Detail-Preserving ASCII Art Generation for Images and Videos

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1. Problem Statement

Current ASCII art generation algorithms often sacrifice fine details or fail to maintain temporal consistency in video applications.

Understanding this our aim will be to develop a comprehensive pipeline that addresses these limitations through algorithmic enhancements, focusing on detail preservation techniques and video-specific optimizations.

2. Approach

This project falls into the research-oriented category as we are developing novel algorithmic approaches to ASCII art generation with specific focus on detail preservation and extending these techniques to video processing

Phase 1: Baseline ASCII Generation We begin with a foundational approach that transforms input images through grayscaling and luminance-based pixel-to-ASCII character mapping. This establishes our baseline for comparison and builds the core pipeline architecture.

Phase 2: Detail Enhancement Through Advanced Filtering To improve detail preservation, we will integrate edge detection and orientation features using advanced computer vision techniques including Difference of Gaussians (DoG) filters and Sobel edge detection. These will enable orientation-aware character selection and enhanced structural preservation.

Phase 3: Video Processing Extension We extend our approach to video sequences, implementing temporal consistency algorithms and motion-aware processing. Additional edge detection steps will be applied to reduce visual fatigue and improve depth perception in animated ASCII output.

Phase 4: Performance Optimization The final phase focuses on computational efficiency through GPU parallelization, memory optimization, and algorithmic refinements. We will systematically document performance improvements and their impact on output quality.

3. Data

Our evaluation will utilize multiple datasets to comprehensively assess performance:

3.1. Image Datasets:

DIV2K High-Resolution Dataset [1]: Contains diverse high-quality images for testing detail preservation capabilities.

The Unsplash Dataset Lite [3]: Contains various images sourced from a high amount of contexts and sources to test various contexts.

3.2. Video Datasets:

DAVIS Video Segmentation Dataset [2]: Provides annotated video sequences for testing temporal consistency

Real-time Camera Stream: Live webcam input for testing real-time processing capabilities

4. Evaluation

We will employ quantitative metrics to evaluate our approach:

4.1. Quantitative Metrics:

Structural Similarity Index (SSIM): Measures structural preservation between original and ASCII-converted images

Edge Preservation Ratio: Custom metric comparing edge detection results between original and ASCII images using Canny edge detection

Processing Time per Frame: Computational efficiency measurement for both image and video processing

Temporal Consistency Score: For videos, measures frame-to-frame character stability using normalized cross-correlation

Detail Retention Index: Novel metric quantifying fine detail preservation through local variance analysis

References

[1] Eirikur Agustsson and Radu Timofte. Ntire 2017 challenge on single image super-resolution: Dataset and study. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops*, pages 126–135, 2017. Available at: https://data.vision.ee.ethz.ch/cvl/DIV2K/. 1

[2] Jordi Pont-Tuset, Federico Perazzi, Sergi Caelles, Pablo Arbeláez, Alexander Sorkine-Hornung, and Luc Van Gool. The 2017 davis challenge on video object segmentation, 2017. Available at: https://davischallenge.org/davis2017/code.html. 1

[3] Unsplash. Unsplash dataset, 2023. Available at: https://github.com/unsplash/datasets. 1