Performance Analysis of Image Coders, ANN, DTCWT

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-----ABSTRACT------

Data compression plays a very important role in storage and transmission of information. High storage and transmission requirements leads us to develop better digital image compression techniques. The wavelet analysis like Discrete Wavelet Transform (DWT) alone does not actually compress a signal. Therefore there will be need of the coding techniques along with wavelet analysis of an image in order to compress the data. The problems of Discrete Wavelet Transforms can be overcome with the uses of Dual Tree Complex Wavelet Transform (DTCWT). Proposed work uses the encoding techniques like Neural networks can helps to train the data in efficient ways without missing any information and it also helps to handle noisy data or missing data. Continuous training of neural networks helps in produce efficient transmission and also to produce generalized solutions. It also helps in reducing non-linearity. Proposed algorithm has been designed and tested with different quality image and analysis has been carried out in MATLAB.

Keywords: DWT, DTCWT, Neural Networks and RNN.

I. INTRODUCTION

Satellite image is considered as Multilayer Image which is form by stacking" the images taken by different sensors from the same area at various wavelengths together [1]. Each component image forms a single layer of the multilayer image. Better characterization and identification of objects can be obtained with specific and accurate spectral information. But sizes of such images are very large ranging from few megabytes to some gigabyte. So it is very expensive to store and slow to manipulate and transmit such huge amount of data. Hence there is need of compression. Image compression techniques are capable of substantially reducing image data, decreasing the costs, and improving user interaction with the information.

Compression is nothing but removing redundancy and irrelevancy present in the image. Redundancy reduction means removing duplication from the signal source (image/video).Redundancy can be Spatial (correlation between neighbouring pixel values), Spectral (correlation between different colour planes or spectral bands) or Temporal (correlation between adjacent frames in a sequence of image).Irrelevancy reduction omits parts of the signal that will not be noticed by the signal receiver. The research of image compression aims at reducing the number of bits required to represent an image by removing unnecessary as much as possible.

This paper mainly focuses on developing better compression algorithm and also helps to remove non linearity of the images. This paper discusses about proposed work and analysis using MATLAB and also discusses about performance characteristics to prove the efficiency of the proposed algorithm

II. PROPOSED WORK

The problems of Discrete Wavelet Transforms can be overcome with the uses of Dual Tree Complex Wavelet Transform (DTCWT). Shift invariance, computational efficiency and good directional selectivity properties of DTCWT make it a good and efficient algorithm for image compression. This paper proposes better encoding techniques like neural networks can helps to train the data in efficient ways without missing any information and it also helps to handle noisy data or missing data. Continuous training of neural networks helps in produce efficient transmission and also to produce generalized solutions.

A) DTCWT

The standard DWT is a very powerful tool for many signal processing applications. But it suffers from three major limitations i.e. shift sensitivity, poor directivity, absence of phase information. DTCWT is also one of the alternate transform to reduce these limitations of standard DWT. The DTCWT for 2-D image is obtained by separate filtering along rows and then columns. However, if row and column filters both suppress negative frequencies, then only the first quadrant of 2-D signal spectrum is obtained. The most computationally efficient way to achieve a pair of conjugate filters is to maintain separate imaginary operator j1 and j2 for row and column processing as in fig 1 The input image X is decomposed into eight sub bands as shown in Fig. 1, the first stage consists of row processing, and the second stage consists of column processing filters.

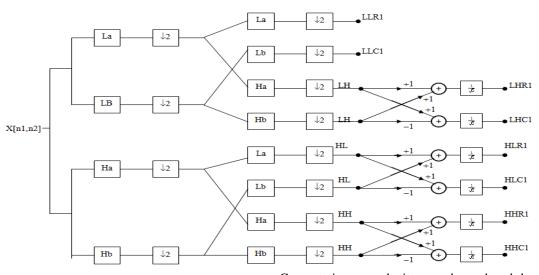


Fig. 12-D Dual- tree complex wavelet transform (2 level)

Computation complexity can be reduced by using the butterfly structure of DTCWT, which is developed with sign inversion and 2's complement operation. The division operation at second stage is replaced with the threshold operation. The proposed architecture performs 3 levels decomposition along with neural networks of the input image.

N/2 x N/2

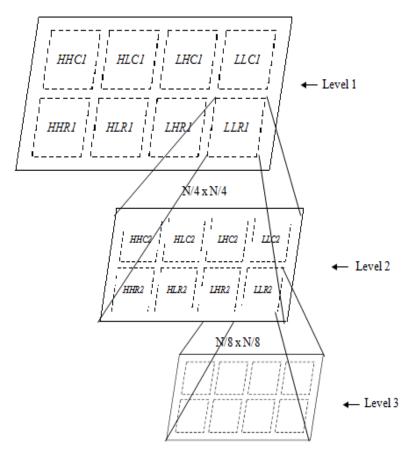


Fig. 2Pyramid structure of DTCWT

The two LL real and complex sub band capture the low frequency components. The decomposed sub bands are in pyramidal form and are organized in a hierarchy as shown in fig. 2. The six wavelets defined by oriented shown above have the sum/difference operation is ortho normal, which constitutes a perfect reconstruction wavelet transform. The imaginary part of 2D DT-CWT has similar basis function as the real part. The 2D DT-CWT structure has an extension of conjugate filtering in 2D case.

As there are eight sub bands at each level, each capturing the features at different frequency resolutions.

coefficients from the LL band are identified. The features selected from LL band comprises of significant features at that level.

B) Recurrent Neural Networks

A computing system is made up of a number of simple, highly interconnected processing elements and they process information to external inputs with their dynamic state response. A neuron has the ability to produce a linear or a non-linear response. A non-linear artificial network is made by the interconnection of nonlinear neurons. Non-linear systems have inputs which will not be proportional to outputs.

1) Decoder

The Recurrent Neural network is a form of neural network which performs conditional probability of the given input sequence to generate the output sequence. Here the output sequence analysis is done without assumption of fixed alignment. O and T are the lengths of input and output respectively. The lengths of input and output may be different.

The idea of this approach is to produce a hidden representation for the given input sequence and to produce the output y0. Decoder computation is done based on previous output symbols and the context vector

$$\begin{array}{c|c} P(y_{1,\dots,y_{0}} & | & x_{1},\dots,x_{T} &) = \\ \prod_{o=1}^{O} p(y_{0}|y_{1},\dots,y_{0-1},c_{0}) & (1) & \end{array}$$

3) Model Training

Model training is done on given input and output sequence. Model training helps to generate the hidden representations of the sequence. The model of overall trained data can be trained by maximizing the average likelihood as

C) PROPOSED ARCHITECTURE

Fig. 3 shows the proposed architecture. Input images of different pixel values are considered which is in RGB format and hence three intensities has to be provided for each Red, Green and Blue component, so it contains more information. In order to reduce the information the The proposed work estimates the features from all sub bands and the best feature is selected for registration. The LL sub band at level three is considered for feature selection, gradient along the rows and columns is estimated using the sobel operator. The maximum gradient along each row and column is selected by comparison. The maximum gradient point indicates the presence of significant feature at that point in an object. The gradient map is computed from the maximum points obtained and are combined to obtain combined gradient map. From the gradient map estimated, the corresponding approximation

The probability of the output P(yo,y1; :::; yo-1) is dependent on the previous outputs and also the context vector of the input sequence. Recurrent Neural Network can be used to find the probability which remembers the history of previous recurrent layers.

2) Encoder

The conditional probability computation depends on the availability of the information vector co for each output sequence. The context vector is generated from the encoder which generates space representation in continuous form by reading the input. The context vector co is generated by all hidden representations of recurrent neural network in form of the weighted average.

$$c_0 = \sum_t \alpha_{0t} h_t \quad (2)$$

Where
$$\alpha_{0t} \in [0,1]$$
 and $\sum_t \alpha_{0t} = 1$;

 $h_t = (\overrightarrow{h_t}, \overrightarrow{h_t})$ and $\overrightarrow{h_t}, \overrightarrow{h_t})$ denote the hidden representations of forward and backward recurrent neural network. The context vector is universal, for instance, $c_0 = h_T$. The context vector does not depend on the zero index. Zero index means the entire input sequence is encoded in fixed format. Recurrent Neural Network approach has given positive results in machine translation and also in artificial intelligence.

$$\widehat{\mathcal{M}} = \arg \max_{M} \frac{1}{N} \sum_{n=1}^{N} log P(y_1^n, \dots, y_0^n | x_1^n, \dots, x_T^n, \mathbf{M})$$
(3)

M represents the set of model parameters, and N is the number of trainings.

image is converted into grayscale , in which the only colors are shades of gray and it is the one in which the R,G and B components will all have equal intensities and only a single intensity value is provided. The matrix form of the image is converted into serial signal form to be provided to DTCWT. DTCWT employs two real DWTs; the first DWT gives the real part of the transform while the second DWT gives the imaginary part. The analysis and synthesis filter bands used to implement the DTCWT. The two real wavelet transforms use two different sets of filters, the two sets of filters are jointly designed so that the overall transform is approximately analytic. LaLa, LaHa denotes the low-pass/high-pass filter pair for the upper filter band, and LbLb, LbHb denotes the low-pass/high-pass filter pair for the lower FB. The LaLa component is considered for further processing as it provides higher quality and accuracy compared to other components.

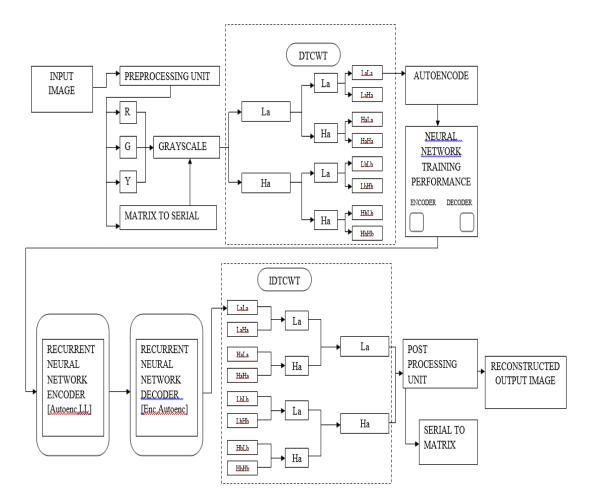


Fig. 3 the proposed architecture

Neural networks provide adaptive learning and real time operation and it is latest type of coding technique. Before the encoding procedure starts the neural network is trained, to start this process initial weights are chosen randomly and training procedure starts. We are using supervised training procedure which involves a mechanism of providing the network with the desired output either by manually grading the network's performance or by providing the desired outputs with the inputs. The network processes the records in the training data one at a time using the weights and functions in the hidden layers, then compares the resulting outputs against the desired outputs, errors are then propagated back through the system causing the system to adjust the weights for application to the next record to be processed. The training is performed for 1000 iterations. The neural network toolbox of MATLAB is utilized for the procedure, it includes command line functions and graphical tools for creating, training and simulating neural networks. The performance graph is plotted.

The output from the training neural network is utilized along with the LaLa component from the DTCWT for the encoding procedure. The matrix structure of LaLa component is combined with the trained auto encoder output for the encoding procedure. The encoded output along with the auto encoder trained output is utilized for the decoding procedure.

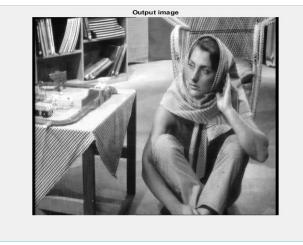
The decoded output obtained is further provided to the inverse DTCWT. The inverse of each of the two real DWTs are used to obtain two real signals. These two real signals are then averaged to obtain the final output. The original signal can be recovered from either the real part or the imaginary part alone. The output signal obtained from IDTCWT is given to the post processing unit where the signal is converted from serial form to matrix form to obtain the original reconstructed image.

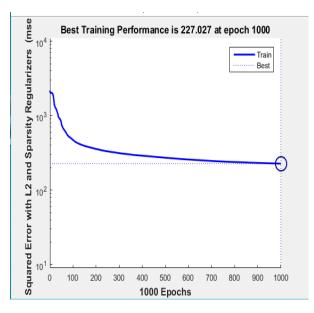
III. RESULTS AND ANALYSIS

Fig. 4 shows the input gray scale image and reconstructed image using proposed algorithm

Grayscale image	📣 Neural Network Training (nntraintool) — 🗆 🗙		
	Neural Network Encoder Decoder Output b 256 25 256 256		
	Algorithms		
	Data Division: Training Only (dividetrain) Training: Scaled Conjugate Gradient (trainscg)		
	Performance: Mean Squared Error with L2 and Sparsity Regularizers (msesparse)		
	Calculations: MEX		
	Progress		
	Epoch: 0 1000 iterations 1000 Time: 0:00:13 1000		
	Time: 0:00:13 Performance: 2.18e+03 227 0.00		
	Gradient: 183 19.5 1.00e-06		
	Validation Checks: 0 0 0 6		
	Plots		
	Performance (plotperform)		
	Plot Interval:		
	Maximum epoch reached.		
	Stop Training Cancel		

Fig. 4 Grayscale input image and reconstructed image using DTCWT





Encoding and decoding is performed after training the image using different epochs. In neural networks training is done for the LaLa component which is obtained from DTCWT for 1000 iterations which is as shown in fig. 5.

Fig. 5 Neural Network Training of propose compression technique and its performance characteristic of 1000 epochs Table 1 shows the PSNR, SNR and CR values for different test images. The proposed algorithm provide better compression ration as shown.

IMAGE	IMAGE SIZE	PEAK SIGNAL TO NOISE RATIO (PSNR)	SIGNAL TO NOISE RATIO (SNR)	COMPRESSION RATIO (%)
A	1920x1080	37.7080	27.2171	99.0782
В	960x640	40.1419	32.0849	97.3333
С	720x576	38.1962	28.1936	95.3909
D	555x340	45.6477	43.0966	91.3174
Е	510x340	37.3433	26.4878	88.9765
F	340x226	32.6391	17.0794	78.6778
G	300x168	30.3417	12.4846	67.4921
Н	229x220	39.1694	30.1399	67.4792

Fig. 6 and fig. 7 shows performance analysis of various test images. Analysis shows the proposed work gives PSNR above 50 and CR of 99

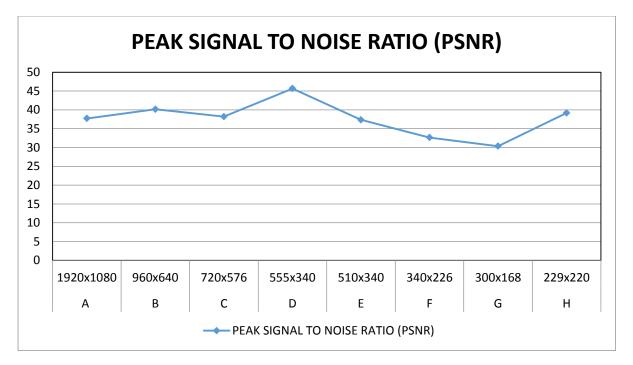


Fig. 6 PSNR of various images

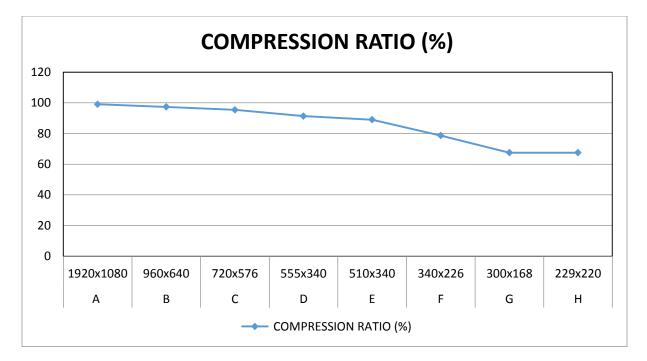


Fig. 7CR of various images

IV. CONCLUSION

In this paper the traditional encoding technique such as Huffman encoding is replaced with the latest neural network encoding method which provides efficient accuracy in image compression. Neural networks is easy to use as it does not require any complex algorithm and it offers higher speed and accuracy compared to other conventional techniques. DTCWT provides higher degree of freedom compared other wavelet techniques and is used for image compression. Higher compression ratio is obtained for higher pixel values using the proposed algorithm which saved the space required during transmission. MATLAB results shows that a compression ratio of 99.0782 is obtained for higher pixel value of an image.

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