INSPIRATION: Enhancing Underwater Images Using Reinforcement Learning

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Motivation and Context

- Underwater images often suffer from poor quality due to wavelength-dependent absorption and scattering, resulting in color casts, low contrast, and blurred details.
- Enhancing these images is crucial for applications in ocean exploration, underwater engineering, and robotics.
- Traditional deep learning models require reference images, which are scarce, limiting their effectiveness in diverse underwater scenes.

State of the Art

1. Physical Model-Based Methods:
   - Estimate parameters modeling degradation mechanisms to restore clear images.
   - Methods include robust color recovery and backscatter correction techniques.
2. Non-Physical Model-Based Methods:
   - Enhance visual quality by directly manipulating pixel values.
   - Techniques include adaptive frameworks, retinex-inspired corrections, and variational methods.
3. Deep Learning-Based Methods:
   - Use end-to-end learning processes to map underwater scenes to clear images.
   - Incorporate semantic attention, hierarchical attention mechanisms, and unsupervised enhancement methods.

The Proposed Approched

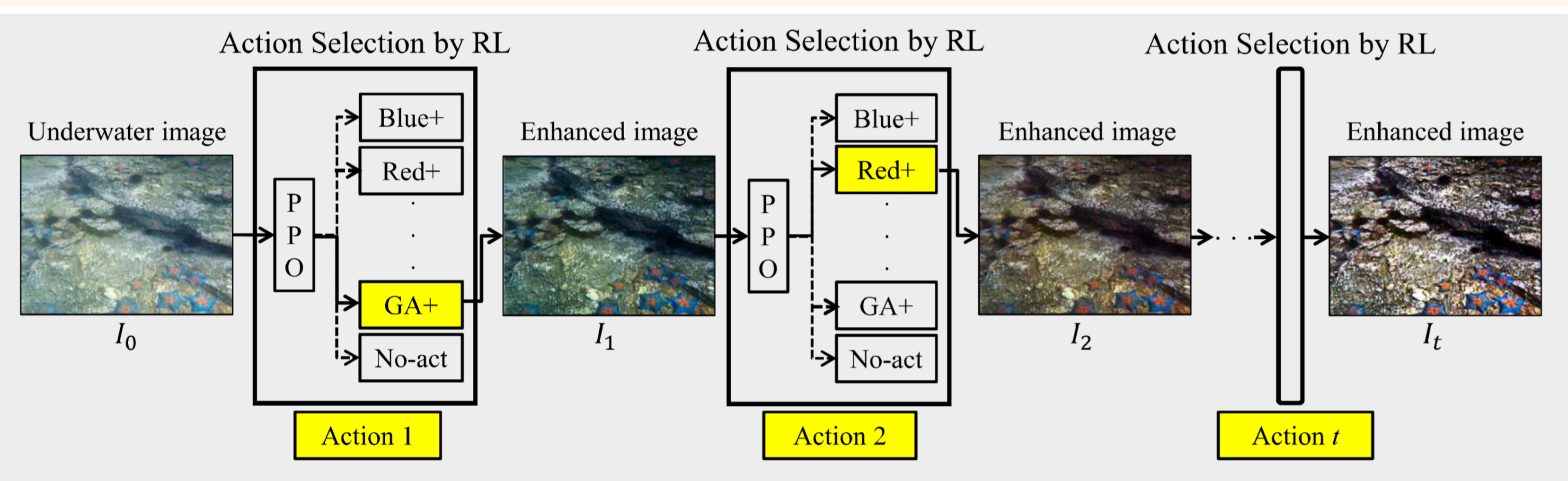


Figure 1. The overview of the paradigm's enhancement process.

- Utilizes reinforcement learning (RL) driven by human visual perception for image enhancement.
- Employs a residual-enhancement network for feature extraction and proximal policy optimization (PPO) for RL.
- No need for reference images during training or implementation.
- Constructs rewards based on human visual perception metrics like UIQM, UCIQE, and MCL.
- Selects and organizes image enhancement algorithms in a step-wise process to align enhanced images with human visual perception.

	Action description		Action description
#	Basic attribute adjustment	#	Color component balance
1	Brightness adjustment ↑	8	Red channel adjustment ↑
2	Brightness adjustment ↓	9	Red channel adjustment ↓
3	Contrast adjustment ↑	10	Green channel adjustment ↑
4	Contrast adjustment ↓	11	Green channel adjustment ↓
5	Saturation adjustment ↑	12	Blue channel adjustment ↑
6	Saturation adjustment ↓	13	Blue channel adjustment ↓
7	High-pass fusion	14	Gray world assumption
#	Attenuated channel compensation	#	Linear/nonlinear transformation
15	Blue–green channel compensation	18	Rescale intensity
16	Green-red channel compensation	19	Gamma correction ↑
17	Color channel compensation (3C)	20	Gamma correction ↓
#	Termination		
21	No-action option		

Figure 2. The actions.

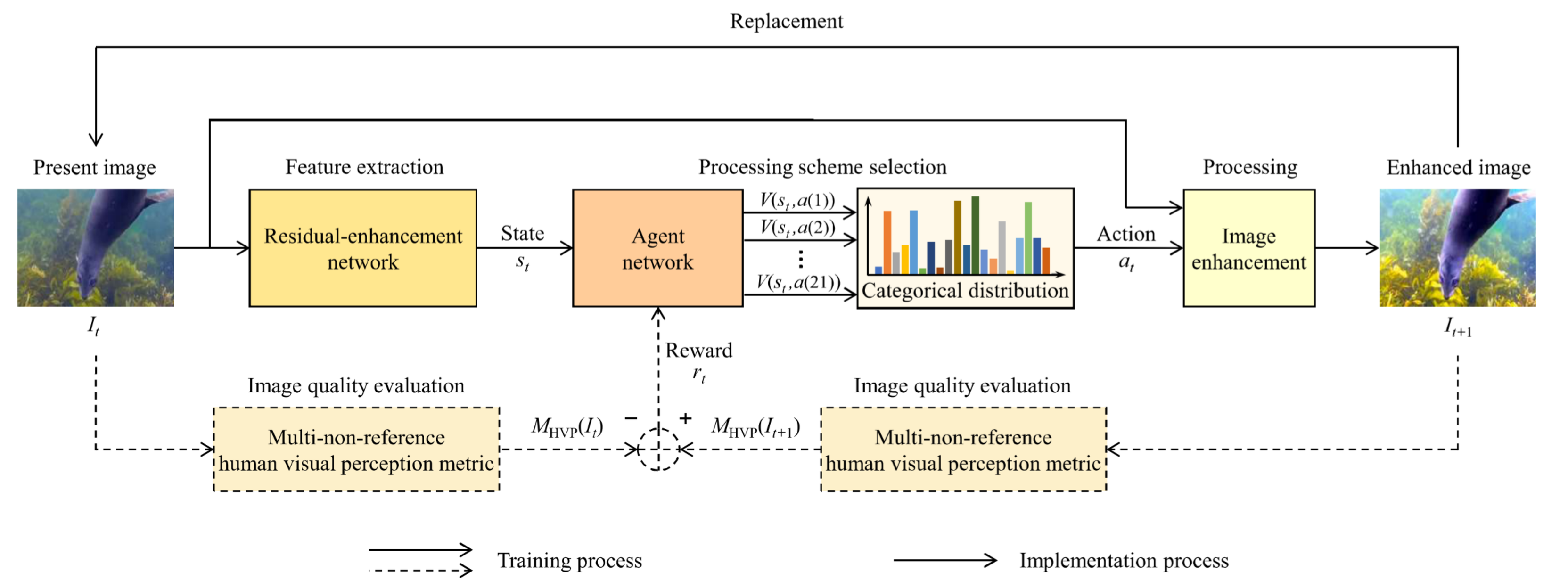


Figure 3. The training and implementation processes of the reinforcement learning-based paradigm.

Results

- compared to nine state-of-the-art methods.
- Tested on three underwater image datasets (U45, RUIE, UIEB)

Efficiency and Applicability:

- Faster processing times across different image resolutions.
- Potential advantages as a preprocessing step in other underwater computer vision applications.

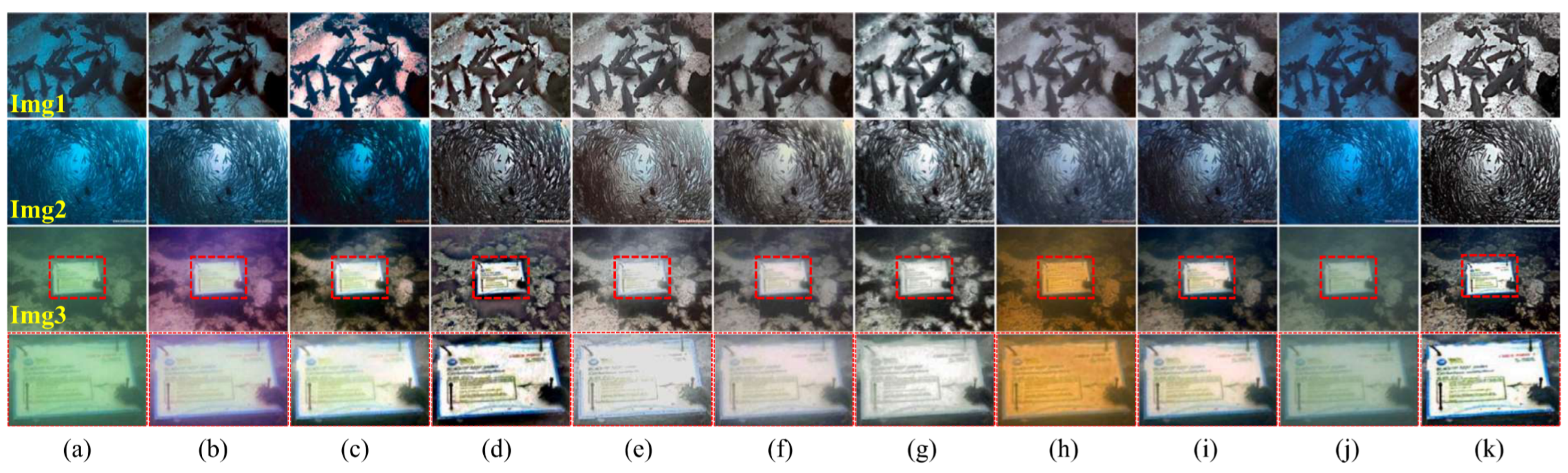
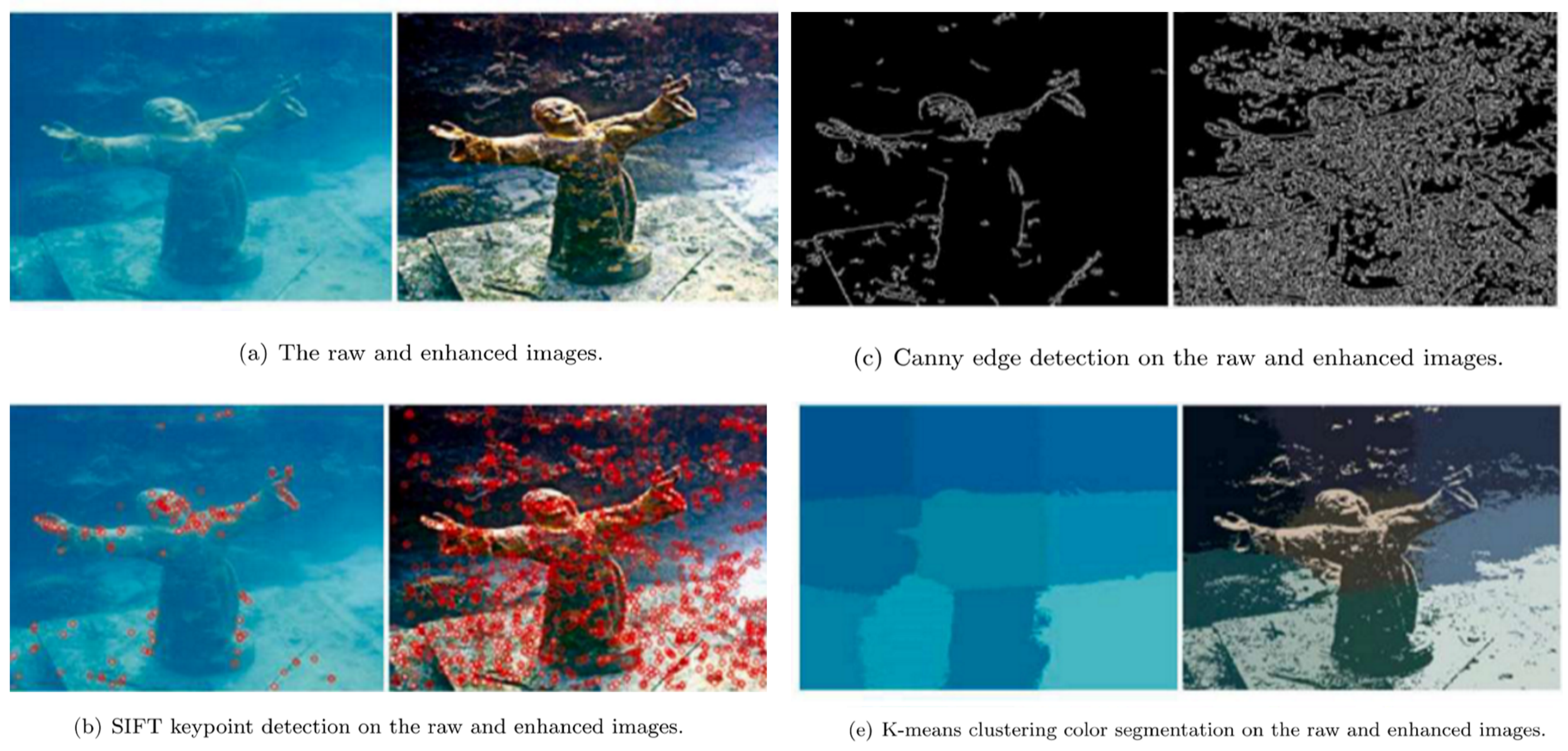


Figure 4. Qualitative evaluation results on the UIEBR subset.



(a) The raw and enhanced images.

(c) Canny edge detection on the raw and enhanced images.

(b) SIFT keypoint detection on the raw and enhanced images.

(e) K-means clustering color segmentation on the raw and enhanced images.

Limitations and Future Work

- Current Limitations:
  - Model retraining needed when the list of actions (image enhancement algorithms) is extended.
  - Focuses on enhancing images to align with human visual perception but does not address effectiveness for tasks like classification and object detection.
- Future Directions:
  - Explore solutions for extending the action list on a well-trained model.
  - Develop training strategies to enhance images for both human visual perception and other tasks like object detection.
  - Explore more efficient feature extractors, image enhancement algorithms, underwater image quality measures, and reinforcement learning models to optimize the paradigm's performance.

References

[1] Hao Wang, Shixin Sun, Laibin Chang, Huanyu Li, Wenwen Zhang, Alejandro C. Frery, and Peng Ren. Inspiration: A reinforcement learning-based human visual perception-driven image enhancement paradigm for underwater scenes. *Engineering Applications of Artificial Intelligence*, 133:108411, 2024.