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CSD415 PROJECT PHASE 1

Literature Review

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1 Introduction

This project aims to develop a web extension that identifies and highlights bias in online news articles, empowering users to critically assess the information they consume. Leveraging advanced Natural Language Processing (NLP) techniques, the extension will analyze articles in real-time, identifying patterns and classifying sentiment to detect potential biases. By integrating a pre-trained BERT model, the system will offer a nuanced understanding of the article's content, providing users with an objective evaluation of its bias and encouraging informed decision-making.

2 Literature Review

2.1 *Intelligent Underwater Object Detection and Image Restoration for Autonomous Underwater Vehicles*[1]

Abstract: This paper proposes a **two-stage framework** for AUVs:

- **Object Detection:** Uses YOLOv8 for fast ROI detection (94.6
- **Image Restoration:** A novel dehazing algorithm estimates per-channel transmission maps to reduce artifacts.

Achieves **UCIQE = 3.09** and **0.55s runtime**, enabling real-time underwater monitoring.

Methodology:

- **Detection Stage:**
  - YOLOv8 processes images in **0.028ms** (compared to YOLOv4's 94.35
  - Trained on a curated dataset including fish, divers, and submarines.
- **Restoration Stage:**
  - Estimates **transmission maps for RGB channels** separately.
  - Uses **Underwater Dark Channel Prior (UDCP)** and guided filtering.
  - Key equation:

$$t_{bl}(e) = 1 - \left(\frac{\min_{c \in \{b,g\}} (\min_{y \in \pi(e)} I_c(y))}{c_{\mathrm{err},g,b} A_{mc}} \right)$$

Advantages:

- **High accuracy:** 94.6
- **Real-time performance:** 0.55s total processing time.
- **Robust dehazing:** Handles color distortion and scattering.

Disadvantages:

- **Prior dependency:** Restoration fails if transmission maps are inaccurate.
- **Limited depth testing:** Primarily validated at shallow depths (<5m).

2.2 *Comprehensive Underwater Object Tracking Benchmark Dataset and Underwater Image Enhancement With GAN[2]*

Abstract: Introduces **UOT100**, the first underwater tracking dataset (104 videos, 74K frames), and **CRN-UIE**, a GAN model for enhancement. Benchmarks 20 trackers, showing performance drops underwater (e.g., SiamRPN++ precision drops from 0.914 to 0.230).

Methodology:

- **Dataset Creation:**
  - Curated from natural and artificial underwater videos.
  - Categorized by distortion type (blue/green/yellow water).
- **CRN-UIE GAN:**
  - Uses **cascaded residual blocks** and **gradient profile loss**.
  - **Multi-scale discriminators** improve sharpness.

Advantages:

- **Diverse dataset:** Covers real-world underwater challenges.
- **Enhanced tracking:** CRN-UIE improves tracker precision by 30%.

Disadvantages:

- **Computational cost:** GAN training requires high resources.
- **Synthetic bias:** Artificial videos may not reflect all real conditions.

2.3 *A Non-Reference Evaluation of Underwater Image Enhancement Methods Using a New Underwater Image Dataset[3]*

Presents **CDUIE**, a real-world dataset (85 plant images at 1–3m depth), and benchmarks 9 enhancement methods (e.g., WaterNet, UColor) using **non-reference metrics** (BRISQUE, NIQE, CCF).

Methodology:

- **Dataset:** Collected via ROV in turbid lake water.
- **Evaluation Metrics:**
  - **Entropy:** Measures detail retention.
  - **CCF:** Combines colorfulness, contrast, and fog density.

Advantages:

- **Real-world focus:** Turbid water images challenge enhancement methods.
- **Comprehensive metrics:** Highlights trade-offs (e.g., GLN-HE improves contrast but distorts colors).

Disadvantages:

- **Small dataset:** Only 85 images.
- **Limited scenes:** Focused on plants, not diverse objects.

2.4 *A Wavelet-Based Dual Stream Network For Underwater Image Enhancement[4]*

Abstract: This method enhances underwater images by applying a wavelet-based decomposition that separates structural and detail components. A dual-stream neural network then restores color and texture independently, and fuses them to generate high-quality results. The use of multi-color space fusion and GAN-based training improves realism and visual clarity.

Methodology:

- **Wavelet Decomposition (DWT):** Splits the image into low- and high-frequency sub-bands (ILL, ILH, IHL, IHH).
- **Dual-Stream Network:**
  - **Multi-color space fusion network:** Enhances low-frequency ILL using color correction and multi-color space fusion.
  - **Detail Branch:** Enhances high-frequency ILH, IHL, IHH sub-bands to recover texture and edges.
- **Reconstruction (IDWT):** Merges enhanced sub-bands to produce the final output.
- **Training:** Uses combined L1 + MSSIM (structure), detail loss, and adversarial loss.

Advantages:

- Works well even on real-world underwater images.
- GAN improves visual realism.

Disadvantages:

- Computationally heavier due to dual networks and GAN.
- Requires a large dataset for robust training.

2.5 *Color Correction Based on CFA and Enhancement Based on Retinex With Dense Pixels for Underwater Images[5]*

Abstract: This paper proposes a novel method combining color correction based on the Color Filter Array (CFA) characteristics and illumination enhancement using Retinex theory with dense pixel paths. The approach involves compensating the red channel using green and blue channels, applying white balance, enhancing illumination via a modified McCann Retinex algorithm with dense sampling, and performing a piecewise linear adaptive histogram transformation. Experimental results demonstrate superior visual quality and improved objective metrics compared to existing state-of-the-art methods.

Methodology:

- Red channel compensation based on CFA
  - Uses the dependency between channels introduced by CFA interpolation.
  - The red channel is compensated using a weighted combination of local averages from green and blue channels.
- Applies standard white balancing
- Retinex with dense pixels
  - Spiral path estimation is sparse and directionally biased.
  - Uses eight directional paths (clockwise and counterclockwise from diagonals) to uniformly sample the image.
  - Yields better global illumination estimation and local detail enhancement.
- Adaptive Histogram Transformation
  - Gray-World theory; average intensity for a balanced image should be 128 per channel.
  - Piecewise linear transformation shifts channel means into [100, 140] range.
  - Compared to gamma correction and global histogram stretching, it shows improved perceptual quality.

Advantages:

- **No Training Required**
  Unlike deep learning models, this method is unsupervised and model-free.
- **Red Channel Restoration from CFA Dependency**
  Utilizes inherent sensor properties for more accurate color correction.
- **Enhanced Illumination Estimation**
  Dense Retinex paths provide uniform enhancement across the image, including darker corners.
- **Robust to Various Underwater Conditions**
  Tested across multiple datasets and turbidity levels with consistent performance.
- **Superior Quantitative Metrics**
  Outperforms baselines in Entropy, NIQE, IL-NIQE, UIQM, and UCIQE.

Disadvantages

- **Fixed Parameters**
  Certain constants like α and ε are manually tuned and not adaptive to image content.
- **No Learning or Semantic Understanding**
  Cannot distinguish object-level features or adapt to scene semantics (unlike GAN-based methods).
- **Computational Overhead from Dense Paths**
  Dense pixel processing can be more computationally expensive compared to sparse methods.
- **Not Optimized for Real-Time Use on Low-Power Devices**
  Although efficient, the method may still be heavy for embedded or low-resource systems without further optimization.
- **Limited Evaluation on Extreme Scenarios**
  While robust, it may underperform in highly turbid or low-visibility waters compared to some deep learning models.

2.6 *Lightweight Underwater Image Enhancement via Impulse Response of Low-pass Filter Based Attention Network*

Abstract: This paper proposes an **improved Shallow-UWnet model** for underwater image enhancement targeting resource-constrained underwater robots:

1. **Skip Connection Enhancement:** Incorporates raw underwater images and impulse response of low-pass filter (LPF) to solve vanishing gradient problems.
2. **Attention Integration:** Integrates parameter-free SimAM attention modules into each Convolution Block for enhanced visual quality.
3. **Lightweight Design:** Achieves comparable performance with **216,000 parameters** (fewer than original Shallow-UWnet) and **0.05 s testing time** per image.

Demonstrates superior results with **PSNR = 27.87**, **SSIM = 0.84**, and **UIQM = 2.96** on the EUVP-Dark dataset.

Methodology:

- **Architecture Enhancement:**
  - Modifies Shallow-UWnet by adding skip connections that concatenate raw underwater images with LPF impulse responses.
  - Reduces ConvBlock features from 61 to 58 to accommodate additional input channels.
  - Maintains three successive ConvBlocks with ReLU activation and dropout regularization.
- **Low-Pass Filter Integration:**
  - Evaluates four LPF variants: Sparsity-based LPF (SLPF), Direct LPF (DLPF), Gaussian LPF (GLPF), and Butterworth LPF (BLPF).
  - *SLPF formulation:* Power spectrum sparsity

$$S = \frac{P_a}{P_h + P_v}, \quad \gamma = \lambda S.$$

  - *Frequency response:*

$$H_S(\omega_1, \omega_2) = \begin{cases} 1, & P(\omega_1, \omega_2) \le \gamma, \\ 0, & \text{otherwise.} \end{cases}$$

- **SimAM Attention Module:**
  - Parameter-free 3D attention mechanism based on energy theory.
  - *Energy calculation:*

$$\varepsilon_T = \frac{4(\rho^2 + \alpha)}{(T - \eta)^2 + 2\rho^2 + 2\alpha},$$

    where $\eta = \frac{1}{N} \sum_i y_i$ and $\rho^2 = \frac{1}{N} \sum_i (y_i - \eta)^2$.
  - *Attention output:*

$$\widetilde{Y} = \sigma\left(\tfrac{1}{E}\right) \odot Y.$$

Advantages:

- **Lightweight architecture:** 216,000 parameters vs. 219,456 in original Shallow-UWnet.
- **Fast processing:** 0.05 s per image enabling real-time enhancement.
- **Robust performance:** Comparable or superior PSNR/SSIM/UIQM across EUVP-Dark, UFO-120, and UIEB.
- **Noise reduction:** Better distinguishes image content from noise.

Disadvantages:

- **Marginal PSNR improvement:** Only slight gain over baseline (27.87 vs. 27.86 on EUVP-Dark).
- **Color artifacts:** Overcontrast with reddish hue in heavily hazy regions persists.
- **Dataset dependency:** Trained mainly on EUVP, may generalize poorly to other conditions.
- **LPF variant selection:** No clear guidance on optimal filter choice; benefits similar across variants.

2.7 *Underwater Image Enhancement via Medium Transmission-Guided Multi-Color Space Embedding[6]*

Abstract: This paper proposes a multi-color space encoder network that incorporates characteristics of differeent color spaces into a unified structure. It uses an attention mechanism to find discriminative features and adaptively highlights them. The decoder network is guided by phisical models to find quality degraded areas

Methodology:

- Multi-Color Space Encoder
  - Transforms input into RGB, HSV, and Lab color spaces
  - Each color space is passed through a Residual Enhancement Module that has convolution laters with Leaky ReLU activation and Pixel-wise addition with the original image
  - Pixel wise addition prevents vanishing gradients and preserves low level details
- Medium Transmission Based Decoder
  - Use a reverse medium transmission map as an attention mask
    - Medium transmission T(x) represents how much light from the scene at pixel x reaches the camera after being attenuated and scattered in water.
    - It can be measured mathematically based on scene radiance and background light
    - Reverse Medium Transformation (RMT) is measured as RMT(x) = 1-T(x) and represents how much degradation is caused in the image due to water
  - Combine encoder features with the RMT map to emphasize degraded areas
  - Reconstruct output via resifual enhancement and upsampling layers

Advantages:

- **Combines Physical and Data-driven Approaches**
  Uses medium transmission (from physical modelling) within a deep learning pipeline
- **Multi-Color Space Feature Learning**
  Capture richer information by processing data across different color spaces
- **Attention Mechanism based on Medium Transmission**
  Enhance important features based on degradation
- **Superior Quantitative Metrics**
  Outperforms baselines in PSNR,MSE, UIQM, and UCIQE.

Disadvantages

- **Dependence on Medium Transmission Estimation**
  Inaccurate transmission maps can degrade performance in severly degraded regions
- **Computational Complexity**
  Multi-color space embedding and attention modules increase computational costs and are not suitable for real time applications
- **Lighting Conditions**
  Performance is limited in images with very low lightin
- **Lack of Real Ground Truth for Transmission Maps**
  Medium transmission map is estimated based on heuristics and may not capture true degradation levels

2.8 *Blind Underwater Image Restoration using Co-Operational Regressor Networks*[7]

Abstract: This paper proposes **Co-Operational Regressor Networks (CoRe-Nets)** which combine two cooperating networks: the Apprentice Regressor (AR) for image restoration, and the Master Regressor (MR) that estimates image quality (PSNR) and provides feedback to the AR

Methodology:

- Apprentice Regressor(AR)
  - A U-Net like structure trained to restore underwater images.
  - Image quality is measured by PSNR (Peak Signal-to-Noise Ratio).
  - AR is trained to minimize a loss composed of:
    * PSNR-based feedback from MR
    * Actual PSNR compared to ground truth
    * Focal Frequency Loss (FFL) used to align patterns in the frequency domain and optimize image restoration by focusing on major spectral components
- Medium Transmission Based Decoder
  - Use a reverse medium transmission map as an attention mask
    * Medium transmission T(x) represents how much light from the scene at pixel x reaches the camera after being attenuated and scattered in water.
    * It can be measured mathematically based on scene radiance and background light
    * Reverse Medium Transformation (RMT) is measured as RMT(x) = 1-T(x) and represents how much degradation is caused in the image due to water
  - Combine encoder features with the RMT map to emphasize degraded areas
  - Reconstruct output via resifual enhancement and upsampling layers

Advantages:

- **High performance**
  Has 24.54 dB PSNR
- **Low Complexity**
  Has only 7.2 milliom parameters
- **Real Time capable**
  The processing time to restore a 256x256x3 image takes around 6.1 msec for a single CPU implementation

Disadvantages

- **No Physics-Guided Constraints**
  CoreNets are purely data driven and have no physics guided constraints

- **Feedback Loop**
  Cooperative setup can create interdependence and non linearity in training, making it hard to tune convergence behaviour

- **Dataset Diversity**
  The model was trained and tested on the LSUI dataset, and not on other challenging underwater datasets like UIEB, EUVP, or in-the-wild underwater conditions, limiting the paper's claims of robustness.

- **Lack of Real Ground Truth for Transmission Maps**
  Medium transmission map is estimated based on heuristics and may not capture true degradation levels

2.9 *IGFU: A Hybrid Underwater Image Enhancement Approach Combining Adaptive GWA, FFA-Net With USM[8]*

Abstract: This paper proposes a three-stage pipeline that combines an Improved Grey World Algorithm (IGWA), Feature Fusion Attention Network (FFA-Net) architecture, and Unsharp Masking (USM) to create a three-stage pipeline for enhancing underwater images.

Methodology:

- **Improved GWA**
  - GWA works on the principle that the average color in an image is gray. The colors are normalized between 0 to 1 and scaled up based on the mean gray value.
  - GWA can lead to overcorrection and cause the image to be too red.
  - Improved GWA makes minute changes based on channel-specific statistics alongside iterative retuning to prevent overcorrection.
- **FFA-Net**
  - FFA-Net stands for Feature Fusion Attention Network.
  - It uses a deep learning model for dehazing the image.
  - The model has a channel and pixel attention module.
- **USM**
  - Unsharp masking enhances details in the image.
  - It applies a Gaussian blur and subtracts the blurred image from the original image to obtain edges.
  - The edges are then added back to the original image.

Advantages:

- **Hybrid Design**
  Both traditional and deep learning methods are used.

- **Adaptive Correction**
  Improved GWA algorithm corrects the image adaptively based on channel-specific statistics.

- **Component Modularity**
  Each component is a separate module and focuses on a different aspect of image enhancement.

Disadvantages:

- **Computational Complexity**
  High computational overhead due to multi-stage pipeline.
- **Requires Careful Tuning**
  Thresholds and coefficients are empirically determined.
- **Execution Time**
  Improved GWA requires iterative processing.
- **Artificial Edges**
  USM may amplify noise and introduce artificial edges.

3 Literature Review Summary

Year	Paper Title	Methodology	Advantages	Disadvantages
2024	Fayaz, S. et al. "Intelligent Underwater Object Detection and Image Restoration for Autonomous Underwater Vehicles"	YOLOv8 for image processing and UDCP for image restoration	Robust dehazing	Limited depth testing
2021	Panetta, K. et al. "Comprehensive Underwater Object Tracking Benchmark Dataset and Underwater Image Enhancement With GAN"	CRN-UIE GAN	Improves tracker precision by 30%	Computational cost and synthetic bias
2023	Saleem, A. et al. "A Non-Reference Evaluation of Underwater Image Enhancement Using a New Underwater Image Dataset"			
2022	Ziyin Ma and Changjae Oh "A Wavelet-Based Dual-Stream Network for Underwater Image Enhancement"	DWT, U-NET, GAN	GAN improves visual realism	Computationally heavier
2024	Fayaz, S. et al. "Intelligent Underwater Object Detection and Image Restoration for Autonomous Underwater Vehicles"	YOLOv8 for image processing and UDCP for image restoration	Robust dehazing	Limited depth testing
2020	Li, C. et al. "Color Correction Based on CFA and Enhancement Based on Retinex With Dense Pixels for Underwater Images"	CFA-based red channel correction, dense-path Retinex, and adaptive histogram transformation	Accurate color correction without training data	Manually tuned parameters reduce adaptability

4 Conclusion

This project aims to bridge the gap between content consumption and critical analysis by providing a robust tool for identifying and understanding bias in online news articles. By leveraging cutting-edge NLP techniques and machine learning models, the proposed web extension will empower users to engage with media more thoughtfully and objectively. Ultimately, this solution aspires to combat the effects of media polarization, promote transparency, and encourage balanced perspectives, fostering a more informed and equitable information ecosystem.

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