Efficient M-Band Wavelet Based Inpainting Technique to Detect and Impound the Distorted Digital Images

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Abstract

Image in painting or completion is a technique to restore a damaged image. In this paper M band complex wavelet transform is used for frequency domain conversion of the image subsequently using the iterative shrinkage technique, inpainting process of the cracked image is carried out successfully. In the proposed approach M-band dual tree wavelet transform which decompose the each input wavelets into set of subbands with each sub band wavelets occupying a portion of the original frequency band and hence produced better frequency analysis for image in painting process. Each sub bands and its coefficients preferentially will be captured different directions and hence it will be detected cracks in different direction. The performance of the proposed approach is evaluated and analyzed by the various cracked images.

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

1. Introduction

Inpainting, the technique of modifying an image in an undetectable form, is as ancient as art itself. The goals and applications of inpainting is numerous, from the restoration of damaged paintings and photographs to the removal/replacement of selected objects [7]. Image inpainting [1, 5] provides a means to restore damaged region of an image, such that the image looks complete and natural after the inpainting process. 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]. Traditionally, skilled artists have performed image inpainting manually. But given its range of applications, it would be desirable to have image inpainting as a standard feature of popular image tools such as PhotoShop. Bertalmio et al [6] have introduced a technique for digital inpainting of still images that produces very impressive results [8]. 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, 19], all the way to software tools that allow a sophisticated but mostly manual process [4]. Cracks usually have low brightness and therefore it is considered as local intensity minima [2]. Inpainting is a technique, used for altering an image in an undetectable form. The main intention of inpainting is the restoration of damaged paintings and photographs for the purging of selected objects [9]. Inpainting is the process of recreating lost or damaged portions of images and videos [15]. Inpainting is an image interpolation technique [16]. In the mathematical field of numerical analysis, interpolation is a technique of creating new data points within the range of a discrete set of known data points [17].

For the crack detection and analysis, several 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 been employed [10]. Wavelet is a promising method, very useful for the detection of structural damages [13]. The 2D discrete wavelet transformation is applied to the model of digital image data in order to find the locality and length of the crack [18]. In mathematics, a wavelet series is a depiction of a square-integrable (real- or complex-valued) function by a certain orthonormal series created by a wavelet [11]. The wavelet transform itself gives great design flexibility. Basis selection, spatial-frequency tiling, and different wavelet threshold approaches can be optimized to achieve best adaptation.
for processing application, data characteristics and feature of interest [12]. In wavelet packet transform, the data is transformed using a far more comprehensive range of space-frequency analysis functions, which is expected to mine more information of interest [20].

The structure of the paper is organized as follows: A brief review of the researches related to image inpainting is discussed in Section 2. The proposed wavelet transform based image inpainting is given in Section 3. The experimental results of the proposed approach are presented in Section 4. Finally, the conclusion is given in Section 5.

2. Related Work

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. But, 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.Sivabala 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. This paper proposed a dual-tree complex wavelet transform (CWT) based algorithm for image inpainting problem. The approach is based on Cai, Chan, Shen and Shen’s framelet-based algorithm. The complex wavelet transform outperforms the standard real wavelet transform in the sense of shift-invariance, directionality and anti-aliasing. Numerical results illustrate the good performance of algorithm.

3. Wavelets Based Image Inpainting

Let ‘a’ be an image in the domain ‘D’

\[ a = \{ a_{ij}, \quad 1 < i \leq P, \quad 1 < j \leq Q \} \]  

(1)

And the ‘a’ be known, observed region and \( \hat{D} \) is the inpainting domain. The intensity value

\[ V(a_i) = V_{0}(i) + \Delta(i) \]  

(2)

in the domain ‘D’ where \( \Delta \) 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 (a) Initial value assignment, (b) Converting to frequency domain (c) coefficients thresholding , (d) Reconstruction , (e) 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 entries 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 following procedure represents the nearest neighbor algorithm.

Procedure 1: Nearest Neighbor Algorithm

Step 1: Read an initial value $a_i$

Step 2: Find K neighbors of $a_i$

Step 3: Find the data matrix $a'_i$ consisting of $a_i$ and K neighbors

Step 4: Apply an imputation algorithm to $a'_i$ and impute missing values in $a_i$

Step 5: Rate the above steps until $d'$ are filled.

3.2. Conversion of Image to Frequency Domain By Means of Wavelet

The proposed system uses the M-band Complex 2D Dual tree wavelet t 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 parallel in the real case, or four in the complex case. 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 $\psi_0 \leq m < M$, $\hat{\psi}_m \leq m < M$ which satisfy the following scaling equations expressed in the frequency domain.

$$M^{1/2} \psi_m(M\sigma) = H_m(\sigma) \psi_m(\sigma)$$  \hspace{1cm} (3)$$

$$M^{1/2} \hat{\psi}_m(M\sigma) = H_m(\sigma) \hat{\psi}_m(\sigma)$$  \hspace{1cm} (4)$$

Here $\psi$ is the father wavelet and $\hat{\psi}$ are mother wavelets. $m \in \{1, \ldots, M-1\}$ which defined a dual M-band multi resolution analysis. Specifically the mother wavelets will be obtained by Hilbert transform. In the Fourier domain the desired property reads,

$$|\hat{\psi}_m(w)| = -i \, \text{sign}(w) \, \hat{\psi}(w)$$

$$\forall m \in \{1, \ldots, M-1\}$$

The sign is the signum function and $\hat{\psi}$ designates the fourier transform of a function $d$. The Hilbert condition (4) yields

$$\forall m \in \{1, \ldots, M-1\} \mid \hat{\psi}_m(w) \mid = |\hat{\psi}_m(w)|$$ \hspace{1cm} (5)$$

The scaling equation leads to

$$\forall m \in \{1, \ldots, M-1\} \mid G_m(w) = e^{-i\pi \theta_m} H_m(w)$$ \hspace{1cm} (6)$$

Where $\theta_m$ is $2\pi$ periodic. The frequency phase functions should also be odd (for real filters) and thus only need to determined over $[0, \pi]$. In the 2 band case (under weak assumptions) $\theta_m$ is a linear function on $[-\pi, \pi]$. In the M band the constraint is slightly restricted on a smaller interval by imposing

$$\forall m \in [0,2\pi/M]\, \theta_m(w) = \varphi \theta \text{ where } \varphi \in R.$$ \hspace{1cm} (7)$$

It can be deduced that, Para-unitary M band filter bank conditions are obtained by choosing the phase functions defined by

$$\forall m \in [0,2\pi/M]\, \theta_m(w) = \varphi \theta \text{ where } \varphi \in R.$$ \hspace{1cm} (8)$$

Where $\varphi \in Z$ denotes the upper integer part of real $\varphi$. The scaling function associated to the dual wavelet composition is such that

$$\forall m \in N, \forall w \in [2\pi, 2\pi + 1] \pi \hat{\psi}_m(w) = (-1) \cdot e^{-i\pi \varphi \theta} \hat{\psi}_m(w)$$ \hspace{1cm} (9)$$

Find that except in the 2 band case $\theta_0$ exhibits discontinuities on $0, \pi$ due to the b $\pi$ term.

The two dimensional separable M-band wavelets bases can be derived from the 1D dual tree decomposition. Thus we obtain two bases of $L^2(R^2)$. The first one corresponds to the classical 2D separable wavelet basis but the second one results from the tensor product of the dual wavelet basis function. A discrete implementation of these wavelet decompositions starts from level j=1 to go up to the coarsest resolution level $j \in N$. The decomposition on to the former 2D wavelet basis function yields coefficients $\delta_{j,m,m}[k,l]$, whereas the decomposition on to the dual basis generates coefficients $\hat{\delta}_{j,m,m}[k,l]$.
The wavelet transform is a continuous-space formalism which is applied to the discrete image. The analog scene corresponds to the 2D field
\[ f(p,q) = \sum_{g,l} f(g,l) x(p - g, q - l). \] (10)

Here the 'x' is the interpolation functions and \( f(g,l) \) is the image sample sequence. The image is projected on to the approximation space \( V_0 = \text{span} \{ \psi_\nu(p - g, q - l) \} \). (11)

The projection of 'f' reads \( EV_0(f(p,q)) = \sum_{\nu} \delta_{\nu,0} \psi_\nu(p - q) \psi_\nu(q - l) \). (12)

Where the approximation coefficients are
\[ \delta_{\nu,0}[g,l] = f(y,z) \lambda, \psi_{\nu}(k - y, l - z). \] (13)

Similarly the analog image is projected on to the dual approximation space \( V^d_0 = \text{span} \{ \tilde{\psi}_{\nu}(p - g, q - l), (k,l) \in Z^2 \} \). (16)

Where \( \tilde{\psi}_{\nu}(p,q) = \psi_{\nu}^*(p) \psi_{\nu}^*(q) \) (17)

Then the dual approximation coefficients are given by
\[ \delta^d_{\nu,0}[g,l] = f(y,z) \lambda, \tilde{\psi}_{\nu}(k - y, l - z). \] (18)

Obviously Eq.(13) and (18) can be interpreted as the use of two of pre filters on the discrete image \( f(g,l) \), before the dual tree decomposition and the frequency responses of these filters are
\[ H(\sigma_g, \sigma_l) = \sum_{m,n} \tilde{\psi}_m(n) \psi_m(l) + 2 \pi \psi_m(l), \psi_n(l) \] (19)

\[ H^2(\sigma_g, \sigma_l) = \mathcal{H}H^* \] (20)

Different kinds of interpolation function may be considered, for instance the separable functions of the form \( x(p,q) = \phi(p) \psi(q) \). the two pre filters are then separable with the impulse responses \( \lambda \phi \psi_{\nu}(p) \) and \( \lambda \phi \psi_{\nu}^*(q) \) respectively.

3.2.1. Direction Extraction in the Different Sub Bands
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

\[ \tilde{\psi}_{\nu}(p,q) = \psi_{\nu}(p,q) + i \psi_{\nu}^*(p,q) \] (21)

\[ \psi_{\nu}(p,q) = \psi_{\nu}(p,q) - i \psi_{\nu}^*(p,q) \] (22)

The tensor product of the two analytic wavelets \( \tilde{\psi}_{\nu}^m \) and \( \psi_{\nu}^m \).

And the real part of the tensor product is
\[ \tilde{\psi}_{\nu,m}(x,y) = \mathcal{R}e[\tilde{\psi}_{\nu,m}(p) \psi_{\nu,m}^*(q)] \] (23)

For \( m,m \in \{1,\ldots,M-1\} \) the Fourier transform of this function is equal to
\[ \Psi_{\nu,m}(p,q) = \mathcal{F}[\tilde{\psi}_{\nu,m}(p) \psi_{\nu,m}^*(q)] \] (24)

The above function allows us to extract the directions that falling in the first third quadrant of the frequency plane. Like wise the real part of the tensor product of an analytic wavelet and anti analytic one is denoted by \( \tilde{\psi}_{\nu,m} \). This function is used to select the frequency components which are localized in the second fourth quadrant of the frequency plane. This corresponds to opposite directions to those obtained with \( \tilde{\psi}_{\nu,m} \).

At a given resolution level \( r \), for each sub band \( m,m \) with \( m \not= 0 \) and \( m \not= 1 \), the directional analysis is achieved by computing the coefficients
\[ C_{r,m,m} = \mathcal{F}[\tilde{\psi}_{\nu,m}(p,\sigma) \ast \psi_{\nu,m}^*(p,\sigma)] \] (25)

\[ C_{r,m,m} = \mathcal{F}[\tilde{\psi}_{\nu,m}(p,\sigma) \ast \psi_{\nu,m}^*(p,\sigma)] \] (26)

According to equation (21), (22) and (23) for all \( m,m \in \{1,\ldots,M-1\} \)
\[ C_{r,m,m} = \frac{1}{\sqrt{2}} \delta_{r,m,m} [k,l] + \delta_{r,m,m}^H [k,l] \] (27)

\[ C_{r,m,m} = \frac{1}{\sqrt{2}} \delta_{r,m,m} [k,l] - \delta_{r,m,m}^H [k,l] \] (28)

3.2.2. Coefficients Thresholding

Initially the diagonal matrix \( \Delta D \) is obtained as follows.
\[ \Delta D \eta = \begin{cases} 1 & \text{if } a_{\eta} \in \eta \\ 0 & \text{if } a_{\eta} \notin \eta \end{cases} \] (29)

Subsequently the initial guess of the original image is done. by using the \( \text{For } n=1,2,\ldots \).
By using the shrinkage procedures as in [14] are carried out for all the M-bands of 2DCWT coefficients. As follows

\[
\text{shrink}(u, λ) = \begin{cases} 0 & \text{if } |u| ≤ λ \\ \frac{u}{|u|} & \text{if } |u| > λ \\ \end{cases}
\]

(30)

Where ‘l’ is the given intensity. And then the iterative algorithm

\[
l_{n+1} = D(l - ΔD)f
\]

(31)

is repeated until the ‘n’ convergence. Using [25], if \( l^* \) is the output of (35) then

\[
l(l^*) = \sum_{i=1}^{N} |I_i| \leq \epsilon
\]

(33)

for every values of \( \eta \) and \( \nu \). Then it will be the solution of the interpolation problem. Otherwise the solution \( l^* = v^* \text{Shrink}(ψ, λ) \) 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 \( δ^R \) be the vector of coefficients produced by dual one. The global decomposition operator is

\[
D : f \rightarrow \begin{bmatrix} C \\ C^R \end{bmatrix} = \begin{bmatrix} D_1f \\ D_2f \end{bmatrix}
\]

(32)

Where \( D_1 = U_1F_1 \) and \( D_2 = U_2F_2 \). \( F_1 \) and \( F_2 \) being the pre filtering operations and \( U_1 \) and \( U_2 \) be the orthogonal m-band decomposition then the following can be proved. Assume that \( x(p, q - I) \) is an orthonormal family of \( L^2(R^2) \). Provided that there exist \( I, J, J^r \in (R^2)^d \) for almost all \( \alpha, \beta \in [-π, π]^2 \),

\[
|\hat{x}(\alpha, \beta)| < \sum_{j,k \in Z} |\hat{x}(\alpha + 2πj, \beta + 2πk)|^2 \delta(j, k)
\]

(34)

The D is the frame operator. The “dual” frame reconstruction operator is given by

\[
l = (F_1F_1 + F_2F_2)^{-1}(F_1U_1^T δ + F_2U_2^T δ')
\]

(35)

Where \( F_1 \) designates the adjoint of an operator \( F_1 \). The formula (32) minimizes the impact of possible errors in the computation of the wavelet coefficients. \( U_1^T \) and \( U_2^T \) are the inverse of M-band wavelet transforms and \( F_1^T F_1 \) and \( (F_1^T F_1 + F_2^T F_2)^{-1} \) correspond to filtering with frequency responses. \( |(F_1^T(σ_1, σ_2))^T F_1^T(σ_1, σ_2)|^2 \) and \( |(F_1^T(σ_1, σ_2))^T F_1 (σ_1, σ_2) (σ_1, σ_2)|^2 \) respectively.

### 4. Experimental Results

The proposed image inpainting system is implemented in MATLAB platform (version 7.10) and it is evaluated using the various images. Also the performance of the proposed wavelet based inpainting system is tested and analyzed by increasing the crack level. The (a),(b),(c) of Figure 1, Figure 3, Figure 5, Figure 7 and Figure 9 represents the three levels of cracked images and (d),(e),(f) of those images represents the inpainted images using the proposed technique. The performance of the proposed technique is analyzed quantitatively by using the metrics Peak Signal to Noise Ratio (PSNR) and standard deviation to mean ratio (S/M).

The performance of the proposed technique is also evaluated by comparing it with the inpainting techniques using the wavelets DWT, Haar, Daubechies, and CWT based technique. The Table 1, 2 and 3 represents the psnr values of the inpainted images and evaluation values. The Figure 11 and Figure 12 represents the PSNR mean ratio comparison graph of the proposed technique with the other inpainting techniques using the comparison wavelets. Like wise the Figure 13 represents the S/M comparison graph.
Figure 2: In painted output images using various comparison wavelets for image-1.

Figure 3: The cracked and inpainted image-2 (Proposed Approach)

Figure 4: In painted output images using various comparison wavelets for image-2.

Figure 5: The cracked and inpainted image-3 (Proposed Approach)

Figure 6: In painted output images using various comparison wavelets for image-3.

Figure 7: The cracked and inpainted image-4 (Proposed Approach)
Table 1: Performance comparison table_1 (PSNR)

<table>
<thead>
<tr>
<th></th>
<th>Image1</th>
<th>Image2</th>
<th>Image3</th>
<th>Image4</th>
<th>Image5</th>
<th>Total</th>
<th>Average</th>
<th>Standard Deviation</th>
<th>S/M</th>
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<tbody>
<tr>
<td>DWT</td>
<td>15.682659</td>
<td>17.38496</td>
<td>17.204759</td>
<td>16.78396</td>
<td>19.2851</td>
<td>86.34143</td>
<td>17.26829</td>
<td>1.307092</td>
<td>0.075693</td>
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<tr>
<td>Haar</td>
<td>14.702661</td>
<td>16.87209</td>
<td>17.003936</td>
<td>16.52693</td>
<td>18.72821</td>
<td>83.83382</td>
<td>16.76676</td>
<td>1.43463</td>
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<tr>
<td>Daubechies</td>
<td>14.74743</td>
<td>17.06256</td>
<td>17.133125</td>
<td>16.59035</td>
<td>18.96635</td>
<td>84.49982</td>
<td>16.89996</td>
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<tr>
<td>CWT</td>
<td>15.528204</td>
<td>17.34496</td>
<td>17.211023</td>
<td>16.71531</td>
<td>19.22632</td>
<td>86.02581</td>
<td>17.20516</td>
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<tr>
<td>Proposed</td>
<td>15.668087</td>
<td>17.3652</td>
<td>17.218906</td>
<td>16.77732</td>
<td>19.23909</td>
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Table 2: Performance comparison table_2 (PSNR)

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<tr>
<td>Haar</td>
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Table 3: Performance comparison table_3 (PSNR)

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<th>Average</th>
<th>Standard deviation</th>
<th>S/M</th>
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<tr>
<td>Haar</td>
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<td>13.05952</td>
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<td>12.70727</td>
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<td>Daubechies</td>
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</tr>
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</table>

The standard deviation values and S/M values shows the better result of the proposed approach.

5. Conclusion
In this paper, 2D CWT_M band based iterative image inpainting approach was proposed. The approach was implemented and experimented with different images with various crack level also the proposed approach was compared with the various inpainting techniques with different wavelets. The analytical results confirmed that the proposed approach has shown a better performance than the other comparative wavelets based approaches. Overall, the proposed approach has achieved 0.032192 %, 0.00223%, 0.14945%, 0.318375% more PSNR values than the traditional DWT, Haar, Daubechies and CWT based inpainting techniques (i.e. In the circumstance of achieving 100% performance by proposed approach, the other comparative wavelets based inpainting approaches are able to achieve only 99.97%, 99.8%, 98.59% 99.68% for DWT, Haar, Daubechies and CWT) respectively. Such performance has been achieved because of the M band nature of 2d dual tree complex wavelet transform and its improved directional analysis as well as a frequent analysis feature.

References