Performance Evaluation of Change Detection in SAR Images Based on Hybrid Antlion DWT Fuzzy c-Means Clustering

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Abstract: *In this paper, the main objective is to detect changes in the geographical area of Ottawa city in Canada due to floods. Two multi-temporal Synthetic Aperture Radar (SAR) images have been taken to evaluate the un-supervised change detection process. In this process, two ratio operators named as Log-Ratio and Mean-Ratio are used to generate a difference image. Performing image fusion based on DWT by selecting optimum filter coefficients by satisfying the wavelet filter coefficient properties through a novel image fusion technique is named as ADWT. GA, PSO, AntLion Optimization algorithms (ALO) and Hybridized AntLion Algorithm (HALO) have been adapted to perform the ADWT based image fusion. Segmentation has been performed based on fuzzy c-Means clustering to detect changed and unchanged pixels. Finally, the performance of the proposed method will be analysed by comparing the segmented image with the ground truth image in terms of sensitivity, accuracy, specificity, precision, F1-score.*

Keywords: *ADWT, ALO Algorithm, HALO Algorithm, GA Algorithm, PSO Algorithm.*

1. Introduction

SAR is able to generate images in all weather conditions that means it is capable of producing images in the night as well as in cloudy conditions. It can monitor the objects and is able to generate images 24 hours irrespective [1] of atmospheric conditions. Usually, the change detection process is performed in three steps. In the first step, image pre-processing will be performed, in the second step the difference image will be generated and finally, changes could be detected. It is a known fact that the segmentation can be done by using clustering, where clustering is the grouping of similarities, which indicates that separation between similar and non-similar

objectives could be possible. Based on this concept [1] detection of changes can be performed by using image fusion and clustering. Change detection can be attained by using Adaptive Discrete Wavelet Transform (ADWT) with Fuzzy c-Means (FCM) clustering [2-5].

Image fusion has been employed [1] to extract more information and to achieve symmetry between the altered pixel and unaltered pixels. To fix this an improved methodology is proposed to increase the performance of the change detection process based on image fusion by using the ADWT with FCM clustering. Firstly, images are picked up at the geographical area at various timings. Consequently, difference images are generated by performing ratio (Log-Ratio and Mean-Ratio) operations. The image fusion is performed with two difference images, i.e., one is the result of the Log-Ratio operator and the other one is the result of Mean-Ratio operator. This image fusion is performed by choosing the optimized filter coefficients rather than conventional wavelet filter coefficients (Daubechies, Haar). The process of performing DWT by choosing the optimized filter coefficients is named as Adaptive Discrete Wavelet Transform (ADWT). After image fusion, the early image is be reconstructed by using the IDWT. Clustering is be performed for the reconstructed image and the resulting image is compared with the ground truth image. Finally, the performance is measured in terms of measuring parameters.

2. Literature review and motivation of the problem

In 2019, Z h a o, L i n g and L i [22] have implemented a novel unsupervised Change Detection (CD) technique of flood mapping in SAR images. In 2018, L i et al. [23] have developed an unsupervised SAR change detection framework for spotting out the changes in SAR with the aid of robust semi-non-negative matrix factorization with TV. In 2017, L a z a r o v and M i n c h e v [24] proposed ISAR Image Recognition Algorithm and Neural Network Implementation. In 2014, H o u et al. [25] have invented a novel unsupervised SAR change detection approach on the based on GLR-IM and compressed projection for transformation discovery in SAR images. In 2014, Z h e n g et al. [26] have introduced a simple and effective unsupervised approach for CD in SAR images using the KMC. In 2013, Z h a n g, C h e n and M e n g [27] have developed a robust as well as a fast-unsupervised SAR change-detection framework for detecting the modifications in SAR images. In 2012, G o n g, Z h o u and M a [28] have formulated an unsupervised CD in SAR images based on distribution-free approach for determining the modifications in SAR images using the image fusion strategy as well as a novel fuzzy clustering algorithm. In 2009, M o s e r and S e r p i c o [29] have formulated a new model for multichannel amplitude SAR image contextual change-detection in an unsupervised and automatic manner.

The main objective of this proposal is to improve the overall performance of CD by maximizing the accuracy through the proposed methodology over conventional methodologies. Change detection process has been performed for Ottawa data set captured from the geographical area of Canada. Two multitemporal SAR images have been taken to detect the changes, and changes occurred due to floods, land cover

changes. Hence, this process could be used for society to identify the damages, which would occur due to natural disasters or changes in the earth's surface.

3. Proposed methodology

The proposed methodology is to improve the overall performance of the change detection process by using image fusion based on ADWT and segmentation by using Fuzzy c-means clustering. ADWT is performed by choosing optimized filter coefficients of wavelets based on the Genetic Algorithm (GA), Particle Swarm Optimization Algorithm (PSO Algorithm) and AntLion Optimization Algorithm (ALO Algorithm).
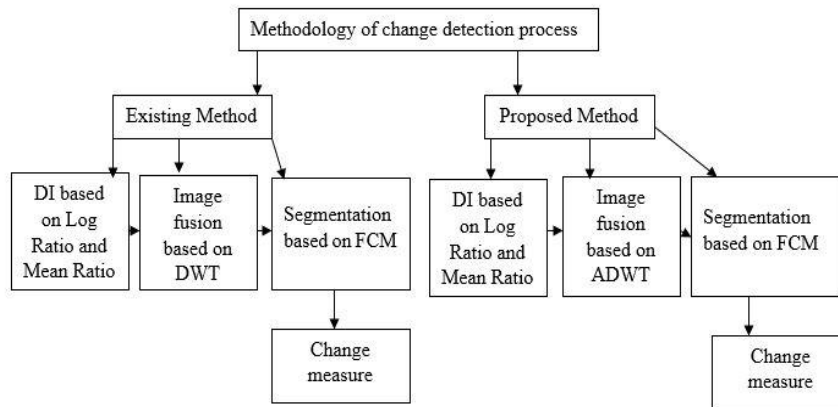

Fig. 1. Proposed methodology

The proposed methodology is illustrated in Fig. 1 and the following steps are involved in this process:

Step 1. Difference images are generated through the Log-Ratio operator and Mean-Ratio operator.

Step 2. Image fusion using conventional DWT and ADWT (using GA, PSO, ALO).

Step 3. Segmentation using FCM clustering.

Step 4. Measurement comparison of ground truth image and segmented image.

As illustrated in Fig. 2. Optimized filter coefficients have been chosen based on GA, PSO and Antlion optimization algorithms. The decisive thing is the selection of filter coefficients based on satisfying the orthogonality property to reconstruct the original image by minimizing the error. As it is known some content of input will be lost during the process of DWT which causes unfaithful reconstruction of the original image. In this paper, it is proposed that the loss in the DWT process could be reduced through the optimal selection of filter coefficients. After image fusion process, segmentation has been done based on Fuzzy C-Means clustering (FCM). In the latter,

the segmented image is compared with the ground truth image, and performance has been analysed [2-5].
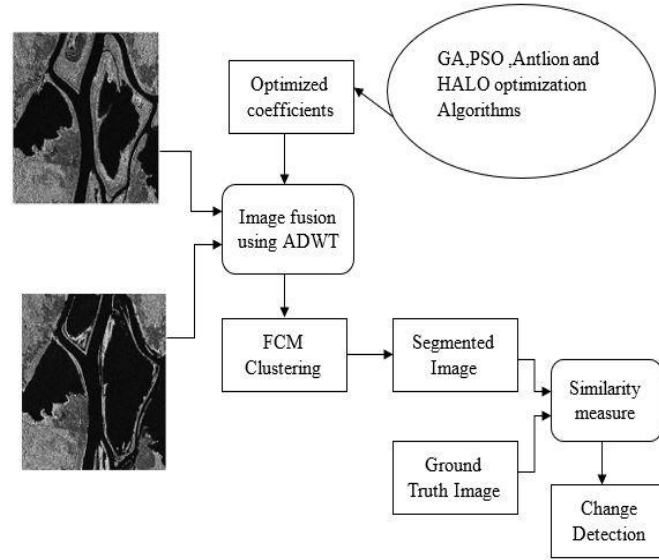

Fig. 2. Overall Architecture of the proposed methodology

3.1. Adaptive Discrete Wavelet Transform (ADWT)

The proposed ADWT [2-5] is performed by adapting optimized filter coefficients through the optimization algorithms rather than using conventional wavelet filter coefficients (Daubechies, Haar). As depicted in Fig. 3. The hidden thing in choosing ADWT is to reduce the quantization error during the DWT process, proportionally minimizing error in the reconstructed image to achieve faithful reconstruction.
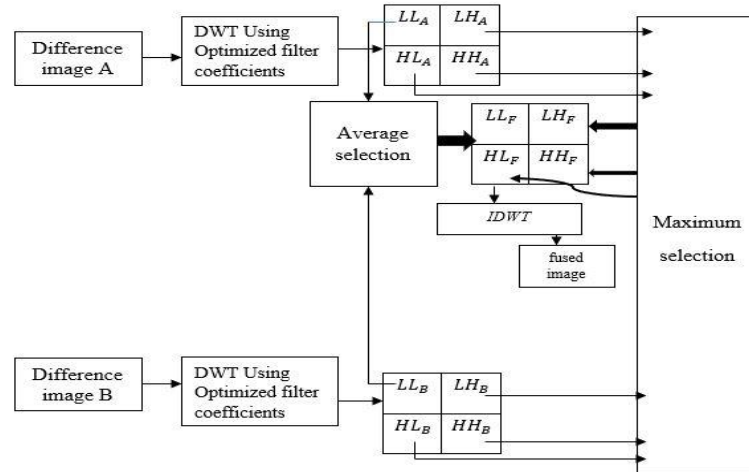

Fig. 3. Proposed 2D-ADWT architecture

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The DWT is used to redistribute the energy of a given signal. The major components of DWT are given as (1) scaling function $\phi(t)$ and (2) wavelet function $\psi(t)$. Instead of using conventional wavelet coefficients (Hi_D, Li_D) in image fusion, optimized filter coefficients {Hi_D(OP), Li_D(OP)} are optimally chosen through GA, PSO and ALO Algorithms. ADWT-based image fusion is executed for difference Image (DI) A (Log-ratio) and difference image B (Mean-Ratio) and the Inverse Discrete Wavelet Transform (IDWT) is be performed, to reconstruct the original image by using images $LL_F, LH_F, HL_F,$ and HH_F. The decomposition images after performing 2D-ADWT are abbreviated as follows:

- LL_F is an approximation image by taking the average of LL_A and LL_B images;
- LH_F is Horizontal image by selecting the maximum of LH_A and LH_B images;
- HL_F is a vertical image by selecting the maximum of HL_A and HL_B images;
- HH_F is Diagonal image by selecting the maximum of HH_A and HH_B images;
- LL_A and LL_B are the decomposition images of approximation images of DI of A and DI of B, respectively;
- LH_A and LH_B are the decomposition images of horizontal images of DI of A and DI of B, respectively;
- HL_A and HL_B are the decomposition images of vertical images of DI of A and DI of B, respectively;
- HH_A and HH_B are the decomposition images of Diagonal images of DI of A and DI of B, respectively.

The overall performance analysis is measured between conventional DWT (using Daubechies wavelets) and ADWT (using optimized filter coefficients through GA, PSO and ALO Algorithms). In [7-10] Daubechies wavelet with two vanishing moments is called as Daubechies 2 wavelet. The transfer functions of decomposition filters are expressed in the next equations:

(1) $\qquad H(z) = h_{-2}z^2 + h_{-1}z^1 + h_0 + h_1 z^{-1},$
(2) $\qquad G(z) = -h_1 z^2 + h_0 z - h_{-1} + h_{-2}z^{-1}.$

The transfer function of reconstruction filter coefficients is expressed in the equations

(3) $\qquad \bar{H}(z) = h_1 z + h_0 + h_{-1}z^{-1} + h_{-2}z^{-1},$
(4) $\qquad \bar{G}(z) = -h_1 z^{-2} + h_0 z^{-1} - h_{-1} + h_{-2}z^1,$

where

(5) $$h_0 = \frac{3-\sqrt{3}}{4\sqrt{2}},$$

(6) $$h_1 = \frac{1-\sqrt{3}}{4\sqrt{2}},$$

(7) $$h_{-1} = \frac{3+\sqrt{3}}{4\sqrt{2}},$$

(8) $$h_{-2} = \frac{1+\sqrt{3}}{4\sqrt{2}},$$

where $\bar{H}(z) = H(z^{-1})$ and $\bar{G}(z) = G(z^{-1})$.

Instead of using standard wavelet filter coefficients (Equations (5)-(8)) optimized filter coefficients could be used by satisfying the orthogonality property.

3.2. Optimization algorithms for performing ADWT

Three types of optimization algorithms have been adapted for performing ADWT. The overall parameters of optimization are illustrated in Table 1.

Table 1. Function details for the Optimization process

Testing function: SPHERE		
No	Parameter	Value
1	Search Agents	30
2	Max iteration	100
3	Lower bound	−10
4	Upper bound	10
5	Dimension	10

3.2.1. Conventional Antlion Algorithm (ALO)

This algorithm has been developed based on the searching mechanism for the prey of antlions [18, 19, 21]. ALO is a new stochastic algorithm that has been developed from the inspiration of the antlions hunting mechanism. In this regard, antlions and ants act as searching agents for hunting the prey. The steps, which are involved in hunting prey, are given as random walk of the ant, forming paths of traps, enmeshment of ants in traps, capturing the prey and rebuilding the trap. The mathematical model of the algorithm is elaborated as follows.

In the process of hunting ant moves by a random walk and the optimization process is expressed as

$$(9) \qquad A_i = \left[0; s(1); s(1) + s(2); \ldots \sum_{j=1}^{T-1} s(j); \sum_{j=1}^{T} s(j)\right],$$

where $i = 1, \ldots,$ Dim, Dim is the dimension of ant and antlions, T is the maximum iteration;

$$(10) \qquad A_i = [A_1 \ldots A_{\text{dim}}],$$
$$(11) \qquad A_i = (T + 1) \times 1 \text{ matrix},$$

where $s(j)$ is expressed as

$$(12) \qquad s(j) = \begin{cases} 1 & \text{if rand} > 0.5, \\ -1 & \text{if rand} \leq 0.5, \end{cases}$$

where "rand" indicates random numbers in the interval [0, 1]. Based on Lower Bound (LB) value and Upper Bound (UB) value the random walk of search agents will be converted into a possible search space, which is calculated as per Equation (12). The Bound of i-th ant is

$$(13) \qquad B_i = \frac{A_i - x_i}{z_i - x_i} \times (d_i - c_i) + c_i,$$

$A_i \in [0, 1]$. By changing the ant movement antlions trap the ant. This can be formulated as

$$(14) \qquad c = c' + \text{Antlion},$$
$$(15) \qquad d = d' + \text{Antlion},$$

where c' and d' are lower limit and upper limit of the movement of the ant, respectively. Based on the Roulette wheel the position of the antlion will be selected

[19]. Once ants are trapped then the radius of ant movement would be decreased and formulated as Equations (14)-(15);

$$(16) \qquad c' = \frac{\text{LB}}{10^w \times (t/T)},$$

$$(17) \qquad d' = \frac{\text{UB}}{10^w \times (t/T)},$$

where w is constant value and $t \in [0, 1]$.

Elitism is adopted in this algorithm, therefore based on the Roulette wheel and Elitism ant updates its new position. Hence, the new position of the ant could be represented as

$$(18) \qquad \text{Ant} = \frac{R_A + R_B}{2},$$

where R_A, R_B are the random walk of antlion based on the Roulette wheel and Elitism, respectively.

3.2.2. Hybridized Antlion Algorithm (HALO Algorithm)

In this paper, the proposed algorithm is named as HALO (Hybridized ALO) Algorithm which is implemented to perform ADWT through selection of optimized coefficients. The concept in developing this algorithm is hybridizing the Artificial Bee Colony algorithm with ALO Algorithm. In conventional ALO the new position of the ant will be updated as per Equation (18) but to reduce the search space the new position will be updated according to HALO Algorithm is according to next equation:

$$(19) \quad A_{i,j} = \frac{R_A + R_B}{2} + \text{rand}(0, 1)[(R_{A\max}, j - R_{A\min}, j) - (R_{E\max}, j - R_{E\min}, j)].$$

After calculating the fitness value according to ABC algorithm $R_{A\max}$ and $R_{E\max}$ are current positions of the ant based on ABC Algorithm respectively and $R_{A\min}$, $R_{E\min}$ are previous positions of ant according to conventional ALO. In this way the performance of ALO Algorithm has been improved.

The execution of HALO Algorithm is explained as in Fig. 4.

Step 1. Initialize population size $A_i = [A_1 \dots \dots \dots A_{\text{dim}}]$
Step 2. Calculate fitness of both ant and antlions
Step 3. Based on roulette wheel select antlion for every ant
Step 4. Update the position based on Equation (18)
Step 5. Calculate the fitness of all ants
Step 6. If the end criterion is satisfied, return the elite. Otherwise, return to Step 3

Fig. 4. Pseudocode of HALO Algorithm

3.2.3. Fuzzy c-Means clustering (FCM)

In this paper, the FCM clustering technique has been adapted for segmentation. It is a known fact that changed pixels and unchanged pixels could be separated by segmentation. The composing of FCM clustering is illustrated in Fig. 4. In order to reduce the search space.

Step 1. Initialize= $[t_{ij}]$ matrix T^0

Step 2. At k-step calculate the centre vectors $B^{(K)} = [B_i]$ with $T^{(k)}$,

$$B_j = \frac{\sum_{i=1}^{N} t_{ij}{}^m . x_i}{\sum_{i=1}^{N} t_{ij}{}^m}$$

Step 3. Update $T^{(k)}, T^{(k-1)}$,

$$t_{ij} = \frac{1}{\sum_{k=1}^{b} \left(\frac{\|x_i - b_j\|}{\|x_i - b_j\|} \right)^{\frac{2}{m-1}}}$$

Step 4. if $\|T^{(k+1)} - T^k\| < \varepsilon$ then stop; otherwise return to Step 2

Fig. 5. Composing of FCM clustering

4. Results and discussions

In this paper to endorse the performance of the proposed methodology over the conventional method (image fusion with Daubechies wavelets) satellite images with SAR, sensors have been taken into account. Ottawa data set is taken as data set to validate the proposed methodology. Fig. 6a shows the geographical image of Canada and Fig. 6b shows its capital city Ottawa. Fig. 7 shows the Radar sat images of Ottawa city in Canada. Fig. 7a shows the satellite image before occurrence of the flood, the image after the flood is shown in a Fig. 7b, and the majority of the affected areas are marked in red. The corresponding ground truth image is shown in a Fig. 7c.
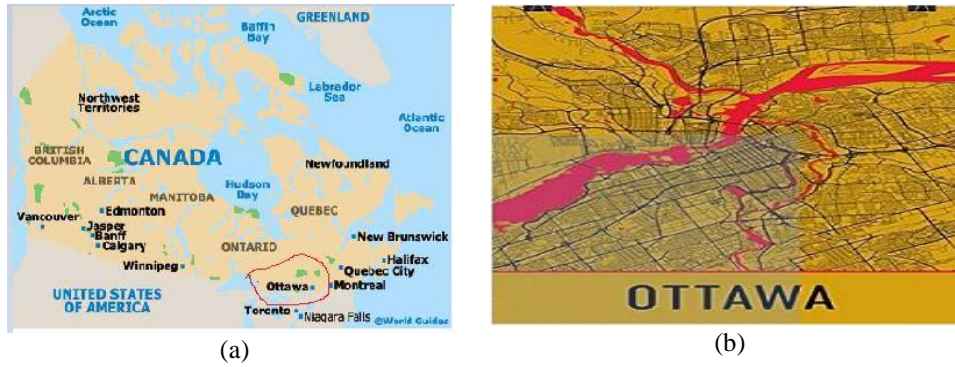

(a)   (b)

Fig. 6. Geographical map of Canada (a); Ottawa city map (b)

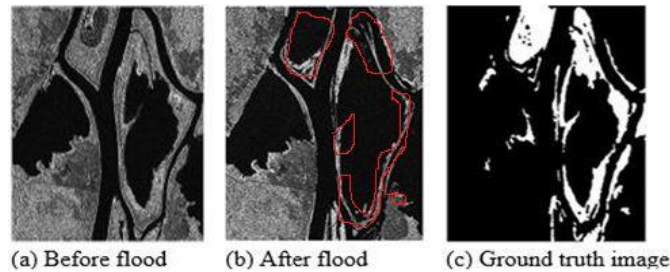(a) Before flood   (b) After flood   (c) Ground truth image

Fig. 7. Ottawa data set

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As illustrated in Fig 1 the initial step in the proposed methodology is generating the DI by Log-ratio operator and Mean-ratio operator. The difference images are depicted in Fig. 7. Log-ratio operator DI is shown in Fig. 8 a and the Mean-ratio operator DI is illustrated in a Fig. 8b.
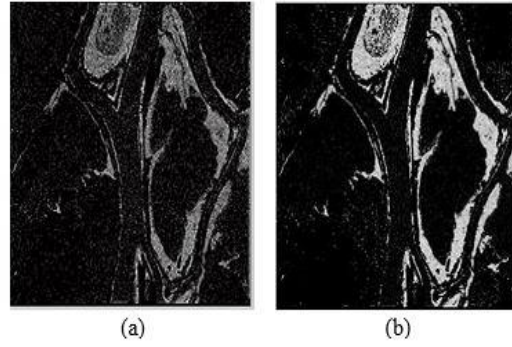

Fig. 8. Difference Images: Log-ratio operator (a); Mean-ratio operator (b)

As per Step 2, image fusion will be performed based on conventional DWT (with Daubechies 2 wavelets) and ADWT and the corresponding images are illustrated in Fig. 9.
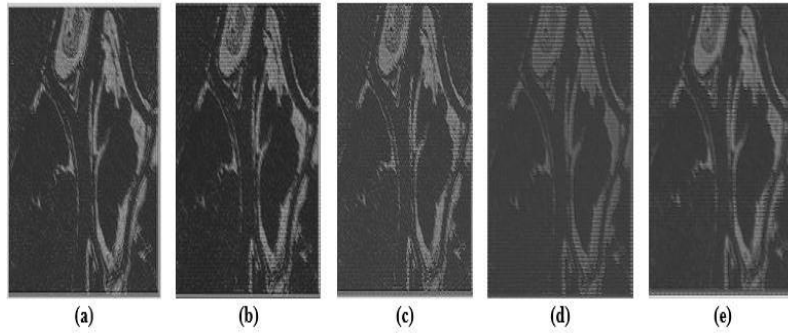

Fig. 9. DWT (a); ADWT_GA (b); ADWT_PSO (c); ADWT_ALO (d); ADWT_HALO (e)

Image segmentation has been employed to differentiate changed pixels and unchanged pixels. In this regard, FCM clustering has been performed for segmentation and the resulting output images are exploited in a Fig. 10.
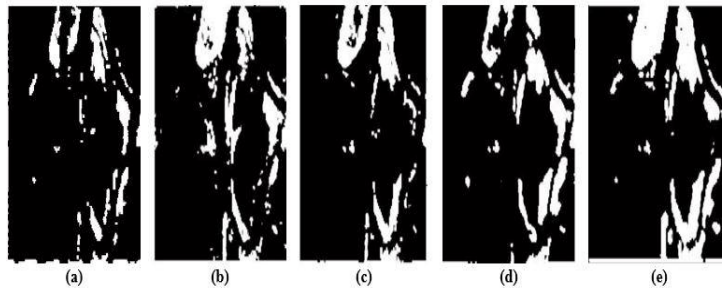

Fig. 10. DWT_FCM (a); GA_FCM (b); PSO_FCM (c); ALO_FCM (d); HALO_FCM (e)
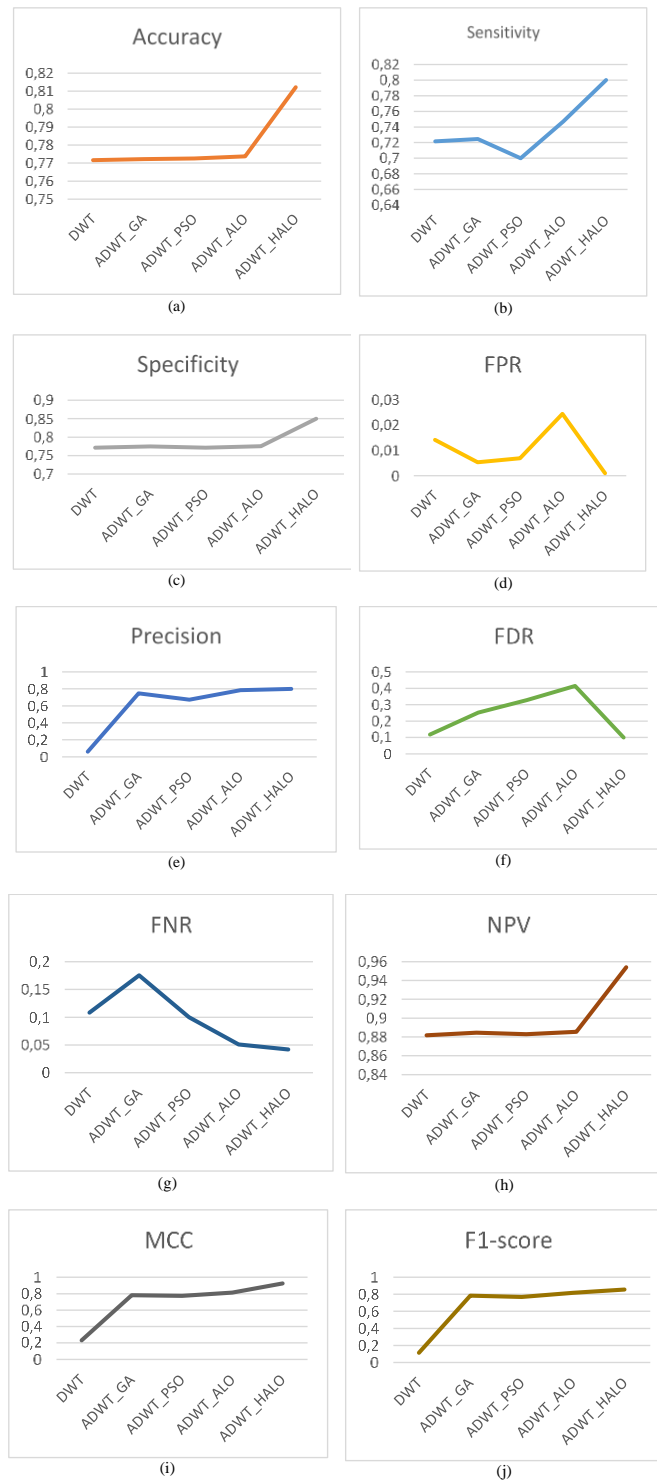
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Fig. 11. Graphical representation of proposed methodology over the conventional method

Table. 2. Performance analysis of proposed methodology over conventional DWT

Measure	DWT	ADWT_GA	ADWT_PSO	ADWT_ALO	ADWT_HALO
Sensitivity	0.7217	0.7245	0.7	0.7471	0.8
Accuracy	0.7716	0.7722	0.7726	0.7737	0.8122
Specificity	0.7714	0.7746	0.7715	0.7754	0.8501
FPR	0.0143	0.0054	0.007	0.0246	0.001
Precision	0.0607	0.7475	0.6723	0.786	0.7991
FDR	0.1174	0.2525	0.3277	0.414	0.1
FNR	0.1081	0.1755	0.1	0.0508	0.0421
NPV	0.8817	0.8846	0.883	0.8854	0.9541
MCC	0.2308	0.7807	0.7738	0.8138	0.9243
F1-score	0.114	0.7841	0.7687	0.8164	0.8556

5. Conclusion

As in the previous literature, the majority of researchers opt two types of ratio operators (Log-Ratio operator and Mean-Ratio operator) to generate DI for CD in SAR images. However, Log ratio operator does not represent altered pixels and unaltered pixels symmetrically, in the same way, the Mean-ratio operator does not represent difference images smoothly. To fix these problems image fusion has been introduced. Even though the difference image is fused but some of the original image information will be lost in the DWT process. By adapting the ADWT technique, maximum error could be reduced in the DWT process. Finally, it has been proved that ADWT (using GA, PSO, ALO and HALO optimization Algorithms) can give more accuracy than a conventional DWT.

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