Image compression based on Wavelet Support Vector Machine Kernels

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***Abstract- In* this recent multimedia world, the major challenges are the optimized use of storage space and Bandwidth. Compression plays the crucial role to reduce the storage space of images and transmission of information with limited Bandwidth availability without degrading the quality of image. Inorder to fulfil the above demand, in literature various compression algorithms were proposed for different applications. In this paper, we evaluated the performance of Wavelet Support vector machines (WSVM) with different combinations of kernel function and wavelets.SVM regression is applied to wavelet coefficients inorder to approximate the obtained coefficients from wavelets so that better compression can be achieved by removing the additional redundancy. From training data and realized compression, Support Vector Machine Regression (SVMR) has the possibility to learn about the dependency by the use of support vectors inorder to represent the real data and to eradicate redundancy. .Run-length coding is used to encode the support vectors and its corresponding weights, obtained from the SVM regression. Performance evaluation of WSVM is done in terms of compression Ratio, MSE and PSNR Experimental results shows that the compression performance can be improved with rbio4.4 combined with RBF kernel gives high compression ratio without loss in the image quality**

Keywords- Discrete Wavelet Transform (DWT), Support Vector Machines (SVM), SVM Kernels, Compression Ratio

I. INTRODUCTION

Image processing deals with processing of images in digital form. Normally digital images require more storage space and bandwidth for transmission. Due to demand in bandwidth and to achieve less storage space we go for image compression.

Image compression is a technique used for sinking or minimising the number of bits required to represent the image without corrupting the quality of an image. **.** Image compression is an effective tool to transmit data in efficient form by reducing the irrelevance and improving the redundancy

In earlier period international standards like JPEG is used for compressing still images JPEG uses DCT (Discrete Cosine Transform) based encoder and decoder for transforming the images from one form to another though it gives better compression ratio it results blocking artifacts at lower bit rate [1]

In recent years machine learning algorithms like SVM (Support Vector machine) and Relevance vector machines are often used for image compression. Robinson et al [2] Presented a novel based image compression algorithm which combines DCT along with SVM (Support Vector Machines) it results in better quality when compared with JPEG whose compression ratios are greater than 30:1 but reconstructed image results in blocking artifacts particularly at higher compression ratio.

For past few years Discrete Wavelet Transform (DWT) is used for image compression which is a powerful technique for compression than DCT due to its multi resolution feature, scalability and flexibility. Jio [3] suggest a compression method by combining Discrete Wavelet Transform along with SVM, it is observable that it removes blocking artifacts and the quality of the image gets improved. Wavelet Transform segregates the information present in the image into approximate and detail signals. The approximation signals display pixel values of image and detail signal displays the horizontal, vertical, and diagonal details of an image. More over wavelets provides transaction between frequency and time localization [4]. Based on this SVM is applied on the wavelet coefficients for further compression by removing the redundancy which results in better quality of image and higher compression ratios.

The main objective of this paper is to investigate the effect of wavelet for image compression along with machine learning algorithms with different types of kernels

II. MATERIALS AND METHODS

A. software:

MATLAB7.0.

B. Discrete Wavelet Transform (DWT)

Wavelets**:** It is small wave obtained from mother wavelet, i.e. all functions are generated from the mother wavelet by scaling and shifting property. It provides localisation in both time and frequency. When compared with Fourier Transform, DWT has increased popularity in image coding [4]. Similar to that of Fourier decomposition approach Wavelet Transform decompose complex signals into sum of basic functions. Decomposition of image using wavelet transform is computed using the concept of filter banks. It consists of high pass and low pass filter. The decomposition of images consists of two parts detailed coefficient part (high frequency component) and approximate coefficient part (low frequency component). Fig.1 shows the four level decomposition of image using wavelet Transform.

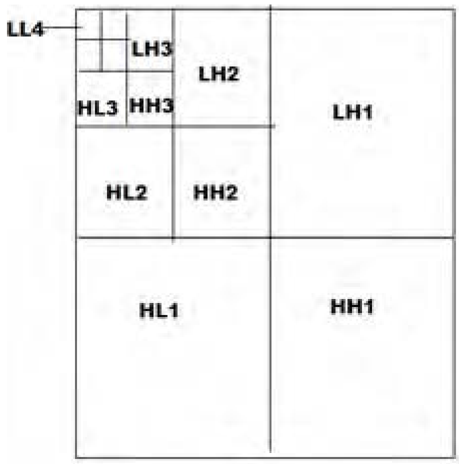

Fig. 1: Sub-bands of 2D Discrete Wavelet Transform

From Fig.1 LL1, HL1,LH1 and HH1 represents one scale decomposition of wavelet transform on continuous decomposition we get 4 sub bands , LHD+1, HLD+1,LLK+1,HHD+1 (D ranges from ($1 \leq D \leq 4$). The benefit of wavelet transform is it performs Multi-resolution Analysis (MRA) of an image. Another important feature is compaction of energy i.e. energy conservation. The sum of the squares of the transform coefficient is equal to the energy of the wavelet transform .This energy is alienated among detail and approximate coefficients but there is no change in total energy, Still loss of energy will takes place during compression this is because of changes in coefficient values due to thresholding.

C. Wavelet coefficient extraction for further compression using SVM:

In discrete wavelet transform normally most of the energy will be concentrated in the low-frequency part of transformed image, so the high- frequency component alone is taken as consideration for further compression by removing the redundant data using SVM regression.

Due to good generalization ability, the support vectors can be obtained through SVM by learning the original data and the original data can be regressed. Kernels also play a major role to reduce the redundancy. In literature the available kernels for SVM are Polynomial kernel, gauss kernel, linear kernel, Radial basis function. With the combination of the kernels; further redundancy can be reduced as much as possible. Reverse biorthogonal 4.4 is applied to the image, it decomposes the given image into low frequency (approximate coefficients) and high frequency components (detail coefficients). The high frequency component represents the details of diagonal, horizontal and vertical of the decomposed image. After wavelet decomposition ,we have to take out the data from the available data and have to train with SVM, for training the data, scanning of data also plays a major role . Original data can be obtained by combining vertical scan, level scan and diagonal scan for extracting the original data.

III. IMAGE COMPRESSION USING SVM

SVM is a machine learning algorithm which has been comprehensively used for solving the problems of pattern recognition, classification, and regression. Regression is nothing but expansion of classification. One of the advantages of choosing SVM is that it's performance is optimized with the proper selection of kernel function for the given data. SVM helps to reduce or decrease the number of parameters used to represent the data with all essential information. In Regression by selecting the lowest number of training points from the given set of training points, it's real function can be approximated within a predefined errorer, these chosen lowest training points are termed as support vectors, and these support vectors along with their weights are encoded, hence compression of data can be accomplished by SVM regression.

The regression problem is given by

$$f(x,w) = \sum_{i=1}^{N} W_i \quad {}_i(x) \qquad (1)$$

The input-output function or it's relationship can be obtained from the given set of training points (x_1, y_1), (x_2, y_2)............. (x_i, y_i) where $x_i€R^n$ and y_i€R,

N Indicates support vectors

W_i Indicates weights to be found

${}_i$(x) Indicates kernels

In case of regression the error is defined as a measure of error between f(x) and y it is given by

$$\text{Error} = |\, f(x,w) - y| = \begin{cases} 0 & if\ |y - f(x,w)| \leq \\ |y - f(x,w) - & if\ |y - f(x,w)| > \end{cases} \qquad (2)$$

If $f(x,w)$ and y is less than then the error is equal to 0 otherwise the error is equal to

$y - f(x,w) -$

From this we come to know that, larger the er value, smaller the number of support vectors, we can achieve higher compression ratio.

A. Kernel function

Support Vector machine (SVM) is a dot product kernel, the function of kernel is to map the low dimension space into high dimension space, then it's target data can be classified by using the hyperplane. SVM kernel function must satisfy the Mercer's conditions [6]

Conditions:

$$g(x) \in L_2(R^n)\,, k(x,x') \in L_2(R^n\, X\, R^n) \qquad (3)$$

If

$$\iint k(x,x')g(x)g(x')dxdy \geq 0 \ \text{ then } \ (x,x') = ((x).(x')) \qquad (4)$$

Where k represents the inner product

In the literature of SVM, the available kernels are polynomial kernel, gauss kernel, radial basis function, linear kernel, sigmoidal and so on. These kernels should satisfy the Mercer's condition to be used along with SVM

1) *Polynomial kernel:* It's function is given by

$$k(x_i\,, x_j) = [(x_i\,, x_j + 1]^q \qquad (5)$$

q- Degree of polynomial,

It has good and strong ability to forecast the lower degree

2) *Linear Kernel :* it is the simplest kernel function, it is given by

$$k(x,y) = x^T + C \qquad (6)$$

(x,y) is the inner product, C is constant

3) *Gaussian Radial Basis function :* it's function is given by

$$k(x_i\,, x_j) = \exp\,(\frac{-|x_i - x_j|^2}{\sigma^2})$$

This function gives the specific information about the local data, if the parameter increases it's forecat ability will get decrease.

4) *Sigmoidal Kernel:* it's function is given by

$$k(x_i\,, x_j) = \tanh\,(v(x_i\,, x_j) + C \qquad (7)$$

The experimental outcome shows the power of the WSVM learning algorithm and results are computed by comparing the kernels which are mentioned above.

IV. METHODOLOGY

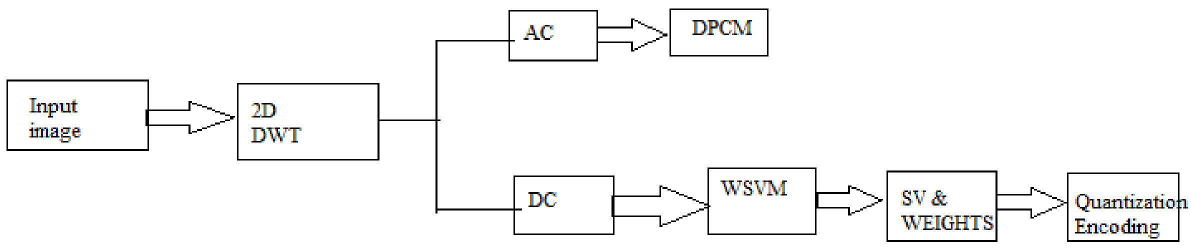

Fig 2. Block diagram of proposed methodology

It shows the block diagram of proposed algorithm. Input image – standard 256* 256 image Input image is decomposed by means of Reverse Biorthogonal 4.4 (rbio4.4 DWT) wavelet into Approximate and detailed co-efficient by employing Discrete Wavelet Transform (DWT). DWT is applied to each row and column of the image to get AC and DC co-efficient. The approximation signals display pixel values of image and detail signal displays the horizontal, vertical, and diagonal details of an image. The unwanted minimum information's are then removed by means of quantization. Further encoding is employed to balance the influence caused by the result of co-efficient that are eliminated by quantization to maintain the image quality.

A. SVM to regress the wavelet coefficients: After decomposing the image into subbands, each subband represents the image in different frequency range. Most of the energy will be compacted in lowest frequency subbands as it is sensitive to human eyes, it helps to reconstruct the image and it is lossless, by using DPCM (Differential Pulse Code Modulation) these lossless images is encoded.SVM regression is used to compress other subbands which represents the finer details, this SVM regression is applied to each coefficients of finer detail subands to approximate the wavelet coefficients using support vectors and weights

B. Compression of Wavelet coefficients: DWT is applied to the input image, it transforms the image from one domain to another, it removes the redundancy to increase the performance of compression. Though wavelet removes the redundancy there is still redundancy present between the coefficients of wavelet, inorder to remove the existing redundancy further and to increase the compression performance WSVM. WSVM helps to achieve better compression ratio by compressing the wavelet coefficients by removing the redundancy between the coefficients. The input and the desired output for WSVM regression is position of the wavelets and the coefficient values. Proper scanning order is to be followed for mapping coefficient block to produce one dimension vector for training the data in SVM regression, besides this choosing of kernel also plays a major role to achieve better compression performance. After training, we obtain support vectors and it's weights as output it should be quantized and encoded.

V. RESULTS

This algorithm is implemented on gray scale image of size 512 x 512. Compression results are compared with each kernel; it is clear that RBF kernel outperforms with other kernels whose compression ratio is high. It is clear that redundant datas have been removed, and the quality of the image gets improved.

TABLE 1
Results for the image Lena compared with different kernels

Picture name	Wavelet	Kernel	Compression Ratio
Lena(512 x 512)	Reverse Biorthogonal(4.4)	RBF Kernel	38.2%
		Polynomial Kernel	31.3%
		Linear kernel	24.3%

VI. CONCLUSION

Wavelet is a tool; it can separate the given input image into low- frequency and high-frequency data. SVM, and machine learning algorithm used for solving the problems in classification, pattern recognition, regression and so on, which has fine approximation capability and generalization ability. From simulation results, we compare different types of kernels; the importance of kernel is to get better quality of the image following SVM compression. Experimental results shows that RBF kernel function performs well when compared with kernel function whose compression ratio is high and better quality of image can be obtained through RBF Kernel.

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