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Wavelet based Image Compression to Gray Scale images using SPIHT, EZW and SOFM

SP Manikanta[1], Dr. P.Santosh Kumar Patra[2] & Bandari Shubhaker[3]

[1](Associate Professor, Electronics and Communication Engineering, St.Martin's Engineering College, Secunderabad)
[2](Principal & Professor, Computer Science & Engineering, St.Martin's Engineering College, Secunderabad)
[3](Electronics and Communication Engineering, BVRIT HYDERABAD College of Engineering for Women, Bachupally)

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Abstract:
Image processing is any form of signal processing for which the input is an image, such as a photograph or video frame; the output of image processing may be either an image or, a set of characteristics or parameters related to the image. Most image-processing techniques involve treating the image as a two-dimensional signal and applying standard signal-processing techniques to it. Image processing usually refers to digital image processing, but optical and analog image processing also are possible.

Image processing applications include Computer vision, Optical sorting, Augmented Reality, Face detection, Feature detection, Lane departure warning system, Non-photorealistic rendering, Medical image processing, Microscope image processing, Morphological image processing, Remote sensing.

Keywords: Feature detection, Lane departure warning system & Non-photorealistic rendering.

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I. INTRODUCTION

1.1 DIGITAL IMAGE

A digital image is a representation of a two-dimensional image using ones and zeros. Depending on whether or not the image resolution is fixed, it may be of vector or raster type. Without qualifications, the term "digital image" usually refers to raster images also called bitmap images.

The raster images will have a finite set of digital values, called picture elements or pixels. The digital image contains a fixed number of rows and columns of pixels. Pixels are the smallest individual element in an image, holding quantized values that represent the brightness of a given color at any specific point. Typically, the pixels are stored in computer memory as a raster image or raster map, a two-dimensional array of small integers. These values are often transmitted or stored in a compressed form.

Raster images can be created by a variety of input devices and techniques, such as digital cameras, scanners, coordinate-measuring machines, seismographic profiling, airborne radar, and more. They can also be synthesized from arbitrary non-image data, such as mathematical functions or three-dimensional geometric models; the latter being a major sub-area of computer graphics. The field of digital image processing is the study of algorithms for their transformation.

1.1 PRINCIPLES BEHIND THE COMPRESSION

A common characteristic of most images is that the neighboring pixels are correlated and therefore contain redundant information. So the foremost task is to find less correlated representation of an image.

Two fundamental components of compression are:

- REDUNDANCY REDUCTION: It aims at removing duplication from the signal source (image or video).
- IRRELEVANCY REDUCTION: It omits parts of the signal that will not be noticed by the signal receiver, namely the human visual system (HVS)

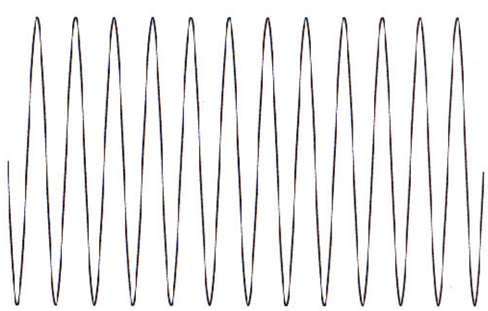
1.2 REDUNDANCY

Data compression is the process of reducing the amount of data required to represent a given quantity of information. Different amounts of data might be used to communicate the same amount of information. If the same information can be represented using different amounts of data, it is reasonable to believe that the representation that requires more data contains what is technically called data redundancy.

Image compression and coding techniques explore three types of redundancies coding redundancy, interpixel redundancy, and psycho-visual redundancy.

1.3 WAVELET AND ECOMPOSITION

A wave is an oscillating function of time or space and is periodic. I n contrast, wavelets are localized waves. They have their energy concentrated in time or space and are suited to analysis of transient signals.



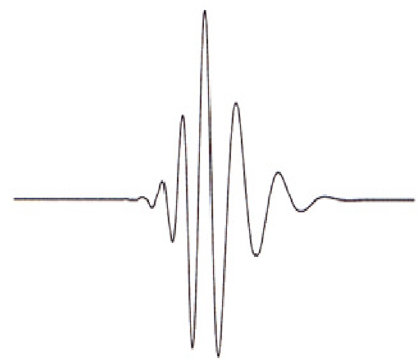


Fig 1.3: Demonstration of (a) A wave and (b) A wavelet

Wavelet theory is applicable to several subjects. All wavelet transforms may be considered forms of time-frequency representation for continuous-time (analog) signals and so are related to harmonic analysis. Almost all practically useful discrete wavelet transforms use discrete-time filterbanks. These filter banks are called the wavelet and scaling coefficients in wavelets nomenclature. These filter banks may contain either finite impulse response (FIR) or infinite impulse response (IIR) filters. The wavelets forming a continuous wavelet transform (CWT) are subject to the uncertainty principle of Fourier analysis respective sampling theory: Given a signal with some event in it, one cannot assign simultaneously an exact time and frequency response scale to that event. The product of the uncertainties of time and frequency response scale has a lower bound. Thus, in the scaleogram of a continuous wavelet transform of this signal, such an event marks an entire region in the time-scale plane, instead of just one point. Also, discrete wavelet bases may be considered in the context of other forms of the uncertainty principle. Wavelet transforms are broadly divided into three classes: continuous, discrete and multiresolution-based.

1.3.1 WHY WAVELETS

- Traditional DCT & sub band coding: trends “obscure” anomalies that carry info.
  E.g., edges get spread, yielding many non-zero coefficients to be coded
- Wavelets are better at localizing edges and other anomalies
  - Yields a few non-zero coefficients & many zero coefficients

- Difficulty: telling the decoder "where" the few non-zeros are!!!
- Natural images in general have a low pass spectrum.
  - the wavelet coefficients will, on average, be smaller in the higher sub bands than in

  The lower sub bands.
- Large wavelet coefficients are more important than smaller wavelet Coefficients.
- Significance map (SM): binary array indicating location of zero/non-zero Coefficients
  - Typically requires a large fraction of bit budget to specify the SM
  - Wavelets provide a structure (zerotrees) to the SM that yields efficient coding

1.4 DISCRETE WAVELET TRANSFORM

A discrete wavelet transform (DWT) is any wavelet transform for which the wavelets are discreetly sampled haar wavelets. The Discreet wavelet transform (DWT), which is based on sub band coding is found to yield a fast computation of wavelet transform. It is easy to implement and reduce the computation time and resources required.

$$\lambda_{j-1}(k)= \sum_m h(m-2k)\, \lambda_j(m)$$

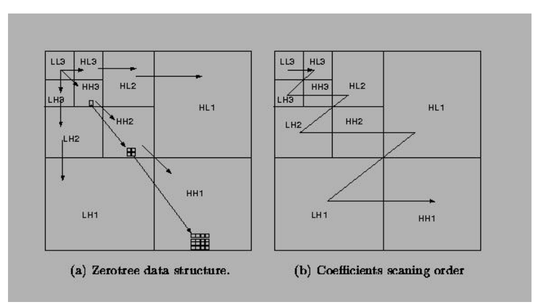
$$\lambda_{j-1}(k)= \sum_m g(m-2k)\, \lambda_j(m)$$

2. EMBEDDED ZEROTREE WAVELET CODING

The Embedded Zero tree Wavelet algorithm (EZW) is a simple, yet remarkably effective, image compression algorithm, having the property that the bits in the bit stream are generated in order of importance, yielding a fully embedded code. The embedded code represents a sequence of binary decisions that distinguish an image from the "null" image. Using an embedded coding algorithm, an encoder can terminate the encoding at any point thereby allowing a target rate or target distortion metric to be met exactly. Also, given a bit stream, the decoder can cease decoding at any point in the bit stream and still produce exactly the same image that would have been encoded at the bit rate corresponding to the truncated bit stream. In addition to producing a fully embedded bit stream, EZW consistently produces compression results that are competitive with virtually all known compression algorithms on standard test images.

2.1 ZEROTREE DATA STRUCTURE

A wavelet coefficient x is said to be insignificant with respect to a given threshold T if |x|<T. The zero tree is based on the hypothesis that if a wavelet coefficient at a coarse scale is insignificant with respect to a threshold, then all wavelet coefficients of the same orientation in the same spatial location at the finer scale are likely to be insignificant with respect to the same threshold. More specifically, in a hierarchical sub band system, with the exception of the highest frequency sub bands, ever coefficient at a given scale can be related to a set of coefficients at the next finer scale of similar orientation. The coefficient at the coarse scale is called the parent, and all coefficients corresponding to the same spatial location at the next finer scale of similar orientation are called children. Similar, we can define the concepts descendants and ancestors. The data structure of the zerotree can be visualized in Figure . Given a threshold T to determine whether or not a coefficient is significant, a coefficient x is said to be an element of a zerotree for the threshold T if itself and all of its descendents are insignificant with respect to the threshold T. Therefore, given a threshold, any wavelet coefficient could be represented in one of the four data types: zerotree root (ZRT), isolated zero (IZ) (it is insignificant but its descendant is not), positive significant (POS) and negative significant (NEG).



(a) Zerotree data structure. (b) Coefficients scaning order

Fig 2.1: Parent child relation

There are two types of passes performed: a dominant pass and a subordinate pass.

2.2 DOMINANT PASS

The dominant pass finds pixel values above a certain threshold, and the subordinate pass quantizes all significant pixel values found in this and all previous dominant passes previous.

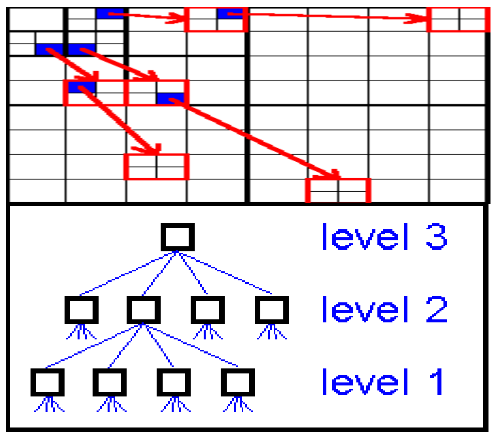


Fig 2.2: The relations between wavelet coefficients in different subbands as quad-trees.

A zero tree is a quad-tree of which all nodes are equal to or smaller than the root. The tree is coded with a single symbol and reconstructed by the decoder as a quad-tree filled with zeroes. To clutter this definition we have to add that the root has to be smaller than the threshold against which the wavelet coefficients are currently being measured.

3. SPIHT ALGORITHM

This SPIHT algorithm uses the principles of partial ordering by magnitude, set partitioning by significance of magnitudes with respect to a sequence of octavely decreasing thresholds, ordered bit plane transmission, and self-similarity across scale in an image wavelet transform. The realization of these principles in matched coding and decoding algorithms is a new one and is shown to be more effective than in previous implementations of EZW coding.

3.1 SPIHT CODING SCHEME

SPIHT is primarily a wavelet-based image compression scheme. In SPIHT, the image is first converted into its wavelet transform and then the wavelet coefficients are fed to the encoder. The primary reason behind the use of wavelet transformation is that, the transform coefficient ci, j has a greater significance than that of the pixel p(i, j) in image compression. In image compression, wavelet representations have produced better objective and subjective results owing to their energy compaction properties and correspondence with the human visual system.

$$c = \Omega(p)$$

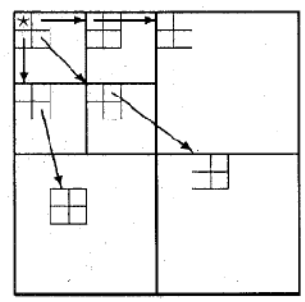


Fig 3.1: Examples of parent-offspring dependencies in the spatial-orientation tree

The notation is defined in the patent description of the algorithm. For a quick reference, here are some of the important definitions.

Bit Row sign	s	s	s	s	s	s	s	s	s
MSB 5	1	1	0	0	0	0	0	0	0
4		→	1	1	0	0	0	0	0
3				→	1	1	1	0	0
2							→		0
1									→
LSB 0									→

$$S_n(\tau)= \begin{cases} 1, & (I,j)^{max}\tau_m|c_{I,j}|\geq 2^n \\ 0, & \text{otherwise} \end{cases} \quad \text{...(6.2)}$$

3.2 ALGORITHM

1) **Initialization:** output $n=[\log_2 (\max_{(I,j)} \{|c_{i,j}|\})]$;

Set the LSP as an empty list, and add the coordinates (i,j) ϵ H to the LIP, and only those with descendents also to the LIS, as type A entries.

2) **Sorting pass:**

2.1) for each entry (i,j) in the LIP do:

2.1.1) output S_n(i,j);

2.1.2) output S_n(i,j)=1 then move (i,j) to the LSP and output the sign of $c_{i,j}$;

2.2) for each entry (i,j) in this LIS do:

2.2.1) if entry is of type A then

- Output S_n (D(i,j));
- If S_n (D(i,j))=1 then
- For each (k,l) ϵ O(i,j) do:
- Output S_n (k,l);
- If S_n (k,l)=1 then add (k,l) to the LSP and output the sign of $C_{i,j}$;
- If S_n (k,l)=0 then add (k,l) to the end of LIP;
- If L(i,j) $\neq$ 0 then move (i,j) to the end of the LIS, as an entry of type B ,go to step 2.2.2); otherwise, remove entry (i,j) from the LIS;

2.2.2) if the entry is of type B then

- Output S_n(L(i,j));
- If S_n(L(i,j))=1 then
- Add each (k,l) ϵ O(i,j) to the end of the LIS as an entry of type A;
- Remove (i,j) from the LIS.

3) **Refinement pass:** for each entry (i,j) in the LSP, expect those included in the last sorting pass(i.e., with same n), output the n^{th} most significant bit of $|C_{i,j}|$;

4) **Quantization-step update:** decrement n by 1 and go to step 2.

Some of the advantages of SPIHT encoding include: (i) allows a variable bit rate and rate distortion control as well as progressive transmission [27] (ii) an intensive progressive capability-we can interrupt the decoding at any time and a result of maximum possible detail can be reconstructed with one-bit precision.(iii)very compact output bitstream with large bit variability-no additional entropy coding or scrambling has to be applied.

4. SELF ORGANIZING FEATURE MAP

Due to the widespread use of Multimedia applications, the need for image compression is increasing day-by-day. The image compression schemes are aimed to reduce the transmission rates for still images without sacrificing much of the image quality. In this paper, an Artificial Neural Network (ANN) approach for image compression is presented. The Codebook for Linear Vector Quantization (LVQ) is designed using Self Organized Feature Maps (SOFM). huffman Coding is then used to remove redundancies between indexes of vectors corresponding to the neighboring blocks in the original image, which then leads to further compression. The simulation results demonstrate the improved coding efficiency of the this method.

4.1 SOFM IMAGE COMPRESSION SCHEME

In this image compression scheme, The image is first decomposed into 4×4 non-overlapping blocks and each block is transformed into vectors of 16 elements. These vectors serve as inputs to the Kohonen layer in the SOFM algorithm. Then a supervised algorithm LVQ is used to modify the codebook in a labeled training data. Since the consecutive blocks of an image are often similar, the topology preserving SOFM based LVQ will then quantize to some nearest codeword, hence removes redundancy. huffman Coding is then used to code the indexes of the codeword The use of Arithmetic Coding is done in order to exploit the occurrence of similar codebook indexes corresponding to neighboring blocks, which then leads to further compression .The decompression scheme performs the inverse operation to regenerate the original image.

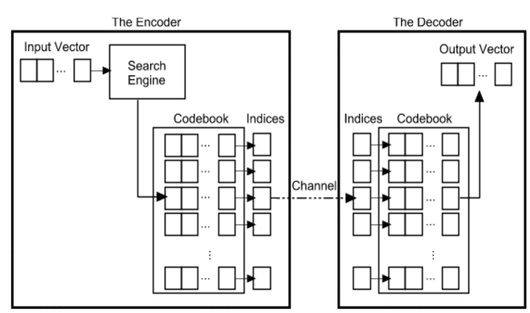


Fig 4.1: Vector quantization using sofm

4.2 SELF ORGANIZING FEATURE MAPS (SOFM)

Self Organizing Feature Maps has formed a basis for a great deal of research into applying network models to the problem of codebook design in Vector Quantization. The SOFM introduced by Kohonen is an unsupervised learning method which has both clustering and visualization properties and creates a correspondence between the input space of stimuli and the output space constituted of the codebook elements (the code words or neurons).

For each vector X in the training set

1. Classify X according to

$$X \in Ci \quad if \ |X - W_i| = min|X - W_j|$$

2. Update weights W_j according to:

$$W_j(t+1) = \begin{cases} W_j(t) + lr\left(X - W_j(t)\right)^2 & \text{if } C_j \in N(C_i,t) \\ W_j(t) & \text{if } C_j \notin N(C_i,t) \end{cases}$$

Where W is the feature vector, lr is the learning parameter in the range of 0-1 and N (Ci, t) is the set of classes, which are in the neighborhood of the winning class Ci at time t. The subscript 'j' represents the index of all vectors in the neighborhood of the ith feature vector. Typically the learning rate parameter is initialized to some value and then decreases monotonically with each iteration to ensure a good convergence of the algorithm. After a suitable number of iterations, the codebook converges and training is terminated. When an input pattern is presented, the SOFM learning Algorithm updates the winner node and also nodes in its topological vicinity,. As a result of application of SOFM algorithm, nodes eventually become ordered and neighboring nodes in the topology become associated with weight vectors that are near each other in the input space

5. EXPERIMENTAL RESULTS

5.1 ORIGINAL IMAGES

Table 5.1 PSNR and MSE Values For EZW

5.2 OUTPUT IMAGES FOR EZW

Fig 5.2: Decompressed Images Using EZW

Image	PSNR	MSE	CR
lena	31.49	46.11	3.07
baboon	25.59	179.40	2.38
cameraman	27.06	127.86	3.29
peppers	28.74	86.74	2.72
barbara	24.42	232.89	2.60
bridge	26.74	137.68	2.37

5.3 OUTPUT IMAGES FOR SPIHT

Fig 5.3: Decompressed Images Using SPIHT

TABLE 5.2 PSNR & MSE VALUES FOR SPIHT

Image	PSNR	MSE	CR
lena	34.09	25.33	5.95
baboon	34.34	23.90	2.16
cameraman	32.81	34.02	4.24
peppers	34.24	24.43	4.77
barbara	27.95	104.24	3.52
bridge	30.28	60.92	2.27

5.4 OUTPUT IMAGES FOR SOFM

Fig 5.4: Decompressed Images Using SOFM

TABLE 5.3 PSNR & MSE VALUES FOR SOFM

Image	PSNR	MSE	CR
lena	29.45	73.72	8.92
baboon	25.27	193.15	8.50
cameraman	27.65	111.52	8.92
peppers	28.75	86.64	8.91
barbara	25.85	168.98	8.84
bridge	25.40	187.20	8.44

6. CONCLUSION & FUTURE WORK

The objective of this paper is to implement the concept of wavelet based image compression to gray scale images using different techniques. The techniques involved in the comparison process are SPIHT (set partition in hierarchial trees), EZW (embedded zero tree wavelet), and SOFM (self organizing feature map). These techniques are more efficient and provide a better quality in the image. In compression, wavelets have shown a good adaptability to a wide range of data, while being of reasonable complexity. This paper focuses important features of wavelet transform in compression of still images, including the extent to which the quality of image is degraded by the process of wavelet compression and decompression. The above techniques have been successfully used in many applications. The techniques are compared by using the performance parameters PSNR and MSE. Images obtained with those techniques yield very good results.

These three above methods are taking slightly time consuming and we may expect to reduce the time delay and also reduce complexicity by adadting new methods in the future.

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