



An image segmentation approach based on fuzzy c-means and dynamic particle swarm optimization algorithm

Nameirakpam Dhanachandra¹ · Yambem Jina Chanu¹

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Abstract

Image segmentation has considered an important step in image processing. Fuzzy c-means (FCM) is one of the commonly used clustering algorithms because of its simplicity and effectiveness. However, FCM has the disadvantages of sensitivity to initial values, falling easily into local optimal solution and sensitivity to noise. To tackle these disadvantages, many optimization-based fuzzy clustering methods have been proposed in the literature survey. Particle swarm optimization (PSO) has good global optimization capability and a hybrid of FCM and PSO have improved accuracy over tradition FCM clustering. In this paper, a new image segmentation method based on Dynamic Particle swarm optimization (DPSO) and FCM algorithm along with the noise reduction mechanism is proposed. DPSO has the advantages to change the inertia weight and learning parameters dynamically. It adopts the inertia weight according to the fitness value and learning parameters along with time. The proposed method combines DPSO with FCM, using the advantages of global optimization searching and parallel computing of DPSO to find a superior result of the FCM algorithm. Moreover, a noise reduction mechanism based on the surrounding pixels is used for enhancing the anti-noise ability. The synthetic image and Magnetic Resonance Imaging (MRI) have been used for testing the proposed method by introducing different types of noises and the results show that the proposed algorithm has better performance and less sensitive to noise.

Keywords Image segmentation · Clustering · Fuzzy c-means · Dynamic particle swarm optimization · MRI image

✉ Nameirakpam Dhanachandra
dhana.namei@gmail.com

Yambem Jina Chanu
jina@nitmanipur.ac.in

¹ National Institute of Technology Manipur, Imphal, Manipur, India

1 Introduction

Image segmentation can be defined as a process where an image has been divided into different regions in such a way that each region should have similar features [9, 17, 18]. There are several segmentation approaches which are already implemented and used in different applications. Some of the new applications are presented in [21–23]. Clustering is one of the widely used image segmentation approaches and some of the new recent works in clustering include subspace clustering like Xiao-Dong Wang [27] et al. proposed a new subspace clustering model known as Fast Adaptive K-means subspace clustering algorithm for high-dimensional data by integrating K-means and feature selection into a single framework without the eigenvalue decomposition. They also designed an adaptive loss function in order to provide a flexible cluster indicator calculation mechanism. Again, a new robust clustering algorithm is introduced by Xiao-Dong Wang [26] et al., using a robust extension of DCLA, known as RDCLA. They used an $l_{2,1}$ norm-based loss function to calculate the weighted cluster centroid of the k-means. Fuzzy c-means (FCM) clustering algorithm is one of the most used clustering algorithms because of its simplicity and unsupervised approach. But FCM does have disadvantages such as sensitive to random initial values, sensitive to noise and falling easily into a locally optimal solution. Many improved algorithms are proposed to solve the dependence on the initial user values such as kernel possibilistic c-means [13], intuitionistic FCM [2]. Fasahat Ullah Siddiqui [20] introduced outlier rejection fuzzy c-means (ORFCM) by introducing a new term while updating the membership value and objective function which helps the FCM algorithm less sensitive to the outliers. It enhances the outlier rejection characteristic of the FCM algorithm. Eman Abdel-Maksound et al. [5] proposed a hybrid clustering technique using k-means integrating with FCM algorithm (KIFCM). In KIFCM, k-means has been used to initialize the initial centroid of the FCM algorithm. Abdenour Mekhmoukh et al. [12] proposed an improved FCM by using PSO algorithm to get the optimal values of cluster centroids. They used spatial information in order to have less sensitive to the noise. Telmo M. Silva Filho et al. [24] introduced a hybrid method of fuzzy clustering combining the FCM algorithm and improved particle swarm optimization (FCMIDPSO). The improved particle swarm optimization adjusts the PSO parameters dynamically during the execution by providing a better balance between exploration and exploitation. This helps to avoid the PSO algorithm falling into the local minima easily and is able to find a better solution. To overcome the limitation of the FCM algorithm, many researchers proposed different approaches by combining FCM with naturally evolutionary optimization algorithms like Genetic Algorithm, Particle Swarm Optimization and Artificial Fish Swarm Algorithm etc. These hybrid algorithms had given better and improved performance than the conventional FCM algorithm.

Particle swarm optimization (PSO) was first introduced by Kennedy [10] in 1995 and it has been first applied to image segmentation by Omran [14] in 2002. Later in 2005, Omran [15] improved PSO algorithm by modifying the fitness function and also analyzed the different values of the control parameters of the PSO. In recent years, many improved PSO algorithms are introduced. In 2011, Dazhi et al. [16] proposed an improved PSO method by enlarging the search space and producing four velocities for each particle and thus enhancing the global search ability. In 2015, Haiyang Li et al [8] proposed dynamic particle swarm optimization (DPSO) by proposing a new approach to update the inertia weight and the learning parameters of the PSO algorithm.

In this paper, we proposed a hybrid dynamic particle swarm clustering algorithm. The proposed algorithm combines Dynamic Particle Swarm Algorithm (DPSO) with FCM. It used the advantages of DPSO by adopting the dynamic inertia weight and learning factors to

calculate the particle velocity. Moreover, the inertia weight values are dynamically changed along with the fitness value. The learning factor values automatically vary with time, thus the particles will possess strong self-learning capability and weak social-learning capability. These enhanced the PSO global search capability. Noise reduction mechanism is introduced into the proposed algorithm based on the fuzzy membership value of the global best particle. The spatial neighborhood information has been also used to enhance the ability to detect noise. The synthetic and MRI images are utilized in the experiment. The results are compared with FCM, SKM, KIFCM and DPSO using the evaluation indices. These results verify that the proposed method is more effective and more able to sensor the noise.

The main contribution of our works could be highlighted as:

1. A hybrid of DPSO and FCM is proposed by integrating the advantages of DPSO and FCM algorithms.
2. Noise reduction mechanism is introduced which has the ability to detect a noisy pixel and converting it based on neighbour cluster attributes, thereby not only improving the convergence rate but also taking advantage of spatial neighbourhood information to enhance anti-noise ability.
3. Later, a synthetic image and medical images are considered for evaluating the effectiveness of the proposed method.

2 Materials

2.1 Fuzzy c-means (FCM) algorithm

FCM algorithm was first introduced by Dunn [4] and later it was improved by Bezdek [1]. It is one of the commonly used clustering methods and it classifies the given set of data into a different similar group. Let us consider a finite dataset of n number as $X = (x_1, x_2, \dots, x_n)$. The FCM algorithm divides the given dataset X into a group of c fuzzy cluster based. It is an iterative process and it tries to minimize the objective function. The objective function is given below.

$$J_m = \sum_{i=1}^n \sum_{j=1}^c u_{ij}^m \|x_i - c_j\|^2 \tag{1}$$

where m is defined as fuzzification parameter, u_{ij} is the degree of membership of x_i in j^{th} cluster, x_i is i^{th} data points and c_j is j^{th} cluster center and $\| \cdot \|$ is the Euclidean distance. FCM algorithm minimizes the cost function by changing the value of the degree of membership of each data point and cluster center in each iteration.

$$u_{ij} = \frac{1}{\sum_{k=1}^c \left(\frac{d_{ij}}{d_{kj}}\right)^{\frac{2}{m-1}}} \tag{2}$$

$$c_j = \frac{\sum_{i=1}^n u_{ij}^m x_i}{\sum_{i=1}^n u_{ij}^m} \tag{3}$$

Where d_{ij} is the distance between the data point x_i and j^{th} cluster center and d_{kj}^* is the distance between k^{th} cluster center and j^{th} cluster center.

2.2 Dynamic Particle Swarm Optimization (DPSO)

Particle Swarm Optimization (PSO) is an optimization technique based on the population and it has been used to solve various optimization problems. In the PSO algorithm, the

position and velocity of each particle are initialized. The position and the velocity of each particle are updated based on the fitness value of the particle, moving towards the optimal solution of the particle in each and every step. Firstly, the initial position is considered as $x_i = (x_{i1}, x_{i2}, x_{i3}, \dots, x_{id})$ and the initial velocity as $v_i = (v_{i1}, v_{i2}, v_{i3}, \dots, v_{id})$ in d -dimensional space. The velocity and location of the particle at the instant $(t+1)$ is calculated as follow:

$$v_i(t+1) = w_i(t)v_i(t) + c_1r_1(pb_{best}(t) - x_i(t)) + c_2r_2(gb_{best}(t) - x_i(t)) \quad (4)$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (5)$$

where w is the inertia weight, c_1 and c_2 are the learning parameter of the PSO, r_1 and r_2 are the random numbers distributed between 0 and 1. pb_{best} and gb_{best} are the personal best of each particle and global best of the particle respectively. In the PSO algorithm, the value of inertia weight and the learning parameter are fixed values. Different approaches had been introduced to calculate the inertia weight. Shi et al. [19] proposed a new way to calculate the value of inertia weight with inertial weight decreasing linearly with the algorithm converges. Zhang et al. [28] proposed a detection function to calculate the inertia weight to improve and better PSO algorithm. Lastly, Haiyang Li et al. [8] proposed a better and improved Dynamic Particle Swarm Optimization (DPSO) by introducing a new way of calculating the inertia weight and the learning parameter.

$$f(x) = \begin{cases} w_{min} - \frac{(w_{max}-w_{min}) \times (f_i - f_{min})}{f_{avg} - f_{min}}, & \text{if } f_i < f_{avg}. \\ w_{max}, & \text{if } f_i > f_{avg}. \end{cases} \quad (6)$$

where w_{max} and w_{min} are the maximum and the smallest inertia weight respectively, f_i and f_{avg} are the current fitness of particle i and current average fitness of all swarm particles respectively. f_{min} is the minimum fitness of all swarm particles. The values of inertia weight are changed automatically and adapted according to the fitness value. If the fitness value is larger than the average value, then the inertia weight of the particle will obtain smaller value and therefore, the particle will be protected because of the low the flight velocity. Similarly, if the fitness value is smaller than the average fitness value, then the inertia weight of the particle will be decreased and the particle will be moving fast towards the best particles because of high flight velocity. The learning parameters of the DPSO are updated using the relation given below.

$$c_1 = c_{1,int} + \frac{c_{1,fin} - c_{1,int}}{t_{max}} \times t \quad (7)$$

$$c_2 = c_{2,int} + \frac{c_{2,fin} - c_{2,int}}{t_{max}} \times t \quad (8)$$

Where $c_{1,int}$ and $c_{2,int}$ are the initial value of c_1 and c_2 such that $c_{1,int} > c_{2,int}$. Similarly, $c_{1,fin}$ and $c_{2,fin}$ are the final values of c_1 and c_2 such that $c_{1,fin} < c_{2,fin}$. The value of c_1 and c_2 are changed in such a way that the particles will have strong self-learning capability and weak social-learning capability in the early stage of optimization. In the later stage, the particles will exhibit weak self-learning capability and strong social-learning capability. Consequently, this learning capability will help to accelerate towards convergence.

3 Proposed algorithm

In this paper, a hybrid of DPSO algorithm and FCM algorithm has been used along with a noise reduction mechanism. The global best and the personal best position of the particles

are selected according to the fitness function. The way of selecting the fitness function is very significant in designing an optimization algorithm. The fitness function is defined by the objective function of the fuzzy c-means algorithm. Moreover, the noise pixels are detected based on the fuzzy membership values of local surrounding neighbourhood pixels.

For every iteration, a global best particle and its corresponding fuzzy membership values will be there. Based on these membership values, the cluster attribute $c_k \in \{1, 2, 3...k\}$, has been assign to each pixel value. k is the number of clusters. For example, consider a pixel x_{ij} and its 8 nearest neighbour $\{x_{(i-1,j-1)}, x_{(i-1,j)}, x_{(i-1,j+1)}, x_{(i,j-1)}, x_{(i,j+1)}, x_{(i+1,j-1)}, x_{(i+1,j)}, x_{(i+1,j+1)}\}$ as shown in Fig. 1a. If the number of neighbour pixels with the same cluster attribute of the pixel x_{ij} is less than n , then the pixel x_{ij} will be defined as a noisy pixel. n is an integer and its value is set based on the density of the noise. If the density of the noise is high, the value of n can be set a larger value so that it can able to recognize the adjacent noises with higher efficiency. After the noises have been detected, each noise pixel will be replaced with the mean of the surrounding pixels of the noise pixel.

Therefore, for every iteration, there will be a reduction of the noise pixels. Consider a pixel x_{ij} with its neighbours having different cluster attributes. We can represent the different situation of the pixel x_{ij} and its surrounding cluster attribute into three different ways.

1. Assuming the cluster attribute of x_{ij} pixel be c_1 and its neighbors are surrounded by cluster attribute c_2 only as shown in Fig. 1b. As there is no neighbor whose cluster attribute is assigned as c_1 , x_{ij} is recognized as a noisy pixel. The noisy pixel is replaced with the mean of the surrounding pixels.
2. In the second case, c_1 is surrounded by c_1 and another attribute c_2 as shown in Fig. 1c. In this case, the pixel x_{ij} will be recognized as a noisy pixel if n has a value equal to or larger than 2. If the density of the noise increases, we need to increase the value of n

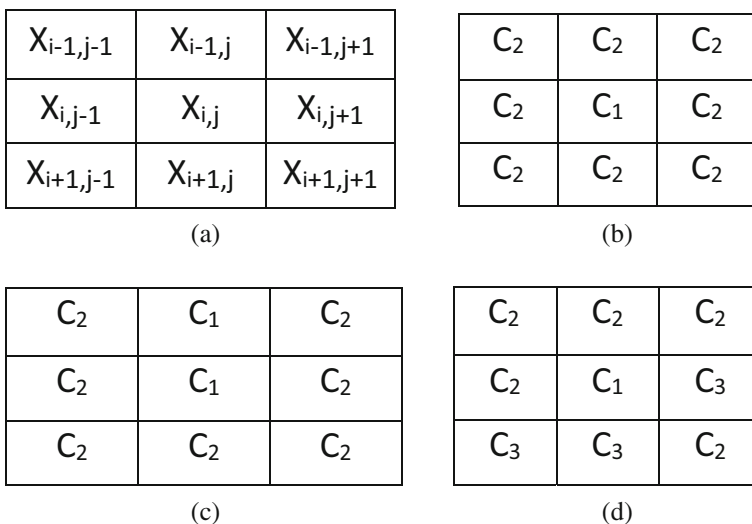


Fig. 1 Noise pixels and neighbour regions

so that we can detect the noise pixels more efficiently. The noise pixel will be replaced with the mean of the surrounding pixels with a cluster attribute c_2 .

3. In the third case, c_1 is surrounded by two or more different cluster attributes, let's say c_2 and c_3 as shown in Fig. 1d. As can be seen in the figure, the number of the cluster attribute c_2 is 5 and the number of cluster attribute c_3 is 3. Therefore, the pixel x_{ij} is replaced by the mean of neighbor pixels with the larger number of cluster attribute, c_2 in this case.

The above method represents a mechanism to detect a noise pixel based on the fuzzy membership value of the global best particle after each iterative and convert it into a pixel based on the local pixels. For every iteration, there will be a reduction of noise and subsequently, converges.

Computational complexity: The computational complexity of the proposed method are involved with different parts-initialization (T_{ini}), evaluation (T_{eva}), velocity and position update (T_{upd}), objective function of FCM (T_{FCM}) and conversion of noisy pixels (T_{noise}). Assuming D is the dimensionality of the search space, $M \times N$ is the dimension of the input image and Maxgen is the maximum number of function evaluation allowed for the algorithm. Thus, the time complexity of the proposed method can be defined as:

$$\begin{aligned}
 T(D) &= T_{ini} + (T_{eva} + T_{upd} + T_{FCM} + T_{Noise}).Maxgen \\
 &= D + (D + D + D + (M \times N)).Maxgen \\
 &= D + (3D.Maxgen) + (M \times N).Maxgen \\
 &= D(1 + 3D.Maxgen) + (M \times N).Maxgen \\
 &= (D.Maxgen) + (M \times N).Maxgen \\
 &= (D + (M \times N)).Maxgen \\
 &= D.Maxgen \\
 &= O(D.Maxgen)
 \end{aligned} \tag{9}$$

Convergence speed: The convergence of the particle is determined by control parameters of the algorithm. As we know that a fixed inertia weight and fixed learning parameters would result in slow convergence or trapping in local optima. In the proposed method, we have dynamic inertia weight and changes depending on the fitness values. This dynamic inertia weight helps the particle to move towards the best particles. Similarly, the dynamic learning parameters helps the particle to exhibit weak learning capability and strong social-learning capability. Thus, these two properties help the algorithm to accelerate towards convergence, thereby increasing the convergence speed.

Parameter setting: The limit of particle velocity could negatively affect the performance of PSO algorithm if it is not properly set. Different works are done by different authors to determine the velocity limits in order to improve on the performance of the PSO algorithm. Three major approaches are discussed: (1) $V_{max} = \delta(X_{max} - X_{max})$ and $V_{min} = -V_{max}$, (2) Multiply both minimum and maximum limit of search space separately with certain percentage, δ i.e. $V_{max} = \delta(X_{max})$ and $V_{min} = \delta(X_{min})$ and (3) Assigning the search space upper limit to X_{max} . Different values of δ have been used to determine the velocity clamping for particles. Out of these methods, the first approach is most commonly used by the authors and therefore, we have used the first approach for our method. For other parameters, we have used the standard values: $w_{max} = 0.9$, $w_{min} = 0.4$, $c_{1,init} = 2.5$, $c_{1,fin} = 0.5$, $c_{2,init} = 0.5$ and $c_{2,fin} = 2.5$.

Algorithm for image segmentation approach based on Fuzzy c-means and Dynamic Particle Swarm Optimization Algorithm:-

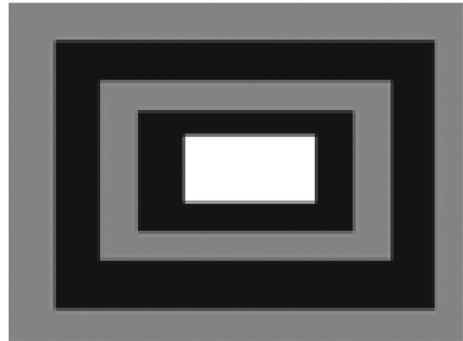
1. Initialization of parameters of DPSO: population size P , maximum iteration $Maxgen$, maximum and minimum inertia weight w_{max} and w_{min} respectively, initial and final learning parameters $c_{1,int}$, $c_{2,int}$, $c_{1,fin}$ and $c_{2,fin}$.
2. Initialization of parameters of FCM: fuzzy modification value, m and convergence threshold,
3. Create P particles, and initialize the position and velocity of each particle.
4. Calculate then Fuzzy c-means objective function of each particle using the relation 1.
5. Select global best particle and personal best particle.
6. while reach $Maxgen$ do
 - (a) Update the velocity of each particle using the relation 4.
 - (b) Update the position of each particle using the relation 5.
 - (c) Update the personal best and global best of each particle using the relations 1.
 - (d) Update the inertia weight, w of each particle using the relation 6.
 - (e) Update the learning parameters c_1 and c_2 using the relation 7.
 - (f) Return the membership value of the global best particle.
 - (g) Assign the cluster based on the membership value of the global best particle.
 - (h) Search for the noisy pixels.
 - (i) Update the input image by converting the noisy pixel into mean of the surrounding pixel of the noisy pixels.
7. end while
8. Return the center and the membership value of the best particle.
9. Segment the image

4 Results and discussion

In this section, the result of the proposed method are discussed and it has been compared with different known algorithms: FCM, DPSO [8], KIFCM [5], ORFCM [20], FCM-IDPSO [24], IFCM [3], FRFCM [11] and SFCM [25]. These algorithms are implemented in Matlab 2013. We have used synthetic data as well as real MRI data and Blood image to test anti-noise ability and the segmentation effect on the real-world environment. Moreover, we have many numerical indexes to evaluate the effectiveness of the segmentation result.

Assessment of Segmentation performance: The performance of the segmentation results of FCM, DPSO, KIFCM, ORFCM, FCMIDPSO, IFCM, FRFCM, SFCM and the proposed method are evaluated using the numerous indices. They are variance partition entropy (vpe), variance partition coefficient (vpc), mean square error (MSE), Peak signal to noise ratio (PSNR) and correlation coefficient (ρ).

Description of noise: Different types of noises are present in different medical images [6, 7]. For example, CT images are prone to Gaussian noise due to the electronic signal. Ultrasound images have lower visual quality due to the presence of Gaussian noise and Speckle noise. Noises in MRI images are primarily Gaussian noise, salt and pepper noise and Rician Noise. Remote sensing images present Gaussian, Rayleigh and Poisson noise. Thus, some of the common noises present in the medical images are Gaussian noise,

Fig. 2 Original image

Poisson noise etc. Therefore, for testing the performance of proposed methods, we have corrupted the synthetic images by taking Gaussian noise (variance=0.05), salt and pepper noise (5%), uniform noise (variance=0.01), poisson noise and speckle noise (5%).

4.1 Synthetic image

A synthetic image with three gray levels is used which is shown in Fig. 2. The synthetic image is added with different types of noises (Gaussian noise, salt and pepper noise and uniform noise). The synthetic image corrupted with salt and pepper (5%), Gaussian (variance=0.05) and uniform noise (variance=0.01) are shown in the Fig. 3.

Figure 3 shows the segmentation results using FCM, KIFCM, DPSO, ORFCM, FCMIDPSO, IFCM, FRFCM, SFCM and proposed method. Visually, we can see that all the comparing methods fail to give results without artefacts except FCMIDPSO and FRFCM. FCMIDPSO give coherent result in the case of the uniform noise and FRFCM gives a good result in all three types of noise. However, the proposed method gives better and coherent results in all the cases and thus we can conclude that the proposed method gives the best results as compared to other methods. Tables 1, 2 and 3 give the evaluation results of Salt and pepper noise, Gaussian noise and Uniform noise respectively. From the results, we can clearly see that the proposed method outperform the other methods.

We also applied Poisson noise and Speckle noise (5%) to the original image. The segmentation results of the image with Poisson and Speckle noise are shown in Figs. 4 and 5 respectively. The performances of the various indices are given in Tables 4 and 5. The results show the higher performance of the proposed method as compared to other methods.

4.2 MRI image

We have used Medical Resonance Imaging (MRI) (mr030. pgm in <http://decsai.ugr.es/cv/gbimages/gbio256.php>) as shown in Fig. 6. For experimentation, we have introduced noise of 5 % salt and pepper in the MRI image. We know that a healthy brain matter consists of three tissues, namely White Matter (WM), Gray Matter (GM) and Cerebrospinal Fluid (CSF). Figure 7 presents the segmentation results using FCM without noise. As we can be observed in the figure, the FCM algorithm clearly classifies the MRI image into three different matters.

Figure 8 shows the output of the proposed method at different intermediate stages and Fig. 9 shows the classification of different brain matters and the final segmentation of the MRI image. The WM, GM, CSF and final segmentation output of MRI images are shown

Fig. 3 Noised images and segmentation output of different methods: **a)**Noised images, **b)**FCM, **c)**DPSO, **d)**KIFCM, **e)**ORFCM, **f)**FCMIDPSO, **g)**IFCM, **h)**FRFCM, **i)**SFCM, **j)**Proposed method

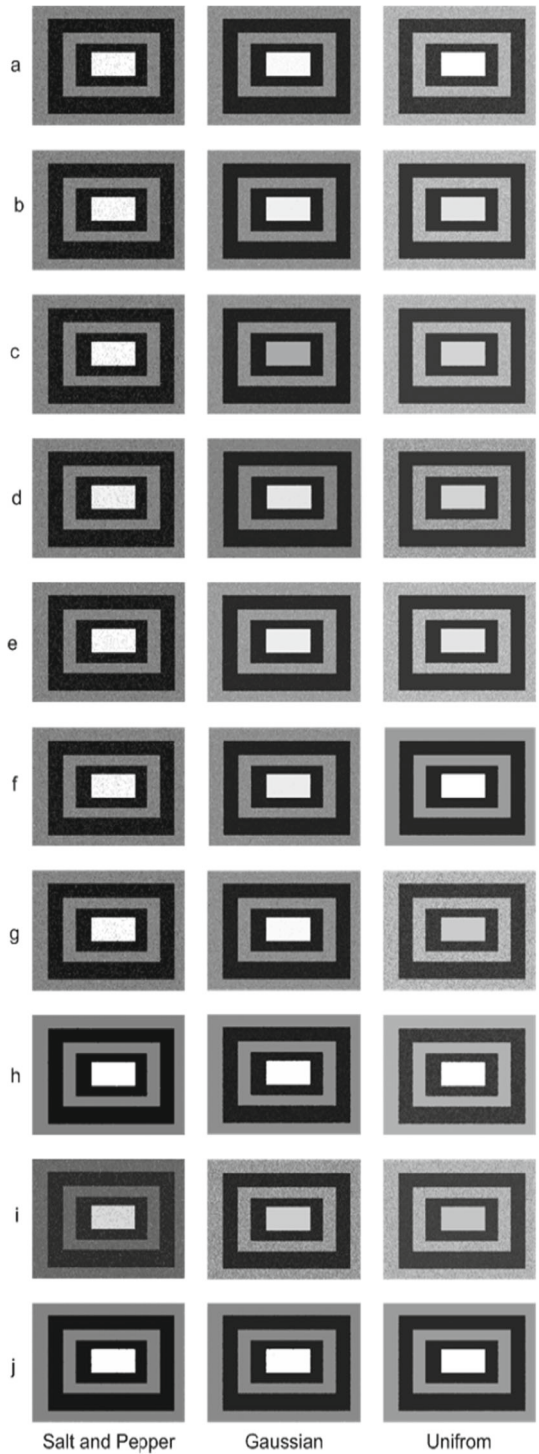


Table 1 Evaluation result of image with Salt and pepper noise

	V_{pc}	V_{pe}	PSNR	MSE	ρ
FCM	0.97	0.013	39.15	7.82	0.89
DPSO	0.97	0.014	39.14	7.92	0.89
KIFCM	0.97	0.013	38.77	8.62	0.89
ORFCM	0.97	0.013	39.15	7.89	0.89
FCMIDPSO	0.97	0.013	39.21	7.79	0.89
IFCM	0.97	0.013	39.42	7.65	0.91
FRFCM	0.96	0.012	41.21	5.08	0.98
SFCM	0.96	0.013	37.59	11.32	0.89
Proposed	0.99	0.011	41.44	4.66	0.99

Table 2 Evaluation result of image with Gaussian noise

	V_{pc}	V_{pe}	PSNR	MSE	ρ
FCM	0.88	0.23	35.92	16.44	0.87
DPSO	0.92	0.16	35.63	17.77	0.91
KIFCM	0.89	0.21	35.40	18.75	0.97
ORFCM	0.88	0.23	35.77	17.18	0.96
FCMIDPSO	0.72	0.24	35.74	17.34	0.97
IFCM	0.70	0.32	29.81	67.92	0.86
FRFCM	0.93	0.13	37.09	12.68	0.97
SFCM	0.84	0.28	33.51	28.92	0.89
Proposed	0.94	0.11	37.89	10.56	0.97

Table 3 Evaluation result of image Uniform noise

	V_{pc}	V_{pe}	PSNR	MSE	ρ
FCM	0.79	0.36	34.47	14.65	0.91
DPSO	0.70	0.55	36.44	14.74	0.91
KIFCM	0.79	0.36	36.40	14.85	0.89
ORFCM	0.79	0.36	36.40	14.85	0.89
FCMIDPSO	0.79	0.36	36.45	14.71	0.90
IFCM	0.71	0.38	31.92	79.82	0.89
FRFCM	0.95	0.11	43.12	2.89	0.99
SFCM	0.79	0.36	33.01	32.46	0.85
Proposed	0.95	0.11	44.11	2.52	0.99

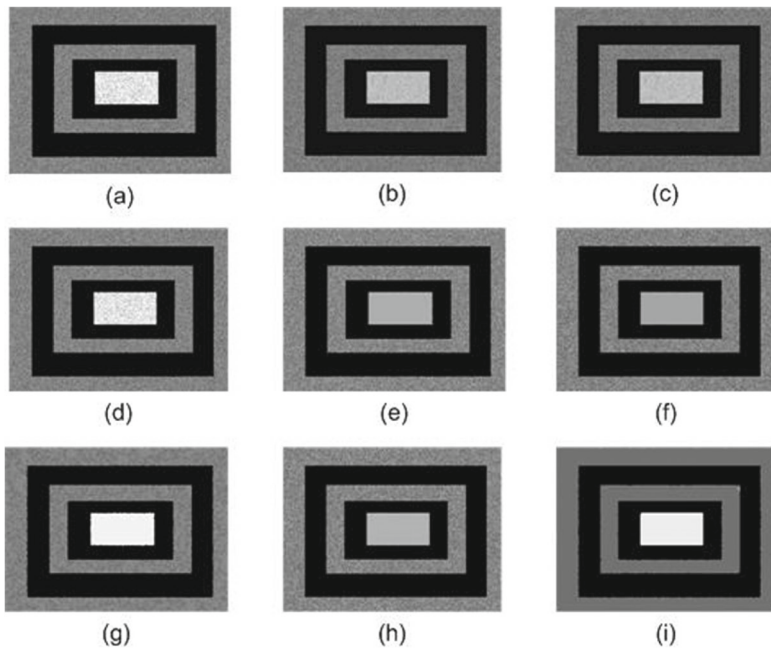


Fig. 4 Segmentation of Original noise with Poisson noise (a)FCM, (b)DPSO, (c)KIFCM, (d)ORFCM, (e)FCMIIDPSO, (f)Proposed method

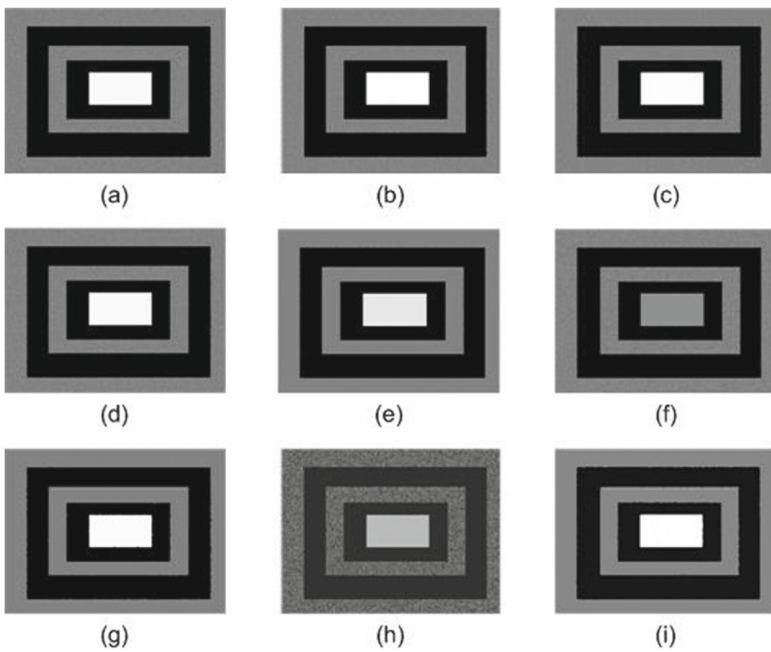


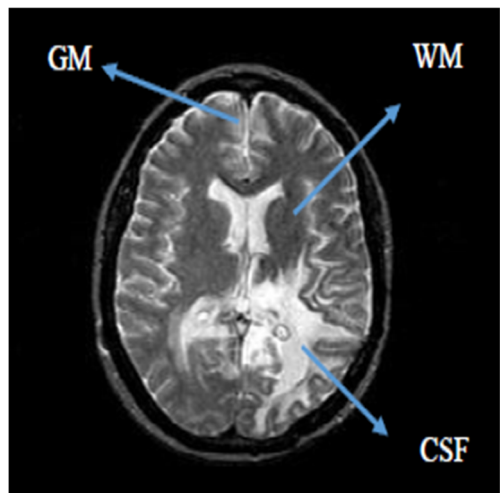
Fig. 5 Segmentation of Original noise with Speckle noise (a)FCM, (b)DPSO, (c)KIFCM, (d)ORFCM, (e)FCMIIDPSO, (f)Proposed method

Table 4 Evaluation result of image Poisson noise

	V_{pc}	V_{pe}	PSNR	MSE	ρ
FCM	0.87	0.186	33.00	32.54	0.99
DPSO	0.72	0.40	35.27	19.28	0.99
KIFCM	0.89	0.18	35.49	18.33	0.99
ORFCM	0.89	0.18	36.46	33.10	0.99
FCMIDPSO	0.92	0.11	34.47	23.20	0.90
IFCM	0.87	0.19	33.67	27.90	0.94
FRFCM	0.99	0.10	39.61	7.10	0.98
SFCM	0.90	0.19	33.46	29.25	0.98
Proposed	1	0.05	39.23	7.752	0.99

Table 5 Evaluation result of Speckle noise

	V_{pc}	V_{pe}	PSNR	MSE	ρ
FCM	0.89	0.21	29.51	72.68	0.95
DPSO	0.70	0.46	30.28	60.92	0.98
KIFCM	0.89	0.21	29.02	81.37	0.98
ORFCM	0.89	0.20	29.53	72.35	0.95
FCMIDPSO	0.88	0.22	29.59	71.34	0.97
IFCM	0.92	0.15	31.30	48.11	0.97
FRFCM	0.90	0.19	30.62	56.30	0.97
SFCM	0.90	0.19	30.54	57.37	0.91
Proposed	0.95	0.10	33.62	54.08	0.98

Fig. 6 MRI image

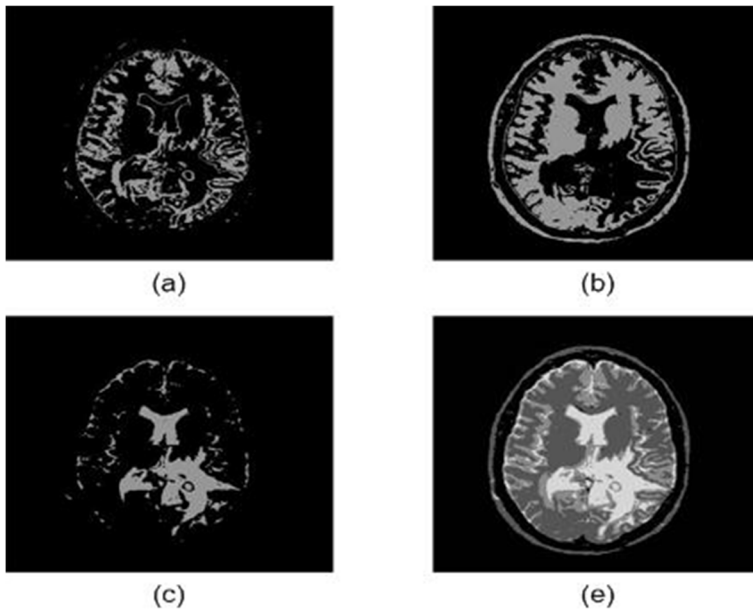


Fig. 7 Standard FCM result without noise. (a) GM, (b) WM, (c) CSF and (d) MRI

in first, second, third and fourth column respectively. FCM, DPSO, KIFCM, ORFCM, FCMIDPSO, IFCM, FRFCM and SFCM have effectively classified the MRI image into three matters but with a lot of trivial and rough areas. Moreover, the details of the target

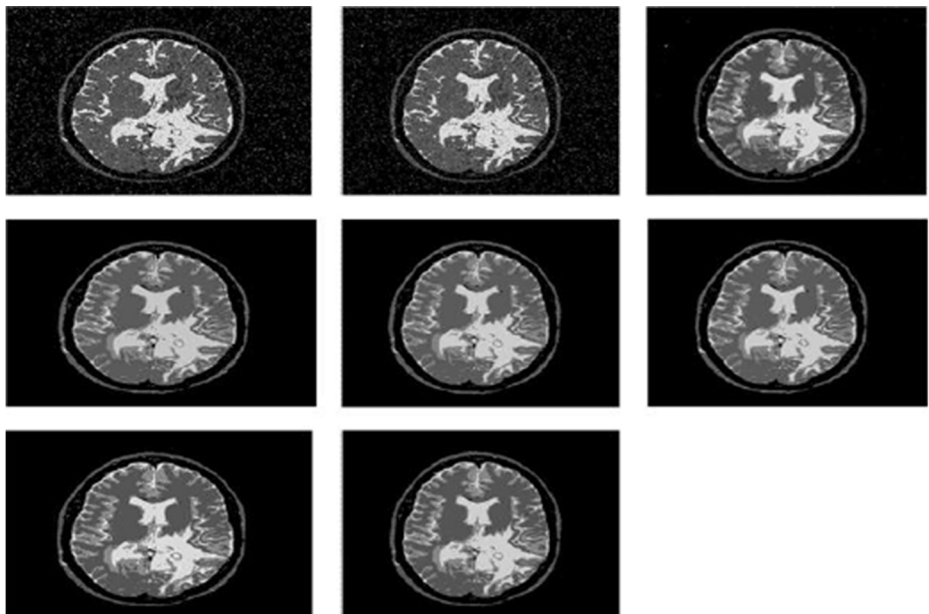


Fig. 8 Different stages of Proposed method

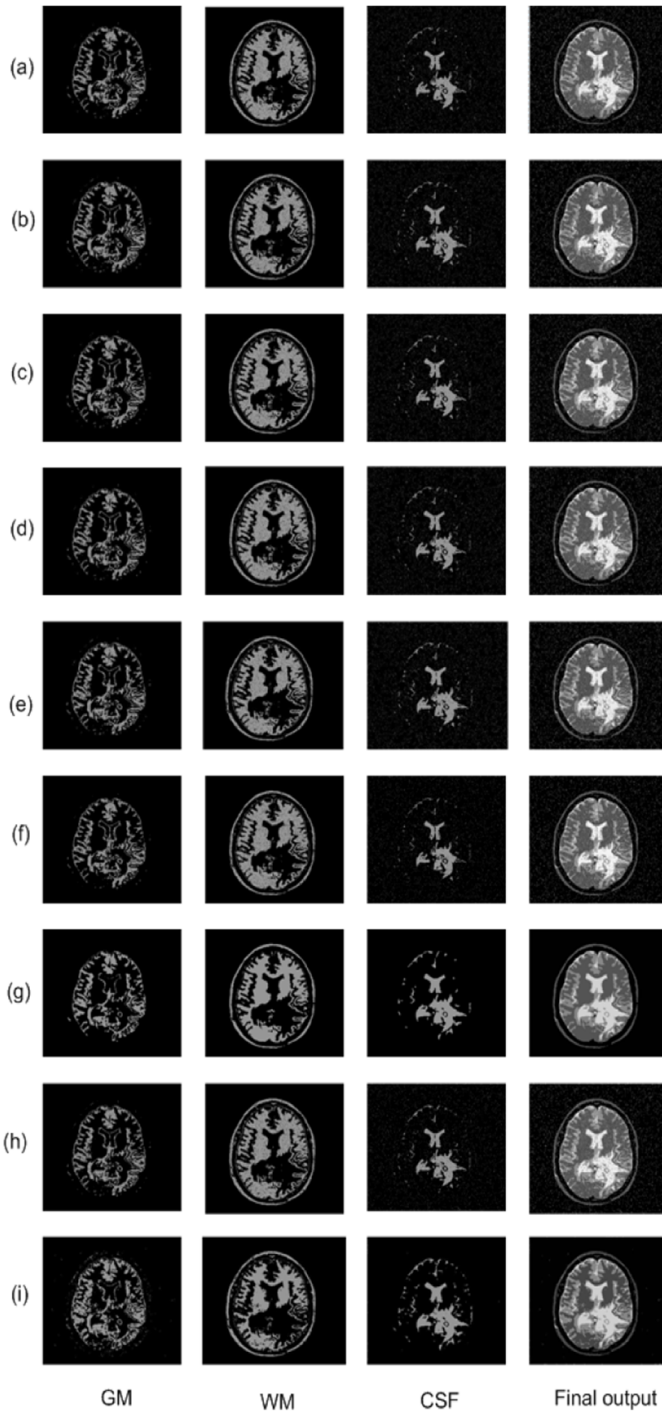


Fig. 9 (a)FCM, (b)DPSO, (c)KIFCM, (d)ORFCM, (e)FCMIDPSO, (f)IFCM, (g)FRFCM, (h)SFCM, (i)Proposed method

Table 6 Evaluation result for the simulated MRI image for different methods

	V_{pc}	V_{pe}	PSNR	MSE	ρ
FCM	0.90	0.14	33.02	32.43	0.85
DPSO	0.89	0.18	32.93	33.10	0.87
KIFCM	0.92	0.14	33.42	29.58	0.86
ORFCM	0.92	0.14	33.27	30.56	0.89
FCMIDPSO	0.92	0.14	33.27	30.59	0.86
IFCM	0.92	0.14	32.98	32.69	0.86
FRFCM	0.93	0.14	33.40	29.69	0.89
SFCM	0.92	0.14	33.26	30.67	0.86
Proposed	1	0.11	33.90	26.47	0.97

regions are not able to distinguish clearly. However, the proposed method gives good results and classify the target regions effectively and maximum similarity with the standard segmentations, despite the fact that the images were affected by the noise. Table 6 shows the evaluation result of the different indices of the proposed method and other methods. The results clearly show that the proposed method gives better performance as compared to other methods.

The above results analysed the effectiveness of the FCM, DPSO, KIFCM, ORFCM, FCMIDPSO, IFCM, FRFCM, SFCM and the proposed method to segment an image in the presence of the noise using synthetic and real MRI images. As from the figures, we have observed that the presence of the noise affects the segmentation result to some extent and the degree of effect are varied for different algorithms. However, the proposed method has shown the best ability adapt to the noise effect and gave the precise segmentation result.

The MRI image classification of WM, GM and CSF are again evaluated by using sensitivity, specificity and accuracy. The sensitivity measures the proportion of foreground that is correctly identified and Specificity measures the proportion of the background that is correctly identified. Accuracy can be defined as correctly classified instances. They are

Table 7 Evaluation of WM

	Sensitivity	Specificity	Accuracy
FCM	0.950	0.984	0.979
DPSO	0.951	0.997	0.990
KIFCM	0.950	0.988	0.982
ORFCM	0.940	0.986	0.980
FCMIDPSO	0.743	0.998	0.958
IFCM	0.941	0.956	0.952
FRFCM	0.925	0.966	0.959
SFCM	0.910	0.954	0.947
Proposed	0.973	0.995	0.995

Table 8 Evaluation of GM

	Sensitivity	Specificity	Accuracy
FCM	0.790	0.985	0.970
DPSO	0.962	0.992	0.981
KIFCM	0.837	0.986	0.974
ORFCM	0.812	0.986	0.972
FCMIDPSO	0.925	0.964	0.961
IFCM	0.841	0.982	0.973
FRFCM	0.901	0.985	0.979
SFCM	0.921	0.986	0.977
Proposed	0.970	0.995	0.982

calculated using the True Positive (TP), False Positive (FP), True Negative (TN) and False Negative (FN).

$$\text{Sensitivity} = \frac{TP}{TP + FN} \quad (10)$$

$$\text{Specificity} = \frac{TN}{TN + FP} \quad (11)$$

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \quad (12)$$

Where TP=pixels correctly segmented as foreground, TN=pixels falsely segmented as foreground, TN=pixels correctly detected as background, FN=pixels falsely detected as background. Tables 7, 8 and 9 show the Sensitivity, Specificity and Accuracy values of WM, GM and CSF respectively. As we can be observed that the proposed method gives best results as compare to other methods. These validate that the proposed method has more efficient to classify the different matters of MRI image in the presence of noise.

The above results analysed the effectiveness of the FCM, DPSO, KIFCM, ORFCM, FCMIDPSO, IFCM, FRFCM, SFCM and the proposed method to segment an image in the presence of the noise using synthetic and real MRI images. As from the figures, we have observed that the presence of the noise affects the segmentation result to some extent and the degree of effect are varied for FCM, DPSO, KIFCM, ORFCM, FCMIDPSO, IFCM, FRFCM, SFCM and the proposed method. However, the proposed method has shown the

Table 9 Evaluation of CSF

	Sensitivity	Specificity	Accuracy
FCM	0.752	0.974	0.961
DPSO	0.851	0.975	0.968
KIFCM	0.764	0.975	0.962
ORFCM	0.765	0.975	0.962
FCMIDPSO	0.970	0.973	0.973
IFCM	0.711	0.974	0.964
FRFCM	0.931	0.990	0.991
SFCM	0.824	0.976	0.961
Proposed	0.976	0.992	0.990

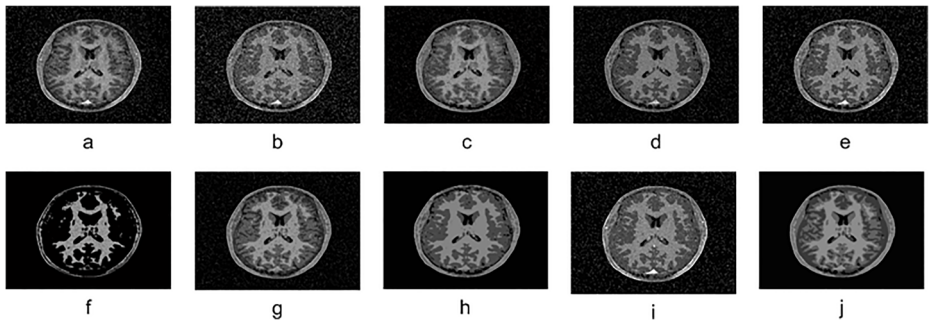


Fig. 10 MRI image:(a)Original Image, (b)FCM, (c)DPSO, (d)KIFCM, (e)ORFCM, (f)FCMIDPSO, (g)IFCM, (h)FRFCM, (i)SFCM, (j)Proposed method

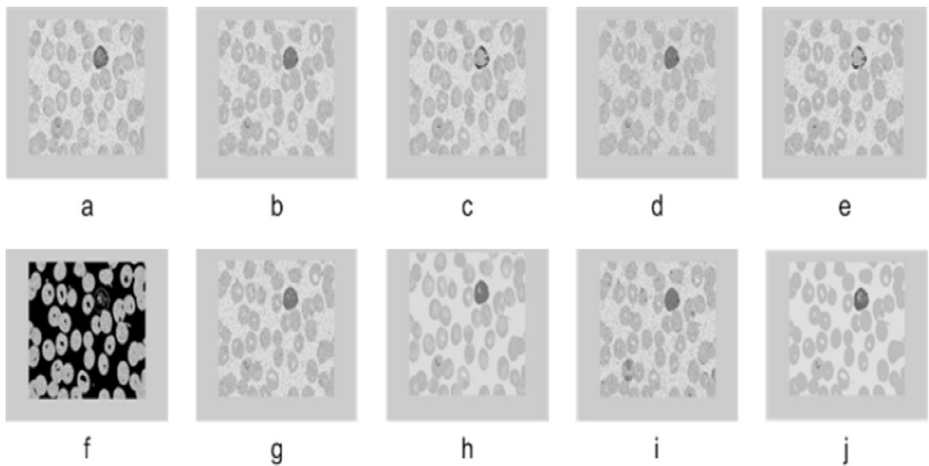


Fig. 11 Blood image:(a)Original Image, (b)FCM, (c)DPSO, (d)KIFCM, (e)ORFCM, (f)FCMIDPSO, (g)IFCM, (h)FRFCM, (i)SFCM, (j)Proposed method

Table 10 Evaluation result for MRI image for different methods

	V_{pc}	V_{pe}	PSNR	MSE	ρ
FCM	1	0.16	32.13	39.81	0.66
DPSO	0.57	0.72	32.50	36.50	00.92
KIFCM	0.9	0.17	30.8	53.15	0.83
ORFCM	0.9	0.17	33.54	39.51	0.79
FCMIDPSO	0.74	0.19	28.90	83.7	0.69
IFCM	0.91	0.17	31.08	42.76	0.80
FRFCM	0.91	0.16	32.39	32.33	0.92
SFCM	0.89	0.19	32.95	32.90	0.79
Proposed	0.94	0.13	33.05	32.16	0.97

Table 11 Evaluation result for Blood image for different methods

	V_{pc}	V_{pe}	PSNR	MSE	ρ
FCM	0.90	0.17	33.95	23.46	0.85
DPSO	0.84	0.28	34.95	18.55	00.49
KIFCM	0.91	0.17	31.30	42.96	0.43
ORFCM	0.66	0.53	33.54	30.25	0.42
FCMIDPSO	0.22	0.21	25.80	151	0.47
IFCM	0.90	0.17	33.88	26.60	0.91
FRFCM	0.91	0.16	34.99	18.40	0.91
SFCM	0.86	0.20	32.26	33.44	0.47
Proposed	0.95	0.11	36.32	13.52	0.95

best ability adapt to the noise effect and gave the precise segmentation result, which means that the proposed method is more suitable for practical application.

Lastly, we have taken two more images- MRI and Blood images for comparing and evaluating the proposed method. Again, 5% Salt and Noise is introduced to see the anti-noise ability. The segmentation of the MRI and Blood images are shown in Figs. 10 and 11 respectively and the evaluation using different parameters are shown in Tables 10 and 11 respectively. As we can observe in Tables, the proposed method outperformed all other methods (Tables 10 and 11).

5 Conclusion

In this paper, we have presented a hybrid method of DPSO and FCM with noise reduction mechanism. It has the advantage of in-sensitiveness to the initial values and the noise and gives precise segmentation result. The proposed method was tested on synthetic and MRI images. We have compared the performance of Fuzzy C-Means, Dynamic Particle Swarm Optimization, K-means integrated with Fuzzy C-Means, Outlier Rejection Fuzzy C-Means and Fuzzy C-Means with improved Particle Swarm Optimization with the proposed method. The experimental results show that the proposed method shows a significant improvement concerning the robustness to noise.

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Nameirakpam Dhanachandra He completed B.Tech in Electronics and Communication and M.Tech in Microelectronics. He is doing PhD at NIT Manipur, India. He has published research papers in international and national journals. His area of interest are image processing, data mining and optimization methods.



Yambem Jina Chanu She received doctoral degree from NERIST, India and completed B.Tech and M.tech in Computer Science Engineering. She has published many national and international journals. She is currently working as Assistant Professor at NIT Manipur, India. Her area of interest are image processing, steganography, data mining.