21AIE332T- Image and Video Processing

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Image Compression

Image Compression Techniques

Image compression reduces the size of image data for efficient storage and transmission while preserving quality to an acceptable degree. Compression techniques are broadly categorized into **lossless** (no data loss) and **lossy** (some data loss for higher compression ratios). The choice depends on the application—lossless is critical for medical imaging or archival purposes, while lossy is common in multimedia where slight quality loss is tolerable.

Lossless Coding

Introduction

Lossless coding ensures that the original image can be perfectly reconstructed from the compressed data, with no loss of information. It exploits statistical redundancies in the image (e.g., repeated patterns or predictable pixel values) without discarding any data.

Basics of Lossless Image Coding

Lossless compression relies on modeling the image data's statistical properties:

•**Redundancy Removal**: Spatial correlation between neighboring pixels or temporal correlation in video frames is exploited.

Image Compression

•**Entropy Coding**: Assigns shorter codes to frequent symbols and longer codes to rare ones, based on information theory (e.g., Shannon's entropy).

•Common techniques include predictive coding (predicting pixel values and encoding differences) and transform coding (e.g., using reversible transforms).

Lossless Symbol Coding

This involves encoding individual symbols (e.g., pixel values or differences):

•**Huffman Coding**: Uses variable-length codes based on symbol frequency. A prefix-free code ensures unambiguous decoding.

•**Arithmetic Coding**: Encodes an entire message into a single fractional number, offering better compression for small alphabets or skewed distributions.

•**Run-Length Encoding (RLE)**: Compresses sequences of identical symbols (e.g., "AAAAA" becomes "5A"), effective for images with large uniform areas.

Image Compression

1. Lossless Image Coding

Introduction

Lossless image compression ensures perfect reconstruction of the original image by eliminating redundancy without losing information. It is critical in medical imaging, archival storage, and legal documents.

Basics of Lossless Image Coding

Redundancy Types:

- **Spatial Redundancy**: Correlation between neighboring pixels.
- **Coding Redundancy**: Inefficient symbol representation.

Entropy: Theoretical minimum bits per symbol (Shannon's entropy: $H = -\sum p_i \log_2 p_i$).

Lossless Symbol Coding

•**Huffman Coding**: Assigns variable-length codes based on symbol probabilities. Optimal for dyadic distributions.

•**Arithmetic Coding**: Encodes entire messages into a fractional value, handling non-integer probabilities efficiently.

•**Lempel-Ziv-Welch (LZW)**: Dictionary-based coding (used in GIF, TIFF).

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Lossless Coding Standards

- **PNG**: Uses DEFLATE (LZ77 + Huffman coding).
- **JPEG-LS**: Combines prediction (LOCO-I algorithm) and Golomb-Rice coding.
- **TIFF**: Supports LZW, ZIP, and PackBits.

Other Developments

- **Context-Based Coding**: Adapts probabilities based on local pixel context (e.g., CALIC).
- **Lossless JPEG 2000**: Uses wavelet transforms and arithmetic coding.
- **Hybrid Methods**: Combining prediction, transform coding, and entropy coding.

Entropy: Theoretical minimum bits per symbol (Shannon's entropy: $H = -\sum p_i \log_2 p_i$).

Block Truncation Coding (BTC)

Introduction & Historical Overview

Developed in the 1970s, BTC is a simple, lossy compression method for grayscale images. It balances quality and computational efficiency.

Basics of BTC

1.Block Division: Split the image into 4×4 blocks.

2.Mean & Variance Calculation: Compute block mean (μ) and standard deviation (σ).

3.Quantization: Create a binary mask where pixels above μ are 1, others 0. Store two reconstruction levels (q1,q2) to preserve block statistics.

Moment Preserving Quantization

Ensures the quantized block retains moments (e.g., mean and variance):

•First moment (mean): μ=q1+q2 $\mu=2q1+q2$.

•Second moment (variance): $\sigma 2=(q1-\mu)2+(q2-\mu)2$.

Block Truncation Coding (BTC)

Variations & Applications

•**Absolute Moment BTC (AMBTC)**: Uses absolute moments for robustness.

•**Color BTC**: Extends to RGB by processing each channel separately.

•**Applications**: Early digital cameras, real-time systems, and low-complexity devices.

Fundamentals of Vector Quantization (VQ)

Introduction

VQ compresses data by mapping vectors (groups of pixels) to entries in a pre-designed codebook. It exploits correlations between pixels for higher efficiency than scalar quantization.

Theory of Vector Quantization

- **Codebook**: A set of representative vectors (codewords).
- **Distortion Measure**: Mean Squared Error (MSE) quantifies reconstruction quality.
- **Rate-Distortion Trade-off**: Larger codebooks reduce distortion but increase bitrate.

Design of Vector Quantizers

- **LBG Algorithm** (Linde-Buzo-Gray):
    - Initialize codebook.
    - Cluster input vectors using the nearest-neighbor rule.
    - Update codewords as cluster centroids.
    - Iterate until convergence.

Fundamentals of Vector Quantization (VQ)

VQ Implementations

- **Full-Search VQ**: Exhaustively matches input vectors to codewords (high complexity).
- **Tree-Structured VQ**: Hierarchical codebook reduces search time.

Structured VQ

- **Multi-Stage VQ**: Cascades multiple low-dimensional quantizers.
- **Lattice VQ**: Codewords form regular grids (e.g., hexagonal, cubic) for fast search.

Variable-Rate Vector Quantization

- **Entropy-Coded VQ**: Applies Huffman/Arithmetic coding to codeword indices.
- **Adaptive VQ**: Dynamically updates codebooks based on input statistics.

Applications

- Speech coding (e.g., CELP), image coding (JPEG 2000 variants), and video compression.

Wavelet Image Compression

What Are Wavelets: Why Are They Good for Image Coding?

Wavelets are mathematical functions that decompose data into different frequency components and analyze them at varying scales. Unlike sinusoidal waves (e.g., Fourier transforms), wavelets are localized in both time and frequency, making them ideal for image coding:

- •**Localization**: Capture both global trends (low frequencies) and local details (high frequencies).
- •**Multiresolution**: Enable hierarchical representation, matching human visual perception (coarse-to-fine detail).
- •**Sparsity**: Most image energy is compacted into fewer coefficients, enhancing compression efficiency.
- •**Decorrelation**: Reduce redundancy across scales, improving coding performance.

The Compression Problem

Image compression seeks to reduce data size while preserving quality. Challenges include:

- •**Redundancy**: Spatial and statistical correlations in pixel values.
- •**Perceptual Quality**: Balancing data loss with human perception (lossy) or ensuring perfect reconstruction (lossless).
- •**Complexity**: Efficient algorithms for real-time applications.

Wavelet Image Compression

The Transform Coding Paradigm

Transform coding converts image data into a domain where energy is compacted and redundancy is reduced:

- **Process**: Apply a transform, quantize coefficients, and encode them.
- **Wavelet Advantage**: Unlike block-based transforms (e.g., DCT), wavelets process the entire image, avoiding block artifacts and providing scalability.

Subband Coding: The Early Days

Subband coding, a precursor to wavelet coding, splits the signal into frequency bands:

- **Filter Banks**: Use low-pass and high-pass filters to create subbands (e.g., horizontal, vertical, diagonal details).
- **Downsampling**: Reduces data by half in each dimension per level.
- **Early Limitation**: Fixed filter designs lacked adaptability to image content.

Wavelet Image Compression

New and More Efficient Class of Wavelet Coders

Modern wavelet coders improve efficiency:

- **Embedded Zerotree Wavelet (EZW)**: Exploits hierarchical relationships in wavelet coefficients, encoding significant coefficients first.
- **Set Partitioning in Hierarchical Trees (SPIHT)**: Refines EZW with better bitrate control and progressive transmission.
- **JPEG 2000**: Uses discrete wavelet transform (DWT) with biorthogonal wavelets (e.g., 9/7 for lossy, 5/3 for lossless), followed by arithmetic coding.

Adaptive Wavelet Transforms: Wavelet Packets

Wavelet packets generalize DWT by allowing adaptive decomposition:

- **Flexibility**: Decompose both low- and high-frequency subbands based on image content.
- **Cost Function**: Optimize the transform tree to minimize distortion or entropy.
- **Applications**: Suited for images with non-stationary statistics (e.g., textures).