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Illumination Map Estimation Based Low Light Image Enhancement Using Sped up Solver Method

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***Abstract*— Nowadays digital images are used in several applications. It is used in almost every area in our life and technology. To improve the quality of an image, image enhancement plays a major role. Enhancing the low light image is a critical process. In this paper, we propose a simple technique called Low light image enhancement(LIME). In this, first we find the maximum value of each pixel by separating the R, G and B channels as a initial illumination map. Further, we refine the illumination map by imposing a structure prior as the final illumination map. Depending upon the gamma values, we tune the final illumination map for good quality of an image. The noise can be removed by using BM3D method. For a low light image enhancement, the objective assessment is Lightness order error(LOE), which represents the light directions and lightness variations. However, for the good quality of an image in the image enhancement, naturalness is essential. Comparing with the other techniques, LIME is superior in terms of image enhancement quality and efficiency.**

***IndexTerms*— Illumination estimation, Illumination Transmission, Low light image enhancement.**

I. INTRODUCTION

Digital scenes are used in many applications like object detection and tracking [1], medical applications and many other PC based applications. Pictures captured during day time having a good visibility with high dynamic range and useful for extracting the details. But the pictures captured during night time or in low light condition having a low dynamic range with noise and indistinguishable details. In poor light condition, image degradation can takes place, it not only affect the recognition of the human eye but also affect the performance in the computer based application. To improve the quality of an image, image enhancement can takes place. This gives the essential details of the information, to analyze and understand the object behavior. For one thing, the low light pictures are good. For another thing, it can affect the performance of many algorithms that are designed for high visibility inputs. Fig.1 shows such examples, from which we can see many details which are hidden in poor light condition. To make the hidden details visible, low light image enhancement is definitely demanded.

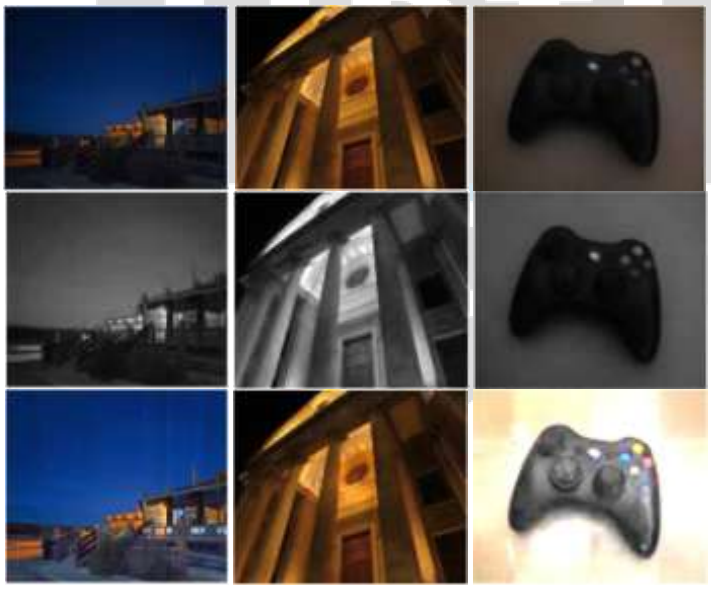

Fig.1: Top Row: Low-light images. Middle Row: Illumination maps for input image. Bottom Row: The results enhanced by Sped-up solver method.

II. METHODOLOGY

The formation of a low light image is explained by following Retinex model [3].

$$L = R \circ T \quad (1)$$

where L represents the captured image and R represents the desired recovery. T represents the illumination map and $\circ$ operator is element-wise multiplication. In this proposed technique, we assumes, for color images, three channels share the same illumination map. From the Eq. (1), it tells that the observed image is decomposed. The decomposed image consists of the product of desired light enhanced image and illumination map [2]. In the intrinsic image decomposition, the reference image is decomposed into two components. In the intrinsic image decomposition method, the reflectance component is recovered. By taking only reflectance component, it losses the shape of an image so it does not satisfy the purpose of low light image enhancement. In this work, we are expecting to recall the visual content of dark region as well as keep the visual realism. But, if the task is just to lighten the low light image, it is not required to decompose the input image into two components. Just by transforming the Eq. (1) we have $R = L/\hat{T}$, where the division is element wise. The estimation of T is key factor for recovering the R. The problem is simplified in this way. Only demanding the estimation of T. Here we notice that $L/\hat{T}$ can directly act as the enhanced result.

2.1 Illumination Map Estimation

In the color constancy methods, find the illumination of each pixel, estimated by taking maximum value of R, G and B channels. But this estimation can only amplify the global illumination. Here we have to handle the non-uniform illumination. The initial estimation is given by Eq. (2)

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

For each individual pixel x. The principle behind using this operation is, at a certain location, illumination is at least the maximum value of the 3-channel. The obtained T(x) assures that the recovery will not be saturated, because of Eq. (3)

$$R(x) = L(x) / \left(\max_c L^c(x) + \in \right) \quad (3)$$

Where $\in$ is a very small value to neglect zero denominator. The main aim of this work is to enhance the non-uniformly illumination of the low light scene, instead of excluding the color shift caused due to light sources. In this work, with reference to Eq. (2), initially find the estimate illumination map T, several methods have been introduced to improve the accuracy. The local consistency of illumination is considered by taking neighboring pixels within a small region surrounded by target pixel. The two representations are given by the Eq. (4) and (5)

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

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

where (x) is a region centered at pixel x and y is the location index within the region. These methods increase the local consistency, but they are structurally blind. A good solution continuously preserve the general structure and details. This issue is addressed based on the initial illumination map $\hat{T}$, we proposed a technique to solve the following optimization problem given in Eq. (6)

$$\min_T \left\| \hat{T} - T \right\|_F^2 + \alpha \left\| W \circ \nabla T \right\|_1 \quad (6)$$

where α is the coefficient which balances the two terms and $\|\cdot\|_F$ and $\|\cdot\|_1$ indicates the Frobenious and l_1 norms respectively. W is the weight matrix and ∇T is the first order derivative filter. In Eq. 6, the first term take cares the fidelity between the initial map $\hat{T}$ and the exact one T. Smoothness is represented by second term. Eq. (6) is solved by Sped-up solver method.

2.2 Sped up Solver Method

Consider Eq. (6). The origin gives the iterative procedure is the sparse weighted gradient, i.e. $\|W \circ \nabla T\|_1$. The l_1 norm together with the gradient operation on T makes it complex. Therefore the relationship holds good as given in Eq. (7)

$$\lim_{c \leftarrow 0^+} \sum_x \sum_{d \in \{h,v\}} \frac{W_d(x)\left(\nabla_d T(x)\right)^2}{\left|\nabla_d T(x)\right| + \varepsilon} = \|W \circ \nabla T\|_1 \quad (7)$$

With reference to the above, we use $\sum_x \sum_{d\in\{h,v\}} \frac{W_d(x)(\nabla_d T(x))^2}{|\nabla_d T(x)|+\varepsilon}$ to approximate $\|W \circ \nabla T\|_1$. The approximate problem to (6) is written as given by the Eq. (8)

$$\min_T \left\| T - \hat{T} \right\|_F^2 + \alpha \sum_x \sum_{d\in\{h,v\}} \frac{W_d(x)(\nabla_d T(x))^2}{|\nabla_d T(x)|+\varepsilon} \quad (8)$$

Compared to the original, the objective function changes, the aim of extracting the structure of illumination from the initial illumination estimate $\hat{T}$ is consistent with the original. Specifically, when $\left|\nabla_d \hat{T}(x)\right|$ is small. $|\nabla_d T(x)|$ is to be suppressed. So the value $\frac{(\nabla_d T(x))^2}{|\nabla_d T(x)|+\varepsilon}$. In other words, the target T is constrained to avoid creating gradients where the initially estimated illumination map has small magnitude of gradient. In contrary, if $|\nabla_d T(x)|$ is strong, the above suppression alleviates, because this location is more likely on structure boundary than on regular texture. As observed, the problem Eq. (8) contains only the quadratic terms. Thus, this problem can be obtained by solving the following Eq. (9):

$$\left(I + \sum_{d\in u,v} D_d^t Diag(\tilde{w}_d) D_d \right) t = \hat{t} \quad (9)$$

where $\tilde{w}_d$ is the vectorized version of $\tilde{W}_d$ with $\tilde{W}_d(x) \leftarrow \frac{w_d(x)}{\left|\nabla_d \hat{T}(x)\right|+\varepsilon}$. Further, the operator Diag(x) is to construct a diagonal matrix using vector x. Since $\left(I + \sum_{d\in\{u,v\}} D_d^t iag(\tilde{w}_d) D_d \right)$ is a symmetric positive definite Laplacian matrix, there are many techniques are available for solving it [5] [6].

2.3 Weighting Strategy

The key design is W for the structure-aware refinement on the initial illumination. Here we are using the strategy as follows.

Strategy I: By setting the weight matrix as defined by the Eq. (10)

$$W_h(x) \leftarrow 1; W_v(x) \leftarrow 1 \quad (10)$$

2.4 Other Operations

Having the refined illumination map T, we can recover R by Eq. (3). It can also manipulate the illumination map using gamma transformation, $T \leftarrow T^{\gamma}$. From Fig.2 we can see the difference between the results by γ =0.5, 0.8 and 1. In this experiment, we adopt γ =0.8. It can also reduce the noises previously hiding in the dark region especially for the very poor light images. To improve the visual quality of the image denoising techniques are used, To remove the noise in the enhanced image, we chosen BM3D technique[7]. In our implementation, we execute BM3D on the Y channel by changing over from the RGB into YUV colorspace. BM3D treats different patches equally. Dark regions are well denoised and brighter region are over smoothed, to avoid this process of imbalance, we employ this operation

$$R_f \leftarrow R \circ T + R_d \circ (1-T) \quad (11)$$

Where R_d indicates denoising and R_f indicates recomposing respectively. For any low light pictures enhancing technique, denoising and recomposing are the post processing steps.

Fig.2 Gamma Correction for different values 0.5, 0.8, 1

Fig.3 Each step of LIME

Algorithm 1: *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 $\hat{T}$ on L using Eq. (2)
2. Refine illumination map T based on $\hat{T}$ by sped-up solver method using Eq. (9)
3. Apply gamma correction on T via $T \leftarrow T^{\gamma}$
4. Enhance L using T by Eq. (1)
5. If denoising and recomposing needed, then denoise R by using BM3D and recompose by Eq. (11)
Output: Final enhanced result

III. Experimental Results

In this section, we compare our method with Histogram Equalization (HE) and see the effects of parameters involved. Fig. 3 shows the each step of LIME. The very low light input image hides information and intensive noise in the dark. After performing the LIME, the details of image get enhanced, noise is also come out. This is inevitable problem in all the low light image enhancement methods. Denoising is necessary for removing the noise component. From which, we can see the improvement in terms of visual quality of a low light image. To measure the performance of a low light image enhancement, the objective parameter is Lightness order error (LOE) [4]. LOE is used to preserve the naturalness of an image. The naturalness of an enhanced image is related to the relative order of lightness represents the light source directions and lightness variation in different local regions. LOE can be defined as follows:

$$LOE = \frac{1}{m}\sum_{x=1}^{m}\sum_{y=1}^{m}\left(U\left(Q(x),Q(y)\right)\oplus U\left(Q_r(x),Q_r(y)\right)\right) \tag{12}$$

where m is the pixel number. The function U(p,q) returns 1 if P >= q, 0 otherwise. $\oplus$ is the exclusive-or operator. In addition $Q(x)$ and $Q_r(x)$ are the maximum values of R,G and B channels at location of the enhanced and reference images respectively. To preserve the naturalness of lightness of the enhanced image LOE must be lower. From the definition of LOE, Q_r plays a important role for measuring the quality of enhancement. Using the low light image for input as problematic, because at extreme case LOE is 0 when no enhancement is performed. It is difficult to construct such datasets, for the sake of objectiveness, we have to choose a reliable a datasets. Table I shows a LOE of a different images compare with the HE. Fig. (4) From that, we observe our method is efficient compare to the others. The results obtained by LIME are more visually pleasant.

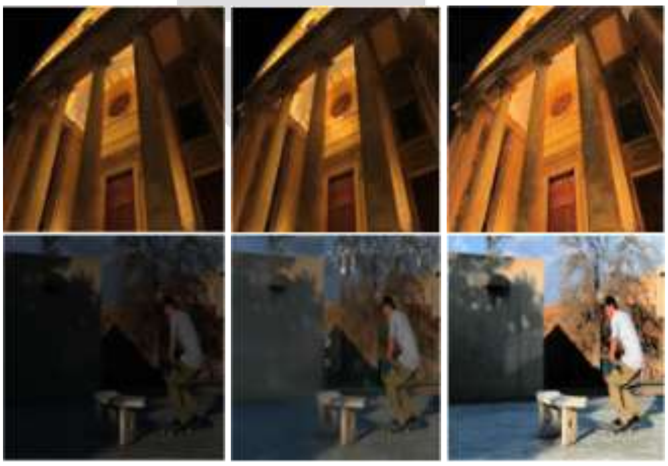

Fig.4 Visual comparison of LIME and HE

TABLE I
QUANTITATIVE PERFORMANCE COMPARISON ON THE IMAGE DATASET IN TERMS OF LOE

Image Name	LIME	HE
Church wall	1.8652	4.0762
Skater	2.7480	3.8535

IV. Conclusion

In this paper, we have proposed efficient technique to enhance the poor light pictures. The key design of enhancing the poor light pictures is based on constructing the illumination map. To improve the consistency of illumination, we are using a refine illumination map(Sped-up solver). This approach preserves the naturalness in all local regions of the resultant image. So lightness order error is small. Our low light image enhancement method can feed to many vision based application such as edge detection and object recognition and tracking.

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