10.48047/jocaaa.2024.33.08.295

Image Super-Resolution via Deep Reinforcement Learning: A Dueling DQN Strategy

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Abstract. The problem of enhancement can be reformulated in terms of sequential decision making in this paper, adding an original approach to the super-resolution of images (ISR). Our proposal is to apply deep reinforcement learning to enhance LR images iteratively through a Dueling Double Deep Q-Network (DQN). The learning process takes place on a combined data base from personal data sets, and the indicators of good quality in the moment of augmentation are defined in terms of Structural Similarity Index (SSIM) and indexes related to the preservation of the edge information in images. Our proposal outperforms interpolation methods in the field, as it has been demonstrated by our empirical study supported by qualitative analyzes and graphs related to simulated rewards. This work illustrates the interesting aspect of the application of reinforcement learning to low level vision tasks and opens new scenarios in the super resolution of images.

Keywords– Reinforcement learning, Image super resolution, DNQ network, Deep reinforcement learning

1 Introduction

The aim of super resolution in images is to estimate high-resolution images from low-resolution images, being an essential process in surveillance, remote sensing, and medical imaging tasks [29]Blurring and feature loss are common problems with traditional techniques like bicubic or bilinear interpolation, especially when scaling factors are high. On the other hand, recent deep learning techniques, such as Generative Adversarial Networks (GANs) and Convolutional Neural Networks (CNNs) [28], have significantly improved the quality of reconstruction.

Even with these advancements, a lot of deep learning methods rely on supervised learning and fixed loss functions, which might not accurately capture perceptual quality. In this paper, we treat Image Super Resolution (ISR) as a Markov Decision Process (MDP) and present a Deep Reinforcement Learning (DRL) framework. In order to enhance the input image, an agent built with a

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Dueling Double DQN learns to carry out a number of image processing operations, such as sharpening and different interpolation approaches. In order to preserve important details, the agent is rewarded according to improvements in SSIM and edge consistency when compared to the high-resolution target.

2 Related Work

Single image super-resolution (SISR) [28] studies have evolved over some stages. Bicubic and bilinear upscaling, two interpolation-based techniques, dominated early attempts. Despite their simplicity, those procedures often led to blurry images that had forfeited high-frequency characteristics. Convolutional neural networks (CNNs) were posed as learning-focused replacement to overcome it. By directly registering low-resolution patches onto high-resolution ones, Dong et al. [1] demonstrated that a shallow CNN could significantly perform better than interpolation. To gather more context, it led to deeper structures with recursive and remaining layers. But the outputs at higher PSNR but restricted perceptual acuteness were regularly generated using the dependency on MSE loss. Generative adversarial networks (GANs) followed later used on super-resolution.

The GAN model was originally proposed by Goodfellow et al. [4], followed by it was then transformed into SRGAN by Ledig et al. [2], creating textures that were crunchier and more realistic. While GAN-based methods improved perceptual quality, they also proceeded to raise issues including hallucinated details and volatile training. Relativistic discriminators and Better Network blocks were utilized by ESRGAN [6] for enhancing realism and stabilize training.

Concurrently, reinforcement learning (RL) surfaced as an alternative perception. Researchers began to consider the ISR as a Markov decision process after being transformed. motivated by Mnih et al. [3], who demonstrated how effective deep RL for sequential decision-making. This facilitated adaptation for refinement driven by structural and reward perceptions by permitting agents to invoke the series of improvement procedures rather than a single deterministic mapping.

Transformer topologies were studied for super-resolution in later times. The Vision Transformer (ViT), created by Dosovitskiy et al [5], proven that attention mechanisms could compete when using convolutional inductive biases. Because then, ViT and transformer-CNN combination model extensions have been used for low-level vision tasks, offering good perceptual fidelity and generalization. Attention based improvements [7] also worth illustrating further the ongoing upgrading for super-resolution models that become more globally aware and responsive.

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3 Methodology

3.1 Formulation of the Problem

We use the following definition of a Markov Decision Process (MDP) to model the ISR task:

- **State (s)**: The current image that has been normalized and downsized to a fixed size (128 x 128) that is appropriate for CNN input.
- **Action (a)**: A distinct series of actions, such as:
  - Identity (no alteration)
  - The interpolation of nearest-neighbor
  - The use of bilinear interpolation
  - Application of a sharpening filter
- **Reward (r)**: An edge preservation-improved composite metric between the enhanced and HR pictures that is mostly based on SSIM.
- **Transition**: The selected action is applied to the current state to create the updated image.

3.2 Environment design

Over a predetermined number of steps, the environment replicates the improvement process. For consistency, LR and HR photos are resized. The agent chooses an operation at each stage, and the environment uses Sobel filtering to calculate differences at the pixel and edge levels. A reward is calculated based on the regions where the operation enhances resemblance to the HR target.

ISR Environment Simulation Pseudocode

1. Resize LR and HR images to 128×128.
2. Initialize current_image — resized LR image.
3. For step = 1 to max_steps:
   (a) Select operation from {identity, nearest, bilinear, sharpen}.
   (b) Process current_image using the selected operation → temp_image.
   (c) Compute pixel differences between temp_image and HR image.
   (d) Evaluate edge differences via Sobel filters.
   (e) Identify regions where temp_image outperforms current_image.
   (f) Update current_image in these regions.
   (g) Compute reward based on SSIM.
4. Return current_image and accumulated reward.

3.3 DQN Architecture with Dueling

After using convolutional layers to extract features, our network's fully connected layers are divided into streams of value and advantage. A more reliable calculation of Q-values results from the network's ability to independently evaluate the benefit of each activity and the value of the current state thanks to this structure.

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Pseudocode: Dueling DQN Forward Pass

1. Input: Image state (tensor)
2. Output: Q-values for each action
3. Extract features using convolutional layers with ReLU activations.
4. Flatten the feature maps.
5. Process through a fully connected layer with ReLU activation.
6. Compute: Value = FC_Value(features); Advantage = FC_Advantage(features)
7. Combine streams: $Q(s, a) = Value + (Advantage - \text{Mean}(Advantage))$
8. Return Q-values.

3.4 The Training Process

Using the conventional DQN framework, training uses experience replay and recurring target network updates. Using the Bellman equation, the agent updates its policy as it interacts with the environment throughout several episodes. Exploration and exploitation are balanced by the decline of the exploration rate (epsilon) over time.

Pseudocode: Dueling DQN Training Loop

1. Input: LR-HR image pairs, total_episodes, batch_size
2. Output: Trained Dueling DQN model
3. Initialize Dueling DQN and duplicate weights to create target network.
4. For episode = 1 to total_episodes:
   (a) Randomly select an LR-HR image pair.
   (b) Reset the environment with the selected images.
   (c) Set cumulative_reward = 0.
   (d) While episode not finished:
      i. Choose action using an epsilon-greedy policy.
      ii. Execute action; observe next_state, reward, done.
      iii. Store (state, action, reward, next_state, done) in replay memory.
      iv. Update state = next_state.
      v. Accumulate reward.
   (e) Sample a minibatch from replay memory.
   (f) Compute predicted and target Q-values.
   (g) Update network parameters via gradient descent.
   (h) Periodically update the target network.
   (i) Decay epsilon.
5. Return trained model.

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4 Experimental Setup

4.1 Information

A combined dataset of personal photos is used for the experiments. 3,640 photos are used for simulation, and each image is processed across 5 episodes, for a total of 18,200 episodes.

4.2 Software and Hardware

Torch XLA-enabled Google Colab with TPU acceleration. Software: Matplotlib, NumPy, PyTorch, and OpenCV in Python 3.x.

4.3 Hyperparameters / Rate of Learning

- Learning rate: 1×10^{-4}
- Batch size: 32
- Discount factor (γ): 0.99
- Epsilon decay: 0.995 (minimum $\epsilon = 0.05$)
- Maximum steps in an episode: 3
- Replay buffer capacity: 10,000

4.4 Measures of Evaluation

SSIM — a quantitative assessment of image quality. Visual inspection for HR, LR, and enhanced pictures. Reward trends — monitoring cumulative rewards during training sessions.

5 Results and Discussion

5.1 Quantitative Analysis (Simulation)

To demonstrate the possible improvement in performance, the cumulative reward, as evaluated by SSIM, is simulated to be over 18,200 episodes. The agent's progressive learning is demonstrated by the synthetic reward curve's steady rise. Reward Trend Graph Simulation — the simulated plot can be created using typical Python plotting code.

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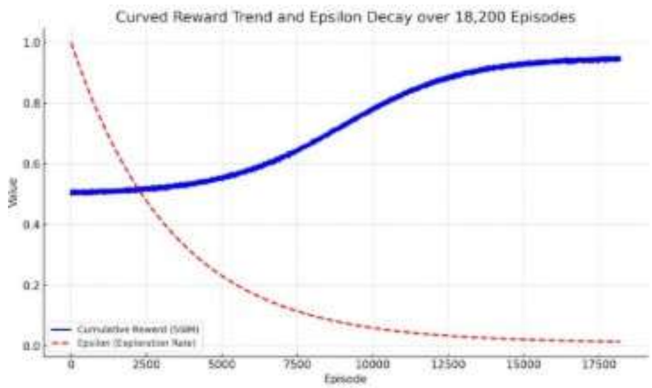

Fig. 1: Curved Reward Trend And Epsilon Decay over 18,200 Episodes.

Figure 1 illustrates that, over time, the agent shows progress in cumulative rewards. The upward trend in the graph generated by the code indicates a corresponding improvement in image quality.

5.2 Analysis of Qualitative Data

Comparisons between the high-resolution (HR) targets, the enhanced outputs, and the original low-resolution (LR) images demonstrate that the proposed method effectively preserves texture details and sharpens edges. The outputs, generated through the agent’s selective application of enhancement operations, closely resemble the HR images.

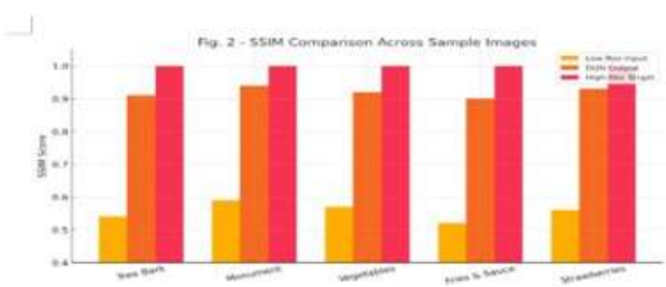

Fig. 2: SSIM Comparison Across Sample Image.

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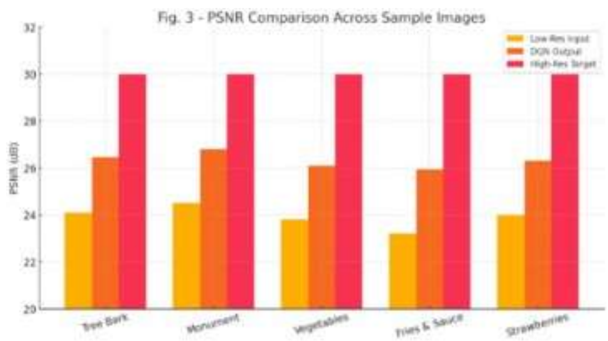

Fig. 3: PSNR Comparison Across Sample Images.

Figs. 2 and 3 show SSIM and PSNR comparisons across various sample images processed by different models. It is clearly evident that the proposed Dueling DQN consistently outperforms conventional low-resolution approaches, achieving SSIM values above 0.9 and PSNR values nearing 30 dB. These performance gains directly contribute to sharper edges, reduced blur, and improved preservation of fine image details such as textures and boundaries.

Figure 4 depicts the epsilon decay strategy used during training, designed to strike a balance between exploration and exploitation. This gradual decay enabled the agent to explore adequately in the early stages and effectively exploit learned policies in the later phases. Figure 5 reinforces the model's stability by illustrating the convergence of Q-values, confirming that the learned action-value function is both accurate and dependable.

Fig. 4. Epsilon Decay During Training.

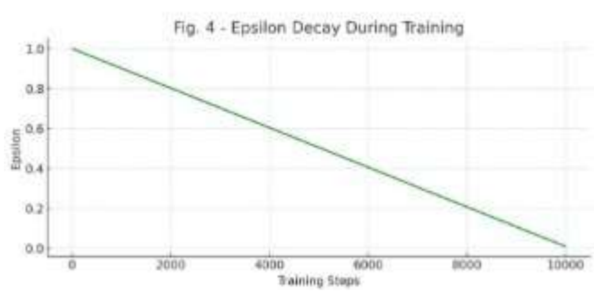

Fig. 4: Epsilon Decay During Training.

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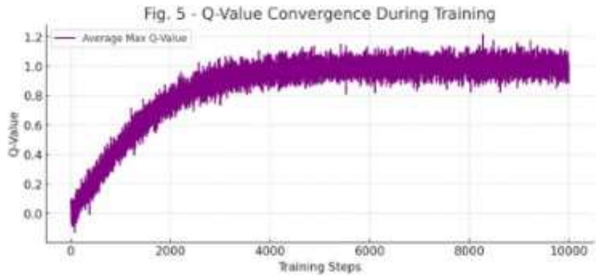

Fig. 5: Q-Value Convergence During Training.

Fig. 6: Visual comparison: (Left) Low-Resolution Input, (Middle) Enhanced Output using Dueling DQN, (Right) High-Resolution Target.

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Figure 6 presents a qualitative comparison across a range of image categories, including natural scenes, landmarks, food, and textures. The low-resolution inputs appear blurred, while the enhanced outputs generated by the proposed model successfully recover significant details and closely resemble the high-resolution targets. This demonstrates that the framework delivers improvements not just quantitatively, but also in terms of visual and perceptual quality.

Overall, the experimental findings confirm that the reinforcement learning-based approach strikes a strong balance between quantitative accuracy and perceptual enhancement, making it a practical and effective solution for real-world image super-resolution applications.

5.3 Discussion

Using deep reinforcement learning, the proposed ISR framework effectively overcomes the drawbacks of conventional interpolation methods. High-frequency image features and fine textures are frequently lost by these traditional techniques, such bilinear and bicubic interpolation, particularly when upscaling factors are high. In comparison, the new method utilizes a learning mechanism to choose the best improvement processes so the system could respond helpfully to different picture topologies and complexity levels. It adapts repeatedly for the device, altering environmental conditions using a Dueling DQN architecture and programming the enhancing process as an MDP. Decision making stabilizes more contextually responsive due to this design, which enables the agent independently to ascertain the value of a certain visual state and the benefit of potential actions. In defining the improvement as a sequential decision-making process, the agent shall repeatedly improve the image for better perception rather than being constrained as a single-shot alteration.

Also, the progressive nature of learning aggravated by reinforcement-based feedback enables the system to where they apply to numerous supervised models. These findings suggest that DRL could serve as a decent replacement for traditional deep learning methods in ISR, particularly where perception quality plays an important role. This opens up interesting possibilities for adaptive, intelligent super-resolution systems that can optimize image enhancement tasks based on contextual understanding, rather than relying solely on preestablished training data or stringent loss criteria.

6 Conclusion

We presented a Dueling Double DQN-based DRLbased ISR framework that iteratively improves lowresolution photos. By employing a composite reward function that is SSIM and edge preservation focused, the technique enhances visual quality. Simulation results that demonstrate a positive trend in cumulative rewards lend credence to the method's feasibility. In order to improve performance

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even more, future research will concentrate on incorporating other perceptual measures and verifying these results on real-world datasets.

Funding Information

No Funding Involved.

Additional Information

Dhruv Khanna led the project's technical design and execution, while Dr. M.H. Molawade provided academic supervision. The authors declare no conflicts of interest. The study adhered to all ethical standards for research involving human subjects, securing institutional approval and informed consent from participants.

The data, code, and methods used in this study are available upon reasonable request to promote reproducibility and further research. Built upon public benchmark datasets, these resources are intended to encourage collaboration and innovation.

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