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Low-Light Image Enhancement Using Sped-Up solver Method via Illumination Map Estimation

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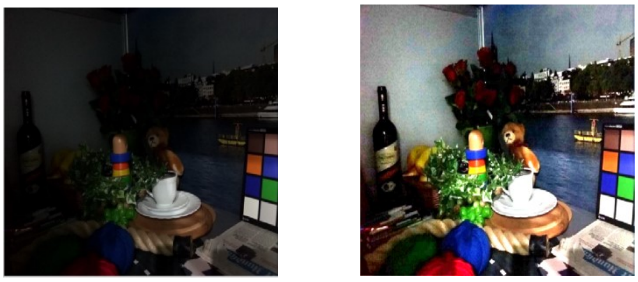
ABSTRACT

In the present scenario digital images are playing very important role in several applications. When one captures images during night times or low light conditions, the images often suffer from low visibility. In order to improve the quality of an image, image enhancement can be used. This type of low light images may decrease the performance of computer vision and other multimedia algorithms that are essentially designed for high-quality inputs. In order to estimate the high quality image in this paper we proposed a low light image enhancement method. In this method, first we estimate the illumination of each pixel individually by finding the maximum value in R, G and B channels. Further we refine the initial illumination map by imposing a structure prior on it, as the final illumination map. The noise can be removed by using BM3D method. For a low light image enhancement we consider the one parameter called Lightness order error (LOE) which gives the light source direction and the lightness variations.

Keywords: Illumination Estimation, Illumination Transmission,Low Light Image Enhancement.

I. INTRODUCTION

The images which are captured during day time or in the presence of light contain clear information when compared to low light images. The images which are taken in low light condition have loss of data. The visual quality of images captured under low-light conditions, for one thing, is barely satisfactory. For another thing it very likely hurts the performance of algorithms that are primarily designed for high visibility-inputs. In order to improve the visibility of low light images we have different approaches for the enhancement of images, such as directly amplifying the images, it is the simplest way to recall the visibility of dark regions. But, this operation gives birth to another problem, say nearly bright regions might be saturated and thus loss corresponding details, and we also have the histogram equalization(HE), variational contrast enhancement(CVC) these are all used to enhance the low light images but every method has some limitations and required further processing. In this paper we proposed Retinex theory based method called low light image enhancement using sped up solver method via illumination map estimation. In Retinex, retina means a small part of eye and cortex means a small part of brain which in turn processes the information. In this theory the image can be disintegrate into illumination and reflectance. The previous methods based on Retinex theory treat the reflectance as the final output. Now in our method we treat the illumination is the final result. By considering the illumination as the final result we can reduce the data loss and also decrease the cost. First make the illumination map by finding the maximum intensity of each pixel in R, G and B channels. Then we refine the illumination map. An Augmented lagrangian Multiplier (ALM) is used to solve the refinement problem and also a sped up solver is used to decrease the computational load.



(a) (b)

Figure 1. (a) low light image (b) output image enhanced by sped up solver method.

II. METHODS AND MATERIAL [Page Layout]

The low light image formation based on Retinex theory is explained below.

$$\mathbf{L} = \mathbf{R} \circ \mathbf{T} \quad (1)$$

Where **L** and **R** are the captured image and the desired recovery, respectively and T represents the illumination map, and the operator ◦ means element wise multiplication. Here we consider that, for color images, three channels share the same illumination map. With slight difference in notations, we use **T** (ˆ **T**) to indicate one-channel and three-channel illumination maps interchangeably. From the above model(1) , say the observed image can be decomposed into the product of the desired light-enhanced scene and the illumination map. This model is related to the intrinsic image decomposition, which perform the decomposition of the input into two components. The main aim of the intrinsic image decomposition is to estimate the reflectance component and the shading one from the the image. By estimating the only reflectance component it loses the the shape of the image, which does not satisfy the purpose of low light image enhancement. For that reason in our proposed method we consider the illumination map which in turn recalls the visual content of the dark regions. From eq(1) **R=L/T**, where the division is element-wise. The estimated is the key to the recovery of **R.** By estimation of **T** the problem is solved. We have to notice that **L/T^** can directly act as the light-enhanced result

2.1 Illumination Map Estimation

In this we estimate the illumination map by finding the maximum value of three color channels, say R, G and B. But this estimation can only enhance the global illumination. In order to handle non-uniform illuminations, we consider the following initial estimation:

$$\hat{\mathbf{T}}(x) \leftarrow \max_{c \in \{R,G,B\}} \mathbf{L}^c(x), \quad (2)$$

For individual pixel x. The principle behind the operation is the particular location where the maximum values of three channels are located. The obtained ˆ**T***(x)*

Ensure that the recovery will not be saturated, because of

$$\mathbf{R}(x) = \mathbf{L}(x) / (\max_c \mathbf{L}^c(x) + \epsilon), \quad (3)$$

Where is a very small constant to avoid the zero denominator. The goal of this work is to non-uniformly enhance the illumination of low-light images, instead of eliminating the color shift caused by light sources.

In this work, we employ (2) to initially estimate illumination map ˆ**T**, due to its simplicity, although various approaches have been developed to improve the accuracy in past decades. Most of these improvements essentially consider the local consistency of illumination by taking into account neighbouring pixels within a small region around the target pixel. Two representative ways are:

$$\hat{\mathbf{T}}(x) \leftarrow \max_{y \in \Omega(x)} \max_{c \in \{R,G,B\}} \mathbf{L}^c(y); \quad (4)$$

$$\hat{\mathbf{T}}(x) \leftarrow \operatorname*{mean}_{y \in \Omega(x)} \max_{c \in \{R,G,B\}} \mathbf{L}^c(y), \quad (5)$$

where *(x)* is a region centered at pixel *x*, and *y* is the location index within the region. These schemes enhance the local consistency, but they are structure-blind.

A "good" solution should simultaneously preserve the overall structure and smooth the textural details. In order to address this issue, based on the initial illumination map ˆT, we propose to solve the following optimization problem:

$$\min_{\mathbf{T}} \|\hat{\mathbf{T}} - \mathbf{T}\|_F^2 + \alpha \|\mathbf{W} \circ \nabla \mathbf{T}\|_1, \quad (6)$$

Where α is the coefficient to balance the terms $\|\cdot\|_F$ and $\|\cdot\|_1$ to represent the frobenious and l1 norms rerespectively. W is the weight matrix, and ∇T is the first order derivative filter. In this work, it only contains ∇*h*T (horizontal) and ∇*v*T (vertical). The first term takes care of the fidelity between the initial map ˆT and the refined one T, while the second term indicates the smoothness. Prior to discussing possible strategies of constructing W, in order to solve the eq(6) we proposed medthod called sped up solver method.

2.2 Sped-Up Solver Method

Consider the eq(6), the origin shows the iterative procedure is the sparse weighted gradient term, i.e. $\|\mathbf{W} \circ \nabla \mathbf{T}\|_1$ .The *l1* norm together with the gradient operation on T makes it complex. It holds the relationship given below

$$\lim_{\epsilon \to 0^+} \sum_x \sum_{d \in \{h,v\}} \frac{\mathbf{W}_d(x)(\nabla_d \mathbf{T}(x))^2}{|\nabla_d \mathbf{T}(x)| + \epsilon} = \|\mathbf{W} \circ \nabla \mathbf{T}\|_1. \quad (7)$$

In relation with the above, we use $\sum_x \sum_{d\in\{h,v\}} \frac{\mathbf{W}_d(x)(\nabla_d \mathbf{T}(x))^2}{|\nabla_d \hat{\mathbf{T}}(x)|+\epsilon}$ to approximate $\|\mathbf{W} \circ \nabla \mathbf{T}\|_1$. the problem can be simplified as

$$\min_{\mathbf{T}} \|\hat{\mathbf{T}} - \mathbf{T}\|_F^2 + \alpha \sum_x \sum_{d \in \{h,v\}} \frac{\mathbf{W}_d(x)(\nabla_d \mathbf{T}(x))^2}{|\nabla_d \hat{\mathbf{T}}(x)| + \epsilon}. \quad (8)$$

When compared to the original, the aim of the structure of illumination from the initial illumination estimate ^T is consistent with the original. Esspecially, when $|\nabla_d \hat{\mathbf{T}}(x)|$ is small, $|\nabla_d \mathbf{T}(x)|$ is can be suppressed, so the value $\frac{(\nabla_d \mathbf{T}(x))^2}{|\nabla_d \hat{\mathbf{T}}(x)|+\epsilon}$. In other terminology , T is constrained to avoid making gradients where the initially estimated illumination map has small magnitudes of gradient. In contrary, if $|\nabla_d \hat{\mathbf{T}}(x)|$ is strong,the suppression alleviates, because this location is more likely on structure boundary than on regular texture.

The problem can be solved by solving the below equation

$$(\mathbf{I} + \sum_{d \in \{u,v\}} \mathbf{D}_d^T \operatorname{Diag}(\tilde{\mathbf{w}}_d)\mathbf{D}_d)\mathbf{t} = \hat{\mathbf{t}}, \quad (9)$$

Where ˜ **w***d* is the vectorized version of ˜**W***d* with $\tilde{\mathbf{W}}_d(x) \leftarrow \frac{\mathbf{W}_d(x)}{|\nabla_d \hat{\mathbf{T}}(x)|+\epsilon}$. The operator Diag(x) is to form adiagonal matrix using vector x. since $(\mathbf{I} + \sum_{d\in\{u,v\}} \mathbf{D}_d^T \operatorname{Diag}(\tilde{\mathbf{w}}_d)\mathbf{D}_d)$ is a symmetric positive definite laplacian matrix, and there different techniques available to solve it(5),(6).

2.3 Possible Weighting Strategies

For the structure-aware refinement on the illumination map , we have to design **W.** There are three weighing strategies given below

StrategyI: It can be seen that setting the weight matrix as

$$\mathbf{W}_h(x) \leftarrow 1; \mathbf{W}_v(x) \leftarrow 1, \quad (10)$$

Leads to (6) to a classic l2 loss total variation reduce problem.

StrategyII: It uses the gradient of the illumination map as the weight.

We have

$$\mathbf{W}_h(x) \leftarrow \frac{1}{|\nabla_h \hat{\mathbf{T}}(x)| + \epsilon}; \quad \mathbf{W}_v(x) \leftarrow \frac{1}{|\nabla_v \hat{\mathbf{T}}(x)| + \epsilon}. \quad (11)$$

StrategyIII: Inspired by relative total variation (RTV), for each location, the weight is set via.

$$\mathbf{W}_h(x) \leftarrow \sum_{y \in \Omega(x)} \frac{G_\sigma(x,y)}{|\sum_{y\in\Omega(x)} G_\sigma(x,y)\nabla_h \hat{\mathbf{T}}(y)| + \epsilon};$$
$$\mathbf{W}_v(x) \leftarrow \sum_{y \in \Omega(x)} \frac{G_\sigma(x,y)}{|\sum_{y\in\Omega(x)} G_\sigma(x,y)\nabla_v \hat{\mathbf{T}}(y)| + \epsilon}, \quad (12)$$

Where *Gσ (x, y)* is given by the Gaussian kernel with the standard deviation *σ*. *Gσ (x, y)* is given by

$$G_\sigma(x,y) \propto \exp\left(-\frac{\operatorname{dist}(x,y)}{2\sigma^2}\right), \quad (13)$$

Where (x,y) is used to measure the spatial euclidiean distance between locations x and y. The second one is the instance of this one.W needs to be calculated only once.

2.4 Other Operations

Having the refined illumination map **T,** we can recover the **R** by considering(3). We can also manipulate the illumination map through gamma transformation, say **T T**γ. we can put γ to 0.5, 0.8 and 1 for different results. We adopt γ = 0.8 in order to eliminate the possible noises for low light images. Denoising techniques are used to improve the visual quality. We consider the BM3D technique to reduce the noise in enhanced image. We execute thBM3D on y channel by changing RGB into YUV colorspace. Different patches can be treated as equally by BM3D. Dark regions are denoised and brighter region are over smoothed, to avoid this process of imbalance, we employ the operation given below.

$$\mathbf{R}f \leftarrow \mathbf{R} \circ \mathbf{T} + \mathbf{R}d \circ (1 - \mathbf{T}), \qquad (14)$$

Where **R**d and **R**f are the results after denoising and recomposing, respectively. The post processing techniques for any low light images are denoising and recomposing.

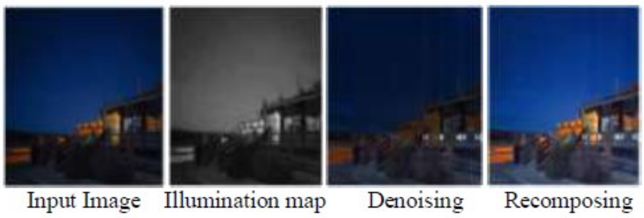


Figure 2. Each step of LIME

Algorithm: LIME

Input: Low light image L and gamma transformation parameter.

Initialization: Construct a weight matrix by Eq. (10)

Do the job

1. Find initial illumination map $T^{\wedge}$ on L using Eq. (2)
2. Refine illumination map T based on $T^{\wedge}$ by sped-up solver method using Eq. (9)
3. Apply gamma correction on T via T← 7
4. Enhance L using T by Eq. (1)
5. If denoising and recomposing needed, then denoise R by using BM3D and recompose by Eq. (14)

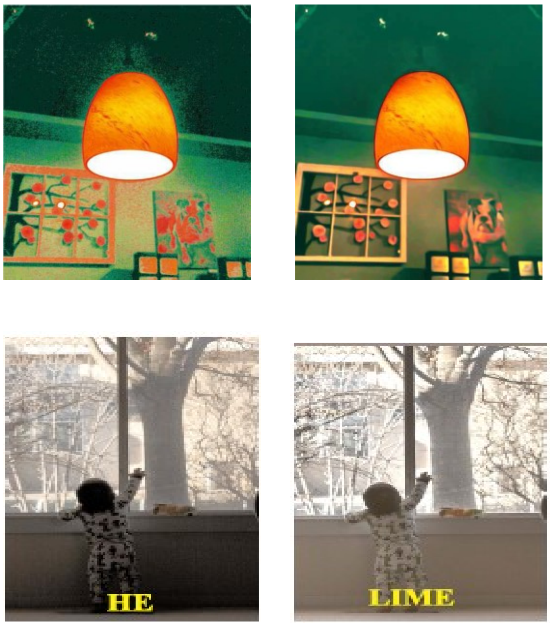
Output: Final enhanced result.

III. EXPERIMENTAL RESULTS

Here we compare our proposed method with the Histogram equalization and see the effects of parameters. The fig(2) shows the steps involved in LIME. The information is not visible in the low light images and noise present. By using LIME method we can extract the information hidden in the low light image and noise also reduced. In order to remove the noise component we use the denoising process. Then we can see the improvement in the low light image in term of visible quality. The lightness order error (LOE) gives the performance of the low light image enhancement. In order to preserve the naturalness of the images we are using lightness order error(LOE). The enhanced image contains the naturalness, which is related to the relative order of lightness. It represents the directions of light sources and the variations in the lightness. Therefore, we consider the lightness order error (LOE) as our objective metric to measure the performance.

$$LOE = \frac{1}{m}\sum_{x=1}^{m}\sum_{y=1}^{m}\left(U(\mathbf{Q}(x),\mathbf{Q}(y)) \oplus U(\mathbf{Q}_r(x),\mathbf{Q}_r(y))\right) \qquad (15)$$

where m is the pixel number. The function $U(p, q)$ returns1 if $p >= q$, 0 otherwise. $\oplus$ stands for the exclusive or operator. In addition, $\mathbf{Q}(x)$ and $\mathbf{Q}r\ (x)$ are the maximum values among R, G and B channels at location x of the enhanced and reference images, respectively. In order to maintain the better enhancement to preserve the naturalness of the lightness we have to maintain low LOE. When no enhancement is performed the value of LOE is 0. To reduce the complexity we set resize factor r to 100/min(h,w), where h represents the height and w represents the width of the image. By considering the below image we can say that the method we are using low light image enhancement is the best one to enhance the low light images.



(a) HE (b) LIME

Figure 3. Comparison of LIME with HE

Table 1. Quantitative Performance Comparison On The Hdr Dataset In Terms Of Loe. Loe Has A Factor 103.

Image name	LIME	HE
Light	2.513	3.759
Baby at window	3.263	4.536

IV. CONCLUSION

In this paper, we have proposed the efficient technique to enhance the low light images. Illumination map is estimated to enhance the low light images. The illumination consistency is maintained by considering structure-aware smoothing model. We have designed a algorithm to solve the problem with significant saving of time. The experimental results have revealed the advance of our method compared with the existing methods. This method can feed many vision-based applications, such as edge detection, object recognition and tracking with high visibility inputs, and thus improve their performance.

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