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Scientific Paper

Automatic segmentation of lesion from breast DCE-MR image using artificial fish swarm optimization algorithm

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Abstract

Interpreting Dynamic Contrast-Enhanced (DCE) MR images for signs of breast cancer is time consuming and complex, since the amount of data that needs to be examined by a radiologist in breast DCE-MRI to locate suspicious lesions is huge. Misclassifications can arise from either overlooking a suspicious region or from incorrectly interpreting a suspicious region. The segmentation of breast DCE-MRI for suspicious lesions in detection is thus attractive, because it drastically decreases the amount of data that needs to be examined. The new segmentation method for detection of suspicious lesions in DCE-MRI of the breast tissues is based on artificial fishes swarm clustering algorithm is presented in this paper. Artificial fish swarm optimization algorithm is a swarm intelligence algorithm, which performs a search based on population and neighborhood search combined with random search. The major criteria for segmentation are based on the image voxel values and the parameters of an empirical parametric model of segmentation algorithms. The experimental results show considerable impact on the performance of the segmentation algorithm, which can assist the physician with the task of locating suspicious regions at minimal time.

Key words: breast DCE-MRI; segmentation; artificial fishes swarm optimization algorithm.

1. Introduction

The breast cancer is a malignant lesion originates from cells of the breast. Malignant lesions are defined as space-occupying mass [1]. For breast cancer screening X-ray mammography is widely used [2]. But, the mammography will not perform best to perceive breast tumors present in dense breast tissues [3-6]. This has motivated the search of alternate imaging techniques. Among most popular breast imaging techniques such as Ultrasound (US), Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) [7-10], MRI is most widely used for detection of multiple malignant present in women with dense breasts than mammography. In particular, DCE-MRI is employed for breast cancer screening because it has a high sensitivity and is most capable for improved breast cancer screening [11]. The acquisition DCE-MRI requires the injection of a paramagnetic contrast agent into the patient vines which leads to a contrast enhancement of the tissues over time [12-15].

When trying to detect malignant tissue in a breast volume, it is observed that malignant tissues might have different benign tissue characteristics, depending upon the scale of the image acquisition intensity values. The differentiation can appear either in rough intensity, in boundary shape, texture or any combination of them. In DCE-MR imaging, differences can be perceived on the time axis also. Various DCE-MRI breast lesion segmentation methods have been developed to allow for rapid and more accurate image interpretation and diagnosis [14-23]. Among many MRI segmentation methods, artificial intelligence techniques draw more attention from researchers for using it for breast DCE-MRI segmentation. Even though significant effort has been employed in developing efficient algorithms for image segmentation, there is quite much research work to be done.

Artificial Fish Swarm Optimization (AFSO) is an optimization algorithm, it was initially designed and developed in 2002 [24]. AFSO algorithm is developed by mimicking the behaviors of fish swarm. Many kinds of optimization problems has employed AFSO algorithm, it has also confirmed better performance [24-30]. AFs (Artificial Fishes) search the problem space based on the four behavioral activities designed in the algorithm. The position, in which AF resides, considerably is solution space and other AF's sphere. AFs achieve a solution point where its degree of food consistency is maximum, which is also, called as global optimum. Initialization phase of the algorithm starts with random behavior. The key step in the fish swarm algorithms is the visual scope. A basic biological behavior of any animal is to discover an area with more food, by its vision or sense, depending on present state of the individual in the population [25].

Segmentation algorithm with a high sensitivity to suspicious lesions is thus desirable. In this paper, segmentation algorithm applies artificial fish swarm intelligence method based clustering approach for segmenting the suspicious lesions in breast DCE-MRI. The proposed method is examined for segmentation by clustering the breast DCE-MR image followed by edge enhancement and thresholding in order to find the ROI of the breast images. This proposed algorithm demonstrated a high sensitivity of detecting lesions on DCE-MRI data from clinical practice.

The organization of remaining of this paper is as follows. **Section 2** details the artificial fish swarm optimization algorithm. In **Section 3** exhaustive discussion of segmentation based on artificial fish swarm optimization algorithm is represented. **Section 4** discusses in detail the experimental results and its analysis. Conclusion is dealt in the final **Section 5**.

2. Artificial Fish Swarm Optimization Algorithm (AFSOA)

The AF recognizes external knowledge by its vision shown in **Figure 1**. X is the present location of an artificial fish (AF), visual is the visual area or distance, and x_v is the visual location of AF. If the fitness value of the solution at the visual location is better than the current solution, it moves forward a step in that direction, and arrives the x_{next} position; else, continues to investigate in the vision space. If the AF does larger number of investigating trials, it will gain more knowledge about overall positions of the vision. AFSO imposes features such as gradient information independent on the type of objective function chosen and has the capability to solve complex nonlinear optimization problems. Additionally; they can also attain quicker convergence speed than other optimization algorithms.

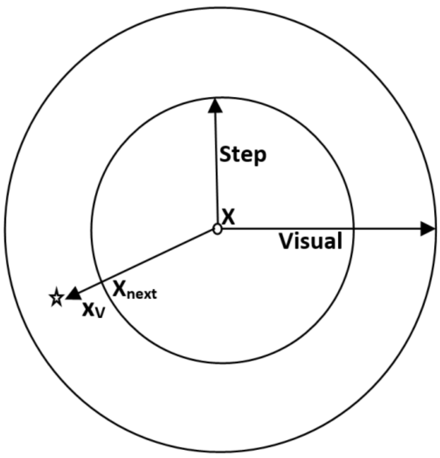


Figure 1. Vision sense perception of the Artificial Fish Optimization method

The AFSO algorithm model based on four major activities of fish, preying, swarming, following, and random, these four activities entirely carry out the local search so that the population diversity is guaranteed extremely and premature convergence of solution is evaded by local optimal solution. Artificial fish swarm optimization design method comprise of two parts: variables part and functions part, the variables part incorporate X (present location of artificial fish), step (maximum step length), visual (view area), iteration-number (maximum test iterations) and crowd factor δ ($0 < \delta < 1$). The function part is modeled to have four set of behaviors: they are prey, swarm, follow and random. In each step of the algorithm, artificial fish swarm searches for solutions with better fitness values in the provided problem search space by implementing these four activities based on the given algorithm procedure [24-27].

3. Artificial Fish Swarm Clustering For Segmenting Lesions in Breast DCE-MR Images

This work is an experiment of using artificial fish swarm algorithm for segmenting DCE-MR images, particularly in the detection of Region of Interest (ROI) on breast DCE-MR images. Each input DCE-MR image undergoes a number of sequential processing steps: pre-processing, artificial fish swarm algorithm based clustering, enhancing the edges of clustered output and extracting the region of interest. This segmentation tool provides the physician with description of the disease.

3.1. Clustering of DCE-MR Image using Artificial Fish Swarm Optimization Algorithm

The input image is preprocessed before clustering for removal of artifacts, noises and makes the pre-processed image suitable for further process such as segmentation and detection of region of interest (ROI). The most commonly affected noises in breast DCE-MRI images are salt and pepper and Poisson noise, the main property of a de-noising model is to remove the noise from the input image and also preserve the edges, the denoising algorithms may eliminate diagnostically important small details in the image. The use of median filter in the preprocessing phase reduces the effects of random, salt and pepper and Poisson noises whereas at the same time minimizing the loss of resolution. The median filter has also proved to be much better at preserving sharp edges in the MRI images than other filters and make the preprocessed image suitable for further processing [16-17].

The preprocessed image is used for clustering. Clustering in MRI image data is the process of identifying clusters in the given multidimensional image data based on attributes space through similarity measure. The most commonly used method to compute a similarity measure is the distance measures. The Euclidean distance measure defined in **Equation 1** is used, where $x_i(j)$ is the i^{th} data point belonging to the j^{th} cluster, c_j is the j^{th} cluster centre, m designates the number of clusters and n is the number of data points present in cluster j.

$$E = \sum_{j=1}^{m} \sum_{i=1}^{n} \left\| x_i^j - c_j \right\| \quad \text{Eq. 1}$$

The major task of artificial fish swarm clustering method is to search for appropriate cluster centers (c_1, c_2,...,c_m) such that the clustering measure, Euclidean distance (**Equation 1**) is minimized.

The basic steps of artificial fish swarm clustering operation are:

step1: Initialization: Generate N individuals randomly. The fish population size of N is defined as $x=(x_1,x_2,\ldots,x_n)$.

step2: Fitness value calculation: calculate the corresponding fitness value to every individual fish using **Equation 2**; select the fittest solution of the artificial fish.

$$f_1 \ (x) = \sum_{i=1}^{n} x_i^2 \quad \text{Eq. 2}$$

step3: Select implementation behavior: the artificial fishes initially simulates swarm and follow behavior; then it implements the suitable behavior by comparing the fitness value of the solutions; by default AFs does forage behavior and then optimal solution is added in the next generation Gen=Gen +l using **Equations 3** and **4**.

$$X_i^v = X + \text{Visual.rand()} \quad \text{Eq. 3}$$

$$X_{NEXT} = X + \frac{X_V - X}{\left\| X_{V-X} \right\|} \text{Step.rand()} \quad \text{Eq. 4}$$

step4: Update of values: compare the fitness value of every artificial fish in current location with the previous location value, update the AFs location to the new value if it is better than the previous value; else, the location of AFs is kept unchanged.

step5: End condition: when the generation size exceeds maximum allotted size (Gen>Genmax), end the algorithm and output the optimal value; otherwise, turn to **step2**.

In the proposed fish swarm optimization clustering algorithm, each fish in the algorithm provides a potential clustering solution for the set of M cluster centers, for clustering the given breast DCE-MR image dataset five clusters are sufficient to categorize between five different types of tissues such as adipose tissue, glandular tissue, ducts, air, benign or malignant lesions.

Assume that the swarm of artificial fish consists of N artificial fish, current location of artificial fish is shown by vector $x=(x_1,x_2,\ldots,x_n)$ where $x_i=(i=1,2,\ldots,n)$ is the solution to be optimized of artificial fish swarm algorithm. Y=f(x) is the quality of food (fitness of solution) of the artificial fish at the particular solution location and Y is the objective function. The search process of the algorithm must be designed in such a way to evade the regions around local minima in order to approach the global optimum. The sphere objective function is used; the sphere function is unimodal simple and strongly convex function. The particular advantage of using this objective function is that it is well adapted to constrained optimization. The other significant parameters such as the visual area of the artificial fish, the maximum moving step value, the congestion factor and the maximum number of try in every search are expressed as Visual, Step, δ and Iteration-number. Congestion factor present in the algorithm restricts the swarm size of artificial fish swarm. The visual area is equal to sight field (distance) of artificial fish and xv is a random location value in visual field area where the artificial fish wants move. If the new x_v location has better food quality than present solution, then the location of artificial fish is changed from x to x_{next}, but if the food quality at current location is better than x_v location, it continues to search in the visual field area. The distance between two artificial fishes x_i and x_j are measured using Euclidean distance measure, which is expressed by $d_{ij}=||x_i-x_j||$. These parameters are selected empirically. In each step of AFSO algorithm, AF search for solutions with better fitness values in solution search space by implementing these four behaviors depending on the algorithm procedure [24-27].

Based on the behavioral description of the artificial fish, all the artificial fish in the algorithm searches its search space and makes its allied fishes to select a suitable behavior to move advance at the earliest towards in the direction of optimal solution. The preying behavior is a biological behavior which moves towards the food; this is represented by randomly selecting a state within its visual area distance, by this the AF more easily finds the global solution and converges. The swarming behavior is represented by making a move towards the midpoint in the visual field scope of x_i. The swarming behavior is progressive stage that is initiated only if the newly found solution has a better fitness function value than the current location x_i. Else, the point x_i follows the searching behavior. The following behavior presents a movement of fish towards the solution that has the last function value, x_{min}. The swarm and follow behavior can be termed as local search. When the objective function value in the search space does not change for a certain number of iterations, the algorithm uses random behavior. In such a case the algorithm selects random individual from the search space. The AFSO algorithm is not sensitive to its initial points of cluster centers, it has acceptable convergence speed based on number of iterations and local optimum with more potential progress.

The artificial fish swarm optimized clustered breast DCE-MR image output is then edge enhanced by unsharp filter [31], followed by proper thresholding [32], the tumor or ROI is extract from the edge enhanced breast DCE-MR image.

4. Experimental Results and Analysis

This section presents the statistical experimental analysis results of employing the artificial fish swarm optimization based clustering algorithm for detecting lesion from the given breast DCE-MR image dataset.

4.1. Evaluation data and methods

The main objective of the experiment is to evaluate the performance of the proposed artificial fish swarm optimization based clustering algorithm for detecting lesion from the given breast DCE-MR images received from the Radiology Department of Kovai Medical Center and Hospital (KMCH), Coimbatore, Tamil Nadu, India. The dataset examined is breast DCE-MR images acquired under different spatial-temporal resolutions from a Siemens Magnetom Avanto 1.5 Tesla MR scanner, the current analysis in breast DCE-MRI is mainly based on dynamic contrast enhanced T1-weighted (DCE T1-w) images and the breast DCE-MR images obtained from the online source (http://cancerimagingarchive.net), were also used. Examination of these real and simulated breasts DCE-MR image datasets helps to exhibit that the artificial fish swarm optimization based segmentation approach to breast DCE-MRI analysis is more reliable, robust to different imaging protocols.

Table 1. Parameters used in AFSO clustering algorithm.

Parameters	Values
Population size of fish	50
Visual range	10
Crowding factor	0.9
Step factor	8
Genmax (maximum generation)	5
Maximum number of iterations, R	1000

Table 2. Algorithm measures of AFSO clustering based segmentation algorithm.

Image	Ground truth (lesion size in pixels)	Mean of fitness function	Standard deviation	Lesion size in pixels	Accuracy (%)
Image 1	292	0.04602	0.00000	291	99.65
Image 2	3273	0.16065	0.00000	3219	98.35
Image 3	298	0.09423	0.00000	295	98.99

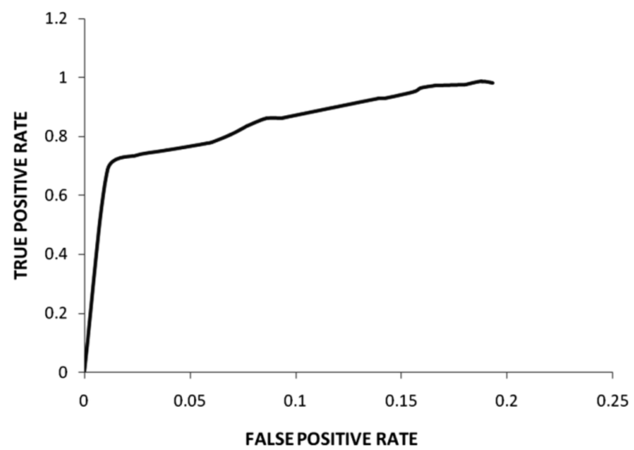


Figure 2. The ROC curve of AFSO clustering based segmentation.

The proposed segmentation method utilizes the artificial fish swarm optimization clustering algorithm to search for the set of M cluster centers that minimizes a given clustering measure. **Table 1** presents the parameter values used in the artificial fish swarm optimization based clustering algorithm implementation, which are selected empirically. By applying a suitable threshold value to the clustered output image the ROI or lesion region is extracted. When the extracted lesion overlaps with a true lesion given in the ground truth of the provided image, is called a true positive detection. When the extracted lesion part does not overlaps with a true lesion given in the ground truth of the provided image, is called a false positive detection. The accuracy of the algorithm is calculated by comparing the extracted lesion with its corresponding ground truth provided by the physicians and it is mathematically defined in **Equation 5**. The accuracy for each segmented image shown in **Figures 3** to **5** are calculated using **Equation 5** and tabulated in the **Table 2**. The sensitivity and 1-specificity values for the segmented images are acquired at several threshold values using **Equations 6** and **7**, which are used to evaluate the performance of the algorithm. The threshold values are varied from 0.42 to 0.68 in steps of 0.01. These rates are calculated and illustrated using ROC curve and the best solution has been plotted as shown in **Figure 2**, The ROC or free response ROC (FROC) provides the most comprehensive description of the detection accuracy [33]. The proposed AFSO based segmentation technique produces consistently higher accuracy at a threshold value of 0.64 and achieves a high sensitivity of 98.7%.

Accuracy: $$ACC = \frac{TP+TN}{TP+FP+FN+TN} \quad \text{Eq. 5}$$

Specificity: $$SP = \frac{TN}{TN+FP} \quad \text{Eq. 6}$$

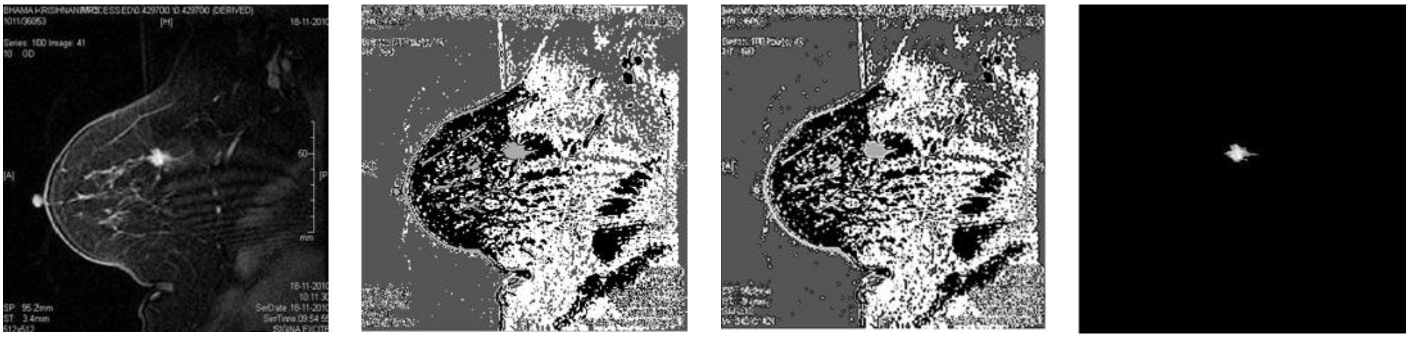
Sensitivity: $$SN = \frac{TP}{TP+FN} \quad \text{Eq. 7}$$

Where TP = true positive, TN = true negative, FP = false positive, and FN = false negative.

By using AFSO clustering algorithm the breast region is segmented efficiently and the segmentation algorithm has high accuracy is for detecting suspicious ROIs and the preliminary results of the proposed algorithm illustrated in **Figures 3** to **5** shows a reasonable match between manual division and that of proposed method and gives better results in all aspects.

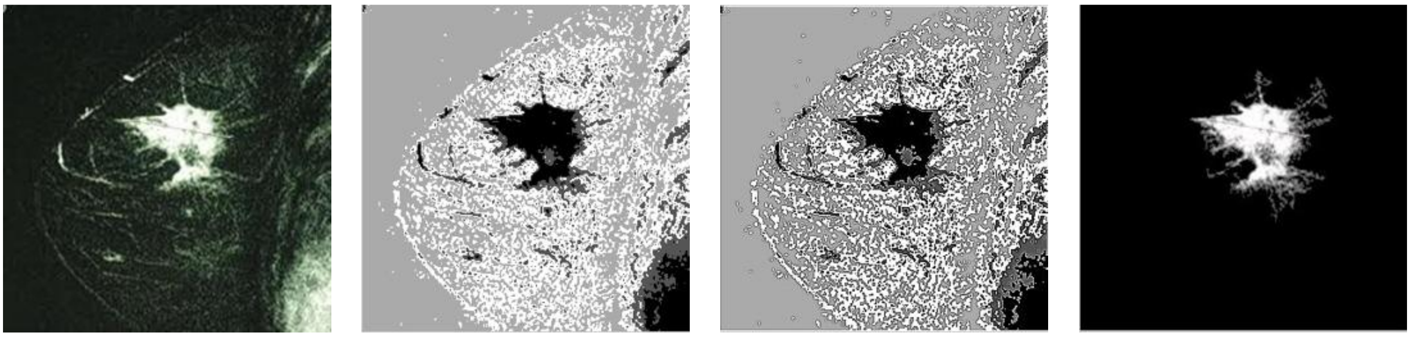
4.2. Performance Evaluation of Algorithm

The performance measures of AFSO clustering based segmentation algorithm such as mean of fitness function, standard deviation and accuracy for each segmented image shown in **Figures 3** to **5** are calculated and tabulated in the **Table 2**. The sphere function is used to evaluate the fitness of the solution. The mean of fitness function measure indicates searching quality of optimum solution.



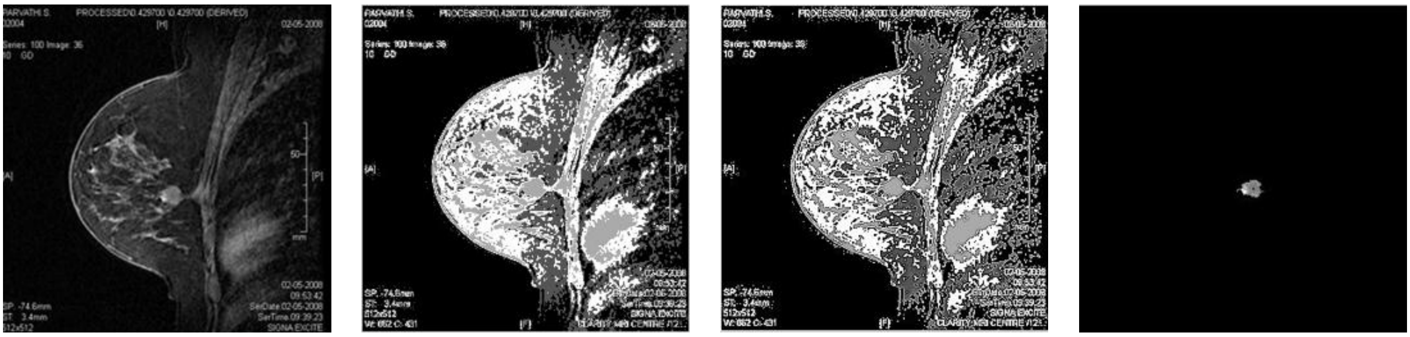
a) Input image **b) AFSO clustering output** **c) Edge enhanced output** **d) Segmented output**

Figure 3. AFSO based segmentation algorithm output



a) Input image **b) AFSO clustering output** **c) Edge enhanced output** **d) Segmented output**

Figure 4. AFSO based segmentation algorithm output



a) Input image **b) AFSO clustering output** **c) Edge enhanced output** **d) Segmented output**

Figure 5. AFSO based segmentation algorithm output

The predominant performance measure criterion is accuracy that is the degree to which an algorithm's segmentation results matches with the given ground truth. The algorithm is achieves a high sensitivity of 98.7%, the algorithm's performance can be better analyzed by experimenting it over different breast DCE-MR images. This proposed segmentation algorithm is more reliable because it accomplishes same partition of given input image in all executions. To prove that AFSO algorithm is adaptable to variability of images, breast DCE-MR image from online source is used, the segmented output is shown in **Figure 4** and accuracy results are tabulated in **Table 2**. It is a robust algorithm, the measure of robustness of a solution can be defined using the standard deviation of the objective function, smaller the robustness measure (standard deviation value) more robust the solution is. The algorithms efficiency is tested by measuring the time required for executing the algorithm, it takes 102 seconds and the algorithm occupies very little space. The results confirm that the new segmentation method has high sensitivity, convergence speed, high accuracy, reliability and robustness for the diagnosis of lesions independently identified by a radiologist.

4.3. Comparing performance of different clustering techniques

The availability of a number of high-quality extrapolative methods supposed to encourage the clinician to adopt these CAD tools into everyday clinical practice. Segmentation performance has been compared in order to determine optimal segmentation algorithms for detecting lesions from breast DCE-MR images. The comparison of the performance of different segmentation methods is very difficult and unfeasible due to the use of different databases.

Table 3. Qualitative performance comparison of the various popular clustering techniques with the proposed fish swarm optimized clustering for segmentation.

	Type of Clustering algorithm	Ground truth (tumor size in pixels)	Standard deviation	Tumor size in pixels	Accuracy (%)
Image1	SOM (Self Organizing Map)	292	0.347	276	94.52
	K-means		0.386	274	93.83
	Fuzzy C-means		0.423	266	91.09
	Enhanced SOM based K-means		0.335	282	96.57
	ABC(Artificial Bee Colony)		0.000	290	99.31
	AFSO (Artificial Fish Swarm Optimization)		0.000	291	99.65
Image2	SOM (Self Organizing Map)	3273	0.531	2930	89.52
	K-means		0.544	2897	88.51
	Fuzzy C-means		0.589	2840	86.77
	Enhanced SOM based K-means		0.437	2981	91.07
	ABC (Artificial Bee Colony)		0.000	3204	97.89
	AFSO (Artificial Fish Swarm Optimization)		0.000	3219	98.35
Image3	SOM (Self Organizing Map)	298	0.396	275	92.28
	K-means		0.415	273	91.61
	Fuzzy C-means		0.542	265	88.92
	Enhanced SOM based K-means		0.379	281	94.29
	ABC (Artificial Bee Colony)		0.000	293	98.32
	AFSO (Artificial Fish Swarm Optimization)		0.000	295	98.99

The **Table 3** provides a performance comparison of the results of the proposed segmentation algorithm with those of other research works presented in [16, 17, 34, and 35] in terms of accuracy and robustness. The breast DCE-MR image datasets used by all the clustering techniques presented in **Table 3** is same.

The first and most significant conclusion that can be obtained from this experimentation is that self-organising map (SOM) is less susceptible to local optima than K-means. During experimental analysis it is quite obvious that the search space is better reconnoitred by SOM. The self-organising map (SOM) offers the possibility for an early exploration of the search space and as the search process continues it progressively narrows the search. At the end of the search process the SOM clustering is exactly the similar to K-means clustering. K-means clustering approach provides reasonably higher accuracy and requires less computation. The results Fuzzy C-means clustering and K-means clustering are closer, but the fuzzy measure calculation needs more computation time. The K-means algorithm does not work well for high dimensions and sensitive to initialization problem. These constraints can outperformed by employing enhanced SOM based K-means clustering algorithm which is a fusion of SOM and k-means clustering methods. Enhanced SOM based K-means is applied on the provided image dataset for reducing the dimension keeping intact the topological structure of the data. By observing the standard deviations of the results obtained it is understood that the robustness of enhanced SOM based K-means is better than SOM, K-means and Fuzzy C-means clustering algorithm. It is well-known that in enhanced SOM based K-means clustering, the training or learning speed depends on the choice of the learning rate which makes the convergence rate slower, and it also has trapping at local minima. By examining the **Table 3** it is clear that the ABC optimization based clustering algorithm performance is more robust and provides high accuracy than enhanced SOM based K-means clustering algorithm. The ABC clustering algorithm is able to provide the same partition of image in all runs which makes it more reliable, the efficiency of the ABC clustering algorithm is better since the time required is only 120 seconds and space required is also less. ABC algorithm also had few drawbacks such as slow convergence rate and prematurely falling into local optima. The accuracy of the proposed fish swarm clustering based segmentation algorithm is higher compared to artificial bee colony algorithm. Since the accuracies of ABC and AFSO algorithms are high, their efficiency is tested by measuring the time required for executing the algorithm. ABC requires 120 seconds whereas Fish swarm requires only 102 seconds, therefore the convergences speed is also comparatively high. Fish algorithm has many advantages including fault tolerance, faster convergence rate, adaptability and high accuracy compared to artificial bee colony clustering.

Examining the results of performance evaluation obtained in **Table 3**, according to comparisons it is found that the best results were obtained when using fish swarm optimization clustering based segmentation method. The experimental results demonstrate that the proposed fish swarm clustering optimized segmentation algorithm has provided refined accurate segmentation image with detail abnormal tissue and confirms the usefulness of the algorithm as an efficient segmentation tool for the provided breast DCE-MR image dataset. It shows that the artificial fish swarm algorithm is very successful on producing optimization in selection of cluster centers in clustering of given image data. The proposed segmentation model is implemented using MATLAB 7.5 with its image processing and statistical toolboxes. The specification of personal computer used for programming is the Intel (R) Core (TM) 2 Duo CPU T6600 @ 2.20 GHz. The computerized detection of lesions may therefore useful for discriminating between disease stages. Further analysis will be performed with a different imaging data set to determine the generalizability of the results.

5. Conclusions

In the proposed new segmentation method, artificial fish swarm structure was configured for segmenting abnormal regions from breast DCE-MR images. Experimental results shows that the proposed algorithm converges towards global optimum value and obtained results that are relatively stable in different performance. It has many advantages, such as strong robustness, global search ability, has better efficiency, high accuracy, insensitive to employed initial values and tolerance to parameter settings. Thus artificial fish swarm algorithm has been proved that it provides good results for breast DCE-MR imaging segmentation of the provided dataset and hence can be used for medical image analysis purpose effectively.

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