Enhancing Low-Light Images Using Retinex Theory: An Approach to Illumination Map Estimation through Local Variance Analysis and Weighted Total Variation

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Course: EECS 6154 [Project]

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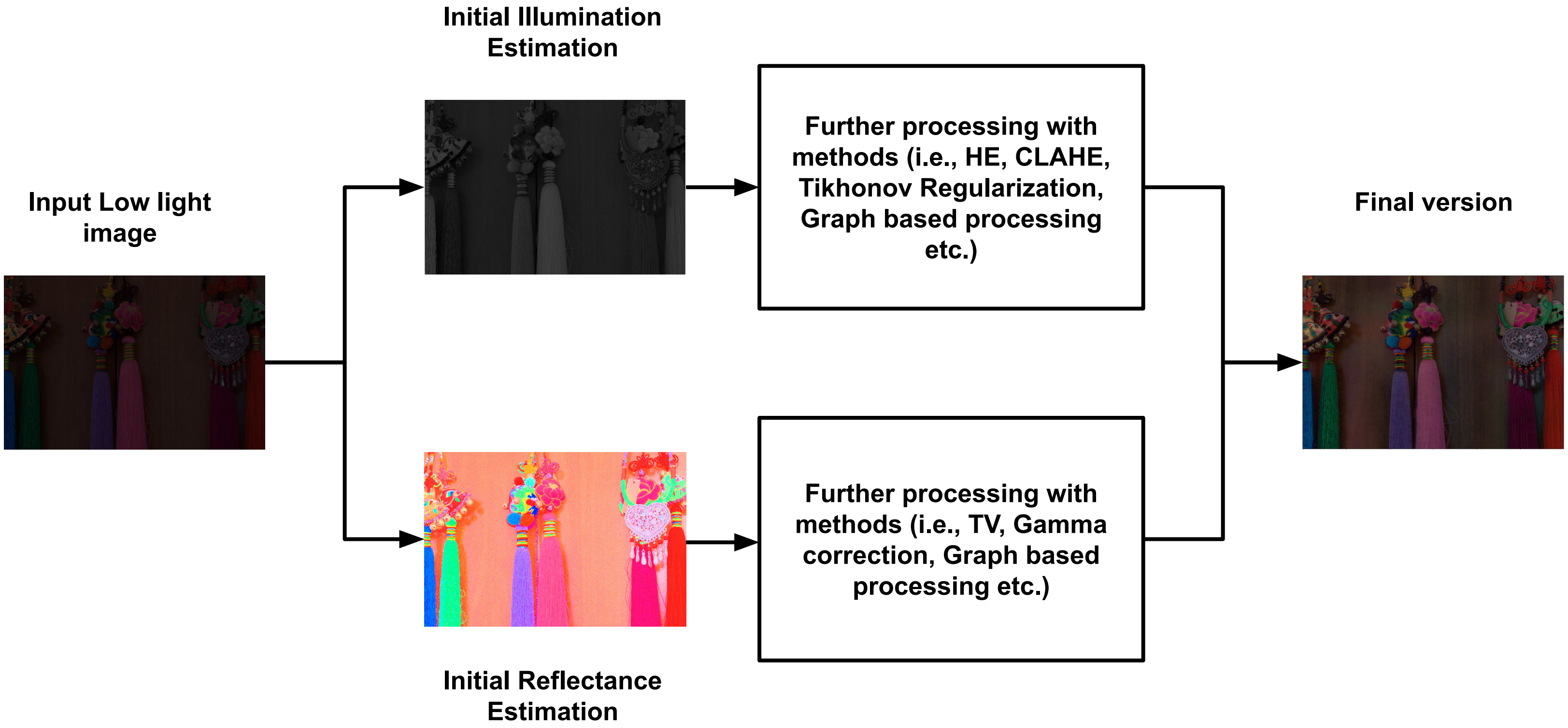
Retinex Theory

The Retinex theory [1, 2] denotes that any observed image, denoted as I, can be represented as a pixel-by-pixel multiplication of the two components, the reflectance component R, and the illumination component L. This is depicted as:

$$I(x,\, y) \;=\; R(x,\, y) \,\cdot\, L(x,\, y)$$

Here, R encapsulates the scene's inherent attributes, including details and the color characteristics of the original scene, whereas L corresponds to the light's intensity and its spatial distribution within the scene's environment.

Retinex Theory based low-light image enhancement process



Methods of enhance low light images via estimation of Illumination and Reflectance components in literature

- Various methods have been proposed to estimate the Reflectance component and the Illumination component
- Many approaches [4, 6] compute these estimation via solving an optimization problem
- Researchers have also proposed variational methods such as Total Variation, L1-variational method [7] to estimate the different components
- Some recent studies [5] introduced graph based techniques to estimate the Illumination and Reflectance component
- With the advances in Deep Learning techniques, recent works have focused on data driven techniques to estimate the illumination and reflectance component, however, these techniques rely on datasets which are often synthetic and limited in size

Proposed Approach (Initial Illumination Estimation)

Pixel Neighborhood Analysis with Adaptive Neighborhood size

Given an image I, for each pixel at location $(x,\ y)$, an initial neighborhood $N_{init}(x,\ y)$ is defined which is a square region of size ***(neighborhood_size)×(neighborhood_size)*** centered at $(x,\ y)$

The variance $Var\ (N_{init}(x,\ y))$ within this neighborhood is calculated as:

$$Var(N_{init}(x,\ y))\ =\ \frac{1}{|N_{init}|}\sum_{(i,\ j)\in N}(I(i,\ j)\ -\ \mu(N_{init}(x,\ y)))^2$$

where: $|N_{init}|$ is the number of pixels in the neighborhood, $I(i,\ j)$ is the intensity of the pixel at $(i,\ j)$

$\mu(N_{init}(x,\ y))$ is the mean intensity of the pixels in the neighborhood, calculated as:

$$\mu(N_{init}(x,\ y))\ =\ \frac{1}{|N_{init}|}\sum_{(i,\ j)\in N_{init}} I(i,\ j)$$

Proposed Approach

Pixel Neighborhood Analysis with Adaptive Neighborhood size

Next, based on the result of initial variance $Var\left(N_{init}(x,\, y)\right)$ calculation, a new neighborhood size is selected based on the following criteria,

- If $Var\left(N_{init}(x,\, y)\right)$ is greater than ***`variance_threshold`***, then a small neighborhood size (3x3) is selected
- The small neighborhood size indicates the presence of piecewise smoothness with sharp discontinuities

Proposed Approach

Constructing the Illumination component

Finally, for each pixel at (x, y), we compare the ***neighborhood_size***,

- If ***neighborhood_size*** > ***small_neighborhood_size***, the pixel is assumed to be part of a smoothly varying region (illumination), and its value in the illumination component $L(x, y)$ is set to the maximum of the intensity value across three channels $max(I(x, y))$ *[with the assumption that the illumination is at least the maximal value of three channels at a certain location]*

- If ***neighborhood_size*** == ***small_neighborhood_size***, the pixel is in a region with significant variation (more likely reflectance), and its value in $L(x, y)$ is set to the average intensity of its neighborhood, which is calculated as $\mu(N_{new}(x, y))$.

where $N_{new}(x, y)$ is the newly selected neighborhood size.

Proposed Approach

Constructing the Reflectance component

For each pixel at $(x,\, y)$, the reflectance component is constructed as,

$$R(x,\, y) \;=\; I(x,\, y) \,/\, L(x,\, y)$$

Proposed Approach

A weighted version of the Total Variation Denoising for Reflectance estimation

- A discrete gradient operator ∇u for an image $u \in \mathbb{R}^{N \times N}$ is defined by,

$$(\nabla u)_{i,j} = \left((\nabla u)^h_{i,j}, \, (\nabla u)^v_{i,j} \right)$$

where,

$$(\nabla u)^h_{i,j} = \begin{cases} u_{i+1,j} - u_{i,j} & if \ i < N \\ 0 & if \ i = N \end{cases}$$

$$(\nabla u)^v_{i,j} = \begin{cases} u_{i,j+1} - u_{i,j} & if \ j < N \\ 0 & if \ j = N \end{cases}$$

Proposed Approach

A weighted version of the Total Variation Denoising for Reflectance estimation

- The weighted version of the discrete gradient operator $\nabla_w u$ would be,

$$(\nabla_w u)_{i,j} = \left(w_{m,\,n} \cdot (\nabla u)^h_{i,j}, w_{o,\,n} \cdot (\nabla u)^v_{i,j}\right)$$

where m corresponds to coordinate $(i+1,\ j)$, n corresponds to $(i,\ j)$ and o corresponds to $(i,\ j+1)$

Here, the weight $w_{p,\,q}$ is defined as,

$$w_{p,\,q} = \exp\left(-\frac{\|p-q\|_2^2}{\sigma_s^2} - \frac{\|u(p)-u(q)\|_2^2}{\sigma_r^2}\right)$$

where $\|p-q\|_2^2$ is the euclidean distance between two pixels and $\|u(p) - u(q)\|_2^2$ is the pixel intensity difference and σ_s and σ_r are smoothing parameters

Proposed Approach

A weighted version of the Total Variation Denoising for Reflectance estimation

- The total variation will be calculated as,

$$TV(u) \;=\; \sum_{1\leq i,j\leq N} \left|(\nabla_w u)_{i,\,j}\right| \;=\; \|\,\nabla_w u\|_1$$

- The optimization equation becomes,

$$\min_x \Big(\|\, y - u \,\|_2^2 + \mu \,\|\, \nabla_w u \,\|_1\Big)$$

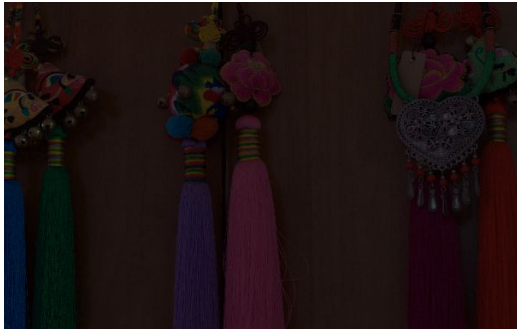
- This equation is then solved via ADMM and Proximal Gradient method to estimate the reflectance component

Proposed Approach

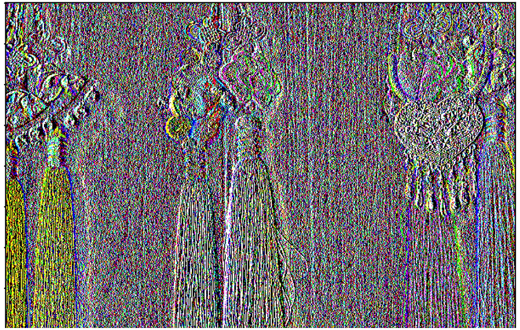
Estimating the Illumination component and contrast enhancement

- If the illumination component becomes too noisy initially, the Tikhonov regularization is employed in order to perform denoising operation on the illumination component
- Finally, to enhance the contrast of the overall image, the Contrast Limited Histogram Equalization (CLAHE) is applied.

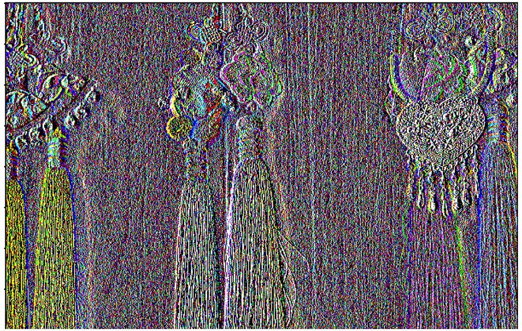
Final Results (Comparison of Horizontal and Vertical Gradient of an image with and without weight)



Original Low light Image

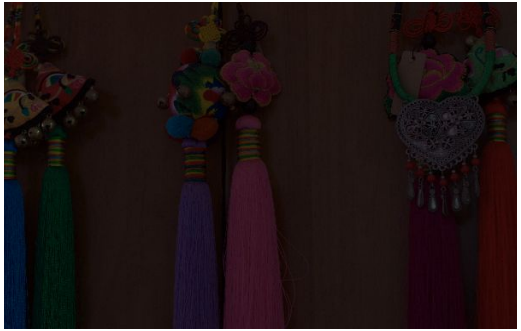


Horizontal Gradient without weight

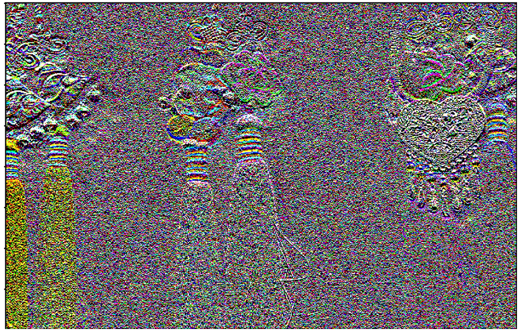


Horizontal Gradient with weight

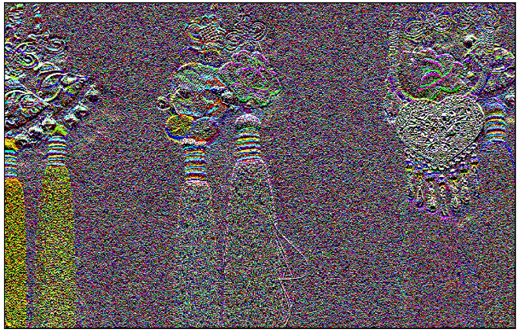
Final Results (Comparison of Horizontal and Vertical Gradient of an image with and without weight)



Original Low light Image



Vertical Gradient without weight



Vertical Gradient with weight

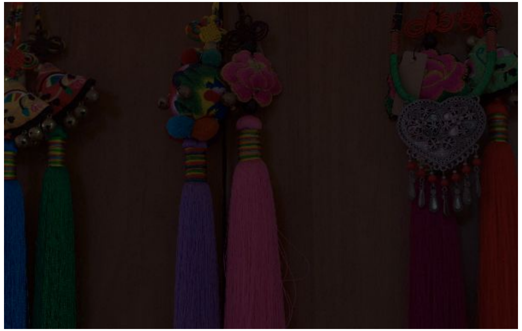
Final Results (Initial Reflectance vs Regular TV vs Weighted TV)

Initial Reflectance

Denoising via Regular TV

Denoising via Weighted TV

Final Results



Original Low light Image
Original Low light Image

After enhanced contrast (without weighted TV)

After enhanced contrast (with weighted TV more color accurate and less noisy)

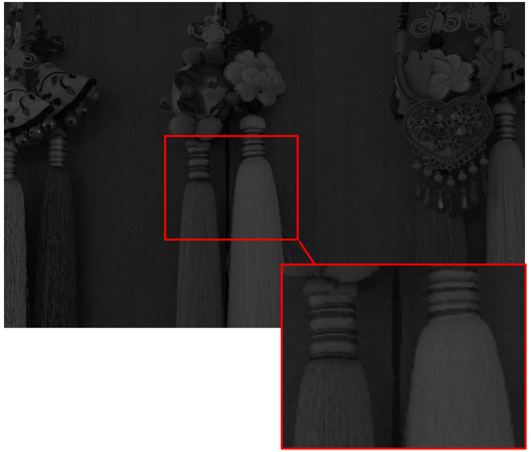
References

1. E. H. Land and J. J. McCann, “Lightness and Retinex theory,” J. Opt. Soc. Amer., vol. 61, no. 1, pp. 1–11, 1971.
2. T. Wu, W. Wu, Y. Yang, F. -L. Fan and T. Zeng, "Retinex Image Enhancement Based on Sequential Decomposition With a Plug-and-Play Framework," in IEEE Transactions on Neural Networks and Learning Systems, doi: 10.1109/TNNLS.2023.3280037.
3. X. Ren, W. Yang, W. -H. Cheng and J. Liu, "LR3M: Robust Low-Light Enhancement via Low-Rank Regularized Retinex Model," in IEEE Transactions on Image Processing, vol. 29, pp. 5862-5876, 2020, doi: 10.1109/TIP.2020.2984098.
4. Wei, Chen, Wenjing Wang, Wenhan Yang, and Jiaying Liu. "Deep retinex decomposition for low-light enhancement." arXiv preprint arXiv:1808.04560 (2018).
5. Gharedaghi, Yeganeh, Gene Cheung, and Xianming Liu. "Retinex-based Image Denoising/Contrast Enhancement Using Gradient Graph Laplacian Regularizer." In 2023 IEEE International Conference on Image Processing (ICIP), pp. 2710-2714. IEEE, 2023.
6. Guo, X., Li, Y., & Ling, H. (2016). LIME: Low-light image enhancement via illumination map estimation. IEEE Transactions on image processing, 26(2), 982-993.
7. W. Ma, J. -M. Morel, S. Osher and A. Chien, "An L1-based variational model for Retinex theory and its application to medical images," CVPR 2011, Colorado Springs, CO, USA, 2011, pp. 153-160, doi: 10.1109/CVPR.2011.5995422.

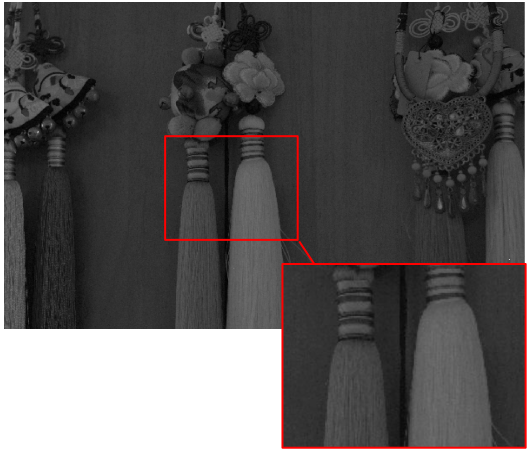
Thank You

Results

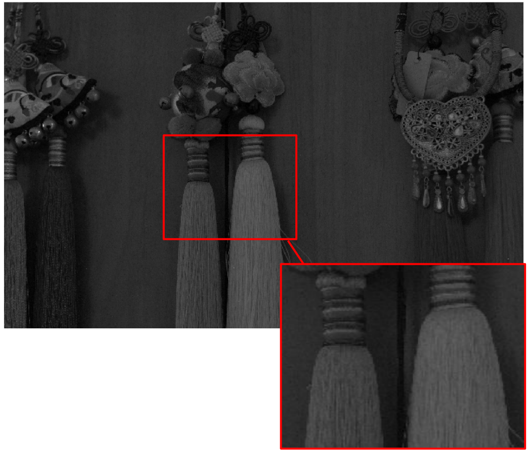
Comparison of Illumination component between other methods



Neighborhood variance method
(more smooth than others)



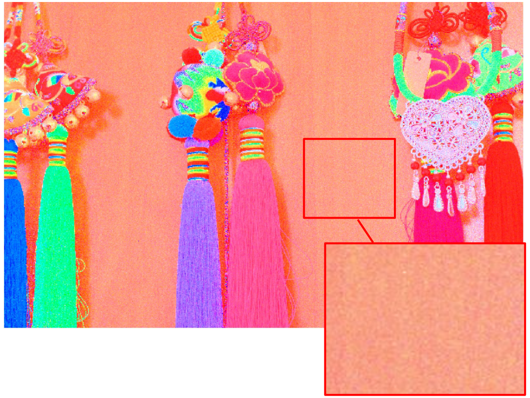
maxRGB



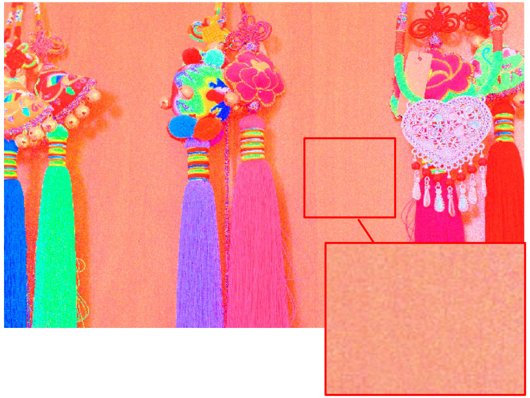
meanRGB

Results

Comparison of Reflectance component between other methods



Neighborhood variance method (less noisy while preserving the details)



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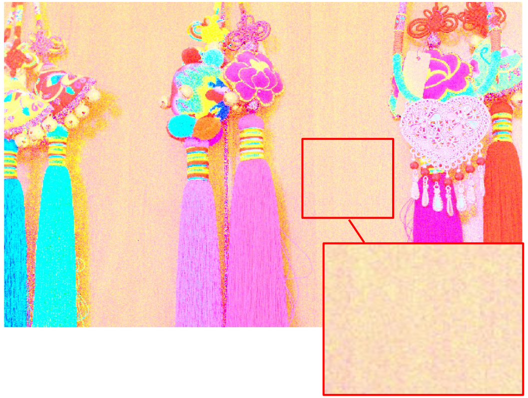

meanRGB