www.ijecs.in
International Journal Of Engineering And Computer Science ISSN: 2319-7242
Volume 4 Issue 10 Oct 2015,Page No. 14559-14564

A Review on Image reconstruction using Haar DWT on Crack Images

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Abstract

The main aim of this paper is to provide a better reconstruction technique for image by solving the drawbacks that currently exist in the literary works. Thus, we intended to propose an efficient image reconstruction technique by exploiting the Haar DWT to remove cracks to input image and accurate threshold values to very high PSNR compared to input cracked image by improved particle swarm optimization used for better theshold values. Normally in image reconstruction, the input image which is corrupted by noise is given to the reconstruction process and obtained the reconstructed image with high quality. we exploit a renowned filtering technique to yield high quality reconstructed image. The low quality blurred image will be processed by our renowned filtering technique and obtain a reconstructed image with high contrast. Thus, we finally obtain a reconstructed image from our proposed technique with enhanced quality. To prove the performance of our proposed technique, the reconstructed image quality will be compared with the conventional techniques. Overall, our proposed technique can reconstruct the image more effectively by two phases (i) training phase and (ii) investigation phase achieving higher image quality ratio than the conventional reconstruction techniques.

***Index Terms*—Haar DWT ,IPSO DWT.**

1. INTRODUCTION

Image reconstruction embraces the overall image formation function and furnishes a base for the successive phases of image processing.Image reconstruction issue involves precisely modeling the physics of the imaging task.Image Reconstruction is to recover the original image from its given horrible form. An image that is corrupted by noise or that has some scratched regions will be reconstructed. Different reconstruction methods were utilized for performing the image reconstruction process.

In our proposed Image Reconstruction Technique initially the images are gathered from the database d which are affected by cracks with different variances are reconstructed using IPSO with Haar DWT method. Image Reconstruction method contains two stages such as the training stage and investigation stage. In the training stage, with a view to wipe off the cracks from the image.Initially we perform Haar DWT to the crack images and obtain optimal threshold value, which is realized by optimization technique known as IPSO. In the investigation phases at diverse divergence levels the cracks are applied to the testing image. Thereafter, the testing images with difference crack divergence levels are saved and analyzed with the analogous threshold values in the threshold database. In the testing, image reconstruction is obtained by analyzing testing image divergence level with threshold database.

The proposed Image Reconstruction technique consists of two stages namely
1.Training phase 2.Investigation phase.

1.Training phase :

Crack images are applied to training stage at different crack varience levels .the pixel values are refined by computing the avg by using neighbour pixel values for all affected images and first apply Haar DWT to images to find optimal threshold values by IPSO.

2.Investigation Phase :

More than training phase images are exploited to evaluate the reconstruction images performance in investigation phase and initially find out vector values for all input images.

2.Discrete wavelets transform (DWT):

The discrete wavelets transform (DWT) performs th image decomposition in different kinds of coefficients preserving the original information of an image. The iterative decomposition helps in increasing the frequency resolution. The approximation coefficients are then disintegrated

through high and low pass filters along with the down sampling operation The DWT is computed by successive lowpass and highpass filtering of the discrete time-domain signal.This is called the Mallat algorithm or Mallat-tree decomposition. Its significance is in the manner it connects the continuous time multi-resolution to discrete-time filters. In Continuous Wavelet Transform (CWT), the signals are analyzed using a set of basis functions which relate to each other by simple scaling and
translation. In the case of DWT, a time-scale representation of the digital signal is obtained using digital filtering techniques. The signal to be analyzed is passed through filters with different cutoff frequencies at different scales.

a)One stage Filtering:

For many signals, the low-frequency content is the most important part. It is what gives the signal its identity. The high-frequency content, on the other hand, imparts flavor or nuance. In wavelet analysis, approximations and details are the most important terms. The approximations are the high-scale, low-frequency components of the signal.

b)Multilevel filtering:

With this approach, the time resolution becomes arbitrarily good at high frequencies, while the frequency resolution becomes arbitrarily good at low frequencies. The time-frequency plane is thus resolved. The filtering and decimation process is continued until the desired level is reached. The maximum number of levels depends on the length of the signal. The DWT of the original signal is then obtained by concatenating all the coefficients.reconstruction is the reverse process of decomposition.coefficients at every level are upsampled by two, passed through the low pass and high pass synthesis filters and then added. This process is continued through the same number of levels as in the decomposition process to obtain the original signal. Wavelet Transform (DWT) is the mathematical tool being an efficient, highly intuitive framework for the representation and storage of multi-resolution images, the DWT provides powerful insight into an image's spatial and frequency characteristics

2.1 Standard Haar Wavelet Transform:

The Haar wavelet transformation is composed of a sequence of low-pass and high-pass filters, known as a filter bank.The low pass filter performs an averaging/blurring operations. The high-pass filter performs a differencing operation The low and high filter's equations above, can be formulated simultaneously through four filters i.e., (LL, HL, LH, and HH) each of (2x2) adjacent pixels which are picked as group and assed .In this transform, the bases of these 4-filters could be derived as follows:

Haar wavelet transform contents four filters. The decomposition low-pass filter ,the decomposition high-pass filter, the reconstruction low-pass filter and the reconstruction high-pass filter. At first we take an original image. The original image is decomposed by using the decomposition low-pass filter and the decomposition high-pass filter of haar wavelet transform. After decomposition through threshold value we eliminate all redundant data. Finally we obtained compressed image.To obtain a reconstructed image we have used the compressed image (Destroyed image), the reconstruction low-pass filter and the reconstruction high-pass filter of haar wavelet transform. It is possible to reconstruct an image as well as original image whn we use the compressed image, the position of the pixel's coefficient, low pass reconstructed coefficient of haar wavelet transform, and high pass reconstructed coefficient of haar wavelet transform

3.Particle swarm optimization (PSO):

Particle swarm optimization (PSO) is a population based algorithm, which is inspired by the social behavior of animals such as fish schooling and bird flocking.This evolutionary computation technique, based on the information about the previous best performance of each particle and the best previous performance of its neighbors,has been largely applied as a problem-solving technique in engineering and computer science. In PSO, each particle can communicate with every other individual, forming a fully connected social network. In this case, each particle is attracted toward the best particle (best problem solution) found by any member of the entire swarm.PSO is widely accepted and focused by researchers due to its profound intelligence and simple algorithm structure. Currently PSO has been implemented in a wide range of research areas of functional optimization, pattern recognition, neural network training and fuzzy system control and is successful. In PSO, each potential solution is considered as one particle. The system is initialized with a population of random solutions (particles) and searches for optima (global best particle), according to some fitness function, by updating particles over generations; that is, particles "fly" through the N-dimensional problem search space to find the best solution by following the current better- performing particle. When compared with Genetic Algorithm, PSO has very few parameters to adjust and easy to implement. Binary PSO, Hybrid PSO, Adaptive PSO and Dissipative PSO are variants of PSO and used in various image processing applications.In PSO, we assume that the problem is in a D- dimensional space, which includes many particles; each particle represents a feasible solution of optimization problem. On every iteration, each particle updates itself by the two extreme values, one is individual extreme value pbest, which is personal best value for that particle p_{id} , the other is the global best value for that particle (gbest) p_{gd} . Each particle adjusts its flight speed and direction according to current rate, pbest and gbest using Equation 1 and 2 repeatedly:

$$v_{id}(t+1) = w v_{id}(t) + c_1 \, rand_1(.)(p_{id} - x_{id}) + c_2 \, rand_2(.)(p_{gd} - x_{id}) \quad (1)$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1), 1 \le i \le N, 1 \le d \le D \quad (2)$$

where, N is the number of particles and D is the dimensionality:

3.1 PSO ALGORTHM:

Step1: Initialise the population randomly
Step2: Start the iteration.
Step 3: Calculate the fitness for each iteration
Step 4:Calculate the local best position and global best position

Step 5:Update the particle velocity and position ,by equations 1 and 2 given below

Pi(t+1)=Pi(t)+Vi(t+1)..................(1)
and
Vi(t+1) =C*W*Vi(t)+c1*R1(t)*[P best -Pi(t)]
+c2*R2(t)* [G best -Pi(t)]..............(2)
Let Pi(t) denote the position of the particle and this position is changed by adding a velocity component Vi(t) to it.
The velocity and position of the particle are initialised randomly. Each particle have to maintain its positions Pbest known as local best position and the Gbest known as global best position among all the particles. That is for each iteration the velocity and position of the particle are updated.

4.BACKGOUND WORK:

Image reconstruction is a robust means by which the underlying images hidden in blurry and noisy data .image reconstruction methods in current use. Progressively more sophisticated image restrictions have been developed, including (a) filtering the input data, (b) regularization by global penalty functions, and (c) spatially adaptive methods that impose a variable degree of restriction across the image.Image reconstruction is difficult because substantial fluctuations in the image may be strongly blurred, yielding only minor variations in the measured data. This causes two major, related problems for image reconstruction. First, noise fluctuations may be mistaken for real signal. Over interpretation of data is always problematic, but image reconstruction magnifies the effect to yield large image artifacts. The high wave numbers (spatial frequencies) of the image model are particularly susceptible to these artifacts, because they are suppressed more strongly by the blur and are therefore less noticeable in the data.

There are several excellent reviews of image reconstruction and numerical methods by other authors.In image reconstruction, the main challenge is to prevent measurement errors **i**n the input data from being amplified to unacceptable artifacts in the reconstructed image.

4.1 NONITERATIVE IMAGERECONSTRUCTION:

A non iterative method for solving the inverse problem is one that derives a solution through an explicit numerical manipulation applied directly to the measured data in one step. The advantages of the non iterative methods are primarily ease of
implementation and fast computation

a)Fourier Deconvolution

Fourier deconvolution is one of the oldest and numerically fastest methods of image deconvolution. If the noise can be neglected, then the image can be determined using a discrete variant of the Fourier deconvolution.

b)Wavelets

‘wavelet transform consists of a series of convolutions, so each wavelet coefficient is a Fourier filter. Wavelet filtering is similar to Fourier filtering and involves the following: Wavelet-transform the data to the spectral domain, attenuate or truncate wavelet coefficients, and transform back to data space. The wavelet filtering can be as simple as truncating all coefficients smaller than $m\sigma$, where σ is the standard deviation of the noise. Alternatively, soft thresholding reduces the absolute values of the wavelet coefficients .Once the data have been filtered, deconvolution can proceed by the Fourier method or by small-kernel deconvolution. Of course, the deconvolution cannot be performed in wavelet space, because the wavelets, including the a trous wavelets, are not eigenfunctions of the point-response function. Wavelet filtering can also be combined with iterative image reconstruction.

c)Quick Pixon

It is an iterative image restriction technique that smoothes the image model in a spatially adaptive way. A faster variant is the quick Pixon method, which applies the same adaptive Pixon smoothing to the data instead of to image models. This smoothing can be performed once on the input data, following which the data can be deconvolved using the Fourier method or small-kernel deconvolution

4.2 ITERATIVE IMAGE RECONSTRUCTION

a)Statistics in Image Reconstruction

non iterative methods take into account the statistical properties of the noise.Iterative methods are more flexible and can go a step further, allowing us to fit image models to the data. They thus infer an explanation of the data based upon the relative merits of possible solutions. More precisely, we consider a defined set of potential models of the image. Clean, an iterative method that was originally developed for radio-synthesis imaging , is an example of parametric image reconstruction with a built-in cutoff mechanism.

4.3PARAMETRIC IMAGERECONSTRUCTION

1.Parametric Modeling

Parametric fits are always superior to other methods, provided that the image can be correctly modeled with known functions that depend upon a few adjustable parameters. One of the simplest parametric methods is a least-squares fit minimizing χ 2 , the sum of the residuals weighted by their inverse variances:

4.3NONPARAMETRICIMAGE RECONSTRUCTION

nonparametric method accomplishes this by defining an image model on a grid of pixels equal in size to that of the data. The method must then by some means determine image values for all pixels in the image grid. Among these many related works done in image reconstruction which was presented by various authors ,and some of related works r presented below
Ravi Saharan et al. have resourcefully thrashed out the fact that digital images can be construed as set of pixels. If a single image is separated into multiple segments, then these subparts are considered as fragments for an image. Fusion of 2D fragments of an image requires these image fragments to be re-configured.This method was founded on the data created from the border line and from the color contents of the two fragments. Restricted curvature has been estimated to attain alteration independent coordinates. Taking the related data into consideration, assessment has been made to attain

DOI: 10.18535/ijecs/v4i10.4

utmost harmonizing elements among fragments. At last, greatest identical segments have been synthesized to achieve single image.

Laura B. Montefusco *et al.* got a bunch of bouquets for launching novel reconstruction techniques, targeted at the recovery of the misplace data either by utilizing the spatio-temporal correlations of the image series, or by thrusting appropriate restraints on the reconstructed image volume. The vital contribution of their research centres round the blending of this technique in a compact sensing structure by using the gradient sparsity of the image volume. The consequent inhibited 3D minimization challenge has been successfully addressed by means of a penalized forward–backward splitting method that paves the way for a convergent iterative two-phase process. In the initial phase, the rule accords are updated with the sequential behavior of the data acquisitions and subsequently, a genuine 3D filtering strategy employs the spatio-temporal correlations of the image sequences. The consequent Non-linear Filtering Compressed Sensing (NFCS)-3D algorithm turns out be to a very common and appropriate one for various types of medical image reconstruction hassles. Further, it shines with the quality of swiftness, stability, and invariably ushers in superb reconstructions, especially in the case of highly under sampled image sequences. The cheering outcomes of various arithmetical tests have vouchsafed the optimal performance of the innovative technique and proved without any iota of doubt that it maintains a clear, unsurpassable edge over the hi-tech algorithms.

Peyman Rahmati *et al.*have shown the first clinical results using the level set based reconstruction algorithm for electrical impedance tomography data. The level set based reconstruction method allows the reconstruction of non-smooth interfaces between image regions, which were typically smoothed by traditional voxel based reconstruction methods. They have developed a time difference formulation of the level set based reconstruction method for 2D images. The proposed reconstruction method has been applied to reconstruct clinical electrical impedance tomography data of a slow flow inflation pressure-volume manoeuvre in lung healthy and adult lung injury patients. Images from the level set based reconstruction method and the voxel based reconstruction method have been compared. The results have shown the comparable reconstructed images, but with an improved ability to reconstruct sharp conductivity changes in the distribution of lung ventilation using the level set based reconstruction method.

Diego Álvarez et al present a level-set based technique to recover key characteristics of a defect or crack in a two-dimensional material from boundary electrical measurements. The key feature of this work is to extend the usual level-set technique for modeling volumetric objects to very thin objects. Two level-set functions are employed: the first one models the location and form of the crack, and the second one models its
length and connectivity.

Rabab M. Ramadan at el novel feature selection algorithm based on particle swarm optimization (PSO). PSO is a computational paradigm based on the idea of collaborative behavior inspired by the social behavior of bird flocking or fish schooling.The algorithm is applied to coefficients extracted by two feature extraction techniques: the discrete cosine transforms (DCT) and the discrete wavelet transform (DWT) .PSO-based feature selection algorithm is utilized to search the feature space for the optimal feature subset where features are carefully selected according to a well defined discrimination criterion. Evolution is driven by a fitness function defined in terms of maximizing the class separation

And many Recent related works presented in my previous works .

5.OUR PROPOSED WORK:

The previous image reconstruction technique reconstructs the cracked images by exploiting the DWT and IPSO methods. In the training phase, the cracked image is reconstructed by the DWT method and in DWT the optimal threshold values are selected by the IPSO technique. In the investigation phase, the threshold values are selected based on image crack levels. This image reconstruction technique based on IPSO-DWT reconstructs the images with good quality, but the PSNR value of the reconstructed images .

In this paper, we have proposed an IPSO-Haar DWT image reconstruction technique to reconstruct high quality images which are affected by cracks with different variances. **T**he proposed system mainly comprises two phases namely, (i) training phase and (ii) investigation phase. These two phases are consecutively performed and the input crack images reconstructed.

Let us consider an image I (x , y) **,** where $0 \le x \le X - 1$, & $0 \le y \le Y - 1$, and the image is influenced by cracks n with diverse crack n divergence levels v is symbolized as I v (x , y) ,

where v is arbitrarily created between the interval [0.1, 1]. To wipe off the cracks from the predefined input image I v n (x , y) , at first we execute a Haar DWT to the input image. In image renovation the Haar DWT technique is employed to banish the existing cracks n . In our ambitious method, we employ a novel optimization method like IPSO to choose the optimal threshold value. Subsequently, in research stage the testing image is rebuilt by employing precise threshold value. The procedure of optimal threshold values choice and the image renovation function by means of guidance and testing stage.

5.1 Training phase:

In training phase, initially cracks are applied to the training images at different crack variance levels. The crack pixels values are refined by computing the average by using the neighbor pixel values. The average value is computed by,

$$a = I \sum_{i=1}^{I} p_i \quad (1)$$

p i is the pixel value and I represents the number of neighbor pixel value of the pixel which is affected by the cracks. Compute the average pixel values for all pixels which are affected by the cracks and replace those pixel values with the average pixel values. The result image from the above process is denoted n as I v (x , y) . After that, we apply the Haar DWT to the images and find the optimal threshold values by IPSO.

Initially the particles are generated between the intervals [0, 1]. The defined particles are composed of threshold values t c . The particles length is defined as l , l denotes the number of filter coefficients in the particles. In

our proposed technique, the particle length l is defined as 1 i.e. the threshold value in the particles is generated between the intervals [0, 1]. This generated particles value is a threshold value, and n this value is applied to the image $I_v(x, y)$ with the crack variance level v. The result image is n represented as $R(I_v(x, y))$.
Update particle individual best (p best), global best (g best), particle worst (P worst) in the velocity formula given in Equation and obtain the new velocity.

$$V_i = w * V_i + C_{1b} * r_1 * (P_{besti} - S_i) * P_{besti} + C_{1w} * r_2 * (S_i - P_{worsti}) * P_{worsti} + C_2 * r_3 * (G_{besti} - S_i)$$

In the above Equation
w - Inertia weight
V_i - Velocity of the particle
C_{1b} - acceleration coefficient in best position
C_{1w} - acceleration coefficient in worst position
P_{besti} - the best position of the particle i
S_i - Current position of the particle
P_{worsti} - the worst position of the particle i
r_1, r_2, r_3 - Uniformly distributed random numbers in the range [0 to 1].

The process is repeated until the maximum number of iterations is reached. The final optimal threshold values from IPSO technique are exploited in the Haar DWT reconstruction process. The crack variance level v is changed and select best particles for each crack variance level. For each crack variance level the best particles are stored in the threshold database DT.
The reconstruction process by optimal threshold values performance is tested by giving new input image with varying crack variance levels.

5.2 Investigation Phase:

In the investigation phase, several numbers of testing images are exploited to evaluate the reconstruction performance.our proposed IPSO-Haar DWT technique achieves better image reconstruction performance than the PSO-DWT and average filtering techniques.crack variance levels our proposed IPSO-Haar DWT technique produces better reconstructed image results than the PSO-DWT and average filtering technique in terms of their PSNR and image quality. Hence our proposed IPSO-Haar DWT image reconstruction techniques produces better performance results in the image reconstruction process than those of PSO-DWT.The figure 1 explains image reconstruction by Haar DWT and IPSO.

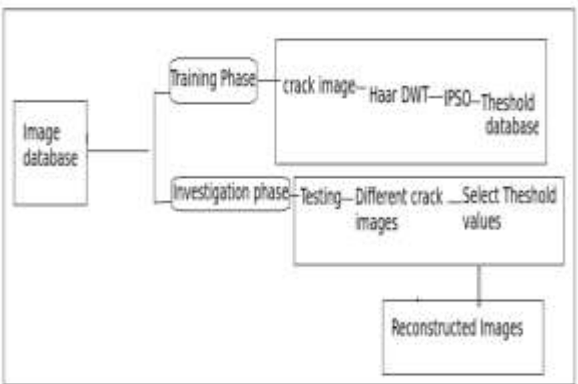

Fig 1 image reconstruction by Haar DWT and IPSO

6.Results:

The proposed image reconstruction technique based on IPSO with Haar DWT performance has been analyzed by exploiting different images taken from the database with different crack variance levels.The input Images with varying crack levels are reconstructed using the proposed image reconstruction technique based on IPSO-Haar DWT method.

i.noisy image

ii .DWT using PSO

iii. Haar DWT using PSO

iv.Haar DWT using IPSO

7. CONCLUSION

Our proposed technique performance is compared with the Existing IPSO-DWT, average filtering image reconstruction technique. The comparison result shows that our IPSO-Haar DWT has given more PSNR than the Existing IPSO-DWT, average filtering technique Therefore by utilizing the IPSO-Haar DWT technique; our proposed image reconstruction technique proficiently reconstructed the images.propose an efficient image reconstruction technique by exploiting the Haar DWT to remove cracks to input image and accurate threshold values to very high PSNR compared to input cracked image by improved particle swarm optimization used for better theshold values. .

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