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A Refined Zero DCE Framework For Enhancing and Interpreting Lunar Permanently Shadowed Images

Varolia Jesalkumari[1], Pamidimarri Karthika[2], Kambakaya Gayathri[3], Mareddy Sanjana[4]

[1]Thakur College of Engineering and Technology, Cyber Security, India, Email: jesaljoshi29@gmail.com
[2]Gokaraju Rangaraju Institute of Engineering and Technology, AIML, India, Email: karthika22241a66a6@grietcollege.com
[3] Gokaraju Rangaraju Institute of Engineering and Technology, AIML, India, Email: gayathri22241a6686@grietcollege.com
[4]Gokaraju Rangaraju Institute of Engineering and Technology, AIML, India, Email: sanjana22241a6695@grietcollege.com

Abstract
This study outlines a system driven by deep learning technologies to improve lunar imaging at low light levels to make them more useful for scientific analyses. In particular, lunar images obtained from Permanently Shadowed Regions (PSRs) exhibit very low light levels, excessive noise, and a loss of detailed features, making them extremely difficult to analyze. The proposed solution incorporates the Zero-DCE model, which establishes brightness and contrast adjustments without the need for paired training data. It will also employ Tri-Curve enhancements along with a convolutional neural network (CNN)-based refinement module to achieve improved feature preservation and reduced noise in lunar imagery. The quality of the output images will be evaluated through the Peak Signal to Noise Ratio (PSNR), Structural Similarity Index Method (SSIM), and the BRISQUE method assessments; subsequently, the output exhibiting the highest quality will be used to drive a crater detection model based on the YOLO v8 architecture to validate the results of crater detection against task-based metrics. In summary, the entire system constitutes an end-to-end imaging improvement and analytical pipeline and provides value for researchers studying lunar or planetary-based images.

Keywords: Low-light enhancement, Lunar imaging, Zero-DCE, Deep learning, Image enhancement, PSNR, SSIM,BRISQUE

Introduction

The process of essay evaluation has traditionally been labor-intensive, subjective, and time-consuming, Image enhancement in low light is a demanding job in the field of computer vision especially in the field of space exploration where image quality is severely limited. The imaging on the lunar surface particularly in the Permanently Shadowed Regions (PSRs) are very dark, very noisy and have very low contrast making it very difficult to see things and perform operations like terrain analysis and crater detection [8], [11].
Conventional methods of enhancing images such as histogram equalization and fusion-based methods have been used to enhance the visibility of images in low-light scenarios [3]. Nevertheless, these methods frequently fail in very dark conditions and can enhance noise or reduce structural images. Newer surveys point out weaknesses of these techniques and the importance of more adaptive, learning-based solutions [1], [6].
Deep learning methods have demonstrated great gains in low-light enhancement through learning of intricate illumination mappings. Attention-driven networks and retinex-based models attempt to maintain structural and contextual details [2], [5]. Most of these techniques however are based on the use of paired datasets which are not readily available in the case of real lunar images.
In order to address this weakness, zero-reference techniques like Zero-DCE have been suggested, that train enhancement mappings without corresponding data [13]. The latest developments, such as optimization of structural losses and tri-curve estimations, have also served to enhance the quality of improvement and details [14], [17]. In spite of these advances, there is scant research on the relative performance of such models in lunar imaging applications.
In this paper, a framework of multi-model low-light lunar image enhancement is presented, which includes baseline Zero-DCE, tri-curve estimation, and hybrid Zero-DCE with convolutional neural networks. The models are tested with full-reference and no-reference measures, such as PSNR, SSIM, and BRISQUE. A crater detection module is also a downstream task that can be used to confirm the usefulness of the improved images.

The key findings of this paper are:

- Multi-model image enhancement of low-light lunar images based on zero-reference learning.
- Comparison between variants of Zero-DCE models, such as tri-curve and CNN-based models.
- Evaluation based on quantitative and perceptual quality measures.
- checking or verification using crater detection experimental applicability.

2. Related work

Enhancing images in low-light conditions has been actively researched in general imaging, as well as in domain-specific use, including lunar exploration. This section is a survey of previous work in three categories, namely, general improvement techniques, lunar techniques, and zero-reference techniques.

2.1 General Low-Light Image Enhancement Methods

Histogram equalization and fusion-based techniques are traditional approaches, which have been used to enhance visibility in low-lights images, but they tend to amplify noise and structural details are lost [3]. These drawbacks, as well as the necessity to find more adaptive methods, have been pointed out in surveys [1], [6].

Deep learning techniques have excelled tremendously in performance by being able to learn multi-faceted illumination mappings. Images are decomposed into illumination and reflectance components with Retinex-based models [2], and further refined with contextual understanding and global feature representation with attention-based and transformer-based ones [5], [7]. Although effective, most of them are based on paired datasets and cannot perform in extreme low-light conditions.

2.2 Lunar-Specific Deep Learning Methods.

Lunar imaging, especially Permanently Shadowed Regions (PSRs), is a very challenging task in terms of illumination. The techniques of deep learning have been implemented to improve visibility and permit mapping of terrain in these areas [8], [9]. Approaches to physics-based learning also make use of domain knowledge to enhance the quality of the enhancement [10], and space research projects also stress the significance of the shadowed regions of the moon [11]. Moreover, the techniques of the crater detection and retrieval have been investigated with the help of feature-based and the deep learning approaches [12]. Nevertheless, these publications pay more attention to single tasks, and the comparison of various improvement models or their effects on the downstream applications is not the main priority.

2.3 Zero-Reference Deep Learning Methods.

Zero-reference schemes overcome the need to have paired data. Zero-DCE proposed a curve-based enhancement lacking ground truth supervision [13]. Later advances include structural similarity loss and performance optimisation techniques [14], [15], [20].

More complex models, like tri-curve estimation, offer more precise control over illumination and better detail preservation [17], whereas hybrid and diffusion-based models additionally improve their ability to perform in more challenging situations [16], [18]. Video enhancement extensions also show a wider applicability [19].

Table 1. Summary of related work

Category	Method type	Limitation
Traditional	Fusion-based	Noise amplification
Deep learning	Retinex/ Attention	Needs paired data
Zero-DCE	Curve estimation	Limited lunar evaluation

Table 1 summarises the existing work in regard to the image enhancement for the lunar domain. This provides the foundation for the scope of the current study.

3. Methodology

The framework will be used to improve low-light lunar images with various zero-reference deep learning models and test their effectiveness by quantitative measures and downstream analysis. The general pipeline includes data simulation, optimization based on various model variants and evaluation as explained in Fig. 1.

3.1 Data Simulation and Augmentation.

Since there are few real low-light lunar datasets available, a simulation-based method is used. The high-quality lunar images are initially captured and transformed to low-light images by dimming the light and adding noise to mimic the appearance of Permanently Shadowed Regions (PSRs). Fig 1 and fig 2.

Fig 1: Original lunar image

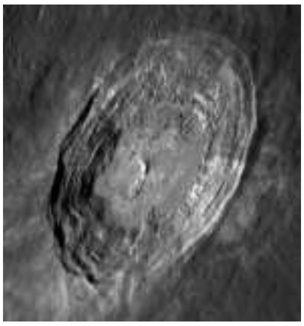


Fig 2: Simulated low light image

To enhance the model generalization, data augmentation methods including rotation, horizontal and vertical flipping, and scaling are used. This will lead to a rich dataset that reflects differences in illumination and surface details, which allow strong model training.

3.2 Improvement Models

Three zero-reference models are used to enhance low-light lunar images. These are modeling models that are based on the iterative estimation of the curves to adjust the illumination.

3.2.1 Zero-DCE Model

Zero-DCE model is an enhancement of an input image through learning a pixel-wise curve mapping. The process of improvement is characterized as a repetitive process:

It+1(x)=It(x)+αt(x)·It(x)·(1−It(x))

In which (It(x)) is the pixel value at iteration (ti), and (αt(x)) is the learnt map of curve parameters. In this formulation, illumination is gradually altered without altering the image structure.

The non-reference loss functions are used to train the model are:

- Exposure Control Loss
- Color Constancy Loss
- Illumination Smoothness Loss

These losses guarantee natural brightness, color balance, and smooth illumination.

3.2.2 Zero-TCE (Tri-Curve) Model

The Zero-TCE model builds on Zero-DCE with several curve estimates to obtain more precise illumination control. The improvement can be represented as:

Iout=f3(f2(f1(Iin)))

in which (f1, f2, f3) are three consecutive curve mappings acquired by the network.

Each curve has a similar formulation:

f(I)=I+alpha.cdotI.cdot(1−I)

The tri-curve method enables a greater range of intensities to be processed, resulting in increased brightness distributions and detail in very low-light images.

3.2.3 Zero-DCE with CNN Enhancement Model.

Convolutional layers are incorporated into the Zero-DCE framework to enhance the representation of features. The CNN extracts spatial features:

F=sigma(W∗I+b)

In which (*) is convolution, (W) is filter weights, (b) is bias, and (sigma) is the activated function.

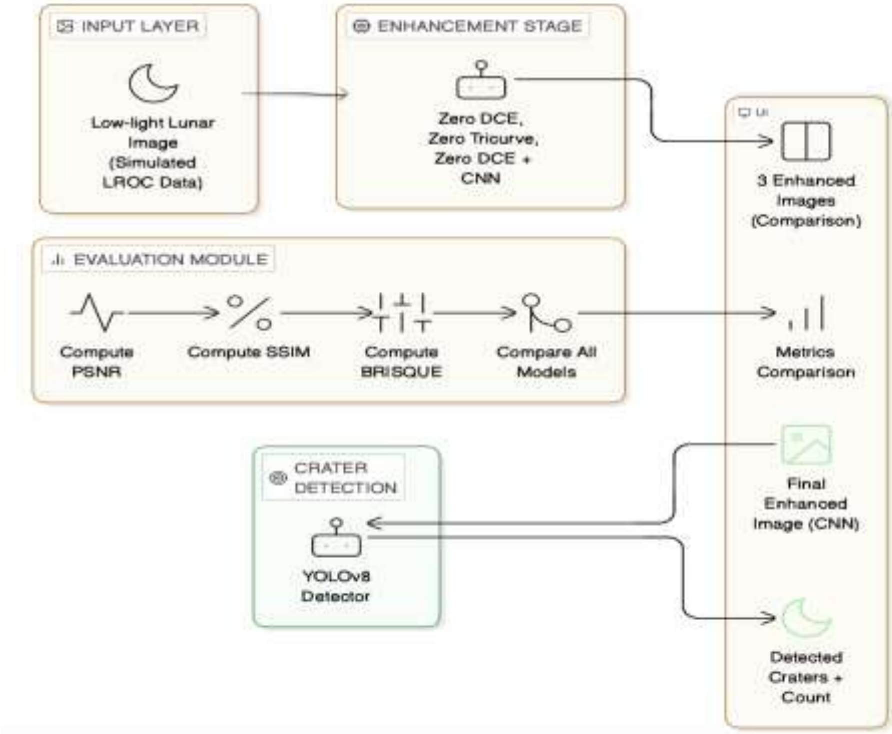
We will use the extracted features to estimate the curve parameters:

alpha = g(F)

(g(.)) is a mapping function (e.g., convolution layers). This allows the adjustment of the adaptive improvement according to the local textures and edges to enhance the structural details of lunar images.

3.3 System Architecture

Fig 3: System architecture



The general system (Fig 3) is sequential pipeline. In the first step, actual lunar images are transformed into simulated low-light images. The images are then fed into the three enhancement models- Zero-DCE, Zero-TCE and Zero-DCE with CNN to produce enhanced results.
The improved images are then measured by quantitative measures and again analyzed by a crater detector module to gauge its usefulness in practice.

3.4 Evaluation Metrics

Full-reference and no-reference measures are employed to measure enhancement performance quantitatively:

- Peak Signal-to-Noise Ratio (PSNR): It is used to measure the quality of reconstruction and noise reduction.
- Structural Similarity Index (SSIM): Measures structural and perceptual similarity.
- BRISQUE: It is a no-reference measure of the perceptual image quality without ground truth.

These measurements offer an in-depth assessment of the visual quality and structural conservation.

3.5 Crater Detection Module.

In order to verify the usefulness of the improved images in practice, a crater detecting module is added as a downstream task. An object detection model, which has been trained before, is used to detect craters in the enhanced images.
Crater detection performance can be used as a proxy of quality of enhancement since enhanced images that are better are supposed to have increased feature visibility and accuracy of feature detection.

4. Results and Discussion

The results of the suggested framework of improvement are measured in terms of qualitative (visual) and quantitative analysis. The findings are a comparison of effectiveness of the three models, Zero-DCE, Zero-TCE (tri-curve), and Zero-DCE with CNN in simulated low-light lunar images.

4.1 Visual Results

The visual outputs of the three enhancement models are shown as follows:

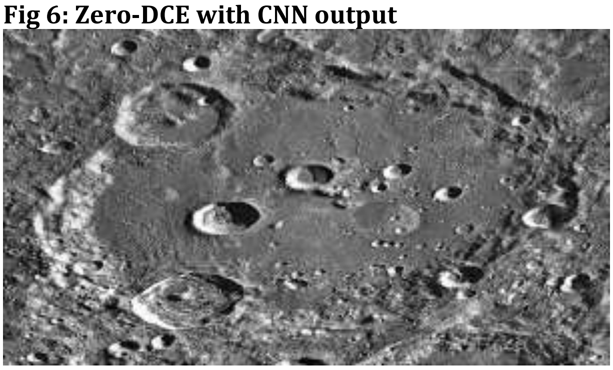
Fig 4: Zero-DCE output

Fig 4 is the Zero-DCE model, which is better in enhancing overall brightness though it tends to over-enhance the images hence excessive illumination is attained. This causes contrast loss and observable blurring of fine features especially in areas that contain fine lunar surface features. Also, structural features, like crater boundaries, are less prominent because of this over-brightening effect.

Fig 5: Zero-TCE output

Fig 5 depicts the tri-curve model of Zero-TCE, which shows a better detail preservation than the baseline. The multi-curve estimation allows more control over various areas of intensities with the benefit of having more defined surface structures and less noise. Nonetheless, the outputs tend to be grayish, which means that the balance of brightness-darknesses is lost. This "gray-washing" effect reduces visual realism despite better structural clarity.

Fig 6: Zero-DCE with CNN output



The Zero-DCE with CNN model offers the most balanced improvement among the three models, Fig 6. This model is capable of maintaining edges, textures, and fine details of lunar surfaces since it uses convolutional feature extraction. Meanwhile, it has a more natural light distribution without being over-brightened or gray-washed. As a result, geological features such as craters are more clearly visible and better defined.

Fig 7: YOLO crater detection on the enhanced lunar image

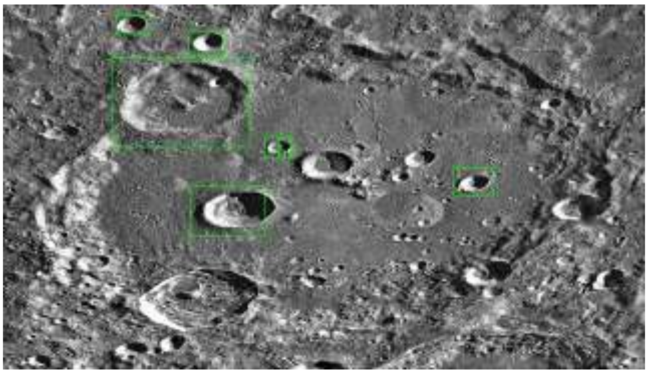


Fig 7 represents a crater detection module output which was used as a downstream task to further test the practical efficiency of the enhanced images. The results indicate that the quality of enhancement directly impacts detection performance. Photos that were improved with the model baseline Zero-DCE showed weaker detections since they were over-brightened and blurred and had blurred structural features. The Zero-TCE model enhanced the visibility of craters and edges, resulting in a moderate enhancement of detection results.

Nevertheless, the results of the Zero-DCE based on CNN model were the most stable because it was able to retain finer details, edges, and general balance of illumination, which allowed the boundaries of the craters to be more easily identified. The detection performance was not ideal at very dark areas, but the findings indicate that enhanced performance goes a long way towards enhancing better feature extraction and object identification in lunar images.

4.2 Quantitative Results

PSNR, SSIM and BRISQUE are quantified measures of the performance of the models. Table 2 summarizes the results.

Table 2: Quantitative comparison of enhancement models

Model	PSNR	SSIM	BRISQUE
Zero DCE	12.90	0.24	39.52
Zero TCE	14.34	0.47	37.97
Zero DCE + CNN	19.41	0.76	37.07

The Zero-TCE model achieves higher SSIM values compared to the baseline, indicating improved structural preservation and better retention of spatial details. However, the Zero-DCE + CNN model significantly outperforms both other models in terms of PSNR, demonstrating superior reconstruction quality and enhanced detail representation.

In terms of perceptual quality, the BRISQUE scores show a decreasing trend from Zero-DCE to Zero-TCE amd to CNN-based model. This indicates that the enhanced models produce more natural and visually appealing results compared to the baseline, although the improvement in BRISQUE is relatively moderate.

Overall, the results suggest that while the Zero-TCE model improves structural consistency, the Zero-DCE + CNN model provides the most balanced performance, achieving better detail reconstruction, higher structural similarity, and improved perceptual quality.

4.3 Discussion

The suggested multi-model model illustrates that zero-reference learning is effective in the case of low-light lunar image enhancement. Zero-DCE model offers a good foundation, and the Zero-TCE model enhances illumination stability and detail conservation by using multi-curve estimation. The CNN integration also improves texture and edge data, which is useful in the location of surface features of the moon.

Nonetheless, there are trade-offs between the models. Although CNN-based methodology enhances sharpness, it can cause small artifacts, but the tri-curve model has a more reasonable balance between brightness and a natural look. Also, when simulated low-light data is used, there is a domain gap between

simulated and real lunar data which can impact on generalization performance.
There are some instances of failure in very dark areas where none of the models can retrieve meaningful information. In these situations, amplification of noise and structural information loss might take place. In spite of these, the improved images have a great contribution to visibility and aid downstream activities like crater identification, which proves the usefulness of the suggested method.

5. Conclusion

In this paper, a multi-model architecture of low-light lunar image enhancement through the use of zero-reference deep learning was introduced. Three models, Zero-DCE, Zero-TCE (tri-curve) and a hybrid Zero-DCE with CNN were introduced and tested to overcome the issues of low illumination and noise in lunar images, especially in simulated Permanently Shadowed Regions.

It was experimentally shown that the baseline Zero-DCE model, though able to boost brightness, suffers over-enhancement, and deterioration of structural details. Zero-TCE model enhances structural preservation by estimating with multi-curve yet it comes up with a grayish color that compromises the visual reality. Conversely, the Zero-DCE with CNN model is the best in terms of overall performance as it successfully balances lighting, maintains edges and texture, and natural image contrast. These results are also backed by quantitative analysis, where the CNN-based model scores higher in PSNR, SSIM, and perceptual quality.

The presented framework indicates that zero-reference learning is effective in improving low-light lunar images and the downstream processes, like crater detection. The future scope will be oriented to minimizing domain difference between simulated and real lunar observations, enhancing performance on extremely dark areas, and incorporating the use of advanced deep learning structures to make more robust and real-time applications.

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