Medical Image Segmentation With Fuzzy C-Means and Kernelized Fuzzy C-Means Hybridized on PSO and QPSO

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Abstract: *Medical image segmentation is a key step towards medical image analysis. The objective of medical image segmentation is to delineate Region Of Interests (ROI) from the images. Hybridization of nature inspired algorithms with soft computing provides accurate image segmentation results in less computation time. In this work, various algorithms for medical image segmentation which help medical practitioners for better diagnosis and treatment are discussed and the following global optimized clustering techniques are proposed; Fuzzy C-Means (FCM) optimized with Particle Swarm Optimization (PSO), Kernelized FCMPSO (KFCMPSO), FCM optimized with Quantum PSO (FCMQPSO) and KFCMQPSO to extract ROI from the medical images. The experiments were conducted on Magnetic Resonance Imaging (MRI) images and analysis were carried out with respect to average intra cluster distance, elapsed time/computation time and Davies Bouldin Index (DBI). The conventional FCM is noted to be more sensitive to noise and shows poor segmentation performance on the images corrupted by noise. The experimental results showed that the proposed hybridized FCM and KFCM with PSO and QPSO performs well with good convergence speed. The convergence speed is found to be approximately three units lesser than other algorithms.*

Keywords: *Medical image segmentation, clustering, FCM, KFCM, PSO ,QPSO and DBI.*

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1. Introduction

Image segmentation refers to grouping of similar pixels which reveal Region Of Interests (ROI) of an image. Among many segmentation algorithms, the clustering approaches split the images into homogeneous and inhomogeneous classes with respect to the intensity of pixels. The intensities of all pixels within a homogeneous cluster are similar but the intensities of inhomogeneous clusters are different from homogeneous one. Medical imaging modalities; Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), mammography, ultrasound etc., capture images of the human organs to diagnose and examine the diseases for clinical studies. MRI and CT are most commonly used techniques but MRI modalities provide information aids to discriminate tissues in terms of healthy and unhealthy tissues by evaluating physical and biochemical properties and are a preferred imaging technique for examining diseases in different parts of the body, such as the brain, spine, knee, etc. The images from various modalities reveal many tissue properties and complicated anatomical structure. Medical image analysis is mainly dependent on effective image segmentation to extract suspicious regions from complex medical images [16].

1.1. Literature Survey

Fuzzy C-Mean (FCM) groups data into predefined clusters according to membership grade and information it provides better than hard clustering methods. ROI detection using FCM proposed by Jianchao *et al.* [12, 13, 29]. A new fuzzy level set algorithm [4] has been proposed for medical image segmentation where different imaging modalities were considered and the efficiency and robustness of the algorithm have been compared with other standard algorithms. Kernelized FCM (KFCM) with spatial constraints has been proposed for optimal and automatic medical image segmentation [4, 27] where Gaussian radial basis function classifier is replaced with Euclidean distance. A novel robust kernel induced distance is used for clustering image pixels in Magnetic Resonance (MR) images. The experiments were executed on the noisy images and the superiority of the proposed method was compared with basic FCM and KFCM [14]. The same metric is applied on corrupted images by replacing Euclidean norm in standard FCM to segment homogeneous groups [18] and its effectiveness is proven with FCM and its variants.

The performance of a novel algorithm with kernel induced distance is better than FCM and is robust for noise [6]. A fast clustering segmentation algorithm [24, 25] has been proposed to improve the clustering performance of basic FCM. A generalized rough FCM algorithm is proposed for accurate and reliable segmentation of brain images and is more robust to initialization and noise [28]. The effect of otsu thresholding and morphological reconstruction has been demonstrated to segment breast cancer images and results have been compared with other standard methods [20].

An extended otsu thresholding has been applied with wavelet transform for analyzing medical images [26]. To facilitate medical image segmentation by considering the fact of fuzziness in pixel distribution, fuzzy clustering has been demonstrated to extract objects of interest from abdominal aortic aneurysm and degraded human brain images [17]. An improved biogeography based optimization technique using the principle of maximizing fuzzy entropy has been applied on CT images of the human head and analyzed that its performance is found to be better than Genetic Algorithm (GA), Particle Swarm Optimization (PSO) and basic biogeography-based optimization. A Swarm Intelligence (SI) inspired algorithm is presented [2] to detect contours in images where the agents are distributed over important positions of image and the positions of agents are changed according to fitness value. Urich *et al.* [23] insist that the boundary detection is an essential step in image segmentation and the algorithm is evaluated on Berkeley Segmentation Data Set (BSDS) and results were compared with other standard methods.

2D otsu image thresholding plays vital role in segmenting CT images, but the process suffers from high computation time and complexity. The combination of PSO and otsu was introduced to find the optimal threshold for better segmentation [11]. To identify early diagnosis of brain tumor, FCM clustering has been optimized with GA and PSO [9]. The statistical features of ROI from the mammogram images and clinical data set are identified and grouped by k-means clustering followed by Support Vector Machine (SVM), classification and accuracy are compared to traditional method [1]. An automatic genetic fuzzy clustering of multispectral MRI has been proposed and demonstrated on MRI brain slices and the superiority of the method is compared over other recent multiobjective clustering algorithms [3]. Clustering of pixels in MRI images using traditional FCM by concentrating pixels relative locations and features of neighboring pixels has been proposed and better results were observed over conventional FCM [19]. A novel method called Twice FCM (TFCM) is applied on thoracic CT to segment suspicious regions of the lung cancer image and extract regions belonging to the pulmonary parenchyma [10]. A new region based image segmentation called seeded region growing optimized using PSO is discussed [8]. The best location of seeds is identified using PSO. The performance is tested on the cameraman image and experimental section shows the proper segmentation of objects present the image. Fahd *et al.* [8] state that the method is suitable for medical image segmentation too.

The rest of the paper has been structured as follows: FCM clustering and its algorithm is explained in section 2 while KFCM is explained in section 3. Section 4 describes the optimization methods; PSO and QPSO. Optimization of KFCM using PSO and Quantum PSO (QPSO) discussed in sections 5 and 6 respectively. The results and analysis are given in section 7. In section 8, the cluster validity index is mentioned. Conclusions are mentioned in section 9. The terminology used are: Optimization of FCM using PSO is referred by the term FCMPSO and the term FCMQPSO refers to the optimization of FCM using QPSO. KFCM optimized using PSO is referred as KFCMPSO. And finally, KFCMQPSO refers KFCM optimized using QPSO.

2. Standard FCM

Fuzzy clustering was introduced by Dunn (1974) and extended by Bezdek (1983). It is an iterative clustering technique produces c optimal clusters through the minimization of objective function given in Equation 1.

$$J_{fcm} = \sum_{i=1}^{c}\sum_{k=1}^{n}(\mu_{ik})^{m}\|x_k - v_i\|^2 \tag{1}$$

Where $X=\{x_1, x_2, \ldots, x_n\}$ is a finite collection of elements, the outcome of FCM are cluster centres $C=\{c_1, \ldots, c_c\}$ and fuzzy partition matrix of size $c*n$ whose data elements represents degree of membership lies in the range between [0, 1]; $U= u_{ij} \in [0, 1]$ where i=1, 2, …, c and j=1, 2, …, n.

$$v_i = \frac{\sum_{k=1}^{n} x_k(\mu_{ik})^m}{(\mu_{ik})^m} \tag{2}$$

And

$$\mu_{ik} = \frac{1}{\sum_{j=1}^{c}\left(\frac{\|x_k - v_i\|}{\|x_k - v_j\|}\right)^{2/m-1}} \tag{3}$$

Where m ($1 \leq m < \infty$) is the fuzziness parameter, v_i is the centre of cluster i and x_k is the input vector. Fuzzy clustering is different from hard clustering, here data element or pixel belongs to multiple clusters based on membership grade.

3. Kernalized Fuzzy C-Means

KFCM is the kernel version of FCM, where Euclidean distance is replaced with kernel induced distance measure [30]. Thus, the objective function is written as in Equation 4.

$$J_{kfcm} = \sum_{i=1}^{c}\sum_{j=1}^{n} u_{ij}^{m} \left\| \psi(x_j) - \psi(C_i) \right\|^2 \tag{4}$$

Where ψ is a nonlinear function.

$$\left\| \psi(x_j) - \psi(C_i) \right\|^2 = K(x_j, x_j) + K(C_i, C_i) - 2K(x_j, C_i) \tag{5}$$

$$K(x, y) = \psi(x)^T \psi(y) \tag{6}$$

$$J_{kfcm} = 2\sum_{i=1}^{c}\sum_{j=1}^{N} u_{ij}^{m} (1 - K(x_j, C_i)) \tag{7}$$

Where the partition matrix.

$$U_{ij} = \frac{\left(1 - K(x_j, C_i)\right)^{1/m-1}}{\sum_{k=1}^{c}\left(1 - K(x_j, C_i)\right)^{1/m-1}} \tag{8}$$

And the cluster centres.

$$C_i = \frac{\sum_{i=1}^{n} U_{ij}^{m} K(x_j, C_i) x_j}{\sum_{i=1}^{n} U_{ij}^{m} K(x_j, C_i)} \tag{9}$$

There are different kernel functions commonly used in pattern recognition such as polynomial kernel, Gaussian kernel and sigmoid kernel. In this paper Gaussian kernel is used to perform tasks of clustering. In this work, the fitness function is calculated as:

$$F_{kfcm} = \frac{1}{J_{kfcm} + 1} \tag{10}$$

4. PSO and QPSO

PSO and QPSO are nature inspired heuristic methods. A swarm of particles move around the D-dimensional search space in search of optimal solutions. PSO is a nature inspired method which simulates social behavior of birds, fishes, etc. It was developed by Eberhart and Kennedy [15]. In PSO, the positions of the particles are calculated based on their previous positions and current velocity as in Equation 1. The velocity of particles is found using personal best position and global best positions as in Equation 12.

$$X_i(t+1) = X_i(t) + V_i(t+1) \tag{11}$$

$$V_i(t+1) = \omega V_i(t) + c_1 rand_1 (pbest_i(t) - x_i(t)) + c_2 rand_2 (gbest(t) - x_i(t)) \tag{12}$$

Where *pbest* is the personal best positions and *gbest* is the global best positions of particles, *Rand*() generates a random number in the range [0, 1], c_1 and c_2 are positive constants, ω is the inertia weight set between the range 0 and 1. Quantum concepts introduced into PSO to develop a new method called QPSO [21, 22]. It is a variant of PSO takes less parameters and superiority is analyzed against GA and PSO in terms of training speed and convergence in local optimal point [5]. In quantum model, the state of particles can be denoted by wave function $\Psi(x, t)$ instead of velocity and position of particles. $|\Psi(x, t)|^2$ represents the probability of particles appearing in a certain position and positions is denoted with iterative Equation 13. Where β is called contraction-expansion coefficient to control the convergence speed of the algorithm. M is the population size, P_i is the personal best (*Pbest*) positions of particles, computed by the Equation 14 and *Mbest* is the mean of *Pbest* values given in Equation 15. The parameters u and φ are random numbers distributed in the range [0, 1].

$$x_i(t+1) = P_i \pm \beta * \left| Mbest - x_i(t) \right| * \ln(1/u) \tag{13}$$

$$P_i = \varphi * pBest_i + (1 - \varphi) * gBest_i \tag{14}$$

$$Mbest = \left(1/M \sum_{i=1}^{M} Pi1, 1/M \sum_{i=1}^{M} Pi2, \ldots, 1/M \sum_{i=1}^{M} PiD\right) \tag{15}$$

5. KFCMPSO

Hierarchical and partitional clustering algorithms involve the minimization of some extrinsic optimization criteria. Improper selection of initial partition may converge at a local optimum point. These drawbacks are limited when it employs with optimization strategies. PSO has been extensively used as a hybridization technique in clustering and classification for better performance. In KFCMPSO, the objective function given in Equation 7 is optimized using PSO.

6. KFCMQPSO

QPSO takes less parameters and more robustness than PSO. The main parameter of QPSO is β, contraction expansion coefficient to control the computing speed of algorithm and it is updated as:

$$\beta = (\beta_1 - \beta_2) x \frac{(MAXITER - t)}{MAXITER} + \beta_2 \tag{16}$$

Where β_1 is normally assigned with 1.0 and β_2 with 0.5. The fitness function shown in Equation 10 is optimized using the following procedure.

6.1. Procedure of KFCMQPSO

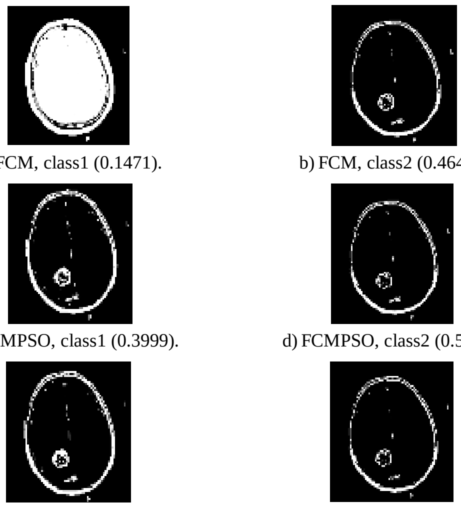
Initialize swarm size M and Dimension D
For each particle i, do
  Initialize positions X[*i*]
  Assign initial positions to pbest[*i*]
End For
  find mbest positions of particles
While(*population size*)
  Find fitness according to Equation 10
  update pbest, mbest and set best of pbest as gbest positions of particles
 For each dimension
    update positions
 End For
End While

7. Results and Discussions

The effectiveness of the proposed algorithms is tested on the MRI brain image obtained from http://www.healthtap.com and on the same image corrupted with 5% of gaussian noise shown in Figures 1-a and b respectively. Gaussian noise is added to the image to show the robustness of the algorithms. The qualitative and quantitative comparisons of algorithms are shown in Figures 2, 3, 4 and 5 whereas, Table 2 shows the numerical results of these algorithms on various criteria. The objective function of FCM and KFCM are optimized with PSO and QPSO where number of classes is set as 2.

a) Original image. b) Gaussian noisy image.

Figure 1. MRI brain images.

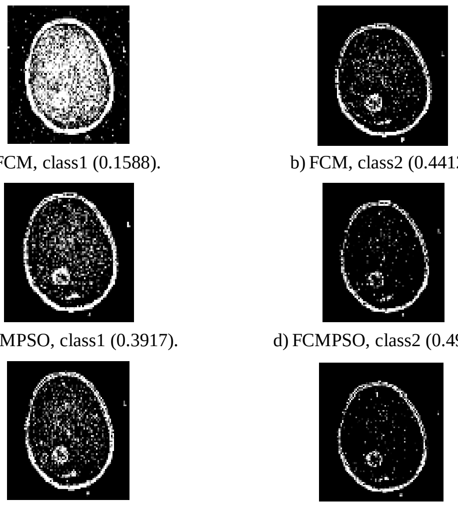


a) FCM, class1 (0.1471). b) FCM, class2 (0.4647).

c) FCMPSO, class1 (0.3999). d) FCMPSO, class2 (0.5000).

e) FCMQPSO, class1 (0.4000). f) FCMQPSO, class2 (0.5000).

Figure 2. Results of FCM, FCMPSO and FCMQPSO on the original image 1.

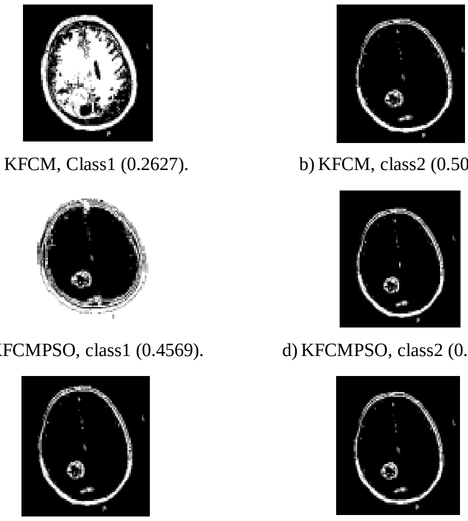


a) FCM, class1 (0.1588). b) FCM, class2 (0.4412).

c) FCMPSO, class1 (0.3917). d) FCMPSO, class2 (0.4987).

e) FCMQPSO, class1 (0.4100). f) FCMQPSO, class2 (0.5100).

Figure 3. Results of FCM, FCMPSO and FCMQPSO on Gaussian noisy image 2.

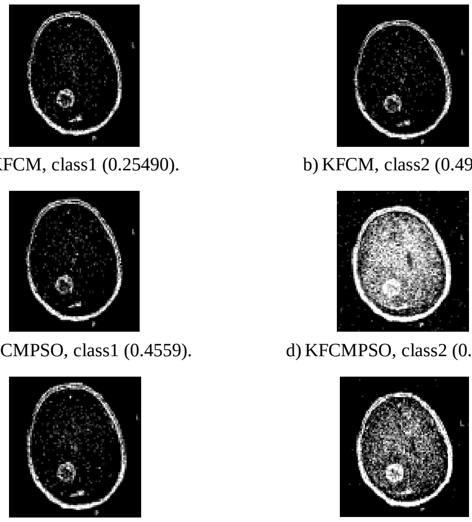


a) KFCM, Class1 (0.2627). b) KFCM, class2 (0.5000).

c) KFCMPSO, class1 (0.4569). d) KFCMPSO, class2 (0.5000).

e) KFCMQPSO, class1 (0.5000). f) KFCMQPSO, class2 (0.5000).

Figure 4. Results of KFCM, KFCMPSO and KFCMQPSO on the original image 1.



a) KFCM, class1 (0.25490). b) KFCM, class2 (0.4995).

c) KFCMPSO, class1 (0.4559). d) KFCMPSO, class2 (0.5000).

e) KFCMQPSO, class1 (0.4876). f) KFCMQPSO class2 (0.5000).

Figure 5. Results of KFCM, KFCMPSO and KFCMQPSO on gaussian noisy image 2.

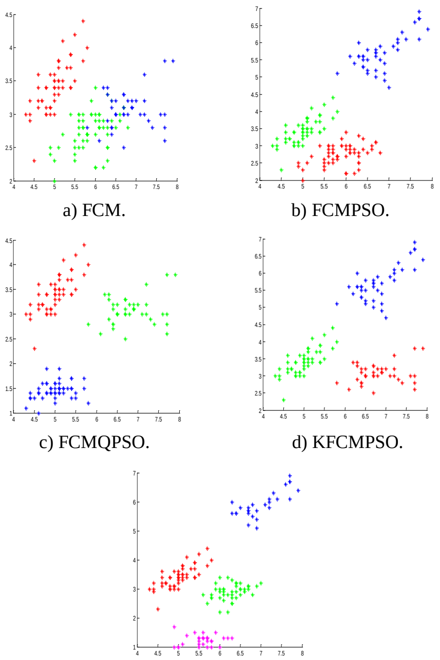
The results of KFCM, KFCMPSO and KFCMQPSO are seeing better than FCM, FCMPSO and FCMQPSO and computing speed of KFCM based algorithms are slightly higher than FCM based methods. Mean while KFCMQPSO segments faster than KFCMPSO and KFCM. The various parameters set for these methods are shown in Table 1.

Table 1. Parameters settings for FCM, FCMPSO, FCMQPSO, KFCM, KFCMPSO and KFCMQPSO algorithms.

Method	Parameters
FCM	M=2; MAXITER=100; K=2
FCMPSO	Popsize=30; centroid=2; dimension=2; MAXITER=100 c1=1.49; c2=1.49; w=0.72; M=2
FCMQPSO	Popsize=30; centroid=2; dimension=2; MAXITER=100; Beta=0.5
KFCM	Expo=2; MAXITER=100; epsilon=0.0001; numberofclasses=2; kernel_b=0.5;
KFCMPSO	Popsize=30; centroid=2; dimension=2; c1=1.49; c2=1.49; w=0.72; kernel_b = 0.5; MAXITER=100; expo=2
KFCMQPSO	Popsize=30; centroid=2; dimension=2; MAXITER=100; Beta=0.5; numberofclasses=2; kernel_b=0.5;

Table 2. Analysis of clustering.

Method	Image and Dataset	Intra Distance(Avg)	Cluster Centres	Number of Classes	Threshold Level (Class 1)	Threshold Level (Class 2)	Elapsed Time(Secs)	DBI
FCM	1	0.3020	0.3373 0.4510	2	0.1471	0.4647	24.6408	0.4156
	2	0.2990	0.4157 0.7137	2	0.1588	0.4412	26.2200	0.4178
	IRIS dataset	0.1328	3.9958 2.5665	2	-	-	0.1365	-
FCMPSO	1	0.2933	0.3174 0.4689	2	0.3999	0.5000	26.7892	0.4123
	2	0.2919	0.4234 0.6790	2	0.3917	0.4987	23.8654	0.4140
	IRIS dataset	0.0989	3.7958 2.1665	2	-	-	4.1121	-
FCMQPSO	1	0.2921	0.3578 0.4698	2	0.4000	0.5000	22.4567	0.4123
	2	0.2912	0.3988 0.7098	2	0.4100	0.5100	22.691547	0.4136
	IRIS dataset	0.0398	3.7958 2.4665	2	-	-	3.3914	-
KFCM	1	0.3012	0.3961 0.4510	2	0.2627	0.5000	25.6108	0.4038
	2	0.2960	0.3961 0.7212	2	0.25490	0.4995	26.5418	0.4124
	IRIS dataset	0.1012	4.1998 3.1665	2	-	-	2.8067	-
KFCMPSO	1	0.2819	0.3789 0.5034	2	0.4569	0.5000	26.23673	0.4021
	2	0.2890	0.3821 0.6967	2	0.4559	0.5000	26.88644	0.4122
	IRIS dataset	0.0810	3.9958 2.5665	2	-	-	3.3918	-
KFCMQPSO	1	0.2798	0.3145 0.4634	2	0.5000	0.5000	24.13856	0.3910
	2	0.2813	0.3978 0.7188	2	0.4876	0.5000	24.420331	0.3987
	IRIS dataset	0.0810	3.9958 2.5665	2	-	-	3.1256	-



a) FCM. b) FCMPSO. c) FCMQPSO. d) KFCMPSO. e) KFCMQPSO for k=4.

Figure 6. Clustering results of iris dataset.

In this experiment fuzzy parameter *m* is set to 2 and other constant values of PSO is set as $c1=c2=1.49$, $w=0.72$, swarm size=30 and maximum iterations=100. The same number of iterations is followed in all the algorithms and termination parameter is set as $\varepsilon=0.001$. The algorithms FCM, FCMPSO, FCMQPSO, KFCMPSO and KFCMQPSO are also tested on iris dataset. The dataset iris included 178 instances and each instance has four features representing Petal Width (PW), Petal Length (PL), Sepal Width (SW) and Sepal Length (SL) the experiment considers all the attributes to segment the data into three and four classes. The clustering results of Iris are shown in Figure 6. The execution time of FCM and its variants are better than KFCM but good accuracy is achieved while applying KFCM based methods.

8. Davies Bouldin Index (DBI)

DBI index is the ratio between intra cluster distances and inter cluster distances. The intra distance refers distance within the cluster scatter which has to be as low as possible while inter refers the distance between the clusters which has to be as large as possible. The formula for *DBI* index [7] is given below:

$$DBI = \frac{1}{n}\sum_{i=1}^{n} max\left[\frac{s_i + s_j}{M_{i,j}}\right] \quad (17)$$

Where n is the number of clusters, S_i and S_j are the intra distances of cluster i and j and $M_{i,j}$ is the inter cluster distance between cluster i and j

9. Conclusions

In this paper, FCM and KFCM have been hybridized with PSO and QPSO. The idea of optimization is to reduce computational cost and to get optimum clustering accuracy. MRI image has been segmented by FCM, FCMPSO, FCMQPSO, KFCM, KFCMPSO and KFCMQPSO. Kernel induced algorithms segment

ROI well, even on the noisy images. The same set of algorithms has also been applied to IRIS data set to test the performances in the synthetic data set. The clustering metric DBI is computed for the segmented resultant images and noted that it is lower when QPSO is applied to FCM and KFCM. Our future work is to use the segmented results to train the neural network for better classification in reduced computational cost.

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