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CSE4019 - Image Processing

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J Component Report

On

Detail Preserved Contrast Enhancement of Low-Light Images

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ABSTRACT

Low-light images are images taken in conditions where there is not enough ambient light to produce a well-exposed image. The cause of low light images can be anything from instrument damage or calibration issues, or absence of enough illumination to presence of unwanted noise or filter. This can happen at night, indoors, or even outdoors on a cloudy day. Images taken in low light might have a number of issues, including underexposure, decreased contrast, and noise. These problems can make it difficult to identify objects and people in low-light images and can also make the images less visually appealing. By enhancing the images, the user experience of applications such as mobile photography, security surveillance, autonomous driving, space photography, nocturnal wildlife imaging and various other such applications of object imaging can be improved. It can also enable computer vision tasks such as object detection, tracking, image segmentation, facial recognition or video analytics to be performed more accurately in low-light conditions. In this project, we aim to address these problems via attenuated color channel correction and detail-preserved contrast enhancement. The proposed method is a five step process beginning with attention weight attached color correction of the image to reduce reddish hue in low light photos, continuing on to contrast improvement globally as well locally, followed by a multiscale fusion of the two. Experimenting with these techniques on a dataset consisting of nearly 500 such photos results in quantitative and qualitative enhancement. Metrics considered for evaluation are average gradient, BRISQUE, NIQUE, Information Entropy and Patch based contrast quality index. The results show that our method performs well for the LOL dataset. A slight change in parameter improves overall performance and a clear well contrasted image for a corresponding low light image.

Keywords: Low-light, contrast enhancement, fusion, color correction, exposure

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INTRODUCTION

Image processing for low light images is a challenging task, but it is essential for many applications, such as night vision, security cameras, and medical imaging. Low light images often suffer from poor contrast, noise, color distortion, low visibility, color deviations, hazing, fading, low contrast etc.These problems can make it difficult to see objects and features in the images affecting systems that need to perform object detection for low-light images captured digitally[1]. This requires a method to be developed to counter these problems to improve object detection accuracy for low-light digital images. Image processing techniques can be used to enhance low light images and improve their visual quality. Some common image processing techniques for low light images include:

a) Histogram equalization: This technique spreads out the pixel values in an image, which can improve the contrast and make it easier to see details in the image.
b) Noise reduction: This technique removes noise from an image, which can improve the overall quality of the image.
c) Color correction: This technique corrects the color balance in an image, which can improve the realism of the image.
d) Image sharpening: This technique enhances the edges of objects in an image, which can make the image appear sharper and more focused.

In addition to these basic techniques, there are also more advanced image processing techniques that can be used to enhance low light images. For example, deep learning models can be used to learn the relationship between low light images and their corresponding well-lit images. This knowledge can then be used to enhance low light images in a more sophisticated way.

With the advancement of deep learning and its numerous uses in image processing in recent years [2], [3], [3], there has been a growing interest in deep learning-based techniques for improving low-illumination images [5], [6], [7]. For instance, a convolutional neural network with various Gaussian convolution kernels is used for contrast enhancement in [8], a stacked encoder is used for low-illumination enhancement in [9], and a decomposition network based on the Retinex theory is proposed for low-illumination image enhancement in [10] and [11]. When upgrading low-illumination photos, deep learning techniques can yield superior feature representations because to their vast datasets and high computational capabilities, which set them apart from older methods. But as Fig. 1 illustrates, even if the improved image produced by the deep learning technique [12] is more distinct than the one produced by the conventional fusion-based method [see Fig. 1(b)], [18], some areas of the improved image still have poor brightness and hazy features.

Fig 1.

Another promising area of research is the development of real-time low light image enhancement methods. Real-time methods are essential for applications such as security systems, surveillance cameras, and autonomous vehicles. One way to achieve real-time low light image enhancement is to use lightweight deep learning models. Lightweight models are smaller and faster than traditional deep learning models, which makes them suitable for real-time applications.

In addition to deep learning and real-time processing, other areas of research that are important for the future of low light image processing include:

- Developing new metrics for evaluating the quality of low light images. Existing metrics are often not well-suited for evaluating the quality of low light images, as they may not take into account factors such as noise and color distortion.
- Collecting and annotating large datasets of low light images. Large and well-annotated

datasets are essential for training and evaluating deep learning-based low light image enhancement methods.

- Developing new hardware and software platforms for low light image processing. New hardware and software platforms can enable faster and more efficient processing of low light images.

In this study, we address the quality decline of low light photos by using enhancement-based techniques. We suggest an attenuated color channel correction (ACCC) and detail preserving contrast enhancement method to produce high-quality high-light images, for their low-light counterparts, which is inspired by multiscale fusion (MSF) [13], [14]. MSF is a technique that can be used to combine multiple images to produce a single enhanced image. MSF works by fusing the images at different scales, which allows it to preserve the global and local contrast of the images.We use ACCC technique to first generate the color-corrected image from a supplied underwater image. ACCC can be used to correct the color distortion in low light images. ACCC works by attenuating the color channels of the image based on the brightness of the image. This helps to restore the natural colors of the image, even in low light conditions.Next, using an iterative dual-histogram-based threshold method and a limited histogram method with Rayleigh distribution, we extract the global and local contrast-enhanced versions from the color-corrected image, respectively. MSF technology combines the benefits of global and local contrast-enhanced images in a novel way. Instead of using the entire image for fusion, we use only the brightness weight map of the luminance channel in CIELAB color space and the saliency weight map of the combination of hue, saturation, and value channels in HSV color space. This allows our model to better preserve the global and local contrast of the original images. Finally, our proposed model uses a multiscale unsharp masking (MSUM) strategy to sharpen the edges and details of the result.

Our proposed method is evaluated using five relevant metrics. The evaluation metrics used are:

a) Average Gradient
b) Information Entropy
c) Patch Based Contrast Quality Index
d) NIQE
e) BRISQUE

Image processing for low light images is a rapidly developing field, and new techniques are being developed all the time. As image processing techniques continue to improve, we can expect to see even more dramatic improvements in the quality of low light images.

LITERATURE SURVEY

Low-light images suffer greatly from various image degradations like low contrast, low visibility, haziness, etc. Zhu et. al.[17] suggested a dual transformation deep network architecture that consists of two parallel branches where both learn two different transformations. The first learns a global; transformation curve (improves global contrast) and the second branch learns a transformation for local contrast enhancement. The paper proposes a novel loss method to measure training loss. Apart from a local loss function, a differential histogram loss function is designed to measure global contrast enhancement. The image histogram has a count of discrete values of intensity in an image which is not differentiable which is why the histogram is transformed such that it is differentiable and can participate in the backpropagation that updates parameters. A gradient loss is also used to preserve image details and to not introduce artefacts. This method retains the 1D input histogram shape and obtains a better 2D image visual quality at the same time. Same deep learning methods are also adopted in [18], that solves the problems of brightness correction, contrast enhancement, removing noise etc, simultaneously. The proposed method can be combined with other Retinex based models like histogram equalisation, LIME, Gamma correction etc. The authors first prove that the V channel in the HSV (Hue, Saturation, Value) model is the maximum channel in the RGB model. Hue and Saturation are different for day and night images so are the same for low and high light images. This happens due to the various types of responses of each colour channel, with each response being non-liner (curved). This is why simple Retinex models cannot ensure that the output image looks like the high light images. The proposed model takes the V channel as an extra input, and it learns the values of H and S channels as it differs with V. Therefore, the network learns the curve responses of each channel based on V, and then for a given V value the model is able to predict the values for the H and S channels. [19] suggests a novel deep network that assists linear contrast enhancement methods. The gradient recovery network and the brightness enhancement network are used separately by the proposed LCENet (linear contrast enhancement network) to restore texture, brightness, and contrast enhancement. In order to boost the brightness and contrast, the LCENet introduces a module which simulates linear contrast enhancement in the backbone. It consists of two encoder and decoder based subnets for gradient map restoration and brightness enhancement, and a backbone network for contrast enhancement and adaptive brightness. The suggested LCENet module may improve the brightness and contrast of feature maps and apply it to each residual block in the backbone network. The texture and details of the final product can also be further restored by fusing the gradient features from the gradient recovery network during the decoding phase of the backbone network. To obtain better performance L1 loss, SSIM loss and perceptual loss is used to train and optimise the LCENet.

Apart from deep network architectures, some modified histogram equalizations are also adopted by some. [20], [21] and [22] all use a modified version of Adaptive Histogram Equalization. [20] suggest a simple but evolved way of dehazing real world images. Based on past works a new AHE technique is devised along with a new modified SPD-MEF technique that is used for dehazing real world images. The algorithm involves three essential steps: a) Gamma Correction: Gamma correction is often employed for dynamic range adjustment because of its mathematical traceability. The authors employ a range of gamma values {2,3,4,5} to generate a set of Gamma corrected images from the original image; b) Colour-Preserving AHE: The authors then modify AHE to retain the colour of the original images. When normal AHE is performed, the objects in the image closer to the capturing instrument appear darker than the ones far away. AHE is usually performed on every colour channel's histogram, but this paper performs AHE jointly by first converting the 3D image to a 2D one, that is image reshaping is carried out which the authors term as the Reshaping Transformation (RT). On this transformed image the AHE is performed; c) Image Dehazing: A modified SPD-MEF is employed, where each image is converted to sub-blocks/patches and each patch is processed into a different image model where the components are signal strength, signal structure and mean intensity. They employ a fast multi scale fusion technique to dehaze the images. The fusion technique is realised via mean filtering technique. The proposed method does not rely on atmospheric models and does not require expensive training resources. [21] relies on a modified AHE but for images taken underwater. Underwater images suffer from scattering of lights of certain wavelengths, which begs for a colour correction solution too. [21] involves a 4 step process consisting of colour compensation, colour correction (the above two steps are necessary for contrast enhancement of underwater images), detail sharpening and contrast enhancement. a) Colour Compensation: Since light decays as we go further down under water, images taken there suffer a great deal of blurring, noise, colour distribution problems etc. Red light is scattered the most and green light the least, which is why the red channel is compensated for, before any kind of colour correction is done so that the green channel does not dominate the output images later on; b) Colour Correction: The second step is colour correction using multi scale retinex (MSR). Since images have two components, reflection and illumination, the paper focuses on convolving the reflection component using Gaussian kernel functions. An auto-level based colour correction for MSR images is proposed where first, auto-levels are used to calculate the R, G, and B channels' grey histogram. Then, using the clipping percentage, the highlight and shadow values of the R, G, and B channels are used as the clipping boundary.

Finally, the middle portion of each channel receives the same linear stretch, and each grey value is confirmed to be within the range [0, 255]; c) Detail Sharpening: Based on the fact that finer the scale sharper the image, scale spaces are extracted from the images. To implement feature extraction at various resolutions, the scale spaces are extracted from these sequences. Image defogging, image classification, and underwater picture enhancement all eventually adopted pyramid transformation due to its satisfactory performance for both edge preserving and feature extracting. The reconstructed image and original image are finally fused to get the final detail enhanced image; d) Contrast Enhancement: The paper adopts a local contrast enhancement method. It uses the CLAHE (due to less robustness of AHE) which uses a limiting factor to better suppress image noise and preserve more details. Image is divided into sub-blocks, the histograms of which are clipped. The clipped histograms are enhanced using the Rayleigh distribution. The output image undergoes a simple linear local enhancement, to counter the mutation effect, after which a bilinear interpolation is performed for each pixel of the output image to remove the boundary artefacts. [22] also adopts a modified AHE but focuses on a particular domain, object detection in Overhead Power Transmission Systems. Due to the low lighting conditions, object detection becomes a challenge in UAV images. The CLAHE (Contrast Limited Adaptive Histogram Equalization) method is used to enhance these images without over exaggerating the noise which helps the object detection accuracy. [22] The image is changed from RGB to YCbCr colour model. This is done so that the image enhancement can be focused on the luminance instead of its chrominance, thus not disturbing the noise in the image. The new images are then subjected to a transformed Adaptive Histogram Equalization (AHE) technique. In AHE, a normalised histogram is computed for each pixel of an image using the following formula: p(x,y)(i) =n(x,y)(i)n The images is transformed as follows: fx,y(i) = 255 × cx,y. According to [22], AHE tends to exaggerate noise by over-amplifying contrast in smooth regions, which significantly lowers the accuracy of sequential detection. In CLAHE, a limiting factor Φ, which aims to reduce noise exaggeration during contrast enhancement. When the contrast is overemphasised, the noise will also be enhanced, which will cause a mistake in object detection. Therefore, it is crucial to strike a balance between contrast increase and noise suppression. The contrast limiter is optimised using grid search over the search space {1,2,4,6,8,10}. The optimal Φ is then obtained based on the maximum detection accuracy. The details in dark regions are enhanced using gamma correction and then the image is again transformed to the RGB colour model. The suggested approach increased the insulator detection accuracy from 58.0% to 82.0% and significantly improved the contrast of the resulting images.

Just like low light images, images taken underwater also suffer a great deal of image degradation. Due to the scattering of lights of certain wavelengths, underwater images may often appear bluish/greenish. [24] [23] and [24] both are from the same authors and they solve similar problems as seen in images taken underwater. [23] proposes a contrast enhancement method called MILLE. The image is locally adjusted with respect to colour and details in accordance with the minimum colour loss principle and a maximum attenuation map guided fusion strategy. The image is first converted to a detailed image, an attenuated image and three redefined colour channels. These images are then "fused" using maximum attenuation map-guided fusion strategy. The integral and squared integral maps are effectively used in the locally adaptive contrast enhancement (LACE) to compute the local mean and variance for adaptively changing the local contrast of the colour-corrected image. A locally adaptive contrast enhancement is adopted to enhance the contrast of underwater photos in addition to colour correction. On the one hand, the luminance channel L's contrast is increased, in the CIELAB colour space, on the other hand, the colour differences between the 'a' and 'b' colour channels are equalised. [24] employs a novel method to tackle a number of issues that arise in underwater imaging. The method involves five steps: a) Attenuated Colour channel correction: The original image first undergoes a colour channel correction. Since underwater images tend to scatter blue light less than red lights, the images taken underwater have higher values in the blue/green channel as compared to the red. Hence, images are colour balanced using weights for each channel.; b) Local Contrast Enhancement: Local contrast enhancement is done by converting the histogram of each channel into a Rayleigh distribution.; c) Global Contrast Enhancement: A dual histogram based iterative thresholding method is used to first transform the image into foreground and background images which are then stretched under a dynamic range.; d) Multiscale Fusion: The fusion of the globally enhanced image and locally enhanced image is carried out. Brightness weight maps and saliency weight maps are used to fuse the two images.; e) Multiscale Unsharp Masking: Image dehazing is carried out using MSUM. Three different Gaussian kernels with different scales are used to de-blur each colour channel. The three different de-blurred images for each colour channel are then combined to give the de-blurred image for each channel.

In [25], a Bayesian retinex algorithm is developed to enhance single underwater images using multiorder gradient priors for both reflectance and illumination. The method begins with a straightforward colour correction step to eliminate colour casts and restore naturalness. Then, a maximum a posteriori formulation for underwater image enhancement is established, incorporating multiorder gradient priors on both reflectance and illumination.The complex problem of underwater image enhancement is simplified into two denoising subproblems, each with a mathematically provided convergence analysis. Solutions are derived through an efficient optimization algorithm. Importantly, this model is implemented using pixel wise operations, enabling fast processing without requiring additional prior knowledge about underwater imaging conditions. In [26], the challenge of enhancing low-light images without introducing unwanted artefacts like amplified noise and degraded contrast is addressed. Inspired by Retinex theory, the authors propose an innovative approach. They develop an end-to-end network guided by signal priors and layer-specific constraints for single-image low-light enhancement. The model, called Sparse Gradient Minimization sub-Network (SGM-Net), effectively preserves major edge information while removing low-amplitude structures. This process aids in extracting illumination maps for both low and normal-light images. Subsequently, two sub-networks, Enhance-Net and Restore-Net, are employed to enhance illumination and reflectance maps, respectively. These networks improve contrast and reduce noise in the reflectance map. The integration of various constraints and regularisation techniques results in high-quality visual reconstructions. The proposed models are rigorously evaluated on synthetic and real images, including those with intensive noise and compression artefacts. The results demonstrate the superior performance of the proposed approach compared to existing state-of-the-art methods.

The authors in [27] introduce a novel neural network, the Progressive-Recursive Image Enhancement Network (PRIEN), designed to enhance low-light images effectively. Unlike previous approaches, PRIEN employs a recursive unit consisting of a recursive layer and a residual block for iterative feature extraction from the input image. The unique aspect of this study is the direct input of low-light images into a dual attention model for global feature extraction. The method combines recurrent layers and residual blocks for local feature extraction and generates the enhanced image as the output. Notably, global feature maps from dual attention are progressively integrated into each stage, enhancing the network's performance. The local feature extraction module incorporates a recurrent layer that shares depth features across stages and performs recursive operations on a single residual block, reducing parameters while maintaining high performance. Despite its simplicity, the network yields impressive results across various low-light conditions. [28] presents a comprehensive review and evaluation of existing single-image low-light enhancement algorithms. In addition to conventional low-level vision assessments, the study explores machine vision performance in low-light conditions, focusing on face detection tasks to investigate the potential of joint optimization for high-level and low-level vision enhancement. To facilitate this research, the authors introduce a large-scale low-light image dataset called Vision Enhancement in the LOw-Light condition (VE-LOL).Unlike typical datasets, VE-LOL includes paired low/normal-light images as well as annotated face images in low-light conditions. The evaluation involves various criteria such as full-reference, no-reference, and semantic similarity metrics for low-level vision. Additionally, the study assesses the impact of low-light enhancement on face detection. Leveraging VE-LOL, the paper explores the novel challenge of joint low-light enhancement and face detection. The authors develop an enhanced face detector that combines low-light enhancement and face detection seamlessly.

The study in [29] focuses on integrating two prominent enhancement techniques: Retinex-based and learning-based methods. First, the authors introduce a novel "generative" strategy for Retinex decomposition, treating it as a generative problem. Building on this strategy, a unified deep framework is proposed to estimate latent components and enhance low-light images. Importantly, the proposed method, called RetinexDIP, performs decomposition without external images, allowing easy adjustment of the estimated illumination for enhancement purposes. Enhancing low-light images poses a challenge due to the need to address not only brightness recovery but also intricate issues such as colour distortion and noise, which are often concealed in the dark regions. Simply adjusting brightness can amplify these artefacts. To tackle this issue, [30] introduces a novel end-to-end method guided by attention mechanisms within a multi-branch convolutional neural network framework. The authors first create a synthetic dataset using meticulously designed low-light simulation strategies, surpassing the diversity and scale of existing datasets. With this new dataset, the proposed method learns two attention maps: one for guiding brightness enhancement and another for denoising tasks. The first attention map distinguishes underexposed areas from well-lit ones, while the second map separates noise from genuine textures. These attention maps guide the multi-branch decomposition-and-fusion enhancement network to adaptively process inputs. Additionally, a reinforcement-net further enhances the colour and contrast of the resulting image. [31] introduces a novel approach called Zero-Reference Deep Curve Estimation (Zero-DCE) for enhancing low-light images. Zero-DCE treats light enhancement as an image-specific curve estimation task using a lightweight deep network, DCE-Net. The network is trained to estimate pixel-wise and high-order curves for dynamic range adjustment in a given image, considering factors like pixel value range, monotonicity, and differentiability. This is achieved through carefully formulated non-reference loss functions, which implicitly measure enhancement quality and guide network learning.

DATASET DESCRIPTION

The dataset chosen for the task was the LOL Dataset. It consists of 500 light and dark pairs of images. The images are taken in a dim light setting. The images are of everyday objects taken inside a bedroom. 485 images (each for light and dark) are training sets and the other 15 images (each for light and dark) are testing sets.

a)

High light image

Low light image

b)

High light image

Low light image

Proposed work is a heuristic based approach to solving the issues faced by low illumination images. Both training and testing datasets are not used for their intended purposes. Instead only used to enhance and evaluate using chosen metrics.

METHODOLOGY

This study follows five important phases: 1) Attenuated color Channel Correction; 2) Global Contrast Improvement; 3) Local Contrast Improvement; 4) Multiscale Fusion; 5) Noise Removal. Fig 2. shows the progression of the images through the process. And Fig 3. shows the flow of the process.

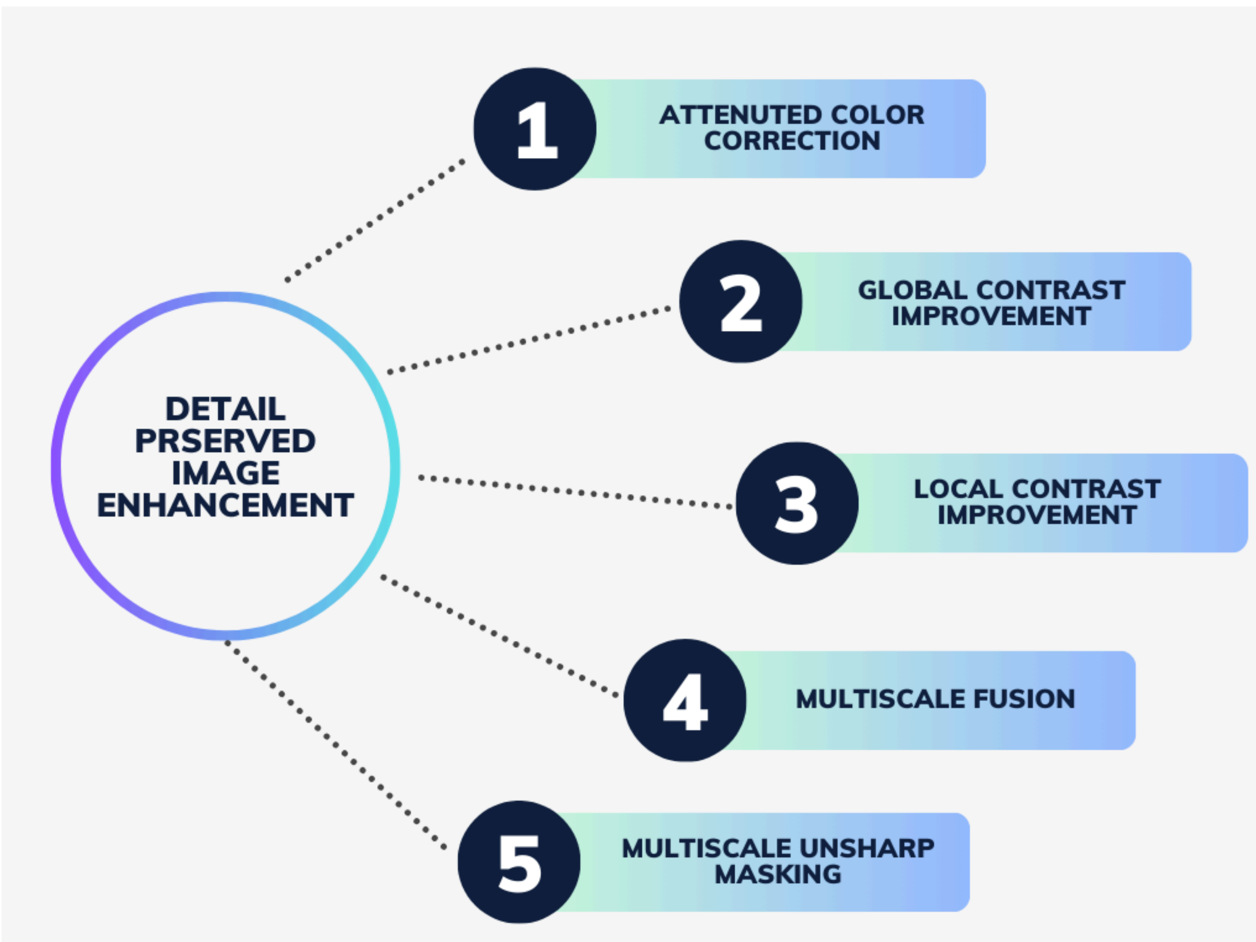

Fig 3.

1) **Attenuated Color Channel Correction:** In this phase we first try to find the color channel, from the RGB color model, dominant in the given image. In low light images usually, the red color channel is the dominant one with very low values for the green and blue channels. We do that by calculating the mean of all pixels of the image belonging to the color channel (eq.

1). By comparison we find which color channel is maximum named I_{max}, minimum named I_{min} and the intermediate channel named I_{int}.

$$Mean_c = \frac{1}{MN}\sum_{i}^{M}\sum_{j}^{N} I_c(i, j),\ c \in \{R, G, B\} \qquad \text{(eq.1)}$$

Using the above intensities we calculate attention weights as follows:

$$Attint(i, j) = Imax(i, j) - Iint(i, j) \qquad \text{(eq. 2)}$$

$$Attmin(i, j) = Imax(i, j) - Imin(i, j) \qquad \text{(eq. 3)}$$

Where Imax, Iint and Imin are the superior, intermediate and inferior color channels respectively. The attention weights from eq. 2 and eq. 3 are crossed with Imin and Iint respectively to balance out their values against the dominant color channel. The final corrected image is obtained using eq. 4.

$$I_{cr} = O_{min} + (I_{in} - I_{low}) \times \left(\frac{O_{max} - O_{min}}{I_{high} - I_{low}}\right) \qquad \text{(eq. 4)}$$

Where I_{low} and I_{high} are the highest pixel value and lowest pixel value for the color compensated image I_{in}. O_{max} and O_{min} are the maximum and minimum values for the output image. I_{cr} is the final corrected image.

2) **Global Contrast Improvement:**The histogram has been divided into two sections recently using the mean point [15], median point [16], and average point of the mean and median [32]. Nevertheless, these techniques only split the histogram into two sections and fail to provide enough consideration to separating the image into foreground and background subimages. In contrast to these techniques, it was found that the majority of underwater photos were taken with bright areas in the foreground and dark areas in the background. More specifically, areas close to the light source have greater brightness than areas farther away. Consequently, it is important to separate the underwater image into subimages for the foreground and

background.Here Dual-Histogram-Based Iterative Threshold was applied.The current underwater image is divided into red, green, and blue channels in the first stage. Next, the minimum, maximum, and optimal separation points are determined for the three-color channels.Each channel's foreground (the high-pixel-value histogram) and background (the low-pixel-value histogram) are also divided. The red, green, and blue channel histograms are split into two categories, background-stretched histograms and foreground-stretched histograms, once the optimal separation point has been identified. Next, the foreground histograms are stretched from the optimal separation threshold Iopt to the maximum intensity value I_{max} of the dynamic range, and the background histograms are extended from the minimum intensity value I_{min} to the optimal separation threshold I_{opt} of the dynamic range.Thus, the background and foreground histograms are stretched as follows:

$$I_B = I_{min} + (I_{opt} - I_{min}) \times CDF(I_{CR}),\ I_{CR} \in [I_{min}, I_{opt})$$

$$I_F = (I_{opt} + 1) + (I_{max} - (I_{opt} + 1)) \times CDF(I_{CR}),\ I_{CR} \in [I_{opt}, I_{max}]$$

where I_B and I_F are the background-stretched and foreground-stretched histograms for each color channel, respectively. I_{CR} and CDF() are the color-corrected image and the cumulative distribution function (CDF), respectively. I_{min} and I_{max} are the minimum and maximum values of the current image, respectively.All background-stretched histograms are composed to generate an under enhanced image. Likewise, all foreground-stretched histograms are composed to generate an over enhanced image. Then, the under- and over-enhanced images are integrated into the enhanced image I_{BF} based on the optimal threshold point I_{opt}.

3) **Local Contrast Improvement:** Some methods [15], [16] prove that the Rayleigh distribution is good for maintaining naturalness. The Rayleigh distribution is a bell-shaped curve of the intensity level distribution. The intensity levels of each color channel in the image histogram are transformed to follow the Rayleigh distribution. In other words, the intensity values of each pixel in each color channel are changed so that they match the Rayleigh distribution. The Rayleigh distribution is a probability distribution that describes the magnitude of a random variable that is the sum of two independent and identically distributed normal variables. It is

commonly used in signal processing and image processing to model the noise in a signal or image. Enhancement filters can use the Rayleigh distribution to improve the contrast and sharpness of an image. The proposed method applies the Rayleigh distribution to the histogram of the color-corrected image using eq. 5.

$$I_{RW} = \frac{\left[(I_{CR} - I_{min}) \times \left(\frac{O_{max} - O_{min}}{I_{high} - I_{low}}\right)\right]}{\alpha^2} \cdot e^{-\left[\frac{O_{min} + \left[(I_{CR} - I_{min}) \times \left(\frac{O_{max} - O_{min}}{I_{high} - I_{low}}\right)\right]}{2\alpha^2}\right]^2} \quad \text{(eq. 5)}$$

The proposed method also uses limits in the stretching processes. Unlike previous methods, which apply the limits to the input image, the proposed method applies the limits to the output image. For each channel, the minimum stretching value of the output image is set to the minimum intensity value of the original histogram if it is greater than 3.5% of the minimum intensity value of all three RGB channels. Otherwise, the minimum intensity value of the output image is set to 3.5% of the minimum intensity value of all three RGB channels. When we improve the overall contrast of an image, we can lose some of the detail in the image. This is because the contrast enhancement process compresses the dynamic range of the image. To compensate for this, we designed a special histogram that helps to improve the local contrast of the image. This histogram is applied directly to the image after the color correction step.

4) Multiscale Fusion: The global contrast improved image from 2) and the local contrast improved image from 3) are fused in this step to get the wholly contrast improved image. Two weight maps are used for the fusion process.

a) Brightness Weight map: This is used to assign larger values to well-exposed pixels and vice versa for not so well-exposed pixels. An image should be balanced, not too bright or dark. In the CIELAB color model, a Gaussian model is used to model the distance to the normalized mean range, for the brightness weight map.

b) Saliency Weight map: This is used to highlight the saliency regions of the image and improve contrast between the bright and dark regions. The map is applied in the HSV color space or color model using eq. 6.

$$WS,k(i,\ j) = (Hk(i,\ j)\ -\ MHk)^2 + (Sk(i,\ j)\ -\ MSk)^2 + (Vk(i,\ j)\ -\ MVk)^2$$
(eq. 6)

where Hk, Sk, Vk, MHk, MSk, and MVk are the hue, saturation, value, mean hue, mean saturation, and mean value of the kth input image, respectively.

c) The two weight maps are fused to give a final weight map using a normalizing constant β. The final output image is a cross of the fused weight map and the contrast improved image.

5) **Noise Removal:** Noise removal is done via Gaussian filter. A Gaussian filter is a type of low-pass filter that is used to blur images. Since it is a convolution filter, each pixel in the image is subjected to a weighted average of its neighbors' pixels. A Gaussian function, a bell-shaped curve with a peak in the middle and a decline towards the edges, determines the weights. This indicates that the filtered pixel is more influenced by the pixels in the kernel's center than by those on its boundaries. Images with noise can be effectively cleaned up with Gaussian filters. A wide range of additional image processing activities, including edge detection, picture sharpening, and image mixing, also make use of them. A Gaussian filter is implemented by convolving the image with a Gaussian kernel. The Gaussian kernel is a weighted average of the neighboring pixels, where the weights are determined by a Gaussian function. To convolve the image with the Gaussian kernel, we simply slide the kernel over the image and compute the weighted average of the pixels under the kernel. This is done for each pixel in the image.

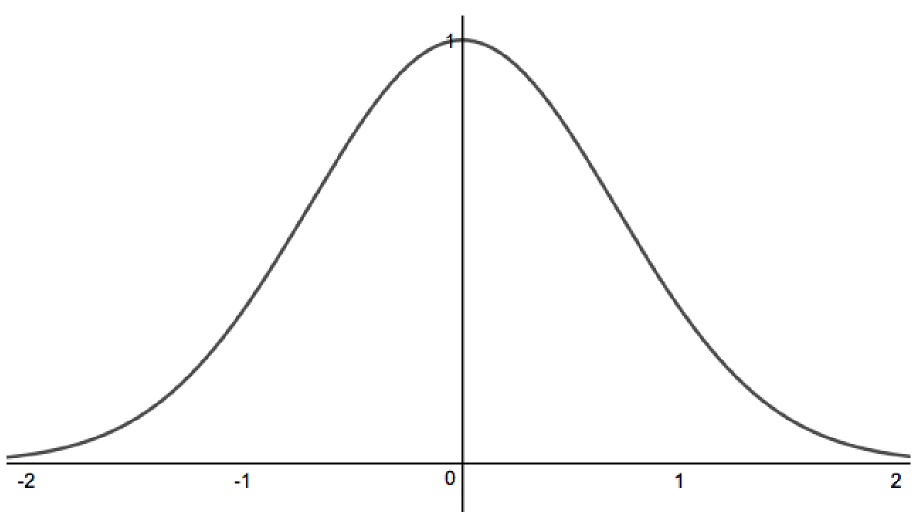

Fig. 9. Gaussian Function Curve [33]

RESULTS AND DISCUSSION

Our model was evaluated using the following metrics:

a) **BRISQUE (Blind/Referenceless Image Spatial Quality Evaluation):** A no-reference IQA metric that measures the naturalness of an image by analyzing the local spatial statistics.
b) **Average Gradient:** A simple IQA metric that measures the average magnitude of the image gradient.
c) **PCQI (Perceptual Quality Criterion Index):** A no-reference IQA metric that measures the perceived quality of an image by modeling the human visual system.
d) **NIQE (Naturalness Image Quality Evaluator):** A no-reference IQA metric that measures the naturalness of an image by analyzing the local and global statistics.
e) **Information Entropy:**A measure of the randomness of an image.

The results are shown in Table 1 and Fig 4.

BRISQUE	Average Gradient	PCQI	NIQE	Information Entropy
37.8714	38.6984	17.7023	0.8226	4.9418

Table 1. Results of evaluations

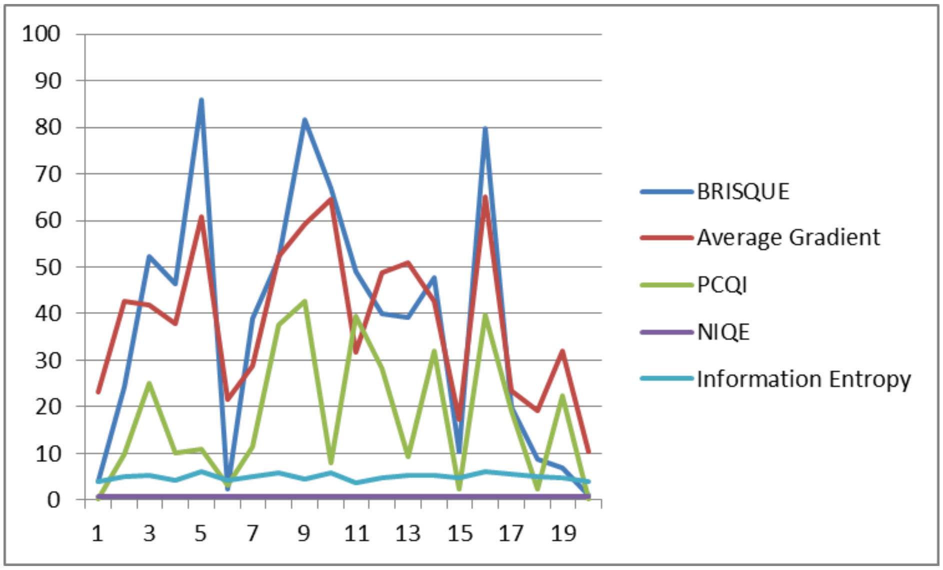

Fig. 4.

Experimental analysis showed a particular trend where extremely dark images gave a better BRISQUE, Average Gradient and PCQI output. In darker images, blue and green color channels are more dominant than red. Thus, our model tends to perform better for extremely dark images such as in Fig. 5.

Fig. 5. Extremely dark image

For NIQE that detects naturalness and for Information Entropy which detects information content in the image, our proposed model performs better when the dominant channel is red i.e. images are not completely dark and objects are slightly visible such as Fig. 6. BRISQUE, PCQI and Average gradient values for our model on an average are 38, 18 and 39. These metrics with these values are ideal for object detection and identification applications.

Fig. 6. Low light image

On the other hand our model's NIQE and Information Entropy values are 0.8 and 5 respectively, ideal for classification applications due to its naturalness and high information content. Thus, our model can serve two purposes: a) Object detection and recognition for extremely dark images; b) Classification for low light images. Fig 7. and Fig. 8 highlight the same.

Fig. 7. (a) Dark Low light image

Fig. 7. (b) Processed image with better edges

Fig. 7. (c) Corresponding highlight image

Fig. 8. (a) Low-Light image

Fig. 8. (b)

Fig. 8. (c)

CONCLUSION

In this project, we proposed a new low-light image enhancement method that consists of attenuated color channel correction (ACCC) and detail-preserved contrast enhancement. Our method is able to effectively improve the global and local contrast of low-light images, while preserving fine details and avoiding artifacts. We also proposed a multiscale fusion strategy to combine the global and local contrast-enhanced images, and a multiscale unsharp masking strategy to further sharpen the corrected image.

We believe that our proposed method has the potential to be used in a variety of applications, such as photography, security, and autonomous vehicles. For example, our method could be used to enhance the quality of low-light images captured by security cameras, which could help to improve public safety. Our method could also be used to enhance the quality of low-light images captured by autonomous vehicles, which could help to improve the safety and efficiency of transportation.

This work can be extended in the following directions:

- Investigating the use of deep learning techniques to further improve the performance of our method.
- Developing a real-time version of our method that can be used to enhance low-light images in real time.
- Testing our method on a wider range of low-light images, including images from challenging real-world scenarios.

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