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Multiple Iteration DWT based Image Compression Algorithm for PSNR Improvement

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Abstract

There is an increase in demand of the storage capacity in mobiles, laptops and other digital devices therefore external memory is required to include, but one has limitation of increasing amount of memory. Therefore, data and image compression techniques are in great requirement. Discrete wave remodel based mostly compression algorithms had been planned by several researchers and any goes on to boost output image quality and increase compression ratio. In our proposed work, in order to increase compression ratio only low frequency part is transmitted. Arithmetic coding is applied for further compression. In order to improve the compression ratio, iteration of DWT is performed and results show up to 35 times improvement in CR with satisfactory PSNR value. In order to improve the image quality (PSNR) further, median filters has been applied. Switching median filter and simple median filter has been studied for multiple iterations. Analysis on window size has also been done to find the best window size for PSNR improvement.

Keywords*: PSNR (Peak Signal to Noise Ratio); Arithmetic Coding; DWT; HAAR Transform; Compression Ratio; Median Filter*

INTRODUCTION

Many researchers are working to speed up communication and provide multimedia services without buffering. A part from speed of communication if data is compressed properly then quality of multimedia services can be improved even in low data rate communication networks.In order to utilize bandwidth optimally, telecommunication use data compression.

It also solves the problem of storing huge data on disk and servers. In case ofoptical emission spectrum (OES) images, images contains important information but it takes large data storage, like one OES image comes out from single processing has size from Kilobytes to Megabytes. OES processing requires too much data and therefore high resolution images are required which results in consumption of heavy data bandwidth [1].

This issue can be solved by using an integrated data collection & data compression (IDCC) as shown in Fig. 1. In IDCC, as the OES images are formed, they have been compressed immediately. But IDCC will be significant only if the uncompressed image maintains its integrity and possess expected information. In order to get significant compression ratio with taking care of data authenticity; the researchers are moving towards multi-level discrete-wavelet transform (DWT) based data compression techniques [1].

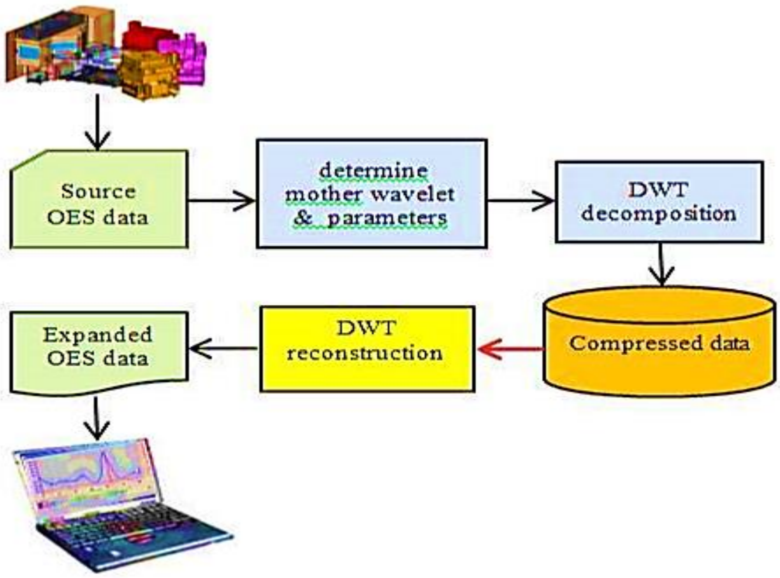

Fig. 1: *IDCC to make OES Data Storage [1].*

Compression is divided into lossy compression & lossless compression. In lossy type compression, approximated image is obtained with some loss of information. It is not exact replica of original image. In lossless compression, image is reconstructed with none loss of knowledge. Thus, use of lossless compression is determined in text information compression, medical imaging etc. On the opposite hand lossy compression is utilized in image, video compression wherever some loss of knowledge happens and it is not detected by human eyes [2]. Since DCT (Discrete Cosine Transform) compacts energy in few low frequency co-efficient located at top left corner of transformed image therefore wavelet transform was introduced as it analyzes the signal in time as well as in frequency domain. Wavelet transform became popular as it has greater energy compaction property and it reduces blocking effect observed in DCT based compression [2]. In wavelet transform, the wavelet compression methods are actually representing transients like audio percussion sounds, high frequency parts in 2D images, an image of stars on a night sky resembles such case.

The objective of a picture compression is to cut back redundancy within the image information to transmit information in associate economical type. Samples of lossless compression techniques are Arithmetic-coding, Huffman-coding; Run-Length-coding etc that are capable of reconstruct the compressed image into actual original imagebut with low chromium (compression ratio). Samples of lossy compression techniques are JPEG, Vector division, shape compression, separate trigonometric function remodel (DCT) etc. In lossy compressions, image quality degrades with high rate however the advantage comes within the sort of high chromium. In multimedia system communication, high chromium is of utmost demand and it is additionally expected to preserve smart fidelity of decompressed image [4].

In our proposed work, DWT is used to compress the colored images, then data is reshaped into array from matrix form and then at last arithmetic coding is applied before transmitting data stream. At the receiver end, the received data stream is first passed through decoding algorithm that is reverse of arithmetic coding and then it is reshaped into matrix to make two dimensional back. Then this 2D matrix is passed through reverse DWT or inverse discrete wavelet transform (IDWT). After all the above process, the recovered image quality is quite satisfactory. But in our proposed work, multiple iterations of DWT have been performed, which results in increase in compression ratio and PSNR are satisfactory.

DICRETE WAVELET TRANSFORM (DWT)

In Wavelet transform, high frequencies takes short data frames while low frequencies takes longer frames. That is why wavelet transform comes up with some additional features which are not available in the traditional Fourier transform (FT). Continuous Wavelet Transform (CWT) for a signal x (t) is given as [1, 5]

$$CWT_x(\tau, a) = \frac{1}{\sqrt{a}} \int x(t)\, h^*\left(\frac{t-\tau}{a}\right) dt \qquad (1)$$

Where h (t-τ/a) is scaled and shifted version of selected mother wavelet. CWT possesses animportant concept that a signal can be represented by a combination of the scaled & shifted versions of the mother wavelet, as represented in Fig. 2. The two continuous variables of the scale a & shift τ, makes equation (1) inappropriate to utilize in digital computation [1].

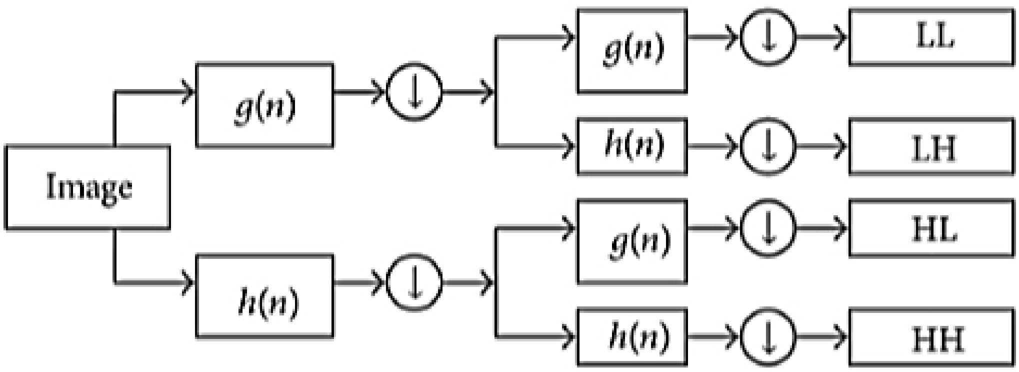

Fig. 2: *Two Dimensional DWT with Four Sub Band Images.*

Wavelets are performs start off from single function by its dilations & translations. The only of them is Haar remodel. Matrix for Haar transformation that is diagrammatical by T is truly associate orthonormal matrix as a result of it is seen that its rows are orthogonal to every different. Therefore, output of Haar wavelet image which is represented by y equals to TxT^T within put image x. DWT divides low and high frequency components of the image by making use of filters and after that they are down sampled by a factor of two. Fig. 3 shows the DWT image decomposition. Digital images are actually a matrix which consists of rows and columns. At each decomposition in DWT, level filtering is performed in two stages. Stage 1 containsLPF (Low Pass Filter) and HPF (High Pass Filter) which is applied on rows, while stage 2 containsthe same configuration butit is applied on the columns. Result will be four sub bands of image which are LL, LH, HL and HH. The low frequency sub bandis LL which is also called as approximate image while rest three sub bands LH, HL and HH are collectively called as detail sub bands [3].

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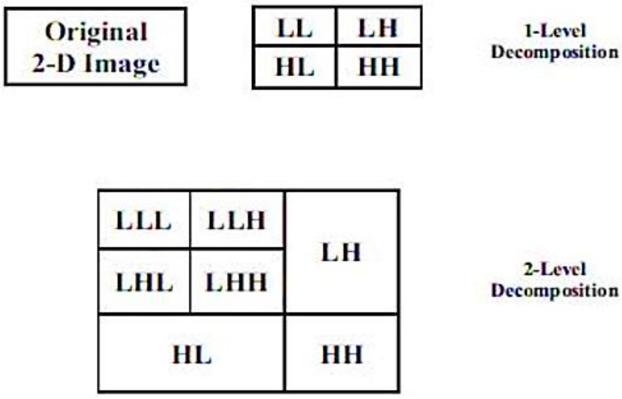

Fig. 3: *Two Level Decomposition of an Image.*

If input image size is M*N, then the size of sub bands (LL, LH, HL, HH) is M/2*N/2. In case of two-level decomposition, the output size is M/4*N/4[3].

ARITHMETIC CODING
Arithmetic coding comes in the category of lossless coding. Sometimes it is also called as variable length encoding. The base of arithmetic coding is probability value. Here input symbol sequence is a real number in between 0 & 1. Context formation includes decision & context generation, and then it is encoded in arithmetic encoder. Arithmetic encoder is based on recursively probability distribution. There are two sub-intervals in arithmetic encoder. If probability value or decision is 1 then it is taken asMPS (more possible symbol) else it is taken as LPS (less possible symbol). The probability of MPS and LPS are represented in a gray interval and a white interval. Basic function of an arithmetic encoder is to return value of MPS and LPS in accordancewith the context and decision taken out from context formation. The intervals of MPS and LPS are changed dynamically [7].

MEDIAN FILTER (SWMF)
Median filter is extremely vital non-linear filter; implementation of this filter is extremely straight forward. Massive window size median filter destroy the fine image details because of its rank ordering method. This filter behaves like low pass filter that blocks all high frequency part of the pictures like noise and edges, so blurs the image.

For the filtering of high density corrupted image need large window size so that the sufficient number of noise free pixels will present in the window. So the size of the sliding window in the median filter is varying according to the noise density. A center pixel either it is corrupted by impulse noise or not is replaced by the median value. Due to this reason this filter blurs the image. The window size 3×3, 5×5, 7×7, and 9×9 median filter are mainly applicable.Output of the median filter is given by

$$y(i,j) = median\{x(i-s, j-t), x(i,j)/(s,t) \in W, (s,t) \neq (0,0)\}$$

Where {x} is the noisy image and y (i, j) is the recovered image with preserve edges.

SWITCHING MEDIAN FILTER (SMF)
Switching median filter [9] uses a threshold value to detect the noise in the pixel. If the intensity difference between the center pixel value and median value in the window is greater than the threshold value then center pixel is considered as a noisy pixel and replaced by median value, otherwise center pixel is considered as non-noisy and remain unchanged [9]. Difference in intensity between the center

pixel value and median value in the window is given by,

$\Delta x = |x\ (imp) - x\_med\ |$ (2)

Where median value in the window x_med is given by

x_med={x (i-N, j-N), w_c*x (i, j), x (i-N, j-N)} (3)

Here w_c is the weight of the center pixels.

Suppose {X} is the noisy image and (2N+1) × (2N+1) is the sliding window size, centered at (i, j). The adjustment of the center pixel is given by following equation,

$$y(i,j) = \begin{cases} x_{med}, & \Delta x \geq T_i \\ x(i,j), & \Delta x < T_i \end{cases} \quad (4)$$

y (i, j) is the recovered image with preserve edges.

PROPOSED ALGORITHM

MATLAB is used as a simulation tool to create an algorithm. As shown in the fig. 4, first image is read by

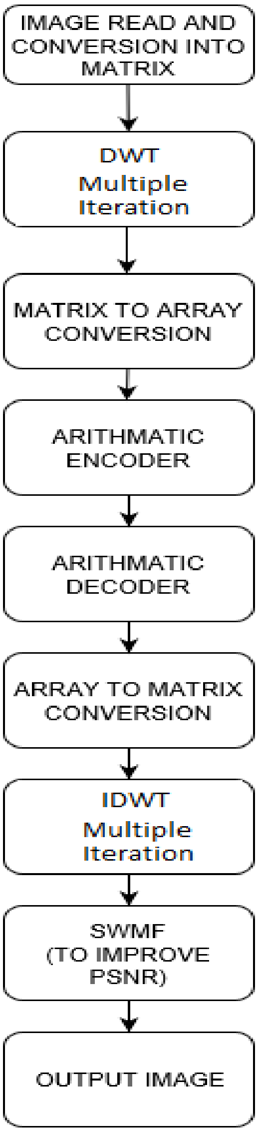

Fig. 4: *Proposed Algorithm.*

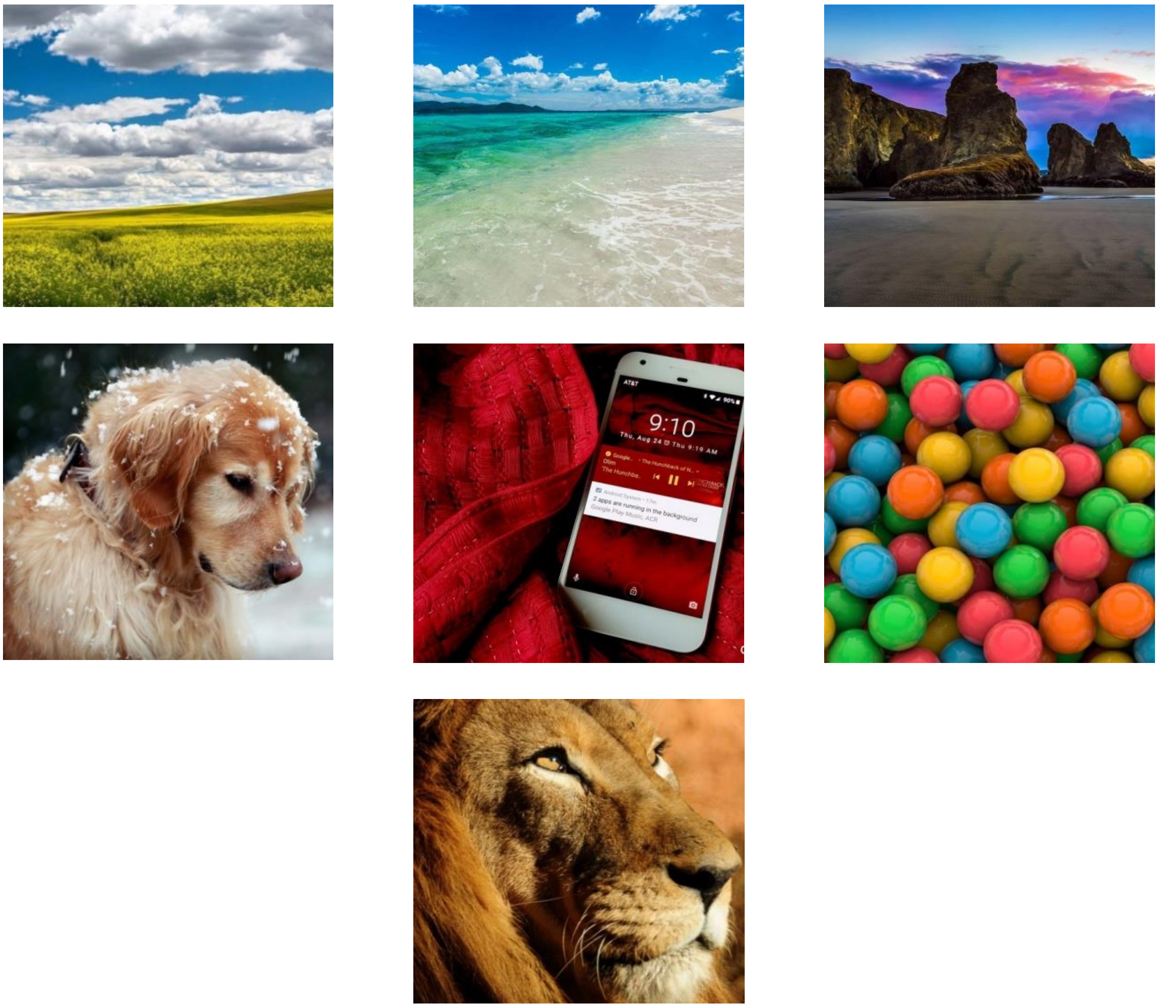

Fig. 5: *High Definition (HD) Colored Image A1, A2, A3, N1, N2, N3, PIC5.*

MATLAB function, which converts it into matrix form. Then DWT is applied on the matrix by using DWT function, which provides four different frequency components. LL is the most important part of the image and therefore it is used for further work. Then this LL component is passed again in DWT for further compression. Then LL component is first converted into array from matrix and then it is fed to arithmetic encoder. The compressed image out of arithmetic encoder is transmitted.

At receiver, the received image is first passed through arithmetic decoder. The output of decoder is first convertedinto matrix again. Then this matrix image is decompressed using IDWT (inverse discrete Fourier transform) by taking received image as a LL part and rest of the frequency components are taken as zero matrix (or black image) [6]. The decompressed image is then passed through SWMF to increase the quality of image. The result of the proposed work is shown in result section.

Table 1: *CR vs. PSNR up to 4 Iterations for Image A1.*

ITERATIONS	COMPRESSION RATIO	PSNR1	PSNR2	PSNR3
1	2.9697	32.9906	33.5090	23.4775
2	9.2485	27.6768	27.7111	23.5324
3	22.6551	24.6199	24.6249	23.5293
4	71.9951	22.6634	22.6639	22.8896

SIMULATION RESULTS & DISCUSSIONS

Simulation is performed in MATLAB software. Fig. 5 to Fig. 11 shows the colored images used for compression. Compression ratio and PSNR are taken as quality parameters. Table 1 below shows the simulation results.

Table 1 contains the data of PSNR and CR A1 image and Fig. 6 contains the plots of PSNR vs. CR.

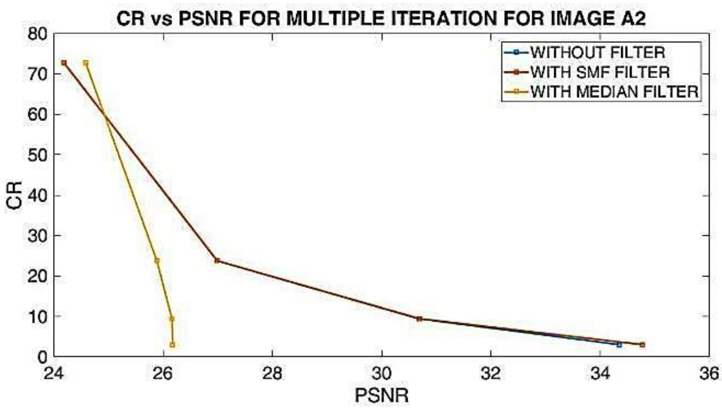

Fig. 6: *CR vs. PSNR up to Four Iterations for Image A1.*

Table 2: *Iteration vs. PSNR for Image A1.*

Iterations	PSNR1	PSNR2	PSNR3
1	32.9906	33.5090	23.4775
2	27.6768	27.7111	23.5324
3	24.6199	24.6249	23.5293
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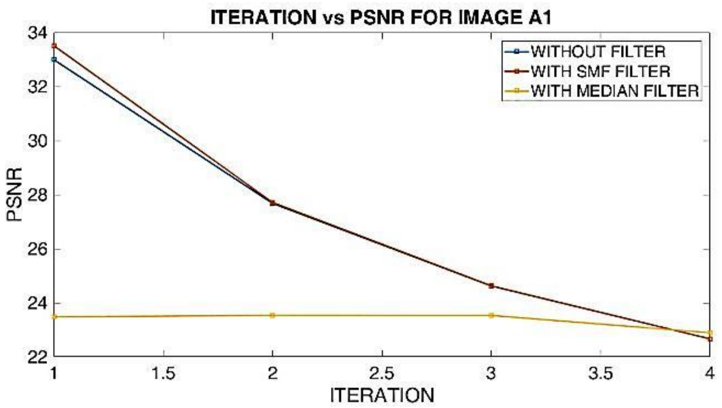

Fig. 7: *Iteration vs. PSNR for Image A1.*

Table 2 contains the data of PSNR and iteration for without filter, with SMF & median filter and Fig. 7 contains the plots of PSNR vs. ITERATION. Similarly data for other images has been taken and from those tables and plots, it can be seen that median filter has better PSNR than other two at high iteration; therefore media filter can be used with high iteration in order to get both good PSNR and good CR.

Similarly, data for other images has been taken and from those tables and plots, it can be concluded that PSNR (PEAK SIGNAL TO NOISE RATIO) decreases with increase in CR (compression ratio).

Table 3: *Cr vs. Iteration.*

Iterations	CR_A1	CR_A2	CR_A4	CR_N1	CR_N2	CR_N3	CR_PIC6
1	2.9697	3.0396	3.1073	3.0176	3.4145	3.1344	3.0812
2	9.2485	9.4450	9.6330	9.3243	10.3693	9.6151	9.4070
3	22.6551	23.7596	24.0297	23.3925	27.1560	25.5640	23.1599
4	71.9951	72.7438	73.9756	72.9740	78.6748	75.6434	73.1094

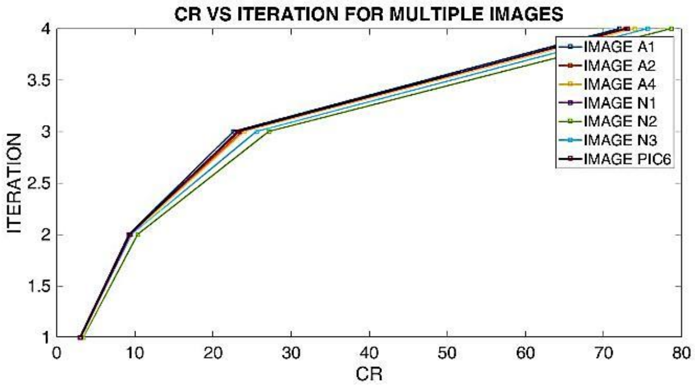

Fig. 8: *CR vs. PSNR up to 4 Iterations for all Images.*

Table 3 contains the data of CR and ITERATION for multiple images and Fig. 8 contains the plots of CR vs. ITERATION. Similarly data for other images has been taken and from those tables and plots, it can be concluded that CR increases with increase in number of iterations.

Table 4: *Window Size of Median Filter vs. Iteration.*

Window Size	A1	A2	A4	N1	N2	N3	Pic6
3*3	22.6845	24.2140	21.4038	21.8469	26.9164	26.4349	26.2112
9*9	22.7891	24.3759	21.5422	21.9133	27.0474	26.5631	26.5742
15*15	22.8954	24.5627	21.7300	21.9838	27.1805	26.7250	27.0996
21*21	22.8896	24.5825	21.8263	21.9901	27.1680	26.7771	27.3709
27*27	22.6831	24.3117	21.7647	21.8695	26.8835	26.6523	27.2882

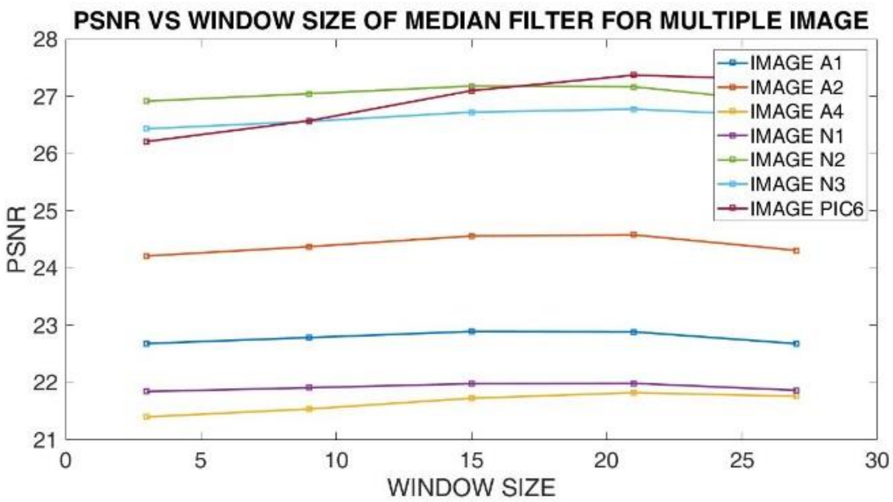

Fig. 9: *PSNR vs. Window Size of Median Filter for all Images.*

Table 4 contains data of PSNR for different window size of median filter and Fig. 9 shows plots of PSNR vs.Window Size of Median Filter for multiple images.Similarly data for other images has been taken and from those tables and plots, it can be concluded that window size 21x21 gives better PSNR value than other window sizes. Therefore, window size 21x21 can be used to get high PSNR.

CONCLUSION

DWT is extremely economical in press the digital pictures, it additionally provides higher output image quality once decompression. To improve compression ratio only LL part is sent and to improve CR, further DWT is applied. Results has been taken upto four iteration of DWT, which gives good compression ratio as well as PSNR within limits in the output image as shown in results. But with increase in CR, PSNR decreases therefore in order to improve the PSNR further, filtering is applied. Two filters have been studied in proposed work, median filter and switching median filter. Median filter works better than switching median filter to improve PSNR value for higher iterations while switching median filter works better for lower iterations means lower CR. Therefore a trade-off has to be made between CR & PSNR to get the best result. Median filter has also been studied for different window size and it is concluded that median filter works best with window size of 21x21 as shown in the results above.

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