Image Signal Processing and Denoising Techniques

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1. Introduction

This report details the implementation of an Image Signal Processing (ISP) pipeline and advanced techniques for image denoising and sharpening. The main focus is on evaluating traditional and Al-based methods for image enhancement. The dataset used for training the Al model is the Smartphone Image Denoising Dataset (SIDD), known for its real-world noisy image samples.

2. Approach and Design

The ISP pipeline processes 12-bit Bayer RAW images and transforms them into high-quality 8-bit RGB images through the following stages:

- Demosaicing: Converts the Bayer pattern to RGB using edge-aware interpolation.
- White Balance: Applies the gray-world algorithm to correct color imbalances.
- Denoising: Reduces noise using various techniques.
- Gamma Correction: Adjusts image brightness using sRGB gamma correction.
- Sharpening: Enhances image details using unsharp mask and Laplacian filters.

3. Assignment 2: Denoising and Sharpening

3.1 Traditional Denoising Techniques

The traditional methods implemented for denoising include:

- Gaussian Filter: Smooths the image by replacing each pixel value with a weighted average of its neighbors, effectively reducing Gaussian noise.
- Median Filter: Replaces each pixel's value with the median of its neighboring intensities, particularly effective against salt-and-pepper noise.
- Bilateral Filter: Preserves edges while smoothing noise by considering both spatial and intensity differences.

3.2 Al-based Denoising: DnCNN Model

The DnCNN model leverages deep learning to adaptively reduce noise. It consists of 17 layers with Batch Normalization and ReLU activation. The model predicts the noise in the input image, which is

then subtracted to produce a clean image.

4. Training the DnCNN Model

The DnCNN model was trained on the SIDD dataset using the following setup:

- Loss Function: Mean Squared Error (MSE) between predicted and ground-truth images.
- Optimizer: Adam optimizer with a learning rate of 0.001.
- Training Data: Resized (256x256), normalized images.
- Batch Size: 16.
- Epochs: 3.

5. Observations and Results

- Traditional Techniques: Gaussian filtering reduces noise but blurs edges; bilateral filtering preserves edges but is computationally intensive.
- Al-based Techniques: The DnCNN model significantly outperforms traditional methods in noise reduction and detail preservation.
- Sharpening Methods: The unsharp mask enhances details but may amplify noise, while Laplacian sharpening produces sharper edges but can introduce artifacts in noisy regions.

6. Summary and Conclusion

This project demonstrates the superiority of Al-based denoising techniques over traditional methods. The DnCNN model trained on the SIDD dataset adapts to real-world noise patterns and produces superior results. The ISP pipeline effectively processes RAW images, providing a robust framework for image enhancement.