A Novel LBG algorithm for Image Compression in Wavelet Transform Domain

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Abstract: -The paper presents a novel LBG algorithm for image compression in wavelet transform domain. The performance of the algorithm is evaluated by using standard 512×512 benchmark still images and the results compared to the traditional well-known JPEG standard. The important metric of time and Peak Signal to Noise Ratio are used to evaluate the novel algorithm. The results show that the strength of the algorithm lies in the speed of operation as it is much faster than the JPEG standard. It has speed advantages of almost 41% over the JPEG standard. Further more, the accuracy of the prediction of the Novel algorithm is better than that of the JPEG standards.

Key-Words: - Wavelet transform, Vector quantization, Joint Photographic Experts Group (JPEG), Novel LBG , Partial search

1 Introduction

Radiology is a main application of medical imaging technology. The major imaging modalities include: computed tomography (CT), magnetic resonance imaging (MRI), Ultrasonography US), positron emission tomography(PET), single photon emission computerized tomotography (SPECT), nuclear medicine (NM) [1],[2]. These images are usually represented in digital forms supporting image transfer and archiving into the picture archiving and communication systems (PACS). The amount of the medial images is huge and increasing rapidly every year. Thus, the image compression is needed to reduce the data volume of these radiologic images. There are several image compression techniques available at the moment. One of the widely used techniques is Wavelet Transform. The wavelet transform is a powerful mathematical tool widely used in many areas specially for data compression [3].Wavelet transform (WT) had been initially developed from Fourier transform (FT). The wavelet concepts can be traced back to 1910, however the mathematics of wavelets have only recently been formalized. By exploiting spatial and spectral information redundancy in images, wavelet-based methods offer significantly better results for compressing medical images than do compression algorithms based on Fourier methods, such as the discrete cosine transform used by the Joint Photographic Experts Group. Furthermore, wavelet-based compression does not suffer from blocking artifacts, and the restored image quality is generally superior at higher compression rates [4].The wavelet basis functions have short support for high frequencies and long support for low frequencies, smooth area of an image may represent with very few bits. Most of the energy is also concentrated in low frequency information, and for the remaining high frequency components of the image, most energy is spatially concentrated around the edges.

Indeed, before the wavelets had been introduced, a number of closely related coding works was extensively studied in the coding community, including pyramid coding [5], where the coarse version use derived form the original image by filtering. From this coarse version, the original image can be predicted and the prediction error can be calculated. If the prediction error is small it can be well compressed. The process can be iterated on the coarse version. A perfect reconstruction can be achieved if the compression of difference signals is lossless by simply predicting the original image and adding back the predicted image and the difference, the compression rate depends on how well the original image can be predicted from the filtered and down sampled image . Also subband coding [6] and transform coding. They split up the input image into frequency bands and then code each subband using coder bit rate method to the statistics of the band. Initial efforts in using wavelet transform in compression research concentrated on the hope of more efficient compaction of energy into a few numbers of low frequency. This generated some of wavelet based coding algorithms [7] [8] [9] [10] which were designed to exploit the energy compaction properties of the wavelet transform by applying scalar or vector quantizers for the statistical of each frequency band of wavelet coefficients.

2 Image Compression Framework

Similar to other digital compression fields, there are 3 major components to the transform based image compression algorithm: image transformation, quantization and entropy coding [11][12]. A block diagram of a general wavelet-based image compressor-decompressor is shown in Fig.1.

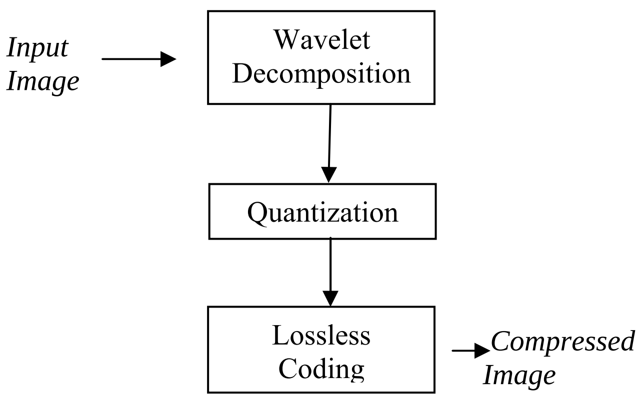

Fig.1 Block diagram of the components of wavelet image compression. Image reconstruction is the inverse of this process

The image transformation is used to reduce the dynamic range of the range of the signal and also redundant information. The wavelet transform is preferably used in many areas including science and engineering. The wavelet transformation is based on the idea that the coefficients of a transform that decorrelates the pixels of an image can be coded more efficiently than the original pixels themselves.

The wavelet transform decomposes the input image into low-frequency coefficients or coarse band and a number of high frequency bands or detail signals according to the level of decomposition. These results can be considered as low-pass and high-pass versions of the original image. The low band pass has a flat distribution and its approximation of the distribution of luminance and chrominance values are similar to those of the original image.The high band coefficients have probability distribution that is similar to laplacian characters with mean zero. Moreover, the wavelet transform generates coefficients that are much less correlated than the original images and are easier to code. Also, it can be observed that all the same corresponding position bands look like scaled versions of each other, vertical to vertical lower of higher band and horizontal to horizontal and the same diagonal to diagonal. However, it is noted that the bulk energy in the high bands is concentrated more or less in the vicinity of areas that correspond to edge activity in the original image. This recommends that areas, which contain most of the information, must be encoded more precisely than the rest. Therefore, for image compression proposes a wavelet transform must be combined with another technique for coefficient coding. In fact the compression of wavelet coefficients is based on the assumption that details at high resolution are less visible to human eye and therefore can be reconstructed with low processing

Quantization is the process for approximating the continuous set of values in the image data with a finite (preferably small) set of values. The input to a quantizer is the original data, and the output is always one among a finite number of levels. The quantizer is a function whose set of output values are discrete, and usually finite. There are two types of quantization: Scalar Quantization and Vector Quantization. In scalar quantization, each input symbol is treated separately in producing the output, while in vector quantization the input symbols are clubbed together in groups called vectors, and processed to give the output.

An entropy encoding further compresses the quantized values losslessly to give better overall compression. It uses a model to accurately determine the probabilities for each quantized value and produces an appropriate code based on these probabilities so that the resultant output code stream will be smaller than the input stream. The most commonly used entropy encoders are the Huffman encoder and the arithmetic encoder, although for applications requiring fast execution, simple run-length encoding (RLE) has proven very effective.

3 A novel LBG Algorithm (NLBG) using Partial Search Strategy

In the conventional Vector Quantization (VQ), a full search technique is used, where the Euclidean distance measure is calculated for the entire code vector in the codebook. The full search technique is the best technique in terms of the quality of the predicted image and the simplicity, however, the Full Search requires intensive computations. These are the most serious problems facing VQ. To alleviate these problems, the novel LBG algorithm has been implemented. The conventional LBG algorithm is modified to make it more efficient in speed up of codebook generation and in case of encoding phase. The novel LBG algorithm is based on the fact that two equal-sized image blocks cannot be closely matched unless their variance (σ) are closely matched. This proposed algorithm uses the combination of variance (σ) and means (m)to reject a large number of code vectors from the search consideration without calculating their distortion function from the training vectors. Then, the partial search is used to find the best matching code vectors from the remaining codebook. One main advantage of this novel algorithm lies in the time consuming and also the power consumption.

The steps of the novel LBG algorithm are summarized as follow:

Step 1 : an initial codebook $C_1 = \{c_1, c_2, c_j, \ldots c_N\}$ with size N is given, in which the N codewords are randomly and where cardinality of each codeword c_j is the same as the input image block's dimension (k)

Step 2 : set run-counter t =1 and average distortion $D_t=0$

Step 3 : Compute the variance σ^2 and mean value m of code vector in the codebook then find $h = \frac{\sigma^2}{m}$ and sort the codebook in ascending order according to the increase h.

Step 4 : Calculate the minimum distortion partition. All training vectors are group into clusters using the minimum distortion rules as follows:

i) Compute $h_x = \frac{\sigma^2}{m}$ for the input vector

ii) Find the best match of h_x from the sorted codebook

iii) Define the partial codebook by setting the search limit at L.

iv) Find the best match code vector of the input vector from the partial codebook by calculating the distortion of each codevector by select the minimum distortion

v) Repeat (i) to (iv) for all training vector

Step 5 : Measure the average distortion D_{t+1}

Step 6 : Check the following inequality:

$$\left|\frac{D_{i+1}-D_i}{D_i}\right| \leq \varepsilon \qquad (1)$$

Where ε is the threshold value. If inequality is true, the resultant codebook is the outcome; otherwise, go to Step 7.

Step 7 : Compute the centroid of each cluster and then set t=t+1 and go to step 1 for the next iteration.

4 Algorithm Testing

The algorithm is implemented on the Dell PC with Pentium 4 of 2.8 GHz. In order to evaluate the performance of this algorithm, it is compared to the standard JPEG. The simulations are performed on 512×512 monochrome still images containing 256 gray levels and the well-known standard still images, Lena, Cameraman and Boat are selected.

A: Cameraman B: Lena C: Boat

Fig.2 The tested still image

The Haar filters were used in the simulation with 4-level wavelet decomposition. In this paper, the metrics time and PSNR (Peak Signal to Noise Ratio) are used to evaluate the performance. The time is used as a measure of computational complexity. The PSNR is used to determine the quality of compressed images. The PSNR for a gray scale image is defined as follows:

$$PSNR = 10\log\left[\frac{255^2}{1/M\times N\sum_{i=1}^{M}\sum_{j=1}^{N}(x_{ij}-\hat{x}_{ij})}\right] \qquad (2)$$

where are $M \times N$ the dimensions of the frames in pixels and x_{ij} and $\hat{x}_{ij}$ are the luminance components of the original and reconstructed image respectively, at the spatial location (i, j) .

5 Simulation results

The measurement criteria for comparison was PSNR which can be calculated directly from the original and reconstructed image. The simulation was done and compared with the standard JPEG compression. The simulation was tested by using the well-known benchmark images: Cameraman, Lena and Boat. The proposed algorithm can achieve very good prediction at reduced computational complexity and this section shows the performance of proposed algorithm compared with the JPEG. As seen in Fig.3 to 5 the quality of the predicted images of proposed algorithm are shown along with that of the JPEG. The results show that the performance of the proposed algorithm is better than that of the JPEG for all of the tested images. The proposed algorithm can achieve higher PSNR than that of JPEG for all three tested images.

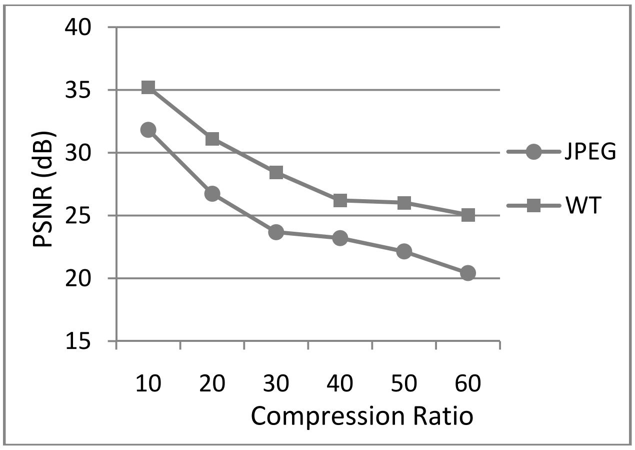

Fig.3 PSNR Comparison between JPEG and proposed wavelet technique for Lena test image

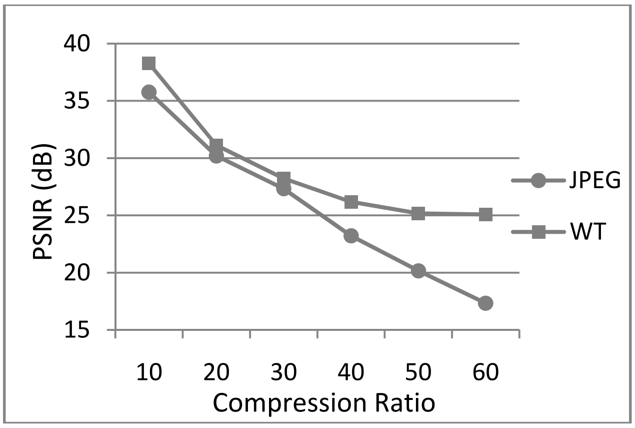

Fig.4 PSNR Comparison between JPEG and proposed wavelet technique for Cameraman test image

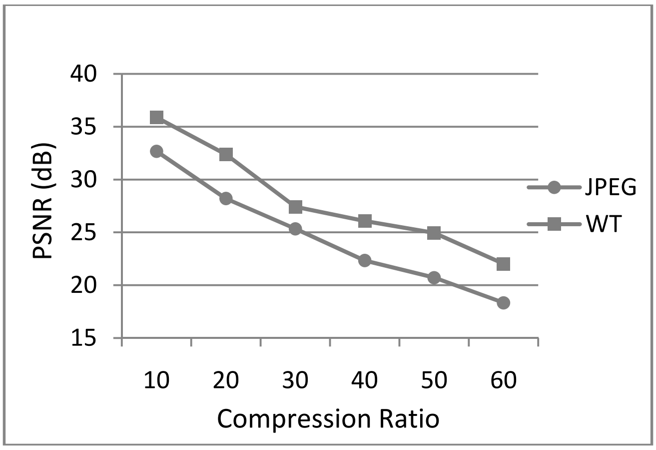

Fig.5 PSNR Comparison between JPEG and proposed wavelet technique for Boat test image

The advantage of the proposed algorithm in terms of the speed of operation (computational complexity) is more dramatic. The comparison of processing time is shown in Table 1. The processing time is the total time of the algorithm spends on encoder and decoder of each still images. As seen in table 1 the processing time of the proposed algorithm is lower for all three benchmark still images.

Table 1
The comparison of the processing time (in seconds)

Still Image	JPEG	WT-NLBG
Cameraman	10.21	6.48
Lena	11.08	7.01
Boat	11.23	7.34
Average	10.84	6.94

Table 1 shows that the average speed of operation is 10.84 seconds for the JPEG and 6.49 seconds for the wavelet transformation with the novel LBG algorithm (WT-NLBG). So the WT-NLBG is 40.13 % faster than the well-known JPEG standard.

6 Conclusion

The WT-NLBG can improve the performance of the processing times and also give a good performance in terms of the quality of the reconstructed images. The performances of the novel algorithms are simulated and the results are compared with the standard JPEG compression. Using the benchmark 512×512 monochrome still images the results show that the strength of the proposed algorithm lies in its speed of operation which is the measure of computational complexity. It is almost 40.13 % faster than the JPEG compression. The quality of the reconstructed frames of the WT-NLBG is better than that of the JPEG compression. Therefore, the proposed algorithm can be an alternative to JPEG.

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