**Abstract:**

Images captured in low-light conditions often suffer from unwanted noise with reduced visibility, that affects not just the image's visual quality but also impairs the performance of many computer vision techniques that require high-quality inputs. This project introduces a retinex-based approach to enhance low-light images. Using retinex theory, the initial illumination map is estimated using a novel method that involves analyzing local neighborhood variance of an image. Subsequently, the initial reflectance component is estimated by dividing each pixel of the image by the estimated illumination map. The reflectance component is then further refined by imposing a Total Variation Prior combined with bilateral filter weights to the component. Finally, contrast enhancement is achieved by applying Contrast Limited Adaptive Histogram Equalization to the image. The experimental results demonstrate that the proposed approach significantly improves the quality of low-light images.

**Introduction:**

Images with high clarity provides detailed representation of target scenes, which is vital for computer vision tasks, such as object detection [<https://arxiv.org/abs/2210.02368>], and tracking [<https://www4.comp.polyu.edu.hk/~cslzhang/CT/eccv_ct_camera.pdf>].

In contrast, images captured in low-light situations often lack visual details and clarity and most of the time contain a great deal of noise distortions, more likely to cause issues for computer vision based algorithms.

One of the most intuitive approaches to tackle this issue is by directly amplifying the dark regions of an image to gain better clarity. To this end, researchers proposed Histogram Equalization based methods like [<https://link.springer.com/article/10.1007/BF03178082>, <https://www.sciencedirect.com/science/article/pii/S105120040300037X>, <https://ieeexplore.ieee.org/document/4266947>]. Although these methods improve the contrast of the image, they increase the noise elements in the image as well. In recent years, the retinex theory has become a much more widely used approach for enhancing low-light image.

Retinex theory [<https://opg.optica.org/josa/fulltext.cfm?uri=josa-61-1-1&id=54240>] states that, an image can be represented by the pixel by pixel multiplication of an illumination component L, and a reflectance component R.

I (x, y) = L (x, y) \* R (x, y)

Here, R corresponds to 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.

Several methods have been proposed to decompose the input image to its illumination and reflectance component. Techniques like single-scale Retinex (SSR) [<https://ieeexplore.ieee.org/document/557356>] and multi-scale Retinex (MSR) [<https://ieeexplore.ieee.org/document/597272>] use a Gaussian filter to decompose the image to its illumination and reflectance component. While [<https://ieeexplore.ieee.org/ielaam/83/7763897/7782813-aam.pdf>, <https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=10144685>] followed another method to separate out the initial illumination component from an image by taking the maximum value across all R, G, B channels of an image. On the other hand, [<https://ieeexplore.ieee.org/document/9056796>] follows the meanRGB approach where the mean value across all R, G, B channel is taken to estimate the initial illumination map, assuming the illumination is same across all channels. Some other studies [<https://arxiv.org/abs/2307.02625>] follow a different approach that converts the RGB image to its HSV counterpart and initializes the illumination component with the blurred V component.

Subsequently, to further refine the the smooth illumination component and the piecewise smooth reflectance layer of the Retinex model simultaneously, [<https://link.springer.com/article/10.1023/A:1022314423998>, <https://epubs.siam.org/doi/pdf/10.1137/100806588>, <https://ieeexplore.ieee.org/document/6853785>] proposed different variational models.

With the recent advances in deep learning architectures, several different methods [<https://daooshee.github.io/BMVC2018website/>, <https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=10144685>] have been proposed to tackle this problem. However, the main limitation of these deep learning based approaches is that they are mostly black box architectures with no explainability and require a lot of data to be properly trained and be viable in real-world applications.

The major contribution of this project is two-folds:

1. A novel approach to estimate the initial illumination map via pixel neighborhood variance analysis
2. A novel approach to estimate the reflectance component of an image via Total variation denoising with the combination of bilateral filter weights

**Related Works:**

A natural yet effective model based methods to enhance the contrast of low-light images are the Histogram Equalization based methods like [<https://link.springer.com/article/10.1007/BF03178082>, <https://www.sciencedirect.com/science/article/pii/S105120040300037X>, <https://ieeexplore.ieee.org/document/4266947>]. Although these methods improve the contrast of the image, they increase the noise elements in the image as well. In order to jointly denoise a low-light image and improve the contrast, retinex theory based methods have become popular recently. To remove unwanted artifacts earliest techniques like single-scale Retinex (SSR) [<https://ieeexplore.ieee.org/document/557356>] and multi-scale Retinex (MSR) [<https://ieeexplore.ieee.org/document/597272>] employed Gaussian filters. Later, retinex theory based variational methods [A total variation retinex, LIME, L3RM, L1-variational method] have been proposed for denoising and contrast enhancement of low-light images. With increasing popularity of graph based processing, [GGLR] proposed a method for contrast enhancement and denoising of low-light images with Gradient Graph Laplacian Regularizer.

With the advancement of convolutional neural networks, methods like [Retinexnet, <https://arxiv.org/abs/1805.01934>], trained end to end deep neural networks architectures for both denoising and contrast enhancement of an image. While [<https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=10144685>] employed a combination of plug and play framework and convoluted neural network to estimate the illumination component and reflectance component respectively.

**Proposed Methodology:**

**Initial Illumination and Reflectance estimation:**

Initial Illumination and reflectance component estimation: According to retinex theory, the observed image can be represented by the multiplication of reflectance component R and illumination component L.

I = R \* L

In order to estimate the illumination component, the proposed approach performs pixel neighborhood analysis based on the fact that

*Illumination typically exhibits a smoother overall variation across an image, while reflectance is usually piecewise smooth with sharp discontinuities*.

**Pixel Neighborhood analysis:**

Initially, a NxN image patch is selected and the variance of the pixel values within that neighborhood is then calculated. A low variance indicates a smoother (more indicative to illumination), while high pixel intensity variance indicates sharp changes (more indicative to reflectance).

**Constructing the Illumination Component:**

Initially, a new image (initialized with zero) to represent the illumination component is created

For each pixel in the original RGB image, an initial neighborhood is defined, and initial variance of that neighborhood is calculated. Then, the corresponding illumination component’s pixel value is set based on the following criteria:

If the variance is below a certain threshold (indicating smoothness), then the max value from all the channels of the image is assigned to that pixel of the illumination component,

If the variance is high, then the neighborhood size is updated to a smaller region and the pixel value is replaced with an average value of the neighborhood (to enforce smoothness and emphasizes the overall illumination).

More formally, the process can be written as:

Given an image I, for each pixel at location (x, y), an initial neighborhood Ninit(x, y) is defined which is a square region of size (neighborhood\_size)×(neighborhood\_size) centered at (x, y)

The variance Var(Ninit(x, y)) within this neighborhood is calculated as:

where: Ninit is the number of pixels in the neighborhood, I(i, j) is the intensity of the pixel at (i, j), is the mean intensity of the pixels in the neighborhood, calculated as:

Next, based on the result of initial variance calculation, a new neighborhood size is selected based on the following criteria,

* If 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

Finally, for each pixel at location of the image, 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 is set to the maximum of the intensity value across three channels [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 is set to the average intensity of its neighborhood, which is calculated as

where is the newly selected neighborhood size.

**Constructing the initial Reflectance component**

For each pixel at location of the image, the reflectance component is constructed as,

**Estimating Reflectance Component:**

After computing the initial reflectance component,

**Experimental Results:**

**Conclusion:**

This project proposes an end-to-end approach for low-light image contrast enhancement and denoising using retinex theory. The project proposes two novel approaches, one based on pixel neighborhood variance analysis to estimate the initial illumination map and the other based on a Total variation denoising approach with the combination of bilateral filter weights to refine reflectance component of the image. Experimental results show promising improvement on both contrast enhancement and image denoising performance.