Adaptive Initialization of Cluster Centers using Ant Colony Optimization: Application to Medical Images

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Abstract: Segmentation is a fundamental preprocessing step in medical imaging for diagnosis and surgical operations planning. The popular Fuzzy C-Means clustering algorithm perform well in the absence of noise, but it is non robust to noise as it makes use of the Euclidean distance and does not exploit the spatial information of the image. These limitations can be addressed by using the Robust Spatial Kernel FCM (RSKFCM) algorithm that takes advantage of the spatial information and uses a Gaussian kernel function to calculate the distance between the center and data points. Though RSKFCM gives a good result, the main drawback of this method is the inability of obtaining good minima for the objective function as it happens for many other clustering algorithms. To improve the efficiency of RSKFCM method, in this paper, we proposed the Ant Colony Optimization algorithm based RSKFCM (ACORSKFCM). By using the Ant Colony Optimization, RSKFCM initializes the cluster centers and reaches good minima of the objective function. Experimental results carried out on the standard medical datasets like Brain, Lungs, Liver and Breast images. The results show that the proposed approach outperforms many other FCM variants.

1 INTRODUCTION

Clustering is an unsupervised learning process in which data objects are assigned into a set of disjoint group so that, objects in the same group are similar among them and different from the objects from the other groups. Clustering algorithms can be categorized into two groups: hierarchical and partitional. Hierarchical algorithms recursively find nested clusters either in a top-down (divisive) or bottom up (agglomerative) fashion (Jain et al., 1999). In contrast, partitional algorithms find all the clusters simultaneously as a partition of the data and do not impose a hierarchical structure. There are two popular partitional clustering algorithms: K-Means (KM) (Ng et al., 2006; Chen et al., 1998) and Fuzzy C-Means (FCM) clustering (Wang et al., 2006; Hadjahmadi et al., 2008). Most hierarchical algorithms have quadratic or higher complexity in the number of information periods and consequently are not suited for big data sets, where as partitional algorithms often have less complexity.

Clustering methods have received significant attention among the researchers due to their wide applicability in many disciplines like object recognition, geographical imaging, medical image processing etc. (Jain et al., 1999). Segmentation plays a vital role in medical image processing. In literature, many clustering algorithms are used to solve the medical image segmentation problem (Chen and Zhang, 2004; Chuang et al., 2006; Aruna Kumar and Harish, 2014). In crisp clustering methods, like K-Means, data are divided into a number of clusters where data elements belong to exactly one cluster. But images must be considered fuzzy due to the uncertainty present in them in terms of region/boundaries and non-uniform intensity variations. Modeling images using fuzzy sets allows us to keep the uncertainty of belonging using a membership function. Thus, fuzzy clustering methods turn out to be well suited for the segmentation of medical images.

In the last few years, variants of FCM clustering algorithms have been introduced by different researchers by pointing out various problems concerning the usage of the spatial information and the distance computation. (Ahmed et al., 2002) proposed a modified FCM (FCM_S) by incorporating spatial constraints into objective function. However, the way in

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which they incorporate the neighboring information limits their application to single-feature inputs. To reduce the computational time of FCM_S, (Chen and Zhang, 2004) proposed two variants (FCM_S1 and FCM_S2) of FCM_S algorithm. These two algorithms introduced the extra mean and median-filtered image, respectively, which can be computed in advance, to replace the neighborhood term of FCM_S. Thus, the execution times of both FCM_S1 and FCM_S2 are considerably reduced. (Chuang et al., 2006) proposed a robust spatial FCM (SFCM) method which incorporates the spatial information into membership function for clustering. (Van Lung and Kim, 2009) proposed a Generalized Spatial Fuzzy C-Means (GS-FCM) algorithm for medical images. This method utilizes both given pixel attributes and the spatial local information which is weighted correspondingly to neighbor elements based on their distance attributes. (Aruna Kumar and Harish, 2014) proposed a Robust Spatial Kernel FCM (RSKFCM). This method considers the properties of local neighborhood pixels and uses the kernel distance function to measure the distance between pixels and cluster centers. The RSKFCM method works effectively for medical image segmentation. However, the performance of the RSKFCM depends on the initialization of the cluster centers. Random initialization of the cluster centers makes the algorithm often to fall into the local optimal solution. Spectral clustering is another clustering method, which is used for many applications such as image segmentation, community detection and database clustering (Kuo et al., 2014; Archip et al., 2005). The main challenge of this method is to create appropriate laplacian.

Nature-inspired methods like Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO) techniques where successfully employed to solve the cluster initialization problem over the recent years. ACO has been applied successfully to numerous optimization problems. The successful applications of ACO attracted many researchers. Compared to other heuristic optimization algorithms, discretion and parallel nature of ACO are well appropriated in clustering, because ACO searches smartly and utilizes characteristics such as positive feedback, robustness and distributed computing. (Zhang et al., 2011; Yu et al., 2012; Han and Shi, 2007). (Yu et al., 2012) proposed an adaptive Ant Colony Optimization based fuzzy clustering algorithm. This method uses Ant Colony Optimization to initialize the cluster centers. (Han and Shi, 2007) developed an improved ACO method which reduces the computation time by improving the heuristic function and initialization of the clustering centers.

In this paper, to overcome cluster initialization problem of RSKFCM, we employed ant colony optimization to initialize the cluster centers. We tested our proposed method on medical images from different modalities including MRI Brain images, CT scan of Lung tumor images, CT scan of Liver images and MRI Breast images. Finally, the performance of the proposed method is evaluated using four cluster validity functions.

The rest of the paper is organized as follows: Section 2 present the background information regarding RSKFCM and Ant colony Optimization. Section 3 presents proposed method. Experimental setup, dataset used for experimentation and results are presented in section 4. Conclusion are drawn in section 5.

2 BACKGROUND

2.1 Robust Spatial Kernel FCM (RSKFCM)

The technique of fuzzy clustering has become very important in the application of image segmentation. This is due to the large role of uncertainty and imprecision in the images. Traditional Fuzzy C-Means (FCM) leads to its non robust result mainly due to: not utilizing the spatial information in the image and use of Euclidean distance. To overcome these problems, (Aruna Kumar and Harish, 2015) proposed Robust Spatial Kernel FCM (RSKFCM). RSKFCM consider the spatial information and uses Gaussian kernel function to calculate the distance between the center and data points. RSKFCM incorporates the spatial function into membership function of the traditional FCM. The Spatial function is defined as follows:

$$s_{ij} = \sum_{k \in NK(x_j)} u_{ik} \tag{1}$$

where $NK(x_j)$ represents a square window centered at pixel x_j in the spatial domain. This spatial function represents the probability that pixel x_j belongs to i^{th} cluster. The spatial function is incorporated into membership function as follows:

$$w_{ij} = \frac{u_{ij}^p s_{ij}^q}{\sum_{k=1}^{c} u_{kj}^p s_{kj}^q} \tag{2}$$

where p and q are parameters controlling the relative importance of both functions. (Aruna Kumar and Harish, 2014) incorporated the kernel function to robust spatial method to improve the performance and proposed Robust Spatial Kernel Fuzzy C-Means (RSKFCM). The individual stages of Robust Spatial Kernel Fuzzy C-Means (RSKFCM) are described in Algorithm 1.

Data: Image Data
Result: Segmented Image
Initialize cluster centers, ε, m
repeat
Compute all membership values u_{ij} of each pixel against centers as:

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\left\| \frac{x_j - v_i}{x_j - v_k} \right\| \right)^{\frac{1}{m-1}}} \tag{3}$$

Compute the new membership value w_{ij} using equation 2
Calculate the objective function J as follows:

$$J = 2\sum_{i=1}^{c}\sum_{j=1}^{N} w_{ij}^{m} \left(1 - K\left(x_j, v_i\right)\right) \tag{4}$$

Calculate new cluster center values v_i

$$v_i = \frac{\sum_{j=1}^{N} w_{ij}^{m} K\left(x_j, v_i\right) x_j}{\sum_{j=1}^{N} w_{ij}^{m} K\left(x_j, v_i\right)} \tag{5}$$

until $\{J(i) - J(i-1)\} < \varepsilon$;

Algorithm 1: Robust Spatial Kernel Fuzzy C-Means (RSKFCM).

2.2 Ant Colony Optimization (ACO)

Ant Colony Optimization (ACO) is an evolutionary algorithm which is inspired by the food searching behavior of ants. ACO approach was proposed by (Dorigo et al., 1996). Ants are social insects exhibiting great organization and construction ability by the colony behaviors. One of the most important and fascinating is their food searching behavior. The ants find the shortest path between a food source and their nest with the help of pheromone trails. While walking from their nest to the food source, ants deposit a chemical called pheromone. While searching a food source, ants move randomly, but when they encounter a pheromone trail, they decide whether or not to follow that path based on the amount of pheromone deposited. If they select that path, they deposit their own pheromone on the path, which reinforces that path. The probability that an ant chooses one path over another is based on the amount of pheromone on that path.

In ACO, the construction of the path and updating the pheromone are the main steps. Let path (*i*,*j*) denotes the path which connects node i to j. Each ant going from node i to j has pheromone ς_{ij} on path (i,j). In the construction of a path solution, the ant chooses its path based on the following probability:

$$p_{i,j} = \frac{\varsigma_{ij}^{\alpha}(t)\zeta_{ij}^{\beta}(t)}{\sum_{s \in S} \varsigma_{ij}^{\alpha}(t)\zeta_{ij}^{\beta}(t)}, \; j \in S \tag{6}$$

$$\varsigma_{ij} = \begin{cases} 1 & \text{if } d_{ij} < r, \\ 0 & \text{if } otherwise, \end{cases} \tag{7}$$

where $\zeta_{ij}(t) = \frac{r}{d_{ij}}$, denotes heuristic information at time t and d_{ij} is the distance between i and j, and $\varsigma_{ij}(t)$ denotes the pheromone concentration on path (i,j) at time t. The control parameters α and β explain the relative importance of pheromone versus the heuristic value, r is the radius of the cluster, and $S = \left\langle \frac{s}{d_{ij}} \leq r, s = 1,2,...,N \right\rangle$ is set of feasible nodes. After all ants have finished path construction, the quantity of pheromone is updated according to the following equation:

$$\varsigma_{ij}(t+1) = \rho\, \varsigma_{ij}(t) + \sum_{k=1}^{N} \Delta\varsigma_{ij}^{k} \tag{8}$$

where ρ is the evaporation rate of pheromone, N is the number of ants, and $\Delta\varsigma_{ij}^{k}$ is the amount of increased pheromone laid on path (i,j) by the k^{th} ant.

3 PROPOSED METHOD

The iterative optimization of RSKFCM is essentially a local searching method, which is likely to fall onto a local minima and very sensitive to the initialization of cluster centers. Usually, cluster centers are initialized randomly based on some experience. The clustering results mainly depends on initial cluster centers. To address this problem, in this paper we are employing ACO method for cluster initialization. In Ant Colony Optimization, the solution space is modeled as a graph representation. On the graph each ant moves from one node to another node and deposit the pheromone on the path traversed.

To segment an image, it is necessary to identify the features. In this paper, we have taken gray values of the pixels as features. In proposed method, we assumed each pixel as ants and cluster center as food sources. At each iteration step, an ant randomly select ungrouped pixel and adds a new node to its partial solution by considering both pheromone and heuristic information. The node with stronger pheromone attracts ants. Here the heuristic information indicates the desirability of assigning a pixel to particular cluster. This heuristic information is obtained by computing the inverse distance from cluster center to ants. The pixel which has highest heuristic value would be more likely to be selected by ants.

The proposed ACORSKFCM consists of two steps. In the first step, cluster centers are initialized using ACO. ACO is applied to find the optimal cluster centers in three steps: initialization, construction and updating process. In initialization process c pixels are assigned randomly on the input image as cluster centers. The initial value of pheromone ς^0 is set to be a constant value. In construction process, for each ant i in input image calculate the distance between cluster center and ant as $d_{ij} = K(X_i, V_j)$, where, $K(X_i, V_j)$ is the kernel distance metric. If d_{ij} then set $p_{ij} = 1$, otherwise if $d_{ij} \leq r$ then calculate the p_{ij} using equation (6). If $p_{ij} \geq \lambda$, assign the ant i to A_j and update the pheromone information using equation (8) and update the cluster centers as $V_j = \frac{1}{A_j} \sum_{j \in A_j} x_j$. This process is repeated until the successive difference between cluster centers is less than or same as stopping threshold. In second step RSKFCM method is applied to segment the given input image. RSKFCM uses the cluster centers found in the first step. The membership value is calculated for each pixel against the centers using equation 2. Next the cluster centers are updated using the equation 5. This process is repeated until the successive difference between cluster center is less than an assigned threshold ε (stopping criteria). The proposed algorithm (ACORSKFCM) is described in Algorithm 2.

Data: Image Data
Result: Segmented Image
Initialize cluster center V_j, $\alpha, \beta, \rho, \varepsilon, r$
A_j is the ant set that contains the member of cluster V_j
$t = 0$
repeat
  t= t+1
  For each ant i in Input image, calculate distance between ant and cluster center as: $d_{ij} = K(X_i, V_j)$
  If $d_{ij} = 0$ then set $p_{ij} = 1$, otherwise if $d_{ij} \leq r$ then calculate the p_{ij} using the equation 6
  If $p_{ij} \geq \lambda$, assign the ant i to A_j and update the pheromone information using equation 8
  Update the cluster centers using the following equation:

$$V_j = \frac{1}{|A_j|} \sum_{j \in A_j} x_j$$

until $\{V(t) - V(t-1)\} < \varepsilon$;
Use these cluster centers as initial cluster centers and perform RSKFCM algorithm to segment the input image

Algorithm 2: Proposed Method (ACORSKFCM).

4 EXPERIMENTAL VALIDATION

This section presents an experimental validation of the proposed method.

4.1 Evaluation Metrics

The performance of the proposed method is evaluated using cluster validity indices. These indices help to validate whether clustering method accurately presents the structure of the data set or not. Wide varieties of cluster validity indices are proposed in the literature. In this paper we have used four widely used cluster validity functions, namely the Partition Coefficient (V_{pc}), the Partition Entropy (V_{pe}), the Fukuyama-Sugeno function (V_{fs}), and the Xie-Beni function (V_{xb}).

(Bezdek, 2013) proposed the Partition Coefficient (V_{pc}) and the Partition Entropy (V_{pe}) which uses only the membership values to evaluate the cluster validity:

$$V_{pc}(U) = \frac{1}{n} \sum_{j=1}^{n} \sum_{i=1}^{c} u_{ij}^m \tag{9}$$

$$V_{pe}(U) = \frac{1}{n} \sum_{j=1}^{n} \sum_{i=1}^{c} u_{ij}^m \log u_{ij} \tag{10}$$

The value of V_{pc} varies between $[\frac{1}{c}, 1]$ where c indicates the number of clusters. The value of V_{pe} ranges between $[0, \log_a c]$ where c is the number of cluster and a is the base of the logarithm. When V_{pc} is maximal or V_{pe} is minimal, the optimal clusters are achieved.

The Fukuyama-Sugeno function (V_{fs}) (Fukuyama and Sugeno, 1989) which is given by:

$$V_{fs}(U, V; X) = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^m \left(\|x_j - v_i\|^2 - \|v_i - \bar{v}\|^2 \right) \tag{11}$$

where $\bar{v} = \frac{1}{c} \sum_{i=1}^{c} v_i$. V_{fs} uses both the membership information and input data. When V_{fs} value is minimum, the better clustering results are achieved.

The Xie-Beni function (V_{xb}) function, which was initially proposed by Xie-Beni (XB) in (Xie and Beni, 1991) and modified by Pal and Bezdek in (Pal and Bezdek, 1995), is defined as:

$$V_{xb}(U) = \frac{\sum_{i=1}^{c}\sum_{j=1}^{n} u_{ij}^{m} \left\|x_j - v_i\right\|^2}{n\left(\min_{i\neq k}\left\{\left\|v_i - v_k\right\|^2\right\}\right)} \tag{12}$$

In V_{xb} the numerator indicates the compactness of the fuzzy partition and denominator indicates the strength of the separation between clusters. When V_{xb} minimal, the best clustering result is achieved.

4.2 Dataset

In order to demonstrate the effectiveness of the proposed method, we conducted experiments and evaluated the performance on medical images from different modalities including MRI Brain images, CT scan of Lung images, CT scan of Liver images and MRI Breast images. The MRI image of the brain chosen for the experiment is available in three bands: T1-weighted, proton density (pd)-weighted and T2-weighted. The normal brain images are obtained from Brain-web database (Brainweb). In this paper, we have used the transversal slice map, the slice thickness is 1 mm and the size is 217 x 181 pixels. We have choosen the lung, liver, breast datasets from (Aruna Kumar and Harish, 2015). Dataset consists of 50 different lung images, 30 different liver images and 50 MRI breast images.

4.3 Experimental Setup and Results

To evaluate the performance of the proposed algorithm, we have compared our proposed method with other three cluster initialization methods, namely random initialization, k-means ++ based initialization (Arthur and Vassilvitskii, 2007), and genetic algorithm based initialization (Aruna Kumar et al., 2015). We combined these initialization methods with FCM variants, namely FCM, Kernel FCM, Spatial FCM, RSKFCM. Table 1 gives the description of these algorithms.

In the experimental comparison, for all the algorithms we used a fuzziness coefficient $m = 2$, a neighboring window size of 3×3, $p = 1$ and $q = 1$ for the spatial function s_{ij}, and a stopping criterion that stops the iterations when the largest difference between all cluster centers and their updated values are smaller than $\varepsilon = 10^{-5}$ or the maximum iteration number of 100 has been achieved.

Table 1: Description of the algorithms considered for comparison.

Method	Description
FCM_1	Random Fuzzy c-means (FCM)
KFCM_1	Random Kernel FCM
SFCM_1	Random Spatial FCM
RSKFCM_1	Random Robust Spatial Kernel FCM
FCM_2	K-means++ based Fuzzy c-means (FCM)
KFCM_2	K-means++ Kernel FCM
SFCM_2	K-means++ Spatial FCM
RSKFCM_2	K-means++ Robust Spatial Kernel FCM
GAFCM	Genetic algorithm based FCM
GAKFCM	Genetic algorithm based Kernel FCM
GASFCM	Genetic algorithm based Spatial FCM
GARSKFCM	Genetic algorithm based Robust Spatial Kernel FCM
ACOFCM	Ant colony based FCM
ACOKFCM	Ant colony based Kernel FCM
ACOSFCM	Ant colony based Spatial FCM
ACORSKFCM	Ant colony based Robust Spatial Kernel FCM

In literature, many researches and experiments have revealed some basic properties of the ACO parameters. In the proposed method, α, β, ρ, λ are the major parameters. α and β are two parameters which controls the pheromone concentration and the heuristic value. λ indicates the minimum probability for pixel classification. When α is set to zero, ACO turns into greedy randomized search algorithm. When α is set to, too large value, ACO will become less optimized. Large value of the λ leads to increase in computation time and prevents many pixels from being clustered. In order to prevent from stagnation, ρ should be assigned to less than 1. In this paper, we set the parameters as follows: $\alpha = 1$, $\beta = 2$, $\rho = 0.9$, $\lambda = 0.35$, $r = 20$, as suggested in (Yu et al., 2012). We initialized GA parameters as follows: population size $s = 150$, crossover probability $p_c = 0.25$, mutation probability $p_m = 0.05$, number of generation $g = 300$, as suggested in (Aruna Kumar et al., 2015).

We implemented and simulated all the algorithms with Matlab^R R2013a.

Figure 1-4 shows the segmentation result on medical images. Table 2, Table 3 , Table 4 and Table 5 compare the performance of all the methods with our proposed method on Brain, Lung, Liver and Breast images.

4.4 Time Complexity

The computational complexity of the segmentation method is a major concern for real-time data handling. The time complexity of ACO is approximately $O(n^2)$.

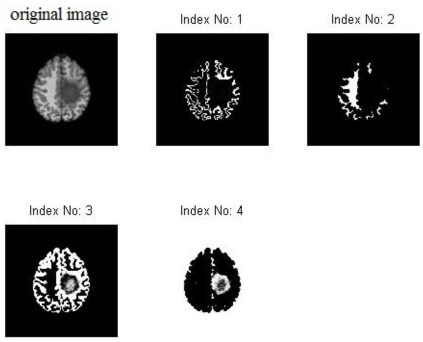

Figure 1: Segmentation results of Brain image with 4 clusters using proposed method.

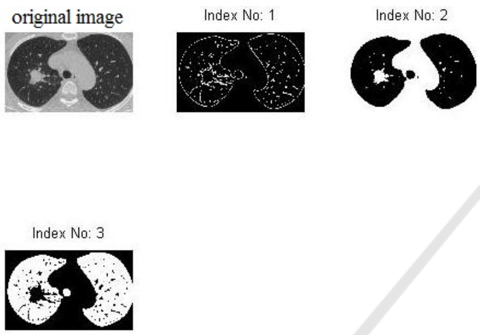

Figure 2: Segmentation results of Lung image with 3 clusters using proposed method.

For the RSKFCM algorithm, during each iteration, the system calculates the distance from each pixel to every cluster center using the Gaussian Kernel metric. After calculating distance, the system computes the new membership function using equation 2. If w is window size, then to calculate the new membership value, the system needs to perform $2w^2$ sum and $2w^2$ multiplication operations. Assuming that each operation is equally dominant, the membership calculation takes $O\left(4w^2\right)$. Therefore, the time complexity of RSKFCM for each pixel is $O\left(c^2d^2w^2\right)$, where d is the input image dimension, c is the number of cluster. If the total number of pixels in the image is n, the time complexity of RSKFCM is $O\left(nc^2d^2w^2i\right)$, where i is the total number of iterations. Therefore the time complexity of our proposed method is:

$$T_M = O\left(nc^2d^2w^2i + n^2\right) \simeq O(n^2) \qquad (13)$$

4.5 Discussion

Table 2- 5 shows the comparison of cluster validity indices of the proposed method with other methods. For any good clustering results the values of V_{pc} should be maximum and V_{pe}, V_{fs}, V_{xb} should be minimum. According to comparison made between the proposed method and other initialization method, the proposed

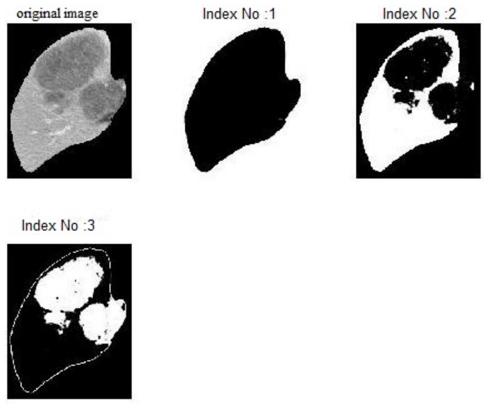

Figure 3: Segmentation results of Liver image with 3 clusters using proposed method.

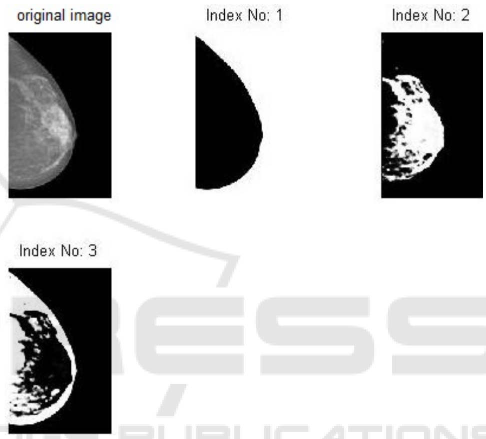

Figure 4: Segmentation results of breast image with 3 clusters using proposed method.

method shows the better results due to high convergence ability of the ACO. The result of the proposed method mainly depends on the ρ that is evaporation rate of pheromone. The larger value of ρ results in low segmentation accuracy. The time complexity of the proposed method is $O(n^2)$.

5 CONCLUSION

Fuzzy clustering is a popular clustering method which as wide varieties of applications including medical image segmentation. Fuzzy clustering algorithm is sensitive to initialization and easily trapped in local minima. The cluster center initialization plays a vital role in fuzzy clustering and its variants. Random initialization of cluster centers does not guarantee the unique clustering results. To overcome this problem, in this paper we presented a cluster center initialization method based on Ant Colony Optimization (ACO). Ant Colony Optimization is an evolu-

Table 2: Performance Comparison for Brain images.

Method	$\mathbf{V_{pc}}$	$\mathbf{V_{pe}}$	$\mathbf{V_{xb}}$ $[\mathbf{1\cdot10^{-3}}]$	$\mathbf{V_{fs}}$ $[\mathbf{-1\cdot10^{6}}]$
FCM_1	0.856	0.275	50.94	317.67
KFCM_1	0.846	0.299	51.82	315.54
SFCM_1	0.932	0.115	52.82	334.14
RSKFCM_1	0.944	0.114	46.93	366.65
FCM_2	0.677	0.620	36.32	170.42
KFCM_2	0.761	0.459	42.73	227.31
SFCM_2	0.886	0.234	38.11	262.45
RSKFCM_2	0.914	0.161	24.14	288.89
GAFCM	0.706	0.513	46.93	123.28
GAKFCM	0.858	0.304	31.59	129.83
GASFCM	0.858	0.139	23.41	130.58
GARSKFCM	0.942	0.099	18.97	132.68
ACOFCM	0.843	0.306	55.86	309.74
ACOKFCM	0.925	0.443	52.49	334.15
ACOSFCM	0.942	0.105	32.71	357.26
Proposed Method	**0.960**	**0.065**	**16.76**	**386.73**

Table 3: Performance Comparison for Lung images.

Method	$\mathbf{V_{pc}}$	$\mathbf{V_{pe}}$	$\mathbf{V_{xb}}$ $[\mathbf{1\cdot10^{-3}}]$	$\mathbf{V_{fs}}$ $[\mathbf{-1\cdot10^{6}}]$
FCM_1	0.934	0.122	38.05	127.79
KFCM_1	0.934	0.126	35.65	129.83
SFCM_1	0.962	0.056	35.90	130.86
RSKFCM_1	0.974	0.045	31.00	132.68
FCM_2	0.887	0.217	59.17	178.91
KFCM_2	0.930	0.131	42.28	144.67
SFCM_2	0.849	0.304	32.84	281.26
RSKFCM_2	0.927	0.129	29.17	269.71
GAFCM	0.911	0.171	56.01	141.39
GAKFCM	0.931	0.124	41.90	154.68
GASFCM	0.943	0.081	44.71	168.18
GARSKFCM	0.964	0.067	43.26	190.34
ACOFCM	0.906	0.182	40.63	264.39
ACOKFCM	0.945	0.064	46.71	269.37
ACOSFCM	0.964	0.023	26.37	347.38
Proposed Method	**0.986**	**0.013**	**26.37**	**347.38**

tionary method which can be applied to solve various function optimization problems. Experiments are performed on medical images from different modalities. The proposed method is compared with the Random initialization, K-means++ based initialization and Genetic algorithm based initialization. The experimental results show that the proposed hybrid method is efficient in terms of cluster validity metrics.

Table 4: Performance Comparison for Liver images.

Method	$\mathbf{V_{pc}}$	$\mathbf{V_{pe}}$	$\mathbf{V_{xb}}$ $[\mathbf{1\cdot10^{-3}}]$	$\mathbf{V_{fs}}$ $[\mathbf{-1\cdot10^{6}}]$
FCM_1	0.910	0.177	32.69	253.68
KFCM_1	0.900	0.198	31.61	251.27
SFCM_1	0.951	0.069	31.05	264.11
RSKFCM_1	0.963	0.065	30.07	267.56
FCM_2	0.657	0.592	70.43	159.74
KFCM_2	0.822	0.326	45.71	241.71
SFCM_2	0.932	0.139	29.74	248.70
RSKFCM_2	0.943	0.104	24.07	264.75
GAFCM	0.892	0.201	55.51	210.56
GAKFCM	0.901	0.198	45.77	224.51
GASFCM	0.931	0.153	42.30	230.16
GARSKFCM	0.952	0.081	40.67	250.17
ACOFCM	0.932	0.127	36.21	127.10
ACOKFCM	0.953	0.046	39.13	230.10
ACOSFCM	0.961	0.049	31.12	192.42
Proposed Method	**0.984**	**0.025**	**29.64**	**286.72**

Table 5: Performance Comparison for Breast images.

Method	$\mathbf{V_{pc}}$	$\mathbf{V_{pe}}$	$\mathbf{V_{xb}}$ $[\mathbf{1\cdot10^{-3}}]$	$\mathbf{V_{fs}}$ $[\mathbf{-1\cdot10^{6}}]$
FCM_1	0.910	0.159	47.75	161.92
KFCM_1	0.904	0.172	55.13	157.77
SFCM_1	0.964	0.062	40.09	129.86
RSKFCM_1	0.967	0.057	34.97	166.14
FCM_2	0.774	0.395	49.06	121.74
KFCM_2	0.878	0.241	28.75	124.76
SFCM_2	0.794	0.373	30.72	138.27
RSKFCM_2	0.825	0.312	24.73	141.97
GAFCM	0.913	0.174	40.08	138.76
GAKFCM	0.910	0.102	37.47	139.29
GASFCM	0.921	0.079	35.46	140.13
GARSKFCM	0.942	0.064	31.63	150.39
ACOFCM	0.892	0.185	44.72	134.39
ACOKFCM	0.948	0.089	39.64	137.27
ACOSFCM	0.949	0.087	30.23	140.78
Proposed Method	**0.984**	**0.071**	**26.71**	**165.71**

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