ML-SRHWT: Machine Learning based Superlative Rapid HAAR Wavelet Transformation for Digital Image Coding

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Abstract: In this paper a digital image coding technique called ML-SRHWT (Machine Learning based image coding by Superlative Rapid HAAR Wavelet Transform) has been introduced. Compression of digital image is done using the model Superlative Rapid HAAR Wavelet Transform (SRHWT). The Least Square Support vector Machine regression predicts hyper coefficients obtained by using QPSO model. The mathematical models are discussed in brief in this paper are SRHWT, which results in good performance and reduces the complexity compared to FHAAR and EQPSO by replacing the least good particle with the new best obtained particle in QPSO. On comparing the ML-SRHWT with JPEG and JPEG2000 standards, the former is considered to be the better.

Keywords: Image coding, wavelet transformation, machine learning, Swarm Intelligence

1. INTRODUCTION:

The easy representation of the converted and organized information is considered as compressing the specific data. In recent days images are in boom as they cover less space, which leads to compression though the losses are not noticed. The changes in more repetitions is sensitive to human eye[11], which can be further used in image compressions process to control the size of more repetitions of an transformed image to the frequency.

Depending on training given the use of machine learning techniques in wide areas helps in choosing of contextual limits. So the use of machine learning techniques in the process of signal and image encoding and decoding has been promoted. The images can be compressed by training LS-SVM a machine learning approach for regression to assign set of values, which can be further approximated using hyper parameters.

The thesis further describes (i) use of machine learning techniques to related work in image coding. (ii) Use of knowledge in proposed image and signal compression technique. (iii) Optimization of Fast HAAR Wavelet Transform using mathematical design. (iv) Optimization of QPSO based parameter search. (v) Design for LS-SVM Regression under QPSO. (VI) proposed image and signal compression technique. (vii) Comparative analysis of the ML-SRHWT and existing JPEG2000 standard results.

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2. RELATED WORK:

The use of Machine learning algorithms in image processing and image compression has seen growth in recent times. A procedure using back-propagation algorithm of neutral network in a feed-forward network has been introduced by M H Hassan et al [1]. On using this algorithm, compression ratio of 8:1 could be achieved. Another method of image coding using Vector Quantization (VQ) on Discrete Cosine Transform (DCT) coefficients using Coonan map was introduced by Amerijckx et al[2], was considered to be the better than JPEG because its ratios were more than 30:1. An image coding method that executes SVM regression on DTC coefficients was introduced by Robinson et al [3]. A SVM regression model with different parameters from [3] was introduced by Kecman et al [4]. In higher compression ratios when compared to JPEG the techniques [3, 4] evolved higher quality image. To lower the compression artifacts the use of SVM regression was introduced by SanjeevKumar et al [5]. In huge data the hyper parameter search complexity for which the technique was considered less efficient.

DWT is used by JPEG2000 the popular compression standard in order to overcome the drawbacks of compression on DCT. Firstly the digital images are converted to YCbCr and then independent compression of digital channels is performed. This helps in finding efficient image and signal coding specially in cases of digital Images.

LS-SVM regression is introduced to optimize DWT models. The mathematical model aims at optimizing FHT technique and QPS search technique for SVM. The comparison between ML-SRHWT and JPEG2000 is done, resulting in better performance of ML-SRHWT.

3. MACHINE LEARNING BASED IMAGE CODING BY SUPERLATIVE RAPID HAAR WAVELET TRANSFORM (ML-SRHWT)

A. Superlative Rapid Haar Wavelet Transformation - SRHWT

There is no requirement of coefficients leaving the level 0 during the reconstruction process in multi-resolution wavelet and are ignored to reduce the storage space. 2^N data is applied in FHT.

For approximation instead of (x + y)/ 2 we use (w+ x + y + z)/ 4 and for differencing process instead of (x − y)/ 2 we use (w+ x − y − z)/ 4. On calculating (w+ x − y − z)/ 4 n−2 level detailed coefficients are obtained and for further detail coefficients differencing process (x − y)/ 2 is to be calculated, which is done using matrix formulation.

The following procedure represents computation of decomposition for the SRHWT for 2^N data:

q=N/4;

Coefficients:

$$N = 2^n$$

$$q = 2^n / 4$$

$$a_m = \bigcup_{m=0}^{2^n/q-1} \frac{\sum_{p=0}^{2^n/q-1} f((2^n/q)m + p}{N/q}$$

If N is divisible by 4 detailed coefficients are given by

$$x = 2^n / q - 1;$$

$$d_m = \bigcup_{m=0}^{2^n/q-1} \frac{\sum_{p=0}^{x/2} f((2^n/q)m + p + \sum_{p=x/2}^{x} - f((2^n/q)m + p}{2^n/q}$$

If N is divisible by 2 detailed coefficients are given by

$$d_y = \bigcup_{y=1}^{N/2} \frac{\sum_{m=y-1}^{y} k.fm}{\sqrt{2}}$$

Where k is -1 for m=n-2…n;

In any other situations the detailed coefficients are given by

$$d_m = \bigcup_{m=2^n/2}^{2^n} \partial$$ Where ∂ is considered to be zero

B. Exaggerate Quantum Particle Swarm Optimization [EQPSQ]

A new Swarm particle is used instead of least good swarm particle so as to obtain Exaggerate QPSO. On putting a quadratic polynomial technique on best fit swarm particles a new equation is obtained, depending on which new particle is recognized. Replacement is possible if the new swarm particle obtained is better than the least good swarm particle and after each search lap the same procedure is followed.

The Exaggerate QPSO is obtained using the following procedure:

Begin

Step 1: Find preeminent mean pm

Step 2: In regard to pm, the positions of the particles rationalized.

Step 3: The fitness value of each particle is calculated.

Step 4: If present fitness value pfv is found to be preeminent than existing comprehensive preeminent cp then consider pfv as cp.

Step 5: perform search to find new particle p_n

Step 6: If p_n found to be with best fitness than the awful particle p_a then discard p_a and retain p_n

Step 7: If $ic < mit$ then go to step1 else abort the process.

Here in the described EQPSO process, the swarm particle can be found by using a particle p_{cp} with comprehensive preeminent and selected any of two random particles p_i and p_j as follows:

$$t_i(p_{cp}) = (p_{cp}^2 - p_i^2) * f(p_j)$$
$$t_i(p_i) = (p_i^2 - p_j^2) * f(p_{cp})$$
$$t_i(p_j) = (p_j^2 - p_{cp}^2) * f(p_i)$$

$$t_i^{'}(p_{cp}) = (p_{cp} - p_i) * f(p_j)$$
$$t_i^{'}(p_i) = (p_i - p_j) * f(p_{cp})$$
$$t_i^{'}(p_j) = (p_j - p_{cp}) * f(p_i)$$
$$p_n = 0.5 * \frac{t_i(p_{cp}) + t_i(p_i) + t_i(p_j)}{t_i^{'}(p_{cp}) + t_i^{'}(p_i) + t_i^{'}(p_j)}$$

Here p_n is considered as new particle

3.1 LS-SVM Regression and QPSO based hyper parameter selection

Considering training set of N data points $\{x_t, y_t\}_{t=1}^{N}$ where $x_t \in R^d$ is input data and $y_t \in R$ is output data. Further LS-

SVM regression technique can be written as $y(x) = w^T \varphi(x) + b$ .... (1)

Where the input data is mapped $\varphi(.)$

The below set of linear equations provides result to LS-SVM for function estimation:

$$\begin{bmatrix} 0 & 1 & .... & 1 \\ 1 & K(x_1,x_1)+1/C & .... & K(x_1,x_1) \\ . & . & . & . \\ . & . & . & . \\ 1 & K(x_1,x_1) & & K(x_1,x_1)+1/C \end{bmatrix} \begin{bmatrix} b \\ \alpha_1 \\ . \\ . \\ \alpha_1 \end{bmatrix} = \begin{bmatrix} 0 \\ y_1 \\ . \\ . \\ y_1 \end{bmatrix}$$
……(2)

Where $K(xi, xj) = \phi(x_i)^T \phi(x_j)^T$ for $i, j = 1...L$ and on applying the Mercer's condition the following LS-SVM model for function estimation is obtained:

$$f(x) = \sum_{i=1}^{L} \alpha_i K(x, x_i) + b \text{ ....(3)}$$

α, b represents solution of the linear system, K(.,.) indicates nonlinear mapping of high dimensional feature spaces from the input space x. Using Eq. (3) function is approximated by LS-SVM. Here we consider the radial basis function (RBF) as the kernel faction:

$$k(x_i, x_j) = \exp(-\| x - x_t \|^2 / \sigma^2)$$

The generalization error can be reduced by proper use of hyper-parameters like kernel width parameter σ and regularization parameter C which are used during the training LS-SVM problem.

C. ML-SRHWT:

i. Hyper-Parameters Selection Based on EQPSO

The optimization of hyper-parameter is done to get better L2 loss result in least-square SVR. The optimized hyper-parameters using QPSO can be obtained using two key elements: (i) representation of hyper-parameters as the particle's position i.e. [10, 11] are too encoded. (ii) Obtaining the goodness of a particle by defining the fitness function. The following will give the two key factors.

Encoding Hyper-parameters:

The parameters kernel and regularization are used to optimize hyper-parameters for LS-SVM. A hyper-parameters combination of dimension m is represented in a vector of dimension m, such as $x_i = (\sigma, C)$ where each particle represents a potential solution which can be solved using the model EQPSO (Intensified Worst Particle based QPSO), which is represented in the graph 5.1

ii. Fitness function:

There are different descriptions for generalization performance which is measured using fitness function and is represented as given below:

$$fitness = \frac{1}{RMSE(\sigma, \gamma)} \text{ .... (12)}$$

RMSE (σ, γ) represents the root-mean-square error of obtained values and it differs as the LS-SVM parameters (σ, γ) vary. The biggest fitness is equivalent to the optimal values of LS-SVM when the end results are achieved.

The approaches to stop criterion are: (i) if the threshold value ε is more than the objective function (ii) if the mentioned iterations are obtained. EQPSO-Trained LS-SVM algorithm is as below:

(1) Randomly each particle is positioned with a vector ix and iP = iX. Hyper-parameters act as a part of each particles position vector used to arrange LS-SVM.

(2) LS-SVM is to be trained.

(3) Using Eq.(12) fitness value of each particle, personal iP and global gP best position are obtained.

(4) On achieving termination proceed with step (6) else step (5).

(5) Using Eq.(7) each particles position vector is rearranged and then proceed with step (2).

(6) Optimized parameters is a part of the gP.

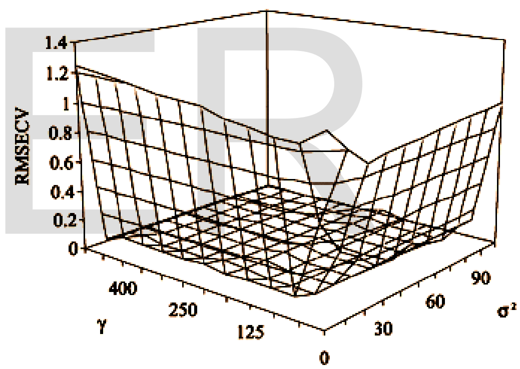

Figure 1: Hyper-Parameter optimization response surface under EQPSO for LS-SVM

Using LS-SVM regression and EQPSO coefficients are achieved and further process for image coding is explained.

The image can be used as both in blocks and multitude blocks of custom size.

Considering SRHWT each block is assigned with 2D-DWT image and its detailed coefficients and result is obtained.

To generalize the data by minimum support vectors on independent coefficient matrix using LS-SVM regression under EQPSO, obtaining the appropriate coefficient values.

Using Huffman-coding principle the coefficients are encoded.

4. Results Discussion

Selection of images which have accuracy and are photographic is done carefully for the purpose of image compression. These images are obtained from past data or from other sources and are minute in size with accuracy 8-bit, 16-bit, 16-bit linear variations, digital and gray. The images can be copied without

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any limit for compression purpose from [19]. The pictorial representation of the original, JPEG2000 standard compressed and ML-SRHWT compressed images results are shown below:

A. COMPARATIVE STUDY:

For loss compression of digital images comparison between ML-SRHWT and JPEG2000 was made. Principle Component Analysis (PCA) a statistical technique was used to compare the correlation between size compressed and compression ratio, between PSNR and RMSE.

Original Image

Compression ratio: 1:1
Size: 87.4kb

Jpeg2000 standard

Compression ratio: 23:1
Size: 44.8kb
PSNR: 42.298615
RMSE: 1.9570847

ML-SRHWT

Compression Ratio: 24:1
Size: 43.3kb
PSNR: 42.474693
RMSE: 1.9178092

Fig 2: The Image considered for Comparative study

B. Results Obtained from jpeg 2000

The following table represents the results obtained from existing JPEG2000 standard:

Ratio(per bit)	PSNR	RMSE
382	27.92663	10.23785
205	32.92759	5.756527
157	34.52446	4.789797
115	35.77153	4.149192
92	38.80287	2.926825
81	36.14165	3.976103
68	38.83935	2.914558
59	40.50812	2.405105
52	42.45808	1.92148
48	38.99128	2.864021
43	42.79325	1.848747
39	43.362	1.73157
36	46.17574	1.25243
33	46.02605	1.2742
31	46.86448	1.156955
29	44.72035	1.480889
27	45.84377	1.301223
26	45.38951	1.371086
24	44.04869	1.599948
23	43.11262	1.782007

Table1: The above table represents compression Ratio, size, PSNR and RMSE of the JPEG2000 standard

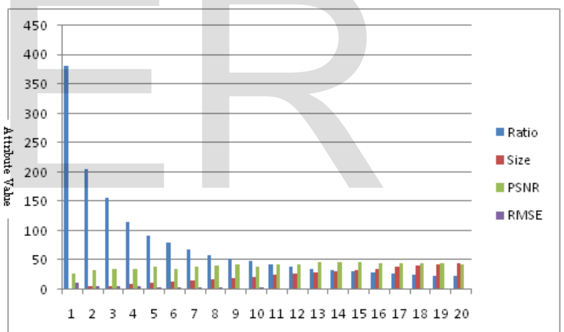


Figure 3: graph represents the frequency between compression Ratio, size, PSNR and RMSE of the JPEG2000 standard

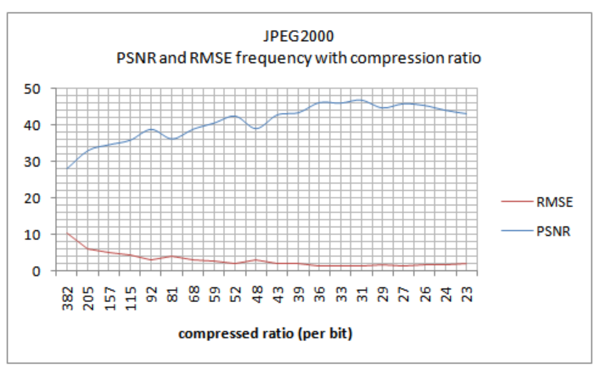


Figure 4: PSNR and RMSE values obtained under divergent compression ratios in JPEG2000

C. Results Obtained from ML-SRHWT

Ratio (per bit)	PSNR	RMSE
567	28.2512	9.862342
246	33.69187	5.271648
180	35.22379	4.41927
128	36.03423	4.02558
99	38.96072	2.874114
92	36.46788	3.829535
72	39.34	2.751316
62	41.1652	2.229875
54	43.02466	1.800144
52	39.0202	2.854502
45	42.82678	1.841625
41	44.23324	1.566311
37	46.474	1.210152
34	46.02834	1.273864
32	46.86378	1.157048
30	44.74467	1.47675
28	45.84192	1.3015
26	45.38717	1.371455
25	44.14166	1.582913
24	43.86201	1.634706

Table2: The above table represents compression Ratio, size, PSNR and RMSE of the ML-SRHWT

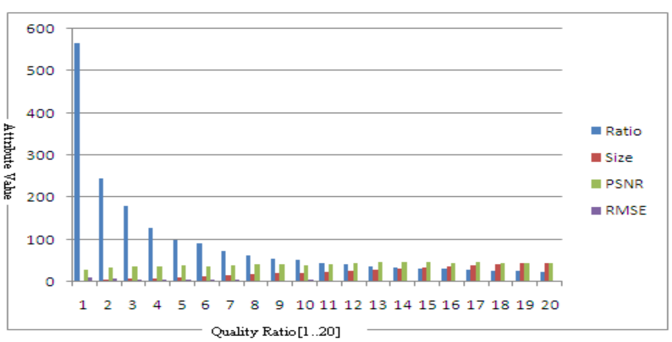


Figure 5: Graph represents the frequency between compression Ratio, size, PSNR and RMSE of the ML-SRHWT

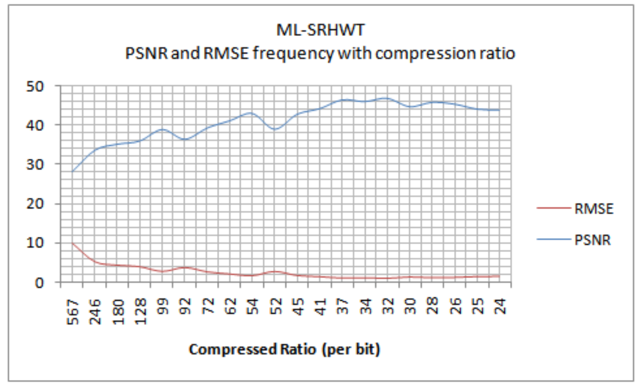


Figure 6: RMSE and PSNR Frequency observed under divergent compression ratios in ML-SRHWT

D. Evaluation of the correlation between size compressed and compression ratio using PCA

According to the obtained result the correlation between size compressed and bit ratio is stable when compared as like in JPEG2000 standard. The graph below represents the correlation between sizes compressed and bit ratio for JPEG 2000 standard and ML-SRHWT.

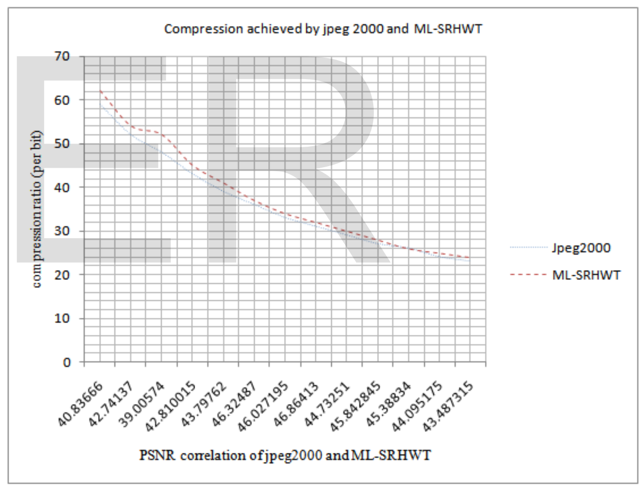
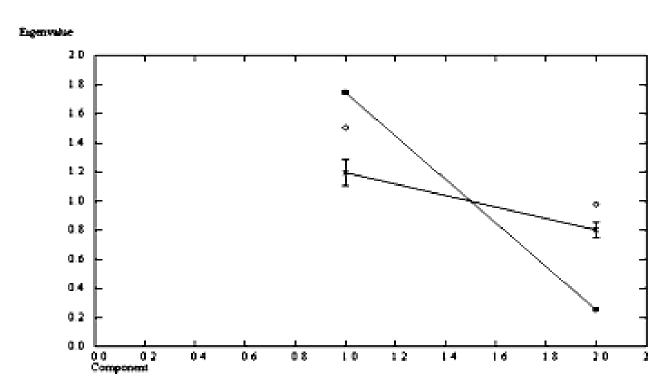
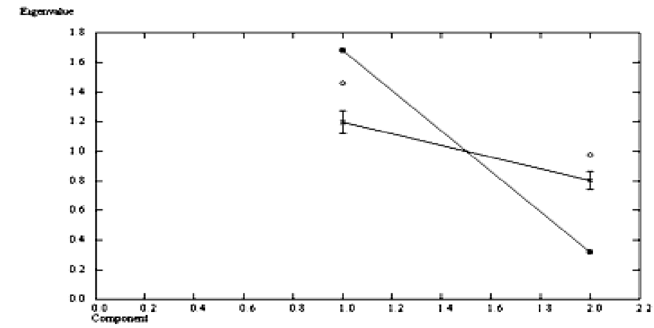


Figure 7: Comparison chart of compression achieved under jpeg 2000 and ML-SRHWT (compared under correlated PSNR values)



(a) JPEG 2000 Standard

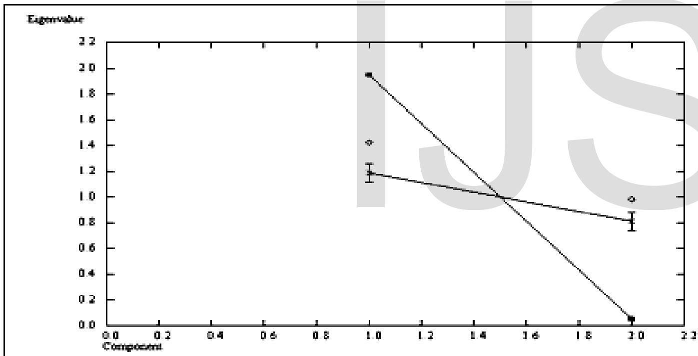


(b) ML-SRHWT

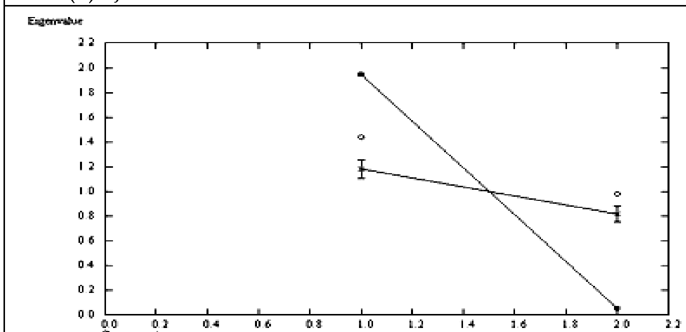
Figure 8: PCA for correlation of compression ratio and size compressed

E. Evaluation of the correlation between PSNR and RMSE using PCA

According to the obtained result the correlation between PSNR and RMSE is stable when compared as like in JPEG2000 standard. The graph below represents the correlation between PSNR and RMSE for JPEG 2000 standard and ML-SRHWT.



(a) *JPEG 2000 Standard*



(b) ML-SRHWT

Figure 9: PCA for PSNR and RMSE correlation

5. CONCLUSION AND FUTURE WORK:

In this paper we have talked about a new machine learning model for digital image compression. To apply on coefficients collected from DWT, LS-SVM regression model was introduced and the model selected hyper coefficient using EQPSO. Two mathematical models proposed to optimize the process of image coding are to optimize the FHT and reduces the complexity which results in new Wavelet transform called Superlative Rapid HAAR Wavelet Transform (SRHWT) and to optimize the QPSO by replacing the least good particle with the new best obtained particle which results in EQPSO (Exaggerate QPSO). Finally we can conclude that a machine learning based Superlative Rapid HAAR Wavelet Transform (ML-SRHWT) has been proposed for digital image compression. On comparing the ML-SRHWT with existing jpeg, jpeg2000 standards we conclude that ML-SRHWT is better. In future this work can be extended to other media compression standards like MPEG4.

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