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Image enhancement in low light conditions utilising a basic network structure

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Abstract
Unfactory lighting can influence taken photos in low light levels. LLIE, or low-light image enhancement, is a digital image processing technique used in digital photography to produce natural normal-light photographs from the low-light source. Reducing noise and artefacts, retaining edges and textures, and replicating natural brightness and colour constitute three key goals covered by LLIE. Many kinds of study have concentrated recently on deep-learning-based methods with outstanding performance. One main drawback of these approaches, though, is that intricate network architectures cause significant inference times. We present a basic network with effective modules to handle the trade-off between the performance and implementation time. We make advantage of a relative global histogram. In image processing, stretching is a method applied to improve image contrast. The technique is modifying an image's intensity values such that they cover a desired range. Faster inference time and better performance than traditional LLIE techniques define the suggested method.

Keywords: Unfactory lighting, low-light levels, LLIE (Low-light image enhancement), digital image processing, noise reduction

1. Introduction
Unfactory lighting can influence taken photos in low light levels. LLIE, or low-light image enhancement, is a digital image processing technique used in digital photography to produce natural normal-light photographs from the low-light source. Reducing noise and artefacts, retaining edges and textures, and replicating natural brightness and colour constitute three key goals covered by LLIE. Many kinds of study have concentrated recently on deep-learning-based methods with outstanding performance. One main drawback of these approaches, though, is that intricate network architectures cause significant inference times. We present a basic network with effective modules to handle the trade-off between the performance and implementation time. We make advantage of a relative global histogram. In image processing, stretching is a method applied to improve image contrast. The technique is modifying an image's intensity values such that they cover a desired range. Faster inference time and better performance than traditional LLIE techniques define the suggested method.

2. Literature Survey
2.1 T. Celik and T. Tjahjadi, "Contextual and Variational Contrast Enhancement," IEEE Transactions on Image Processing, vol. 20, no. 12, pp. 3431–3441, 2011
This paper proposes an algorithm that uses interpixel contextual information to improve the contrast of an input image. The algorithm employs a 2-D histogram of the input image, which is built using a mutual relationship between each pixel and its neighbours. By minimising the sum of Frobenius norms of the differences between the input histogram and the uniformly distributed histogram, a smooth 2-D target histogram is obtained. By mapping the diagonal elements of the input histogram to the diagonal elements of the target histogram, the enhancement is achieved. The algorithm produces better or comparable enhanced images than four state-of-the-art algorithms, according to experimental results.

2.2 S. D. Chen and A. R. Ramli, "Preserving brightness in histogram equalization based contrast enhancement techniques," Digital Signal Processing, vol. 14, no. 5, pp. 413-428, 2004
Histogram equalization (HE) has been a simple yet effective image enhancement technique.

However, it tends to change the brightness of an image significantly, causing annoying artifacts and unnatural contrast enhancement. Brightness preserving bi-histogram equalization (BBHE) and dualistic sub-image histogram equalization (DSIHE) have been proposed to overcome these problems but they may still fail under certain conditions. This paper proposes a novel extension of BBHE referred to as minimum mean brightness error bi-histogram equalization (MMBEBHE). MMBEBHE has the feature of minimizing the difference between input and output image's mean. Simulation results showed that MMBEBHE can preserve brightness better than BBHE and DSIHE. Furthermore, this paper also formulated an efficient, integer-based implementation of MMBEBHE. Nevertheless, MMBEBHE also has its limitation. Hence, this paper further proposes a generalization of BBHE referred to as recursive mean-separate histogram equalization (RMSHE). RMSHE is featured with scalable brightness preservation. Simulation results showed that RMSHE is the best compared to HE, BBHE, DSIHE, and MMBEBHE.

2.3 S. D. Chen and A. R. Ramli, "Contrast enhancement using recursive mean-separate histogram equalization for scalable brightness preservation," IEEE Transactions on Consumer Electronics, vol. 49, no. 4, pp. 1301–1309, 2003

Histogram equalization (HE) is broadly used for distinction enhancement. However, it tends to exchange the brightness of an picture and hence, no longer appropriate for purchaser digital products, the place maintaining the authentic brightness is quintessential to keep away from traumatic artifacts. Bi-histogram equalization (BBHE) has been proposed and analyzed mathematically that it can maintain the authentic brightness to a positive extend. However, there are nevertheless instances that are now not dealt with nicely by means of BBHE, as they require greater diploma of preservation. This paper proposes a generalization of BBHE referred to as recursive mean-separate histogram equalization (RMSHE) to furnish now not solely higher however additionally scalable brightness preservation. BBHE separates the enter image's histogram into two primarily based on its suggest earlier than equalizing them independently. While the separation is achieved solely as soon as in BBHE, this paper proposes to operate the separation recursively; separate every new histogram similarly primarily based on their respective mean. It is analyzed mathematically that the output image's imply brightness will converge to the enter image's suggest brightness as the range of recursive imply separation increases. Besides, the recursive nature of RMSHE additionally permits scalable brightness preservation, which is very beneficial in client electronics. Simulation outcomes exhibit that the instances which are no longer dealt with nicely through HE, BBHE and dualistic sub photograph histogram equalization (DSIHE), have been right superior with the aid of RMSHE.

3. Proposed System

The suggested system dynamically changes pixel intensities over the whole image to improve low-light photographs using the Relative Global Histogram Stretching method. Stretching the histogram worldwide helps to improve contrast without increasing noise or overexposing areas. For real-time uses, the computationally straightforward technique is efficient. The device guarantees consistent redistribution of pixel intensities, therefore improving visibility in dark areas without compromising image quality. This method is appropriate for greyscale and colour photos alike.

3.1 Implementation

3.1.1 Data Collection

IN this project we use unwater images to process with opencv library. Various Low Light images can be used as data for enhancement.

3.1.2 Pre-processing

Pre-processing is a procedure adopted to enhance the quality of images and increase visualization. In under water, image processing is a crucial phase that helps to improve the images quality. This can be one of the most critical factors in achieving good results and accuracy in next phases of proposed methodology. Wound images may contain a different issue that may lead to poor and low visualization of the image. If the images are poor or of low quality, it may lead to unsatisfactory results. During pre-processing phase, we performed background elimination, elimination of non-essential blood supplies, image enhancement, and noise removal.

3.1.3 Histogram Equaization

Now, we divide our dataset into training and testing data. Our objective for doing this split is to assess the performance of our model on unseen data and to determine how well our model has generalized on training data. This is followed by a model fitting which is an essential step in the model building process.

Adaptive Histogram Equalization (AHE) the approach used here is to compute many histograms for the same image, each histogram corresponds to a section of the image. This improves the contrast locally. Disadvantage of using AHE is that it canover-amplify noise in the local region. AHE is still preferred over ordinary HE because it enhances contrast better. Adaptive histogram equalization (AHE) improves the contrast in those regions will not be sufficiently enhanced, by transforming each pixel with a transformation function derived from a neighbor hood region. Here, each pixel is transformed based on the histogram of a square surrounding the pixel. The derivation of the trans formation functions from the histograms is exactly the same as for ordinary histogram equalization. The transformation function is proportional to the Cumulative Distribution Function (CDF) of pixel values in the neighbor hood. Pixels near the image boundary have to be treated specially, because their neighbor hood would not lie completely within the6mage. The image is partitioned into equally sized rectangular tiles. A histogram, CDF and transformation function is then computed for each of the tiles. The transformation functions are appropriate for the tile center pixels. All other pixels are transformed with up to four transformation functions of the tiles with center pixels closest to them, and are assigned interpolated values. Pixels in the bulk of the image are bi-linearly interpolated pixels close to the boundary are linearly interpolated, and pixels near corners are transformed with the transformation function of the corner tile. The interpolation coefficients reflect the location of pixels between the closest tile center pixels, so that the result is continuous as the pixel approaches a tile center.

Figure (row wise, left to right) original image, blurred image, AHE - enhanced image, YCbCr - colour space image, YCbCr equalized image, YCbCr Y-channel, YCbCr Y-channel equalized image. 1.3.2 Gamma correction (GC) the approach used here is to amplify the intensities of the image by a factor gamma. Here the amplification is more for the darker tones than for the lighter ones. Gamma correction is used to make the non-linear output from a CRT monitor linear, as in V out = V in Figure —(row wise, left to right) original image, blurred image, gamma-corrected image, GC - enhanced image. 1.

Brightness preserving Bi-Histogram Equalization (BBHE) Here the input image is converted into two separate images, based on a choice of mean intensity, that is, intensities greater than the mean form one image, while those lesser than the mean form the other image. Histogram equalization is separately performed on each of these images. The equalized image is with intensities lesser than the mean is scaled to have intensities in the range from 0 to the mean, while the other image is scaled to have intensities between mean and 256(assuming 8 bit). This way the intensities range is still preserved. The resulting image has the mean brightness preserved. Thus giving an image with better contrast. Figure —(row wise, left to right) original image, blurred image, BHE - enhanced image 1.3.4 Contrast Limited Adaptive Histogram Equalization (CLAHE) AHE has tendency to over amplify noise in the relatively homogeneous images. CLAHE overcomes this problem by limiting the amplification. CLAHE prevents over amplification by dividing the images into small data regions called tiles rather than the whole image, and then performing contrast enhancement. These tiles are then rejoined to get the overall contrast enhanced image.

Relative global histogram starching algorithm steps

Relative Global Histogram Stretching is a technique used in image processing to enhance the contrast of an image. The method involves adjusting the intensity values of an image so that they span a desired range. Here's a step-by-step breakdown of the algorithm:

Steps for Relative Global Histogram Stretching Algorithm

Input Image

Start with the input image. Let the intensity values of the image pixels be denoted as I(x,y)I(x, y)I(x,y), where xxx and yyy are the pixel coordinates.

Compute the Minimum and Maximum Intensity Values

Find the minimum intensity value IminI_{min}Imin and the maximum intensity value ImaxI_{max}Imax in the image.

Imin=min(I(x,y))I_{min} = \min(I(x, y))Imin=min(I(x,y))

Imax=max(I(x,y))I_{max} = \max(I(x, y))Imax =max(I(x,y))

Define Desired Minimum and Maximum Intensity Values

Set the desired minimum intensity DminD_{min}Dmin and desired maximum intensity DmaxD_{max}Dmax for the output image. These values are typically set based on the desired contrast level (e.g., Dmin=0D_{min} = 0Dmin=0 and Dmax=255D_{max} = 255Dmax=255 for an 8-bit grayscale image).

Stretch the Histogram

Apply the histogram stretching formula to each pixel in the image to adjust its intensity:

Inew(x,y)=(I(x,y)−Imin)×(Dmax−Dmin)Imax−Imin+DminI _{new}(x, y) = \frac{(I(x, y) - I_{min}) \times (D_{max} - D_{min})}{I_{max} - I_{min}} + D_{min}Inew (x,y)=Imax−Imin(I(x,y)−Imin)×(Dmax−Dmin)+Dmin

1. Here, Inew(x,y)I_{new}(x, y)Inew(x,y) is the new intensity value for the pixel at position (x,y)(x, y)(x,y).

Clip the Values

Ensure that the output intensity values Inew(x,y)I_{new}(x, y)Inew(x,y) are within the range [Dmin,Dmax][D_{min}, D_{max}][Dmin,Dmax]. This step may involve clipping any values that fall outside the desired range.

Output the Stretched Image

The resulting image after applying the above transformation will have enhanced contrast with intensity values spread across the desired range.

Example Workflow

1. **Input Image:** An 8-bit grayscale image with pixel intensities ranging from 50 to 200.
2. **Compute IminI_{min}Imin and ImaxI_{max}Imax**: Assume Imin=50I_{min} = 50Imin=50 and Imax=200I_{max} = 200Imax=200.
3. **Define Desired Range:** Set Dmin=0D_{min} = 0Dmin =0 and Dmax=255D_{max} = 255Dmax=255.
4. **Stretch Histogram:** Apply the stretching formula to map the original intensity values to the new range.
   - For a pixel with intensity 50 (the minimum), the new value would be 0.
   - For a pixel with intensity 200 (the maximum), the new value would be 255.
   - Other pixel values will be scaled linearly between these limits.
5. **Clip Values:** Ensure all new pixel values are within the range [0,255][0, 255][0,255].
6. **Output Image:** The final image will have improved contrast, with intensity values distributed from 0 to 255.

This algorithm is straightforward and effective for enhancing image contrast, especially when the image's dynamic range is limited.

Systems architecture, sometimes known as system architecture, is the conceptual model specifying the structure, behaviour, and several perspectives of a system. An architecture description is a formalised account and depiction of a system. arranged so as to facilitate logical analysis of the system's architecture and actions.

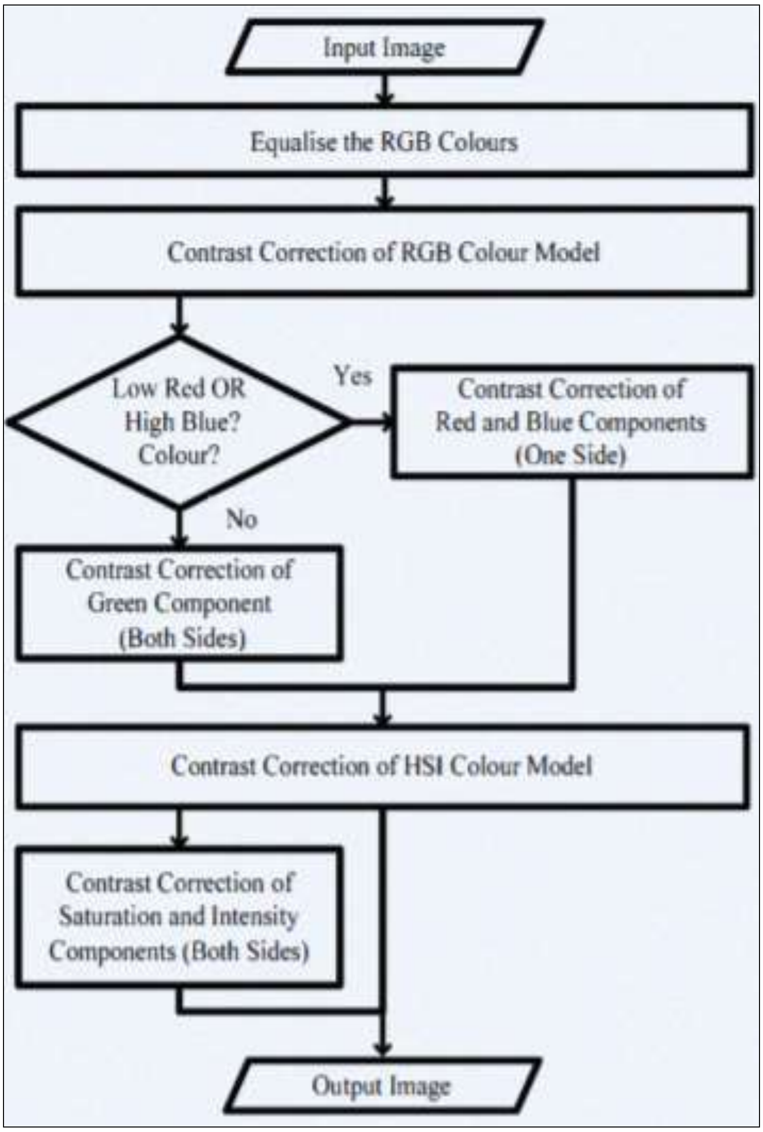

Fig 1: Architecture

4. Results and Discussion

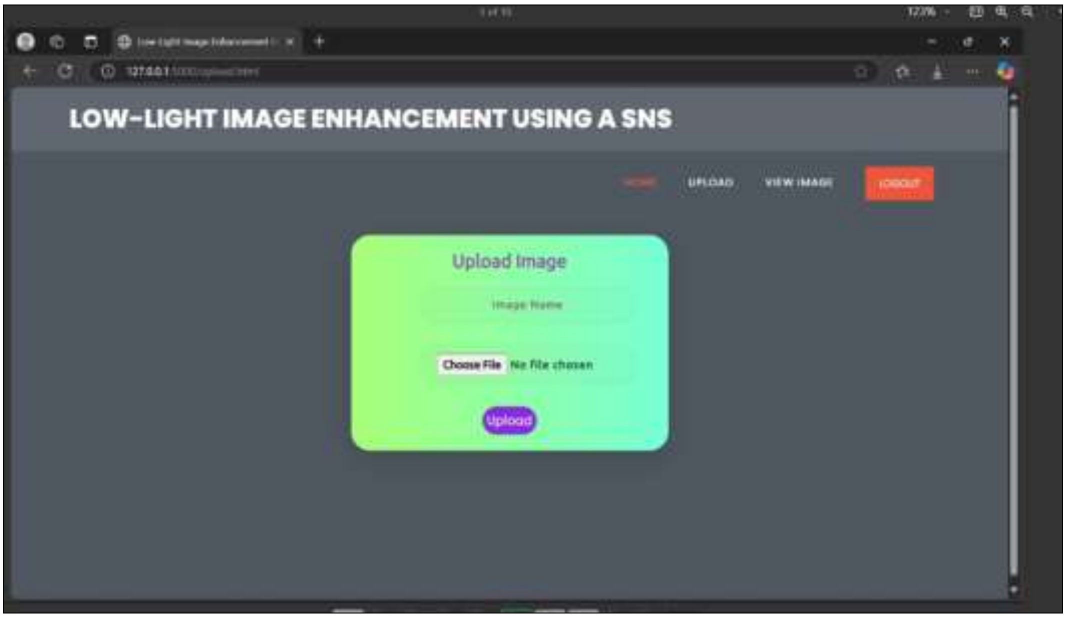

Fig 2: Above screen will be opened and Now upload the Dark imges by click on “Upload Images”

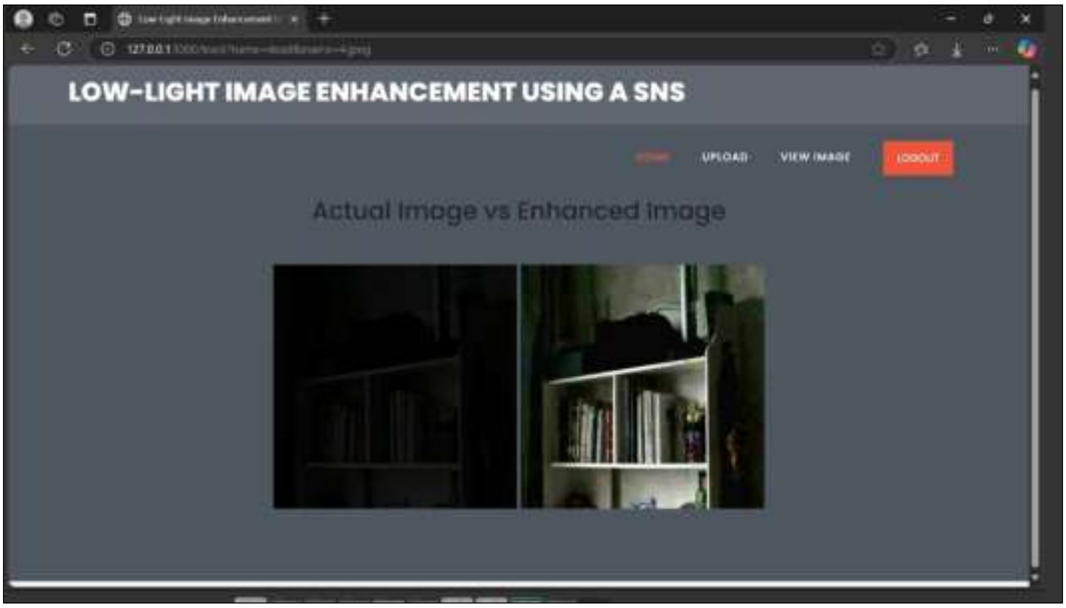

Fig 3: Select the file to enhance from the testdata file.

Uploaded Image will be displayed on the window. Now Click on the Enhance Button.

5. Conclusion

The Relative Global Histogram Stretching algorithm is an effective solution for enhancing low-light images by improving contrast and visibility. It addresses the limitations of traditional methods by maintaining a natural appearance without over-amplifying noise or losing details. The proposed system is computationally efficient and versatile, making it suitable for various applications, including security and medical imaging. By enhancing contrast while preserving image quality, this method proves to be a robust option for low-light conditions.

6. Future Scope

Further research could explore hybrid techniques that combine Relative Global Histogram Stretching with deep learning methods for enhanced feature extraction. The algorithm could be optimized for specific use cases such as medical imaging or autonomous driving. Real-time deployment in resource-constrained environments, such as mobile devices and embedded systems, can be pursued. Extending the system to work with video data in low-light scenarios is another avenue for development. Finally, adaptive versions of the algorithm could be developed to handle extreme lighting variations

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