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IMAGE SEGEMNTATION USING CLUATERING TECHNIQUE ANS SWARM INTELLIANGE

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Abstract: Clustering analysis is an unsupervised learning technique which groups the similar items into one cluster and dissimilar items into another cluster. The clustering techniques are used to efficiently segment the MRI images. The clustering technique used is Fuzzy C Means (FCM). To improve the accuracy, Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) technique is combined with the clustering algorithm. The performance of these is compared and finds that the FCMPSO outperforms than the FCM and FCMACO algorithm.

Keywords:- Fuzzy C Means, Particle Swarm Optimization, Ant Colony Optimization, Image Segmentation, Clustering

INTRODUCTION (HEADING 1)

Partitioning of an image into several constituent components is called image segmentation. Segmentation is an important part of practically and automated image recognition systems, because it at this moment extracts the intensity objects, for further processing such as description or recognition [1]. It is widely used in exploratory pattern-analysis, grouping, decision making, machine learning situations, including data mining, document retrieval and pattern classification. Segmenting the images is used for diagnosing many disorders. Moreover the task is often made more difficult by the presence of noise and artifacts, due to instrumental limitations, reconstruction algorithms and patient movement. Among the fuzzy clustering methods, fuzzy c-means (FCM) algorithm [5] is the most popular method used in image segmentation because it has robust characteristics for ambiguity and can retain much more information than hard segmentation methods The FCM is considered more suitable method for segmenting MRI brain images. Since FCM method does not yield best solution.

The PSO and ACO are the Swarm intelligence techniques that can be implemented in the field of clustering for obtaining approximate solutions to optimization problems in a reasonable amount of computation time. The ability of PSO and ACO is to search for the optimal solution based on the movement of the swarm.

CLUSTERING ALGORITHM FOR IMAGE SEGMENTATION

Clustering is a division of data into groups of similar objects. Representing the data by fewer clusters necessarily loses certain fine details, but achieves simplification. Clustering is grouped under unsupervised learning technique, since the class labels are not known in prior. The quality of clustering is measured by its ability to discover some or all of the hidden patterns. There are different clustering techniques such as, partitioning based, hierarchical based, density based, grid based, model based. In these clustering techniques partitioning based clustering algorithms are chosen to segment the MRI brain images. The advantage of using partitioning based clustering technique is that it constructs various partitions and then evaluates them based on some criterion. Different types of partitioning clusters are K Means, K medoids and fuzzy clustering.

FUZZY C MEANS

Fuzzy clustering is also known as soft clustering, where the data elements can belong to more than one cluster, and associated with each element is a set of membership levels. These indicate the strength of the association between that data element and a particular cluster. Fuzzy clustering is an approach operating towards fuzzy logic and it provides the flexible method of assigning the data points to the clusters. The data points are given partial degree of membership in multiple nearby clusters. The central point in fuzzy clustering is always number of unique partitioning of the data in a collection of clusters. In this membership value is assigned to each cluster. Sometimes this membership has been used to decide whether the data points belong to cluster or not. The most widely used fuzzy clustering algorithm is Fuzzy C Means (FCM). The algorithm introduced by Bezdek. The fuzzification parameter (m) in the range [1,n] was introduced, which determines the degree of fuzziness in the clusters. FCM is a method of clustering which allows one piece of data to belong to two or more clusters. The aim of FCM is to obtain the minimized objective function. The objective function is given equation (1)

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^m \left\| x_i - c_j \right\|^2 \qquad 1 \le m < \infty \tag{1}$$

Where m is the fuzzification parameter which is a real number greater than 1. uij is a fuzzy membership qualification indicating the membership of sample i to the j cluster. xi is the ith data point. cj is the cluster center. || xi- cj|| is the distance matrix from a point xi to each cluster center to with taking the euclidean distance between the point and the cluster center.

Steps in FCM

1. Initialize $U=[u_{ij}]$ matrix, $U^{(0)}$
2. At k-step: calculate the centers vectors $C^{(k)}=[c_j]$ with $U^{(k)}$

$$c_j = \frac{\sum_{i=1}^{N} u_{ij}^m \cdot x_i}{\sum_{i=1}^{N} u_{ij}^m}$$

3. Update $U^{(k)}$, $U^{(k+1)}$

$$u_{ij} = \frac{1}{\sum_{k=1}^{C} \left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|} \right)^{\frac{2}{m-1}}}$$

4. If $\| U^{(k+1)} - U^{(k)}\| < \varepsilon$ then STOP; otherwise return to step 2.

Algorithm for FCM

1. Choose a number of clusters in a given image.
2. Assign randomly to each point coefficients for being in a cluster.
3. Repeat until convergence criterion is met.
4. Compute the center of each cluster.
5. For each point, compute its coefficients of being in the cluster[4-5].

Although FCM is considered good clustering algorithm, the algorithm have some disadvantage. The computational time is more, Sensitivity to the initial guess, Sensitivity to noise. In order to enhance the outcome of the FCM, the algorithm is optimized using Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO).

ANT COLONY OPTIMIZATION (ACO)

The Ant Colony Optimization algorithm (ACO) is a technique, can be applied to any optimization problems. It helps to find good and shortest path through pheromone trial updation. It is used to solve both static and dynamic optimization problem [10]. It uses its intelligent behavior to find the optimal path and contains metaheuristic optimization.

Ants are capable of finding the shortest route between a food source and their nest without the use of visual information and hence possess no global world model, adapting to changes in the environment. The key to such effectiveness is pheromone—a chemical substance

deposited by ants as they travel. Pheromone provides ants with the ability to communicate with each other. Ants essentially move randomly, but when they encounter a pheromone trail, they decide whether or not to follow it. If they do so, they deposit their own pheromone on the trail, which reinforces the path. The probability that an ant chooses one path over another is governed by the amount of pheromone on the potential path of interest. Because of the pheromone, trails that are more frequently traveled by ants become more attractive alternative for other ants. Subsequently, less traveled paths become less likely paths for other ants.

With time, the amount of pheromone on a path evaporates. Prior to the establishment of the most desirable pheromone trails, individual ants will use all potential paths in equal numbers, depositing pheromone as they travel. But the ants taking the shorter path will return to the nest first with food. The shorter pathway will have the most pheromone because the path has fresh pheromone and has not yet evaporated, and will be more attractive to those ants that return to the food source. There is, however, always a probability that an ant will not follow a well-marked pheromone trail. This probability (although small) allows for exploration of other trails, which is beneficial because it allows discovery of shorter or alternate pathways, or new sources of food. Given that the pheromone trail evaporates over time, the trail will become less detectable on longer trails, since these trails take more time to traverse. The longer trails will hence be less attractive, which benefit to the colony as a whole.

Algorithm for ACO

1. Ant traverse around the colony to find the food source
2. After finding the food source it returns to nest.
3. While travelling it deposit some amount of pheromone.
4. The followers of the first ant follow the pheromones which left by the first ant.
5. This transaction will make strengthen the deposition of the pheromone.
6. This strengthens the route of the ant in mean time the amount of pheromone will evaporate in each traversal.
7. If there are two routes to reach the same food source the ant find the shortest route between food and nest with the help of pheromone updating.

FUZZY ANT COLONY OPTIMIZATION

The FCM algorithm results in local optimal solution and hence the method is optimized using ACO. The FCM is integrated with ACO and is known as FCMACO.

Algorithm for FCMACO

1) Initialize ACO parameters (i,j)
2) For each ant k (currently in state i) do
   Repeat
      Choose in probability the state to move into.
      Append the chosen move to the k-th ant's set tabu k.
   until ant k has completed its solution
3) Determine the cluster center using FCM
4) For each ant move (ij) do
   compute Dtij
   update the trail matrix.
5) Terminate when global optimal solution is reached or at end of iteration.
6) Else go to step (2).

PARTICLE SWARM OPTIMIZATION

Particle swarm optimization (PSO) is an algorithm modeled on swarm intelligence, that finds a solution to an optimization problem in a search space, or model and predict social behavior in the presence of objectives. The PSO is a stochastic, population-based computer algorithm modeled on swarm intelligence. Swarm intelligence is based on social-psychological principles and provides insights into social behavior, as well as contributing to engineering applications. The particle swarm optimization algorithm was first described in 1995 by James Kennedy and Russell C. Eberhart. The particle swarm simulates this kind of social optimization. A problem is given, and some way to evaluate a proposed solution to it exists in the form of a fitness function. A communication structure or social network is also defined, assigning neighbors for each individual to interact with. Then a population of individuals defined as random guesses at the problem solutions is initialized. These individuals are candidate solutions. They are also known as the particles, hence the name particle swarm. An iterative process to improve these candidate solutions is set in motion. The particles iteratively evaluate the fitness of the candidate solutions and remember the location where they had their best success. The individual's best solution is called the particle best or the local best. Each particle makes this information available to their neighbors. They are also able to see where their neighbors have had success. Movements through the search space are guided by these successes, with the population usually converging, by the end of a trial, on a problem solution better than that of non-swarm approach using the same methods. Each particle represents a candidate solution to the optimization problem. The position of a particle is influenced by the best position visited by itself i.e. its own experience and the position of the best particle in its neighborhood i.e. the experience of neighboring particles. When the neighborhood of a particle is the entire swarm, the best position in the neighborhood is referred to as the global best particle, and the resulting algorithm is referred to as the gbest PSO. When smaller neighborhoods are used, the algorithm is generally referred to as the lbest PSO. The performance of each particle is measured using a fitness function that varies depending on the optimization problem. Each Particle in the swarm is represented by the following characteristics:

1. The current position of the particle
2. The current velocity of the particle

The particle swarm optimization which is one of the latest evolutionary optimization techniques conducts searches uses a population of particles.

At each step, the particles are manipulated andpbest and gbest locations are identified for iteration t according to the following equations (2) and (3)

$$V(t+1) = \omega V(t) + c1\ rand()(pbest(t) - \mu(t)) + c2\ rand()(gbest(t) - \mu(t)) \quad (2)$$

ω represents the inertia weight to control the speed of each generation of particles and c1,c2 are two positive constants known as cognitive and social components. The velocity is calculated based on previous velocity,

$$\mu i(t+1) = \mu i(t) + Vi(t+1) \quad (3)$$

Here the problem of optimization is by iteratively updating the equation (2) and (3). And the termination criterion for iterations is determined according to whether the maximum generation or a designated value of the fitness is reached.

FUZZY PARTICLE SWARM OPTIMIZATON

The FCM algorithm results in local optimal solution and hence the method is optimized using PSO. The FCM is integrated with PSO and is known as FCMPSO.

Algorithm for FCMPSO

1. Set number of clusters C, Maximum iterations (T) and particle Swarm, in which each particle contains c cluster centers. For each particle, we randomly initialize the memberships, the personal best position pbest and the global best position gbest.
2. For(i=0;i<popsize;i++)
3. Evaluate fitness function.
4. Initialize the value of weight factor, ω;
5. while (termination condition is not true)
6. for(i=0;i<popsize;i++)
7. if(f(X[i])>pbesti) pbesti=X[i];
8. Update gbest;
9. Update(Position X[i], Velocity V[i]);
10. Evaluate f(X[i]);
11. Find the distance matrix between new gbest and original matrix
12. Update Membership
13. endfor
    Endwhile endfor

EXPERIMENTAL RESULTS

The proposed work has been tested on the MRI brain images. The size of the MRI brain image is taken as 256*256. The input image is shown in Fig.1a. The result of segmentation for FCM, FCMACO, FCMPSO is shown in Fig 1 (b-d). The performance of the algorithms are measure using the sensitivity, specificity and accuracy.

(a) (b) (c) (d)

Figure 1 Segmentation results on MRI image (a) Original MRI image (b) segmented MRI brain image using FCM (c) segmented MRI brain image using FCMACO (d) segmented MRI brain image using FCMPSO

The Sensitivity (Se), Specificity (Sp) and Accuracy (acc) for the clustering algorithms are evaluated. The Se, Sp, Acc are derived as shown in the equations (4) – (6)

$$Se = TP/(TP+FN) \quad (4)$$

$$Sp = TP/(TN+FP) \quad (5)$$

$$Acc = TP+TN/(TP+FN+TN+FP) \quad (6)$$

Where, TP-True Positive, FN-False Negative, TN-True Negative, FP-False Positive.

Table I Performance Results of Clustering Methods and Optimization with Clustering Methods

The performance results from Table 1 show that FCMPSO provides sensitivity (Se) of 84.7%, specificity (Sp) of 95.3% and Accuracy (Acc) of 93.1% when compared to FCM and TVFCM, the result of which is shown is the Fig.2.

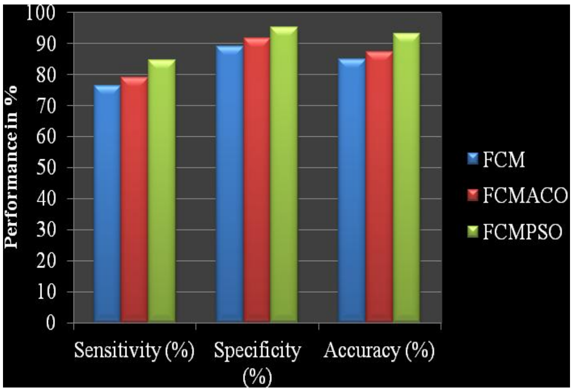

Figure.2 Se, Sp, Acc of FCM, FCMACO, FCMPSO techniques

Conclusion

In this paper, the clustering technique and the optimized clustering are proposed. The proposed methods are measure in terms of performance and shown that FCMPSO algorithm performs better when compared to FCM and FCMACO. -

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Model	Sensitivity (%)	Specificity (%)	Accuracy (%)
FCM	76.5	89	84.8
FCMACO	79	91.6	87.4
FCMPSO	84.7	95.3	93.1