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Image Outlier Filtering (IOF): A Machine Learning Based DWT Optimization Approach

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IMAGE OUTLIERFILTERINGIOFAMACHINELEARNINGBASEDDWTOPTIMIZATIONAPPROACH

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Image Outlier Filtering (IOF): A Machine Learning Based DWT Optimization Approach

R.Sunitha [α] & Yugandhar Dasari [σ]

Abstract - In this paper an image outlier technique, which is a hybrid model called SVM regression based DWT optimization have been introduced. Outlier filtering of RGB image is using the DWT model such as Optimal-HAAR wavelet changeover (OHC), which optimized by the Least Square Support Vector Machine (LS-SVM) . The LS-SVM regression predicts hyper coefficients obtained by using QPSO model. The mathematical models are discussed in brief in this paper: (i) OHC which results in better performance and reduces the complexity resulting in (Optimized FHT). (ii) QPSO by replacing the least good particle with the new best obtained particle resulting in “Optimized Least Significant Particle based QPSO” (OLSP-QPSO). On comparing the proposed cross model of optimizing DWT by LS-SVM to perform oulier filtering with linear and nonlinear noise removal standards.

I. Introduction

Outlier filtering from a specific type of data entails changeover and organizing the data in a way which is easily represented. Images are in wide use today, improving the visual clarity, decreasing the resource required to transmit and store of a given image is a benefit. With images, lossy compression, outlier reduction is generally allowed as long as the losses and outliers are subjectively unnoticeable to the human eye.

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 paper further describes (i) use of machine learning techniques to related work in image processing. (ii) Use of knowledge in proposed outlier filtering approach. (iii) Optimization of Optimal-HAAR Wavelet Changeover using mathematical design. (iv) Optimization of QPSO based parameter search. (v) Design for LS-SVM Regression under QPSO. (VI) Proposed outlier filtering approach. (vii) Comparative analysis of the proposed model and existing DBA[6A] standard results.

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II. Related Work

Noise reductions are basically classified into two types 1) linear techniques and 2) Nonlinear techniques. In linear techniques noise reduction formula is applied to all pixels of image linearly without classifying pixel into noisy and non noisy pixels. The drawback of linear algorithms is it damages the non noisy pixels because the algorithm is applied for both noise and non noisy pixels. Examples of linear filters are average, mean, median filters etc. Nonlinear Noise reduction is a two step process 1) noise detection and 2) noise replacement [20-33]. In the first step, location of noise is detected and in a second step, detected noisy pixels are replaced by estimating value. In literature so many algorithms are proposed but with the low noise condition (up to 50% noise ratio), such algorithms works well but in high noise conditions performance of these algorithms is poor. To improve the range of noise reduction non linear techniques, MMF (Min-Max Median Filter) [20], CWMF (Center Weighted Media Filter)[21], AMF (Adaptive Median Filter) [22], PSMF (Progressive Switching Median Filter) [23], TMF(Tri-state Median Filter)[24] and DBA (Decision Based Algorithm) [25] algorithms are proposed.

The drawback of these algorithms is that as soon as the noise ratio increases the time required to process noise also increases and takes too much time that is not suitable for actual world purpose. To progression real time videos very high speed algorithms are required.

The use of Machine learning algorithms in image dispensation has seen growth in recent times. A procedure using back-propagation algorithm of neural network in a feed-forward network has been introduced by M H Hassan et al [1]. By 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

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considered to be better than other noise removal standards because its ratios were more than 30:1. An outlier filtering method that executes SVM regression on DCT coefficients was introduced by Robinson et al [3]. An SVM regression model with different parameters from [3] was introduced by Kecman et al [4].

Outlier Filtering practices are on the whole classified into two forms 1) linear practices and 2) Nonlinear practices. In linear practices noise lessening formula is applied to all pixels of image linearly without classifying pixel into noisy and non noisy pixels. The drawback of linear algorithms is it damages the non noisy pixels as the algorithm is applied for both noise and non noisy pixels. Examples of linear filters are average, mean, median filters etc. Nonlinear Noise lessening is a two step process 1) noise exposure and 2) noise substitution [20-33]. In the first step, location of noise is detected and in a second step, detected noisy pixels are replaced by estimating value. In literature so many algorithms are projected but with the low noise state, such algorithms work well but in high noise conditions act of these algorithms is poor. To improve the range of noise lessening non linear practices, MMF (Min-Max Median Filter) [20], CWMF (Center Weighted Media Filter) [21], AMF (Adaptive Median Filter) [22], PSMF (Progressive Switching Median Filter) [23], TMF (Tri-state Median Filter)[24] and DBA (Decision Based Algorithm) [25] algorithms are proposed.

The drawback of these algorithms is that as soon as the noise ratio increases the time required to process noise also increases and takes too much time that is not suitable for real world application. To process real time videos very high speed algorithms are required.

In this regard a machine learning based DWT optimization approach for outlier filtering is proposed. The aim of the work is to describe the usage of novel mathematical models to optimize DWT model such as FHT, QPSO, which is an optimal model for selecting hyper parameters for SVM. The result of outlier filtering is the considerable and comparative studies with linear and nonlinear standards concluding the significance of the proposed model.

III. Standards used in Proposed Oulier Filtering Approach (OFA)

a) HAAR and Optimal-HAAR Wavelet Changeover

In the linear and nonlinear outlier filtering process DWT is considered as important [5]. For images we require two-dimensional (2D) DWT separating the image into four parts i.e. into approximation coefficients and three detailed coefficients including horizontal, vertical, and diagonal coefficients. There is no loss of the lower frequency position of the image whereas there is a loss in the higher frequency position which does not affect the vision quality. The original image is preserved and we can apply the DWT to the recent image obtained which is known as wavelet packet decomposition which appears like inverted tree structure. The chattels of the HAAR and FHT as follows:

- HAAR changeover is optimal orthogonal. Therefore

$Hr = Hr^*$ (1) & $Hr^{-1} = Hr^T$ (2)

- HAAR Changeover is quick and has a deprived energy compaction for images
- HAAR matrix vectors are sequential.
- Linear and Orthogonal progression: This enables splitting the signal into high and low frequencies without any duplication and symmetric filters have to be used to achieve linearity.
- Condensed sustain: In cases of frequency where the magnitude is zero the changeover is said to be energy invariant.
- Perfect restoration: If the inversely changeover signal is similar to the input signal which was earlier changeovers and also if it avoid redundancy than the reconstruction is perfect.

Daubechies, bi-orthogonal and HAAR wavelets are optimal Selectives of the changeover [1]. These wavelets satisfy all needs of their application. The advantages of HAAR Wavelet changeover as follows:

- Scalable in terms of calculation is the best and also its speed is miles ahead of other models.
- HAAR changeover is a simple and efficient attribute elimination method for compression and outlier removal.
- As there is no replication, the memory space required is less.

i. *Optimal-HAAR Changeover*

HAAR procedure as a step method be able to present as:

$$f(t) = [[t]];$$

$$H(t) = 1 \qquad 0 <= t < 1;$$

$= 0$ Elsewhere.

The HAAR changeover of an array of n samples:

The average of each pair of samples is determined. ($n/2$ averages). Next the difference between the average and the samples from which it was calculated. ($n/2$ differences). The array is designed as: the first half of the array with averages and the second half of the array with differences. Repeat the process on the first half of the array. (The array length should be a power of two)

Average / Difference

Let 'l' and 'r' be two samples with difference'd' and average 'a'

$$a = (l + r) / 2, \ d = a - l = r - a$$

Can be written as: $l = a - d, r = a + d$

Thus we generate for the process:

$$a_n = \bigcup_{n=1}^{N/2} \frac{\sum_{m=n-1}^{n} fm}{\sqrt{2}} \quad d_n = \bigcup_{n=1}^{N/2} \frac{\sum_{m=n-1}^{n} k.fm}{\sqrt{2}}$$

Where k is -1 for $m = n-2 \ldots n$

b) Quantitative Particle Swarm Optimization

When physicists like Heinsenberg, Schrodinger, Neils Bhor started contributing to the quantum mechanics[6],the subject of particle kinematics became more confusing .How ever according to the classical PSO the position (xi) and velocity (vi) of the particle are enough to decide the particle trajectory but this wasn't satisfying the Uncertainty principle of Heinsenberg.But if the quantum behavior of the particles is considered than it would be diverting from the classical PSO [7].The quantum mechanics states $\psi(x,t)$ as a wave function and $|\psi(x,t)|^2$ as a density function, the form of which depends on the potential field the particle lies in [10].

The iterative equations [8], [9] shown below describe the motion of the particle:

$$x(t+1) = p + \beta^* | mbest - x(t) | {}^* \ln(1/u) ifk \geq o.5$$

$$x(t+1) = p - \beta^* | mbest - x(t) | {}^* \ln(1/u) ifk < o.5$$

Where,

$p = (c_1 p_{id} + c_1 p_{gd})/(c_1 + c_2)$

mbest = $\bigcup_{k=1}^{d} 1/M \sum_{i=1}^{M} Pik$

Mean-Best (mbest) of the population is the mean of the best location of every particle. 'u', 'k', '$c1$' and '$c2$' are uniformly distributed random numbers over the interval $[0, 1]$. 'b' Is contraction-extension coefficient. The subsequent procedure used to solve QPSO explained below:

(i) Instigate the swarm.
(ii) Evaluation of best mean and particles position is optimized.
(iii) 'P_{best}'and 'P_{gbest}' are rearranged till the specified iterations are obtained.

c) LS-SVM

The tribulations like pattern identification, categorization and deterioration can be solved by using a valuable tool called Support vector machine (SVM) projected by Vapnik [12, 13]. SVM scales in minimizing structural risk and because of its recompenses when matching up to other methods it has got a lot of gratitude [9, 12]. Both linear and nonlinear regression is performed and solutions are obtained from the formulas. The nonlinear equations solutions are used to compute the least SVM model. A modified version of SVM called least-squares SVM was introduced for simple achievement of results by Suykens and Vandewalle[14]. The clear introduction of SVM [15, 16], theory of LS-SVM by Suykens et al [14, 15] and application of LS-SVM in quantification and classification [17, 18] is described.

A linear relation $(y = w_x + b)$ between regression (x) and a reliant variable (y) is fit by LS-SVM and is considered to be optimum if the cost method (Q) containing a penalized regression error is minimized:

$$Q = \frac{1}{2} w^T w + \frac{1}{2} \gamma \sum_{i=1}^{N} e_i^2 \qquad (1)$$

Subject to: $y_i = w^T \phi(x_i) + b + e_i \quad i = 1, \ldots\ldots, N$ (2)

Firstly the regularization of weight sizes is done using cost function as a weight decay because of which there are no changes in the values of weight. Secondly for the training data cost function is the regression error. The user optimizes the comparison between the current and first part which is represented by 'g'.

The combination of parameters indicates the performance of LS-SVMs. To attain support vector the kernel function is used as the radial basis function (RBF) and the degree of the Gaussian and polynomial functions are used for optimization. To obtain a good generalized model for the RBF kernel and the polynomial kernel a proper selection of parameters and regularization constant g is to be done.

IV. Image Oulier Filtering Approach(OFA)

a) Optimal-HAAR Changeover- OHC

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 are applied in FHT.

For approximation instead of $\frac{(x + y)}{2}$ we use $\frac{(w + x + y + z)}{4}$ and for the differentiating process instead of $\frac{(x - y)}{2}$ we use $\frac{(w + x - y - z)}{4}$. On calculating '$\frac{(w + x - y - z)}{4}$', '$n-2$' level detailed coefficients are obtained and for further detail coefficients differentiating process $\frac{(x - y)}{2}$ is to be calculated, which is done using matrix formulation.

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

$$q = \frac{N}{4};$$

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

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

If N is divisible by 2 detailed coefficients are given by

$$d_y = \bigcup_{y=1}^{N/2} \frac{\sum_{m=y-1}^{y} k.fm}{\sqrt{2}} \text{ Where k is } -1 \text{ for } m = n-2\ldots n$$;

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) Optimized Least Significant Particle based QPSO [OLSP-QPSO]

A new Swarm particle is used instead of least good swarm particle so as to obtain optimized QPSO. By 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 optimized QPSO is obtained using the following procedure:

Step 1: Instigate the horde.

Step 2: Compute 'mbest'

Step 3: elements spaces ought to be restructured.

Step 4: The vigor significance of every element is measured.

Step 5: On matching up to the current vigor significance and the best vigor significance (Pbest), either is best is taken into account.

Step 6: Update 'Pgbest'

Step 7: A fresh element is to be traced.

Step 8: On matching up to the fresh element with most awful element either is better is taken into account.

Step 9: Go over step 2 till utmost iterations are attained.

On by means of the following table the swarm particle can be obtained. The swarm particle can be found using the following.

$t_i = \sum_{k=1}^{3} (p_i^2 - q_i^2) * f(r)$	$p = a, q = b, r = cfork = 1;$ $p = b, q = c, r = afork = 2;$ $p = c, q = a, r = bfork = 3$
$t1_i = \sum_{k=1}^{3} (p_i - q_i) * f(r)$	$p = a, q = b, r = cfork = 1;$ $p = b, q = c, r = afork = 2;$ $p = c, q = a, r = bfork = 3$

$$\overset{o}{x_i} = 0.5 * (\frac{t_i}{t1_i})$$

Where 'a' is considered as a best fit swarm particle, 'b' and 'c' are considered as randomly selected swarm particles $\overset{o}{x_i}$ are considered as a new swarm particle.

Regression by '$LS - SVM$' and agitated parameter selection by '$QPSO$'

Considering the training set of *N* data points $\{x_t, y_t\}_{t=1}^{N}$ where $x_t \in R^d$ input data is and $y_t \in R$ is output data. Further LS-SVM regression technique can be written as $y(x) = w^T \phi(x) + b$ ……………..……… (1)

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

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

$$\begin{bmatrix} 0 & 1 & \ldots & 1 \\ 1 & K(x_1, x1) + 1/C & \ldots & K(x_1, x_1) \\ . & . & . & . \\ . & . & & . \\ 1 & K(x_1, x_1) & & K(x_1, x_1) + 1/C \end{bmatrix} \begin{bmatrix} b \\ \alpha_1 \\ . \\ . \\ \alpha_1 \end{bmatrix}$$

$$= \begin{bmatrix} 0 \\ y_1 \\ . \\ . \\ y_1 \end{bmatrix} \text{…….(2)}$$

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

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

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) Outlier Filtering: Optimizing Transformation by Machine learning

i. *Hyper-Parameters Selection Based on OLSP-QPSO*

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.

ii. *Training 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 OLSP-QPSO (Optimized Least Significant Particle based QPSO), which is represented in the graph 5.1

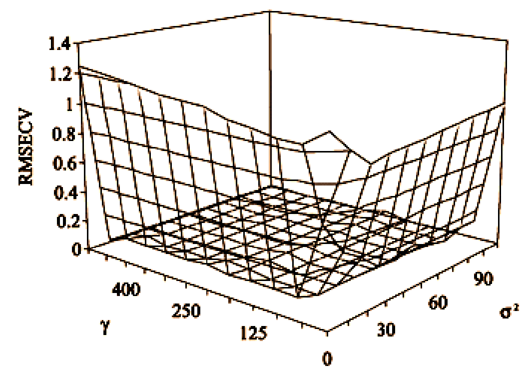
iii. *Vigor method :*

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

$$vigor = \frac{1}{RMSE(\sigma, \gamma)} \qquad (12)$$

'$RMSE(\sigma, \gamma)$' Represents the root-mean-square error of obtaining 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. OLSP-QPSO-Trained LS-SVM algorithm is as below:



Graph 5.1: Hyper-Parameter optimization response surface under OLSP-QPSO for LS-SVM

1) Randomly each particle is positioned with a vector ix and iP = iX. Hyper-parameters act as a part of each element position vector used to arrange LS-SVM.
2) LS-SVM is to be trained.
3) Using Eq.(12) vigor significance of each particle, personal 'iP' and global gP best position is obtained.
4) On achieving termination proceed with step (6) else step (5).
5) Using Eq.(7) each particle position vector is rearranged and then proceed to step (2).
6) Optimized parameters is a part of the gP.

iv. *Outlier Filtering :*

Using LS-SVM regression and OLSP-QPSO coefficients are achieved and further process for outlier filtering is explained.

- The image can be used as both in blocks and multitude blocks of custom size.
- Considering OHC each block is assigned with 2D-DWT images and its detailed coefficients and result is obtained.
- To generalize the data by minimum support vectors on independent coefficient matrices using LS-SVM regression under OLSP-QPSO, obtaining the appropriate coefficient values.
- Using the Huffman - coding principle to filter the coefficients that are distinct.

V. Results Discussion

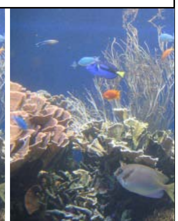
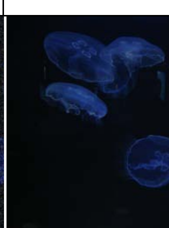
Original Image	Image with outliers	Resultant of DBA	Resulatant of OFA
			
Original Image	outliers by guassian model with intensity of 0.12	Ouliers filtered by DBA	Outliers filtered by OFA
			
Original image	Outliers by poisson model with intensity of 0.25	Ouliers filtered by DBA	Outliers filtered by OFA
			
Orginal Image	Ouliers of speckle with intensity of 0.40	Ouliers filtered by DBA	Outliers filtered by OFA

Table 1: Images and results of outlier filtering by DBA and OFA

Selection of images which have accuracy and are photographic is done carefully for the purpose of outlier filtering. 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, RGB and gray. The images can be copied without any limit for experiment's purpose from [19]. The pictorial representation of the original, noise added, DBA [25] noise removal standard and oulier filtering approach that proposed is shown in table 1.

VI. Results Analysis

For Outlier filtering of RGB images comparison between proposed model and DBA was made. The influence of the oulier filtering ratio on existing DBA[25] and proposed OFA model has been compared in the form of PSNR and RMSE percentage.

Fig 1 : The Image considered for Comparative study.

Table 1 : The results obtained from existing DBA standard:

Quality	Oulier filtering ratio (R)	Size compressed ratio	PSNR	RMSE
1	388	3.107804	28.606872	10.33527
2	211	5.546348	33.788950	6.702779
3	161	7.298222	34.898287	4.903699
4	117	9.497002	36.347839	4.661059
5	98	11.80054	39.279044	2.967337
6	83	13.77292	36.833082	4.893237
7	76	16.12473	39.239933	3.429187
8	61	18.90566	41.435035	2.674366
9	59	20.62013	42.706003	1.971018
10	55	23.19557	39.396384	3.355773
11	47	25.61548	43.675025	2.638899
12	46	27.66886	43.713415	1.755872
13	44	29.82042	46.295324	1.335152
14	40	32.07001	46.063484	1.514999
15	34	34.93525	47.350056	1.891448
16	33	36.06998	45.465762	1.894038
17	35	38.50481	46.568662	2.09902
18	28	40.70558	45.391035	1.861799
19	26	43.87018	44.324986	2.312027
20	24	45.23771	44.099152	2.666287

Table 2 : Results Obtained from OFA

QUALITY	Oulier filtering ratio (R)	Size compressed ratio	PSNR	RMSE
1	569.00	2.744253	28.77016	10.48553
2	249.00	5.022253	34.10943	6.152693
3	184.00	6.183361	36.21566	4.619115
4	133.00	9.212381	36.50637	4.813236
5	103.00	11.40636	39.52442	3.307031
6	96.00	11.62107	36.69631	4.523026
7	73.00	15.66123	39.69439	3.205598
8	67.00	18.16065	41.6445	3.209784
9	57.00	19.91655	43.71898	2.229024
10	54.00	21.33654	39.62734	2.993972
11	46.00	24.14933	43.73133	2.309553
12	44.00	26.34806	45.09799	2.074782
13	41.00	28.83657	46.99521	1.49826
14	39.00	32.14516	46.86183	1.578477
15	37.00	33.84327	47.41084	1.485134
16	34.00	35.31944	45.60309	1.861443
17	31.00	38.29239	46.46973	1.6009
18	29.00	40.00721	45.8981	2.119537
19	28.00	42.6345	44.74294	2.448485
20	26.00	43.49564	43.87592	2.273431

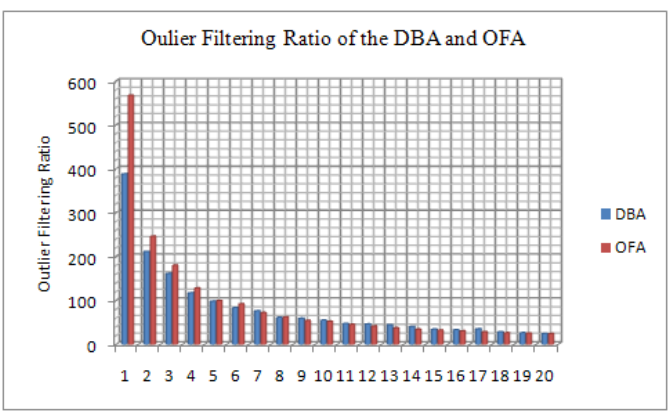


Fig 2 : The 20 different outlier filtering ratios applied under DBA and OFA models

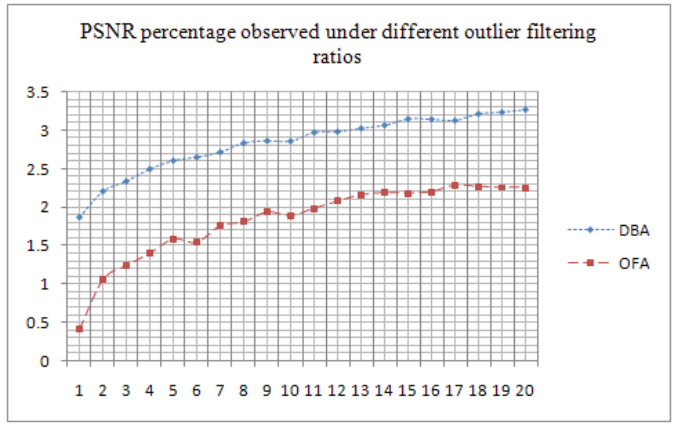


Fig 3 : A comparison chart that indicating the PSNR percentage at different outlier filtering ratios for DBA and OFA models

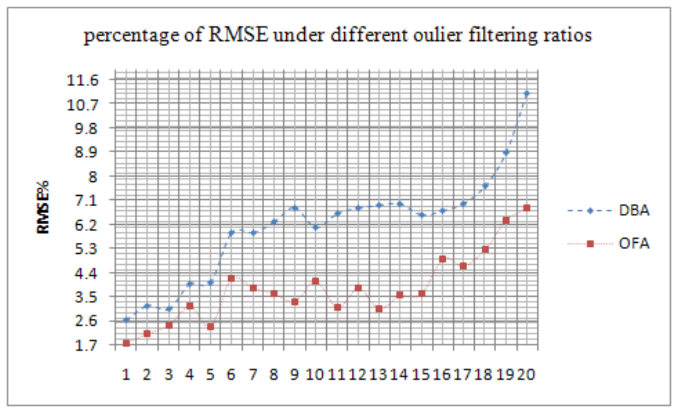


Fig 4 : A comparison chart that indicating the RMSE percentage at different outlier filtering ratios for DBA and OFA models.

VII. Conclusion and future work

In this paper we have explored a new machine learning model for outlier filtering from RGB images. To apply on coefficients collected from DWT, LS-SVM regression model was introduced and the model selected hyper coefficient using QPSO. Two mathematical models were proposed to optimize the process of outlier filtering: (i) to optimize the Fast HAAR, which results in better performance and reduces the complexity which results in new Wavelet changeover i.e. Optimal-HAAR Changeover (OHC). (ii) To optimize the QPSO by replacing the least good particle with the new best obtained particle which results in OLSP-QPSO (Optimized Least Significant Particle based QPSO). Finally we can conclude that an optimized LS-SVM regression model for outlier filtering from RGB images has been proposed using models for OHC and OLSP-QPSO. On comparing the proposed model with existing linear and nonlinear standards we conclude that proposed model is better. In future this work can be extended to outlier filtering from multimedia standards.

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