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Trainable Nonlinear Reaction Diffusion (TNRD) based Low Light Image Enhancement

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ABSTRACT

In the present days, digitalised images are used in various applications. For these applications the images should have more quality. But, images captured in low light conditions are with low visibility and highly degraded. To improve the poor quality of the image, we proposed a novel technique named Low light image enhancement through Trainable Non-reactive Reaction Diffusion (TNRD). This technique is largely benefited from the training of the parameters and finally lead to the best reported performance on common test data sets for the tested applications. Our trained models preserve the structural simplicity of diffusion models and take only a small number of diffusion steps, thus they are highly efficient.

Keywords : Illumination Estimation, Illumination (Light) Transmission, Low light Image Enhancement.

I. INTRODUCTION

Digital Image systems are traditionally bad in low light conditions because lacking in natural light-source leads to low-contrast and blurs in image. Hence the image should be enhanced. Image enhancement plays an important role in the field of Image processing. The objective of image enhancement is to improve the visibility of low-contrast features. It improves digital quality of image. Image has locally varying statistics, which has different edges and smoothness in it. These Subtle differences in brightness value can be highlighted either by: Contrast modification or by assigning quite different colors to those levels (density slicing).

- Point operations change the value of each individual pixel independent of all other pixels.
- Local operations change the value of individual pixels in the context of the values of neighboring pixels.

The main objective of image enhancement is a processing an image in order to make it more appropriate for certain applications. Image enhancement mainly sharpens image features such as boundaries, edges or contrasts and reduces the ringing artifacts. The enhancement improves the quality of the images so that the information contained in them could be extracted in a meaningful sense. The greatest difficulty in image enhancement is quantifying the criterion for enhancement and due to this, a large number of image enhancement techniques are empirical and require interactive procedures to obtain satisfactory results. In order to enhance the low light images there are many techniques such as Histogram equalization, CVC, Low dynamic range, gamma correction, Retinex theory of single scale and multi scale Retinex which explains about the illumination and reflectance components of an image. The above Retinex methods focus on reflectance leads to over enhancement. Next, an image enhancement via illumination map based on BM3D technique is a highly engineered Gaussian image denoising algorithm. Finally, image enhancement via illumination map based on TNRD is proposed to increase the image quality than the previous techniques. The TNRD approach is applicable for a variety of image restoration tasks by incorporating appropriate reaction force. We demonstrate its capabilities with three representative applications, Gaussian image de-noising, single image super resolution and JPEG de-blocking. Experiments show that our trained nonlinear diffusion models largely benefits from the training of the parameters and finally lead to the best reported performance on common test data sets for the tested applications.

II. EXISTING METHOD

The image consists of mainly two components namely illumination and reflectance component. The existing system concentrates on illumination component which is an Image Enhancement via Illumination map based on the block matching and 3D filtering (BM3D). The block diagram for the existing method is as follows:

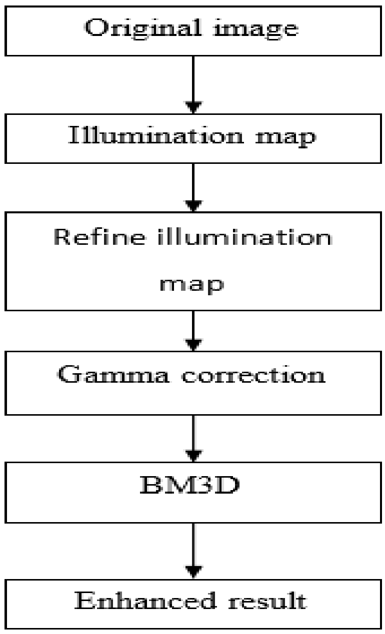

Figure 1 : Block diagram of existing method

i. Original Image:

The original image is the image captured during the low light conditions. This is given as an input to our method 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:

$$L = R*T$$

Where, L and R are the captured and recovered image. T is the illumination map. Hence by finding the illumination map we can recover the enhanced image as R= L / T.

ii. 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:

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

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

Another widely used model is based on inverted low light images 1-L which are similar to haze images. In this model we use dark channel prior to construct transmission map. The recovered image and transmission map of this model is given below:

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

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

For simplifying the computation we consider neighboring pixels within a small region around target pixel.

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. To address this issue, we propose to solve the following optimization problem: $\min\|T' - T\|_F^2 + \alpha\|W \circ \nabla T\|_l$

iii. Refine Illumination Map:

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

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

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

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

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

For Speed up solver, we derived a constant term $t' = t(I + \sum_{d \in \{h,\vartheta\}} D_d^T \mathrm{Diag}(w_d) D_d)$ to minimize the iterations that are used in exact solver. Finally W (weight matrix) is obtained from different strategies. Finally the illumination map is obtained by using the above terms.

iv. Gamma Correction:

Gamma correction matters if you have any interest in displaying an image accurately on a computer screen. Gamma correction controls the overall brightness of an image. Images which are not properly corrected can look either bleached out, or too dark. Trying to reproduce colors accurately also requires some knowledge of gamma. Varying the amount of gamma correction changes not only the brightness, but also the ratios of red to green to blue. The illumination map is gamma corrected with different gamma values such as γ = 0.5, γ = 0.8, γ =1.Then gamma corrected illumination map is used to enhance the captured image according to the equation R=L/T.

v. BM3D (Block Matching and 3D Filtering):

An enhanced image is of low quality due to presence of noise. For de-noising the image we use BM3D technique. In this technique the image fragments are grouped together based on similarity, but unlike standard k-means clustering and such cluster analysis methods, the image fragments are not necessarily dis-joint. This block-matching algorithm is less computationally demanding and is useful later-on in the aggregation step. Fragments do however have the same size. A fragment is grouped if its dissimilarity with a reference fragment falls below a specified threshold. This grouping technique is called Block-matching.

Filtering is done on every fragments group. A dimensional linear transform is applied, followed by transform domain shrinkage such as Wiener filtering, then the linear transform is inverted to reproduce all (filtered) fragments. An image is transformed back into its two-dimensional form. All overlapping image fragments are weight-averaged to ensure that they are filtered for noise yet retain their distinct signal. But in our method we only execute BM3D on Y-channel by converting R from the RGB color space into the YUV. To avoid unbalancing of processing we employ the recomposing technique.

vi. Enhanced Result:

Finally the enhanced desired output is obtained from the image captured in low light with minimum amount of noise.

Disadvantages of BM3D:

1. As the algorithm uses fixed threshold in grouping step, however, when noise level is low, the maximum block-matching distance is overlarge, resulting in too much time consumption, as well as lots of unnecessary similar block.
2. On the other hand, for high noise level, the threshold value is too small, therefore BM3D can't get

enough similar blocks that leads to a sharp drop in de-noising result and that "block effect" appears.

III. PROPOSED METHOD

In the proposed method, TNRD technique is used to remove the noise from the image which is recovered from the gamma corrected illumination map. The block diagram for the proposed system is given below:

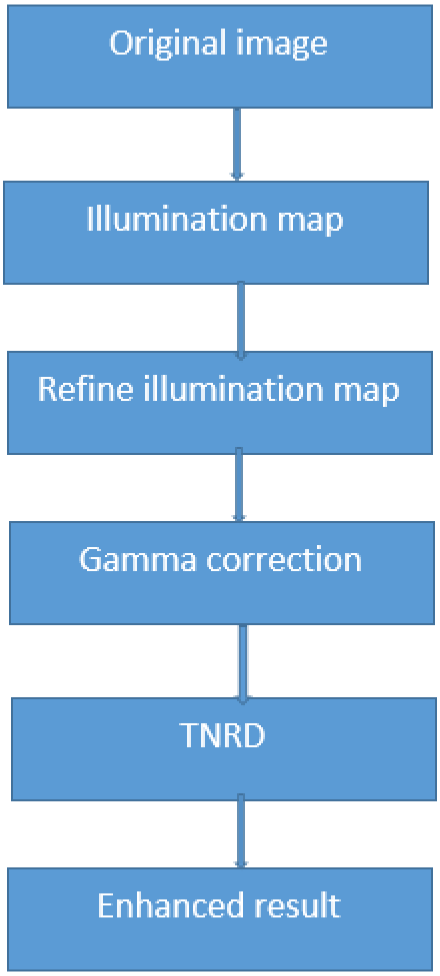

Figure 2 : Block diagram of proposed method

i. Methodology:

In this method the image captured during low light conditions is given as an input. 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. 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 noise and has low quality. For denoising the image TNRD technique is used in the proposed method.

ii. TNRD (Trainable Non-Linear Reaction Diffusion):

In this paper we concentrate on nonlinear diffusion process due to its high efficiency. Taking into consideration the improvements mentioned in existing method, we proposed a trainable nonlinear diffusion model with (1) fixed iterations (also referred to as stages), (2) more filters of larger kernel size, (3) flexible penalties in arbitrary shapes, (4) varying parameters for each iteration, i.e., time varying linear filters and penalties. Then all the parameters (i.e., linear filters and penalties) in the proposed model are simultaneously trained from training data in a supervised way. The proposed approach results in a novel learning framework to train effective image diffusion models. It turns out that the trained diffusion processes leads to state-of-the-art performance, while preserving the property of high efficiency of diffusion based approaches. The block diagram of the TNRD approach is shown below:

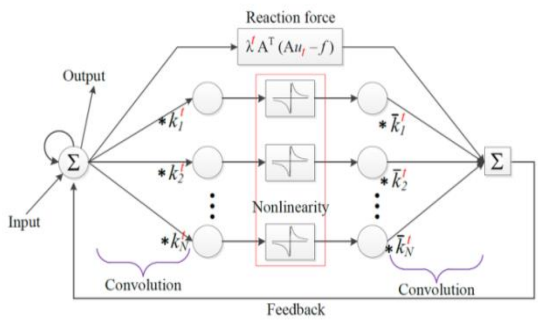

Figure 3 : Block diagram of TNRD filtering

Finally the enhanced denoised image is extracted with high quality.

Advantages:

1) It is conceptually simple as it is merely a standard nonlinear diffusion model with trained filters and influence functions;

2) It has broad applicability to a variety of image restoration problems. In principle, all the diffusion based models can be revisited with appropriate training;

3) It yields excellent results for several tasks in image restoration, including Gaussian image denoising, single image super resolution and JPEG deblocking;

4) It is highly computationally efficient, and well suited for parallel computation on GPUs.

Applications:

TNRD has wide applications in

- Image restoration process
- De-noising techniques
- Speckle Reduction

IV. RESULTS

Figure 4: Input Image

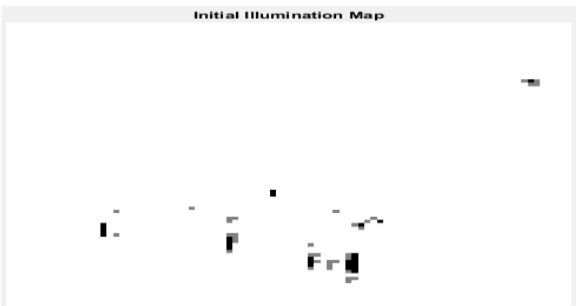

Figure 5: Initial Illumination map Image

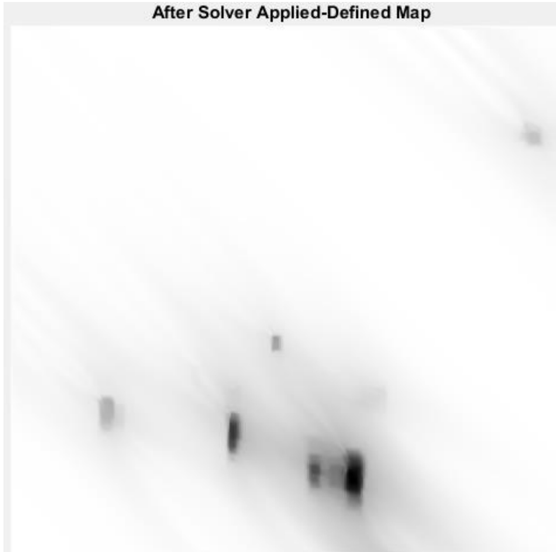

Figure 6: After solver applied defined map

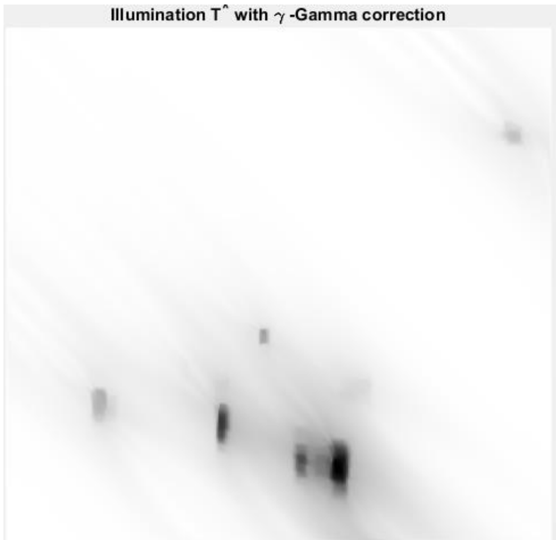

Figure 7: Illumination T^ with γ-Gamma correction

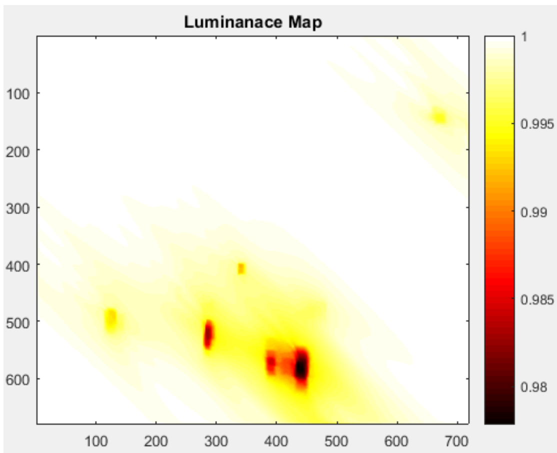

Figure 8: Luminance Map

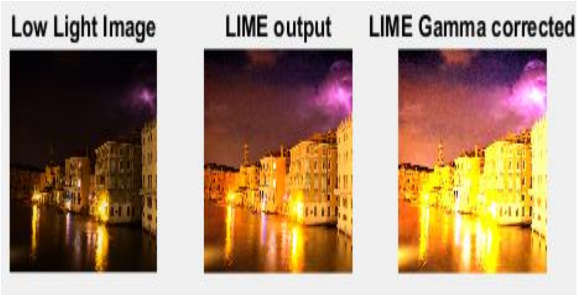

Figure 9 : Low light image, LLIE output and LLIE gamma corrected images

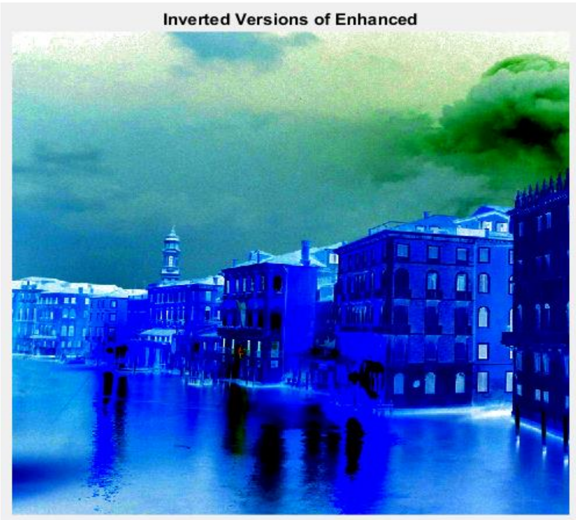

Figure 10 : Inverted versions of enhanced

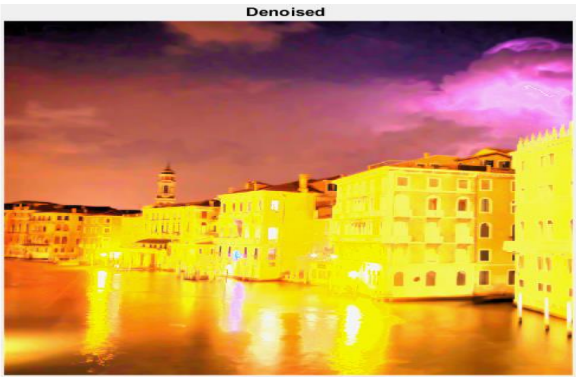

Figure 11: Denoised Image

Figure 12: Recomposed Image

Parameters	BM3D Technique	TNRD Technique
Peak signal to noise ratio (PSNR)	13.0889 dB	60.63 dB
Mean Square Error (MSE)	3.1929 dB	0.0562 dB
Structural similarity index (SSIM)	0.0033	0.7547
Lightness order error (LOE)	0.2809	0.3165

Table 1 : performance metrics of proposed and extension methods

V. CONCLUSION

This paper offers the Trainable Nonlinear Reaction Diffusion (TNRD) 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. It is high excellent that our low-mild image enhancement method can feed many imaginative and prescient-based totally programs, which includes facet detection, characteristic matching, item recognition and tracking, with high visibility inputs, and accordingly enhance their universal overall performance.

VI. REFERENCES

1. K. Zhang, L. Zhang, and M. Yang, Real-time compressive tracking, in Proc. ECCV, 2014, pp. 866-879.
2. Xiaojie Guo, Yu Li, Member and Haibin Ling “LIME: Low-Light Image Enhancement via

Illumination Map Estimation", vol. 26, no. 2, February 2017.

3. E Land "The retinex theory of color vision", Scientific American, vol. 237, no. 6, pp. 108-128, 1977.
4. S Wang, J. Zheng, H. Hu, and B. Li, "Naturalness preserved enhancement algorithm for non-uniform illumination images," TIP, vol. 22, no. 9, pp. 3538-3578, 2013.
5. 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.
6. D Krishnan R. Szeliski, "Multigrid and multilevel preconditioners for computational photography," TOG, vol. 30, no. 6, 2011
7. 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
8. E. Land, “An alternative technique for the computation of the designator in the retinex theory of color vision," in Proceedings of the National Academy of Science, 83, pp. 3078-3080, 1986.
9. D J. Jobson, Z. Rahman, and G. A. Woodell, “Properties and performance of a center/surround retinex," IEEE Trans. on Image Processing 6, pp. 451-462, March 1997.