



Term Project Presentation (II)

Preprocessing Method for DCT-Based Image-Compression

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Outline



I. Introduction

II. Related Work

III. Methodology

- Design & Implementation
- Code segments

IV. Experiment

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I. Introduction

- In DCT-based image compression, such as JPEG, visible ringing artifacts often appear at low bit rates. A straightforward way to reduce this distortion is to apply a global low-pass filter in the preprocessing stage.
- However, this approach inevitably causes the entire image to become blurred. The authors of this paper observed that **ringing artifacts mainly occur around areas with strong edges, rather than in smooth regions.**

I. Introduction

- To address this problem, they proposed a **selective preprocessing method** that calculates the **auto-correlation coefficient** for every pixel. When the coefficient exceeds a certain threshold, a low-pass filter is applied and its result is blended with the original image.
- In this way, only edge regions are filtered, while smooth areas remain untouched. This selective filtering effectively suppresses **ringing artifacts** while preserving overall image sharpness.

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II. Related Work

➤ Pre-Processing Methods

Some methods attempt to **filter the input image before compression** to avoid producing severe artifacts. However, **simple linear filtering** often causes loss of fine detail and over-smoothing.

➤ Post-Processing Methods

Many researchers proposed **artifact removal filters** applied **after decompression**. However, they **require modifications on the decoder side**, which is not compatible with existing hardware or JPEG/MPEG standards.



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III. Design & Implementation

- First, the algorithm analyzes local image characteristics using the **auto-correlation function**, which reflects the similarity between neighboring pixels.
- From this, a modified auto-correlation coefficient, ρ_{mod} , is calculated for each pixel.
- A large positive value of ρ_{mod} indicates a region with strong edges and a high likelihood of ringing distortion, while a negative value corresponds to high-frequency texture regions where ringing is less visible.

III. Design & Implementation

- If ρ_{mod} exceeds a given threshold, a low-pass filter is applied, the filtered result is weighted and combined with the original image.
- This selective filtering process is repeated in both the horizontal and vertical directions.
- As a result, **only edge regions are smoothed to suppress ringing artifacts**, while detailed textures and smooth areas are preserved.

III. Code segments

```
def calculate_rho_mod(self, pixels):  
    mean = np.mean(pixels)  
    centered = pixels - mean  
    R0 = self.calculate_autocorrelation(centered, 0)  
    R1 = self.calculate_autocorrelation(centered, 1)  
    if R0 + self.delta < 1e-10:  
        return 0  
    return R1 / (R0 + self.delta)
```

From the paper:

$$\rho_{\text{mod}} = R_{xx}(1)/(R_{xx}(0)+\delta)$$

Calculate the modified auto-correlation coefficient ρ_{mod}

```
for y in range(height):  
    for x in range(width):  
        start_x = max(0, x - half_window)  
        end_x = min(width, x + half_window + 1)  
        local_pixels = image[y, start_x:end_x].astype(np.float64)  
        rho_mod = self.calculate_rho_mod(local_pixels)  
        rho_map_dir[y, x] = rho_mod  
        if rho_mod > self.rho_threshold:  
            filtered_pixels = self.apply_stronger_lowpass_filter(local_pixels)  
            center_idx = x - start_x  
            if center_idx < len(filtered_pixels):  
                original_value = image[y, x]  
                filtered_value = filtered_pixels[center_idx]  
                intensity = min(1.0, (rho_mod - self.rho_threshold) * self.filter_intensity)  
                filter_map[y, x] = intensity  
                processed[y, x] = original_value * (1 - intensity) + filtered_value * intensity
```

If ρ_{mod} exceeds the threshold, a low-pass filter is applied to the local region. The filtered value is then **combined with the original pixel** using a weighting coefficient α derived from ρ_{mod} .

III. Code segments

```
def preprocess_direction(self, image, direction='horizontal'):
    if direction == 'vertical':
        image = image.T
    H, W = image.shape
    processed = np.copy(image).astype(np.float64)
    filter_map = np.zeros((H, W))
    rho_map_dir = np.zeros((H, W))
    half = self.window_size // 2

    if direction == 'vertical':
        processed = processed.T
        filter_map = filter_map.T
        rho_map_dir = rho_map_dir.T

    self.filter_map = filter_map
    if direction == 'horizontal':
        self.rho_map = rho_map_dir
    return processed
```

- The function `preprocess_direction()` performs preprocessing in one direction at a time.
- When the direction is set to horizontal, it processes each row.
- When set to vertical, the image is transposed, allowing the same code to be reused.
- After both passes, ringing artifacts are suppressed in both orientations.

III. Code segments – Test conditions

```
compressor = DCTCompressor(quality=10)

uniform_preprocessor = UniformPreprocessor(filter_strength=1.0)

fixed_preprocessor = DCTPreprocessorFixed(
    rho_threshold=0.3,
    filter_intensity=2.5,
    window_size=9,
    delta=10
)

adaptive_preprocessor = DCTPreprocessorAdaptive(
    base_rho_threshold=0.3,
    adaptive_threshold=True,
    adaptive_range_variance=(500, 5000), #threshold modify
    adaptive_range_threshold=(0.2, 0.45),
    filter_intensity=2.5,
    window_size=9,
    delta=10
)
```

Compression quality

Global filtering

Fixed Threshold

Adaptive Threshold



III. Code segments - Adaptive Threshold

```
adaptive_preprocessor = DCTPreprocessorAdaptive(  
    base_rho_threshold=0.3,  
    adaptive_threshold=True,  
    adaptive_range_variance=(500, 5000), #threshold modify  
    adaptive_range_threshold=(0.2, 0.45),  
    filter_intensity=2.5,  
    window_size=9,  
    delta=10  
)
```

```
def _calculate_global_variance(self, image_y):  
    return np.var(image_y)
```

```
if self.adaptive_threshold:  
    variance = self._calculate_global_variance(Y)  
    v_min, v_max = self.adaptive_range_variance  
    t_min, t_max = self.adaptive_range_threshold  
    self.current_rho_threshold = np.interp(variance, [v_min, v_max], [t_min, t_max])
```

We calculate the Y channel. This single value represents the image's overall contrast.

- **High Variance:** A complex, high-contrast image (many details and textures).
- **Low Variance:** A simple, low-contrast image (many flat areas).

We use np.interp to create a dynamic mapping:

- If variance is **high**: Use a **high threshold** (0.45). This makes the filter to protect real textures.
- If variance is **low**: Use a **low threshold** (0.2). This makes the filter to reduce noise in flat area.

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➤ Dataset





IV. Experiment

1. Test Conditions

Compression Quality = 10

1. Global filtering intensity = 1.0

2. Fixed threshold

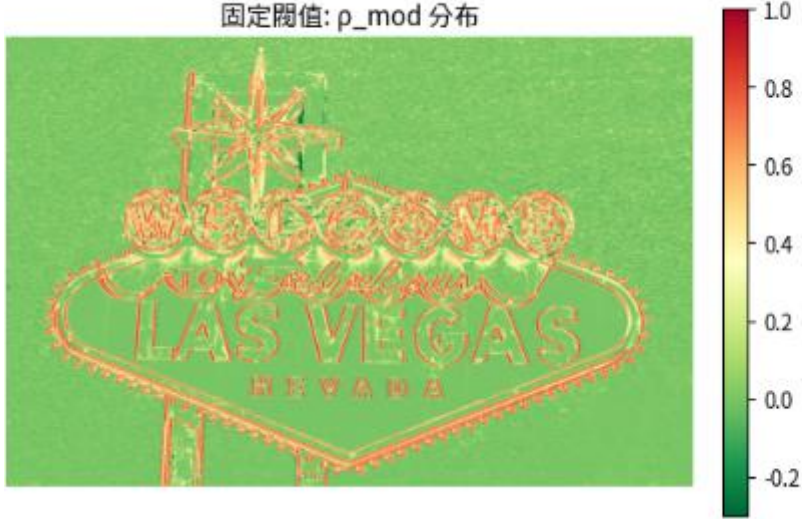
- $\rho_{\text{threshold}}=0.3$
- $\text{window_size}=9$

3. Adaptive threshold

- threshold range = (0.2, 0.45)
- $\text{window_size}=9$

IV. Experiment

固定閾值: ρ_{mod} 分布



固定閾值: 濾波強度
(濾波=21.9%)



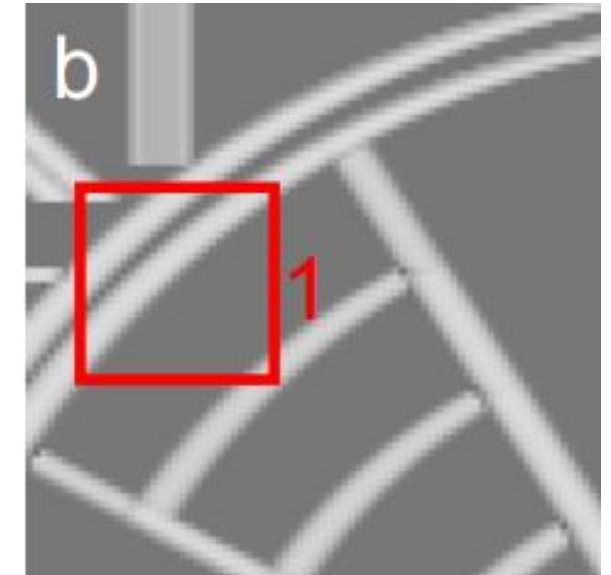
自適應: ρ_{mod} 分布



自適應: 濾波強度
(閾值=0.399, 濾波=19.7%)



Test result



Distribution of ρ_{mod}

IV. Experiment



Original image



Only Compression



Compression with preprocessing
Adaptive Threshold

IV. Experiment

- As we can see that this method successfully reduce the ringing effect

Rinigng effect



Only Compression

Reduce ringing effect



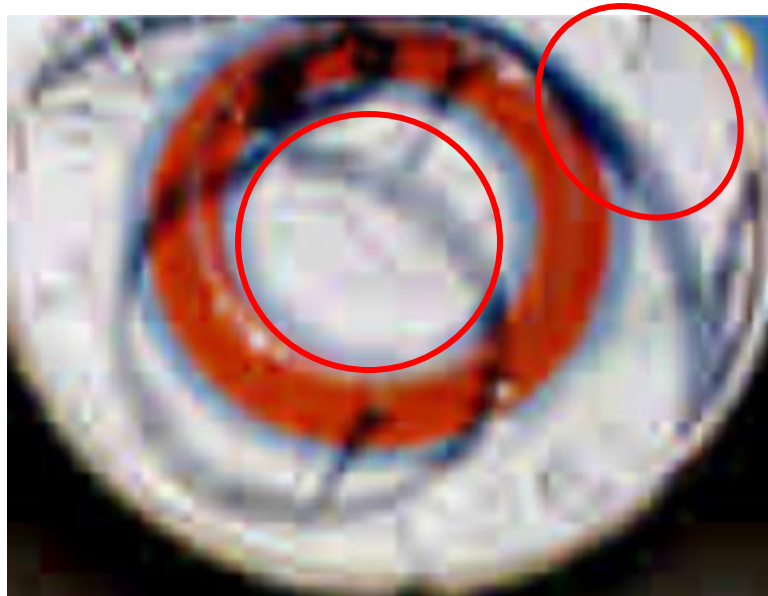
Compression with preprocessing
Adaptive Threshold

IV. Experiment

- As we can see that global filtering will cause all images to become blurred



Original image



Compression with preprocessing
Adaptive Threshold



Global Filtering

IV. Experiment

1. 直接壓縮
PSNR: 30.23 dB
SSIM: 0.9076



2. 固定閾值 (論文)
PSNR: 28.29 dB
SSIM: 0.8882



3. 自適應閾值
PSNR: 28.64 dB
SSIM: 0.8926



4. 全局濾波
PSNR: 27.69 dB
SSIM: 0.8792



Direct Compression PSNR: 30.23 dB | SSIM: 0.9076 | FSIM: 0.8599 | VIF: 0.4729

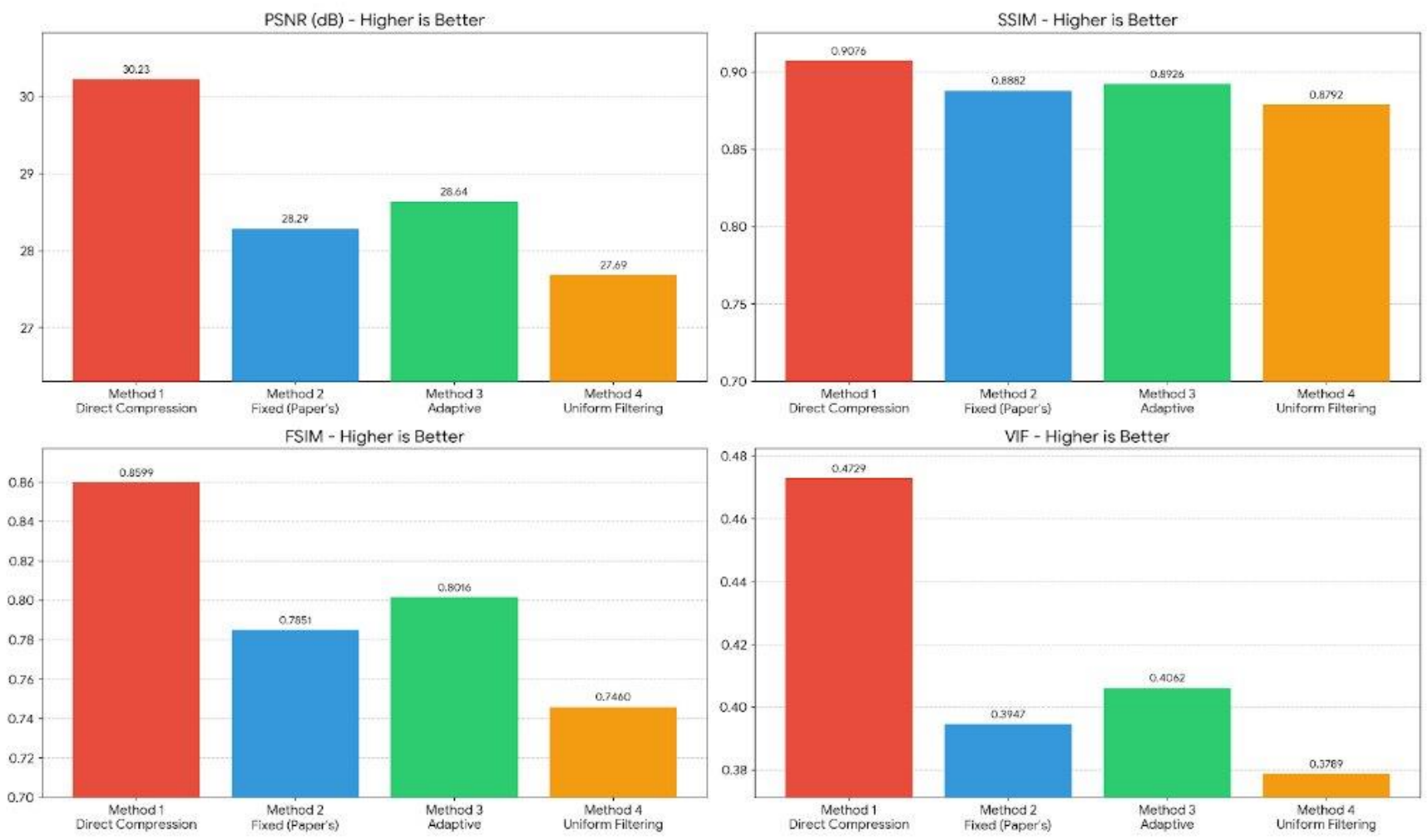
Fixed Threshold Preprocessing (Paper's Method): PSNR: 28.29 dB | SSIM: 0.8882 | FSIM: 0.7851 | VIF: 0.3947

Adaptive Threshold Preprocessing: PSNR: 28.64 dB | SSIM: 0.8926 | FSIM: 0.8016 | VIF: 0.4062

Method 4: Uniform Filtering Preprocessing PSNR: 27.69 dB | SSIM: 0.8792 | FSIM: 0.7460 | VIF: 0.3789

IV. Experiment

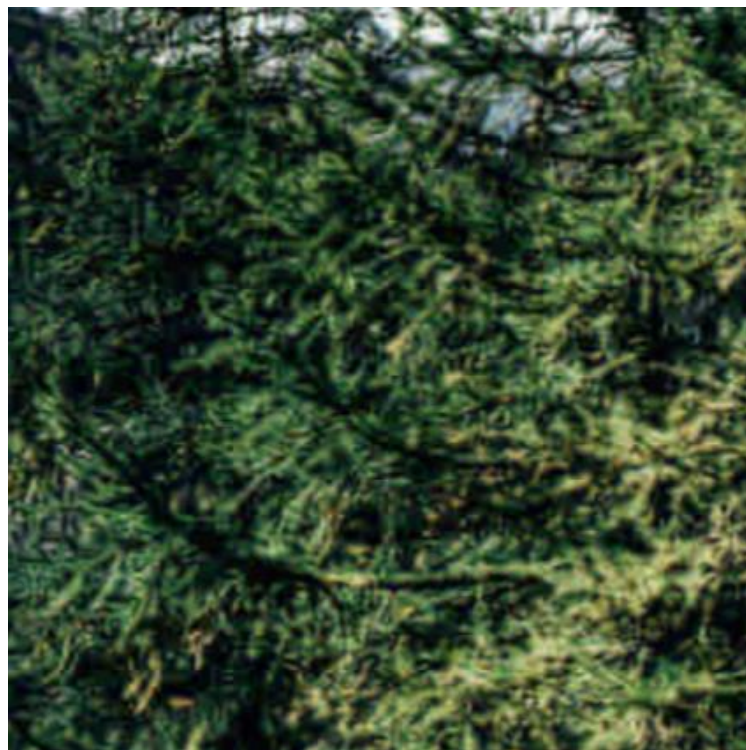
Key Metric Comparison for Compression Methods



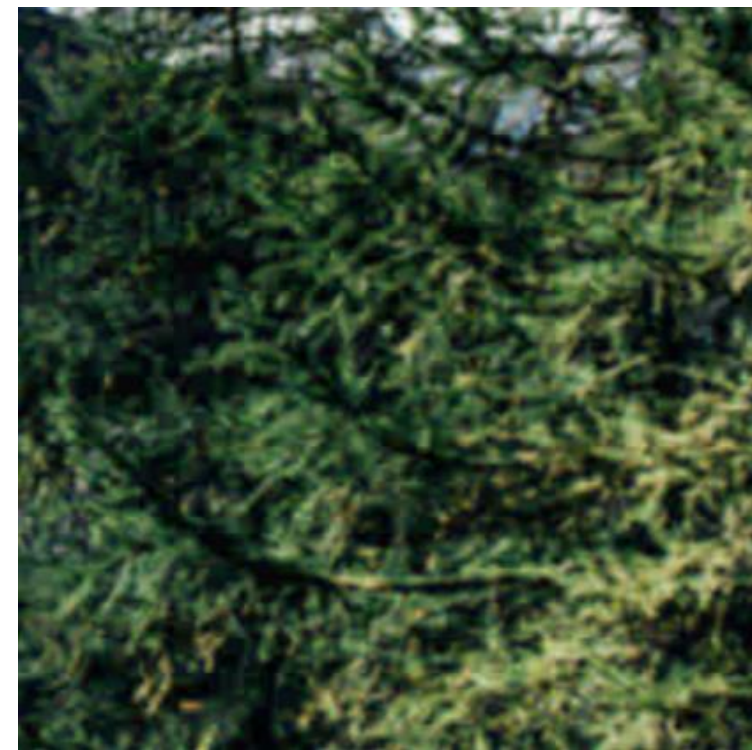
IV. Experiment



Original image



Adaptive Threshold



Global Filtering

IV. Experiment



1. 直接壓縮
PSNR: 26.01 dB
SSIM: 0.8369



2. 固定閾值 (論文)
PSNR: 24.85 dB
SSIM: 0.7868



3. 自適應閾值
PSNR: 25.23 dB
SSIM: 0.8045



4. 全局濾波
PSNR: 23.81 dB
SSIM: 0.7303



Direct Compression PSNR: 26.01 dB | SSIM: 0.8369 | FSIM: 0.8844 | VIF: 0.3624

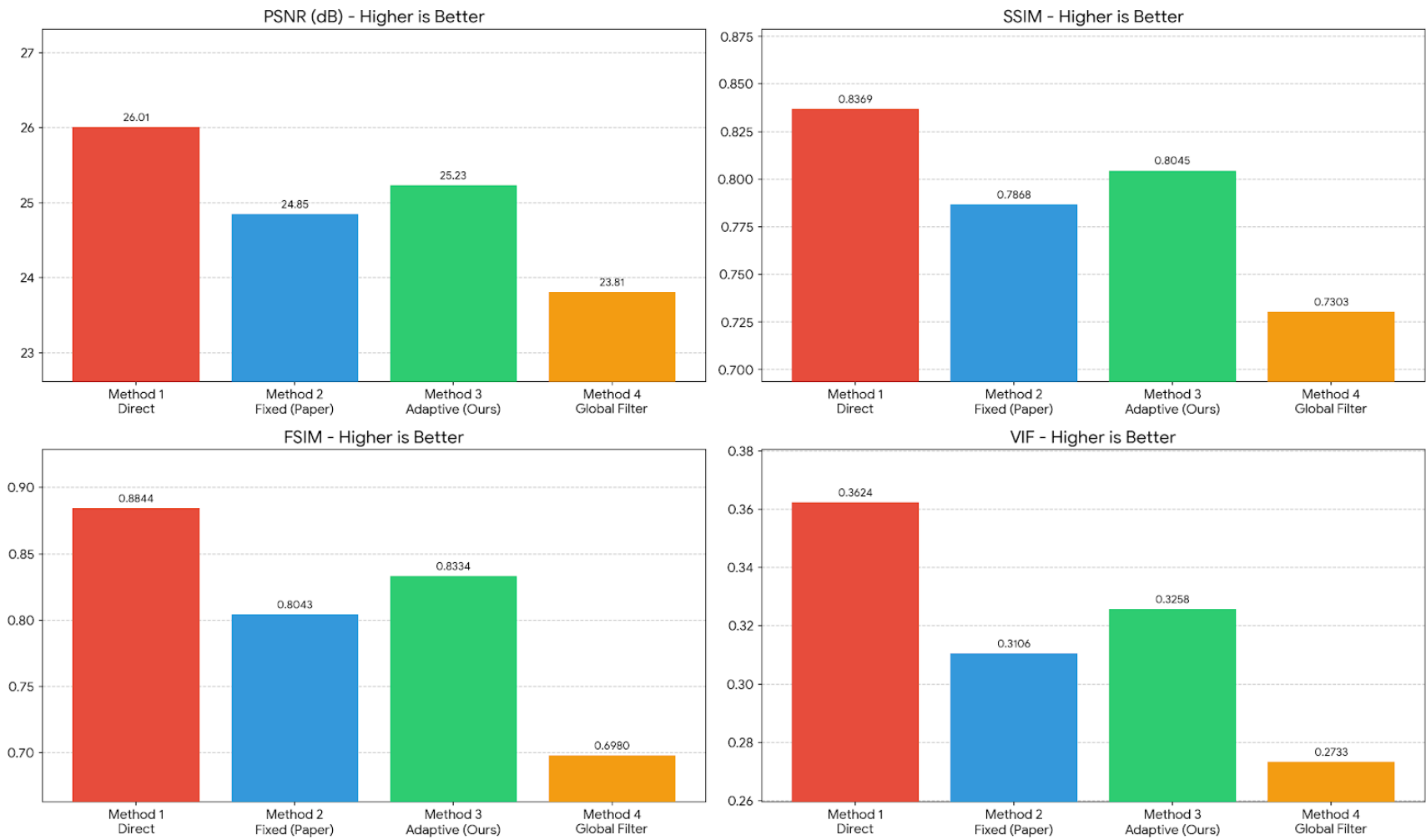
Fixed Threshold Preprocessing (Paper's Method) PSNR: 24.85 dB | SSIM: 0.7868 | FSIM: 0.8043 | VIF: 0.3106

Adaptive Threshold Preprocessing (Optimized Method) PSNR: 25.23 dB | SSIM: 0.8045 | FSIM: 0.8334 | VIF: 0.3258

Global Filtering Preprocessing PSNR: 23.81 dB | SSIM: 0.7303 | FSIM: 0.6980 | VIF: 0.2733

IV. Experiment

Key Metric Comparison for Compression Methods





V. Reference

- [1] Oizumi, M. (2006). "Preprocessing Method for DCT-Based Image-Compression". *IEEE Transactions on Consumer Electronics*.
- [2] Zhang, L., et al. (2011). "FSIM: A Feature Similarity Index for Image Quality Assessment".
- [3] Sheikh, H. R., & Bovik, A. C. (2006). "Image Information and Visual Quality".
- [4] Python Libraries: NumPy, SciPy, scikit-image, piq, Matplotlib.