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Intelligent Agent-Based Architecture for Low-Light Image Enhancement Using an A3C Framework

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Abstract

Low-light image enhancement (LLIE) is an important area of research as many applications such as photography, video surveillance, and security are confronted with image degradation in low-light environments. This paper presents an intelligent agent-based method for LLIE using the Asynchronous Advantage Actor-Critic (A3C) framework. The enhancement task is effectively cast in this work into the framework of a Markov Decision Process. This method enables an agent to learn a policy that successively improves image quality. In the agent, features are extracted by a Fully Convolutional Network (FCN), a policy network for choosing an action, and a value network for estimating the reward. In training, non-reference loss functions are also used to measure image quality without the availability of the reference image or ground truth images. Such functions include spatial consistency loss, exposure control loss, and illumination smoothness loss, and the approach achieves end-to-end enhancement without reference image. The experimental results on LOL and MIT-Adobe dataset also show that the proposed technique enhances image brightness, Contrast, and structure much better as compared to other state-of-the-art methods. Especially, the methodology proposed scored 25.93 PSNR, 0.932 SSIM, and 0.053 LPIPS on the LOL dataset, achieving better results than related strategies. The designed agent-based approach works under a wide range of low-light situations. This approach allows obtaining enhancement results that will be satisfactory in terms of the users' preferences and needs of the specific applications. The findings highlight the method's robustness and flexibility, making it suitable for various practical applications. This work demonstrates that reinforcement learning agents have promising applications in improved image processing capabilities, and establishes a new record for low-light image improvement.

1. Introduction

Low-light image enhancement (LLIE) is considered an important task when it comes to practice or real-world applications such as photography, surveillance, or even security. Such images may turn out to have low contrast, high noise and undesirable visual characteristics and therefore cannot be useful in some of the most sensitive operations [1-3]. These low illumination images need to be improved to get quantifiable data from them; to improve their qualitative characteristics and also for further analysis like object detection and recognition [4-7]. Therefore, the importance of LLIE does not stop at the aesthetic level as it brings a practical effect on systems that deal with relying on optimal visual quality. Enhancement of the low-light image leads to better picture quality and may help preserve details that are essential in photography for commercial and personal purposes [8,9]. In surveillance or security, enhancement of the quality of the recorded images in low light is often vital to establish intruders or to monitor activities that take place under the cover of darkness. As a result, such LLIE methods are essential in consumer as well as industrial applications [10-11].

Improving the quality of low-light images presents some major problems. First, the dynamic nature of the environment, especially in terms of light and noise fluctuations, diminishes the possibility of applying general solutions [12-14]. Images obtained from various imaging environments and systems exhibit various attributes and thus require specific enhancement. Secondly, conventional approaches employed earlier use a low-light and a corresponding bright-light set of images for training, which is a time-consuming and costly affair [15,16]. This limit has a negative impact on the formation of exact and nuanced LLIE models that can be learned. Additionally, the existing methods of LLIE often presuppose the use of deterministic models that yield only one improved version of an input. One drawback of this approach is that it does not consider the subjective personal expectations of a typical user when it comes to image enhancements with respect to brightness, contrast, and colour balance [17-21]. Consequently, there must be a better approach, which is more versatile and can cover different enhancement needs and provide good results in complex low-light situations [22-24]. A set of low-light images at different levels is depicted in Figure 1 [25].

Figure (1): A set of low-light images at different levels [25].

To address the mentioned challenges of improving images in low light, this paper presents a new deep reinforcement learning (DRL) agent. To this end, we suggest that the enhancement task be defined as a Markov Decision Process (MDP). This approach represents the enhancement process as a series of decisions each of which tries to make the image quality better. In the context of LLIE, the MDP is defined by the following components: state, action, and reward.

State: The current image which is a low-light image or the enhanced image of a step is the current state of the state model at step t. Therefore, the state space of this problem consists of all possible intermediate and final images that are obtainable from the low-light image.

Action: The action at each step is to choose the adjustment parameter map. This parameter map determines how much the intensity of the pixel is changed during the enhancement image. The action space is referred to by the number of adjustment parameters that can be made on the image.

Reward: The reward assesses the effectiveness of the changes that have been made to an image by the action performed in the state. The reward function is to encourage good-quality images and functions such as brightness, contrast, and noise reduction are focused on maximizing the rewards. It is calculated from a non-reference quality loss function which estimates the improvement without using original images as a reference. The task of the DRL agent in this MDP framework is to find an action that brings the largest cumulative reward in some states when several steps are taken. This policy is acquired through a process of interacting with the environment in which the agent manipulates the image and receives stimuli in the form of positive/negative signals. Thus, by positioning LLIE as an MDP, we create the foundation for learning a reinforcement learning agent, which will then be capable of making sequential decisions in the enhancement of low-light images. This approach captured the capability of learning from experience and the manner in which the enhancement process can be fine-tuned to fit the variability of a low-light environment.

2. Related Work

Low light image enhancement whether by traditional methods or the contemporary deep learning approaches has undergone a Know-more process. Pizer et al. [26] used the first adaptive histogram equalization, this improved overall image contrast however, it failed to effectively maintain high local contrast and potential for over saturation. In the U-Net architecture for biomedical image segmentations, Ronneberger et al. [27] provided basic ideas of spatial filtering methods in image enhancement, however the designed-specific character prevented them from being directly used in low light conditions. Subsequently, Hu et al. [28] presented a white-box photo post-processing system based on DRL, that provided variability in enhancement sequences but who was severely CPU-bound. Similarly, Yu et al. [29,30] and Furuta et al. [31] used the DRL for image processing tasks providing interpretable improvement steps as well as scalability and real-life application scalability issues. Among the current methods, He et al. [32] introduced a lightweight method for global image modification with Multi-Layer Perceptrons that improved its efficiency, but did not allow for changes in different lighting conditions. Moran et al. [33] made further contributions with deep local parametric filters for selective region boosting, yet, in a number of cases, it led to uneven integrations through all the image. Similarly, Kim et al. [34] proposed the combined global and local enhancement networks which boosted both overall brightness and structural details but at the same time, the proposed model was relatively large and its deployment was difficult in resource-intensive environments. The use of DRL in controlling non-differentiable image editing tools was explored and successfully applied by Kosugi et al. [35] but the researchers realized that the process hampered in terms of stability and speed within real-life processing. However, for real life application, as pointed by Yang et al. [36,37] there is a need for additional optimization of separable and adaptive lookup tables (LUTs) that were combined with neural networks to enhance efficiency as well as quality. Zeng et al. [38] addressed this by creating small or even moderately sized neural networks for prediction of LUT tables, however the issue was how to achieve this while also optimising for the speed of the algorithm without compromising for accuracy. Wang et al. [39] proposed neural colour operators for maintaining whiteness and contrast, colour contrast but the approach did not scale satisfactorily on a large variety of scenes as observed in real-world images. Wu et al. [40] proposed multi-stage trainable end-to-end networks with self-attention in order to achieve better results in terms of enhancement quality, though at the cost of reduced efficiency. Zhang et al. [41] have proposed the deep colour consistent network in order to minimise the colour discrepancies but the problem of obtaining consistent images with good quality details where still solved. Wang et al. [42] used techniques, which were able to handle distribution shift between low-light and normal-light images but using the method calls for proper contrast and colour management to produce images with appropriate contrast and typical colours. In detail, Jiang et al. [43] developed a generative network for degradation learning and content refinement, which improve the feature extraction with multi-scale representation, while the compatibility problem between different image sizes has not been well solved. More recently, Feng et al. [44] and Wang et al. [45] propose certain techniques that augment depth information and multi-scale fusion to improve illumination in different levels as there had been recognized necessity for more elaborate methods of dealing with the question of illumination in its great complexity and yet there are still effective solution to the problem seeking for improvements. Nevertheless, some of the issues still remains, for instance, how to achieve more powerful and at the same time not too power consuming enhancement, how to achieve good performance in terms of low-light conditions variety, and, finally, how to preserve real-life processing. This paper seeks to overcome these limitations by proposing an Intelligent agent based architecture that utilizes the A3C framework that combines the best of reinforcement learning and the end to end neural networks. This integrated approach allows the agent to optimise globally and locally at the same time and could be fine-grained and do this efficiently allowing the avoidance of the problems highlighted in previous work.

3. Proposed Intelligent Agent

The core of the low-light image enhancement we are proposing here is a DRL agent that encompasses the adaptive pixel-wise low-light image enhancement. This agent is endowed with a fully convolutional network (FCN) structure, which facilitates image processing and gives the best feature extraction at all hierarchical levels. The FCN-based DRL agent works in the asynchronous advantage actor-critic (A3C) framework. The A3C framework stands for Asynchronous Advantage Actor-Critic and is a reinforcement learning algorithm that uses multiple actors to make learning asynchronous for stability and efficiency. The main parts of the agent coming in this paper include the policy network and value network, and both of them structurally contain an FCN. The policy network is expected to predict enhancement action which consists of modifying the intensity of each pixel in the image. These actions are put forward as second-order curve adjustments on the input image and they are sequentially and cumulatively imposed. The value network, however, calculates the sum of the future value of this reward for each state, giving a measure of the potential future benefits of a state. In the agent's training process, it learns a policy that accustoms the maximization of expected cumulative reward and bootstrapped from the reference loss and a set of non-reference loss functions. Through the use of the A3C framework, our agent is able to accurately improve images under different low-light settings, as well as produce unique and specific enhancements that are suited to different users and different scenarios. Figure 2 provides a high-level overview of the proposed reinforcement learning agent for low-light image enhancement and how data flows through the different modules or components of the agent. Figure 2 depicts an agent-based architecture proposed to enhance the amount of light and the quality of visible images. Improved image brightness, contrast, and clarity is achieved in this presentation by using the Asynchronous Advantage Actor-Critic reinforcement learning (A3C) model. Also, demonstrates the processes and decisions performed by the agent to improve images with poor luminance conditions. At each step, the agent assesses the image's current quality, selects optimal actions, applies adjustments, and evaluates the resulting improvement. This cyclic process continues until the image reaches a satisfactory level of enhancement or stopping criteria are met. The key components and their interactions are as follows:

3.1. Input Image

The process begins with an input image captured under low-light conditions. This input serves as the initial state in the reinforcement learning framework, which the agent will iteratively improve.

3.2. Fully Convolutional Network (FCN)

The first layer of the processing is performed by a fully convolutional network which convolves the input image to produce features at several scales. These features characterize areas of the image that are important for enhancement decisions, including edges, texture, and intensity distributions. The feature map of the FCN acts as a base for both the policy and value networks.

3.3. Policy Network

The policy network is responsible for generating actions based on the extracted features. In this context, an "action" represents a specific enhancement adjustment, such as modifying brightness, contrast, or exposure. Each action is formulated to incrementally improve the image by addressing specific deficiencies in lighting or detail. The policy network's output is then passed to the action selection stage, where the agent decides the precise enhancement parameters to apply to the image.

3.4. Value Network

In the same way as the policy network, the value network predicts the expected reward which is correlated with a certain state-action pair. This expected reward is another model of reward, which predicts the degree of quality gain in the image based on the given action. Judging these expected rewards guides the value network to the set of actions that will likely contribute significantly to the improvements allowing for optimization of the agent's actions.

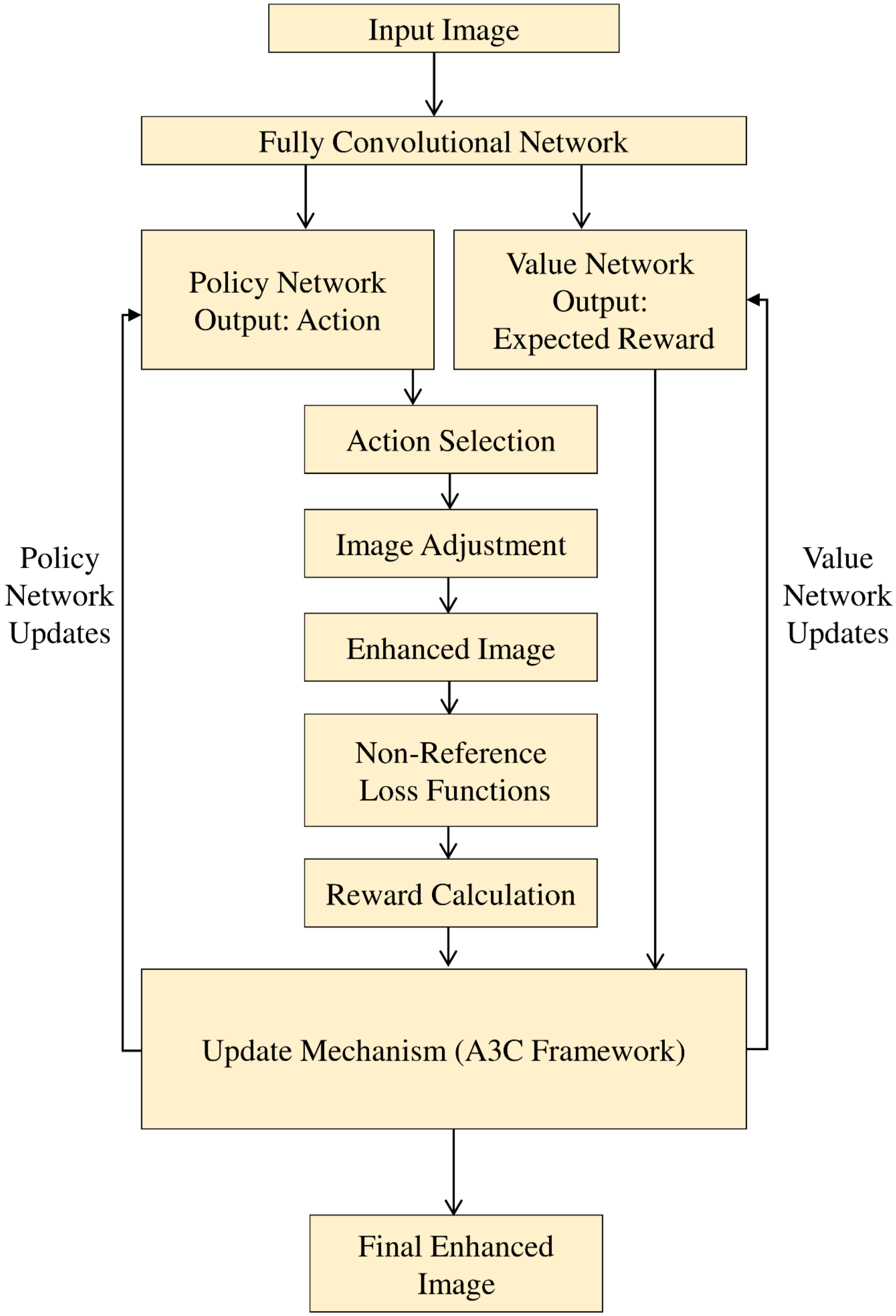

Figure (2): general diagram for the proposed reinforcement learning agent.

3.5. Agent Decision Cycle

Once the policy and value networks output their respective predictions, the agent proceeds through the following steps in a decision-making cycle:

3.5.1. Action Selection

In the action selection step, the enhancement action is decided with a reference to the output of the policy network. The choice of action involves means identifying if both the slight refinements and qualitative change improvements will add value to the achievement of the enhancement objective.

3.5.2. Image Adjustment

The selected action is then applied to the image, and what comes out is an improved image with improved lightening and contrast. This image adjustment involves changing the pixel values as per the requirement of the agent, with the vision of delivering aesthetically good quality and properly exposed images.

3.5.3. Non-Reference Loss Functions

To facilitate the training of the agent, we rely on a set of non-reference metrics that measure the quality of the emergent enhancements made on the images after each adjustment is made in the absence of the paired input images and ground truths in low light conditions. These loss functions are spatial consistency loss, exposure control loss, illumination smoothness loss, and channel-ratio constancy loss.

- Spatial Consistency Loss: This loss ensures that any adjusted contrast and details of the image maintain the original intensity differences with the input image via the enhanced image. They guarantee the enhancement of the image without the creation of artifacts or distortions that affect the spatial distribution of the image.
- Exposure Control Loss: The exposure control loss is calculated on how far away the average intensity of local regions in the enhanced image is from a predetermined well-exposure level. This loss is useful to achieve a balanced exposure across the image, to avoid over-exposed and under-exposed regions in an image.
- Illumination Smoothness Loss: To prevent transitions from being too abrupt to create smooth transitions, the smoothness of illumination adjustment is penalized in illumination smoothness loss when there are large variations in the illumination adjustment map. This loss is important to preserve have natural appearance of enhancements that do not possess high-lighting gradients.
- Channel-Ratio Constancy Loss: The channel-ratio constancy loss ensures that the relation between the red, green, and blue channels is preserved thus eliminating color distortions.

As it preserves the ratio of different color channels, this loss is useful in making the color consistent enhancements that look good and are accurate in color reproduction.

3.6. Reward Calculation

The incentive for each enhancement step is determined from the non-reference loss function outputs. Hence this reward provides feedback to the agent about the result of the recent action taken. The high and low rewards are used to determine if there were successful improvements in the image quality that were implemented in improvements across the health field. This reward signal is a critical bit of reinforcement learning because it continuously aids the agent in enhancing its periodical enhancement plan.

3.7. Update Mechanism: A3C Framework

The fundamental component of learning is the A3C, or Asynchronous Advantage Actor-Critic – the architecture that manages updates to both the policy and values functions. The learning process is therefore asynchronous, multi-threaded, which speeds up convergence since parameters are updated at any random time independently of other processes. The A3C framework operates through the following mechanisms.

3.7.1. Policy Network Updates

In the A3C specifically, the policy network will choose an action according to a state, S, such that the reward accrued over time is of maximum value. The action values are updated by the advantage function which reflects how much better or worse an action is to the expected outcome. The advantage $A(s, a)$ is calculated as calculated equation (1) [46]:

$$A(s,a) = R + \gamma V(s') - V(s) \qquad (1)$$

Where R is the actual reward received, γ is the discount factor, $V(s')$ Is the value of the next state, and $V(s)$ is the value of the current state.
The policy network parameters are updated by maximizing the expected advantage using the policy gradient method. The loss function for the policy network, L_{policy}, incorporates the advantage and the log probability of the action taken as calculated equation (2) [46].

$$L_{\text{policy}} = -\log\pi(a \mid s) \cdot A(s,a) + \beta H\big(\pi(s)\big) \qquad (2)$$

Here, $\pi(a \mid s)$ is the probability of taking action a in state s as predicted by the policy network, and $H\big(\pi(s)\big)$ Represents the entropy of the policy, encouraging exploration. The entropy term, weighted by β, helps prevent premature convergence to suboptimal policies.
Depending on this loss function, the gradient ascent algorithm is then used to update the weight values of the policy network. This adjustment makes it more likely to take the actions that result in higher advantages, enhancing the policy network's decision-making capacity for actions likely to produce higher gains [46].

3.7.2. Value Network Updates

The value network of the A3C framework outputs estimated future cumulative returned rewards for the state, which serves as a frame of reference for the policy network. The changes to the value network are intended to reduce the difference between the expected value and gained returns. The target for the value network is given by the calculated equation (3) [47]:

$$R + \gamma V(s') \qquad (3)$$

The value network's loss function, L_{value}, is defined as the mean squared error between the predicted value $V(s)$ and the target as calculated equation (4) [47]:

$$L_{\text{value}} = \frac{1}{2}\big(R + \gamma V(s') - V(s)\big)^2 \qquad (4)$$

This loss function quantifies the deviation of the value network's estimations. The weights of the value network are then tuned by back-propagation using the gradient descent algorithm to minimize the above loss. The gradients are calculated against the weights of the network and are then used to modify the weights in order to minimize the prediction error.
The weights help to do a more precise prediction of the net future rewards, which serve as a better estimate for baseline than a static one in the policy network improving its weights update in turn. Ideally, this accurate estimation is crucial more on the computation of the advantage function that is involved in the policy update and the improvement of the whole learning scheme in the given agent [47].

3.8. Final Enhanced Image

The final output is a high-quality, enhanced image with improved lighting, contrast, and noise reduction. This image represents the culmination of the agent's iterative adjustments, informed by reinforcement learning and the A3C framework.

4. Results and Discussions

In this section, we will talk about the outcomes that were accomplished by putting the suggested technique into action.

4.1 Datasets Used

Several benchmark datasets were used for the experiments carried out in this project to assess the performance of the Intelligent Agent-Based Architecture for Low-Light Image Enhancement using A3C. The datasets include the LOL (Low Light) dataset: Which contains 500 low light images at different levels providing a direct comparison of enhancement techniques [25]. The MIT-Adobe 5K Dataset: comprises 5,000 images for each class encompassing diverse subjects from intimate portraits and sweeping landscapes to architectural compositions and nocturnal scenes, with each image professionally retouched by five expert photographers, establishing a comprehensive resource for research in photographic enhancement and computational techniques [48]. In addition, a set of other images to compare the performance of the proposed method with other related methods such as the LIME (Low Light Image Enhancement) and the NPE (Naturalness Preserved Enhancement) images [49,50]. They contain a set of images with different lighting conditions. These datasets provide a wide coverage of situations where low light environment is likely to be experienced or where the variation in illumination is significant and therefore provide a thorough test for the proposed method. Table 1 gives an overview of the datasets and images used.

Table 1: An overview of the datasets and images used.

Dataset Name	Number of Images	Resolution / Size
LOL Dataset	500	400×600 pixels
MIT-Adobe – A class	5000	Variable sizes
MIT-Adobe – B class	5000	Variable sizes

4.2 Performance Measures

To assess the effectiveness of our enhancement method, we employed several performance metrics:

PSNR (Peak Signal-to-Noise Ratio): Measures the ratio between the maximum possible power of a signal and the power of corrupting noise, providing a quantitative assessment of image quality [51].

SSIM (Structural Similarity Index): Evaluates the perceived quality of images by comparing structural information, which is crucial for maintaining the natural appearance of enhanced images [51].

LPIPS (Learned Perceptual Image Patch Similarity): A deep learning-based metric that measures perceptual similarity between images, capturing subtle differences in visual quality [51].

Our results demonstrated significant improvements across all datasets. Table 2 shows the results achieved by the proposed method.

Table 2: the results achieved by the proposed method.

Dataset	PSNR (dB)	SSIM	LPIPS
LOL Dataset	25.93	0.932	0.053
MIT-Adobe – A class	23.84	0.918	0.061
MIT-Adobe – B class	24.32	0.941	0.049

For instance, on the LOL dataset, our method achieved a PSNR of 25.93 dB, an SSIM of 0. 932, and an LPIPS of 0.053, outperforming state-of-the-art methods. These metrics indicate that our approach not only enhances the brightness and contrast effectively but also preserves the structural and perceptual quality of the images.

4.3 Implementation Details

The method of low-light image enhancement discussed in this paper was developed and tested in Python programming language with the aid of PyTorch framework, assembled from a Fully Convolutional Network (FCN) architecture that also incorporates the policy and value networks from the Advantage Actor-Critic (A3C) algorithm. The policy network itself chooses the best enhancement actions while the value network estimates potential rewards to the policy and directs policy updates. To increase the model's stability, we performed methods of data augmentation like cropping and flipping. The training process was performed on NVIDIA GeForce RTX 2080 GPU with an initial learning rate of 1e-4. We set the discount factor at 0.99 to factorize the immediate and future reward, clipped the gradient norm at 5 to prevent them from blowing up, and the entropy coefficient at 0.01 to encourage the agent to explore more. The reward signals were scaled by a factor of 1 and Adam optimizer was used to update the weights of the networks. These fine-tuned parameters allowed our agent to perform well and optimally to provide enhanced images within various datasets.

4.4 Visual Result and Comparison

In order to substantiate the presented results, several samples from the datasets are illustrated below to depict how our method works. In Figure 3, we are able to see how well our method preserves the naturalness of the LOL dataset [25].

Figure (3): An illustration of the explaining capabilities of nature preservation of our proposed method on the LOL dataset. In the top row are the low-light images as they are and in the bottom row is after applying the method proposed.

Figure 4, illustrates a sequence of real-life examples which serve to highlight the effectiveness of the proposed customized LLIE. The figure shows how our agent-based approach opens up a way to perform different levels of enhancement steps to meet different levels of image quality boost. In Figure 4, each of the subfigures represents the enhancement from the raw low-light image to the multiple iterations of enhancement.

Figure (4): A set of images with varying degrees of enhancement steps implemented by the proposed method. The first column on the left shows the low-light images, then in the following columns, varying degrees of enhancement appear, and the last column is the final images after enhancement.

The qualitative analysis also supports that our proposed agent-based approach provides better overall image quality while keeping important details and the naturalness of the image intact. To give more insight into the comparative performance of the proposed technique, we have compared our method with existing low-light image enhancement algorithms which are highly popular. The quantitative evaluations of PSNR, SSIM, and LPIPS Metrics compared with related methods on the LOL dataset are demonstrated in the third Table 3.

Table 3: the quantitative comparisons metrics with related methods on the LOL dataset.

Method	PSNR (dB) ↑	SSIM ↑	LPIPS ↓
[40]	19.84	0.824	0.078
[41]	22.97	0.847	0.085
[42]	24.99	0.869	0.077
[44]	25.85	0.876	0.082
[45]	25.90	0.881	0.065
Proposed Method	**25.93**	**0.932**	**0.053**

Compared to these basic methods, our approach was more stable and showed better results for reaching high PSNR and SSIM while having lower LPIPS, which proves the higher image quality and better similarity to the original images.

Conclusion

In this work, low light image enhancement was presented using an intelligent agent-based architecture wherein A3C framework was employed and the scope of the agent was described in terms of its ability to learn and select locally optimal enhancement methods. Our approach, the enhancement process formulated as the

Markov Decision Process, enables an agent to make a sequence of deliberate decisions to improve the quality of an image. Policy and value networks work alongside an FCN for feature extraction to improve decision-making. Altogether, among all the compared methods, our proposed method showed superior performance in terms of PSNR, SSIM, and LPIPS in various datasets, proving effectiveness in increasing brightness, contrast, and structural details while avoiding artifacts. This ability ensures that the enhancements can be localized to meet the needed user requirements and low light levels and makes the system ideal for both professional portable photography and security surveillance. It guarantees that the enhancement can be optimized in accordance with the requirements of various cases and gives the users leverage to control the enhancement level and quality. The results prove that reinforcement learning agents have the ability to enhance image processing methods in low light. This work opens the door for future studies and shows the warrant for further enhancement of these capabilities, determining new fields of use and ways to build more effective, stronger, and more efficient smart agent picture improvement systems. Based on the results of this work, several areas seem to hold potential for the further application of RL within other sophisticated image analysis methods to solve a larger set of visual-related tasks.

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