CS512 Computer Vision – Project Proposal

LYT-Net: Lightweight YUV Transformer-based Network for Low-Light Image Enhancement

Team Members

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Research Paper

Title	:	LYT-Net: Lightweight YUV Transformer-based Network for Low-Light Image Enhancement
Authors	:	Alexandru Brateanu, Raul Balmez, Adrian Avram, Ciprian Orhei, and Cosmin Ancuti
Year	:	2024
Link	:	https://arxiv.org/abs/2401.15204

Problem Statement

Low-light images often suffer from poor visibility, loss of detail, and increased noise. Traditional enhancement methods can introduce artifacts or fail to preserve natural color fidelity. LYT-NET addresses these challenges through a dual-path, lightweight transformer-based architecture that processes chrominance and luminance channels separately. This method allows for effective handling of illumination adjustments and restoration of corrupted image areas

Chosen Option – We aim to **implement** the LYT-NET model as described in the paper.

Technique used in the selected paper - Transformer

The selected paper (LYT-Net) implements the concept of **Transformer** and consists of several layers and detachable blocks, including Channel-Wise Denoiser (CWD) and Multi-Stage Squeeze & Excite Fusion (MSEF). It adopts a dual-path approach, treating chrominance channels U and V and luminance channel Y as separate entities to help the model better handle illumination adjustment and corruption restoration.

Approach

We will implement the LYT-NET model based on the architecture described in the research paper, with a focus on the following key components:

- Dual-Path Approach in YUV Color Space: Separating the processing of chrominance and luminance channels for better handling of color restoration and brightness adjustments.
- Channel-Wise Denoiser (CWD) Block: Designed to improve noise reduction in the chrominance channels (U and V).
- Multi-Headed Self-Attention (MHSA) Block: Applied to the luminance (Y) channel to capture global features and enhance contrast and visibility.
- Multi-Stage Squeeze & Excite Fusion (MSEF) Block: Merges features from different stages to improve feature interaction and refine the image.

- Hybrid Loss Function: Combines adversarial loss, L1 loss, and perceptual loss to optimize output image quality by balancing various objectives.

Data:

For this project, we will use the LOw-Light (LOL) paired dataset for training and evaluation, as described in *Deep Retinex Decomposition for Low-Light Enhancement by Chen Wei, Wenjing Wang, Wenhan Yang and Jiaying Liu (BMVC, 2018)*. This dataset contains 500 low-light/normal-light image pairs, including both real photography pairs and synthetic pairs derived from raw images.

Link: https://daooshee.github.io/BMVC2018website

Team Member Responsibilities (in %)

Task	Tamilarasee	Kavin
Data Preprocessing and Augmentation	50	50
Model Implementation	50	50
Evaluation and Analysis	50	50
Experimentation and Improvement	50	50
Report Writing	50	50
Presentation Preparation	50	50

References:

- C. Wei, W. Wang, W. Yang, and J. Liu, “Deep retinex decomposition for low-light enhancement,” in Proceedings of the British Machine Vision Conference (BMVC), 2018
- S. Park, S.Yu, B.Moon, S.Ko, and J. Paik, “Low-light image enhancement using variational optimization-based retinex model,” IEEE Transactions on Consumer Electronics, vol. 63(2), 2017.
- Shansi Zhang, Nan Meng and Edmund Y. Lam, “LRT: An Efficient Low-Light Restoration Transformer for Dark Light Field Images,” IEEE Transactions on Image Processing, vol. 32, 2023.