Jun. 2000, vol. 1, pp. 1598-1605.

[9] S. G. Narasimhan and S. K. Nayar. “Vision and the Atmosphere,” in Int. Journal Computer Vision, vol. 48, no. 3, pp. 233–254, 2002.

[10] Y. Fang, K. Ma, Z. Wang, W. Lin, Z. Fang, and G. Zhai, 'No-Reference Quality Assessment of Contrast-Distorted Images Based on Natural Scene Statistics', IEEE Signal Processing Letter, 22(7): 838-842, 2015.