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Time Complexity Analysis of M-band Wavelet Inpainting Technique for Distorted Digital Images

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Abstract: Image inpainting is an image processing technique to restore damaged or lost portions in an image. This paper presents a new M - band wavelet based image inpainting technique for digital images and its time complexity analysis for the suitability of energy aware computing applications. The proposed technique will decompose the given original into sub bands using M-band dual tree wavelet. The damaged or lost portions of an image are then identified in different sub bands and it is filled with neighborhood frequency values. The experiment shows that the proposed technique retains the same level of time complexity with respect to Complex Wavelet Transform technique and it is around 50 seconds at an average for the input image of size 512x512. At the same time, it failed to improve the time complexity with respect to other well known techniques in the literature Discrete Wavelet Transform, Haar and Daubechies. The proposed scheme time complexity is reduced 16% at an average for an input grey scale image of size 512x512. The reasons are use of M-band wavelet decomposition and reconstruction in the proposed technique. It is concluded that the proposed scheme can be applied in energy aware computing applications after fine tuning the time complexity of the scheme.

Keywords: In painting, wavelets, DWT, Haar, Daubechies, CWT, 2D Dual tree Complex Wavelet transform

I. Introduction

Image Inpainting is the process of modifying an image in an undetectable form to recover the damaged or lost portions in an image. The applications of image inpainting falls into broad spectrum that ranges from the restoration of damaged paintings and photographs to the removal/replacement of selected objects [7]. Image inpainting provides an interface to restore damaged region of an image completely to make natural look after the inpainting [1 - 5]. Applications of image inpainting range from restoration of photographs, films and paintings, to removal of occlusions, such as text, subtitles, stamps and publicity from images. In addition, inpainting can also be used to produce special effects [8]. Traditional image inpainting is widely replaced by image processing tools such as Photoshop. Bertalmio [6, 8] have introduced a technique for digital inpainting of still images that produces very impressive results. Digital techniques are starting to be a widespread way of performing inpainting, ranging from attempts to fully automatic detection and removal of scratches in film [3, 4, 19].

Image inpainting uses interpolation to forecast the pixel values for the damaged or lost portions in an image using its neighborhood pixels [2, 5, 9, 15-17]. The other techniques such as neural network, wavelet transform, grid cell analysis (GCA), genetic algorithm (GA), artificial life (AL), fuzzy set theory, texture classification and more has also been employed in image inpainting [10]. Wavelet transformation has been identified as a promising technique for all kinds of image inpainting, since it decomposes the image in multi resolution. The damaged or lost portions of an image are considered as either low frequency or high frequency components; it can easily be identified in various bands of wavelet. Therefore, the wavelet is playing significant role in image inpainting [13].

The 2D discrete wavelet transformation is mainly applied to the model of digital image data in order to find the locality and length of the crack [11, 18]. Other purposes include frequency analysis, selection of region of interest (ROI) and transform data [12, 20].

This paper is organized as follows. Section I presents introduction to image inpainting and significance of wavelet in it. Section II explains the related work in the direction of the proposed technique. Section III presents the proposed technique. Section IV discusses the experimental

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results and analysis. The conclusion is given in Section V.

II. Related work

Through the literature survey on Image Inpainting using wavelets, it is found that there are few works in the same direction of proposed technique that gave significant remarks.

Gunamani Jena [21] has presented an inpainting algorithm, which implements the filling of damaged region with impressive results. Many algorithms usually required several minutes on current personal computers for the inpainting of relatively small areas. Such a time is unacceptable for interactive sessions and motivated us to design a simpler and faster algorithm capable of producing similar results in just a few seconds. The results produced by the algorithm are two to three orders of magnitude faster to the existing.

I. A. Ismail *et al*. [22] have proposed an integrated technique for the recognition and purging of cracks on digitized images. Using steepest descent algorithm (SDA), initially the cracks have been identified. Then, the identified cracks have been purged using either a gradient Function (GRF) and processed data or a semi-automatic procedure based on region growing. Lastly, crack filling has been performed using the steepest descent method. The proposed technique has been implemented using Matlab, Surfer and Visual Fortran programming. Experimental results have shown that their technique has performed effectively on digitized images suffering from cracks.

Dayal R. Parhi and Sasanka Choudhury [23] have conducted a comprehensive review of several techniques in the field of crack detection in Beam-Like Structure. Sensibility analysis of experimentally measured frequencies as a decisive factor for crack identification has been employed widely in the last few decades because of its straightforwardness. The determination of crack parameters such as depth and location is complicated. Several techniques have been discussed on the basis of dynamic analysis of Crack. The techniques mostly used for crack detection were fuzzy logic neural network, fuzzy system, hybrid neuro genetic algorithm, artificial neural network, artificial intelligence.

K.N.Sivabalan and D.Gananadurai [24] have utilized Gabor filter and Gaussian filter in order to remove the texture elements in the digital image by separating the defected area. Then, a fast searching algorithm which uses feature extraction parameters has been proposed to find the defected pixels and to robustly segment it. Their proposed method was appropriate for both texture and non texture images. Consequently, the algorithm has successfully detected the damage in the digital texture image using non texture methods.

J. Rupil *et al*. [25] have introduced a digital image correlation technique for recognizing and calculating automatically the micro cracks on the surface of a specimen during a fatigue test. The technique has allowed a quick scanning of the entire surface with all possible (pixel-wise) locations of micro crack centers and the detection of cracks containing a sub-pixel opening. An experimental test case has been presented as a design of the method and a comparison has been conducted with a replica technique.

YANG Jian-bin *et al* [14] used dual-tree complex wavelet transform tool in signal and image processing. From the above discussed survey, it is found that complex wavelet transform outperformed in the sense of shift-invariance, direction and anti-aliasing.

Hence, a dual tree wavelet based image inpainting techniques using the approaches proposed by Cai, Chan, and Shen is proposed in this paperwork towards optimizing the overall performance of the technique on level of recovery and time.

III. Proposed Image Inpainting Technique

Let 'a' be an image in the original image domain 'D'

$$a = \{ a_{ij} ; 1 < i \leq P, 1 < i \leq Q \} \tag{1}$$

And the a' be known, observed region and $\hat{D}$ is the inpainting domain. The intensity value

$$v(a_i) = v_0(i) + \Delta(i) \tag{2}$$

in the domain 'D' where Δ is the noise term. The proposed system finds an image 'b' that matches v_0 in 'D' and have meaningful content in the domain $\hat{D}$ since the value of $v(a_i)$ is arbitrary when $i \in \hat{D}$. The proposed system consists of the following steps Initial value assignment, converting to frequency domain, coefficients thresholding, Reconstruction and Iterative image inpainting.

3.1. Initial value assignment using nearest neighbor algorithm

Initially the closest entries of a' are identified and replaced using nearest neighbor algorithm. The selection of closest entries can be realized in two methods, first, as is, on the set of entities, and, second by considering only entities with non missing entries in the attribute corresponding to that of target's missing entry. The proposed system uses the second approach for initial assignment of the damaged portion. The nearest neighbor algorithm is given below.

Step 1: Read an initial value a'.

Step 2: Find K neighbors of a'.

Step 3: Find the data matrix a' consisting of a' and K neighbors.

Step 4: Apply an imputation algorithm to a' and impute missing values in a'.

Step 5: Repeat the above steps until a' is filled.

3.2. Conversion of image to frequency domain by means of wavelet

The proposed system uses the M-band Complex 2 D Dual tree wavelet transform which posses the unique geometrical features for frequency domain conversion. This decomposition provides local, multi-scale directional analysis. The wavelet transform is self possessed of cascading M-band filter banks. The M-band trees are obtained by performing two M-band multi resolution analyses in parallel in the real case, or four in the complex case. The dual tree decompositions are shift variant, with each trend keeping the same characteristics when the data is delayed. Different sub bands and two sets of coefficients preferentially capture different directions.

The M-band bi-orthogonal wavelet decomposition of $L^2(R)$ is based on the joint use of two sets of basic functions $\psi_0 \le m < M$, $\bar{\psi}_m \le m < M$ which satisfy the following scaling equations expressed in the frequency domain.

$$M^{1/2}\psi_m(M\varpi) = \mathrm{H}_0(\varpi)\psi_0(\varpi) \quad (3)$$

$$M^{1/2}\hat{\bar{\psi}}_m(M\varpi) = \mathrm{H}_0(\varpi)\hat{\bar{\psi}}_0(\varpi) \quad (4)$$

Here ψ_0 is the father wavelet and $\bar{\psi}_m$ is mother wavelets. The mother wavelets are obtained through the Hilbert transform that uses the fourier analysis.

Along with this, the interpolation functions can also be used for the separation of the signals.

3.2.1. Direction Extraction in the different sub bands

After the decomposition, the sub bands are combined together in a linear fashion to extract the directions from the images. Some linear combinations of the primal and dual sub bands are used to extract the local directions present in the image. The defined analytic wavelets for direction sub bands are

$$\psi_m^k(t)\frac{\psi_m(t)}{2^{1/2}} + i\psi_m^H(t) \quad (5)$$

$$\psi_m^k(t)\frac{\psi_m(t)}{2^{1/2}} - i\psi_m^H(t) \quad (6)$$

The above functions are used to extract the directions that falling in the first and third quadrant of the frequency plane. Likewise the real part of the tensor product of an analytic wavelet and anti analytic are used to select the frequency components which are localized in the second /fourth quadrant of the frequency plane. After the direction extraction, the thresholding is applied on the images.

3.2.2. Coefficients thresholding

Initially the diagonal matrix ΔD is obtained as follows.

$$\Delta D_{ij} = \begin{Bmatrix} 1 & if & a_{ij} \in \eta \\ 0 & if & a_{ij} \in \eta' \end{Bmatrix} \quad (7)$$

Subsequently the initial guess of the original image is done. by using the For n=1,2,…. $f_n = \psi^* Shrink(\psi_l, \lambda)$. By using the shrinkage procedures as in [14] are carried out for all the M-bands of 2DCWT coefficients. As follows

$$shrink(u,\lambda) = \begin{Bmatrix} 0 & if\,|l| \le \lambda \\ \dfrac{|l|-\lambda}{[l]}.l & if \;\; l \le \lambda' \end{Bmatrix} \quad (8)$$

Where 'l' is the given intensity. And then the iterative algorithm

$$l_{n+1} = \Delta D l + (I - \Delta D) f_l \quad (9)$$

is repeated until the 'n' convergence. Using [25], if l^* is the output of (35) then $\varepsilon(i) = 0$ for every values 'I' of η (1), then it will be the solution of the interpolation problem. Otherwise the solution $l^* = \psi^* Shrink(\psi_{l^*}, \lambda)$ will be the denoising and interpolation problem.

3.2.3 Reconstruction

Let f be the vector of image samples, δ the vector of coefficients produced by the primal M band decomposition and δ^H be the vector of coefficients produced by dual one. The global decomposition operator is

$$D: f \rightarrow \begin{pmatrix} C \\ C^H \end{pmatrix} = \begin{pmatrix} D_1 f \\ D_2 f \end{pmatrix} \quad (10)$$

Where $D_1 = U_1 F_1$ and $D_2 = U_2 F_2$ $F1$ and $F2$ being the pre filtering operations and $U1$ and $U2$ be the orthogonal m band decomposition then the following can be proved. Assume that $x(p-g, q-l)_{g,l \in Z^2}$ is an orthonormal family of $L^2(R^2)$. Provided that there exist $I_e J_e I_{\psi_0} \in (R_+^*)^3$ for almost all $\varpi_x \varpi_y \in [-\pi,\pi]^2$, $|\hat{x}(\varpi_x, \varpi_y)| < I_e$, $|\hat{\psi}(\varpi_x)| \ge A\psi_0$

(11)

$$\sum_{(p,q)\ne(0,0)} |x(\varpi_p + 2y\pi, \varpi_q + 2z\pi)|^2 \le J_x < I_x^2 I_{\psi 0}^4 \quad (12)$$

The D is the frame operator. The "dual" frame reconstruction operator is given by

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$$I=(F1^{'}F1+F2^{'}F2)^{-1}(F1^{'}U1^{-1}\delta+F2^{'}U2^{-1}\delta^{H}) \quad (13)$$

Where $F1^{'}$ designates the ad joint of an operator $F1$. The formula (33) minimizes the impact of possible errors in the computation of the wavelet coefficients. $U1^{-1}$ and $U2^{-1}$ are the inverse of M-band wavelet transforms and $F1^{'}, F2^{'}$ and $(F1^{'}F1+F2^{'}F2)^{-1}$ correspond to filtering with frequency responses $|(F1_1^{*}(\varpi_p\varpi_q)|^2$, $|(F2_1^{*}(\varpi_p\varpi_q)|^2$ and $(|F1_1(\varpi_p\varpi_q)|^2+|F1_2(\varpi_p\varpi_q)|^2)^{-1}$ respectively. Thus the proposed technique restores the original image from the damages or lost.

IV. Experimental Results and Analysis

The proposed scheme is simulated on Matlab 2010a using test bed that contains 5 standard test images. They are Image1: Barbara, Image2: Boat, Image3: Fruits, Image4: Peppers and Image5; Lena. All the images were taken in Grey Scale Mode and size of 512x512. For the damaged images, above mentioned images are manipulated in three levels for providing the cracked images.

For the quantitative analysis of the proposed technique, the Peak Signal to Noise Ratio (PSNR), Standard deviation to Mean Ratio(S/M) and Tic/Toc functions in Matlab are taken.

The time analysis is done on the aggregate time of 5 test images for a scheme. For the comparison, Discrete Wavelet Transformation (DWT), Haar, Daubechies, and Complex Wavelet Transformation (CWT) are taken from the literature survey [15-20].

IV.1 PSNR and S/M Ration Analysis

The fig.1 to fig.10 shows the screen shot of the proposed technique's PSNR analysis. The PSNR values are listed in the tab.1, tab.2 and tab.3. The entire results are taken for three level cracks in the input images.

From the observation of above mentioned values, it is found that the proposed scheme improves the PSNR 5% at an average for all the input images at all the levels. It shows that the proposed scheme able to replace the damaged or lost pixel values with the values that are very close to the original pixel values.

Figure 1: Proposed Technique Outputs for Image1.

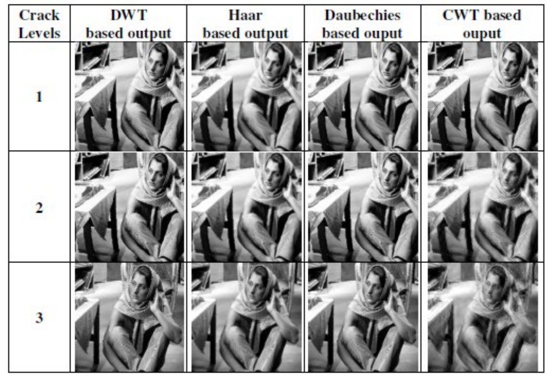

Figure 2: DWT, Haar, Daubechies and CWT Outputs for Image 1.

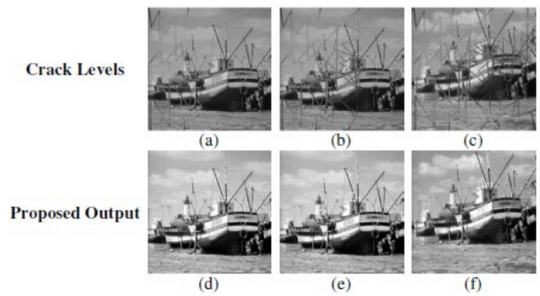

Figure 3: Proposed Technique Outputs for Image 2.

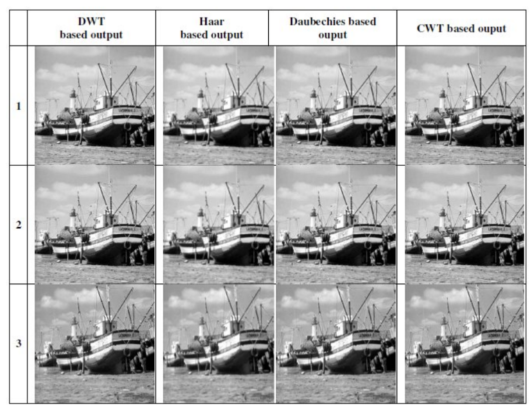

Figure 4: DWT, Haar, Daubechies and CWT outputs for Image2.

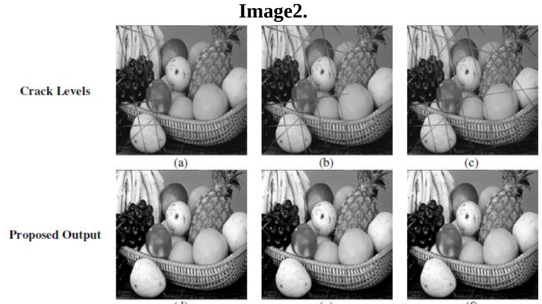

Figure 5: Proposed Technique Outputs for Image 3.

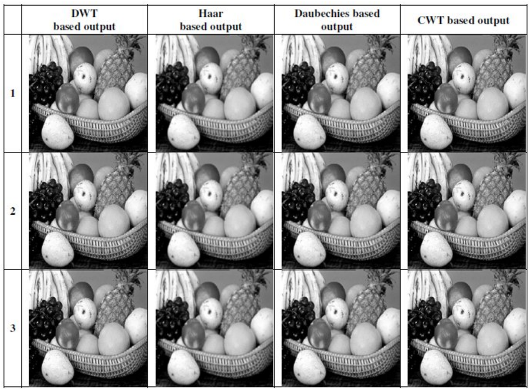

Figure 6: DWT, Haar, Daubechies and CWT Outputs for Image3.

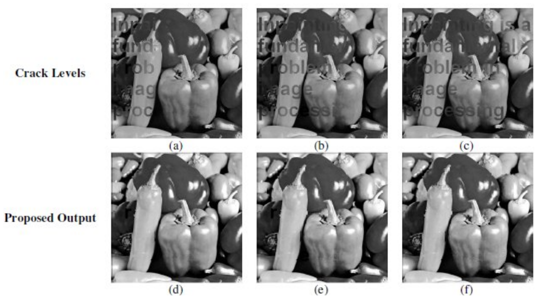

Figure 7: Proposed Technique Outputs for Image 4.

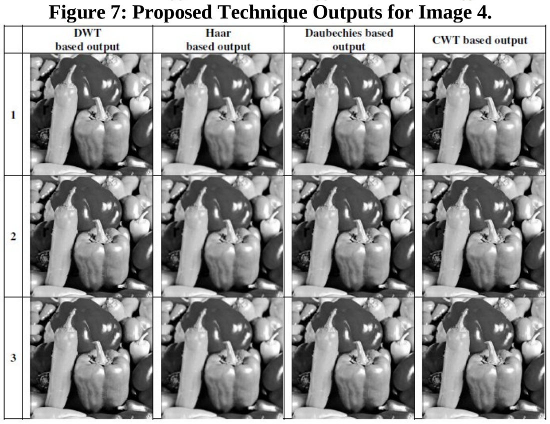

Figure 8: DWT, Haar, Daubechies and CWT Outputs for Image 4.

Figure 9: Proposed Technique Outputs for Image 5.

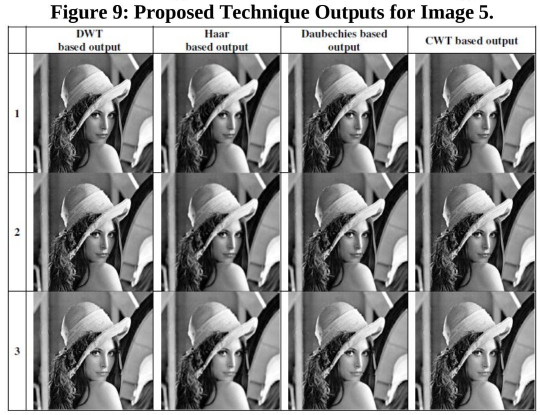

Figure 10: DWT, Haar, Daubechies and CWT Outputs for Image 5.

Table 1: Performance Comparison of Proposed Techniques for Crack Level 1

	Image1	Image2	Image3	Image4	Image5	Total	Average	Standard deviation	S/M
DWT	15.682659	17.38496	17.204759	16.78396	19.2851	86.34143	17.26829	1.307092	0.075693
Haar	14.702661	16.87209	17.003936	16.52693	18.72821	83.83382	16.76676	1.43463	0.085564
Daubechies	14.74743	17.06256	17.133125	16.59035	18.96635	84.49982	16.89996	1.506654	0.089151
CWT	15.528204	17.34496	17.211023	16.71531	19.22632	86.02581	17.20516	1.337609	0.077745
Proposed	15.668087	17.3652	17.218906	16.77732	19.23909	86.26859	17.25372	1.29388	0.074991

Table 2: Performance Comparison of Proposed Techniques for Crack Level 2

	Image1	Image2	Image3	Image4	Image5	Total	Average	Standard deviation	S/M
DWT	12.31413	13.62292	15.3487	14.82145	15.72731	71.83451	14.3669	1.395405	0.097126
Haar	11.84051	13.33268	15.2288	14.66204	15.5623	70.62632	14.12526	1.534543	0.108638
Daubechies	11.86531	13.46868	15.29738	14.73502	15.62703	70.99343	14.19869	1.542118	0.10861

CWT	12.18224	13.58814	15.35559	14.80449	15.70939	71.63985	14.32797	1.444204	0.100796
Proposed	12.29484	13.61145	15.37255	14.82146	15.75517	71.85546	14.37109	1.415034	0.098464

Table 3: Performance Comparison of Proposed Techniques for Crack Level 3

	Image1	Image2	Image3	Image4	Image5	Total	Average	Standard deviation	S/M
DWT	11.38259	13.32602	14.08648	13.54998	12.84451	65.18958	13.03792	1.027402	0.078801
Haar	11.18111	13.05052	13.99956	13.38804	12.70727	64.32649	12.8653	1.055409	0.082035
Daubechies	11.16304	13.16882	14.04156	13.44157	12.81528	64.63029	12.92606	1.082766	0.083766
CWT	11.33501	13.28759	14.09376	13.48232	12.84611	65.04478	13.00896	1.037682	0.079767
Proposed	11.45881	13.30298	14.11342	13.52093	12.89258	65.28872	13.05774	0.99662	0.076324

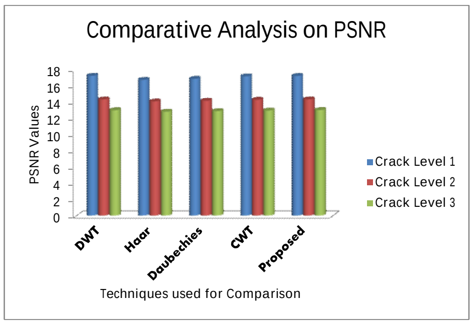

Figure 11: Comparative Analysis on PSNR

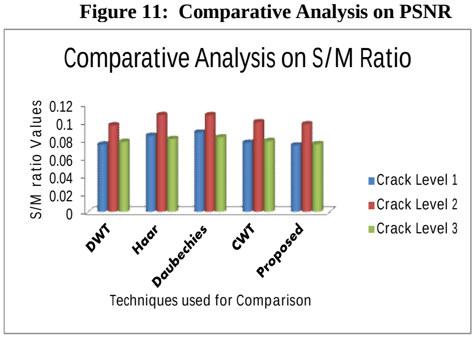

Figure 12: Comparative analysis on S/M Ratio.

IV.2 Time Complexity Analysis of the Proposed Technique

Another experiment is conducted on the proposed technique for measuring its time complexity towards applying the technique for energy aware computing applications such as mobile, WiFi Networks. Such applications use the techniques that are expected to utilize the power to the level best minimum for its all operations. In those cases, time complexity is playing major role and it must be reasonable and minimum.

From the table 4, it is clear that the proposed scheme is not improves the time with respect to the other techniques. The overall time analysis of the proposed scheme decrease 80% at an average with respect to other techniques. The reasons are use of multi band wavelet decomposition and reconstructions. However, the time analysis is taken for aggregate time of 5 images. Therefore, by considering single image, the performance degradation is about 16%. By considering the optimization, such performance degradation is accepted in the proposed scheme. At the same time, the proposed scheme retains the same level of time complexity with respect to CWT and it is around 50 seconds at an average for the input grey scale image of size 512x512. The results are shown in fig. 12 and fig.13.

Table 4: Time Analysis of Proposed Technique with Existing Techniques.

Name of the Technique	Complexity Level		
	Level 1	Level 2	Level 3
DWT	9.0566	11.2536	10.2459
HAAR	37.6459	37.8556	37.7662
DAUBECHIES	40.9068	40.4051	39.3322
CWT	175.3135	218.7938	267.5719
PROPOSED	174.2567	215.8767	250.5678

All the values are given in seconds. For a scheme time value for any level refers the aggregate time of 5 test images.

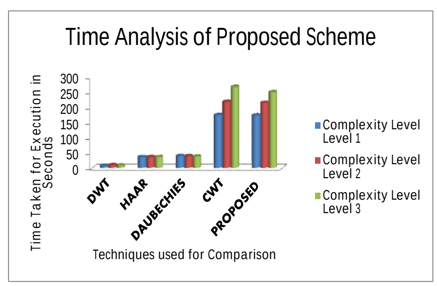

Figure 12: Comparative analysis of proposed technique on Time Taken for Execution for aggregate of all the Input Image at an Average.

From the observation it is concluded that the proposed scheme is best suitable for performing image inpainting and for the energy aware computing allocations sector, it's time complexity need to be further fine tuned.

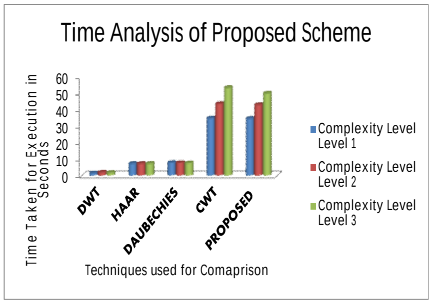

Figure 13: Comparative analysis of proposed technique on Time Taken for Execution for Individual Input Image at an Average.

V. Conclusion

In this paper, an M-band wavelet based image inpainting scheme is proposed for digital grey scale images. It uses M-band wavelet to locate the cracks in an image and fill the same. The experiment shows that the proposed technique retains the same level of time complexity with respect to Complex Wavelet Transform technique and it is around 50 seconds at an average for the input image of size 512x512. At the same time, it failed to improve the time complexity with respect to other well known techniques in the literature Discrete Wavelet Transform, Haar and Daubechies. The proposed scheme time complexity is reduced 16% at an average for an input grey scale image of size 512x512. The reasons are use of M-band wavelet decomposition and reconstruction in the proposed technique. It is concluded that the proposed scheme can be applied in energy aware computing applications after fine tuning the time complexity of the technique.

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