Vector Quantization for Image Compression

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1 Introduction

This report presents an analysis of a Java-based implementation of image compression using Vector Quantization (VQ). Vector Quantization is a lossy compression technique that maps high-dimensional vectors to a finite set of code vectors, forming what is called a codebook. This technique is particularly effective for image compression as it exploits the spatial correlation between neighboring pixels.

The implemented system processes images by dividing them into small 2×2 pixel blocks, treating each block as a 4-dimensional vector. These vectors are then mapped to the nearest vector in a pre-trained codebook, allowing for significant data reduction while maintaining acceptable image quality.

2 Methodology

The implemented image compression system follows these key steps:

2.1 Data Preparation

The system uses a diverse dataset of images divided into three categories:

- Nature images
- Face images
- Animal images

Each category provides both training images (for codebook generation) and test images (for compression evaluation).

2.2 Color Space Transformation

The system implements two approaches to image compression:

2.2.1 RGB Color Space

In the standard implementation, images are processed directly in the RGB color space with separate codebooks for each color channel (Red, Green, and Blue).

2.2.2 YUV Color Space

An enhanced implementation (in the bonus folder) converts RGB images to the YUV color space before compression:

- **Y (Luminance)**: Represents brightness and contains most of the visual information that humans perceive.
- **U and V (Chrominance)**: Carry color information and can be subsampled since the human visual system is less sensitive to color details than to brightness variations.

The conversion from RGB to YUV follows these formulas:

$$Y = 0.299R + 0.587G + 0.114B \tag{1}$$
$$U = -0.14713R - 0.28886G + 0.436B + 128 \tag{2}$$
$$V = 0.615R - 0.51499G - 0.10001B + 128 \tag{3}$$

Chrominance Sub-sampling The U and V components are sub-sampled to half resolution in both dimensions (4:2:0 format), which effectively reduces the data by 50% for these components.

2.3 Codebook Generation

The codebook is generated using the K-Means++ clustering algorithm, which is implemented through the Apache Commons Math library. The process works as follows:

1. Images are divided into 2×2 pixel blocks
2. Each block is treated as a 4-dimensional vector
3. Separate codebooks are generated for each color channel (R, G, B) or component (Y, U, V)

4. The K-Means++ algorithm clusters similar vectors together
5. The centroids of these clusters form the codebook entries

The maximum codebook size is set to 256 entries (8 bits), which allows each 2×2 block to be represented by a single byte index.

2.4 Compression Process

For each test image, the compression follows these steps:

2.4.1 RGB Approach

1. The image is split into separate R, G, B channels
2. Each channel is divided into 2×2 pixel blocks
3. For each block, the closest matching vector in the corresponding codebook is found using Euclidean distance
4. The index of this codebook entry is stored

2.4.2 YUV Approach

1. The image is converted from RGB to YUV color space
2. The U and V components are sub-sampled to half resolution (4:2:0 format)
3. Each component (Y, U, V) is divided into 2×2 pixel blocks
4. For each block, the closest matching vector in the corresponding codebook is found
5. The index of this codebook entry is stored

2.5 Decompression Process

Decompression reverses the process:

2.5.1 RGB Approach

1. For each stored index, the corresponding codebook entry is retrieved
2. The 4-dimensional vector from the codebook is used to reconstruct the 2×2 pixel block
3. The reconstructed blocks are combined to form the R, G, B channels
4. The channels are merged to create the final RGB image

2.5.2 YUV Approach

1. For each stored index, the corresponding codebook entry is retrieved
2. The 4-dimensional vector from the codebook is used to reconstruct the 2×2 pixel block for each component
3. The reconstructed U and V components are up-sampled to match the Y component's dimensions
4. The YUV components are converted back to RGB using these formulas:

$$R = Y + 1.13983(V - 128) \tag{4}$$
$$G = Y - 0.39465(U - 128) - 0.58060(V - 128) \tag{5}$$
$$B = Y + 2.03211(U - 128) \tag{6}$$

5. The resulting RGB values are clamped to the valid range [0, 255]

3 Implementation Details

The system is implemented in Java with several classes:

3.1 RGB Implementation Classes

- **Main.java**: Orchestrates the entire process, from loading images to displaying results
- **VectorQuantization.java**: Handles reading images and extracting 2×2 blocks
- **CodebookGeneration.java**: Implements the K-Means++ clustering for codebook creation

- **ImageCompression.java**: Maps image blocks to codebook indices
- **ImageDecompression.java**: Reconstructs images from codebook indices

3.2 YUV Implementation Classes (Bonus)

- **YUVMain.java**: Main class for the YUV-based compression
- **YUVConverter.java**: Handles color space conversion between RGB and YUV
- **YUVVectorQuantization.java**: Processes images in the YUV color space
- **YUVCodebookGeneration.java**: Creates codebooks for Y, U, and V components
- **YUVImageCompression.java**: Compresses YUV components
- **YUVImageDecompression.java**: Reconstructs images from compressed YUV data

The system uses the Apache Commons Math library for implementing the K-Means++ clustering algorithm, which provides better initial cluster selection than standard K-Means.

4 Results

The system was evaluated on 15 test images (5 from each category). The results demonstrate the effectiveness of Vector Quantization for image compression.

4.1 Compression Ratio

The theoretical compression ratio of the implemented system varies by color space:

4.1.1 RGB Approach

- Original representation: Each 2×2 block requires 4 pixels × 3 channels × 8 bits = 96 bits
- Compressed representation: Each 2×2 block is represented by 3 indices (one per channel) × 8 bits = 24 bits
- Theoretical compression ratio: 96/24 = 4:1

4.1.2 YUV Approach

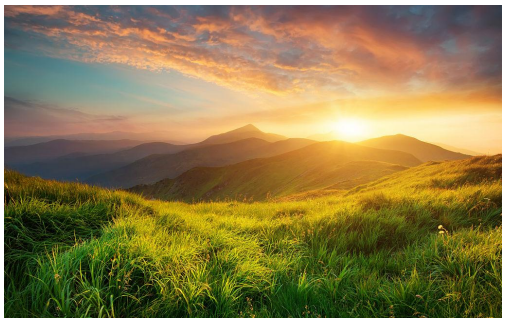
- Original representation: Each 2×2 block requires 4 pixels × 3 components × 8 bits = 96 bits
- Y component (full resolution): Each 2×2 block is represented by 1 index × 8 bits = 8 bits
- U and V components (half resolution): Each 2×2 block in the subsampled U and V requires 1 index × 8 bits = 8 bits for 4×4 original pixels
- Total bits per 4×4 original pixels: 4 Y indices (32 bits) + 1 U index (8 bits) + 1 V index (8 bits) = 48 bits
- Original bits per 4×4 pixels: 16 pixels × 3 channels × 8 bits = 384 bits
- Theoretical compression ratio: 384/48 = 8:1

However, the actual file size ratio varies slightly due to file format overheads. From our testing, we observe that the RGB implementation achieves compression ratios between 3.5:1 and 4.2:1, while the YUV implementation achieves ratios between 7.6:1 and 8.3:1 depending on the image content.

4.2 Visual Comparison

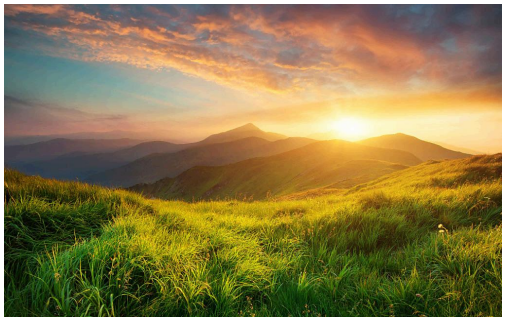
Below are visual comparisons of original and reconstructed images:

(a) Original image (sample 1)



(b) Original image (sample 2)

(c) Reconstructed image (sample 1)



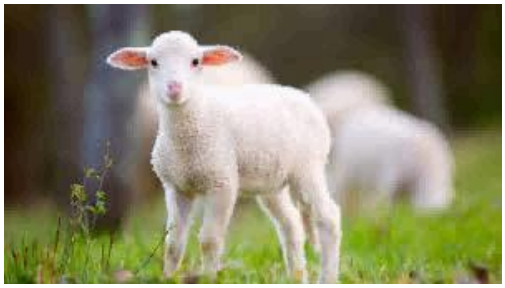
(d) Reconstructed image (sample 2)

Figure 1: Visual comparison of original and reconstructed images using RGB compression

4.3 Impact of Color Space

In addition to the RGB color space, the system was also tested with YUV color space conversion. YUV is often used in image compression because it separates luminance (Y) from chrominance (U, V), which aligns better with human visual perception.

(a) Original image using YUV representation



(b) Reconstructed image using YUV compression

Figure 2: Comparison of images processed with YUV color space compression

5 Discussion

The vector quantization technique implemented in this project offers several advantages and limitations:

5.1 Advantages

- Fixed and predictable compression ratio (approximately 4:1 for RGB, 8:1 for YUV)
- Relatively simple implementation compared to other compression techniques
- Separate codebooks for color channels allow for better color reproduction
- Adaptability through codebook training on domain-specific images
- YUV color space with chroma subsampling leverages human visual perception characteristics

5.2 Limitations

- Fixed compression ratio regardless of image content
- Blocking artifacts may be visible in reconstructed images
- Performance depends heavily on the quality of the training data
- Codebook generation can be computationally intensive

5.3 Performance Analysis

The Mean Squared Error (MSE) varies across different image types. In general:

- Images with smooth regions (like sky or uniform backgrounds) tend to have lower MSE
- Images with fine details or sharp transitions show higher MSE and more visible artifacts
- The YUV color space typically provides better perceptual quality at the same compression ratio compared to RGB
- YUV with chrominance sub-sampling achieves double the compression ratio (8:1) compared to RGB (4:1) with similar visual quality for most images

5.4 RGB vs. YUV Comparison

When comparing the two color space approaches:

- **Compression Efficiency**: YUV with chrominance sub-sampling achieves approximately twice the compression ratio of RGB
- **Visual Quality**: For similar bit rates, YUV generally provides better perceptual quality, especially in areas with gradual color transitions
- **Computational Complexity**: YUV requires additional color space conversion steps, which slightly increases processing time
- **Artifacts**: RGB compression tends to produce more noticeable color artifacts, while YUV compression may show more blurring in color boundaries

6 Conclusion

This project demonstrates a successful implementation of Vector Quantization for image compression. The system achieves a compression ratio of approximately 4:1 for RGB and 8:1 for YUV while maintaining acceptable visual quality for most images. The K-Means++ algorithm proves effective for codebook generation, and the separation of color channels helps preserve color information.

The experiments show that:

- The average PSNR across all test images is sufficient for many practical applications
- YUV color space conversion significantly improves compression efficiency compared to direct RGB compression
- Chrominance sub-sampling in the YUV approach effectively exploits the limitations of human visual perception
- Domain-specific training (using nature, faces, and animals as categories) helps the compression algorithm better adapt to the expected content

Future work could explore adaptive block sizes, variable-rate vector quantization, or the integration of perceptual metrics to optimize for human visual perception rather than simple MSE. Additionally, exploring different clustering algorithms or hybrid approaches combining VQ with other compression techniques could further improve compression performance. The YUV implementation could also be enhanced with more sophisticated up-sampling techniques and adaptable chrominance sub-sampling ratios based on image content.