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JPEG2000 Image Compression Using SVM and DWT

Saeid Fazli[1], Siroos Toofan[2], Zahra Mehrara[3]
[1]Research Institute of Physiology and Biotechnology University of Zanjan, Iran
[2, 3] Electrical Engineering Department, Faculty of Engineering, Zanjan University, Zanjan, Iran
([1]fazli@znu.ac.ir, [2]s.toofan@znu.ac.ir, [3]mehrara.en@znu.ac.ir)

Abstract-Image compression has expensively been developed as an important technique in multimedia applications and communication arena. This paper presents an effective method for image compression standard based on a Neural Network system for Discrete Wavelet Transform (DWT) and JPEG2000 encoder. We employ a Support Vector Machine (SVM) algorithm to compress the coefficients of DWT more efficiently. "Daubechies 9.7" wavelet have been used to DWT and the algorithm is a combination of SVs and corresponding weights and then coefficients are quantized and encoded. Obtained proposed simulation results show that the proposed algorithm achieve better image quality than that of existing methods for a given compression ratio and an improvement in compression performance.

Keywords- *Discrete Wavelet Transform (DWT); Image compression; JPEG2000; Support vector Mechine (SVM); Regression.*

I. INTRODUCTION

The importance of image compression due to extended application of the multimedia, internet and communications field and because of limitations in storage and data transfer has abundant. In general, digital images can be compressed by removing redundancy in data. The elimination of redundancy is often performed by using some reversible linear transform coding to compacting the data.

In the recent years, image compression algorithms based on Neural Networks (NNs) has been done. One of the common methods of machine learning algorithms used in image compression is SVM algorithm. SVM has good generalization capability. Regression can achieve compression between the input and the output with learning data dependency [1]. SVM are a concerned approximation to data modeling [2]. In SVM Regression reduction of weight vector is obtained with a ϵ – insensitive loss function. This algorithm gains better compression results than combining SVM with Discrete Cosine Transform (DCT) and JPEG. J. Robinson and V. Kacman. [3, 4] approach the combination of image compression based on the DCT and SVM to obtain a better quality image compression was present. With this method, the image quality compared the JPEG standard for higher compression ratios achieved. However, the image obtained has block artifacts at higher compression ratios. [5]

The current JPEG standard has been developed based on DCT. To improve the blocking artifacts and the incapabilities in the JPEG standard, the JPEG2000 standard has been developed based on the instructions of DWT instead of 8 × 8 block based DCT. A characterize image compression method based on how the image characteristics are handled. The main difference between DWT and DCT is DWT unlike the DCT is applied to whole image where DCT is applied to subblocks. Therefore, applying DWT the blocking artifacts can be reduced [6]. The DWT technique helps to make one both the lossy and lossless compression and decompression into the same algorithmic stage [7].

In this paper a method based on the two – dimensional (2D) DWT and SVM algorithm to obtain better results is presented.

The remainder of this paper is structured as follows: Section II discuses 2D – DWT and theory used in proposed image compression. Section III describes SVM Regression. Section IV presents the proposed method. Section V shows experimental results; finally section a brief description of conclusion and further work is given.

II. APPLIED IMAGE COMPRESSION TECHNIQUE

JPEG2000 standard to overcome the shortcomings of the jpeg standard has been developed based on DWT and this standard are still in progress.

In this section we briefly describe the basic encoder used in JPEG2000 algorithm and overall 2D – DWT composition. The block diagram of encoding procedure for JPEG2000 algorithm is shown in Fig. 1. As is shown in Fig. 1 (a) pre – processing step, which is done in disparity – compensated (DC) level shift, Forward Component Transformation (FCT) and division of components into tiles. Compression generally consists of three stages: Tile – component division into DWT coefficients step, the next step is quantization of the DWT Coefficients and finally, the entropy coding is executed. [6]

After preprocessing step, using Daubechies (9, 7) biorthogonal spline filter to transform, each tile is decomposed into the 2D – DWT. Choose the number of levels of 2D – DWT can be defined according to the application and quality at higher compression ratios.

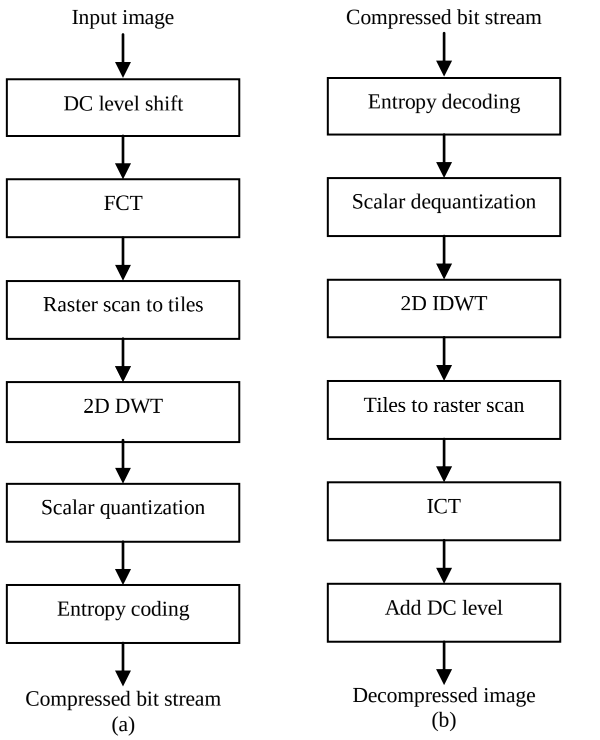

Figure 1. Block diagram of encoding procedure for image compression based on DWT. (a): compression; (b): decompression

A. DWT

Transform coding and DWT – based compression is executed to each tile. Wavelet decomposition is based on the filter bank structure which can be executed repeatedly by continuous filtering. By means of using Daubechies's wavelet each tile into the horizontal and vertical directions, it can be expended for 2D image. Filter bank for first – level image decomposition is shown in Fig. 2 (b).

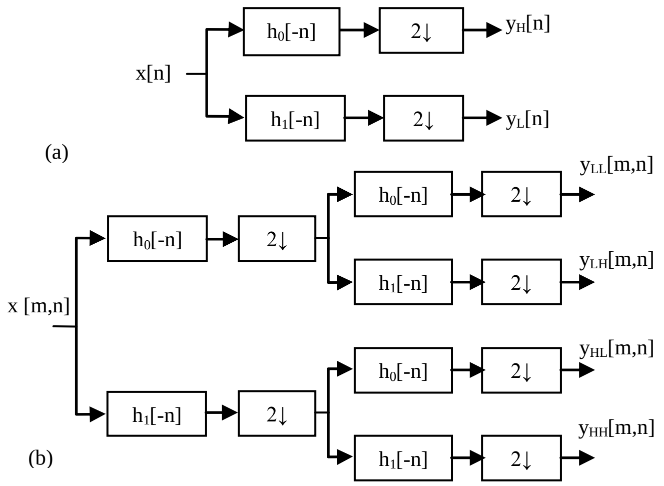

Figure 2. Computation of a one - level DWT via subband coding scheme: (a): 1D DWT; (b): 2D DWT

With 2D – DWT, the image is decomposed into four blocks as shown in Fig. 3 (a). The lower frequency subband includes approximation coefficients and high frequency subbands include the detail information, which consists of HL, LH and HH coefficients. Approximation coefficients have most of energy of the DWT coefficients, which is the coarser approximation of the input image. HL, LH and HH coefficients correspond to high pass in horizontal, vertical and diagonal orientation.

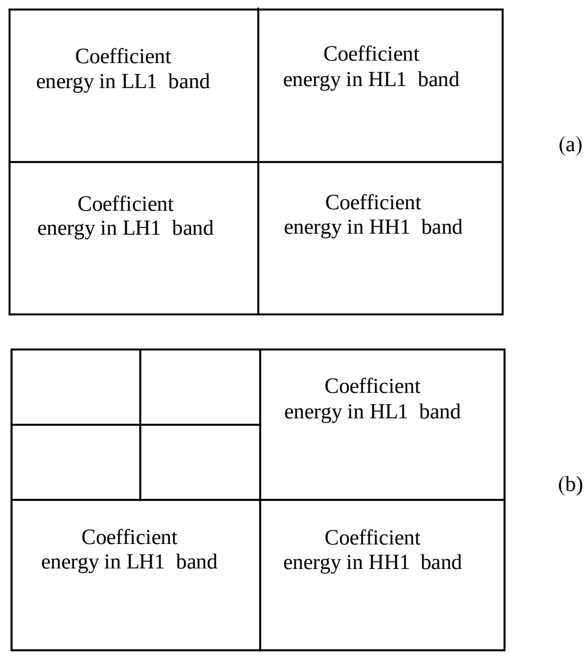

Figure 3. 2D - DWT (a): first - level decomposition; (b): second - level decomposition.

The LL1 can be decomposed into four subbands as shown in Fig. 3 (b), which is a shown approximation and detail coefficients placement in the two – level DWT. This process can be continuing to achieving to the desired level.

B. Quantization and Entropy

After DWT, all wavelet coefficients obtained from the 2D – DWT decomposition are quantized using scalar quantizer with dead zone for decrease the precision of subbands to assist in obtaining compression.

The uniform scalar quantization with a dead-zone for a coefficient in a produced subband is defined in following equation:

$$X_{qb}(u, v) = \text{sign}\,(X_b(u, v)) \lfloor |X_b(u, v)| / Q(b) \rfloor \tag{1}$$

Where the *Q (b)* in equation (1) is the quantization step size for the subband *b* based on the dynamic range of the subband values. The *Q (b)* is calculated from [8]

$$Q(b) = 2^{Rb+gb-\varepsilon b}(1 + \mu b/2^{11}) \quad (2)$$

Finally generation of compressed bitstream is achieved in entropy coding of the quantized DWT coefficients.

III. SVM REGRESSION

In this part we will introduce an overview of the SVM Regression algorithm and its advantages for image compression. Support Vector Machine (SVM), as a particularly useful method of data compression and function estimation has been used for solving multi – dimensional problems and estimating regressions [9].

SVM introduced by Vapnik [9] is a useful method for regression, which is based on constructing relationship between input data and output data from the given training samples (x_1, y_1), (x_2, y_2), …, (x_l, y_l), where $x_i \in R^n$ and $y_i \in R$ and a nonlinear mapping to a higher dimensional space, to achieve compression. The regression problems can be modeled as follow:

$$f(x) = \sum_{i=1}^{N} w_i \phi_i(x) + b \quad (3)$$

Where is the feature that is non - linearly mapped from the input space, b is a bias, w_i is support vector (SV) weight, N represents the total number of data samples, and the general kernel function of SVM is Gaussian.[5]

Several loss functions have been used for minimizing weight vectors in the problems of regression estimation. These include Quadratic, Laplace, Huber and ϵ – insensitive loss function.

In this paper Vapnik's loss function $|y - f(x)|$ is used, as illustrated in Fig. 4, which is known as ϵ – insensitive loss function, error can be defined as:

$$error = \xi = |y - f(x)| = \begin{cases} 0 & ,for\ |f(x) - y| \le \varepsilon \\ |f(x) - y| - \varepsilon & ,otherwise \end{cases} \quad (4)$$

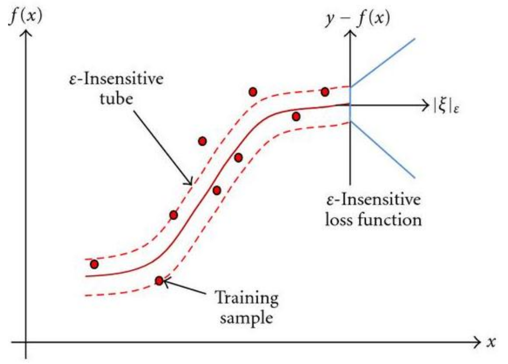

Figure 4. Structure of proposed image compression algorithm

The loss equals zero if the predicted value is within the ε-tube, as indicated in (4), which ϵ is used to fit the training data [10]. If value of the ϵ increases, the number of SVs becomes smaller number and then the higher compression ratio can be obtained.

IV. PROPOSED METHOD

This method is based on using SVM to compression 2D - DWT coefficients, which SVM Regression is used to achieve minimum number coefficients of the wavelet transform. At first, the input image are performed DC level shift by subtract 128 (input image has 8 bits/component), from each pixel. After preprocessing, tiling is performed on whole image. Decomposition image to achieve wavelet coefficients by applying Daubechies (9, 7) FIR filter bank to each tile is following step. To reduce minimum number required of details coefficient, the SVM regression is applied to all finer wavelet subbands that containing details coefficient and then immediately compression obtained by combining the SVs and corresponding weight together. Then this weight vectors are quantized and entropy coding follows quantization, run-length wavelet encoder (RLW) and Huffman coding to be used along with the proposed transform.

In order to achieve higher compression, the highest level DWT coefficients are encoded by Differential pulse code modulator (DPCM) [6].

The algorithm of encoding is consists of the following procedures:

1) preprocessing of original image (DC level shift)
2) raster scan tiling
3) application of 2D – DWT on each tile as an image using 9/7FIR filter bank
4) application of SVM regression to all the wavelet subbands that containing details coefficient
5) combine the SVs and corresponding weight together
6) scalar quantization
7) encoding

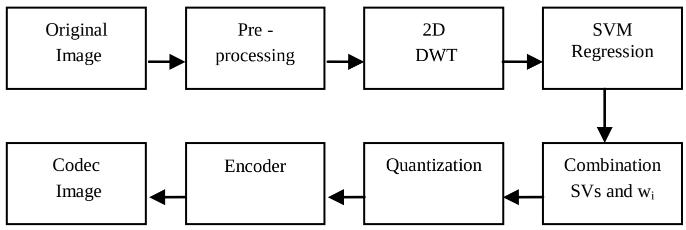

Figure 5. Structure of proposed image compression algorithm

And decoder is reverse of encoding procedures. The structure of the decoder is basically the same as for the encoder. The bit stream is decompressed by decoder and then dequantization procedure is performed. After dequantization, the coefficients are inverse transformed to spatial domain data via inverse DWT (IDWT) and generate the tiles. After inverse 2D – DWT, 128 must be added to the reconstruct the decompressed data. [8]

V. IMPLEMENTATION AND RESULTS

The gray – scale benchmark images of size 512 × 512 (listed in Table 1) has been used to demonstrate this algorithm. The image is tiled into 128 × 128 none - overlap blocks or the entire image may be given as one block. We perform 5 level 2D – DWT on each tile, which is usually used to arrive quality and bit rate. We used Daubechies (9, 7) FIR filter bank for wavelet decomposition of image. Because of the low – frequency subband is a coarser version of the original image, the approximation coefficients have to be quantized by using DPCM. The detail coefficients that applying SVM regression to all have to be generated SVs and corresponding weights, then the SVs and weights have to be combined and quantized using scalar quantization and Huffman coding along with RLE is used to achieve the bit stream. Gaussian Kernel is chosen as the Kernel function in our implementation. Decoder process is reverse of encoding process.

The comparison of compression ratio of the proposed algorithm is shown in Table I, which presents PSNR (dB) and compression ratio of different test images compressed by algorithm designed using SVM regression; it is observed that our algorithms for image compression resulted in better PSNR values with better visual quality of the reconstructed image as compared to existing algorithm.

Fig. 6 gives a visual impression of the increase in image quality obtained by using SVM learning to combine with 2D – DWT for image compressing.

TABLE I. EXPERIMENTAL RESULTS COMPRESSION RATIO AND PSNR(DB)

image	Our algorithm		Jpeg2000 standard		Jpeg standard	
	CR	***PSNR***	***CR***	***PSNR***	***CR***	***PSNR***
cameraman	34.65	20.28	34.44	20.67	38.87	12.45
building	37.39	20.17	33.37	19.85	36.11	13.56
Lena	33.39	18.28	32.56	21.87	35.53	11.36
living room	32.67	21.56	30.68	11.36	33.34	8.30
mandrill	29.84	18.46	29.53	9.91	33.15	6.34
pirate	32.43	20.40	30.38	11.84	32.79	8.48
Tracy	38.24	19.36	42.15	36.94	18.41	40.40
Woman blonde	33.39	20.24	29.26	12.67	18.00	9.30
Woman dark hair	37.38	20.89	36.13	37.33	39.74	15.86

VI. CONCLUSION

Table I. shows that our algorithm is much more compression ratio than that of usual compression algorithms. In this article, new compression algorithm based on the SVM approach is proposed. Fig. 6 Shows reconstructed test image with different compression algorithms that gives a visual impression of the increase in image quality achieved by our algorithm. The future work for development of proposed algorithm is an extension to color images and video.

(a) Original Image

(b) Existing JPEG2000 standard
CR: 32.56

(c) Existing JPEG standard
CR: 35.53

(d) Proposed model
CR: 33.39

Figure 6. Comparison image quality

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