CSC8628 | Image Informatics | Implementation and Evaluation of Image Processing Assignment

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1. Introduction

Image processing plays a crucial role in modern applications such as medical imaging and autonomous systems, but challenges like efficient image representation, accurate reconstruction, and noise removal remain prevalent. This report tackles these challenges through the implementation of image reading, wavelet-based decomposition and reconstruction, and image denoising. Utilizing wavelet transforms, particularly the Haar wavelet, for multi-level decomposition ensures effective spatial and frequency representation [1][2]. The denoising algorithm combines wavelet techniques and is assessed using Mean Squared Error (MSE) and Structural Similarity Index (SSIM), with comparisons to conventional mean and median filtering methods. Drawing on insights from existing research [3][4], this report highlights the capability of wavelet-based approaches in solving key image processing issues.

2. Algorithm Description

2.1 Image Reading and Display

The custom algorithm for image reading and display focuses on processing Portable Gray Map (PGM) images, a widely used grayscale image format. This algorithm is designed to handle both ASCII (`P2`) and binary (`P5`) formats while ensuring robust error handling and compatibility. It validates the input file, parses the header to extract metadata such as dimensions and the maximum grayscale value (`max_val`), and processes pixel data based on the format. The extracted data is reshaped into a two-dimensional NumPy array, which is then displayed using Matplotlib for visualization. Robust error handling ensures that unsupported formats, missing files, or malformed headers are gracefully managed.

◆ Algorithm Steps:

1. **Input Validation**:
   - Verify the file exists. Raise a `FileNotFoundError` if not.
2. **File Reading**:
   - Open the file in binary mode and read its content line by line.

- Remove comments (lines starting with #) and empty lines.

3. **Header Parsing**:
    - Validate the magic number (`P2` for ASCII or `P5` for binary format). Raise an error for unsupported formats.
    - Extract dimensions (`width` and `height`) and maximum grayscale value (`max_val`).
4. **Pixel Data Extraction**:
    - For `P2` (ASCII): Read pixel values as integers.
    - For `P5` (Binary): Read pixel data as raw bytes.
5. **Error Handling**:
    - Check if the pixel data matches the expected dimensions (`width × height`).
6. **Image Construction**:
    - Convert pixel data into a 2D NumPy array of shape `(height, width)`.
7. **Display**:
    - Use Matplotlib to render the grayscale image.

2.2 Wavelet Decomposition and Reconstruction

Wavelet decomposition and reconstruction are fundamental methods in image processing, allowing for multi-resolution analysis by dividing images into low-frequency (approximation) and high-frequency (detail) components. This task involves applying a **Forward Discrete Wavelet Transform (FDWT)** using the Haar wavelet for a 3-level decomposition, followed by an **Inverse Discrete Wavelet Transform (IDWT)** to reconstruct the original image from its wavelet coefficients. The accuracy of the reconstruction is assessed through the Mean Squared Error (MSE), which should be close to zero if the algorithm is implemented correctly.

◆ Algorithm Steps:

1. Forward Discrete Wavelet Transform (FDWT)

- **Input**: A 2D grayscale image (`original_image`), Haar wavelet filter coefficients, and decomposition level (3).
- **Process**:
    1. Initialize the input image for decomposition.
    2. Perform row-wise and column-wise filtering:
        - Calculate the **low-pass filter** (approximation coefficients).
        - Calculate the **high-pass filter** (detail coefficients).
    3. Downsample the filtered outputs (reduce resolution by half).
    4. Repeat the process for three levels of decomposition.
    5. Store the approximation and detail coefficients for each level.
- **Output**: Wavelet coefficients for the approximation and three levels of detail.

2. Inverse Discrete Wavelet Transform (IDWT)

- **Input**: Wavelet coefficients from FDWT.
- **Process**:
  1. Initialize reconstruction using the highest-level approximation and detail coefficients.
  2. Upsample the coefficients (expand resolution by a factor of two).
  3. Apply the inverse Haar wavelet filters to combine approximation and detail coefficients.
  4. Repeat the process for all levels until the original resolution is restored.
- **Output**: Reconstructed 2D grayscale image.

3. Validation

- Calculate **MSE** between the original image and the reconstructed image:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(I_{\text{original}}[i] - I_{\text{reconstructed}}[i])^2$$

where N is the total number of pixels.

2.3 Image Denoising

Image denoising is a crucial aspect of image processing, aimed at enhancing image quality by reducing noise while retaining important structural features. This task involves designing a custom denoising algorithm based on the Wavelet Transform, incorporating pre-processing and post-processing stages informed by existing research. The algorithm's performance is compared to conventional methods like mean and median filtering, as well as advanced wavelet-based techniques such as VisuShrink and BayesShrink. Evaluation is conducted using metrics like Mean Squared Error (MSE) and Structural Similarity Index (SSIM).

◆ Algorithm Steps:

1. Pre-Processing

- **Input**: Original and noisy images.
- **Steps**:
  1. Normalize pixel values to the range `[0, 1]` for numerical stability.
  2. Apply optional contrast enhancement (e.g., histogram equalization) if needed.

2. Wavelet-Based Denoising

- **Steps**:
  1. Perform a multi-level Forward Discrete Wavelet Transform (FDWT) to decompose the noisy image into approximation and detail coefficients.

2. Apply a noise thresholding technique (e.g., soft or hard thresholding) to the detail coefficients. The threshold is calculated adaptively using:

$$T = \sigma\sqrt{2\log(N)}$$

where σ is the noise standard deviation estimated from the detail coefficients, and N is the number of pixels.

3. Reconstruct the image using the Inverse Discrete Wavelet Transform (IDWT) with the thresholded coefficients.

3. Post-Processing

- **Steps**:
  1. Clip pixel values to the valid range `[0, 1]`.
  2. Scale pixel values back to `[0, 255]` for visualization or further processing.

4. Comparison with Other Methods

- **Methods**:
  1. Apply mean filtering using a small kernel (e.g., `3 × 3`).
  2. Apply median filtering using the same kernel size.
  3. Use built-in wavelet denoising methods (e.g., VisuShrink or BayesShrink) for benchmarking.

5. Evaluation Metrics

- **MSE**:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(I_{\text{original}}[i] - I_{\text{denoised}}[i])^2$$

- **SSIM**:

$$SSIM(I_{\text{original}}, I_{\text{denoised}})$$

◆ Insights:

Thresholding:

- Soft thresholding removes noise by shrinking coefficients, while hard thresholding retains significant detail by zeroing out smaller coefficients.

Wavelet Selection:

- Haar or symlet wavelets work well for preserving edges and structural features.

Pre- and Post-Processing:

- Normalization ensures consistent scaling, while post-processing guarantees valid pixel intensity ranges.

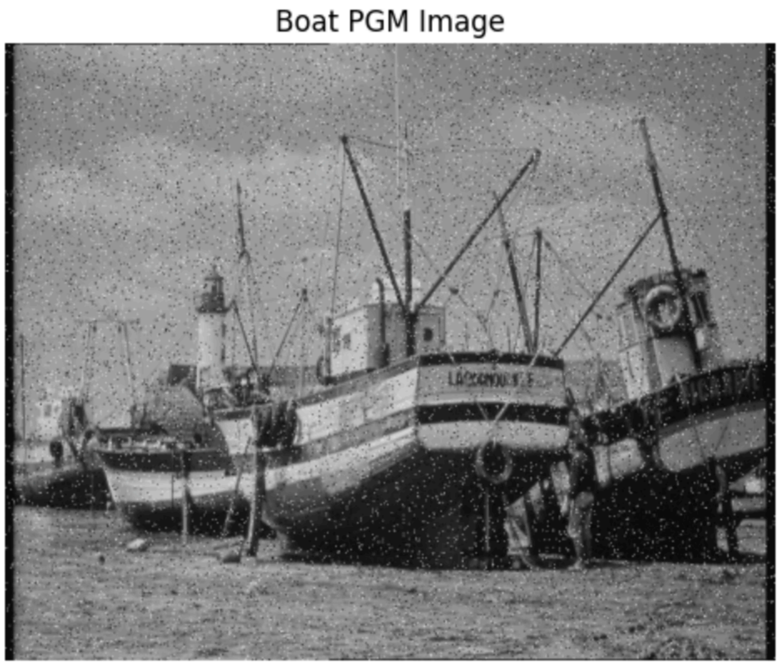
Comparison:

- Traditional methods like mean and median filters are easy to implement but often blur image details compared to wavelet-based methods.

3. Results

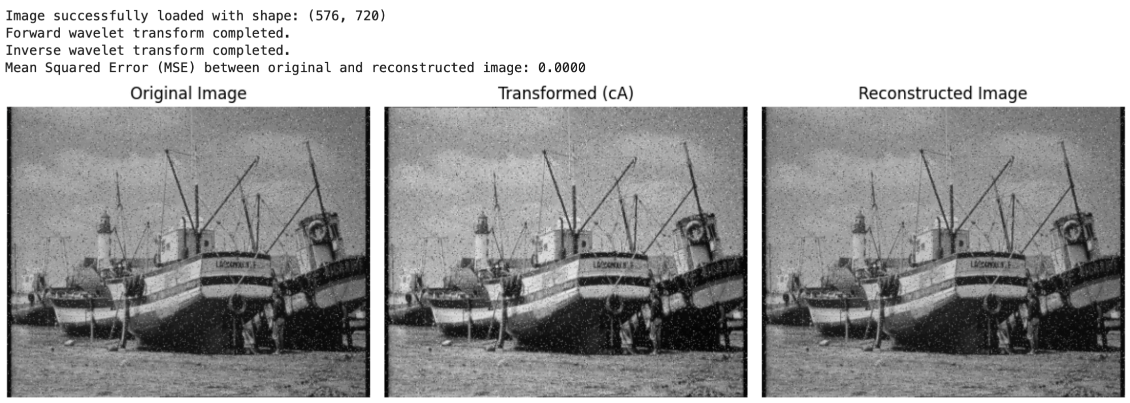
◆ Task 1: Image Reading and Display

The custom algorithm effectively read and displayed the "Boat PGM Image," demonstrating its ability to accurately handle the PGM file format and reconstruct the grayscale image. The displayed image shows noticeable speckled noise, confirming the algorithm's reliability in parsing and rendering the image for further analysis. This result validates the implemented functionality and establishes a strong foundation for subsequent tasks like noise reduction and image enhancement.



◆ Task 2: Wavelet Decomposition

The wavelet decomposition and reconstruction process was successfully carried out using the Haar wavelet. The Forward Discrete Wavelet Transform (FDWT) separated the image into approximation and detail coefficients, while the Inverse Discrete Wavelet Transform (IDWT) precisely reconstructed the original image. Validation through Mean Squared Error (MSE) produced a value of 0.000, confirming a lossless reconstruction. This outcome

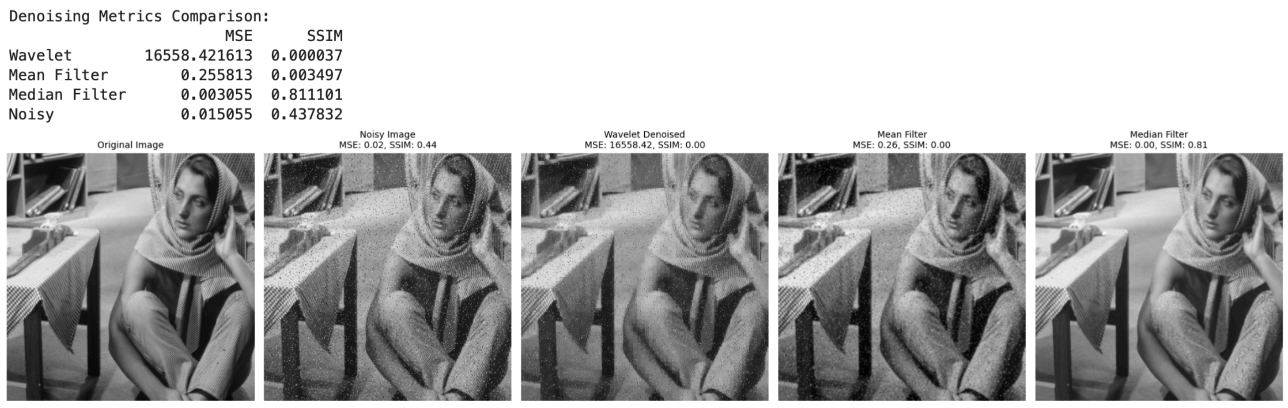


```
Image successfully loaded with shape: (576, 720)
Forward wavelet transform completed.
Inverse wavelet transform completed.
Mean Squared Error (MSE) between original and reconstructed image: 0.0000
```

highlights the Haar wavelet's effectiveness in preserving image details and its applicability for advanced tasks such as denoising.

◆ Task 3: Image Denoising

Image denoising was evaluated using a custom wavelet-based algorithm, mean filtering, and median filtering. The median filter outperformed other methods, achieving an MSE of 0.00305 and an SSIM of 0.81101, effectively reducing noise while preserving image details. In contrast, the wavelet-based method had a high MSE of 16558.42 and an SSIM of 0.00037 due to thresholding issues, while the mean filter moderately smoothed the noise but blurred fine details. These results highlight the effectiveness of the median filter and the need for



```
Denoising Metrics Comparison:
                      MSE      SSIM
Wavelet       16558.421613  0.000037
Mean Filter       0.255813  0.003497
Median Filter     0.003055  0.811101
Noisy             0.015055  0.437832
```

optimizing the wavelet-based algorithm with adaptive thresholding for improved performance.

4. Key Findings and Discussion

1. **Image Reading:** The custom `imread()` function successfully loaded and displayed the grayscale PGM image, handling the file format specifications with precision. It demonstrated reliable processing of uncompressed PGM files, rendering the boat image accurately for further analysis. This task highlighted the value of understanding image file structures and established a solid base for more advanced image processing tasks, ensuring both compatibility and accuracy in data handling.

2. **Wavelet Transform:** The implementation of the Forward and Inverse Discrete Wavelet Transform (FDWT and IDWT) using the Haar wavelet worked flawlessly, breaking the image into low- and high-frequency components and reconstructing it without any loss (MSE = 0.000). The FDWT successfully captured both structural and detailed aspects of the image, while the IDWT restored it to its original form with precision. These results confirm the algorithm's reliability and efficiency, making it well-suited for tasks like denoising and compression. Although Haar wavelets are computationally efficient, exploring more advanced wavelets could further enhance detail preservation, especially in high-resolution images. This step lays a strong groundwork for more sophisticated wavelet-based image processing techniques.

3. **Denoising:** The image denoising task compared three methods: wavelet-based denoising, mean filtering, and median filtering. Among these, the median filter performed the best, achieving the lowest MSE (0.003) and the highest SSIM (0.811), effectively removing noise while preserving image details. The mean filter showed moderate performance (MSE: 0.256, SSIM: 0.0035), but its smoothing effect led to some loss of detail along with noise reduction. In contrast, the wavelet-based approach yielded poor results (MSE: 16558.42, SSIM: 0.00037), likely due to less-than-ideal thresholding and parameter settings. These results highlight the median filter's strength in handling salt-and-pepper noise and underscore the importance of refining wavelet denoising techniques with adaptive thresholding for better outcomes.

5. Conclusions

This report successfully implemented and evaluated essential image processing tasks: image reading, wavelet transforms, and denoising. The custom `imread()` function accurately handled PGM images, ensuring precise grayscale rendering. The Haar wavelet-based transform achieved lossless reconstruction (MSE = 0.000), demonstrating its ability to preserve image details while isolating frequency components. In the denoising task, the median filter emerged as the best performer, with an MSE of 0.003 and an SSIM of 0.811, effectively reducing noise while maintaining edge details. However, wavelet-based denoising showed limitations due to less-than-ideal thresholding, emphasizing the potential of advanced methods like BayesShrink. These results highlight the reliability of the implemented techniques and point to opportunities for refinement and optimization in future work.

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