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# A Review on Enhancement of Images with Lower Contrast

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***Abstract*— Image plays an important role in serval application in our day-to-day actives. One of the key concepts in processing of digital image is image enhancement. The enhancement of image helps in identifying the target object. The features present in the image need to be enhanced for obtaining high visual quality. To realize image enhancement different type of techniques are involved and presented in this paper. Images taken in low-light situations frequently exhibit characteristics like lower level of brightness, inadequate contrast, a limited grayscale, colour deformations, and significant disruption, all of which have a negative impact on the quality of the visual effects on human eyes and severely limit the effectiveness of many automated vision frameworks. The effect of lower contrast images is clearly observed in underwater images, CC footage images, satellite images, areal images, medical images etc. The work presented covers the existing enhancement techniques, availability of datasets for performing the techniques, finally the assessment metrics involved in describing the enhancement quality of image are discussed.**

***Index Terms*— Image processing, Image Enhancement, Traditional methods, Deep learning methods, quality metrics**

## I. INTRODUCTION

It's common practice to obtain images and video data from devices; however, in adverse conditions such as dim lighting, minimal electron count, inadequate exposure, and haze, the images recorded by the system for vision will suffer from diminished information in detail, accompanied disturbances, dark local and overall illumination, and contrast deterioration, which will not only negatively impact the eyes' ability to recognise objects visually, but also create challenges for tasks like recognition of face (Y Xueyi [1]), segmentation based on semantics (P Zhai [2]).Similar to this, surface brightness level plays a significant role in neural network recognition of item faults (I. Konovalenko et al., [3]), and surface brightness augmentation increases the number of faulty segments identified. It is simple to discover that the "area" parameter—which is the most often used tool for picture pre-processing, quality enhancement, and labelling—is more stable to changes in light than the "direction" parameter. As a result, there are several applications for processing low-light photos.
The usage of digital image processing systems has increased significantly across several industries due to the quick

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development of computer vision technology. Applications in the field of medicine, industrial operations, intelligent transportation, surveillance videos, satellite tracking, military applications, and other fields all heavily rely on it.Specifically, under low-light conditions—such as those seen inside during the darker surface or cloudy days—the light which is been reflected from the other object surface may be not clear, which can cause noise and colour distortions to significantly deteriorate the quality of the image. Lower light (LL) as the term implies, describes circumstances in which the level of illumination is below the average. However, there isn't a single, accepted norm since it's been hard to identify the precise theoretical values that characterise a lowlight environment in practice up until now.

One of the primary goals of image processing is enhancing the image, which includes incorporating information or applying certain techniques to transform data into original pictures to adjust the image to fit the features of the visual response and emphasise specific elements of interest. Extracting the contrast among the characteristics of different items in a picture, suppressing uninteresting features, enhancing the quality of the image, adding more information, strengthening the impact of recognition and interpretation of the picture and satisfying specific analysis requirements are the primary goals of enhancing an image. “Fig.1” displays a few low light and poor contrast photos.

Figure 1. Low light and Low contrast Images

To increase the functionality of imaging devices, it is crucial and useful to research image enhancement techniques. Increasing the image's overall and local contrast is the main objective for enhancement of image, whereas avoiding of noise amplification and achieving excellent real-time effectiveness, its visual effect, and its suitability for computer processing or human observation.

This work aims to provide an extensive survey of the literature on picture enhancement from an algorithmic standpoint. Section 2 discusses several current image enhancing approaches based on traditional methods and based on deep learning techniques. Some of the available datasets for processing of enhancement techniques are discussed in section 3. The metrics which are commonly used to evaluate the performance of methodologies is discussed in section 4 and finally overall summary of the work is presented in section 5.

## II. Related Work

Research on enhancement of lower light images is an ongoing work with the goal of enabling the equipment used for acquisition to take excellent pictures in lower light. Clear images are required to obtain the best information possible for most applications. Because of the effects of low brightness, low contrast, and significant noise, improving low light photographs is a challenging undertaking. The different type of image enhancement techniques is shown in “Fig.2”.

To regulate the enhancement rate, the image enhancement method Bi-histogram equalisation with two plateau limits (BHETPL) is presented by Ch. Ooi et al., [4]. This technique allows for the maintenance of the mean brightness. Several HE techniques reduce the impact of saturation, uneven artefact growth, and unnatural effects by maintaining mean brightness and managing enhancing rate. One of the contrast enhancement techniques discussed by M.F Khan et al., [5] is Segmenting selective dynamic histogram equalisation (SSDHE) which helps in minimizing the level of impact. The exposure related sub-image histogram equalisation (ESIHE) approach (K. Sing et al., [6]) equalises a picture by dividing the histogram into two portions and using the exposure measurements as a cutoff.

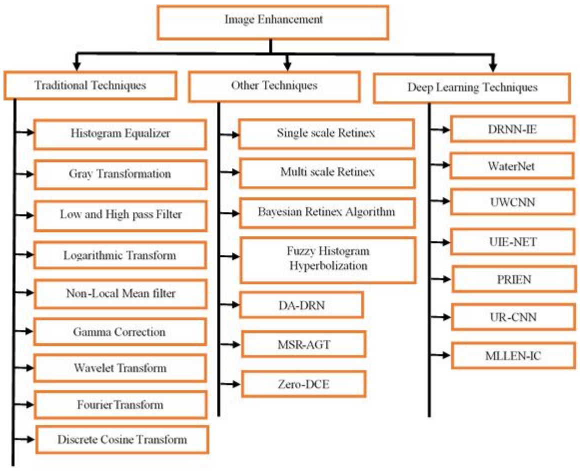


Figure2. Different Image Enhancement Techniques

For picture contrast enhancement, a dynamic histogram equalisation (DHE) (M.A Al Wadud et al., [7]) uses a variation that effectively maintains the mean brightness while cutting down on computation time. It uses both intraclass and interclass variance to split a histogram recursively while maintaining the mean brightness. In this instance, locating the separation point does not require computing the local maxima and minima. Smoothing of the input histogram is not required. Effective usage of this technology can enhance medical imaging.
G. Ulutas et al., [8] integrates global and local contrast enhancement algorithms, two distinct methods, to improve the contrast of picture and enhance visual quality in underwater photos. Adaptive histogram equalisation (CLAHE), a local strategy, considers the image's local brightness qualities in RGB colour space, while layered difference representation (LDR) is a worldwide approach which ensures that the image is improved overall. In addition, this technique uses local colour correction for underwater photography. This approach implements HE to each of the non-overlapping sub-blocks that make up the underwater image, whereas other methods utilise different techniques on the global histogram channels.
As can be observed in Fig.3, the advancement analysis of multiscale image methodology has caused image enhancing techniques to move from the spatial to the frequency domain.

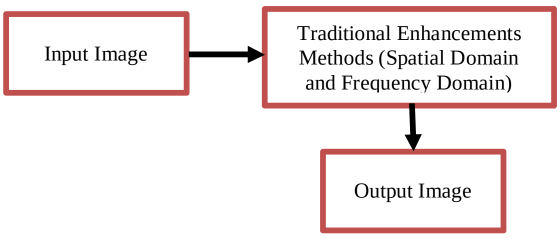


Figure3. Enhancement of Image

Frequency domain image enhancement approaches first convert source pictures into the frequency domain so that they may be filtered using Fourier analysis. After that, the final picture is reversely altered to return it to the spatial domain. Two popular frequency-domain methods are wavelet transform (WT) and homogeneous filtering (HF).In light of the illumination rejection algorithm's attributes, homomorphic filtering-based enhancement techniques convert the refusal and brightness element expressed as a sum in a logarithmic domain as opposed to a product. Filters with high pass characteristics are used in the fourier transform domain to decrease low-frequency illumination components and increase high-frequency rejection components (S. Park et al., [9]).

An approach to enhancement of contrast based on the analysis of multiscale wavelet is suggested by X. Zong et al., [10]. Ultrasonic image improvement is possible by the multiscale non-linear high pass function processing of the wavelet coefficients. In reference to local wavelet coefficient statistics, A. Loza et al., [11] suggests an adaptive methodology for enhancing the contrast. A framework for local wavelet aspects that creates a non-linear boosting function with non-linear properties for the reduction of wavelet coefficients was created in terms of binary Cauchy distribution. A modified knee function and gamma transform function are utilised to enhance lower components in a wavelet transform based on enhancement of image approach connected with strengthened knee transfer function and gamma correction (i-KTFGC) (A.K Bhandari et al., [12]).The lower-frequency and higher-frequency elements are combined after augmentation, and an inverse wavelet transform is then applied to provide a better image. i-KTFGC often enhances the brightness of image and also the contrast parameter.

Finally, inverse WT might be used to recreate the improved picture with a very low amount of noise(H. Lidong et al., [13]). To increase the boosting impact of low light photos, the WT approach has also been merged with Retinex theory by K. Kawasaki et al., [14]. M.H. Asmare et al., [15] presents a curvelet-based multiscale analysis methodology and demonstrates its superiority over the WT method for enhancing colour images. For images that are noiseless or almost noiseless, the WT approach performs better than the curvelet transform-based boosting methodology. The wavelet transforms which is combined with the curvelet transform to improve the picture while preserving its edges, was proposed by J.L. Starck et al., [16].

### *A. Techniques based on Deep Learning*

Rather of being data-driven, the majority of contemporary image enhancing techniques are model-based. Recently, a significant number of images enhancing methods based on machine learning have started to emerge (T.Y Han et al., [17]). To improve underwater photos, P. Gomez et al., [18] created a pixel-to-pixel (P2P) network. This is symmetric to encoder-decoder networks like REDNet(X. Mao et al., [19]). Three convolutional layers make up the encoder portion, whereas three deconvolutional layers make up the decoder portion. ReLU comes after every network element until the final one.

Recently, the underwater generative adversarial network (U-GAN) (C. Fabbri et al., [20])has been created to enhance the quality of photos taken underwater. Instead of clipping the gradients in a certain range, U-GAN uses Lipschitz on gradient norms to pick Wasserstein GAN with gradient penalty (WGAN-GP) (I. Gularajani et al., [21]) and impose the result's soft constraint in relation to its input. The discriminator is completely convolutional and identical to (A. Radford et al., [22]), with the difference that batch normalisation is not applied to the convolutional layer weights (S. Ioffe et al., [23]).

Recently, K. Cao et al., [24] suggested a model of deep networks for underwater picture restoration, which draws inspiration from conventional methods that determine the transmission map independently and the underlying light individually. Consequently, two separate network architectures, the background light network (BL-Net) and the transmission map network (TM-Net), are proposed, even if the network is often referred to as UIR-Net collectively. A basic five-layer network is called BL-Net. The designed three layers consists of convolution layer, batch normalization and pooling layers. The latter two stages are completely linked. The threshold that confines it to the interval [0,1] is the BL-Net output. It is based on a more complicated TM-Net that consists of two subnets: a refine subnet and a coarse global subnet. The course subnet consists of five convolutional layers in which the first two of layers are batch normalisation and pooling layer (D. Eigen et al., [25]).

Utilising the NYU-v2 dataset UIR-Net generates 12,000 artificial undertaker pictures with a total of 29 distinct underwater ambient light variations, in accordance with (Y. Wang et al., [26]). The BL-Net initialises at random, whereas the TM-Net uses weights obtained from VGG. As the name implies, WaterGAN(J. Li et al., [27]) is a GAN that replicates underwater photos for colour correction by manipulating the RGB-D image. These techniques are implemented on different types of datasets. Some of the datasets that are available to identify the performance of the techniques are discussed in section 3.

## III. AVAILABILITY OF DATASETS

When researching image improvement algorithms, many researchers typically share the low illumination picture data sets they gather, making it easier for other academics for future research. Several commonly utilized enhancement of image datasets are listed in this study.

### *A. MIT-Adobe FiveKDataset*(B. Vladimir et al.,[28]):

5000 photos shot using SLR cameras are included in the MIT-Adobe FiveK Dataset. Five human painters then retouch each of the many sceneries, subjects, and lighting situations that are included in the dataset.

*B. LOL dataset(W. Chen et al., [29]):*

The said DS includes 500 low/normal light image pairs of 400x600 pixels recorded in RGB format, this is the first collection of image pairings from real circumstances for lower-light enhancement.

*C. SID*(Chen Chen et al., [30]):

There are 5094 raw short-exposure photographs in the See-in-the-Dark (SID) collection, which includes both indoor and outdoor settings. The 5094 raw short-exposure photos in SID are correlated with 424 distinct long-exposure comparative photographs.The majority of the outside photos were taken at night, when there is often between 0.2 and 5 lux of illumination from the moon or street lights. In interior scenarios, the illumination at the camera typically ranges from 0.03 to 0.3 lux. Two cameras—the Fujifilm X-T2 and the Sony A7S II—were used to take the pictures. The sensors in these two cameras are different: The Sony camera features a full-frame Bayer sensor, whereas the camera Fuji lens uses an APS-C X-Trans sensor. The Sony and Fuji photos have resolutions of 4240×2832 and 6000×4000, respectively.

*D. MEFdataset*(Kede Ma et al., [31]):

The 136 fused photos in Multi-exposure Image Fusion (MEF) include both interior and outdoor vistas, natural scenery, and man-made buildings. At least three input images—representing underexposed, overexposed, and in-between cases—are included in each image series. These datasets, however, are tiny in scope and only include a few scenes.

*E. SCIE dataset*(Jianrui Cai et al.,[32]):

The SCIE dataset consists of589 number of sequences from the closed and outdoor environments. These sequences feature 3, to 18 low-contrast photos of varying exposure levels, totalling 4,413 multi-exposure images. The image sequences are captured using seven different consumer-grade camera types: Sony 𝒔7RII, Sony NEX-5N, Canon EOS-5D Mark II, Canon EOS-750D, Nikon D810, Nikon D7100, and iPhone 6s. Most of the photographs have resolutions ranging from 3000×2000 to 6000×4000.

*F. NPE dataset(S. Wang et al.,[33]):*

The NPE dataset comprises 110 photographs that were downloaded from the websites of various corporations and organisations, including Google and NASA, and 46 images that were taken with a digital camera made by Cannon. Every image in the sample has significant lighting fluctuation in global space but poor contrast in local locations.

*G. ExDARK*(P.L Yuen et al.,[34]):

The Exclusively Dark (ExDARK) dataset comprises 7,363 low-light photographs from extremely low-light scenarios to twilight (i.e., 10 unique circumstances) with 12 object classes (similar to PASCAL VOC), annotated on both picture class level and local object bounding boxes. It is typically applied to studies on object identification in dimly lit environments.

## IV. ASSESSMENT METRICS OF IMAGE QUALITY

The parameters which are been used by many researchers to evaluate the effectiveness of proposed methodology are:

- Peak Signal to Noise Ratio (PSNR)
- Structural Similarity Index (SSIM)
- Visual Information Fidelity (VIF) and
- Average Brightness (AB)
- Entropy
- Underwater image quality metric (UIQM)
- Universal image quality index (UIQI)

*A. Peak Signal to Noise Ratio (PSNR)*

PSNR is a crucial metric for assessing how well the suggested strategy performs. Peak signal-to-noise ratio (PSNR) is the ratio of an image's highest potential power to corrupting noise's ability to degrade the quality of image's portrayal. A picture's PSNR must be estimated by comparing it to the best feasible clean image with the highest power. The quality of the compressed or rebuilt image improves with increasing PSNR. For input image X and denoised image R, the PSNR is expressed as,

$$PSNR = 10 \times log_{10}\left(\frac{255\times255}{MSE}\right) \quad (1)$$

*B. Structural Similarity Index (SSIM)*

SSIM is a perception-based approach that incorporates key perceptual phenomena, such as contrast and brightness masking terms, and views image deterioration as a perceived change in structural information. These methods estimate absolute errors, which sets them apart from other approaches like MSE or PSNR. The concept of structural information states that pixels have significant relationships with one another, particularly when they are close in space.

$$SSIM\ (x, y) = \frac{(2\mu_x\mu_y+c_1)(2\sigma_{xy}+c_2)}{(\mu_x^2+\mu_y^2+c_1)(\sigma_x^2+\sigma_y^2+c_2)} \quad (2)$$

*C. Visual Information Fidelity (VIF)*

A full-reference picture quality metric called visual information fidelity (VIF) measures image fidelity using a data-theoretic criteria. In an information-theoretic framework, natural scene statistics (NSS), HVS, and an image distortion (channel) model are used in the VIF approach to quantify the information that the picture might ideally retrieve from the source image and information loss due to the effect of distortion.

*D. Average Brightness*

Average value of all the pixels (i.e. sum up all the brightnesses of all the pixels, then divide by total amount of pixels, i.e. width * height).

*E. Entropy*

Entropy, which may be represented as, is a measure of the amount of data contained in a picture.

$$H(F) = -\sum_{i=0}^{255} p_i log_2 p_i \quad (3)$$

Where $p_i$indicates the $i$intensity occurring probability at a pixel in image F.

*F. Underwater image quality metric (UIQM)*

It is based on the human visual system concept and operates without a reference image. The three primary components of UIQM are UICM, that evaluates the colour of underwater images; UISM, which evaluates the sharpness of underwater images; and UIConM, which analyses the contrast of images in underwater. The following formula are used to calculate UIQM as,

$$UIQM = Coeff_1 \times UICM + Coeff_2 \times UISM + Coeff_3 \times IConM \quad (4)$$

Greater UIQM levels indicate a satisfactory level of improvement.

*G. Universal image quality index (UIQI)*

With UIQI, every picture distortion is modelled as a combination of three factors: distortion of contrast, distortion of luminance, and loss of correlation, as opposed to using conventional error summation techniques.
Let $x = \{x_i | i = 1,2, \dots \dots N\}$ and $y = \{y_i | i = 1,2, \dots \dots N\}$ are the original and test image signals. The quality metric is given by

$$Q = \frac{4\sigma_{xy}\overline{x}\overline{y}}{(\sigma_x^2+\sigma_y^2)[(\bar{x})^2+(\bar{y})^2]} \quad (4)$$

Here $Q$ has a dynamic range of $|-1,1|$. The best value 1 is attained if and only if $y_i = x_i$ for all $i = 1,2, \dots \dots, N$. The lowest value -1 happens when $y_i = 2\bar{x} - x_i$ for all $i = 1,2, \dots \dots, N$.
Different methods have been evaluated for performing image enhancement for underwater images. The metrics analysed are shown in table 1.

TABLEI. COMPARISON OF PERFORMANCE METRICS USING DIFFERENT TECHNIQUES

| Technique | PSNR | SSIM | MSE | Entropy | UIQI |
|---|---|---|---|---|---|
| LIME (X. Guo et al., [35]) | 26.54 | 0.83 | 582.90 | 4.84 | 0.82 |
| GLADNET (W. Wang et al., [36]) | 28.78 | 0.82 | 662.21 | 3.98 | 0.83 |
| UIENET (Y. Wang et al., [37]) | 26.89 | 0.88 | 687.54 | 5.88 | 0.85 |
| NIBA (Z. Al Ameen et al., [38]) | 34.27 | 0.95 | 464.67 | 4.97 | 0.88 |
| NUM (D. Ngo et al., [39]) | 31.45 | 0.93 | 587.69 | 6.12 | 0.87 |

| | | | | | |
|---|---|---|---|---|---|
| FGAN (C. Ancuti et al., [40]) | 32.89 | 0.96 | 516.93 | 6.83 | 0.90 |
| RADE (Z. Li et al., [41]) | 29.13 | 0.77 | 562.53 | 5.83 | 0.87 |
| CCF-D (M. Muniraj et al., [42]) | 33.37 | 0.93 | 497.88 | 4.87 | 0.91 |
| MFPP (J. Zhou et al., [43]) | 30.30 | 0.87 | 542.16 | 6.72 | 0.93 |
| MSR-AGT (J. Yao et al., [44]) | 31.53 | 0.92 | 572.52 | 5.28 | 0.94 |

## V. Conclusion

For many real-time image processing applications, picture enhancement is a necessary preprocessing step. There are several methods for improving photos, and which one is best depending on the kind of image. This paper offers a thorough overview of previous studies conducted on picture enhancement and its enhanced forms. This review examines a wide range of picture enhancing techniques and classifies and discusses algorithms suggested by scholars in the literature. The benchmark datasets that researchers can use to conduct experimental analysis were described in this work. There has been a thorough discussion of several picture quality characteristics needed for quantitative assessment. The goal of the article was to understand the effectiveness of contemporary state-of-the-art enhancement approaches by experimentally evaluating photos from various datasets using cutting-edge techniques.


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