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A NEW IMAGE RECONSTRUCTION TECHNIQUE WITH AID OF IPSO (IMPROVED PARTICLE SWARM OPTIMIZATION) AND DWT (DISCRETE WAVELET TRANSFORM)

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ABSTRACT

The term 'Image Reconstruction' refers to the retrieval of the original image (or a general signal) from its given awful version, such as an image that is corrupted by noise, blurred by atmospheric turbulence (as in certain astronomic observations), or that has certain scratched regions. The previous image reconstruction technique reconstructs the cracked images by exploiting the DWT and PSO methods. This image reconstruction technique based on PSO-DWT reconstructs the images with good quality, but the PSNR value of the reconstructed images and the threshold selection by PSO degrade the PSO-DWT technique performance. So, to avoid these drawbacks, a new Improved Particle Swarm Optimization (IPSO) technique is proposed in this paper. Here, a new image reconstruction technique is developed with DWT and IPSO techniques. In this proposed technique, the given images are reconstructed by the DWT and the optimal thresholds values are selected by the Improved Particle Swarm Optimization (IPSO) method. Our proposed IPSO technique solves the PSO technique drawback by considering the bad components in the velocity computation process. The proposed technique is implemented and the results are analyzed in terms of their PSNR values. The results show the effectiveness of proposed image reconstruction technique in reconstructing the images and achieving improvement in PSNR ratio. Furthermore, the performance of the proposed IPSO-DWT technique is evaluated by comparing with existing image reconstruction PSO-DWT technique.

Keywords: *Image Reconstruction, Discrete wavelet Transform (DWT), Particle Swarm optimization (PSO), Improved Particle Swarm optimization (IPSO), PSNR*

1. INTRODUCTION

Image reconstruction embraces the whole gamut of image arrangement procedure and establishes a sound base for the succeeding stages of image dispensation. The ultimate aim targets at the restoration of image data vanished during the course of image creation. Contrary to image up gradation, wherein the manifestation of an image is enhanced to adapt to certain subjective standards, image renovation is a purpose-oriented method to restore a damaged image as per numerical and statistical models [1]. Image rebuilding is complicated on account of significant variations in the image such as being robustly blurred, causing only negligible changes in the calculated data. This gives birth to two significant linked dilemmas for image restoration. At first, noise variations may be misconstrued for genuine signals. Moreover, it is highly unfeasible to distinguish between contending image models if the divergences in the data models received from them by means of blurring are sufficiently within the measurement noise [2]. The renovation techniques are separated into logical and iterative methods. Logical modernization techniques present a straight mathematical key for the creation of an image. Iterative technique is founded on a further precise portrayal of the imaging activity causing an intricate mathematical dilemma involving numerous stages to attain an image [3].

Image renovation hassles predominantly entail precisely modeling the physics of the imaging procedure. This is different from several universal

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image dispensation methods such as image solidity, which are not inevitably limited by similar stipulations. Still, several qualities of the latter algorithms such as tempo and vigor are advantageous to the image rebuilding methods [4]. Of late, these Image rebuilding methods have assumed the stupendous role of key devices in computer visualization technologies and several diverse applications which are in need of razor-sharp images received from loud and otherwise tainted ones. Simultaneously, the total variation (TV) configuration has been shown to be endowed with a superior mathematical foundation for various fundamental operations in image rebuilding like de-noising, in-painting, and de-blurring [5].

In numerical image renovations for ECT (emission computed tomography), greater care must be taken on the ensuing three significant features of the dilemma such as the statistical representation, the regularization technique, and the iterative maximization/minimization algorithm. A precise statistical replica is a precondition for an excellent rebuilding [7] [9]. Secondly, the user generally has certain advanced data on the image to be rebuilt, which can be integrated into the regularization technique to turn out "reasonable-looking" images. At last, a good algorithm is essential to guarantee that a superior rebuilt image can be achieved in a reasonable period of time [6]. Diffuse optical tomography [11] is a novel medical imaging modality with latent applications in functional imaging of the brain and in breast cancer recognition, among other applications. This technique tends to recuperate visual constraints of blood and tissue from border dimensions of light diffusion in the perceptible and near-infrared domain. The rebuilt images of the spatial sharing of tissue constraints can be linked straight to physiologically vital properties like blood and tissue oxygenation status [8] [10].

The outline of the paper proceeds as follows. In section 2, a concise assessment is made about the modern investigation studies linked to image rebuilding procedure. Sections 3 offer a vivid picture of the anticipated IPSO-DWT image rebuilding method. Investigational images and replication outcomes ornament Section 4. In Section 5, we come face to face with the befitting Conclusion part of the paper.

2. RELATED WORKS

Some of the modern investigations linked with the image rebuilding procedure are detailed below.

Laura B. Montefusco *et al.* [12] have proficiently put forward rebuilding methods, which endeavor to restore the misplaced data either by utilizing the spatio-temporal correlations of the image sequence, or by inflicting appropriate parameters on the rebuilt image volume. The significant function of their investigation is to blend both these approaches in a compacted sensing structure by utilizing the gradient sparsity of the image volume. The resultant inhibited 3D minimization dilemma has been solved by means of a reprimanded forward–backward splitting method that results in a convergent iterative two-step process. In the initial stage, the updating regulation agrees with the chronological character of the data possessions and in the second stage, a really 3D filtering approach utilizes the spatio-temporal correlations of the image series. The resultant NFCS-3D algorithm was incredibly universal and appropriate for various types of medical image rebuilding dilemmas. Furthermore, it was swift, steady and it supplied superlatively strong rebuilding's, even in the case of extremely under-sampled image series. The outcomes of various statistical investigations have upheld the optimal efficiency of the planned algorithm and established that it was competitive with state- of- the- art algorithms.

Brent A. Williams *et al.* [13] have brightly founded a rebuilding assessor by means of maximum a posteriori probability (MAP) assessment to recuperate the conservative models from deafening scatterometer dimensions. This method facilitates the scatterometer sound sharing to be properly accounted for in the rebuilding activity. The MAP and conservative rebuilding methods have been executed on the Sea Winds scatterometer and the Advanced Wind Scatterometer, and the efficient resolution of the various techniques has been assessed. The outcomes of MAP method were in harmony with the well-entrenched scatterometer image reconstruction (SIR) algorithm. The MAP method has appreciably improved the resolution at the cost of louder noise. Even though an elaborate noise-versus-resolution swap scrutiny was outside the purview of their paper, the novel structure enables a further universal management than the ad hoc tuning constraints of the SIR algorithm.

Hakan Erturk *et al.* [14] have brought to the table of discussion that thermal interfaces are faced in several thermal administration applications and interface materials are utilized to bring down thermal contact resistance arising out of solid-solid contact. For opto-electronic equipments, the

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excellence of the thermal interface is vital for dispensing with the engendered heat for appropriate thermal organization. Flaws in the thermal interface pave the way for supplementary thermal resistance in the thermal pathway which should be put an end to. Recognition of flaws in the thermal interfaces assumes alarming proportions in the course of assembly process expansion. Imaging methods like X-ray computerized tomography or scanning acoustic microscopy that involve extremely costly devices and considerable processing time are indispensable. Thermal tomography along with IR thermometry can be utilized as a cost-effective option to these methods. The viability of thermal tomography for creative portrayal of thermal interfaces has been offered by taking into consideration diverse image renovation algorithms. The captioned algorithms are the iterative perturbation algorithm, Levenberg Marquardt algorithm, and the regularized Newton Gauss algorithm, and they exhibited superior competency in depicting the thermal interface layer.

Ravi Saharan *et al.* [15] 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. The synthesis of fragments to rebuild images and objects is a dilemma linked to many applications such as archeology, medicine, art restoration, and forensics. They have primarily concentrated on 2D Image Reconstruction by blending two 2D fragments. 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 utmost harmonizing elements among fragments. At last, greatest identical segments have been synthesized to achieve single image.

Peyman Rahmati *et al.* [16] have prolifically exhibited the primary clinical outcomes by means of the level set based rebuilding algorithm for electrical impedance tomography data. The level set based renovation technique facilitates the rebuilding of non-smooth interfaces between image regions, which were classically curved by conventional voxel based renovation techniques. They have figured out a time divergence configuration of the level set based renovation technique for 2D images. The projected modernization technique has been carried out to rebuild clinical electrical impedance tomography data of a sluggish flow inflation pressure-volume maneuver in lung healthy and adult lung injury patients. Images from the level set based modernization technique and the voxel based rebuilding system have been assessed. The outcomes have exhibited the similar rebuilt images, with an added superior competence to rebuild keen conductivity variations in the allocation of lung ventilation by means of the level set based modernization scheme.

Kanakaraj *et al.* [17] have successfully propounded a sparse parameter dictionary structure for super-resolution image restoration, which blends the trait pieces of high-resolution and low-resolution images by means of sparse parameter dictionary programming. This method has configured a sparse link between middle-frequency and high-frequency image segments, and follows concomitantly match probing and optimization techniques. Assessment with sparse programming method has proved that sparse parameter dictionary was more solid and proficient. Sparse Kernel-Single Value Decomposition algorithm has been performed for optimization to close the sparse coding procedure. Several tests with genuine images have revealed that sparse parameter dictionary programming has pushed to the back all parallel learning-based super-resolution algorithms with respect to PSNR.

The Problem Statement

The previous image reconstruction technique reconstructs the cracked images by exploiting the DWT and PSO 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 PSO technique. In the investigation phase, the threshold values are selected based on image crack levels. This image reconstruction technique based on PSO-DWT reconstructs the images with good quality, but the PSNR value of the reconstructed images is too low. Moreover, the PSO technique takes additional time to select optimal threshold value and does not find the accurate threshold value because of considering only the best components. Hence to avoid these drawbacks, a new image reconstruction technique is proposed in this paper.

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3. PROPOSED IPSO-DWT IMAGE RECONSTRUCTION TECHNIQUE

In this paper, we have proposed an IPSO-DWT image reconstruction technique to reconstruct high quality images which are affected by cracks with different variances. The 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 more effectively which are discussed in Section 3.1 and 3.2 respectively. Structure of our proposed image reconstruction technique is illustrated in Fig. 1.

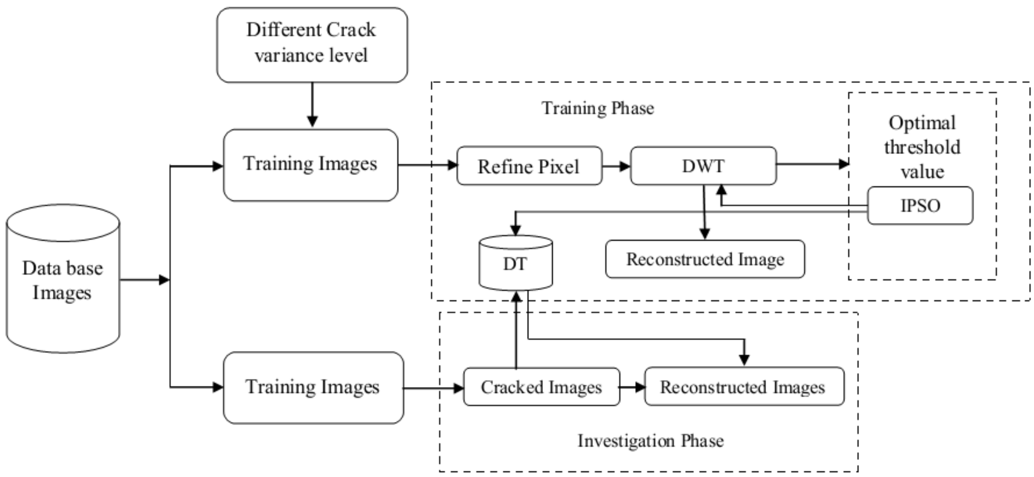

Figure 1: Structure Of Our Proposed IPSO-DWT Image Reconstruction Technique

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 divergence levels v is symbolized as $I_v^n(x, y)$, 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 DWT to the input image. In image renovation the 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 are detailed in the following Sections 3.1 and 3.2.

3.1 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,

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

In Equ. (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 as $I_v^n(x, y)'$. After that, we apply the DWT to the images and find the optimal threshold values by IPSO. The process of optimal threshold value selection is described in Section 3.1.1.

3.1.1 Optimal Threshold Values Selection using Improved Particle Swarm Optimization (IPSO)

In our work, we select the threshold values using the improved particle swarm optimization technique. The selected threshold values from the IPSO technique is utilized in the image reconstruction process. The IPSO technique is an enhanced version of the PSO technique. The main difference is, the PSO technique considered only

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the best components in the velocity computation but the IPSO technique considered the best and worst components in the velocity computation process.

3.1.1.1 Particle Swarm Optimization (PSO)

In biological populations enthused by the collective dealings of bird flocking or fish schooling PSO [18] is an assessment representation founded on the concept of joint conduct and swarming. In various realms like training artificial neural networks, linear constrained function optimization, wireless network optimization, data clustering, and several further domains where GA can be executed, PSO has been found to be advantageous as a competent optimizer. As the entire particles in PSO are expected to congregate to the finest solution swiftly, calculation period in PSO is reduced to drastic levels.

Founded on a population (swarm) of processing rudiments named particles calculation in PSO is given shape to, wherein every particle symbolizes a candidate key. By keeping update of generations the system is initialized with a population of informal keys and is on the lookout for utmost encouraging outcomes. In every generation the particles travels in the path of its personal best (pbest) location to global best location (gbest). Exploiting its individual memory and comprehension gained by the swarm in unison, every particle in the investigation space develops its candidate key over time. In PSO, the only data common among particles is the global best particle located among the swarm. The particle motion is expressed by the velocity function illustrated in Eq. (2) and (3).

$$V_i^{(t+1)} = \omega\, {}^{t}V_i^{t} + C_1.r_1.(p_i - x_i^{(t)}) + C_2.r_2.(g_i - x_i^{(t)}) \quad (2)$$

$$x_i^{(t+1)} = x_i^{(t)} + \delta V_i^{(t+1)} \quad (3)$$

In Eq. (2) C_1, C_2 are the learning factors, ω, δ signify the inertial weight and restriction feature, rand is positive random number between 0 and 1, $V_i^{(t)}$,the velocity of i th particle at iteration t, $x_i^{(t)}$, the current position of the particle i at iteration t, p_i, the position of the best fitness value of the particle at the existing iteration and g_i, the position of the particle with the best fitness value in the swarm.

3.1.1.2 Improved Particle Swarm Optimization (IPSO)

The proposed IPSO technique considered both the bad and the good experience components during the new velocity computation. The bad experience component helps the particle to remember its previously visited worst position. To calculate the new velocity, the bad experience of the particle is also taken into consideration. On including the characteristics of Pbest and Pworst in the velocity updation process along with the difference between the present best particle and current particle respectively, the convergence towards the solution is found to be faster and an optimal solution is reached in comparison with conventional PSO approaches. Our proposed IPSO technique solves the existing technique drawback by considering the bad components in the velocity computation process. The process of optimal threshold value selection by the IPSO technique is described below,

- **Initialization:** 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 this value is applied to the image $I_v^n(x,y)'$ with the crack variance level v. The result image is represented as $R(I_v^n(x,y)')$.
- **Parameters:** In IPSO, the particles position, velocity, learning parameters, inertia, weight and maximum number of iterations are defined.
- **Fitness:** Every particle's fitness value is calculated by using formula given in Equ. (4). The particles that have minimum fitness value are selected as the best particles.

$$f^i = -\frac{1}{b_1 b_2}\sum_{x=1}^{b_1}\sum_{y=1}^{b_2} 20\ln\left|\frac{I_{v\,\max}^n(x,y)' - 2I_{v\,ce}^n(x,y)' + I_{v\,\min}^n(x,y)'}{I_{v\,\max}^n(x,y)' + 2I_{v\,ce}^n(x,y)' + I_{v\,\min}^n(x,y)'}\right| \quad (4)$$

In Equ. (4), where an image I is divided into $b_1 \times b_2$ blocks. $I_{v\,\max}^n(x,y)'$, $I_{v\,\min}^n(x,y)'$ and $I_{v\,ce}^n(x,y)'$ are the maximum, minimum and center pixel values in each block. The objective function which is an image enhancement function is used to improve the contrast of the image. Select particles

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individual best value and particles global best value for each generation. In IPSO, we select the particles individual worst value, i.e. particles far away from the target.

❖ **Velocity and Position:** Update particle individual best (p best), global best (g best), particle worst (P worst) in the velocity formula given in Equ. (6) and obtain the new velocity.

$$V_i = w * V_i + C_{1b} * r_1 * (P_{besti} - S_i) * P_{besti} + C_{1w} * r_2 * (S_i - P_{worsti}) * P_{worsti} + C_2 * r_3 * (G_{besti} - S_i) \quad (5)$$

In Equ. (5),

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].

Thus the obtained new velocity value is updated in the original velocity formulas given in Equ. (2) and obtain the position of the particle by Equ. (3).

❖ **New Particles updation**: The new particles values from Eqn. (2) and (3) are given to the fitness value computation process.

❖ **Stopping Criteria:** The process is repeated until the maximum number of iterations is reached. The final optimal threshold values from IPSO technique are exploited in the 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 database DT contains information of the crack variance level v and the corresponding best particles value i.e. optimal threshold value. The reconstruction process by optimal threshold values performance is tested by giving new input image with varying crack variance levels. The process of investigation phase is presented in Section 3.2.

3.2 Investigation Phase

In the investigation phase, several numbers of testing images are exploited to evaluate the reconstruction performance. In testing image, the cracks are applied to the images in different variance levels. The images difference crack variance levels are stored and the corresponding threshold values are to be searched in the threshold database DT. The testing crack images are reconstructed by comparing their variance level with database DT. Based on the crack variance levels the optimal threshold values v are selected from the database DT and applied to the testing crack image to get the reconstructed result image.

4. RESULTS AND DISCUSSION

The proposed image reconstruction technique is implemented in the working platform of MATLAB (version 7.12) with machine configuration as follows

Processor: Intel core i5
OS: Windows xp
CPU speed: 3.20 GHz
RAM: 4GB

The performance of the proposed system is evaluated with several numbers of images with varying crack levels and the results are compared against those of the existing techniques. The input image is reconstructed using the proposed IPSO-DWT image reconstruction technique. The sample input image and the reconstructed result image by IPSO-DWT and PSO-DWT are shown in Figure 2.

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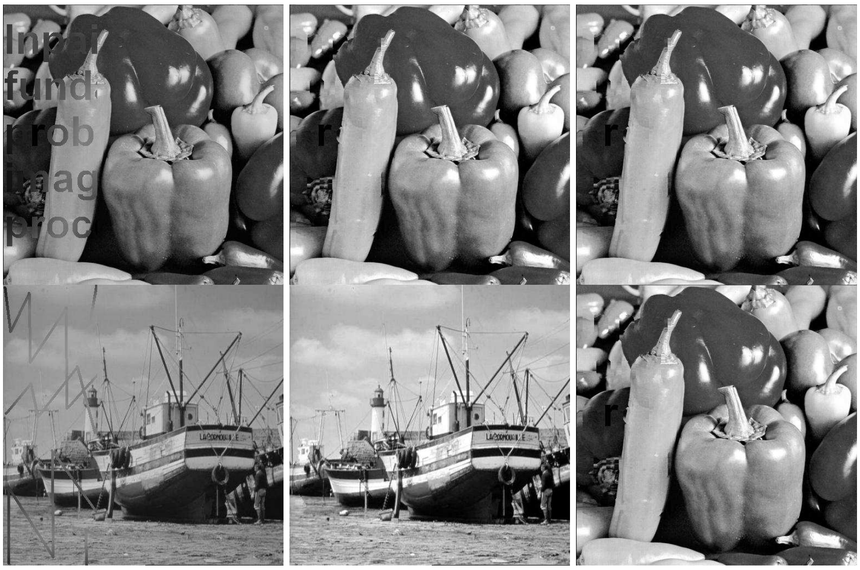

(I) (II) (III)

Figure 2: (I) Input Image And (Ii) Reconstructed Result Image By PSO-DWT (Iii) Reconstructed Result Image By IPSO-DWT.

Our proposed technique performance is evaluated by varying crack levels to 0.1, 0.2, 0.3 and 0.4. Moreover our proposed technique performance is compared with those of the existing wavelet and PSO-DWT technique. In this paper, we have applied an average filtering in the image reconstruction process and evaluated the image reconstruction performance and compared it with PSO-DWT and IPSO-DWT based image reconstruction techniques.

Table 1: Proposed IPSO-DWT, PSO-DWT And Average Filtering Image Reconstruction Techniques PSNR Value Of Five Different Images With Crack Variance 0.1

Images	IPSO-DWT	PSO-DWT	Average Filtering
	PSNR	PSNR	PSNR
1	17.2123	17.2066	15.0543
2	17.4312	17.3842	15.1759
3	18.3904	18.3865	14.0621
4	17.4052	17.4033	16.3064
5	18.2148	18.2038	15.3962

Table 2: Proposed IPSO-DWT, PSO-DWT And Average Filtering Image Reconstruction Techniques PSNR Value Of Five Different Images With Crack Variance 0.2

Images	IPSO-DWT	PSO-DWT	Average Filtering
	PSNR	PSNR	PSNR
1	17.2104	17.1066	14.5041
2	17.1643	17.1342	15.1049
3	17.1409	17.0363	14.2121
4	17.0821	17.0340	15.0324
5	18.2204	18.2038	14.1962

Table 3: Proposed PSO-DWT And Average Filtering Image Reconstruction Techniques PSNR Value Of Five Different Images With Crack Variance 0.3

Images	IPSO-DWT	PSO-DWT	Average Filtering
	PSNR	PSNR	PSNR
1	16.9074	16.7409	13.2341
2	16.1427	16.0487	14.0019
3	16.7204	16.6303	13.1201
4	16.1401	16.0031	13.0474
5	17.7602	17.7430	13.1221

Table 4: Proposed IPSO-DWT, PSO-DWT And Average Filtering Image Reconstruction Techniques PSNR Value Of Five Different Images With Crack Variance 0.4

Images	IPSO-DWT	PSO-DWT	Average Filtering
	PSNR	PSNR	PSNR
1	16.4525	16.4309	13.0431
2	16.1032	16.0190	13.0014
3	16.5704	16.5688	13.1031
4	16.0466	16.0462	12.7074
5	17.4621	17.4403	13.0321

Tables 1 to 4 show the PSNR values of the proposed and existing techniques image reconstruction performance. The PSNR values are obtained for five images by changing the crack variance levels to 0.1, 0.2, 0.3 and 0.4. The comparison graph of our proposed image reconstruction technique with existing image reconstruction techniques is illustrated in Figure 3.

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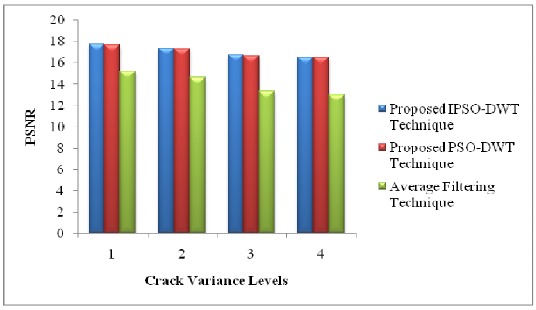

Figure 3: Comparision Graph Of Proposed IPSO-DWT And PSO-DWT, Average Filtering Performance

As can be seen from Fig. 3, our proposed IPSO-DWT technique achieves better image reconstruction performance than the PSO-DWT and average filtering techniques. At the crack variance level 0.1, our proposed IPSO-DWT technique attains the PSNR value of 17.73 dB and PSO-DWT technique attains 17.72dB but the average filtering technique only produces the image with the PSNR value of 15dB. The proposed IPSO-DWT technique has achieved PSNR values of 16.73dB, 16.52dB when the crack variance levels are 0.3 and 0.4 respectively, and for the same crack variance levels the exiting PSO-DWT has attained PSNR values 16.63dB and 16.50dB. When increasing the crack variance levels to 0.2, 0.3 and 0.4, the average filtering technique reconstructed images PSNR value has considerably varied from our proposed IPSO-DWT technique but the PSO-DWT technique undergoes only a marginal variation in PSNR value. However, in all crack variance levels our proposed IPSO-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-DWT image reconstruction techniques produces better performance results in the image reconstruction process than those of PSO-DWT.

5. CONCLUSION

In this paper, we have proposed a new image reconstruction technique based on PSO along with DWT method. This proposed technique selects the optimal threshold values by the IPSO and the images are reconstructed by the DWT method. The technique was implemented and different images with different crack variances were utilized to analyze the results of the IPSO-DWT image reconstruction technique. The performance analysis proved that the IPSO-DWT technique provided high PSNR value. The IPSO-DWT technique was compared with the existing PSO-DWT technique to prove its performance. It was found that the IPSO-DWT technique achieved higher PSNR value than that of the PSO-DWT technique. Hence, it is proved that our IPSO-DWT image reconstruction technique more precisely reconstructs the images.

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