# Multiresolution Edge Detection using Particle Swarm Optimization

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**Abstract**- In this paper, a heuristic approach based on biologically inspired Particle Swarm Optimization (PSO) is proposed to be used at multiresolution level to improve the quality of detected edges. In the pre-processing stage, one level of Discrete Wavelet Transform (DWT) or Dual-Tree Complex Wavelet Transform (DT-CWT) is applied to the input image to create new subbands images. PSO is then applied to each one of these subband images. The output image containing the detected edges is obtained by reconstructing it from the processed subband images using the inverse transform. An objective function is proposed for the PSO to evaluate edges during the heuristic search within the image space. Also, automatic thresholding is introduced which is used to automatically threshold the output of the PSO into binary image. Performance the proposed approach is evaluated and compared with other well-known edge detectors such as Sobel and Canny using Kodak image database. The results from objective evaluation using Peak Signal-to-Noise-Ratio (PSNR) and Root Mean Square Error (RMSE) showed that the proposed approach has a better and/or comparable performance compared to other edge detectors.

**Keywords**- Edge Detection, Discrete Wavelet Transform, Particle Swarm Optimization, Dual Tree Complex Wavelet Transform.

## 1. Introduction

Many applications of image processing and computer vision have significantly deployed the use of edge detection as a key instrument to information extraction. Most of these applications such as contour detection depend directly or indirectly on edge detection for their implementations in addition to overall accuracy [1]. This sudden variation in the intensity value in an image is an indication of presence of edges in that image. The goal of edge detectors is to locate these abrupt changes in intensity within the image space to describe the intensity contour map of objects within the image [1]. These changes become valuable properties that can be used to detect object's boundaries, size and shape. These properties are also useful in image analysis such as segmentation [2] and objects recognition [3].

Extraction of perfect edges from an image is proving to be difficult due to complexity of objects within the image and even the nature of application which the edge detection is intended for. Some of the challenges affecting edge detectors apart from complexity and subjectivity in defining relevant edges in different applications include: edges discontinuity, uneven lightening in the image vicinity, occlusion and so on. Some of these aforementioned challenges lead edge detectors to problems such as detection of broken edges, false edge detection and artifacts which distort the original information in the image [4]. Edge detection as one of the most active areas of research, finding better algorithm in addition to the existing edge detectors that can address some of these challenges became paramount important [4]. A quite sizeable number of edge detectors have evolved over times. Most of these detectors are either gradient-based (Canny [5,6], Sobel [7], Roberts [8], etc.) or biologically-inspired algorithms which are heuristic optimization algorithms (e.g. Ant Colony

Optimization ACO [9,10], Particle Swarm Optimization [11,12], Bee Colony Optimization ABC [13,14] etc.).

One of the common problem with traditional (gradient-based) edge detectors is the use of small size kernel which localize the operators to small and limited area to detect object edge within the image. The accuracy of the detection is affected strongly affected by the area and size being observed as continues edges of an object may cover a large portion within the image. The smaller the area, the more the sensitivity to noise, as well as the less the localization accuracy is. In this proposed approach, a heuristic approach is proposed whereby the whole image is use to search for edges without being localized. PSO is used with a new proposed objective function to detect edges within the image. DWT and DT-CWT is applied to the input image as a preprocessing stage to decompose is to subband images. PSO with the objective function is applied as a heuristic algorithm on each subband image in DWT and DT-CWT. The inverse of the corresponding transform using processed subband images will be taken before applying automatic thresholding to reconstruct the final edge detection result.

## 2. Wavelet Transforms

### *2.1. Discrete Wavelet Transform (DWT)*

The Discrete Wavelet Transform simply operates on 1D, by calculating the columns and rows of an image in a divisible way [15, 16]. The first step of is to apply the analysis filters on the rows of the image. This generates two images, where the first image is a set or coarse row coefficients and the other is a set of detail row coefficients. In the second step, analysis filters are applied to the columns of each new generated image. This will generate four different images known as sub bands or sub-images. *Hi* represents rows and columns that are passed through a high pass filter. in the same manner, *Lo* represents rows and columns which are passed through a low pass filter. For instance, if a sub-band image was generated using a high pass filter on the rows as well as a low pass filter on the columns, it is known as the (HL) subband or sub-image.

### *2.2. Dual Tree Complex Wavelet Transform*

Dual Tree Complex Wavelet Transform (DT-CWT) provides more accurate directional discrimination in 2-D with Gabor alike filters [17, 18]. Ordinary DWT provides the selectivity in 3 fixed directions with low discrimination for diagonal features, whereas DT-CWT has 12 directional wavelets (6 for the real trees and 6 for the imaginary trees) directed at angles of ±15°, ±45°, ±75° and 4 approximate wavelets. The enhanced directional selectivity with more angles supports the improvement of DT-CWT in a broader variety of directional image processing applications. Approximate shift invariance, improved directional selectivity in 2-dimensions, perfect reconstruction, less redundancy and efficient order-N-computations are of the main advantages of DT-CWT.

## 3. Particle Swarm Optimization (PSO)

Kennedy and Eberhart introduced Particle Swarm Optimization (PSO) technique in 2001[11]. The PSO algorithm is described as follows:

every single particle i in a populace has the following possessions: a recent location in an inquest zone, $x_i$ , a recent speed, $v_i$ , and a local best location in inquest zone, $y_i$ . The local best location $y_i$ , reacts to the location in inquest zone, where the objective function $f$ provided the least calculated error for the particle $i$. the location that produced the least error throughout all the $y_i$ is known as the global best location and is represented by $y'$. The local and global best locations are updated using (1) and (2), respectively. It is supposed that the swarm consists of $s$ particles, thus $i \in \{1,...,s\}$

$$y_i\,(t+1)=\begin{cases} y_i\,(t) & \text{if } \; f\big(x_i\,(t+1)\big) \le f\big(y_i\,(t+1)\big) \\ x_i\,(t+1) & \text{if } \; f\big(x_i\,(t+1)\big) > f\big(y_i\,(t+1)\big) \end{cases} \quad (1)$$

$$y'(t) \in \{(y_0(t), y_1\,(t), \dots, y_s\,(t)\},$$

$$f\big(y(t)\big) = min\{f\big(y_0\,(t)\big), f\,\big(y_1\,(t)\big), \dots, f\big(y_s\,(t)\big)\} \quad (2)$$

Throughout every loop, every particle in the group is updated utilizing (3) and (4). The randomly generated, $r_1$ and $r_2$ would be used to influence the nature of the procedure. For all measurement, $j \in \{1, \dots, n\}$, let $x_{i,j}$ , $y_{i,j}$ and $v_{i,j}$ be the recent location, recent local best location and speed of the $j^{th}$ dimension of $i^{th}$ particle. The inertia weight $w$ is utilized to control the convergence behavior of the PSO and the constants $c_1$ and $c_2$ control how far a particle will move in a single loop. The speed update step is:

$$\begin{aligned} v_{i,j}\,(t+1) = w v_{i,j}\,(t) + c_1 r_{1,j}(t) \\ - \; x_{i,j}\,(t)\big[y_{i,j}\,(t) - x_{i,j}\,(t)\big] \\ + c_2 r_{2,j}(t) - x_{i,j}\,(t)\big[y'_j\,(t) - x_{i,j}\,(t)\big] \end{aligned} \quad (3)$$

The next position of the particle $x_i\,(t+1)$ is decided by adding the new speed $v_i\,(t+1)$ to the particle's recent position $x_i\,(t)$

$$x_i\,(t+1) = x_i\,(t) + v_i\,(t+1) \quad (4)$$

Each measurement value of speed vector v_i is arranged to the range $[-v_{max}, v_{max}]$ to in order to decrease the probability of the particle leaves the inquest zone. The value of $v_{max}$is typically selected to be $k \times x_{max}$, with $0.1 \le k \le 1.0$ [11], where $x_{max}$ represents the field of the inquest zone. Notice that the value of $xi$ is not limited to the range $[-v_{max}, v_{max}]$; it is just restricting the greatest displacement which a particle is capable of achieve throughout a single loop. Normally, execution of the PSO modify the value of $w$ throughout the training run, e.g., linearly decreasing it from 1 to near 0 over the run. The acceleration coefficients, $c_1$ and $c_2$ control the maximum distance a particle will cover in one loop.

## 4. The Proposed Edge Detection Approach

The proposed approach implemented a modified PSO algorithm with new objective function derived from the local pixel clusters derivatives. Before an input image is applied to PSO algorithm, DWT and DT-CWT are used separately as preprocessing stage to improve the probability of detecting edges. Since DWT and DT-CWT are both multiresolution algorithms, the idea is to split the original input image into its subbands of frequencies and carry out the edge detection in all the subband images obtained from these two algorithms. The proposed approach is to apply PSO to all the subband images. The results from the PSO operation on the subband images are then used in reconstruction to recreate a single image using the inverse transforms. the reconstructed image is then thresholded to obtain a binary image containing detected edges using the proposed automatic thresholding. two different methods of automatic thresholding are used based on the applied wavelet transform. Figure 1 represents the block diagram of the proposed approach.

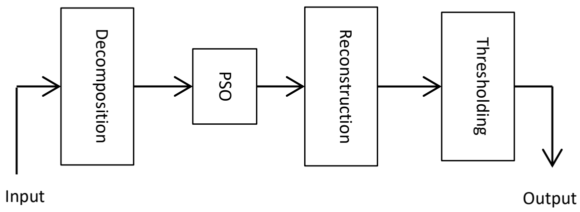



Fig. 1. General block diagram of proposed edge detection approach.

Fig. 2 shows DWT structure (including both decomposition and reconstruction) and how the proposed approach is embedded in the process.

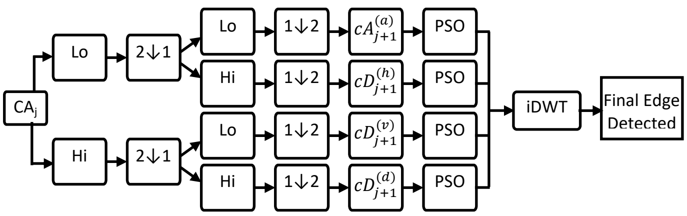



Fig. 2. Proposed DWT+PSO edge detection approach

All filters in DT-CWT have real weights; hence no real complex computation is performed [15]. One level 2D DT-CWT, produces 4 approximation images and 12 wavelets. These oriented wavelets can find edges in directions that DWT cannot reach. Figure 3 shows DT-CWT algorithm embedded within the proposed edge detection approach.

### *4.1. Proposed PSO objective Function*

Generally objective function, as the name implies, is a mathematical or statistical representation of a quantity that is needed to be minimized or maximized in an optimization problems. PSO like any other optimization algorithm requires an objective function. The performance of the algorithm is directly affected by this objective function. In the context of the problem at hand, edges are found at areas of abruptly varying pixel intensity, we proposed the use of Manhattan Distance operator ($l_1$-norm) as the objective function, f. The l1-norm is computed by each particle of the swarm in the PSO. For instance, if a particle, p of a swarm of PSO finds itself on pixel c located at coordinate $(i, j)$ of image $I$, all the 8-neighboorhood pixels around center pixel c are considered and their Manhattan Distance from the center pixel c is computed using equation 4. The proposed objective function based on Manhattan distance can be seen as technically computing discrete derivatives around the neighborhoods which will give clue on the presence or absence of edges. The bigger the output of the objective function the high the probability of edge presence. Hence maximization of the objective function will be the desired optimization operation that is required

$$f = |I_{(i-1,j-1)} - z| + |I_{(i-1,j)} - z| + |I_{(i-1,j+1)} - z| + |I_{(i,j-1)} - z| + |I_{(i,j+1)} - z| + |I_{(i+1,j-1)} - z| + |I_{(i+1,j)} - z| + |I_{(i+1,j+1)} - z| \quad (5)$$

where $|.|$ is the absolute value operator and $z = I_{(i,j)}$ is the center pixel at location $(i, j)$ within an image $I$, where the recent swarm particle is located.

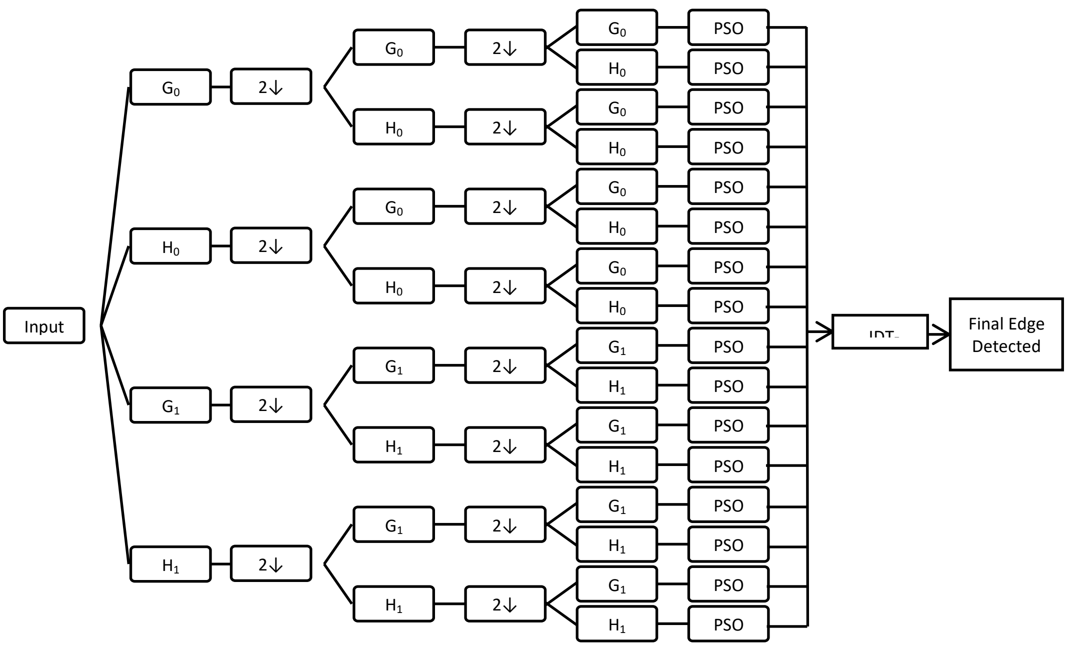



Fig. 3. Proposed DT-CWT+PSO edge detection approach

*4.2. Proposed Automatic Thresholding Function*

The automatic thresholding technique is based on the probability density function (pdf) and mean distribution of the output image from the PSO operation. The concept of using pdf makes it more general because it captures the statistical distribution of the output image which varies from one image to another. When the proposed approach uses DWT in the preprocessing and postprocessing stage the threshold $\theta_{dwt}$ is given by

$$\theta_{dwt} = \frac{\beta}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} I'_{(i,j)} \quad (6)$$

Where, $I'$ is the reconstructed image. $M$ and $N$ are, respectively, representing the number of rows and columns in $I'$, respectively. $\beta$ is a tunable parameter in the interval [0 1] usually close to upper bound (i.e. 1). Whereas in DT-CWT+PSO approach, the threshold $\theta_{dt-cwt}$ is given by

$$\theta_{dt-cwt} = \beta s_{max} \quad (7)$$

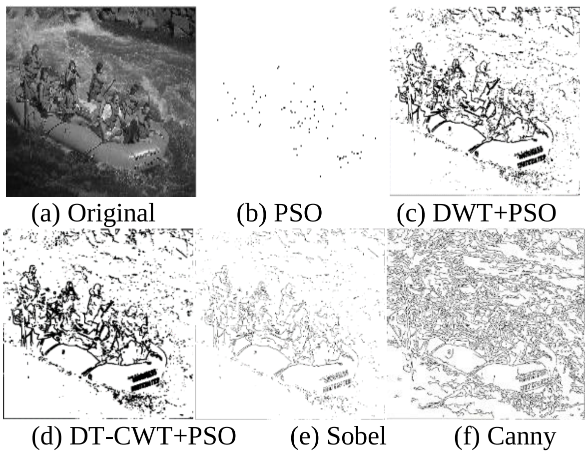
where $s_{max}$ is the pixel intensity with highest probability of occurrence and $\beta$ has same definition as for (6).

## 5. Simulation Results & Discussions

The simulation results of the proposed approach are presented in this section. Kodak color database is used for comparing our approach against other well-known edge detectors. These images are of different sizes and represent scenes of various contents, such as landscapes, people, natural and man-made objects.

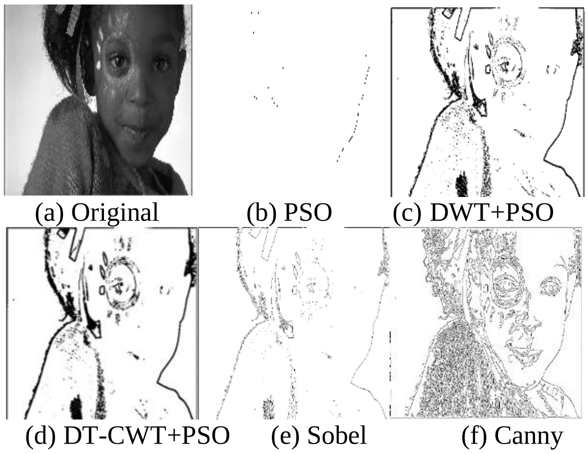
In Figure 4, details of rafters are much clearer in Figure 4(c) and Figure 4(d) which corresponds to output of DWT+PSO and DT-CWT+PSO approaches, respectively. Sobel in Figure 4(e) had very less details while Canny in Figure 4(f) had too much edges that make it hard to tell what is the image is really about.

In Figure 5 and Figure 6, wavelet-based PSO approaches detected the general outlier edges of in both images while canny for example was stuck with tiny details (details of girl shoulder in Figure 5 and sea waves in Figure 6) which is not really required or desired from the detector.



(a) Original (b) PSO (c) DWT+PSO
(d) DT-CWT+PSO (e) Sobel (f) Canny

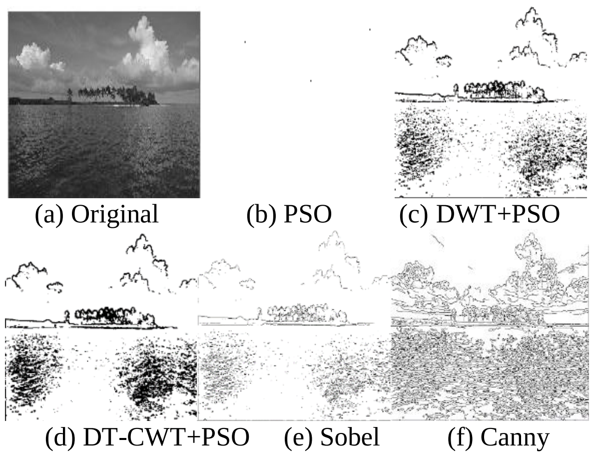
Fig. 4. White Water Rafters



(a) Original (b) PSO (c) DWT+PSO
(d) DT-CWT+PSO (e) Sobel (f) Canny

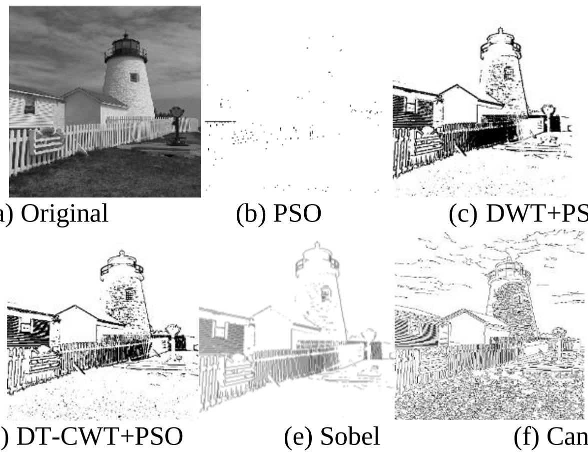
Fig. 5. Girl with Painted Face

Same observations can be derived from results in Figure 7 and Figure 8. Grass in Figure 7 and sea waves in Figure 8 are detected with unwanted or over details. Complex details of the sailboat in Figure 9 was best detected by DT-CWT+PSO approach followed by the results of DWT+PSO approach. Less edges were found by Sobel (Figure 9(e)) while unwanted, mixed and noisy edges were detected by canny (Figure 9(f)).



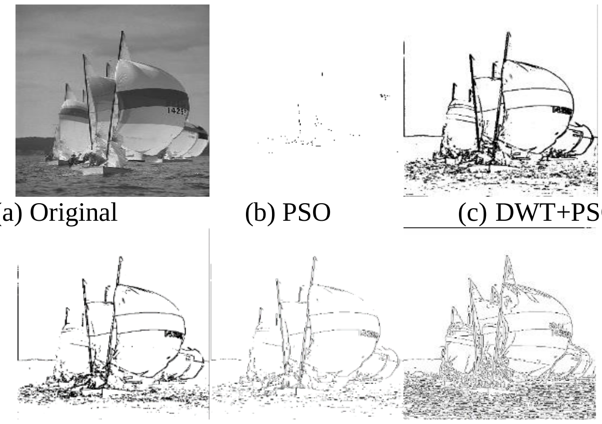
(a) Original (b) PSO (c) DWT+PSO
(d) DT-CWT+PSO (e) Sobel (f) Canny

Fig. 6.Tropical Key



(a) Original (b) PSO (c) DWT+PSO
(d) DT-CWT+PSO (e) Sobel (f) Canny

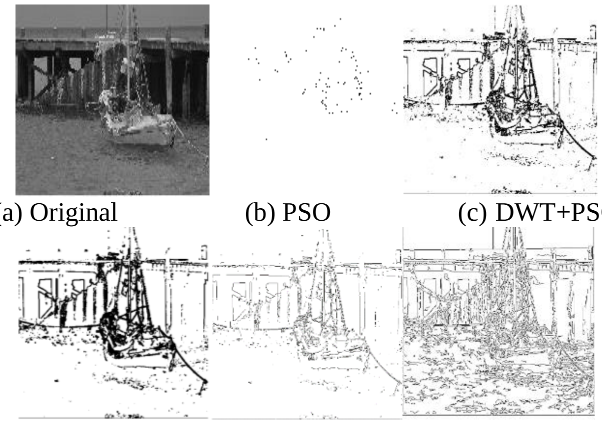
Fig. 7. Lighthouse in Maine



(a) Original (b) PSO (c) DWT+PSO

(d) DT-CWT+PSO (e) Sobel (f) Canny

Fig. 8. Sailboat under Spinnakers.



(a) Original (b) PSO (c) DWT+PSO

(d) DT-CWT+PSO (e) Sobel (f) Canny

Fig. 9. Sailboat at Pier

Quality measure and assessment of any edge detector is still a challenging task since the definition of desirable edges may vary from one application to another. Apart from human evaluation which is subjective, different objective approaches have been used by researcher to evaluate the performance of different edge detectors. In this paper, two objective fidelity methods are used to objectively assess the performance of the proposed approach and comparisons are made with other detectors.

Root-Mean-Square-Error (RMSE) integrates corruption function and statistical characteristics of noise in the edge detected image. It measures the average squared difference between the original gray level images and the binary images containing detected edges. The higher RMSE shows a larger variance between the original and produced image.

$$RMSE = [\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(I_{(i,j)} - I'_{(i,j)})^2]^{\frac{1}{2}} \quad (8)$$

where $I$ is original image, $I'$ is reconstructed image after thresholding. The smaller the RMSE the less the error and the vice versa.

In Table 1, RMSE results are evaluated for the proposed approaches and the conventional edge detectors. Using DWT+PSO and DT-CWT+PSO helped to decrease the RMSE values compared to directly applying PSO to the image for edge detection. DWT+PSO recorded the best average RMSE value (0.46) among all edge detectors in Table 1.

Peak Signal-to-Noise Ratio (PSNR), is the ratio between the maximum possible power of the signal against the power of corrupting noise that affects the quality of its representation. PSNR is a coarse guesstimate to human perception of reconstruction fidelity [1]. A higher PSNR generally shows the higher quality in the image. It is calculated based on RMSE value by

$$PSNR = 20 * log_{10}(\frac{255}{RMSE}) \quad (9)$$

**Table 1.** RMSE values using different edge detection operators on Kodak Database

| image names | PSO | DWT+PSO | DTCWT + PSO | Sobel | Canny |
|---|---|---|---|---|---|
| Sailboat at anchor | 0.60 | 0.42 | 0.57 | 0.64 | 0.69 |
| Shuttered windows | 0.63 | 0.45 | 0.60 | 0.62 | 0.66 |
| Market place | 0.63 | 0.44 | 0.53 | 0.79 | 0.65 |
| Sailboats under spinnakers | 0.50 | 0.35 | 0.64 | 0.35 | 0.80 |
| Sailboat at pier | 0.76 | 0.53 | 0.63 | 0.50 | 0.56 |
| Mountain stream | 0.70 | 0.49 | 0.64 | 0.52 | 0.57 |
| White water rafters | 0.70 | 0.48 | 0.66 | 0.56 | 0.62 |
| Girl with painted face | 0.67 | 0.47 | 0.58 | 0.53 | 0.58 |
| Tropical key | 0.70 | 0.47 | 0.73 | 0.43 | 0.47 |
| Monument | 0.73 | 0.52 | 0.74 | 0.30 | 0.41 |
| Model in black dress | 0.77 | 0.55 | 0.62 | 0.56 | 0.60 |
| Lighthouse in Maine | 0.67 | 0.43 | 0.56 | 0.67 | 0.70 |
| Portland head light | 0.60 | 0.47 | 0.59 | 0.56 | 0.62 |
| Barn and pond | 0.67 | 0.50 | 0.64 | 0.51 | 0.56 |
| Mountain chalet | 0.69 | 0.39 | 0.59 | 0.69 | 0.70 |
| **Average** | **0.67** | **0.46** | **0.62** | **0.55** | **0.61** |

**Table 2.** PSNR values using different edge detection operators on Kodak Database

| image names | PSO | DWT+PSO | DTCWT + PSO | Sobel | Canny |
|---|---|---|---|---|---|
| Sailboat at anchor | 52.60 | 55.62 | 53.02 | 52.05 | 51.29 |
| Shuttered windows | 52.60 | 55.06 | 52.54 | 52.29 | 51.77 |
| Market place | 52.17 | 55.17 | 53.70 | 50.21 | 51.93 |
| Sailboats under spinnakers | 54.11 | 57.17 | 52.03 | 57.20 | 50.11 |
| Sailboat at pier | 50.51 | 53.67 | 52.14 | 54.19 | 53.13 |
| Mountain stream | 51.28 | 54.29 | 52.03 | 53.80 | 53.06 |
| White water rafters | 51.28 | 54.49 | 51.77 | 53.10 | 52.25 |
| Girl with painted face | 51.62 | 54.70 | 52.83 | 53.72 | 52.87 |
| Tropical key | 51.29 | 54.60 | 50.90 | 55.40 | 54.64 |
| Monument | 50.83 | 53.84 | 50.69 | 58.73 | 55.91 |
| Model in black dress | 50.35 | 53.29 | 52.27 | 53.18 | 52.51 |
| Lighthouse in Maine | 51.67 | 55.43 | 53.24 | 51.58 | 51.26 |
| Portland head light | 52.51 | 54.67 | 52.77 | 53.10 | 52.35 |
| Barn and pond | 51.62 | 54.22 | 52.05 | 54.03 | 53.21 |
| Mountain chalet | 51.32 | 56.38 | 52.70 | 51.32 | 51.18 |
| **Average** | **51.77** | **54.90** | **52.36** | **53.39** | **52.43** |

In Table 2, the second evaluation method based on PSNR is tested on all the images using the proposed and the conventional approaches. Again, it can be easily observed that DWT+PSO approach achieved the highest average PSNR value among all approaches. DT-CWT+PSO approach had a comparable average result with canny edge detector.

## 6. Conclusion

The main objective of this paper was to develop a powerful edge detector based on PSO algorithm with enhanced performance using multiresolution approach by DWT and DT-CWT algorithms. PSO which is a heuristic approach that can be applied on the large search space and excerpts the general structure of the edges. PSO was applied on the decomposed subband images in order to gain more connected edges. Subjective results showed that the proposed approaches DWT+PSO and DT-CWT+PSO generated better looking edges compared to conventional detectors such as Canny and Sobel. Objective Simulations using RMSE and PSNR values also support the same findings as DWT+PSO recorded the best results among the other detectors.

## References

[1] D. Marr, & E. Hildreth, "Theory of edge detection", *Proceeding of Royal Society of London*, B, Vol. 207, pp. 187–217. 1980

[2] M. R, M.Radha. "Edge detection techniques for image segmentation", International Journal of Computer Science & Information Technology (IJCSIT) Vol 3, No 6, 2011.

[3] A. Muhammad, I. Bala, M. S. Salman and A. Eleyan, "Discrete wavelet transform-based ant colony optimization for edge detection", *2013 The International Conference on Technological Advances in Electrical, Electronics and Computer Engineering (TAEECE)*, 2013, pp. 280-283.

[4] R.C.Gonzalez, R.E.Woods & S.L.Eddins "*Digital image processing using matlab*", Pearson Education, 2004.

[5] J.F.Canny, "A Computational approach to edge detection", *IEEE Transactions On Pattern Analysis and Machine Intelligence*, Vol. 8, pp. 679-698, 1986.

[6] W. McIlhagga, "The Canny edge detector revisited", *International Journal of Computer Vision*, Vol. 91, pp. 251–261, 2012.

[7] I. E. Sobel, "*Camera models and machine perception*," Ph.D. dissertation, Stanford University, Stanford, USA, 1970.

[8] L. G. Roberts, "*Machine perception of 3-D solids, optical and electro-optical information processing*", MIT Press, 1965.

[9] M. Dorigo and S. Thomas, "*Ant colony optimization*". Cambridge: MIT Press, 2004.

[10] A. M. Ashir and A. Eleyan, "A multi-resolution approach for edge detection using ant colony optimization", *23nd IEEE International Conference on Signal Processing and Communications Applications* (SIU), Malatya, Turkey, pp. 1777 – 1780, May 2015.

[11] J. Kennedy, RC Eberhart, "*Swarm intelligence*", Morgan Kaufmann, 2001.

[12] D. Chen, T. Zhou, and X. Yu, "A new method of edge detection based on PSO", *9th International Symposium on Neural Networks*, Shenyang, China, pp. 239-246, 2012.

[13] D. Karaboga, B.Gorkemli, C.Ozturk, N. Karaboga, "A comprehensive survey: artificial bee colony (ABC) algorithm and applications ", *Artificial Intelligence Review*; Vol. 42, No. 1, pp.21-57, 2014.

[14] M. Çelik, F. Köylü, D. Karaboğa, "CoABCMiner: an algorithm for cooperative rule classification system based on artificial bee colony", *International Journal on Artificial Intelligence Tools*, Vol. 24, pp.1-40, 2015.

[15] A. N. Akansu, R. A. Haddad, "*Multiresolution signal decomposition: transforms, subbands, and wavelets*", Boston, MA: Academic Press, 1992.

[16] S. Mallat, "*A wavelet tour of signal processing*", 2nd ed. San Diego, CA: Academic, 1999.

[17] N. G. Kingsbury: "Complex wavelets for shift invariant analysis and filtering of signals", *Journal of Applied and Computational Harmonic Analysis*, Vol. 10, No. 3, May 2001, pp. 234-253.

[18] I.W. Selesnick, R.G. Baraniuk, N.C. Kingsbury. "The dual-tree complex wavelet transform", *IEEE Signal Processing Magazine*, 2005.