

# Change Detection in Sarimages Based on Artificial Bee Colony Optimization With fuzzy C - Means Clustering

J. Thrisul Kumar, Y. Mallikarjuna Reddy, B. Prabhakara Rao

**Abstract:** Synthetic aperture radar (SAR) generates images with high resolution in all weather conditions for a given application. An Artificial Bee Colony (ABC), optimization algorithm is proposed to detect changes in multitemporal SAR images which are captured at same area in various times. It is well-known fact that the speckle noise existed in SAR images. In order to reduce the speckle noise in the co-registered images, a novel Adaptive Median filter is implemented in this paper. After the minimization of speckle noise, discrete wavelet (DWT) fusion is exploited for further image segmentation. Also, an Artificial Bee Colony (ABC) optimization technique is adopted for effective smoothing the image to make decisive image classification. Using fuzzy c-means clustering classification we can detect changed pixels and unchanged pixels. Finally, the results are compared with DWT-FCM (without optimization), Genetic Algorithm (GA) optimization and proposed ABC optimization Algorithm. The performance of proposed technique is compared in terms of accuracy, sensitivity, precision and F1-score.

**Keywords:** SAR, Optimization, ABC algorithm, GA algorithm and Fuzzy - C means clustering.

## I. INTRODUCTION

Synthetic Aperture Radar (SAR) senses the earth surface at large distances irrespective of weather conditions. It gives high-resolution data regarding targets in all types of environments. The process of detecting changes between two images is most essential in several fields such as medical images [4], remote sensing [2], video surveillance [8], forest monitoring [7] and urban studies [6]. Change detection process can be performed either by supervised or unsupervised detection methods. Unsupervised method categorized into three steps. 1) preprocessing of acquired images 2) Generating difference image 3) Analyzing difference image. In pre-processing geometric corrections and noise reduction can be performed by making co-registration of two images. By comparing pixel by pixel in co-register images difference image can be generated. Image

analysis is performed by using difference image. In this paper, it is proposed that in pre-processing speckle noise will be reduced by using adaptive median filter. After speckle reduction, DWT image fusion was adopted for combining two images. An ABC optimization is applied to get a smooth image. Finally, fuzzy c-means clustering is adopted to classify changed pixels and unchanged pixels.

The paper is divided into five sections. Section I explains about the total procedure carried out in this paper. Section II Conferring about speckle reduction and image fusion using DWT. Section III focal point on Genetic Algorithm and ABC Algorithm optimization techniques. Section IV is focusing on fuzzy c-means clustering. Finally, experiment results are discussed in section V.

## II. SPECKLE REDUCTION AND FUSION:

Speckle noise exists in SAR images [1] because of backscatter returns from radar pulses. In this paper, an Adaptive median filter is implemented for reducing the speckle noise. This filter consists of a square window with size  $2k+1$ , where  $k$  value changes from 1 to  $N$ . Local adaptive filter which calculates local statistics to identify speckle noise occurs in SAR images can be replaced with the median value. Synthetic Aperture Radar speckle noise consists of standard deviation value which is linearly proportional to a value of the mean. High signal strength causes high speckle noise. An Adaptive median filter has some characteristics. 1) Adaptive Mean filter utilizes local statistics values instead of global statistics values 2) It does not change valid values by replacing speckle noise. 3) It considers output local median value instead of mean value. 4) It takes valid pixels 5) It preserves image shape, edges, features. Adaptive Median filter reinstates a central pixel when it tracks central pixel as a speckle noise and if central pixel is a valid pixel then no replacement happens. A Local median value is calculated from valid pixels rather than other filters. A Local median value will be calculated from the pixels which are having only valid values. The algorithm for an adaptive median filter is explained as follows. For example, when moving window  $D(i, j)$  with center pixel  $d(i, j)$  then the size of the window will be  $2k+1$ . The size of the window must be an odd and equal size in both dimensions just as  $3 \times 3$ ,  $5 \times 5$  and  $7 \times 7$ . In this paper  $5 \times 5$  window is adopted. If the moving window consisting of  $N(i, j)$  pixel values, then the total sum of all pixel value will be represented as  $S(i, j)$ . The total sum  $S(i, j)$  can be expressed as

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$$S(i, j) = \sum_{m=i-k}^{i+k} \sum_{n=i-k}^{i+k} d(m, n)$$

Total number of pixels is expressed as

$$N(i, j) = (2k + 1)^2$$

Total sum of all pixel is used to calculate mean value and standard deviation.

The mean value of  $\mu(i, j)$  can be determined by using equation

$$\mu(i, j) = \frac{N(i, j)}{S(i, j)}$$

and standard deviation value computed by equation

$$\sigma(i, j) = \sqrt{\frac{\sum_{m=i-k}^{i+k} \sum_{n=i-k}^{i+k} (d(i, j) - \mu(i, j))^2}{N(i, j)}}$$

Number of valid pixel values can be computed according to local statistics (mean and standard deviation) and M is a user defined multiplexer (Generally value may be either 1 and 2).

$$LB(i, j) = \mu(i, j) - M\sigma(i, j)$$

$$UB(i, j) = \mu(i, j) + M\sigma(i, j)$$

Where  $LB(i, j)$  is Lower Bound and  $UB(i, j)$  is Upper Bound Another mask with moving window L and its center is  $I(i, j)$ . It is used to differentiate the valid pixels and speckle noise pixels on each pixel.

Image fusion technique is a process of combining multitemporal images information captured at different time intervals. The fusion image consists of required information and characteristics of individual input images. Image fusion considers pixel levels of input images. Discrete Wavelet Transform (DWT) works on pixel level image fusion, it separates frequencies in both the space and time. The process involved in DWT- Based image fusion is given as follows.

Step1: Capture two input images at same Geographical area at different times.

Step2: Obtain HH, LH, HL and HH by using wavelet decomposition.

Step3: Apply average technique on low frequency images.

Step4: Execute selection of minimum (or) maximum scheme.

Step5: Perform IDWT on Fused images.

Step6: Finally, new intensity level image results.

### III. GA AND ABC OPTIMIZATION TECHNIQUES:

The Evaluation of GA algorithm is based on individual chromosome fitness [3] [12]. Repopulation of the next generation can be achieved by using three operators: reproduction, crossover, and mutation. Through reproduction, the next generation collects several copies from the high fitness value strings. Whereas low fitness value strings collect a very few or none. GA consists of two parameters named as crossover and mutation. Crossover is also called as parent where it will merge two chromosomes to generate offspring. Offspring is also called as new chromosome. After crossover, the result might have better than parents. The new result will be taken from each parent

separately. New chromosome can gain better properties from one parent and another parent. Let assume that 00110100 is parent A, 00100000 is parent B. After the crossover is performed the net outcome result consists a few elements from parent A and some elements in parent B. The output of crossover can be written as 00110100+00100000=00100000. There will be a chance of that local optimum solution of the solved problem contains total solutions in population. To overcome this drawback mutation will be performed. Mutation relating with crossover and encoding and it randomly changes the new chromosome. Mutation Application explained as follows

Initial new chromosome A- 0010000101100001

New chromosome After mutation

A- 0011000101100001

Initial new chromosome

B- 0010011011001001

New chromosome After mutation

B - 0010010011001001

GA elaborated as follows [5] [12]

function of Genetic Algorithm

{

Initialize population;

Determine fitness function;

While (fitness value! = termination criteria)

{Selection; Crossover; Mutation; Calculate fitness function;}

}

The proposed ABC Optimization algorithm [5] works based on population. [6] Employed bees accomplish their combine food sources seek before and contribute the information regarding nature and location of food sources along with onlooker bees by performing waggle dance. The information gathered by employed bees suggests to onlooker bees for selection of food source. Scout bees are always working to search new food source.

ABC algorithm ensues the following phenomena, one possible solution is present for every food source according to problem deliberation. Nectar amount speaks for nature of the solution and this nature of the solution performed by fitness value. Employed bee (EB) number is equal to the count of food source. Onlooker Bees (OB) considers the probability value (pi) to perform food source selection. This probability value will be collaborated with the food source. The

probability value  $P_i$  is given as

$$P_i = \frac{fit_i}{\sum_{i=1}^S fit_i}$$

$fit_i$  is the fitness of obtained solution, S is the total sources number. The value of S is equal to count of EB and count of OB. This algorithm follows below expression to obtain new food source position  $(v_i)$  from old source position  $(x_i)$  and by choosing k, j as random indexes. It is expressed as

$$v_{i,j} = x_{i,j} + \phi_{i,j} (x_{i,j} - x_{k,j})$$

The position of old food source is expressed as

$$x_i = [x_{i,1}, x_{i,2}, \dots, x_{i,D}]$$

The position of new food source is given as

$$v_i = [v_{i,1}, v_{i,2}, \dots, v_{i,D}]$$

Where  $k \in [1, 2, \dots, S]$

$j \in [1, 2, \dots, D]$

Where D is the count of variables and  $\phi_{i,j}$  is a random number with value range from -1 to 1. Artificial Bee verifies and evaluates the position of candidate and compares with previous position. When present position is better than previous position then previous position will be replaced by present position, otherwise no change in previous position of food source. When better position was not attained through number of repeated cycles then source will be neglected. In this kind of situation Scout Bee hunts for new source by using equation.

$$x_{i,j} = x_{min,j} + \text{rand}(0,1) \left[ (x_{max,j} - x_{min,j}) \right]$$

Based on the above equation Scout Bee replaces previous source with the new source.

Initialization Phase

```
{
REPEAT
Phase of Employed Bee
Phase of Onlooker Bee
Phase of Scout Bee
Register Best solution found so far
UNTIL (Maximum number of cycles)
}
```

#### IV. FUZZY C MEANS CLUSTERING:

The inverse transformed image is clustered by using FCM scheme. Fuzzy c- means clustering technique [10] is an iterative clustering scheme that generates an optimal value of c, partition by reducing the weighted window. FCM cluster algorithm [11] broadly adopted by researchers for image segmentation. It calculates the fuzzy membership degree matrix to show that probability of individual pixelvalue. This probability of pixel value belonging to the set. The FCM clustering algorithm can able to produce pinpoint segmentations compare with hard clustering. The cluster sum of squared error objective function  $J_{FCM}$  equation is

$$J_{FCM} = \sum_{k=1}^n \sum_{i=1}^c (u_{ik})^2 F^2(x_k, v_i)$$

The solution for the objective function  $J_{FCM}$  can be obtained as given below.

Step1: Allot values for c, q, and  $\epsilon$

Step2: Allot partition matrix

Step3: Assign the value  $b=0$  to loop counter

Step4: calculate cluster centers  $\{x_i(b)\}$  with  $y^{(bt)}$  as revealed in equation

$$x_i(b) = \frac{\sum_{k=1}^{n_i} (u_{ik}(b))^q z_m}{\sum_{k=1}^{n_i} (u_{ik}(b))^q}$$

Next, calculate the membership  $u_{ik}^{(bt)}$  for else assign  $b = b+1$  similarly  $i_k = (1, 2, \dots, c)$  for  $k^{\text{th}}$  column of matrix. When  $u_{ik} = \delta$  calculate new membership values

$$u_{ik}^{(bt)} = \frac{1}{\sum_{j=1}^c \left( \frac{F_{ijk}}{F_{ik}} \right)^{\frac{2}{q-1}}}$$

Else  $2k+1$ ,

If  $\|u^{b+1} - u^b\| - u^{b+1} < 1$  stop else assign  $b = b+1$

#### V. RESULTS AND DISCUSSIONS:

Images are collected from ERS -1 satellite. The geometrical area of these images is the city of san Francisco and its bay. Fig 1 shows SAR Image 1 which is captured in August 2003 and Fig 2 shows SAR Image 2 which is captured in May 2004. Fig 3 shows Ground Truth image which is produced by photo interpretation process by considering two input images. Fig 4 exhibits change detection map by applying DWT image fusion and Fuzzy C means clustering. Fig e and Fig f show the change detection map by applying GA - FCM and ABC - FCM respectively. Fig 5 and Fig 6 illustrating the graphical response of performance parameters between existing methods DWT-FCM, GA- FCM and ABC - FCM. The executed results of the proposed method over existing techniques are illustrated in Table1. From the Table1, it can be understood that the ABC algorithm gives 0.15% of better performance in accuracy measurement over the GA algorithm. It gives 3.8% more performance in terms of precision over the GA algorithm. ABC algorithm gives 0.847 % more performance in terms of F1- score.

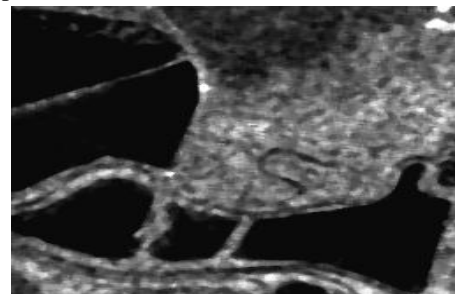


Fig 1.Sar Image 1

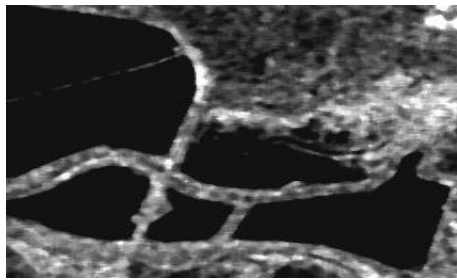


Fig 2. Sar Image 2



Fig 3. Ground Truth Image



Fig 4. DWT-FCM



Fig 5. GA-FCM Image



Fig 6. ABC – FCM Image

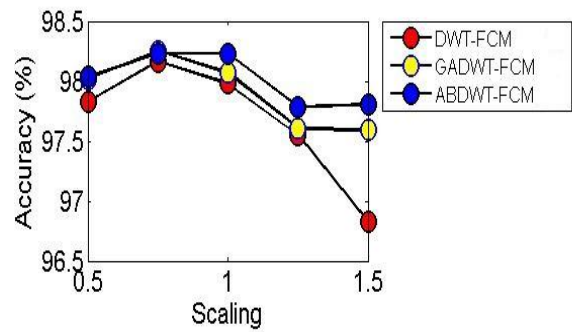


Fig 7. Results of Conventional Methods and Proposed Methods a) Accuracy and b) Sensitivity

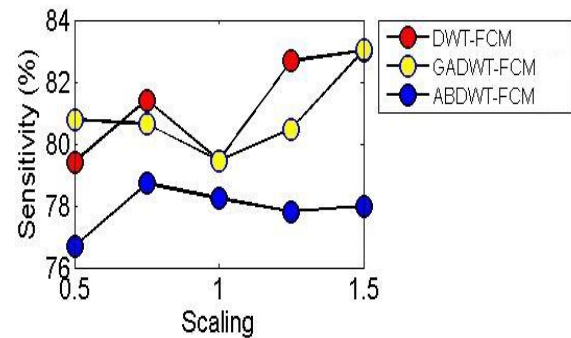


Fig 8. Results of Conventional Methods Versus Proposed Methods a) Precision and b) F1 Score

Table1: Performance Parameters Comparison Between Existing and Proposed Methods

Measurement parameters	DWT-FCM	DWTGA-F CM	DWTABC-FCM
Accuracy	0.97976	0.98069	0.98228
sensitivity	0.79445	0.79466	0.78228
precision	0.91113	0.92473	0.96295
F1-score	0.8488	0.85478	0.86325

## VI. CONCLUSION:

This paper proposed an ABC optimization technique to get improved performance compare with existing GA Optimization technique and DWT-FCM (without optimization). Finally, it can be concluded thatan ABC optimization algorithm performs better than GA optimization Algorithm. The experiment results are indicating that ABC optimization gives better accuracy, precision and F1-score. Total simulation is carried out by using MATLAB Tool Kit.

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