Image Compression using Modified Haar Wavelet-Base Vector Quantization

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ABSTRACT

This research presents an image compression algorithm using modified Haar wavelet and vector quantization. For comparison purposes, a standard Haar wavelet with vector quantization and SPIHT, which is used in JPEG2000, are compared with the proposed method using Peak Signal-to-Noise Ratio (PSNR). The proposed method shows better results on average over the compared methods.

Keywords: Image compression, Haar wavelet, Vector quantization.

1. INTRODUCTION

Multimedia are used in a variety application, Type of method to store in multimedia data is an important although storage is bigger than ever. However it is not enough. Data compression particular multimedia data is an important. Vector quantization (VQ) is a method in image compression. More researcher are interest to apply Discrete wavelet transform (DWT) by using basic wavelet instead of create new block (block base method) for instance image compression in JPEG. This research combines two techniques, DWT and VQ to compress image data to produce a good encryption.

2. THEORY AND CONCEPT

This research proposes image compression using Haar wavelet by transform basic function. Haar basic using one-dimension row transform then transform column. New Haar in this research transform columnrow, row-column in all step. Using new Haar can reduce cycle to compress image and give a good result than ever. After that input data to Vector Quantization to make a good proper data to encrypt data call LBG. Its good advantage, it give high compression ratio and Codebook table to use decrypt data.

2.1 Two-dimensional Haar wavelet transforms

There are two ways we can use wavelets to transform the pixel values within an image. Each is a generalization to two dimensions of the one-dimensional wavelet transform. To obtain the standard decomposition [3] of an image, we first apply the one-dimensional wavelet transform to each row of pixel values. This operation gives us an average value along with detail coefficients for each row. Next, we treat these transformed rows as if they were themselves an image and apply the onedimensional transform to each column. The resulting values are all detail coefficients except for a single overall average coefficient. The algorithm below computes the standard decomposition. Fig.1 illustrates each step of its operation.

```
procedure Standard Decomposition
  (C:array[1..h,1..w]of reals)
     forrow← 1toℎdo
          Decomposition(C[row, 1..w])
     end for
     forcol ← 1towdo
          Decomposition(C[1..h, col])
     end for
end procedure
```

The second type of two-dimensional wavelet transform, called the nonstandard decomposition, alternates between operations on rows and columns. First, we perform one step of horizontal pairwise averaging and differencing on the pixel values in each row of the image. Next, we apply vertical pairwise averaging and differencing to each column of the result. To complete the transformation, we repeat this process recursively only on the quadrant containing averages in both directions. Fig.2 shows all the steps involved in the nonstandard decomposition procedure below.

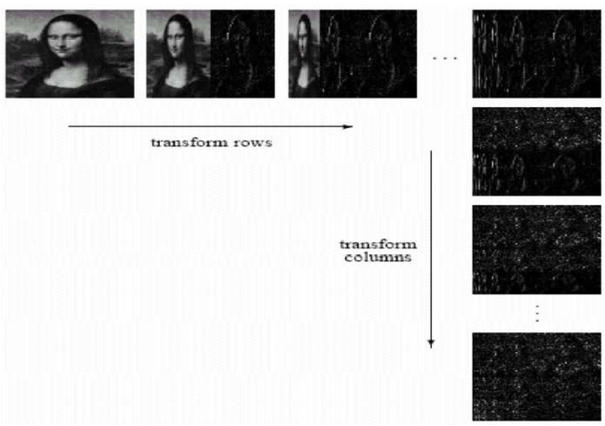

Fig.1: Standard decomposition of an image.

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```
procedure Nonstandard Decomposition
  (C:array[1..h,1..h]of reals)
        C← C/h (normalize input coefficients)
        while h > 1 do
        for row ← 1 to h do
              DecompositionStep(C[row, 1..h])
           end for
           for col ← 1 to h do
              DecompositionStep(C[1..h, col])
           end for
           h ← h/2
        end while
  end procedure
```

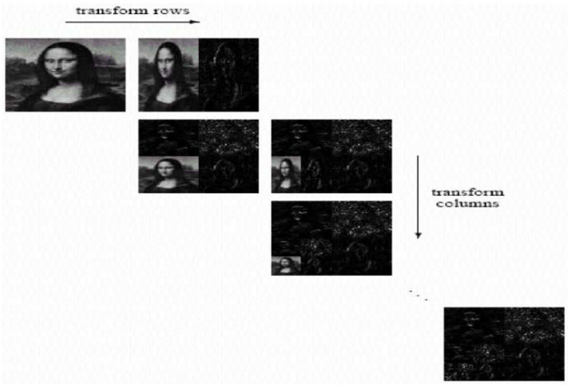

Fig.2: *Nonstandard decomposition of an image.*

2.2 Two-dimensional Haar basis functions

The two methods of decomposing a twodimensional image yield coefficients that correspond to two different sets of basis functions. The standard decomposition of an image gives coefficients for a basis formed by the standard construction [3] of a twodimensional basis. Similarly, the nonstandard decomposition gives coefficients for the nonstandard construction of basis functions.

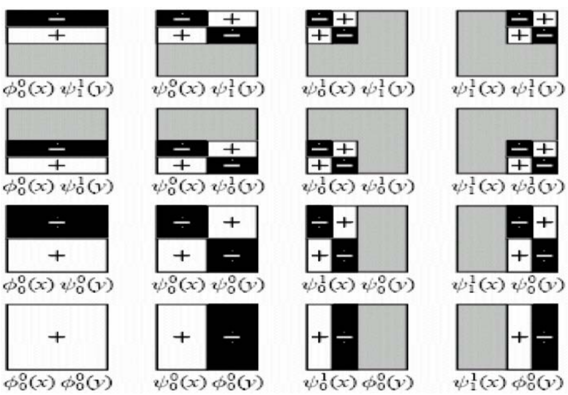

Fig.3: *Standard construction of a two-dimensional Haar wavelet basis for [V^2] . In the unnormalized case, functions are +1 where plus signs appear, -1 where minus signs appear,
and 0 in gray regions*

The standard construction of a two-dimensional wavelet basis consists of all possible tensor products of one-dimensional basis functions. For example, when we start with the one-dimensional Haar basis for V^2 , we get the two-dimensional basis for V^2 shown in Fig.3 Note that if we apply the standard construction to an orthonormal basis in one dimension, we get an orthonormal basis in two dimensions.

The nonstandard construction of a two-dimensional basis proceeds by first defining a two-dimensional scaling function,

$$\phi\phi(x, y) := \phi(x), \phi(y) \tag{1}$$

and three wavelet functions,

$$\begin{aligned} \phi\psi(x, y) &:= \phi(x), \psi(y) \\ \psi\phi(x, y) &:= \psi(x), \phi(y) \\ \psi\psi(x, y) &:= \psi(x), \psi(y) \end{aligned} \tag{2}$$

We now denote levels of scaling with a superscript j (as we did in the one-dimensional case) and horizontal and vertical translations with a pair of subscripts k and l . The nonstandard basis consists of a single coarse scaling function

$$\phi\phi0_{0,0}(x, y) := \phi\phi(x, y)$$

along with scales and translates of the three wavelet functions $\phi\psi, \psi\phi$ and $\psi\psi$

$$\phi\psi^j_{kl}(x, y) := 2^j \phi\psi(2^j\text{x-k}, 2^j\text{y-1})$$

$$\psi\phi^j_{kl}(x, y) := 2^j \psi\phi(2^j\text{x-k}, 2^j\text{y-1}) \tag{3}$$

$$\psi\psi^j_{kl}(x, y) := 2^j \psi\psi(2^j\text{x-k}, 2^j\text{y-1})$$

The constant 2^J normalizes the wavelets to give an orthonormal basis. The nonstandard construction results in the basis for V^2 shown in Fig.4.

We have presented both the standard and nonstandard approaches to wavelet transforms and basis functions because both have advantages. The standard decomposition of an image is appealing because it simply requires performing one-dimensional transforms on all rows and then on all columns. On the other hand, it is slightly more efficient to compute the nonstandard decomposition.For an m x m image,the standard decomposition requires 4(m^2-m) assignment operations,while the nonstandard decomposition requires only 8/3(m^2 - 1) assignment operations.

Another consideration is the support of each basis function, meaning the portion of each functions domain where that function is nonzero. All nonstandard Haar basis functions have square supports, while some standard basis functions have no square supports. Depending upon the application, one of these choices may be preferable to the other.

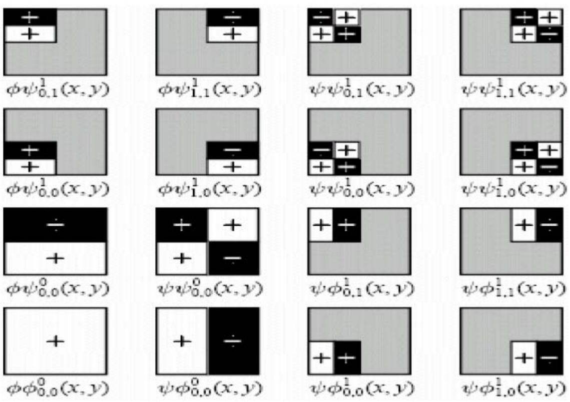

Fig.4: *Nonstandard construction of a two-dimensional Haar wavelet basis for V^2.*

Nonstandard construction of a two-dimensional Haar wavelet basis for V^2.

2.3 Vector Quantization

Image compression using vector quantization (VQ) is a lossy compression technique. It is defined as mapping Q of K-dimensional Euclidean space R k into a finite subset Y of Rk Thus.

$$Q.R^k \rightarrow Y \qquad (4)$$

Where y = (xi; i=1,2,...,N) is the set of reproduction vectors and N is the number of vectors in Y.

A vector quantizer is composed of two parts, encoder and decoder. An encoder will compare each input vector with every codevector in the codebook and generate index which represent the minimum distortion codevector from the input vector. A decoder takes the indexs to locate the codevector in codebook and generate the output vectors.

A codebook is the set of finite codevector for representing the input vector. The popular technique in codebook design is the Linde-Buzo-Gray (LBG) algorithm [4]. The whole image a partitioned into subblocks and all subblocks are used training this codebook.

3. PROPOSED METHOD

Evaluation efficient of all image compression method using standard image 512 x 512 gray scale 8 bpp Lena, Goldhill , Bridge and Camera use Peak signal-tonoise ratio (PSNR) to check similar or nonsimilar from image subbands compression Haar 3 level and input subbands data image to VQ depict in Fig.6 this research set all data in all level VQ as third wavelet level Codebook N= 256 and K = 4 , set second wavelet level Codebook N = 256 and K=16 , first wavelet level no need to encrypt cause it s not effect to efficient of compression [7] . In case of transform subband Haar wavelet we set VQ pattern as the first case

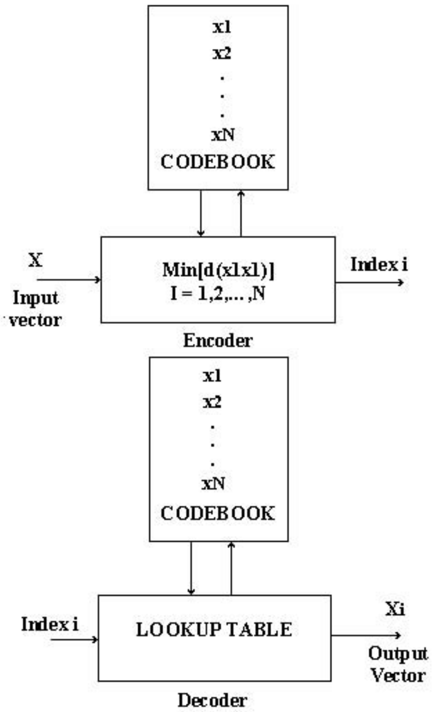

Fig.5: *Block diagram of VQ*

After compare result of subband standard Haar wavelet. Next step we compare efficient between propose method and encryption SPIHT that is use in JPEG 2000[6] by using percentage of coefficient PSNR of Lena image.

Evaluate efficient of image using Peak Signal-to-Noise Ratio(PSNR) from this equation[8].

$$MSE = \frac{1}{K \times K} \sum_{i=1}^{P} \sum_{j=1}^{P} \left(I_{i,j} - \hat{I}_{i,j} \right)^2 \qquad (5)$$

$$PSNR = 10 \log_{10} \left(\frac{255^2}{MSE} \right) dB \qquad (6)$$

KxK is summation of pixel and represent original image and result image from compression High PSNR represent that original image and compression image are similar and high efficient of compression technique

4. RESULTS

This research compare Haar standard wavelet with new Haar that modify inner structure. In this re-

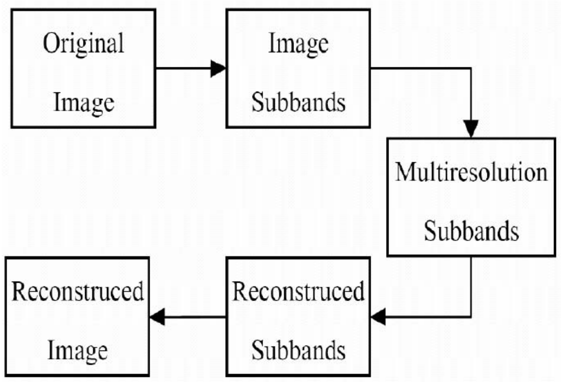

Fig.6: *Process image compression method*

search use DWT2 function in MATLAB. Standard image 512 x 512 gray-scale 8 bpp and Lena image, Goldhill , Bridge and Camera image by using image subband in first level. Results are depict in Table 1

Table 1: *Compare efficient image subband between standard Haar wavelet and Haar wavelet that modify inner structure*

Image	Standard Haar wavelet	Modify inner structure Haar wavelet
Lena	205.87	211.19
Goldhill	206.29	211.57
Bridge	206.13	211.13
Camera	205.80	211.24

Table 1 show that modify inner structure Haar give higher PSNR value than standard Haar wavelet. In this result are related to next process VQ that we use with this Haar. Depicted in table 2.

Table 2: *Compare efficient between propose method and image subband standard Haar with VQ using PSNR value to indicate efficient*

Image	Standard Haar wavelet + VQ	Propose method
Lena	39.96	67.22
Goldhill	39.97	66.29
Bridge	37.66	62.67
Camera	37.33	61.43

Table 2 show that propose method is better than standard Haar wavelet + VQ. This research transform percentage of coefficients image subband to concentrate in efficient depicted in Table 3.

Result from all table show that propose method give the best PNSR however image that high PNSR value is not mean that is s high quality in perceptual from viewer.Next is results of image compression from propose method compare with SPIHT image

Table 3: *Compare efficient propose method and SPIHT encryption using PSNR value*

% Coefficients	SPIHT	Propose method
10	38.73	54.12
20	40.19	65.52
30	41.08	66.21
40	41.81	66.66
50	42.36	66.86
60	42.75	66.99
70	43.09	67.10
80	43.42	67.15
90	43.74	67.18
100	43.99	67.22

Fig.7: *Results of image compression from propose method compare with SPIHT image*

compression using Lena image and set Coefficients of wavelet is 10

From this result show that SPIHT compression give lose of data so we can identify which is mouth and we cannot enhance this image in other method. Result from propose method image look like block cause from VQ but we can separate structure of image and we can use other method to enhance its such as Bilateral Filtering .

5. CONCLUSION

From results of image compression; 512 x 512 gray scale using PSNR to indicate efficient and quality. Propose method is better than other method (image subband standard Haar wavelet, VQ, SPIHT) that use in JPEG2000. This results is better because compression technique make it best to transform image subband Haar wavelet process. Reduce number of standard process from 4(m^2 -m) to 8/3 (m^2 - 1)from m x n image . VQ compression compress lossy data. A lot of process make lots of lose data also so propose method is best from this reason. Comparison SPIHT and propose method; propose method give the better result.

6. SUGGESTION

Propose method concentrate on quality of data from image compression using PSNR value it s not cover Compression ratio. Propose method give the good result but limited in Row and Column of image must be equal. Propose method use VQ also so it make lose of time to process for Codebook when compare encryption with SPIHT compression.

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