FCM-based Image Segmentation Using Bio-Inspired Optimization Techniques: A Comprehensive Study

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Abstract

Background: Fuzzy c means (FCM) clustering is an unsupervised clustering technique used for image segmentation. It is widely used in the image segmentation process due to its simplicity and efficiency. But it also has some weaknesses which need to be addressed and overcome for quality results. Optimization techniques are used to overcome these drawbacks.

Objectives: This paper presented a comprehensive study of bio-inspired optimization-based Fuzzy c-means clustering which tries to overcome these drawbacks of FCM and improve the FCM segmentation results. The study also shows the importance of bio-inspired optimization-based FCM in image segmentation. It includes almost all the important bio-inspired optimization techniques that are used to improve or hybridize FCM for better image segmentation results. An experimental setup is performed using five PSO, ABC, FA, GA and TLBO evolutionary algorithms to segment an image. It provides insight into determining which optimization techniques are best done with FCM.

Methods: The FCM based on five PSO, ABC, FA, GA and TLBO evolutionary algorithms is implemented on Berkeley's test images using Matlab 2013b. The experimental setup is performed for each algorithm separately and results are recorded.

Results: The results for each of these algorithms are compared based on convergence and computation time. From the results, it is found that the PSO-FCM outperforms other optimization algorithms.

Conclusions: from this study it is concluded that FCM with optimization techniques can effectively overcome the standard FCCM drawbacks. The experiments show that the PSO-FCM outperforms other optimization techniques in terms of convergence and computation time.

***Keywords**:* Image segmentation, Fuzzy C-means, optimization technique, genetic algorithm Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Cuckoo search Optimization (CS), Artificial Bee Colony (ABC), crow search Optimization (CSO), Genetic Algorithm (GA), Firefly Algorithm (FA), Teaching Learning Based Optimization (TLBO)

1. Introduction

Image segmentation is one of the challenging tasks in the image processing field. The process of detecting objects from the images is the crucial step of image processing and the classification of an image into different objects depends heavily on the results of image segmentation [1]. Image segmentation is known as the partitioning of an image in such a way that meaningful information can be obtained [2]. Image segmentation plays a vigorous role in various fields including medical, content-based image retrieval, machine vision, object detection, traffic control system and video surveillance. Image segmentation techniques are broadly classified into two categories region-based and edge-based [3]. Then these categories further lead to several image segmentation algorithms that are present in literature such as thresholding [4], region growing [5], k-means clustering [6], watershed [7], histogram-based [8], fuzzy c-means [9] etc.

Clustering is the most important unsupervised image segmentation technique. It divides the image into different regions having similar properties between them and different to objects belonging to other regions. Fuzzy c-means is considered as most widely used clustering technique due to its simplicity and proficiency. But it also suffers from various anomalies which are removed or we can say reduced with the use of Bio-inspired optimization techniques.

Exploitation and Exploration are the two aspects that make Bio-inspired algorithms more proficient to overcome the local optimum and find the global solution to problems. The bio-inspired algorithms are combined with FCM to overcome the various drawbacks of FCM. FCM algorithms suffer from four major problems that are i) cluster number, ii) cluster initialization, iii) trap in local optima and iv) sensitivity to noise. The various bio-inspired algorithms are combined with FCM to overcome these drawbacks and literature shows that these combinations give good results. This paper includes the survey of all bio-inspired algorithms that are combined with FCM during the last 20 years (2000 to 2021), but only the studies presented during the last 6-7 years were described in detail. The contribution of this literature review consists of:

1. Presenting almost all the combinations of bio-inspired algorithms with FCM for image segmentation.
2. Indicating the various research papers address the different problems of FCM and their impact.
3. Suggesting new future scope for exploration to expand this research field.

This paper is organized as follows: section 2 presents the related studies which include the basics of FCM and its evolution, a brief introduction of bio-inspired optimization techniques and the literature review, section 3 includes experiments and results, section 4 comprises discussions and section 5 presents conclusions.

2. Related Studies

2.1 Fuzzy c-Means clustering

Fuzzy c-means is a method of clustering, in which a section of data can belong to two or more clusters. This method has a significant role in image segmentation. It is an iterative process based on the minimization or optimization of the objective function.

$$J(U,V) = \sum_{i=1}^{n}\sum_{j=1}^{c}\left(u_{ij}\right)^{m}\left\|x_i - v_j\right\|^2 \quad (1)$$

$\left\|x_i - v_j\right\|^2$ is the Euclidean distance between the ith data and the jth cluster center. uij represents the membership function and m is constant. The parameter m controls the fuzziness of the resulting partition. The pixels near to the centroid of their clusters are allotted high membership values and low membership values are allotted to pixels with data far from the centroid. The probability that a pixel belongs to a specific cluster depends upon the membership function [10]. In the FCM algorithm, the clustering is based on the feature domain and the possibility is dependent uniquely on the distance between the pixel and each cluster center. The membership function and cluster centers are updated by the following:

$$u_{ij} = 1/\sum_{k=1}^{c}(dij/dik)^{\left(\frac{2}{m}-1\right)} \quad (2)$$

and

$$v_j = \frac{\left(\sum_{i=1}^{n}(u_{ij})^m x_i\right)}{\left(\sum_{i=1}^{n}(u_{ij})^m\right)}, \forall j = 1,2, \dots c \quad (3)$$

Vj represents the new cluster center [11].

The FCM is the most considerable method for image segmentation because it could retain much more information from the original image to the segmented image.

2.2 Bio-Inspired Optimization techniques

Bio-inspired algorithms are inspired by the philosophies of natural biological evolution and distributed collective behaviour of social colonies [12]. These algorithms are used for optimization because they can solve real-world large, complex and ambiguous problems simply. The bio-inspired optimization algorithms are classified into two classes Evolutionary algorithms and swarm intelligence algorithms [13].

The evolutionary algorithms are inspired by the genetic evolution process. They are population-based stochastic search algorithms working with the survival of the fittest criteria such as Genetic Algorithm (GA) and Differential Evolution (DE) [14].

The Swarm intelligence algorithms are based on the collective social behaviour of organisms. They encompass the implementation of the collective intelligence of groups of simple agents based on the behaviour of real-world insect swarms as a problem-solving tool [15]. The various swarm intelligence algorithms are ant colony optimization (ACO), Artificial bee colony optimization (ABC), bat algorithm (BA), Particle Swarm Intelligence (PSO), Cuckoo Search Optimization (CSO), Firefly Optimization (FO), Crow Search Optimization (CSO), Teaching Learning Based Optimization (TLBO) and Whale Optimization (WO).

2.3 Literature review

The most common fuzzy clustering algorithm is fuzzy c-means (FCM) which was proposed by Bezdek et al. [16] and has been broadly used in numerous fields [17, 18]. The goal of FCM is to minimize the objective function and reach the accurate membership matrix gradually. But this iterative process falls into the local optimal solution easily because of the random selection of cluster centers. Furthermore, if the images are noisy or if the datasets are highly dimensional then the FCM does not succeed to achieve the required result. Hence, these shortcomings have motivated the proposal of optimization-based approaches for fuzzy clustering.

Accordingly, this literature review includes the image segmentation FCM algorithms which are improved or hybridized using bio-inspired algorithms.

2.3.1 PSO

PSO is one of the most popular bio-inspired methods due to its versatility and simplicity, and it has been found that it can provide better initial cluster centroids for the FCM algorithm to improve the FCM results, and thus this has led to the proposal of many PSO-based methods for fuzzy clustering.

The authors in [19] found the solution to the cluster number problem of FCM using Multimodal PSO. The algorithm is applied to the color images in RGB color space. The three-dimensional histogram is used to determine the peaks which are used as cluster numbers. The histograms are smoothened using a Gaussian filter. The proposed method focuses only on finding the cluster number and enhances the effectiveness of local search. The method is sensitive to noise and hence affects the segmentation results.

The authors in [20] proposed a PSO-based FCM to initialize cluster centres for color image segmentation. A particle swarm optimization is applied to interval type-2 intuitionistic fuzzy c-means to obtain the appropriate cluster centers and fuzzifiers. The experimental results show that the proposed method efficiently determines the cluster centers and obtains good results. However, the noisy images or complex images could not be segmented effectively by the proposed method. There are lots of methods in the literature that uses PSO to initialize the cluster centers of FCM [21]. These methods focus only on one cluster initialization problem and are hence trapped in other problems of FCM.

The authors in [22] presented an approach using PSO as an initialization method for the FCM algorithm. This method solves the initialization problem by using PSO, to reduce the influence of noise using Mahalabonis distance as an objective function and post segmentation method to obtain good segmentation results. As this method gives good segmentation results and tried to solve all FCM problems. Hence, could not solve the cluster number problem and still, the images having high noise cannot be segmented efficiently.

The authors in [23] address three main problems of FCM center initialization, sensitivity to noise and falling into local optima. The proposed method combines the DPSO with FCM to obtain superior results than FCM using global optimization searching and a noise reduction mechanism. Dynamic PSO (DPSO) changes inertia weight an`d learning parameters according to the fitness function. The proposed method is compared with [24-28] and found a significant improvement concerning noise robustness.

The authors in [29] proposed a chaotic PSO-based FCM technique for color image segmentation. Chaos theory is introduced to initialize the population in PSO. It gives a high-quality initial population because of its ergodicity and randomness. This method avoids falling into local optima due to the pause of some particles in the iteration process. The method successfully spotted color disease spots on the image. However, the inertia and learning factors are of much concern and should also be considered.

The authors in [30] gave a dynamically learned PSO-based neighbourhood-influenced FCM method for CT images. The DLPSO is used to initialize the cluster centers so that the convergence is faster. Then the neighbourhood-influenced FCM is used to segment the image which makes the process less sensitive to noise. Thus an efficient method is achieved to segment a CT image. The results are compared with other methods [31-34] and the proposed method gives better segmentation results.

All these methods are applied to CT images, hence the efficiency of these methods on real-world images is questionable.

2.3.2 **GA**

Genetic Algorithms are widely used optimization algorithms because of their broad applicability, global perspective and ease of use. In image segmentation, they also played a vital role.

The authors in [35] presented an improved method that is a combination of adaptive GA and FCM. The adaptive GA is used to initialize the cluster center and then the kernelized FCM is used to segment the image. This method tries to overcome the two main defects of FCM, sensitivity to noise and convergence to local optima due to sensitivity to initial clustering. The kernelized FCM helps to make the method noise-robust. The proposed method is compared to FCM and KFCM and found that it efficiently overcomes the defects of FCM.

The authors in [36] proposed a modified GA-based FCM that only considers the convergence to the local optima. The modified GA is used to achieve the global optimum value. by initializing the cluster center. The proposed method is applied to MRI images and gives better results than the conventional method. A similar method [37] is applied to retinal vascular images and the method ensures the global optimal solution. The quality of segmentation and the computational time is also less.

There is another similar method where the GA population is initialized by FCM cluster center results and segmentation is done by GA clustering. It also gives good results when compared to GA clustering [38].

The authors in [39] presented an Intuitionistic fuzzy c-means (IFCM) clustering algorithm based on a novel weighted proximity measure and genetic algorithm. This method solves the two main problems of the IFCM method which are noise sensitivity and selection of initial parameters using weighted proximity measure. The improved IFCM aggregates the similarity and correlation measures which evaluate the linear relationship between objects along with the closeness degree of pixels. This improved IFCM applies GA to determine the optimal parameters. The proposed method is applied to UCI datasets and the results are compared with other clustering methods. The comparison shows the efficiency of the proposed method.

The authors in [40] found that the segmentation results of FCM are easily affected by initial cluster centers. The conventional FCM choose the cluster centers randomly and so the results are. Hence, the initialization of cluster centers is done by a Genetic algorithm to get the optimized cluster centers and segmentation is done using FCM. The authors use improved Kernelized FCM having a new objective function with spatial features applied on images with controlled parameters using the level set method so that complex images can also be segmented efficiently. The level set method helps the proposed method to get the global information from the image. The proposed method is compared with FCM, KFCM [40], S-FCM[41], GFCM and KPCM algorithms and results reveal that the proposed method shows significant improvements but the experiments done only on synthetic grey images

The authors in [42] proposed a new method of image segmentation which is a combination of FCM and GA. The FCM has great capability of image segmentation and here the noise sensitivity of FCM is considered as the main problem. To make the method noise robust GA is introduced. The segmentation is done using GA where the objective function of GA is FCM. This method is applied to MRI images and the results are satisfactory.

The authors in [43] introduce a modified quantum-based GA to speed up and make more optimal FCM segmentation. The method makes the FCM more noise robust and stops the early convergence to the local optima. The cluster centers are initialized using modified quantum GA and then FCM is used to segment the image. The results are compared with quantum-inspired modified GA-based FCM, quantum-inspired GA-based FCM and classical modified GA-based FCM based on two colors of MRI images. The results show the superiority of the proposed method for color MRI images. The segmentation is done by the conventional FCM method.

2.3.4 ABC

The artificial bee colony (ABC) algorithm [44] proposed by Karaboga in 2007 is one of the most popular swarm intelligence algorithms and has been used in diverse real-world problems such as clustering [6], neural network training [11], numerical problems [12] etc. The model of the ABC algorithm is established on the honey bee swarm in such a way that the ABC algorithm simulates the foraging behaviours of honey bees such as employed bees, onlooker bees and scout bees in the hive. The ABC is compared with GA and PSO algorithms and found that it can get out of a local minimum and can be efficiently used for multivariable, multimodal function optimization. The effects of control parameters on the performance and convergence speed of algorithms are topics of concern.

The authors in [45] address the two influential factors in FCM segmentation: the first factor is the feature difference between neighbouring pixels and the second is the relative location of neighbouring pixels. The proposed method uses Artificial Neural Network based [46] ABC algorithm to compute these two factors where the objective function is the fitness function of FCM. Simulation results are compared with PSO [47] and GA [48] based algorithms and results are quite promising for ABC. It makes the process more robust to noise.

The authors in [49] proposed a hybrid algorithm, to incorporate the FCM operator into the ABC algorithm. In the conventional ABC algorithm, the scout bees are randomly introduced, but in the proposed approach FCM operator is introduced. The scout bee is introduced after every cycle, which results in a reduced number of cycle iterations. So the results show the proposed method is good in terms of quality and execution time. This algorithm has a drawback in that the cluster number and centers are chosen randomly which affects the quality of segmentation.

The authors in [50] presented a hybrid FCM and ABC algorithm which addresses the trapping into local optima problem of FCM. The proposed algorithm uses the VAT algorithm to find out the cluster numbers and the IRN method to initialize the cluster centers. Then FCM-ABC [49] is applied to segment an image. The method overcomes the drawbacks of FCM-ABC and gives efficient results. The VAT algorithm does not give an accurate cluster number but the nearest number.

2.3.5 Other Optimization Techniques

The ACO algorithms work on the principles of ants. A set of artificial ants search for better solutions to the given optimization problem. It has one drawback in that it requires a large computation time, which is tried to solve in many research papers. Although, it is used along with the FCM to increase the accuracy of segmentation results.

The authors in [51] proposed an MRI image segmentation method based on the ACO and FCM. The improved ACO is used to initialize cluster centers for FCM. The improved version of ACO uses the max-min method to improve the performance of the algorithm. The max-min method helps to find good results with less computation time. The results are compared with conventional FCM and ACA-FCM[52] methods. The segmentation results of the proposed method are more precise and robust.

The authors in [53] presented a hybrid approach for image segmentation by integrating ABC and Firefly algorithm (FA). In this method, the FA investigates the search space globally to locate favourable regions and ABC is employed to perform a local search. To segment the color images using the FCM method. The method also uses pre-processing techniques such as median filter and CLAHE histogram equalization method to enhance the quality of the image. The results of the proposed method are more accurate.

Recently, other metaheuristic approaches have been employed to address FCM optimization problems and can open new perspectives and improve image segmentation. Some of these approaches are:

The authors in [54] proposed a new image segmentation technique using Cuckoo Search Algorithm and FCM algorithms. The CSA has strong overall optimization capability and hybridization of FCM and CSA has improved performance over traditional FCM clustering. The CSA is used to find the optimal cluster centers using the new objective function of having the Sub-area coefficient and partition coefficient. SC measures the ratio of the sum of cluster compactness and separation whereas PC determines the overlap between clusters. The high values of pc while the low SC values make the clustering approach better and more efficient. Then the centres found by CSA are used as input for the FCM algorithm. The proposed method is applied to the Berkeleys dataset and compared with FCM-GA and FCM-PSO. According to the obtained results, we can conclude that the proposed hybrid algorithm shows good performance and gives better results.

The authors in [55] observed that the random cluster initialization of classical FCM often leads to failure in the optimal selection of the cluster centre and thus various optimization algorithms are coupled with FCM. The crow search optimization is used to optimize FCM in the proposed method. When compared with ABC, Firefly, Cuckoo and SA algorithms the CS optimization was found to produce satisfactory and promising results in the segmentation of abdomen CT images using FCM.

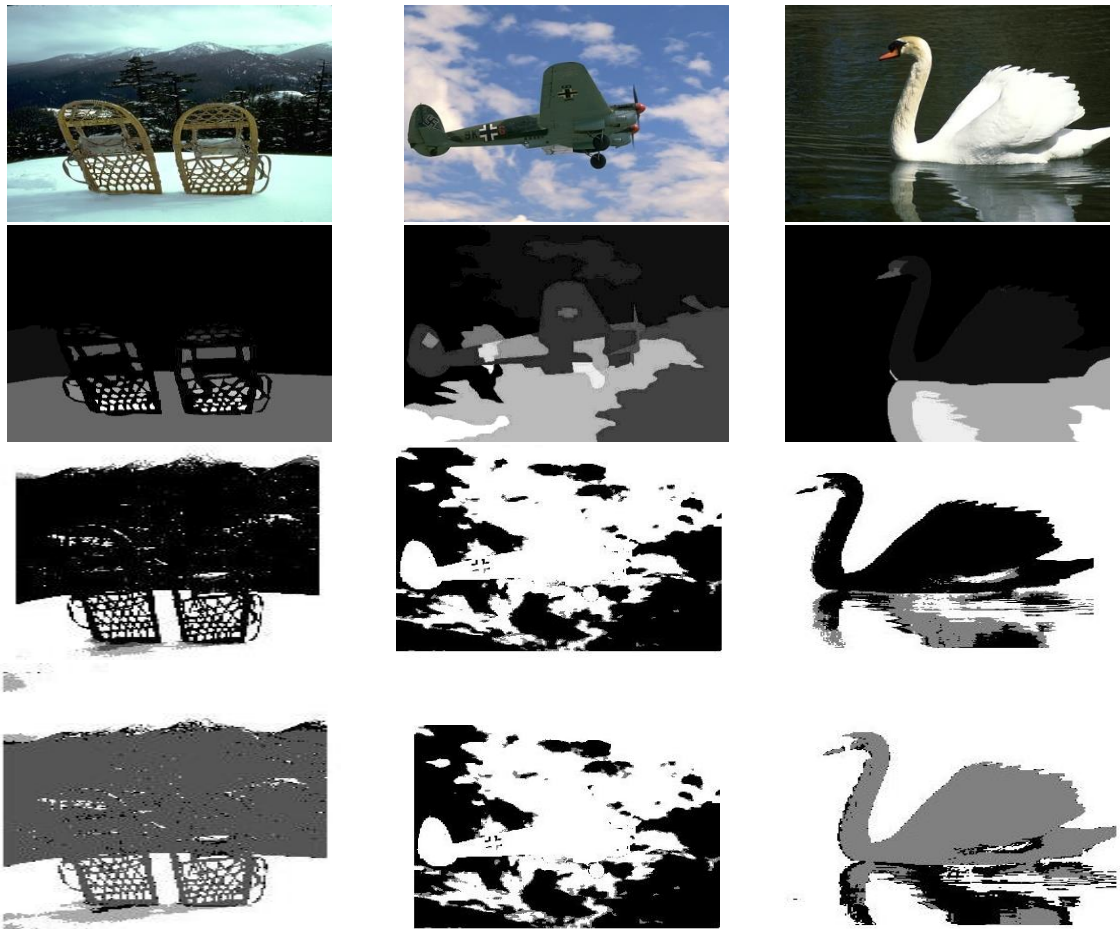
The authors in [56] proposed a new dynamic clustering method for brain tumour segmentation using the hybridization of the Firefly Algorithm (FA) with the Fuzzy C-Means algorithm (FCM). To improve the proficiency of the FCM to automatically produce the proper cluster number and location of cluster centres FA is used. The output of FA is used as input to FCM as cluster centres. The results show the effectiveness of the proposed method but do not work well for noisy MRI images. In 2015 [57] the Firefly Search with FCM (FSFCM) is applied to CT images and the results are satisfactory. In 2018 [58]Firefly Algorithm is hybridized using IFCM to lower the computation time. In 2019 [59] the FAFCM is improved by introducing some pre-processing and denoising methods to make the process more noise-robust. The experiment was done on CT/MRI images and results are compared with CSFCM, ABC and simulated annealing algorithms. Hence, found that the proposed method outperforms others.

3. Experiments and Results

In all the experiments, each optimization algorithm is applied with the FCM algorithm to segment a color image. The three test images are taken from Berkeley's database and programmed using Matlab 2013b. The algorithms are used to initialize the initial cluster centers and then FCM is initialized using these cluster centers. The population size and objective function for each algorithm being compared are the same, due to the fact these are the main parameters to consider.

The experiment is done on three test images and the main focus is on finding the execution time of each algorithm to segment an image. The convergence of each algorithm is also considered to know the number of iterations required to obtain the final results.

Fig. 1 shows the results of image segmentation performed by PSO, GA, FA, ABC and TLBO algorithms. The (a) of Fig. 1 represents the original test images (b) represents the ground truth images and (c), (d), (e), (f) and (g) represent PSO-FCM segmented image, GA-FCM segmented image, ABC-FCM segmented image, FA-FCM segmented image and TLBO-FCM segmented image respectively. The images show that the PSO-FCM segmented images have much more resemblance to the ground truth images than other segmented images.

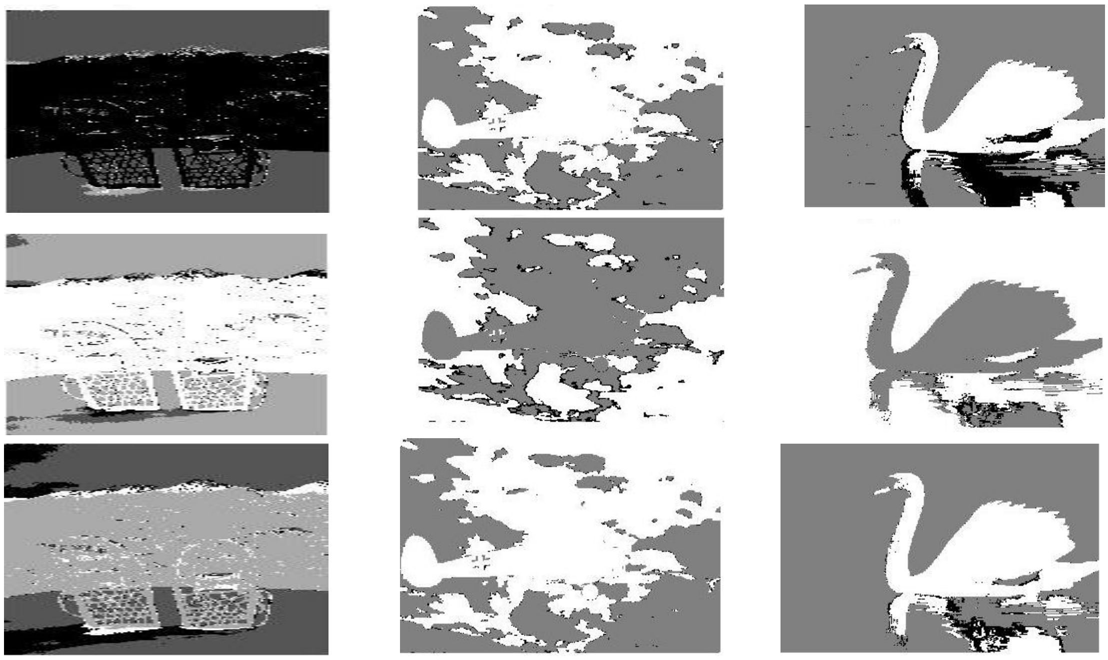


(a)

(b)

(c)

(d)



(e)

(f)

(g)

Fig. 1: Shows (a) original image (b) ground truth image (c) PSO-FCM segmented image (d) GA-FCM segmented image (e) ABC-FCM segmented image (f) FA-FCM segmented image (g) TLBO-FCM segmented image.

The best cost or minimized objective function achieved during the various iterations is shown in the graph. There are three graphs one for each image representing five algorithms convergence. The graph indicates the effectiveness of PSO in achieving the minimum objective function value in fewer iterations.

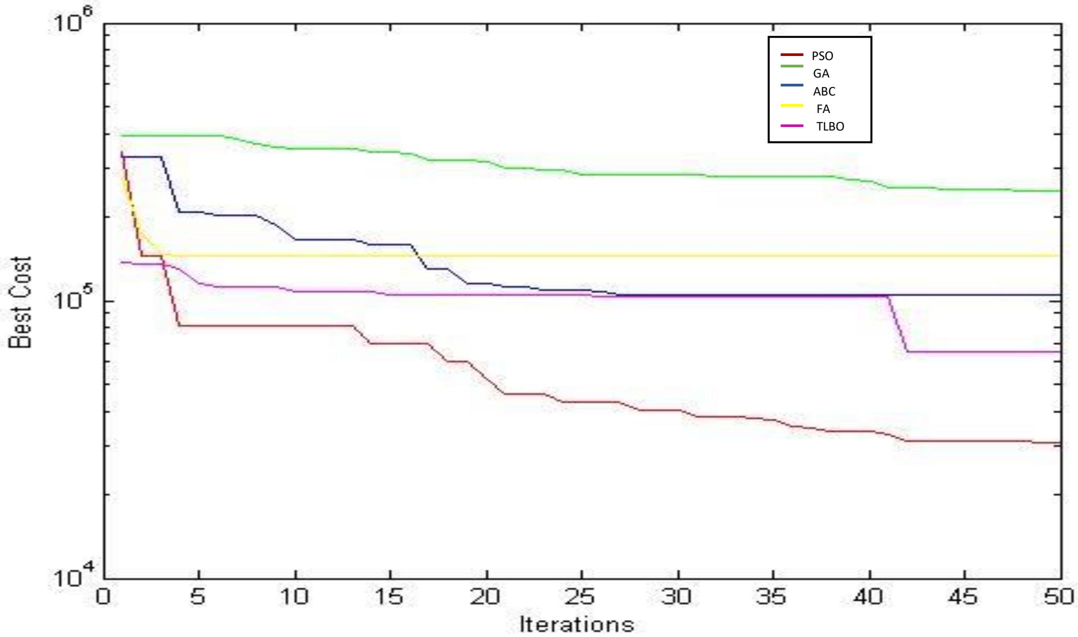


Fig. 2: shows the convergence graph for image 1

Fig. 2 represents the convergence graph for image 1. It indicates the best performance of the PSO-FCM algorithm that successfully achieves the minimum objective function in approx. 45 iterations, whereas TLBO-

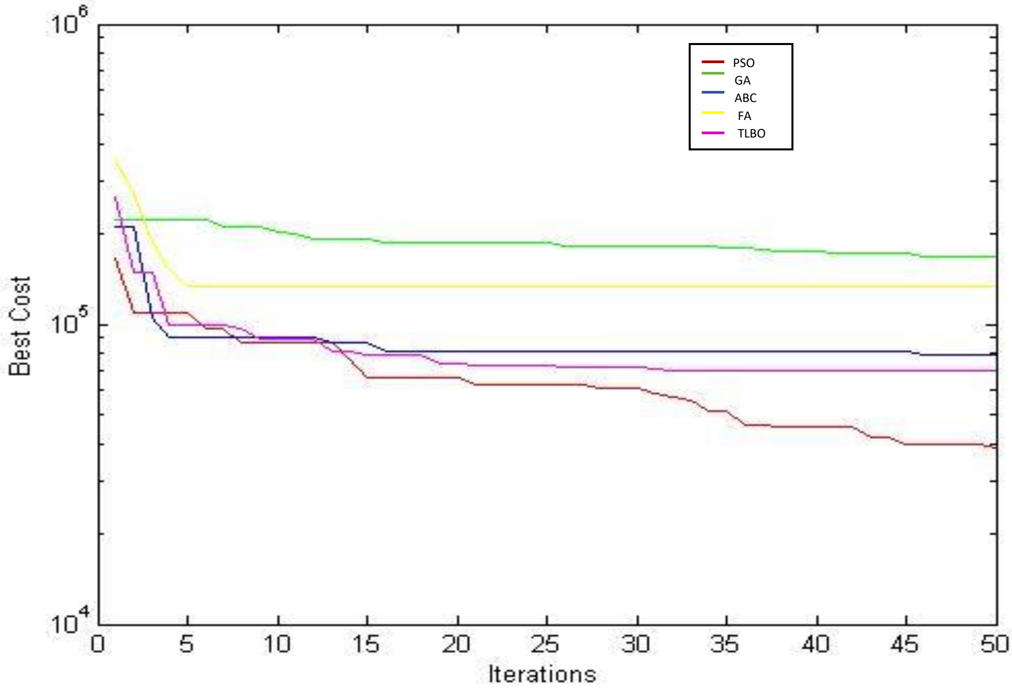


Fig. 3: shows the convergence graph for image 2

FCM is a trailing algorithm which also achieves its minimum objective function in approx. 45 iterations but having a high value of the objective function. The GA-FCM shows minimum performance in the convergence graph. Fig. 2 also shows that the PSO-FCM outperforms the other algorithms while ABC and TLBO also have good results.

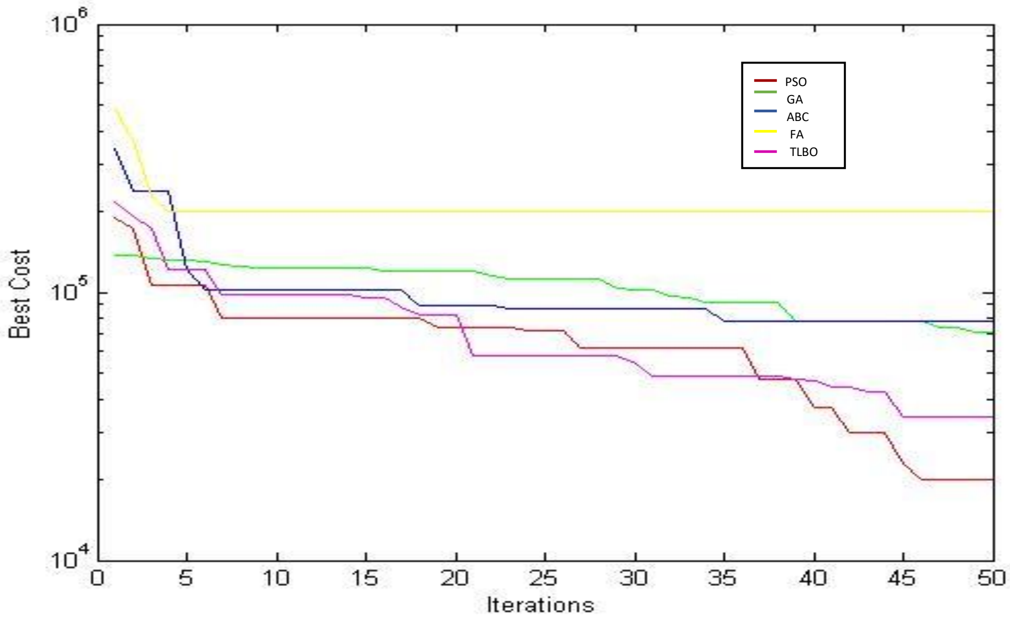


Fig. 4: shows the convergence graph for image 3

Fig. 4 shows the convergence graph for image 3. This graph shows that the FA is the worst performer whereas PSO is the best performer.

Table 1: Shows the computation time of ABC, PSO, FA, GA and TLBO for all three test images.

COMPUTATION TIME	ABC	PSO	FA	GA	TLBO
Image1	26.2475	24.6152	29.3985	27.7063	46.5636
Image 2	26.6679	25.2623	28.8772	27.1805	51.8507
Image 3	26.5733	24.9189	35.6479	26.6787	51.1905

From Table 1 it is found that the computation time of TLBO-FCM is greater than all other algorithms and PSO-FCM has the lowest. The ABC-FCM has nearly equal computation time to the PSO-FCM but has a slight difference.

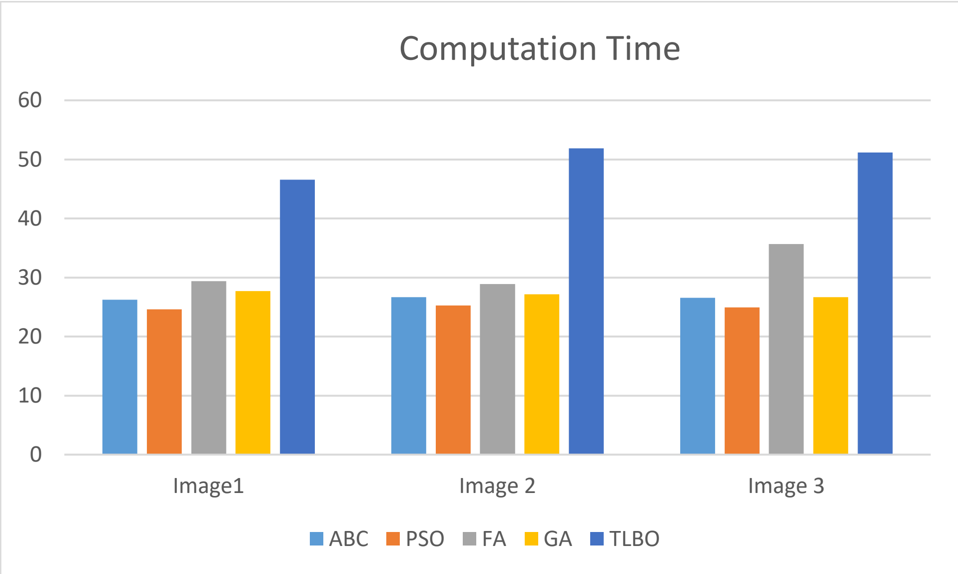


Figure 5: shows the graphical representation of Computation time

The graph indicates the PSO-FCM algorithm effectiveness having the lowest computation time.

The experimental results show that the PSO-FCm outperforms all the other four algorithms in terms of segmentation results, fast convergence and computation time.

4. Discussions

The optimized algorithms used for FCM hybridization have their limitations which should also be considered to get more optimized results.

The GA algorithm works well for small datasets but in the case of large datasets, it required additional running time. Hence the execution time increases with increased computational cost.

The PSO algorithm has less running time but there are many control or initial parameters to be set before the initialization of the algorithm. These parameters have constant values in conventional PSO which do not work for all types of images. Hence there should be a dynamic PSO that calculates the values of initial parameters according to the nature of the problem.

The strong endurance, fast convergence and high flexibility are the pros of the ABC algorithm. However, early convergence in the later search period makes the algorithm less reliable. The correctness of the optimal value cannot lead to the requirements now and then.

The ACO algorithms can run constantly and acclimate to changes in real-time. But it has drawbacks that cannot be overcome by any other method such as stagnation, low convergence speed and local optimum problem. So, the three main limitations of the algorithm are the stagnation phase, exploration and exploitation rate and convergence speed of the algorithm.

Cuckoo Search is suitable for solving continuous problems and multi-objective problems. However, the CS algorithm also has limitations, such as slower convergence, random initialization and wrong boundary detection.

The TLBO also has the advantage of giving accurate results but requires more iterations to achieve that accurate results. It requires more memory as well as time.

The advantages of Firefly algorithms (FA) are that they require less number of iterations and have good efficiency for certain problems. However, one of their main disadvantages is the high probability of being trapped in local optima because they are local search algorithms

Several research works are done to improve or hybridize these algorithms to overcome their disadvantages still there is scope for the future.

5. Conclusions

This survey finds out that the various bio-inspired optimization algorithms are combined with FCM to achieve good performance in image segmentation. The FCM drawbacks that are mainly considered are cluster center initialization, trapping into local minima and noise sensitivity. All the approaches are tried to solve these problems in one or another way. The study concludes that:

1. Bio-inspired algorithms efficiently find out the initial cluster centers and avoid falling into local optima.
2. In many cases, other techniques are also combined to make FCM segmentation noise robust such as pre-processing and noise removal methods.
3. In some cases, the optimization algorithms are also modified to improve their performance.

The experiments are performed to show the performance of the five ABC, PSO, GA, FA and TLBO evolutionary algorithms based on Segmentation results, convergence and computation time. The results show that the PSO outperforms all the other algorithms.

The research shows that the proposed methods are successful in their work to some extent. Hence some shortcomings may be future scope:

1. Mostly the methods consider medical datasets or grey images. Color images or real-world images are the future. So, they should be considered.
2. The optimization methods focus on only one drawback of FCM and try to overcome that and so trapped in another. In other words, there should be one algorithm that overcomes all the drawbacks and give good segmentation results.
3. To enhance the performance of the bio-inspired optimization method another optimization method or multi-objective optimization can be used.

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