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Low-light image enhancement method based on Non-Local means using illumination map estimation

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ABSTRACT- When an image was taken from low light withnoisy condition, this image suffers from low visibility and information loss due to noisy condition. To recover the poor quality of the image, we recommend a new method such as Low-Light image enhancement based on Non local means using illumination map method. In this method is used to overcome low light condition of the image and recover information from low light noisy image.In an image information was recovered by using Non local means (NLM)filter insteadof Block matching and three dimensional (BM3D)filter in the projected method. The NLM filter is efficient for the removal of noise from an image, So the NLM is shows better performance than other enhancement filters.

Keywords: Illumination Estimation, Non local means, BM3D filter

INTRODUCTION

The digital images are look like degrading in nature, when the image is taken under low light condition. Hence the image should be enhanced.Image enhancement plays an primary role in image processing. The target of image enhancement is to support the visibility of low-contrast elements [16]. It improves digital quality of image. Image has in the community various statistics, has exceptional edges and smoothness init.These Subtle variations in brightness value may be highlighted either with the aid of: Contrast change or by using assigning quite extraordinary hues to those degrees (density cutting). Point operations alternate the value of every character pixel independent of all other pixels. Local operations trade the value of character pixels in the context of the values of neighboring pixels.The most important goal of image enhancement is a processing on an image so that you can make it extra appropriate for distinct packages. Image enhancement generally sharpensimage factors including to barriers, edges or contrasts and decreases the ringing artifacts. The enhancement improves the excellent of the images in order that the information contained in them will be extracted in a meaningful experience. The satisfactory problem in image enhancement is quantifying the criterion for enhancement and because of this, an substantial variety of image enhancement strategies are empirical and require interactive techniques to collect best result. In order to enhance the low light images there are many techniques such as Histogram equalization, CVC [1], LDR [2], gamma correction, Retinex theory of single scale and multi scale Retinex [3] [4] [5]which explains about the image factors such as illumination and reflectance. The above Retinex methods focus on reflectance leads to over enhance. Next, a image enhancement via illumination map based on BM3D [15] technique a highly engineered Gaussian image denoising algorithm is implemented. Finally, image enhancement via illumination map based on NLM is proposed to increase the image quality and to remove the blur than the previous techniques. TheNLM process is relevant for a kind of restoration task in image restoration process, by using suitable response force. In these paper we lookout the capabilities of Gaussian image denoising, applications to show our proposed process mostly better than other. In the end lead to the high-quality, performance on usual experiment datasets for the confirmed applications.

RELATED WORK

The image consists of mainly two components namely illumination and reflectance component. The existing system concentrates on illumination component which is Image Enhancement via Illumination map based on the block matching and 3D filtering (BM3D). When both illumination and reflectance factor are consider for the enhancement process , information loss is occur due to this problem, only illumination factor is consider for the enhancement. The flow chart for the enhancement of image using BM3D is

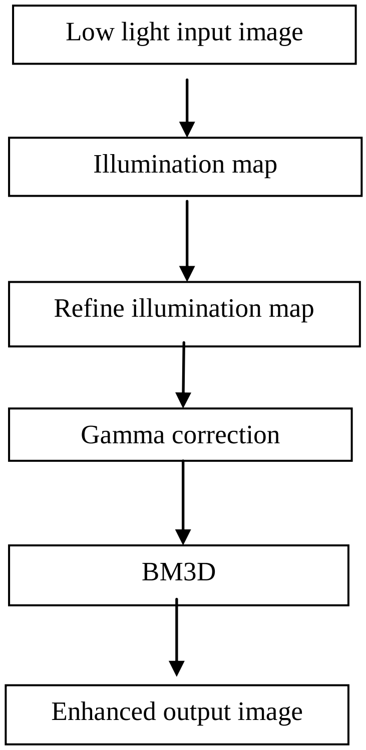

Fig1.flow chart for enhancement using BM3D

1. Original Image

The original image is an image captured for the duration of the low mild conditions .This is given as an input to our approach for further enhancement. The original image consists of illumination component which is to be considered to obtain the illumination map. The basic structure of the image is as follows:

$$L= R_0T \qquad (1)$$

Where, L represent input image and R represent recovered image. T is the illumination map. Hence through locating the illumination map we will recover the improved image as

$$R= L / T \qquad (2)$$

2. Illumination Map

The illumination map can be obtained from two methods, estimating the maximum R, G, B values from each pixel of the image, then the transmission map and recovered image are as follows:

$$T'(x) = \max L^c(x), \text{where } c \in \{R,G,B\} (3)$$

$$R(x)= L(x) / (\max L^c(x) + e) \ (4)$$

Another extensively used technique is rely on inverted low light pixel 1-L which might be just like haze image graphs [6] [7] [8]. In this model we use dark channel prior to construct transmission map. The recovered image and transmission map of this model is given below:

$$T'(x) = 1\text{-}\min\frac{1-L^c}{a} = 1\text{-}\frac{1}{a} + \max\frac{L^c(x)}{a} (5)$$

$$R(x) = \frac{L(x)-1+a}{(1-\frac{1}{a}+\max\frac{L^c(x)}{a}+e)} + (1-a) (6)$$

For simplifying the computation we consider a target pixel surrounded by neighboring pixel within a small region. This can be represented as

$T'(x) = \max [\ \max L^c(y)]$ where $c\epsilon$ {R,G,B},$y\epsilon\Omega(x)$

This model enhances the local consistency but they are structure blind. A solution is provided to preserve the structure. We notice this problem, socan we suggest to solve the following optimization problem:

$$\text{Min}\left\|T' - T\right\|_F^2 + \alpha\|W \circ \nabla T\|_l (7)$$

3. REFINE ILLUMINATION MAP

To resolve the above problem we provide two techniques such as exact solver and speed up solver [9] [10] [11] [12]. In Exact solver the terms T, G, Z, μ is derived by extracting terms from the augmented Lagragian function. The obtained T, G, Z ,μ values are as follows:

$$T^{t+1} = F^{-1}\left(\frac{F\left(2T' + \mu^{(t)}D^T\left(G^{(t)} - \frac{Z^{(t)}}{\mu^{(t)}}\right)\right)}{2+\mu^{(t)}\sum_{d\epsilon\{h,\vartheta\}}\overline{F(D_d)}\circ F(D_d)}\right) (8)$$

$$G^{t+1} = S_{\frac{aw}{\mu^{(t)}}}\left[\nabla T^{(t+1)} + \frac{Z^{(t)}}{\mu^{(t)}}\right] \qquad (9)$$

$$Z^{(t+1)} = Z^{(t)} + \mu^{(t)}(\nabla T^{(t+1)} - G^{(t+1)}) \quad (10)$$

$$\mu^{t+1} = \mu^{(t)}\rho \qquad (11)$$

For Speed up solver we derive a constant term

$$t' = t(I + \sum_{d\in\{h,\vartheta\}} D_d^T \text{Diag}(w_d) D_d) \qquad (12)$$

To minimize the iterations that are used in exact solver. Finally W(weight matrix) is obtained from different strategies [13] [14]. Finally the illumination map is obtained by using the above terms.

4. Gamma Correction

Gamma correction technique is well performed when we want to display the low light image exact in nature. By using Gamma correction, intensityof an imagecan be adjusted automatically. Images which aren't correctly modified, it canappear as decolorized or darkish. To recover R,G and B channels of an image correctly, the gamma required some other additional capabilities. Changing the value of gamma correction, it is not only varying the brightness, but also variesthe color channel.The gamma correction is apply to estimated illumination map with different gamma values such as γ_1 = 0.5, γ_2 = 0.8, γ_3 =1. It is used to enhance the captured image according the equation R=L/T.

5. Block Matching 3d Filter (Bm3d)

The enhanced image is of low quality due to presence of noise. For denoising the image we use BM3D [15] technique. In this manner the image fragments are grouped collectively located on similarity, however in comparison to not unusual k-means clustering and such cluster evaluation techniques, the image fragments aren't normally disjoint. This block-matching set of regulations is computationally annoying and is beneficial later-on inside the aggregation step. Fragments do however have the equal size. A fraction is grouped if its dissimilarity with a reference fragment falls below a specific threshold. This grouping system is referred to as block-matching.

Filtering is performed on every fragments group. A dimensional linear transform is carried out, accompanied with the useful resource of manner of alternate into area shrinkage much like Wiener filtering, after which the linear turn out to be is inverted to breed all (filtered) fragments. The image is changed once more into two-dimensional shape. All overlapping image fragments are weight-averaged to make sure that they may be filtered for noise however preserves their distinct signal. But in our method we implement BM3D only on y channel by replacing R from the RGB color space into the YUV. To avoid unbalancing of processing we employ the recomposing technique.

In BM3D the algorithm uses fixed threshold in grouping step, because of these overlarge distancein black-matching occur, when noise level is low. And BM3D can't get similar blacks, when noise level is high. So that sharp drop in denoising and block effect appears.Finally the enhanced desired output is obtained from the image captured in low light with minimum amount of noise.

METHODOLOGY

In the proposed method,output of the gamma correction having noise in an image, by using NLM technique the presented noise is removed. The flow chart for the proposed method is given below:

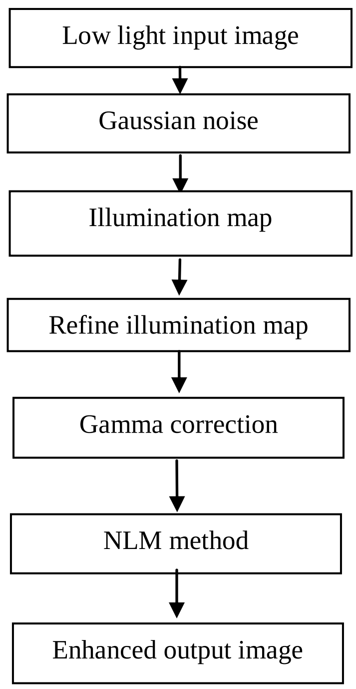

Fig.2 Proposed system flow chart

In this method an image captured during low light conditions is given as an input and apply the Gaussian blur. The illumination map is obtained by acquiring maximum R, G, B components from the image or by using the dark channel prior for the haze image [15]. The structure blind problem obtained during the enhancement of local consistency is rectified by providing a optimized solution solved through two process namely, Exact solver and Speed up solver.Generally, speed up solver is used to minimize the computational speed. By computing T, G, Z, µ values an illumination map is designed. The gamma correction is done for the illumination map to enhance the map. The recovered image acquisition is processed by dividing the each element of the captured image using the original image. The recovered image consists of blur and has low quality. For debluring the image NLM technique is used in the proposed system.

1. NLM(Non Local Means)

The methodology of NL-means out became once delivered via Bauds based mostly on non-nearby averaging of all pixels within the image. The method is used to debluring an image fromdegrade with Gaussian noisy image.

The NL-means filter technique is rely mostly on estimating each and every pixel intensity of the image and thus it exploits the redundancy added on due to the presence of comparable designs and elements inside an image. The NLM method is used to recovered grey scale value of every single image is received via average of weights in the gray scale, its values of every pixel within the image. The allocated weights were proportional to the similarity among the community regional of the pixels were taken. The local much like one in an image have all kind pixels.

Discrete noise image v= v(i) for a pixel I is given the anticipated value of NL[v](i) is calculated. The weighted common of every pixel i.e.,

$$\text{NL [v] (j)} = \sum_{j\in i} w\ (i, j\ ).\,v(\ i) \qquad (13)$$

The likeness among the pixels i and j rely on the own family of weights w(i,j).The likenessamong pixels i and j relies upon the likeness of the intensity gray degree vectors $V(N_i)$ and $V(N_j)$, wherein $N_k$represents a rectangular local of constant measurement and focused at a pixel . The likeness is measured as a reducing function $V(N_i)-V(N_j)$ wherein a > zero is the same old deviation of the Gaussian kernel.
In an image gray stage neighborhood to $V(N_i)$, perform same among the pixels. , it consists of large weights in the neighborhood. These weights are represented as,

$$W\ (\ i, j\ ) = \frac{1}{Z(i)} e^{-\frac{\|v(Ni)-v(Nj\ )\|^2}{h^2}} \qquad (14)$$

In the above equation Z(i) act as normalizing steady and h represent as measure of filtering. It controls the falling-off the exponential perform, because of this the falling-off the weights act as feature of the Euclidean distances.Finally the improved deblur image is extracted with excessive quality.

2. Non Local Means vs BM3D

In the NLM method, the algorithm analyze huge amount of data and keep the entire image as similar features. But in the BM3D method fixed threshold is used, because of these over large in black matching and similar blacks doesn't occur due to low and high noise present. In BM3D apply on y channel only so the unbalancing occurs, where as in NLM is applicable on both channels.The computation and memory complexity only relate to the number of pixel in NLM method. BM3D and NLM both are used as denoising technique but in image restoration process NLM perform better than the BM3D.

RESULTT

1. **Low light input image:** The input image is taken from the low light condition, so the image lose the information from the dark region.

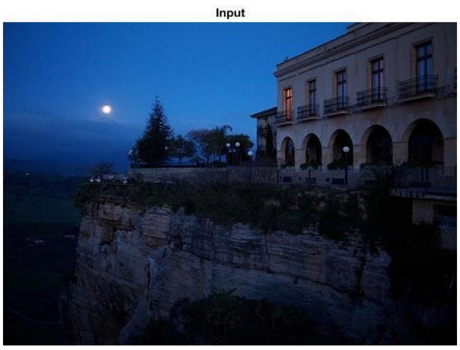

Fig 3.Low light input Image

2. **Blured and low light image:** The Gaussian noise is applied to the input image of the proposed system, after gaussian noise is applied the image is goes under blured nature.

Fig4. Blurred and low light image

3. **Illumination Map:** The illumination map is estimated by using maximum values of R,G and B channel. After illumination map is estimated using speedup solver and Exact solver refine illumination map is estimated at certain weight stretegy.

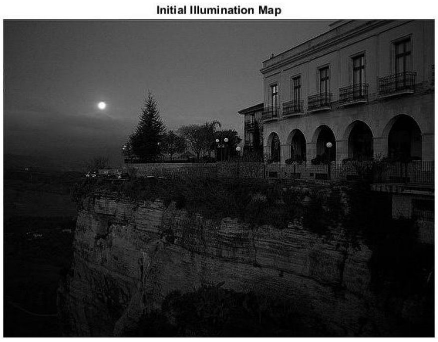

Fig 5. initial Illumination Map

4. **BM3D Enhancement output:** The output of the BM3D enhancement filter the image shows as the oversmoothed and information is recover partially.

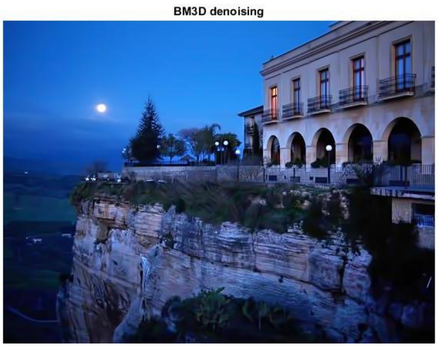

Fig 6. BM3D desoining

5. **NLM Enhanced output:** The output of the NLM enhancement, gaussian noise is removed and information is recoverd efficently.

Fig 7.Enhanced result

TABLE 1

Performance Metrics OfBM3D And NLM

Parameters	BM3D	NLM
PSNR	54.33	63.80
MSE	0.24	0.02

CONCLUSION

This paper offers the Non Local Means (NLM) technique which proves to be higher for enhancing the low light image. The experimental effects have discovered the improvement of our approach in assessment with several contemporary options. Itis high excellent That our low-moderate image enhancement approach can feed many vision-based completely packages, which includes face detection, characteristic matching, item recognition and tracking, with high visibility inputs, and therefore enhance their universal typical overall performance.

REFERENCES

[1] T. Celik and T. Tjahjadi, "Contextual and variational contrast enhancement,"TIP, vol. 20, no. 12, pp. 3431–3441, 2011.

[2] C. Lee and C. Kim, "Contrast enhancement based on layered differencerepresentation," TIP, vol. 22, no. 12, pp. 5372–5384, 2013.

[3] E. Land, "The retinex theory of color vision," Scientific American,vol. 237, no. 6, pp. 108–128, 1977.

[4] D. Jobson, Z. Rahman, and G. Woodell, "Properties and performanceof a center/surround retinex," TIP, vol. 6, no. 3, pp. 451–462, 1996.

[5] D. Jobson, Z. Rahman, and G. Woodell, "A multi-scale retinex forbridging the gap between color images and the human observation ofscenes," TIP, vol. 6, no. 7, pp. 965–976, 1997.

[6] K. He, J. Sun, and X. Tang, "Single image haze removal using dark channel prior," TPAMI, vol. 33, no. 12, pp. 2341–2353, 2011.

[7] S. Narasimhan and S. Nayar, "Contrast restoration of weather degraded images," TPAMI, vol. 25, no. 6, pp. 713–724, 2003.

[8] G. Meng, Y. Wang, J. Duan, S. Xiang, and C. Pan, "Efficient image dehazing with boundary constraint and contextual regularization," in CCV, pp. 617–624, 2013.

[9] Z. Farbman, R. Fattal, D. Lischinski, and R. Szeliski, "Edge-preserving decomposition for multi-scale tone and detail manipulation," TOG,vol. 27, no. 3, 2008.

[10] D. Krishnan and R. Szeliski, "Multigrid and multilevel preconditioners for computational photography," TOG, vol. 30, no. 6, 2011.

[11] A. Levin, D. Lischinski, and Y.Weiss, "Colorization using optimization,"TOG, vol. 23, no. 3, pp. 689–694, 2004.

[12] D. Lischinski, Z. Farbman, M. Uyttendaele, and R. Szeliski, "Interactive local adjustment of tonal values," TOG, vol. 25, no. 3, pp. 646–653,2006.

[13] S. Chan, R. Khoshabeh, K. Gibson, P. Gill, and T. Nguyen, "An augmented lagrangian method for total variation video restoration," TIP, vol. 20, no. 11, pp. 3097–3111, 2011.

[14] L. Xu, Q. Yan, Y. Xia, and J. Jia, "Strucutre extraction from texture via relative total variation," TOG, vol. 31, no. 6, pp. 139:1–139:10, 2013.

[15] K. Dabov, A. Foi, V. Katkovnik, and K.Egiazarian, "Image denoising by sparse 3d transform-domain collaborative filtering," TIP, vol. 16, no. 8, pp. 2080–2095, 2007

[16] Y. Li, F. Guo, R. Tan, and M. Brown, "A contrast enhancement framework with jpeg artifacts suppression," in ECCV, pp. 174–188,2014.