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Features Fusion For Natural Tone - Mapped Image Quality Evaluation Using DL-CNN

B Suresh Babu [1] , T Suman [2] , Venkata Narayana [3] , Venkata Ramana Reddy [4] , N Naveen Kumar [5]

[1, 4] Department of ECE and Dean of IQAC, Viswam Engineering College, Madanapalle, Andhra Pradesh, India
[2] Department of ECE, Dr. K.V. Subba Reddy Institute of Technology, Kurnool, Andhra Pradesh, India.
[3] Department of ECE, KSRM College of Engineering, Kadapa, Andhra Pradesh, India
[5] Department of ECE Anantha Lakshmi Institute of Technology & Sciences, Ananthapuramu, Andhra Pradesh, India

* *Corresponding Author : B Suresh Babu ; sureshdecs10@gmail.com*

Abstract: Tone-mapping is a complex process for displaying HDR pictures on standard displays. There are several ways to tone-map pictures, thus it's important to come up with a fair quality measure to choose the best tone-mapping operator (TMO) and adjust its parameters to get the greatest reproduction quality. This is a novel way to objectively assess tone-mapped photos of real-life settings. It combines perceptually meaningful features picked using an acceptable technique. Additionally, the selection highlights the significance of perceptual factors in evaluating tone-mapped HDR video. A number of state-of-the-art criteria and three publicly available datasets are used to assess the feature combination. A different goal is suggested to optimize the picture quality. The foundation of this strategy is the DL-CNN fusion of many perceptually significant characteristics that have been meticulously chosen utilizing adequate high-level features.
Keywords: CNN, DL, ML, AI, TMO, CMOS, CCD.

1. Introduction

Technology and imaging equipment make billions of digital photos daily. Light source, weather, or imaging instrument malfunction might affect image contrast and tone. Image improvement involves tone mapping. The conventional digital cameras CCD or CMOS array catches photons going through the lens and converts them into a picture. Raw photos are too long for most monitors. Recent image and video processing advances aim towards realism and immersion. This is reflected in new technologies like UHD, 3DTV, HFR, and HDR, and standard is action efforts. All advancements defy quality evaluation. HDR imaging captures and reproduces real-world brightness values. Under real-world situations, the dynamic range (DR) seen by the human eye is one hundred times greater than that displayed on a standard monitor. To replicate an event, minimize DR. Tone Mapping Outlines (TMOs) delineate the methodology for tone mapping. The utilization of TMOs enhances picture quality. Comparing TMO performance is subjective. Summary: Most operators' parameters affect the final result. Manually selecting the TMO and its parameters is problematic in most cases. Trustworthy, objective quality assessment inside and between TMOs (for parameter setting) is necessary. Full-reference measurements cannot be utilized to compare the reference and distorted images because to the difference in DR. Objective data failed to predict human preferences for tone-mapped natural imagery. This study suggests a content criterion. We modelled the criterion after C ad k et al.

Now a day's satellite images and videos are very important to be processed with better quality and resolution. But in present situations we are facing many problems in providing such images. So it can be resolved by using following methods.

Image Enhancement: It is the procedure of adapt the digital images to render them more appropriate for presentation or further analysis.

Adaptive Histogram Equalization: It is an alternative histogram equalization Contrast limited method.
Image segmentation: It describes the steps used to split a picture into its component elements.

Image fusion: It is considered to improves the details and edges of the scene.

Environment images become hazy owing to low visibility, however typical image processing makes

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use of several enhancing methods when taken in the air. Having a variety of effects, such as light absorption, reflection, ambient noise (air, fog, rain), light scattering, camera projection, and so on. Therefore, in our standardization efforts and with systems that have Ultra High Definition (UHD), 3D-TV, High Frame Rate (HFR), or High Dynamic Range (HDR), we want to provide viewers an immersive and realistic imagery experience. Accurate reproduction of the scene's true luminance values on the final device is the primary objective of HDR imaging. Common displays, on the other hand, have a dynamic range that is around a 100 times less than the DR of an average real-world scene as seen by the human eye. It is essential to reduce the scene's DR in order to recreate it. Our tone-mapping operators (TMOs) are the key to doing this.

The final picture quality is affected differently by various TMOs. Most operators allow you change the scenario using a set of parameters, which has a huge effect on the outcome. In most real-life situations, it's either impossible or very hard to choose the right TMO and its settings by hand. The criterion comprised several factors that are crucial to how individuals see things. It is usual practice to propose many estimators and then integrate them using a machine learning technique in order to obtain feature-based objective quality measures.

It is possible to create objective quality measures based on features by combining estimators with ML. Two problems occur with this efficient approach. To begin, it provides no assurance that the selected estimators are optimal or complimentary. Further, the relative worth of estimators is yet unknown, and retraining is required for different circumstances when utilizing a combination based on machine learning.. Due to problems, we adopted a different method. We offer feature selection on a vast collection of new and current estimators to ensure their optimal use. Here it allows a linear combination, which is transparent and less prone to over fitting. The parameters are fixed in a database. Different datasets confirm this.

2. Literature Review

Objective Tone-Mapped Image Metrics

Dynamic Range Independent Metric (DRIM) was the initial objective metric developed for the purpose of evaluating tone-mapped photographs. When comparing the tone-mapped picture to the HDR original, it finds the spots where the contrast is either lost, boosted, or turned around using a model of the HVS. Two new full-reference measurements for contrast loss and contrast waste were presented by Granados et al. They are based on the concept of HVS and camera noise estimate. In our earlier work a simple measure of contrast reversal along with a novel model of naturalness for TMOs parameters optimization. The contrast reversal shows how much the gradient direction changes between the HDR and tone-mapped versions. The naturalness shows how probable the combination of brightness, contrast, and colorfulness in the tone-mapped image is to make a picture seem natural.

In 2018 the authors Hadizadeh and Baji'c discuss "Full-reference objective quality assessment of tone- mapped images". This work presents an innovative way for evaluating the quality of tone-mapped pictures shown on conventional LDR screens. One problem with this study is that there isn't enough contrast. Low dynamic range images have less intensity levels i.e,8,16 so image quality will be less compared to High dynamic range of images.

D. Kundu, D. Ghadiyaram, A. C. Bovik, and B. L. Evans, "No-reference quality assessment of tone-mapped HDR pictures,". This paper describe about the SDR pictures have 8 bits of color and 8 bits of pixel. HDR photos, that are frequently made with multiple exposures of the same subject, may show 16 or 32 bits/color/pixel, but they need to be tone mapped to SDR before they can be seen on regular displays. This paper's shortcoming is that it cannot provide an appropriate assessment of picture quality and fails to identify objects correctly.

3. Results and Discussion

Disceret Wavelet Transform

Wavelets Method: Similarly, wavelet change. Repeated (Short-time Fourier change, Wigner dispersions, etc. provide similar data.) Any ghost can be fascinating. Knowing when these extraterrestrial parts occur can be beneficial. EEG idleness is convincing. Wavelet change creates a period- recurrence image using time and recurrence data. Scaling and wavelet channels are used in DWT. Progressive high pass and low pass sifting yields recurrent groupings. The x[n] channel is used using a half-band high-pass and low-pass configuration. Since the image has a recurrence of /2 radians, half of the instances can be deleted after sifting. Removing one sample sub samples the image by 2. One degradation level is:

$$\text{yhigh}[k] = \sum x[n].\ g[2k-n] \qquad (1)$$

$$\text{ylow}[k] = \sum x[n].\ g[2k-n] \qquad (2)$$

where y high[k] and y low[k] are channel yields after subsampling by 2.

Half-band channels structure orthonormal bases, making recreation easy. Backward recreating follows the above procedure. The images at each level are up sampled by

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two, then passed through g'[n] and h'[n] (high and low passes, separately).

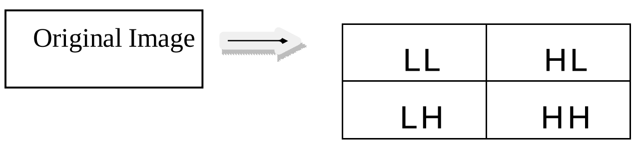
A method to decompose the discrete time signals was presented by Croiser, Estenban, and Galand in 1976, which lay the groundwork for the Discrete wavelet transform. Coding speech signals was the subject of comparable work by Crochiere, Weber, and Flanagan that same year. Sub band coding was the term they gave to their method of analysis. Burt introduced a method that was conceptually comparable to sub band coding in 1983; he called it pyramidal coding and it is now known as multiresolution analysis. After 1989, Vetterli and Le Gall eliminated redundant code in the pyramidal coding system and improved the sub band coding technique. Discrete wavelet transformations and multiresolution analysis are topics that have been thoroughly discussed in previous works; so, this study will refrain from doing so. Pre-processing the image involves image normalization, image enhancement, colour image processing.

In the DWT step, we perform some operations like RGB to Gray and apply some transforms like Haar, DB4, DB7, DB5, Biorthogonal transformations etc. In this algorithm we are using Haar Transform. The detailed analysis and explanation of the Haar transform can be found in several articles that are available on the internet and it is beyond the scope of this paper.The DWT can be performed in multi-levels. The haar transform is applied on the image in each run or every level of DWT. The dimensions of the array are given as powers of two. The arrays are mathematically initialized with a power of two representing the adjusted actual image resolution. The Haar transform separates the image into its high- and low-frequency components.

In the first iteration, the ROW is used to perform the transformation process.

- A: Original Image
- B: First Run along Row
- C: First Run along Column

The details coefficients and converted data are stored in separate sections of the picture array. The high-pass filter generates the detail coefficients while the low-pass filter offers the changed data coefficients. The picture is modified along the column after the row transformation. The technique is repeated until there are three iterations.



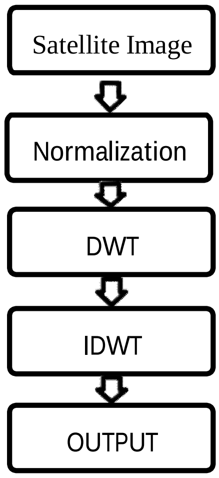


Figure. 1 Flowchart of DWT

From the figure 1 input image is Satellite or medical image. Preprocessing normalize this image. Normalizing pixel intensities. Middle- filtered image. Will allow low and high pass filters . Unlike linear filters, the median filter reduces input noise. This image is segmented. A DWT decomposes a signal into time-frequency coefficients. Unlike Fourier Transform, DWT captures frequency and position (location in time). IDWT reassembles pictures and produces output.

Features Fusion For Tone –Mapping

Selection Of Features Relevant To Tone Mapped Images: Colour, detail, and artifact. Contrast is affected by lightness, chroma, and sharpness. Fusion metrics should be perceptual.Sequential forward selection combines few features while retaining performance. As with other sequential approaches, local minimal likelihood is sensitive to initial conditions. We suggest utilizing a modified Las Vegas algorithm to understand combination behaviour. This helps identify a more credible starting subgroup. . .

Modified Las Vegas Algorithm: Next are algorithmic steps. Subsets: Includes 60 Independent features. Since the subset should be limited and contain just the optimum feature estimators, subsets with two separate metrics computing the same characteristic may be eliminated. Randomly selecting criterion groups forms every Las Vegas subset. Each group had choices. Some organizations permitted only one criterion, some allowed random selection of metrics, while some insisted utilizing all.

(a) Group 1: First category: comparing HDR and tone-mapped versions using full-reference approaches. these estimators: TMQI, TMQI-II, DRIMa, DRIMl, and DRIMr for contrast loss and DRIMr for contrast reversal. Since no two people in Subset 1 assess the same perceptual feature, their selection was entirely at random.

(b) Group 2: Characteristics of FSITMr, FSITMg, and FSITMb. This group employed all

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three measures since assessing feature similarity in one or two channels was not very helpful.

(c) Group 3: Contrasts GCF, Weber, Michelson, SDME, and RMS. Choose one feature.

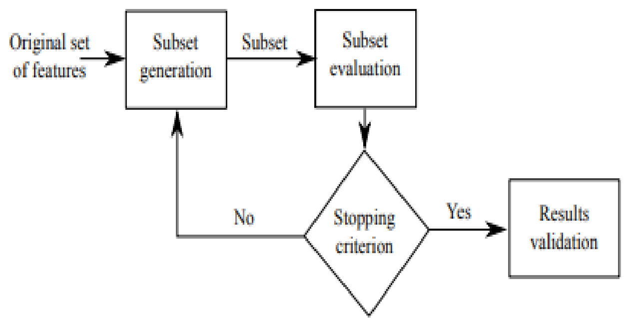
(d) Group 4: Colorlessness. Color estimators CIQI, CQE1 and CQE2 were used (i.e. mean of the S channel in HSV color space). Again, only one could have been included.

(e) Group 5: Sharpness/blur estimators. Variance, Frequency Threshold, Gradient, Laplacian, Autocorrelation metric, Histogram Frequency, Kurtosis, Marziliano, HP, Kurtosis of Wavelet Coefficients, Riemannian Tensor, JNBM, CPBD, S1, S2, S3 with improved pooling (S3III), FISH, and FISHbb.

(f) Group 6: Aesthetics-focused. Clarity, depth, tone. Random subset selection was feasible.

(g) Group 7: Saliency model results. Details highlight more locations. The scores were calculated by averaging the saliency maps, assuming more salient locations result in a higher average. Included models were Frequency- tuned saliency, Graph-based, Itti-Koch, and SUN. Each subgroup picked one.

(h) Group 8: Other estimators NIQE, CS, QAC, BIQI, BRISQUE, BLIINDS-II, Curvelet-based metric, statistical naturalness from TMQI and TMQIII, feature naturalness, mean intensity, proportion of under and overexposed areas, JPEG2000 metric, and JPEG metric. Any selection could include these measures.



Deep Learning Convolution Neural Network

Image contrast enhancement improves visibility. Here, a function modifies pixel grey level intensity. Intensity-based approaches include:

$$I_o(x,y)=f(I(x,y)) \quad (1)$$

Image source (x,y). Image Io is output (x,y). Intensity-based methods affect grey levels.

Even after transformation, grey pixels remain. Contrast stretching isincluded.

Figure 2 displays the underwater picture improvement method utilising DLCNN-MEF (I(x, y)).

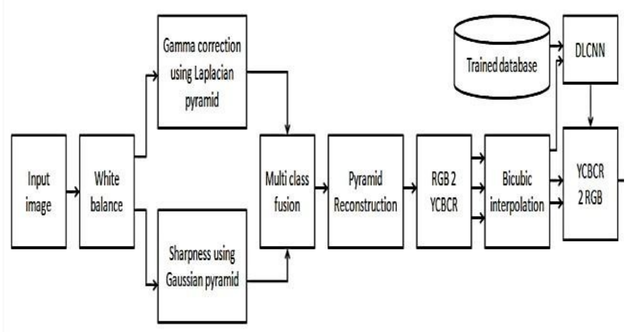


Figure 2:A block diagram illustrating the proposed DLCNN's step-by-step execution using MEF

Step - 1 : Lighting-corrupted photos impair scene visibility. Dehazing degraded images is impossible. The technique uses two degraded image inputs to restore color and visibility. Color correction follows fusing. The suggested technique degrades one input into two. First, white-balance input. Image casts are removed. Red visual channel weakens underwater. I2 improves low- contrast areas. The median-filtered input image is contrast-stretched. I1 removes colour casts while I2 boosts contrast. Weight maps determine these inputs' important properties. Weight maps include exposure,saliency, Laplacian, and colour cast. .

Step - 2 : Apply Laplacian pyramid gamma correction. Weight maps impact fusion. Non-negative weight maps are best. Image weights are input. Picture details. To create an improved image, fine characteristics from each image must be integrated. Weight maps reveal details. Weight maps improved underwater photographs. Weight maps include Laplacian, saliency, color cast, and exposedness. High-visibility regions have higher values than others. It emphasises edges and textures. Better is edge-preserving Laplacian. Laplacian highlights intensity shifts. Noisy second derivatives. Already noise-reduced photographs don't need more. This weight map can't discern flat, valley, or rapid sections.

Step - 3 : Gaussian pyramid sharpening using second input. Underwater photos disclose fewer pixels. Normalized 0.5 pixels are well-exposed. By matching brightness, this weight minimises overexposure. equivalent weight Gaussian distance to the average normalised range is the exposedness weight map (0.5). Underwater, objects lose visibility, making them hard to see. Saliency is a thing's uniqueness. A saliency map is produced based on centre- surround contrast to improve primary object contrast. This

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treatment doesn't affect midtones.

Step - 4 : Multi-Scale Fusion improves visibility in dimly lit environments. This method selects the best features from the input image, applies perceptual-based weight maps, and combines them to produce the enhanced output. The fusion-based technique uses white balancing, median filtering, and contrast stretching. White balancing removes colour casts from input images by estimating four weight maps. One map measures underwater-free pixels' exposedness. Laplacian favours edges and textures. New weight map reduces colour cast by boosting red channel value. Saliency weight map assesses pixel discernability. Both inputs are weighted. Pixel-by-pixel. Fusion combines pictures into a single, more usable image.

Step - 5 : Pyramid reconstruction reconstructs Gaussian and Laplacian outputs.

Step - 6 : The result of the Pyramid reconstruction is used in the RGB2YCBCR process. Results will be produced in three different colors: chromium red (CR), chromium blue (CB), and luminosity (Y).

Step - 7 : For each of the three outputs (Y, CB, and CR), run the bicubic interpolation process separately. Specifically, the ideal area of interest will be produced by these bicubic interpolations.

Step - 8 : A computationally intensive morphological based approach was used to achieve mean brightness utilizing the luminance output of the bicubic interpolation. Our primary goal is to remove a patch, which is just a pixel block centered at $\Omega(x,y)$. Therefore, for each pixel block, we get three values that match to the relevant color. We took the three lowest intensity values and swapped them out at the processed patch's center $\Omega(x,y)$. This process is carried out until the whole picture is processed. It is equivalent to doing a morphological operation to find the minimal value for a pixel block in a grayscale picture. Here, we may execute this procedure on the H, S, and I color channels independently. Next, for each structural piece, determine which of the three color planes is the minimum. Drawing on the mean channel before as a starting point, we create the updated red color priority depth map picture.

No more than three color planes. A revised red priority depth map is produced using the mean channel prior.

$$Io\,(x, y) = f\,(I(x, y)) \qquad (2)$$

I is the intensity channel. This haze map helps establish the mean transmission map. DLCNN means output brightness. DLCNN separates images by mean. First sub image segment has pixels up to mean, second above mean. Two nonoverlapping ranges were constructed. Specifying layers equalized two sub layers. DLCNN standard could maintain actual brightness when picture input features were around their mean. In this technique, input mean presents the mean intensity of every pixel from 0 to M-1. First feature is zero to mean, second mean+1 to M-1. Both equalized images are blended after applying DLCNN to each sub image separately. DLCNN increases consumer electronics input picture and brightness. DLCNN specification improves contrast to preserve images' mean brightness mathematically. It enhances user electrical devices. Assume picture X's mean is X m:

$$Xm \in \{X0\ ,X1\ ,\ldots\ldots,Xl{-}1\} \qquad (3)$$

On the basis of mean, the decomposition of image is done into 2 sub images i.e. X_L and X_U

In this, X_L consists of:

$$(X0,\ X1\ ,\ldots\ldots,Xm) \qquad (4)$$

And consist of:

$$(Xm{+}1\ ,{+}2\ ,\ldots\ldots\ ,XL{-}1) \qquad (5)$$

Same as DLCNN, in this, the CDF is utilized in the form of transform function as:

$$\in \{X0\ ,1\ ,\ldots\ldots,Xl{-}1\} \qquad (6)$$

And

$$(x) = Xm{+}1 + (XL{-}1 - Xm{+}1)(x) \qquad (7)$$

Based on the equation, the equalisation of the divided

sub pictures is done independently, and the resulting sub images' composition contains the DLCNN specification output, i.e., the Histogram specification output image Y.

$$Y = fL\,(XL) \cup (\ ) \qquad (8)$$

Adaptive histogram equalisation eliminates noise in

homogeneous areas. MEF applies every image pixel. Rayleigh, uniform, and exponential distributions create transform functions. Rayleigh improves underwater photographs. This algorithm works only on tiny images. Bilinear interpolation reduces tile boundaries. Contrast prevents homogeneous zone oversaturation. MEF can improve results without clipping (contrast factor). This cuts network depth by 10. 10-layers. Reducing depth improves network performance. Combining DLCNN output with CB and CR creates a contrast-enhanced RGB image.

Input image : Input image is the unclear image that has to be edited using CNN method.

Conversion of RGB to YCbCr: For an input image CNN method cannot be applied. So, the image is converted

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into YCbCr image.

DL-CNN: DL-CNN has 4 layers. By using these layers the features of the image is extracted and the noise is identified andremoved.

Bicubic Interpolation: Bicubic interpolation is used to make the co-ordinates of the image equal and the pixels of the image are divided into cubes of equal parts.

Conversion of YCbCr to RGB: The received image is in YCbCr format. Hence the image is converted to RGB .
Output image: By applying the above methods we can achievea clear output image.

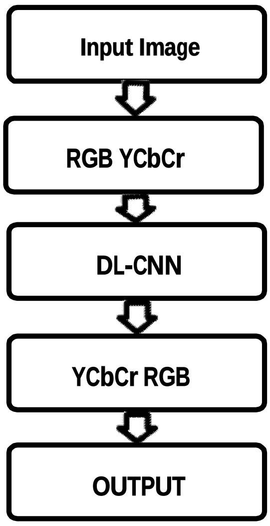

Figure. 3 Flowchart of DLCNN

Experimental Results

Modified Las Vegas Algorithm Result

The input picture is shown in Figure 4, and the result image is shown in Figure 5. Figure 5 shows an improvement in picture quality compared to Figure 4. In terms of quality, Figure 5 outshines Figure 4. To enhance the quality of the output picture, we propose a new aim, which will be elaborated upon in the proposed system outcomes.

Figure. 4 Input Image **Figure. 5 : Output Image**

DL-CNN Algorithm Result

Figure. 6 Input Image

Fig 8 shows that, Image Contrast is Enhanced Compare to fig 6. This Image Enhancement is Increase the visibility of the image and the intensity of the pixel is modified using DLCNN.

Table.1 Comparison Table

Parameters	Modified Las Vegas Algorithm	DL-CNN Algorithm
MSE	241	1.425
PSNR	24.33	41.53
ENTROPY	6.19	10.20

From the above table we can conclude that based on the MSE and PSNR value we can say the quality of the image is more

Figure. 7 MEF Image

In order to find out mean square error we will use below formula

$$MSE = (\sum[I1(i,j)-I2(i,j)]2/(m*n)) \quad (9)$$

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Where I1,I2 =input and output images

Figure. 8 Output Image

In order to find peak signal noise ratio we will use below formula

PSNR = 10log10(R2/MSE) (10)

Where R=255 , Expressed as Db

4. Conclusion and Future Scope

This research provides a criterion for tone- nature pictures. The research identifies estimators that capture perceptually significant components. Combining characteristics linearly ensures transparency and universality. Image-clarification was introduced. Solution improves white- balancing and fakes various underexposures. Our method enhances degraded photos without adding devices or data. Our technique improves dim and foggy photos. It increases photo feature matching. This study revealed an innovative method to enhance the clarity of each image. The suggested solution has two parts: a better way to balance the white color and a fake way to combine numerous underexposed images. Our approach makes pictures that have been bad in diverse ways seem better, and it doesn't need any additional technology or data other than the original image. Additionally, the proposed improves certain images shot in low light or in foggy conditions, all of which are taken in natural settings. It may be useful to increase the amount of matched pairs in picture local feature point matching.

The proposed approach consists of two components: an improved method for balancing the white color and a technique for assembling simulated images with several instances of underexposure. Our method enhances the visual quality of underwater photographs with different levels of deterioration without the need for specialized technology or any data other than the original image. Our research shows that our method could be able to make some images taken in low light or natural light seem better. Other uses include increasing the number of matched pairs and making it easier to match local feature points in underwater photos. Our solution works well in most circumstances, however it could overcorrect the red channel in photographs with particularly bad lighting. The aim of our next research is to persist in examining possible remedies for this constraint. Our future scope is focused on patch segmentation fusion. An image is first split into small patches and the segmentation is performed on each patch. Here, sharpening method is used to smooth the edges to increase the visibility of the underwater image in wide range. Our future scope is focused on patch segmentation.

References

[1]. ITU-R Recommendation BT.2020, Parameter values for UHDTV production and worldwide programme interchange, Oct. 2015.

[2]. F. Banterle, A. Artusi, K. Debattista, and A. Chalmers, Advanced High Dynamic Range Imaging: Theory and Practice. Natick, MA, USA: AK Peters (CRC Press), 2011.

[3]. J. Petit and R. Mantiuk, “Assessment of video tone-mapping: Are cameras’ s-shaped tone-curves good enough?” J. Vis. Commun. Image R., vol. 24, pp. 1020–1030, 2013.

[4]. L. Krasula, M. Narwaria, K. Fliegel, and P. Le Callet, “Rendering of HDR content on LDR displays: An objective approach,” in SPIE Applications of Digital Image Processing XXXVIII, 2015.

[5]. “Preference of experience in image tone- mapping: Dataset and framework for objective measures comparison,” IEEE Journal of Selected Topics in Signal Processing, vol. 11, no. 1, pp. 64–74, February 2017. [6] M. Cˇ ad´ık, M. Wimmer, L.

[6]. Neumann, and A. Artusi, “Evaluation of HDR tone mapping methods using essential perceptual attributes,” Computers & Graphics, vol. 32, pp. 330–349, 2008.

[7]. T. O. Aydın, R. Mantiuk, K. Myszkowski, and H.-P. Seidl, “Dynamic range independent image quality assessment,” in International Conference on Computer Graphics and Interactive Techniques, 2008.

[8]. H. Yeganeh and Z. Wang, “Objective quality assessment of tone-mapped images,” IEEE Transactions on Image Processing, vol. 22, no. 2, pp. 657–667, February 2013.

[9]. Berman, Dana, et al. "Underwater single image color restoration using haze-lines and a new quantitative dataset." IEEE transactions on pattern analysis and machine intelligence (2020).

ISSN: 3107 - 8605 (Online) , http://www.ijcser.com/ , Vol. 2, Issue 4, 2025, https://doi.org/10.63328/IJCSER-V2RI4P8

[10]. Cho, Younggun, et al. "Underwater image dehazing via unpaired image-to-image translation." International Journal of Control, Automation and Systems 18.3 (2020): 605-614.

[11]. Hou, Guojia, et al. "Underwater image dehazing and denoising via curvature variation regularization." Multimedia Tools and Applications 79.27 (2020): 20199-20219.

[12]. Liu, Chenguang, Li Tao, and Yeong-Taeg Kim. "VLW- Net: A Very Light-Weight Convolutional Neural Network (CNN) for Single Image Dehazing." International Conference on Advanced Concepts for Intelligent Vision Systems. Springer, Cham, 2020.

[13]. Hou, Guojia, et al. "Underwater image dehazing and denoising via curvature variation regularization." Multimedia Tools and Applications 79.27 (2020): 20199-20219.

[14]. Liu, Chenguang, Li Tao, and Yeong-Taeg Kim. "VLW- Net: A Very Light-Weight Convolutional Neural Network (CNN) for Single Image Dehazing." International Conference on Advanced Concepts for Intelligent Vision Systems. Springer, Cham, 2020.

[15]. Perez, Javier, et al. "Recovering depth from still images for underwater Dehazing using deep learning."