"Implementation And Comparison Of Wavelet Based SPIHT Technique And SOFM Based Vector Quantization Technique In Image Compression"

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ABSTRACT

Due to widespread use of multimedia applications the use of image compression is increasing day by day. There are different image compression techniques which are aimed at reducing the transmission rate without compromising on image quality. In this paper implementation and comparison of wavelet based SPIHT algorithm and Neural Network based vector quantization Technique in compression of digital images have been presented. Wavelets are mathematical tool for decomposing images hierarchically. The huge numbers of lossy compression techniques are proposed in the past. Among this Wavelet Transform based image compression is the most familiar one. Wavelet-based image compression provides better picture quality even at higher compression ratios. The wavelet based methods implemented here is SPIHT (Set partitioning in hierarchical trees). SPIHT algorithm works on the principle of progressive transmission of bits i.e. it transmits the larger coefficients before transmitting the smaller coefficients. Artificial Neural Network is composed of many interconnected non linear components that operate in parallel and their behavior is just like human brain. These methods are very efficient and are commonly used for compressing images. These methods are implemented using mat lab and parameters such as MSE (mean square error); Bits per pixel, image quality compression ratio, PSNR are evaluated and compared.

INTRODUCTION

Now a days multimedia application is becoming very popular. Multimedia data needs to be compressed because of their large size, less storage requirements, faster transmission rate, and low bandwidth. Image compression is minimizing the size in bytes of a graphics file without degrading the quality of the image to an unacceptable level. Compression can be achieved by reducing redundancy and irrelevance. The reduction in file size allows more images to be stored in a given amount of disk or memory space. It reduces the bandwidth requirement. It also reduces the time required for images to be sent over the Internet or downloaded from Web pages.

IMAGE

An image is essentially a 2-D signal processed by the human visual system. The signals representing Images are usually in analog form. However, for processing, storage and transmission by computer Applications, they are converted from analog to digital form. A digital image is basically a 2 - Dimensional array of pixels. Images form the significant part of data, particularly in remote sensing, biomedical and video conferencing applications. The use of and dependence on information and computers continue to grow, so too does our need for efficient ways of storing and transmitting large amounts of data.

NEED OF IMAGE COMPRESSION

Image compression is a result of applying data compression to the digital image. The main objective of image compression is to decrease the redundancy of the image data which helps in increasing the capacity of storage and efficient transmission. Image compression aids in decreasing the size in bytes of a digital image without degrading the quality of the image to an undesirable level. Image compression addresses the problem of reducing the amount of data required to represent a digital image [21]. It is a process intended to yield a compact representation of an image, thereby reducing the image storage/transmission requirements. Compression is achieved by the removal of one or more of the three basic data redundancies:

1. Coding Redundancy

2. Inter pixel Redundancy

3. Psycho visual Redundancy

Coding redundancy is present when less than optimal code words are used. Inter pixel redundancy results from correlations between the pixels of an image. Psycho visual redundancy is due to data that is ignored by the human visual system (i.e. visually non essential information) [21].

Image compression techniques reduce the number of bits required to represent an image by taking advantage of these redundancies. An inverse process called decompression (decoding) is applied to the compressed data to get the reconstructed image. The objective of compression is to reduce the number of bits as much as possible, while keeping the resolution and the visual quality of the reconstructed image as close to the original image as possible. Image compression systems are Composed of two distinct structural blocks: an encoder and a decoder Compressed image f(x, y) is fed into the encoder, which creates a set of symbols form the input data and uses them to represent the image. If I let n1(original image size) and n2 (compressed image size) denote the number of information carrying units(usually bits) in the original and encoded images respectively, the compression that is achieved can be quantified numerically via the compression ratio,

$$CR = n1 / n2$$

BENEFITS OF COMPRESSION

1. It provides a potential cost savings associated with sending less data over network where cost of transmission is really usually based upon its duration.

2. It not only reduces storage requirements but also overall execution time.

3. It also reduces the probability of transmission errors since fewer bits are transferred. It also provides a level of security against illicit monitoring.

IMAGE COMPRESSION TECHNIQUES

The image compression techniques are broadly classified into two categories depending whether or not an exact replica of the original image could be reconstructed using the compressed image.
These are:

1. Lossless technique
2. Lossy technique

LOSSLESS COMPRESSION TECHNIQUE

In lossless compression techniques, the original image can be perfectly recovered from the compressed (encoded) image. These are also called noiseless since they do not add noise to the Signal (image).It is also known as entropy coding since it use statistics/decomposition techniques to eliminate/minimize redundancy. Lossless compression is used only for a few applications with stringent requirements such as medical imaging [9]. There are several lossless techniques such as run length encoding, entropy encoding etc.

LOSSY COMPRESSION TECHNIQUE

Lossy schemes provide much higher compression ratios than lossless schemes. Lossy schemes are widely used since the quality of the reconstructed images is adequate for most applications by this scheme; the decompressed image is not identical to the original image, but reasonably close to it [9]. There are many lossy compression techniques such as transform coding, fractal compression etc.

LITERATURE REVIEW

1. SPIHT algorithm was initially presented by Amir Said and William A Pearlman et al [3]. In their paper they presented an alternative of the EZW method given by J. M. Shapiro, which is computationally better and gives better performance in terms of reconstructed image quality. They presented a scheme in which the inputted image is first subjected to wavelet transformation , then compression is carried out based on the partial ordering of the magnitude, only high ordered bits are transmitted first. In this algorithm self similarity across different scales of wavelet transform is manipulated to give the better result.
2. Jun Ren Ding & Jarr Far Yang et al [4] presented a simplified SPIHT algorithm; they have considered the relationship between the bit plane and the target bit rate and the relationship between the initial threshold and the target bit rate. Based on these findings they have omitted the refinement pass of the original SPIHT algorithm and also shown that the reconstructed image with this method is at par with that produced by original algorithm and also the algorithm proposed by them has memory requirement less than 50% and computational complexity is less than 30% as compare to the original algorithm.
3. Manik Groach and Dr. Amit Garg et al. [5] has given a hybrid compression scheme based on DCT and SPIHT algorithm. They have proposed to compress the image using DCT first which will compress the low frequency components, then the compressed image is decomposed using biorthogonal wavelet transform. The high frequency components of the decomposed image are further compressed using SPIHT encoding scheme.
4. Li Wern Chew, Li Minn Ang and Kah Phooi Seng et al [6] has proposed a compression scheme based on SPIHT known as virtual SPIHT that is based on strip based image compression and has very low memory requirement as compare to original SPIHT algorithm. The pyramid like tree structure formed as a result of wavelet transforms

named a spatial orientation tree (SOT). In the original SPIHT SOT each node will have 2 x 2 adjacent pixels of the same spatial orientation of the descendents; they have proposed new SOTs where for certain sub bands, the new tree structure take the next 4 pixel of the same row as its children, thus reducing the memory requirement.

5. N. Boukhennoufa, K. Benmahammed, M. A. Abdi and F. Djeffal et al [7] have presented an ECG signal compression method that combines the SPIHT method with vector K tree partitioning coder rather than using arithmetic coding. They have proposed to feed the bit stream generated by the recursive application of the SPIHT algorithm onto the inputted signals to a VKTP encoder for a better compression ratio and reduce the reconstruction error.
6. A. Mallaiah, S. K. Shabbir and T. Subhashini et al.[25] has proposed a compression scheme based on
7. Baiping Li and Xueyan Zhang et al [27] has proposed a scheme that has reduced the complexity and enhanced the efficiency of SPIHT algorithm, they have used one dimensional array instead of chain table structure in the sorting process of SPIHT which resulted in reduced storage requirement and decreased complexity.

8. Arijit Laha, Nikhil R. Pal, and Bhabatosh Chandra et al. [10] have proposed a design of vector quantizer for image compression. Firstly they have used SOFM to generate a set of code vectors. Then, the set of blocks associated with each code vector is modeled by a cubic surface for better perceptual fidelity of the reconstructed images. Mean-removed vectors from a set of training images are used for the construction of a generic codebook. Further, Huffman coding of the indices generated by the encoder and the difference-coded mean values of the blocks are used to achieve better compression ratio. They proposed two indices for quantitative assessment of the psycho visual quality (blocking effect) of the reconstructed image

9. Khashman et al. [11] has proposed a technique for compressing the digital image using neural networks and Haar wavelet transform. Their aim is to achieve an optimum compression ratio. With wavelet based transform the quality of the compressed image is good and the compression ratio depends upon the content of the image. Their paper suggested that that a neural network can be trained to be familiar with an optimum ratio for Haar wavelet compression of an image upon presenting the image to the network.
10. Kazayuki Tanaka et al.[12] has presented a color image compression algorithm making use of Kohonen's Self Organizing Feature Map, he has proposed a scheme in which N neurons were introduced with the aim of reducing a full color image with 224 colors to an indexed color image with N colors. There are controls

parameters for the competitive learning between neurons in the SOFM algorithm and the neurons are updated by considering the relationship among neighboring neurons.

11. Pi and Lo [13] has also proposed a scheme similar to Kazayuki Tanaka et al. but instead of updating only a few control parameters, they have proposed to update all control parameters so as to decrease monotonically and exponentially with respect to each iteration step.
12. Durai S.A. and Saro E.A et al. [14] have estimated a cumulative distribution function for the image that can be used to map the image pixels in such a way that they yield high compression ratio and they converge fast as well, which is a new achievement because images compressed using SOFM takes longer time to converge. The reason behind this is that the inputted image encompasses of many different gray levels with little difference between their neighborhoods pixels. When this difference is minimized both the compression ratio and convergence can be improvised.
13. G.Mohiuddin Bhat ,Asif Baba & Ekram Khan et al. [15] has proposed a technique for image compression in which the codebook for Linear Vector Quantization is designed using SOFM and redundancies between the indices of vectors corresponding to the neighboring blocks in the original image have been removed by arithmetic coding to further compress the image.
14. T.Kathirvalavakumar & E. Ponmalar et al. [16] has given a hybrid approach of image compression using SOFM and DWT. Firstly they have applied SOM based Vector Quantization and stored only the approximation coefficients along with the index value of SOM and then they have applied DWT on the resultant code vector .The result gives a better compression ratio and better PSNR (peak signal to noise ratio) value.
15. Hamdy S.Soliman and Mohammed Omari et al. [17] has given an image compression scheme based on Adaptive Resonance Theorem and the Kohonen's self Organizing Feature Map. In their work the input image is clustered into classes of similar sub images. Each class has a center of mass sub image representative called centroid (codebook). The main goal of the compression phase is to develop a table of all class centroids and map each input sub image into its class centroid index in the codebook. An input image is compressed into a set of centroid indices, one per sub image and a local codebook.
16. Dinesh K. Sharma and Loveleen Gaur et al. [18] has given a global processing technique which processes every pixel on the image without utilizing the blocks for training the Kohonen's network. They have used conventional SOM and stressed on the feature extraction property.
17. Jayanta Kumar Debnath, Newaz Muhammad and Wai- Keung et al.

[19] has presented a approach on image compression in which they had combined the discrete wavelet transform (DWT) and vector quantization method (VQ).They have performed 3 level DWT on the original image which results in ten separate sub bands, ten codebooks are generated using the SOFM algorithm, these are used in vector quantization of the wavelet transformed sub band image. Huffman coding is applied on the VQ indices to increase the compression ratio.

18. Y. H. Dandawate et. al. [22] has proposed a technique to improve the quality of decompressed color images using vector quantizer. They have developed dedicated hardware using VLSI for compression and decompression of images. To improve the quality of reconstructed images they have considered image quality measures such as image fidelity, entropy of the image on RGB color space, structural content, PSNR.
19. S. Esakkirajan, T. Veerakumar, V. Senthil Murugan and P.Navaneethan et al [] have proposed a hybrid vector quantization scheme comprising multistage vector quantization and pyramid vector quantization, they have proposed the application of multistage vector quantization to the low frequency coefficients and they have used the pyramid vector quantization for the quantization of high frequency coefficients resulting in high quality reconstructed image at high compression ratio.
20. Tracy Denk, Keshab K. Parhi And Vladimir Cherkassky et al [24] have proposed an image compression scheme that is a combination of wavelet transform and neural network. They have proposed to first apply wavelet transformation to decompose the image, then the wavelet coefficients are arranged as vectors to be represented using neural network and at the last step the vectors are quantized and entropy encoding is applied on them, resulting in higher compression rates.

WAVELET BASED COMPRESSION

In general wavelets are a mathematical tool for hierarchically decomposing functions. the huge numbers of lossy compression techniques are proposed in the past. Among this Wavelet Transform based image compression is the most familiar one. Wavelet-based image compression provides better enhancements in picture quality even at higher compression ratios. It is an established transform used for a number of image compression standards in lossy compression methods. Wavelet transform has the capability to decompose signals into different scales or resolutions Image compression applications benefit from the following desirable properties of wavelet transforms namely, 1) orthogonality, 2) compact support, 3) linear phase and high approximation/vanishing moments of the basis function, 4) efficient multi-resolution representation, 5) scalability, and 6) embedded coding with progressive transmission.

The discrete cosine transforms, the wavelet transform is not Fourier-based and therefore wavelets do a superior job of handling discontinuities in data. Wavelet Transforms (WT) based image compression is a prevailing method that is favored by most of the researchers to get the compressed images at higher compression ratios with higher PSNR values. The general procedure involved in wavelet transform–based image compression techniques is, first the image data is decor related by applying a wavelet transform, then the resulting transform coefficients are quantized and the quantized values are coded.

SPIHT ALGORITHM

One of the most efficient algorithms in the area of image compression is the Set Partitioning in Hierarchical Trees (SPIHT). It is the refined version of EZW algorithm [2].It applies wavelet decomposition to decompose the image into sub bands; it produces a pyramid structure where an image is decomposed sequentially by applying power complementary low pass and high pass filters and then decimating the resulting images. These are one-dimensional filters that are applied in cascade (row then column) to an image whereby creating four-way decomposition: LL (low-pass then another low pass), LH (low pass then high pass), HL (high and low pass) and finally HH (high pass then another high pass). The resulting LL version is again four-way decomposed [3].

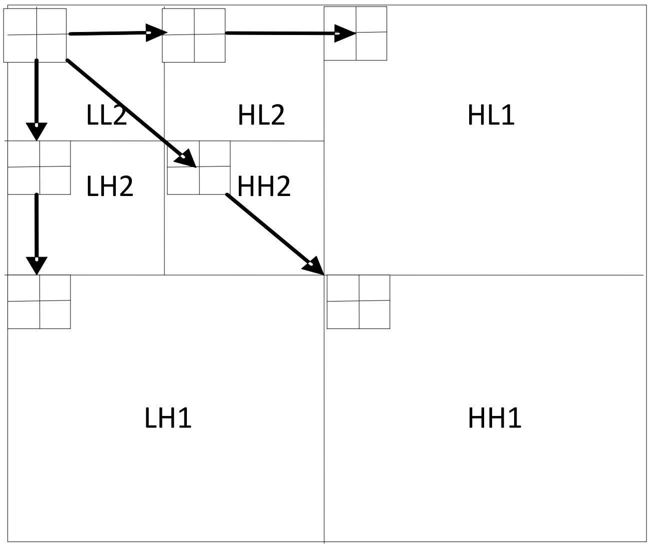


Figure 1 Spatial orientation tree defined in a four sub band recursive pyramid

In SPIHT algorithm the image is first decomposed into a number of sub bands by hierarchical wavelet decomposition. The sub band coefficients are grouped as spatial orientation trees, which exploits the correlation between the frequency bands. The coefficients in each spatial orientation tree are coded progressively from the Most significant bit planes to least significant bit planes, coefficients of highest magnitude are coded first. In SPIHT coding process 3 lists are created :

1.The list of insignificant pixels (LIP) contains individual coefficients that have magnitudes smaller than the threshold.
2. The list of insignificant sets (LIS) contains sets of wavelet coefficients that are defined by tree structures and are found to have magnitudes smaller than the threshold (insignificant). The sets exclude the coefficients corresponding to the tree and all subtree roots and they have at least four elements.
3. The list of significant pixels (LSP) is a list of pixel found to have magnitudes larger than the threshold (significant).

4. The set of offspring (direct descendants) of a tree node, O(i, j), in the tree structures is defined by pixel location (i, j). The set of descendants, D(i, j), of a node is defined by pixel location (i, j). L(i, j) is defined as
L(i, j) = D(i, j) – O(i, j).

For each pixel in the LIP, one bit is used to describe its significance. If it is not significant, the pixel remains in the LIP and no more bits are generated; otherwise, a sign bit is produced and the pixel is moved to the LSP. Similarly, each set in the LIS requires one bit for the significance information. The insignificant sets remain in the LIS; the significant sets are partitioned into subsets, which are processed in the same manner and at the same resolution until each significant subset has exactly one coefficient. Finally, each pixel in the LSP is refined with one bit. The abovementioned procedure is then repeated for the subsequent resolution.

The SPIHT algorithm can be summarized as follows :

1. **Initialization**:
   Output n=[$\log_2$ max{| C(i,j) |}] ; set the LSP as empty list and add the coordinates 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 Sn(i,j),

   2.1.2 If Sn(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 the LIS do:
   2.2.1 if the entry is of type A then
   output Sn(D(i,j));
   if Sn(D(i,j))=1 then
   * for each (k,1) ∈ O(I,j) do:
   Output Sn (k,l)
   If Sn(k,l)=1 then
   add to the LSP and output the sign of C(k,l)
   If Sn(k,l)=0 then add (k,l) to the end of LIP

   * If L(i,j) $\neq \varphi$ then move to the end of the LIS as an empty entry of type B, and 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 Sn(L(i,j))
   If Sn(L(i,j))=1 then

   * add each h_m to the end of the LIS as entry of type A
   * remove (i,j) from the LIS
3. **Refinement Pass**: For each entry (i,j) in the LSP except those included in the last sorting pass (i.e. with the same n), output the nth most significant bit of | $C_{i,j}$ |
4. **Quantization step update**: decrement n by 1 and go to step 2

KOHONEN'S SELF ORGANIZING FEATURE MAP

The concept of Self organizing feature maps was first described by Teuvo Kohonen. They are competitive neural networks, that are trained using unsupervised learning to produce a two dimensional grid representing the feature space. It uses a neighborhood function to preserve the topological properties of the input space [1]. SOMs operate in two modes: training and mapping. "Training" builds the map using input examples (a competitive process, also called vector quantization), while "mapping" automatically classifies a new input vector.

A self-organizing map consists of components called nodes or neurons. Associated with each node is a weight vector of the same dimension as the input data vectors and a position in the map space. The usual arrangement of nodes is a two-dimensional regular spacing in a hexagonal or rectangular grid. The self-organizing map describes a mapping from a higher dimensional input space to a lower dimensional map space. The procedure for placing a vector from data space onto the map is to find the node with the closest (smallest distance metric) weight vector to the data space vector [26].

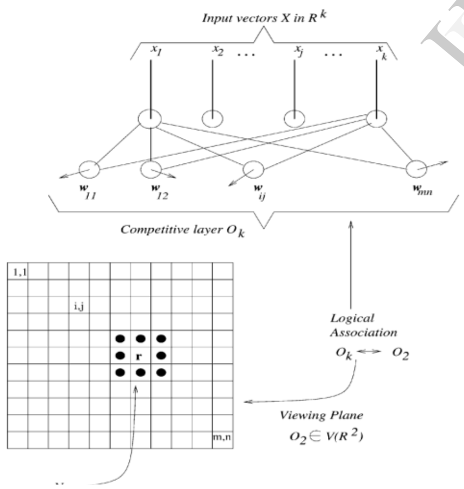
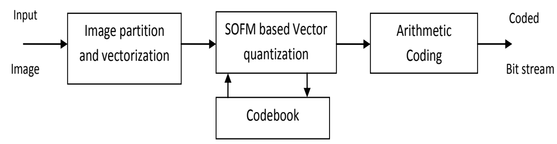


Figure 2 SOFM Architecture

VECTOR QUANTIZATION

Vector quantization is the best way of quantizing and compressing the images. Among different existing algorithms Kohonen's self organizing feature maps are one of the best approaches to perform VQ. Vector Quantization is a clustering technique by which the input space is divided into number of distinct regions and for each region a reconstruction vector id defined. Self organizing maps have been used extensively for Vector Quantization to solve the problem associated with classical quantization techniques which are sensitive to codeword errors[29]. SOFM performs the topological sorting along with efficient codebook design. VQ compression system consists of two components: an encoder and decoder. In VQ approach the image is first partitioned into a size of mxm non overlapping blocks , then each block is transformed into a vector of 16 elements. These vectors serve as a basis to the kohonen layer of the SOFM network. Both the encoder and decoder of the VQ we have a set of d dimensional vector called the codebook of the vector quantizer, the vectors in this codebook are known as code words. The standard way of calculating codebook is by LBG algorithm [20]. Each code vector is assigned a binary index. At encoder the input vector is compared to each codeword in order to find out the closest code word. Since the consecutive blocks of an image are often similar, quantization to the nearest codeword is done to remove redundancy. Binary index of the code vector is transmitted to the decoder and since it has the same codebook it can retrieve the code word from the given binary index.

Figure 3 Vector Quantization Scheme



Algorithm [20]:

Step 1: Divide the input image into m x n non overlapping blocks, S=$\{x_i \in R^d \mid i = 1,2,\ldots\ldots,n\}$

Step 2: Initiate a codebook C = $\{c_j \in R^d \mid j = 1,2,\ldots.,k\}$

Step 3: Set D_0= 0 and let K=0

Step 4: Classify the n training vectors into K clusters according to $x_i \in S_q \; if \; \|x_i - c_q\|p \leq \|x_i - c_j\|p for \; j \neq q$

Step 5: Update cluster centers c_{j} , j =1,2,……,K by $c_j = \frac{1}{|s_j|}\sum_{x_i \in s_j} x_i$

Step 6: Set k = k+1 and compute the distortion $D_k = \sum_j^k = 1 \sum_{x_i \in s_j} \|x_i - c_j\|p$

Step 7: if ($D_{k-1} - D_k / D_k$>ε then repeat step 4 to 6

Step 8: Output the codebook C = $\{c_j \in R^d \mid j = 1,2,\ldots\ldots,k\}$

5. RESULT

In this section the result obtained from the implementation of Both SPIHT and SOFM based Vector quantization methods are presented. The presented scheme is implemented in MATLAB. The schemes are implemented on 512 x 512 grayscale images. The test image used in experiments include Lena. The quality of reconstructed image is measured in terms of its PSNR value and compression ratio.

PSNR is defined as [29]:

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2$$

$$PSNR = 10log_{10}\left(\frac{MAX_I^2}{MSE}\right)$$

$$= 20.log_{10}\left(\frac{MAX_I}{\sqrt{MSE}}\right)$$

$$= 20.log_{10}(MAX_I) - 10.log_{10}(MSE)$$

Compression ratio is defined as:

CR = n1/n2

n1 = size of original image

n2 = size of compressed image

Method	Original Image	Reconstructed Image
SPIHT		
SOFM based VQ		

Image	Compression Ratio		PSNR	
	SOFM based VQ	SPIHT	SOFM based VQ	SPIHT
Lena	2:1	20:1	29.29dB	36.41 dB

6. CONCLUSION

In this paper I have compared wavelet based SPIHT technique and SOFM based vector quantization for compression of images. The comparison is done on the basis of PSNR value and compression ratio and also the quality of output image is taken into consideration for comparison. The image reconstructed with SPIHT method is of better quality than that compressed using SOFM based vector quantization method also the peak signal to noise ratio generated by SPIHT method is higher than that generated by SOFM based vector quantization method. But the computational complexity of SPIHT method is higher than that of SOFM based image compression method.

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