2023 IEEE International Conference on Image Processing (ICIP) | 978-1-7281-9835-4/23/$31.00 ©2023 IEEE | DOI: 10.1109/ICIP49359.2023.10222126

A TWO-DIMENSIONAL DIFFERENCE HISTOGRAM EQUALIZATION WITH FUZZY CUMULATIVE DISTRIBUTION CORRECTION FOR DARK IMAGES

Fan Wang, Jianzhou Zhang, Ang Bian

College of Computer Science, Sichuan University, Chengdu, China

ABSTRACT

Aiming at the problems of over-enhancement, detail loss, and poor subjective visual effect in dark images enhancement, this paper proposes a two-dimensional difference histogram equalization (2DDHE) algorithm using fuzzy C-means (FCM) to cluster and correct the cumulative distribution to enhance the dark image. First, a construction method of the two-dimensional (2D) difference histogram is proposed, which can enhance the dark area details. Then the cumulative distribution correction method based on FCM clustering and membership matrix modification is introduced to improve the over-enhancement and subjective visual effect. The experimental results show that the enhanced results by this method have a better subjective visual effect and outperform many existing algorithms in contrast and detail enhancement.

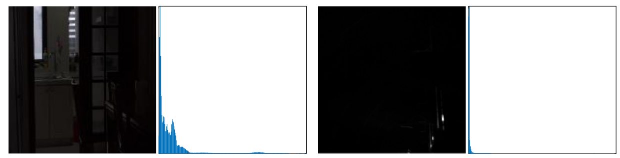
Index Terms— *dark image; two-dimensional difference histogram; fuzzy C-mean clustering; cumulative distribution correction; detail enhancement*

1. INTRODUCTION

Image enhancement is an essential image preprocessing task for computer vision applications like night vision surveillance, assisted driving at night, and tunnel monitoring, where images are acquired in a dark environment. We collected 648 dark images from the tunnel and found that more than 90% of the pixels in the dark images have a grey value of less than 5, and its histogram shows a significant single peak near the value of 0. Fig. 1 shows the images under different lighting conditions, figure 1(a) shows a low-light image and its histogram, and figure 1(b) shows a dark image and its histogram taken from the tunnel.

Many enhancement methods have been proposed to enhance the low-light image and achieve good results, such as methods based on histogram equalization (HE) [1], methods based on model optimization (Retinex or Camera response model) [2, 3], and methods based on deep learning [4-7]. Model-based enhancement methods have high computational complexity, and learning-based methods require massive training data, while HE-based enhancement methods are widely used because of their simplicity and effectiveness.

Traditional HE algorithm uses the global grey scale adjustment method, often leading to the enhanced image brightness being too high, contrast distortion, and loss of detail. Scholars have designed many improved algorithms based on HE to solve the above issues. The multi-histogram equalization technology [8-10] divides the histogram into multiple sub-histograms by characteristic values, such as mean or median. Then the sub-histograms are equalized independently to maintain brightness and prevent excessive enhancement. However, when dealing with dark images, the grey-levels of some sub histograms will be merged on a large scale and lose details, which may lead to binarization in severe cases. The adaptive histogram equalization algorithm with limited contrast [11, 12] effectively limits the excessive local contrast by setting a threshold, truncating the grey values that exceed the threshold, and distributing them evenly to all grey levels. However, the enhancement effect of these methods on dark images is limited, and image visibility still needs to be significantly improved. Recently, some methods [13-15] have focused on human visual characteristics to enhance the image with a higher subjective visual effect. Celik proposed a 2D histogram equalization algorithm [16]. This algorithm fully uses the spatial neighborhood information of pixels, can accurately describe the correlation of neighborhood pixels, and is more conducive to analyzing the statistical characteristics of low-light images. However, in the face of dark images with prominent histogram peaks, the enhancement is still excessive due to too large stretching.



(a) (b)

Fig.1. The low-light image and its histogram (a), and the dark image is captured in the tunnel and its histogram (b).

To improve the contrast of dark images while avoiding over-enhancement and detail loss, we propose an algorithm named 2DDHE, using FCM clustering and membership matrix modification to correct the cumulative distribution, as shown in Fig. 2. Firstly, the 2D difference histogram of the input image is constructed by counting the different gray-level of the pixel and its neighborhood, which can reduce the detail loss by accurately describing the details of dark areas. Second, cluster the cumulative distribution to get

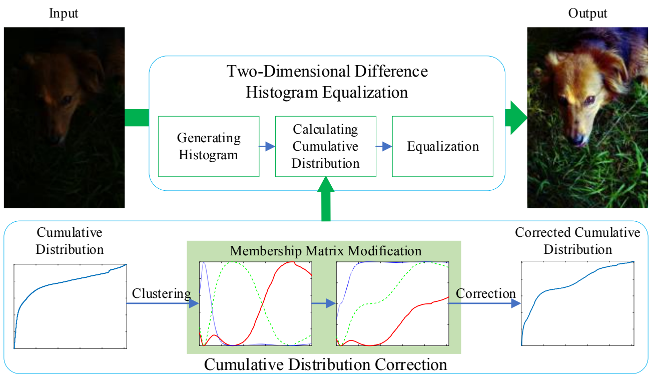


Fig.2. Flow of the proposed method

the membership matrix and correct the cumulative distribution by modifying the membership matrix. Finally, using the corrected cumulative distribution to complete the equalization can improve the image's over-enhancement and subjective visual effect. Experiments show that our method can effectively avoid over-enhancement while improving image contrast. Meanwhile, our method offers advantages in detail enhancement and subjective visual effects compared with other methods.

2. TWO-DIMENSIONAL DIFFERENCE HISTOGRAM EQUALIZATION

Our work is inspired by Celik's method [16]. However, the results will be over-enhanced when Celik's method is used to enhance dark images. Our method only counts the neighborhood difference of grey-level pairs to construct a 2D difference histogram. Using the 2D difference histogram to equalize dark images can improve over-enhancement and reduce detail loss.

2.1. 2D Histogram

For the image $\boldsymbol{I}$ of size $M \times N$ with L distinct grey-levels, its greyscale set is $G = \{g_1, g_2, \ldots g_L\}$ where $g_1<g_2<\ldots<g_L$. Its 2D histogram can be expressed as $H_I = \{h_I(m, n) \mid 1\le m\le L, 1\le n\le L\}$ where $h_I(m, n)$ is computed by Eq. (1).

$$h_I'(m,n)=\sum_{\forall i}\sum_{\forall j}\sum_{k=-\lfloor w/2\rfloor}^{\lfloor w/2\rfloor}\sum_{l=-\lfloor w/2\rfloor}^{\lfloor w/2\rfloor}\varphi_{m,n}(\boldsymbol{I}(i,j),\boldsymbol{I}(i+k,j+l))(|g_m-g_n|+1) \quad (1)$$

where w is an odd integer used to construct a window of size $w\times w$ centered on (i, j); $\boldsymbol{I}(\cdot)$ indicates the pixel value; m and n are grey-level index, (m, n) indicate a grey-level pair, and $|g_m-g_n|+1$ is the weight of the grey-level pair; $\varphi_{m,n}(I(i, j), I(i+k, j+l))$ is a binary function that is used to determine whether the grey values of the pixels at (i, j) and $(i+k, j+l)$ are equal to g_m and g_n respectively, and it is formed as

$$\varphi_{m,n}(\boldsymbol{I}(i,j),\boldsymbol{I}(i+k,j+l))=\begin{cases}1, & \boldsymbol{I}(i,j)=g_m \text{ and } \boldsymbol{I}(i+k,j+l)=g_n\\ 0, & \text{otherwise}\end{cases}$$

In Eq. (1), when the index m and n are equal, the grey-level pair (m, n) is called the same-value grey-level pair; otherwise, it is called the different-value grey-level pair. For a dark image, which has many pixels in its dark area with the same value, the 2D histogram constructed by Eq. (1) cannot describe the grey-level difference accurately.

2.2. 2D Difference Histogram

The texture and details of the region will be reflected only when the pixel values in the neighborhood are different. Similarly, the grey-level difference must be accurately described first to reduce the loss of image details in the enhancement process. Therefore, we improved Eq. (1) by setting the weight of the same-value grey-level pair to 0 to construct the 2D difference histogram that only retains the different-value grey-level pair. The improved formula is as follows

$$h_I'(m,n)=\sum_{\forall i}\sum_{\forall j}\sum_{k=-\lfloor w/2\rfloor}^{\lfloor w/2\rfloor}\sum_{l=-\lfloor w/2\rfloor}^{\lfloor w/2\rfloor}\varphi_{m,n}(\boldsymbol{I}(i,j),\boldsymbol{I}(i+k,j+l))|g_m-g_n| \quad (2)$$

After getting the 2D histogram, its elements $h_I'(m, n)$ should be normalized to give a probability distribution, and then the cumulative distribution functions can be expressed as $P_I=\{p_I(m)|m=1, 2, \cdots, L\}$ where

$$p_I(m)=\sum_{i=1}^{m}\sum_{j=1}^{L}h_I'(i,j) \quad (3)$$

2.3. Equalization

Enhanced image $\boldsymbol{O}$ of $\boldsymbol{I}$ with L distinct grey-levels, literature [14] gives its optimum 2D uniformly distributed target probability distribution function as follows

$$H_O=\{h_O(m',n')=1/L^2 \mid 1\le m'\le L, 1\le n'\le L\} \quad (4)$$

and the target cumulative distribution function is $P_O=\{p_O(m')|m'=1, 2, \cdots, L\}$, where

$$p_O(m')=\sum_{i=1}^{m'}\sum_{j=1}^{L}h_O(i,j)=\sum_{i=1}^{m'}L\frac{1}{L^2}=\frac{m'}{L} \quad (5)$$

To enhance the image, the input grey-level g_m is mapped to the output grey-level $g_{m'}$ by finding an index m' for a given index m according to

$$m'=\underset{i\in\{1,2,\cdots,L\}}{\arg\min}(|p_I(m)\text{-}p_O(i)|) \quad (6)$$

Using Eq. (6), every distinct grey-level of $\boldsymbol{I}$ is transformed to a corresponding output grey-level to create $\boldsymbol{O}$.

3. FUZZY CUMULATIVE DISTRIBUTION CORRECTION

Using 2D difference histogram equalization to enhance the dark image can reduce the loss of details. However, the enhanced results are still over-enhancement, and the subjective visual effect could be better. Therefore, we use the fuzzy cumulative distribution correction method to solve the issue.

3.1. Fuzzy C-means Clustering

FCM was proposed by Dunn [17] and perfected by Bezdek

[18]. This approach minimizes the objective function, which is expressed as follows

$$J_d(\boldsymbol{U},\boldsymbol{v})=\sum_{k=1}^{n}\sum_{i=1}^{c}u_{ik}^{d}\left\|x_k-v_i\right\|^2 \tag{7}$$

where $d\in[1,\infty)$ is the degree of fuzzificatio, usually set to 2; n is the number of clustering samples, and c is the number of the clusters; x_k is the sample to be clustered, $\|\cdot\|$ is the Euclidean distance; v_i is the cluster centers, and the vector $\boldsymbol{v}$ (=$\{v_1, v_2,..., v_c\}$) is composed of various cluster centers; $\boldsymbol{U}=[u_{ik}]_{n\times c}$ is the membership matrix, u_{ik} is the membership value of the sample x_k and class i, where $u_{ik}\in[0, 1]$ and $\sum_{i=1}^{c}u_{ik}=1$, where $k=1,2,\cdots,N$; u_{ik} and v_i can be determined by the Lagrange multiplier method, and the results are shown in Eq. (8) and Eq. (9).

$$u_{ik}=\sum_{j=1}^{c}\left(\frac{\left\|x_k-v_i\right\|}{\left\|x_k-v_j\right\|}\right)^{-\frac{2}{d-1}} \tag{8}$$

$$v_i=\frac{\sum_{k=1}^{n}u_{ik}^{d}x_k}{\sum_{k=1}^{n}u_{ik}^{d}} \tag{9}$$

In this work, we introduce FCM to cluster the cumulative distribution to obtain the membership matrix because FCM is simpler, faster, and better clustered without an accurate definition of cluster boundaries [19].

3.2 Fuzzy Cumulative Distribution Correction

The reason for the over-enhancement, detail loss, and poor subjective visual effect of the dark image after histogram equalization is that a large scale of pixels accumulates in the low-value range, resulting in a significant difference between the generated cumulative distribution and the optimum distribution. The FCM-based clustering correction method proposed in this paper can make the cumulative distribution closer to the optimum distribution, thus improving the image's over-enhanced and subjective visual effect.

After getting the cumulative distribution in Section 2.2, we need to correct the cumulative distribution. The correction method consists of three steps:

1) Cumulative distribution clustering. Take the cumulative distribution $P_I=\{p_I(k)|k=1, 2, \cdots, L\}$ as the sample set to be clustered. Let the number of clusters be c (in this article, c is set to 5), then calculate the cluster center $\boldsymbol{v}$ and the membership matrix $\boldsymbol{U}$ using the Eqs. (7) - (9).

2) Membership matrix modification. To make the cumulative distribution closer to the optimum distribution, the membership matrix needs to be modified as follows:

$$u'_{ik}=\begin{cases}u_{ik}, & p_I(k)\le v_{i=1,2,\cdots,c}\\ 2-u_{ik}, & p_I(k)>v_{i=1,2,\cdots,c}\end{cases}, k=1,2,\cdots,L \tag{10}$$

3) Cumulative distribution correction. The cumulative distribution is normalized with the modified membership matrix according to

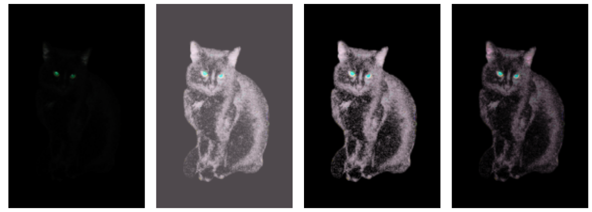


Fig.3. Enhancement results. From left to right: original, 2DHE, 2DDHE without correction, 2DDHE with correction.

$$p'_I(k)=\frac{\sum_{i=1}^{c}p_I(k)u'_{ik}}{c}, k=1,2,\cdots,L \tag{11}$$

4. EXPERIMENTS

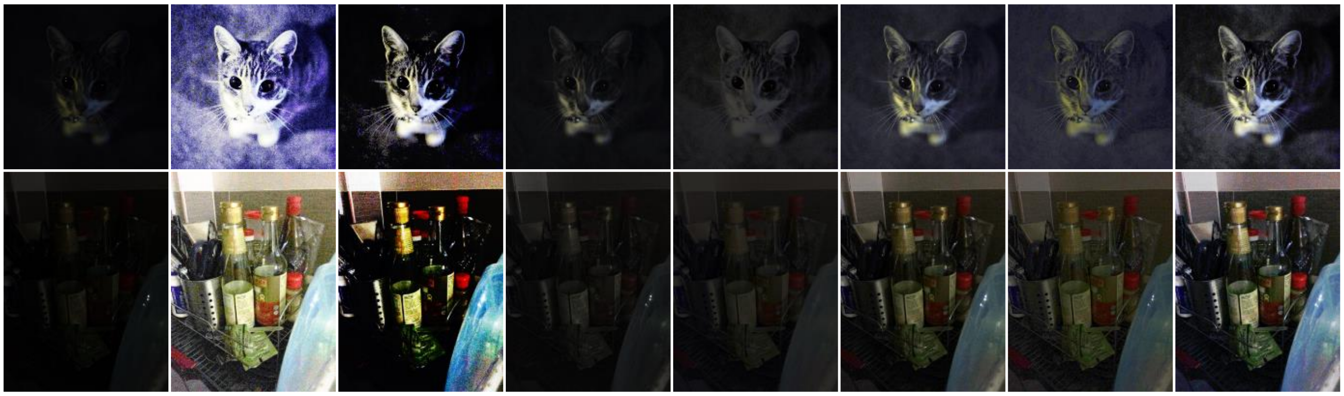
4.1 Experiment Setup

We selected 151 dark images from the ExDark dataset [20] as experimental samples, and the selection criteria are that more than 90% of the image's pixel values are less than 5. Using the proposed method to compare with the following five algorithms, including three HE-based algorithms: HE, BBHE [8], CLAHE [12], and two model-based optimization methods: SRIE [2] and LECARM [3]. SRIE is based on the Retinex model, and LECARM is based on the camera response model. To ensure the objectivity of the comparison experiment, the publicly available code of the above algorithm and the parameter settings recommended by the author are used for the experiment. In the experiment, the custom parameter window size w and the number of clusters c of the algorithm is set to 7 and 5, respectively. The color image is divided into RGB channels for equalization.

4.2 Qualitative Assessment

Fig. 3 shows the enhanced results by 2DHE and 2DDHE. It can be seen that the image enhanced by 2DHE is over-enhancement, and 2DDHE without correction reduced the over-enhancement, but the subjective visual effect is poor. Image enhanced by 2DDHE with correction, the brightness is reduced, but the subjective visual effect is improved.

Fig. 4 shows the enhanced results by different methods. The HE method can significantly improve the image's overall contrast, but the enhanced image's brightness is too high. BBHE can improve the contrast, but the details in the dark area of the image completely disappear. CLAHE and 2DHE enhancement effects are limited, the contrast has not been significantly improved, and the image's overall brightness is still low. The enhancement effect of LECARM and SRIE is similar, which is better than the HE-based method. LECARM is slightly better than SRIE in brightness increase, the subjective visual effect of the SRIE-enhanced image is poor, the cat's beard is not clear enough, and the bottle has low glossiness. The proposed method generally achieves better results in contrast and subjective visual effects.



(a) Original (b) HE (c) BBHE (d) CLAHE (e) 2DHE (f) LECARM (g) SRIE (h) Proposed

Fig.4. Enhancement results by different methods.

Table 1. Average of quantitative metrics. The best result per line is boldface, and the second best is underlined.

	MV↑	EME↑	NIQE↓
Orgs	7.16	54.23	6.84
HE	**132.29**	18.93	5.47
BBHE	45.04	56.47	5.71
CLAHE	15.81	16.39	5.57
2DHE	25.44	20.19	5.41
LECARM	33.93	54.36	**4.92**
SRIE	31.55	43.31	5.37
Proposed	48.23	**67.11**	5.07

4.3 Quantitative Assessment

Three quality metrics are used for quantitative assessment, as shown below.

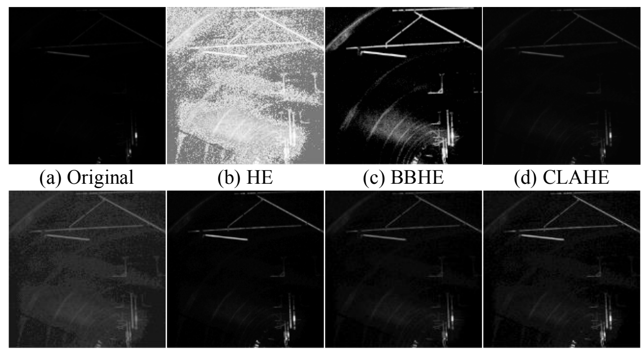
Mean Value (MV) is used to evaluate the ability of algorithms to improve image brightness. The larger MV means the higher brightness of the enhanced image.

Measure of Enhancement (EME) [21] reflects the local dynamic range of an image and can be used to evaluate the image contrast. The high EME means the stronger ability of the algorithm to enhance image contrast.

Natural Image Quality Evaluator (NIQE) [22] can evaluate the subjective visual effect of images. Smaller NIQE means the image quality is better and more consistent with human subjective feelings.

Table 1 compares the average of quantitative metrics of different methods on 151 sample images. Our method (with cumulative distribution correction) achieved the best EME and second MV and NIQE. The results proved the effectiveness of our method in improving image brightness and contrast. They showed that images enhanced by our method have a better subjective visual effect consistent with qualitative assessment.

4.4 Application



(a) Original (b) HE (c) BBHE (d) CLAHE (e)2DHE (f)LECRAM (g)SRIE (h) Proposed

Fig.5. Enhancement results of tunnel patrol image.

The high-speed railway tunnel image, which is used for fault detection of catenary, is used for contrast enhancement experiments to verify the proposed algorithm's effectiveness in practical applications. Fig. 5 shows the results. The brightness of the image enhanced by the HE is too high, the image enhanced by the BBHE tends to be a binary image, the CLAHE cannot effectively improve the image contrast, and the subjective visual effect of images enhanced by 2DHE is poor. LECARM, SRIE, and the proposed method have similar enhancement effects, but the proposed method is superior to the other two methods in brightness and detail.

5. **CONCLUSION**

This paper proposes a novel two-dimensional difference histogram equalization algorithm based on cumulative distribution correction to enhance dark images. A 2D difference histogram can accurately describe the details of dark images to avoid the loss of more information, and cumulative distribution correction can avoid excessive enhancement and give the enhanced images a better subjective visual effect. Experiments show that the proposed method can improve image contrast and avoid over-enhancement when dealing with dark images, and it is better than the methods based on model optimization. In the future, our research focus will be on realizing the adaption of critical parameters (window size w and cluster number c).

6. REFERENCES

[1] R. Hummel, “Image enhancement by histogram transformation,” *Computer Graphics and Image Processing*, vol.6, no. 2, pp. 184-195, Apr. 1977.

[2] X. Fu, D. Zeng, Y. Huang, X. -P. Zhang, and X. Ding, “A weighted variational model for simultaneous reflectance and illumination estimation,” *2016 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, Las Vegas, NV, USA, pp. 2782-2790, 2016.

[3] Y. Ren, Z. Ying, T. H. Li, and G. Li. “LECARM: low-light image enhancement using the camera response model,” *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 29, no. 4, pp. 968-981, Apr. 2019.

[4] Y. Jiang, X. Gong, D. Liu, Y. Cheng, C. Fang, X. Shen, et al., “EnlightenGAN: Deep light enhancement without paired supervision,” *IEEE Transactions on Image Processing*, vol. 30, pp. 2340-2349, Jan. 2021.

[5] S. Jin, B. Yu, M. Jing, Y. Zhou, J. Liang, and R. Ji. “DarkVisionNet: Low-light imaging via RGB-NIR fusion with deep inconsistency prior,” *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 36, no. 1, pp. 1104-1113, Jun. 2022.

[6] C. Guo, C. Li, J. Guo, C. L. Chen, J. Hou, K Sam, and R. Cong. “Zero-reference deep curve estimation for low-light image enhancement,” *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, Seattle, WA, USA, pp. 1777-1786. 2020.

[7] W. Yang, S. Wang, Y. Fang, Y. Wang, and J. Liu. “From fidelity to perceptual quality: A semi-supervised approach for low-light image enhancement.” *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, Seattle, WA, USA, pp. 3060-3069. 2020.

[8] Y. -T. Kim, “Contrast enhancement using brightness preserving bi-histogram equalization,” *IEEE Transactions on Consumer Electronics*, vol. 43, no. 1, pp. 1–8, Feb. 1997.

[9] Y. Wang, Q. Chen, and B. Zhang, “Image enhancement based on equal area dualistic sub-image histogram equalization method,” *IEEE Transactions on Consumer Electronics*, vol. 45, no. 1, pp. 68-75, Feb. 1999.

[10] S. -D. Chen, and A. R. Ramli, “Minimum mean brightness error bi-histogram equalization in contrast enhancement,” *IEEE Transactions on Consumer Electronics*, vol. 49, no. 4, pp. 1310–1319, Nov. 2003.

[11] S. M. Pizer, R. E. Johnston, J. P. Ericksen, B. C. Yankaskas, and K. E. Muller, “Contrast-limited adaptive histogram equalization: speed and effectiveness,” *Proceedings of the First Conference on Visualization in Biomedical Computing*, Atlanta, GA, USA, pp. 337-345, 1990.

[12] K. Zuiderveld, “Contrast limited adaptive histogram equalization,” *Graphics Gems IV*, Academic Press Professional, San Diego, CA, USA, pp. 474–485, Jan. 1994.

[13] W. Kim, J. Jeong, and J. You, “Contrast enhancement using histogram equalization based on logarithmic mapping,” *Optical Engineering*, vol. 51, no. 6, pp. 067002-1 ~ 067002-10, Jun. 2012.

[14] Z. B. Sun, W. Q. Feng, Q Zhao, and L. D. Huang, “Brightness preserving image enhancement based on a gradient and intensity histogram,” *Journal of Electronic Imaging*, vol. 24, no. 5, 053006, Sep. 2015.

[15] X. Wu, X. Liu, K. Hiramatsu, and K. Kashino, “Contrast-accumulated histogram equalization for image enhancement,” *2017 IEEE International Conference on Image Processing (ICIP)*, Beijing, China, pp. 3190-3194, 2017.

[16] T. Celik. “Two-dimensional histogram equalization and contrast enhancement,” *Pattern Recognition*, vol. 45, no. 10, pp. 3810–3824, Oct. 2012.

[17] J. C. Dunn, “A fuzzy relative of the ISODATA process and its use in detecting compact well-separated clusters,” *Journal of Cybernetics*, vol. 3, no. 3, pp. 32–57, 1973.

[18] J. C. Bezdek, “Objective function clustering,” *Pattern Recognition with Fuzzy Objective Function Algorithms*, Springer, Boston, MA, USA, pp. 43–93, 1981.

[19] R. Kumar and A. K. Bhandari, “Fuzzified contrast enhancement for nearly invisible images,” *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 32, no. 5, pp. 2802-2813, Mar. 2022.

[20] Y. P. Loh and C. S. Chan. “Getting to know low-light images with the exclusively dark dataset,” *Computer Vision and Image Understanding*, vol. 178, pp. 30-42, Jan. 2019.

[21] S. S. Agaian, B. Silver, and K. A. Panetta, “Transform coefficient histogram-based image enhancement algorithms using contrast entropy,” *IEEE Transactions on Image Processing*, vol. 16, no. 3, pp. 741–758, Mar. 2007.

[22] A. Mittal, A. K. Moorthy, and A. C. Bovik, “No-reference image quality assessment in the spatial domain,” *IEEE Transactions on Image Processing*, vol.21, no.12, pp.4695–4708, Dec. 2012.