Optimization of Fuzzy C Means with Darwinian Particle Swarm Optimization on MRI Image

A.Murugan, M.Leelavathi, A.P.Shivadharshini, P.Kousalya, B.Gayathridevi

Abstract— **Image segmentation is one of the most important and most difficult low-level image analysis tasks. Automatic target recognition (ATR) often uses segmentation to separate the desired target from the background. Fuzzy c-means (FCM) algorithm is one of the most popular fuzzy clustering techniques because it is efficient, and easy to implement. Fuzzy clustering is a main problem which is the subject of dynamic research in several real world applications. However, FCM is sensitive to initialization and is easily trapped in local optima. In this paper, DPSO is used to escape from local optima and to determine the global optima which are calculated on comparing with single swarm and similar set of swarms, operating on the test problem obtained for PSO**

Index Terms— **Darwinian Particle Swarm Optimization, Fuzzy clustering, Particle Swarm Optimization.**

I. INTRODUCTION

Image segmentation is the method of separating the main objects from background objects and other objects with respect to one or more characteristics. It is mandatory and most difficult low-level image analysis tasks.

Segmentation plays a very important role in medical image processing and it is used in many applications, for instance detection of tumors, detection of the coronary border, measuring tumor volume and its volumetric response to therapy, classification of blood cells, detection of micro calcification on mammograms, surgical planning, heart image extraction from cardiac cine angiograms, etc.

In recent years, many algorithms have been incorporated in MRI segmentation. The most accepted methods are thresholding, region-growing and clustering, Edge detection, and model-based methods. *Thresholding* is one of the most popular segmentation approaches because of its simplicity.

Clustering analysis is frequently used as a vital tool to sort collection of objects into homogeneous groups, which allows discovering similarities and dissimilarities. Clustering is an unsupervised learning strategy that groups related patterns into clusters and can be hard or soft. Soft clustering is supreme as every pixel can be assigned to all clusters with different membership values. The most popular soft clustering methods applied to MR images are fuzzy C-means (FCM) clustering, mixture modeling, and hybrid of both the methods.

A.Murugan, Professor, Department of Electronics And Communication Engineering, Excel College Of Engineering And Technology, Komarapalayam, Namakkal

M.Leelavathi, UG Student, Department of Electronics And Communication Engineering, Excel College Of Engineering And Technology, Komarapalayam, Namakkal

A.P.Shivadharshini, UG Student, Department of Electronics And Communication Engineering, Excel College Of Engineering And Technology, Komarapalayam, Namakkal

P.Kousalya, UG Student, Department of Electronics And Communication Engineering, Excel College Of Engineering And Technology, Komarapalayam, Namakkal

B.Gayathridevi, UG Student, Department of Electronics And Communication Engineering, Excel College Of Engineering And Technology, Komarapalayam, Namakkal

II. FUZZY C-MEANS ALGORITHM

K-means is one of the most accepted hard clustering algorithms which separates the data objects into k clusters where the number of clusters, k, is determined in advance according to the given image. This model is unsuitable for real data sets in which there are no distinct boundaries between the clusters.

After the fuzzy theory launched by LotfiZadeh [1], who situates the fuzzy theory into clustering. Fuzzy algorithms can allocate data object partially to multiple clusters. The degree of membership in the fuzzy clusters depends on the nearness of the data object to the cluster centers.

The most accepted fuzzy clustering algorithm is fuzzy c-means (FCM) which was introduced by Bezdek[2] in 1974 and now it is universally used. Fuzzy c-means clustering is an efficient algorithm; but the random selection in center points makes iterative process diminishing into the local optimal solution easily.

Fuzzy c-means separations set of n objects $p = \{p_1, p_2 \dots p_n\}$ in Rd dimensional space into c $(1 < c < n)$ fuzzy clusters with $o = \{o_1, o_2 \dots, o_c\}$ cluster centers or centroids. The fuzzy clustering of objects is described by a fuzzy matrix μ with n rows and c columns in which n is the number of data objects and c is the number of clusters. μ_{ij}, the element in the i^{th} row and j^{th} column in μ, indicates the degree of association or membership function of the i^{th} object with the j^{th} cluster. The characters of μ are as follows:

$$\mu_{ij} \in [0,1]\ ;\ \forall\, i = 1,2,\dots,n;\ \forall\ j = 1,2,\dots,c \quad (1)$$

$$\sum_{j=1}^{c} \mu_{ij} = 1;\ \ \forall\, i = 1,2,\dots,n \quad (2)$$

$$0 < \sum_{i=0}^{n} \mu_{ij} < n\ ;\forall\, j\ = 1,2,\dots,c \quad (3)$$

The objective function of FCM algorithm is to minimize the Eq. (4):

$$J_m = \sum_{j=1}^{c}\sum_{i=1}^{n} \mu_{ij}^{m}\, d_{ij} \quad (4)$$

Where,

$$d_{ij} = \left\| O_i - Z_j \right\| \quad (5)$$

in which, m $(m>1)$ is a scalar termed the weighting proponent and controls the fuzziness of the ensuing clusters and $\boldsymbol{d_{ij}}$ is the Euclidian distance from object p_i to the cluster center O_j. The O_j, centroid of the j^{th} cluster, is obtained using Eq. (6).

$$O_i = \frac{\sum_{i=1}^{n} \mu_{ij}^{m} \; p_i}{\sum_{i=1}^{n} \mu_{ij}^{m}} \qquad (6)$$

Fuzzy c-means clustering is an effective algorithm, but the random selection in center points makes iterative process falling into the local optimal solution easily. For solving this problem, recently evolutionary algorithms such as genetic algorithm (GA), simulated annealing (SA), ant colony optimization (ACO), and particle swarm optimization (PSO) have been successfully applied.

III. ANT COLONY ALGORITHM

Ant colony method is a system for optimization that was launched in the premature 1990's. Ant (ACO) Colony Optimization is a currently projected meta-heuristic approach for solving hard combinatorial optimization problems. The inspiring source of ACO is communication medium. During the algorithm's affecting to reflect their search experience, the first model of such an algorithm is Ant System (AS). It had the important role of stimulating further research on algorithmic variants obtain much better computational performance, as well as on applications[4] to a large variety of different problems like the quadratic assignment, vehicle routing, sequential ordering, scheduling, routing in Internet-like networks, and so on . Motivated by this success, the ACO meta-heuristic has been projected as a common framework for the existing one application and algorithmic variants. Algorithms which follow the ACO meta-heuristic will be described in the following ACO algorithms. Recent applications of ACO algorithms [5] fall into the two important problem classes of static and dynamic combinatorial optimization problems. Static harms are those whose topology and cost do not modify while the problems are being solved. Differently, in dynamic problems the topology and costs can modify while solutions are built. An example of such a problem is routing in telecommunications networks, in which traffic patterns change all the time. The ACO algorithms for cracking these two classes of problems are very similar from a high-level perspective, but they differ significantly in implementation details.

IV. IMPLEMENTATION OF ACO

Probabilistic technique, searching for optimal path in the graph based on behavior of ants seeking a path among their colony and Source of food. In Meta-heuristic optimization, Ants navigate the shortest path is exposed via pheromone trails. Each ant moves at random Pheromone is dumped on path more pheromone on path raises probability of path being followed. This problem might seem trival to us, but to the certain inferior specious, this considered "Hard".

V. OVER VIEW OF THE SYSTEM

Virtual trail accumulated on path segments. Path preferred at random based on amount of "trail" present, on probable paths from initial node. Ant attained next node, chooses next path that keeps on until reaches starting node. Entire tour is a solution. Tour is examined for optimality. ACO is meta-heuristic three Soft computing techniques for solving hard discrete optimization problems, First major improvement over Ant Systems are Decision Rule - Pseudorandom proportional rule, Local Pheromone Update, Best only offline Pheromone Update. The Ant Colony Optimization is applied over many fields such as Routing in telecommunication networks, Traveling Salesman, Graph Coloring, Scheduling and Constraint Satisfaction. Like Wise, ACO plays a vital role in Optimization Method because of following advantages namely, Inherent parallelism, Positive Feedback accounts for hurried discovery of good Solutions, capable for Traveling Salesman Problem and which can be used in dynamic applications. (Adapts to changes such as new distances, etc)

VI. PARTICLE SWARM OPTIMIZATION

Ant Colony Optimization method contribute some Disadvantages such as Theoretical analysis is difficult compared with other Optimization methods, Sequences of random results (not independent), Probability distribution modifies by iteration, Research is heuristic rather than theoretical, Time to convergence uncertain (but convergence is Guaranteed!).To overcome these problems the Particle Swarm Optimization is widely preferred. An Experimental results show that the PSO image classifier performs better operation than *state-of-the-art* image classifiers (viz, K-means, Fuzzy C-means, K-Harmonic means and Genetic Algorithms) in all measured criteria. The influence of dissimilar values of PSO manage parameters on concert is also established.

OVERVIEW

Particle Swarm Optimization is an evolutionary computation technique developed by Eberheart & Kennedy [6] in 1995 and is based on bird gathering and fish schooling. PSO is a meta-heuristic technique as it makes few assumptions about the problem being optimized and can explore very large spaces of candidate solutions. Its simplicity and faster convergence make it an attractive algorithm to employ. The population is called swarm and the individuals are termed as particles. The word 'swarm' is inspired from pointed faction of particles [7] in the problem region. The particles are implicit to be mass-less and volume-less.

IMPLEMENTATION

The dimension of the problem is dogged by the number of generating units. Then the current position of i^{th} particle can be represented by $P_i = [P_{i1}, P_{i2}, P_{i3} \ldots P_{iN}]$ where Pi belongs to problem space S. The particle flies with the current velocity given by $V = [V_{i1}, V_{i2}, .. V_{iN}]$ which is generated randomly in the range of $[-_{Vjmax,Vmax]}$. The objective function morals are calculated and are set as values of the particles. The best rate, based on individual fitness function is denoting by or the global best value of swarm. New velocity for every dimension in each particle is updated as,

$$V_{ij}^{t+1} = W^{*} V_{ij}^{t} c_1^{*} rand^{*}\left(P_{best} + P_{ij}^{t}\right) + C_2^{*} rand^{*}\left(G_{best} - P_{ti}^{t}\right) \qquad [6]$$

Where w is the weight vector whose value is to be suitably chosen, c_1&c_2 are constants, *rand* is a uniformly circulated arbitrary value between [0 1], t represents iteration and P_{ij}^{t} the current position of the j^{th} dimension in the i^{th} particle. The new particle position is given by

$$P_{new} = P_{old} + V_{new} \qquad [7]$$

When the stopping criteria are satisfied and there is no further improvement in the objective function, the position of the particles represented by gives the optimal *best G* gives the optimal dispatch.

DARWINIAN PARTICLE SWARM OPTIMIZATION (DPSO)

Some of the particular algorithm like PSO could not able to work over many problems at the homogeneous time. Such that the PSO is used to test the solution only in the single swarm, it doesn't have the capability to compare the set of swarms for the analysis which leads to failure in time (*Time-Out*)[8] and restart the algorithm or delete the information obtained in the global optimum hopes that it will not return to it. Angelin [9] executed a type of selection process. Hence, to overcome these problems DPSO is raised.

This DPSO is used to test the solution by comparing all the set of swarms at any instant. It carries out its specific function on each swarm similar to that of PSO which hold on the respected rules of governing the collection of swarms for simulating the natural selection. The collection of swarms [10] is altered constantly which can be done by the selection of swarms through the implementation of the selection process.

IMPLEMENTATION OF DPSO:

Some of the assumption adapted in DPSO is spawning a swarm, favorable adaptation and unfavorable adaptation. The simple ideas are implemented similar to the natural selection. The swarm is taken to the prolonged survive, has more chance of possessing offspring. The swarm will have its exceeded life time to find more fit state like favorable adaptation and in contrast, the life time of swarm is reduced for failing to find fit state like unfavorable adaptation.

ALGORITHM DETAILS IN DPSO:

i. Initialize the appropriate range of particle array element $\bar{Q}_i$ and velocities $\bar{u}_i$.
ii. Allow the particle to traverse at $\bar{u}_i = u_{max}$.
iii. Evolve swarm algorithm, to find new global fitness.
iv. Checks the conditions as follows
   - If m_{min} is decreased, the swarm is deleted. A swarm particle population encircle with $m_{min} < m < m_{max}$.
   - If maximum critical threshold SC_c^{max} exceeds, a particle is detected from the swarm at scheduled time.
v. Collection of swarm is maintained.
vi. Each swarm may spawn a new swarm.

If N_{kill}=0, then a new swarm can able to be produced with the probability of $p = \frac{f}{N_s}$

Where, $f \rightarrow$ uniform random number on [0,1]

$N_s \rightarrow$ Number of swarm

$\frac{1}{N_s} \rightarrow$ To compress number of swarm creation in existence (at large number of swarm)

The main function of reduction in tolerance for stagnation is performed to maintain the collection of swarms which improves in active manner. In order to chosen the value of SC in the reset period at the number of particles got deleted in certain period, the expression is described as follows:

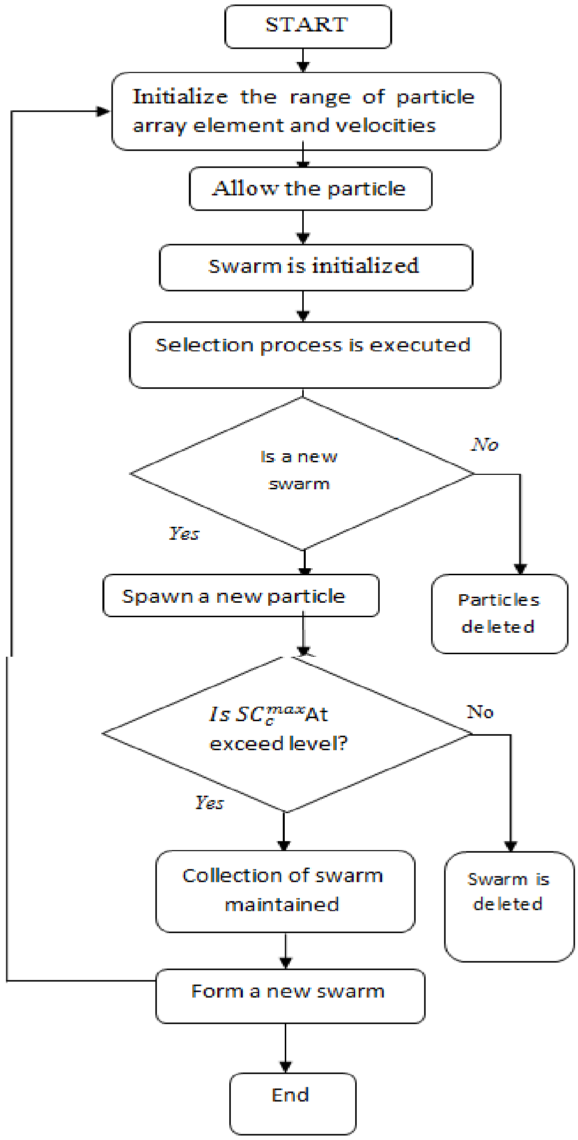
$$SC_c(N_{kill}) = SC_c^{max}\left[1 - \frac{1}{N_{kill} + 1}\right]$$

Where,

$N_{kill} \rightarrow$ Amount of the particle deleted from a swarm over a period in which there is no improvements in fitness.

$SC_c \rightarrow$ Critical threshold of search counter

FLOWCHART:



VII. DISSCUSSION

The main result of the paper is that Darwinian PSO helped get around local optima in the selected experiments. Since this work is preliminary and the algorithm personalized only velocity control, it is our opinion that the result could be improved by mounting the set of possible adaptations. In the upper panel, the algorithm is seen to achieve an on average steady state number of swarms throughout the experiment. In the lower panel, the Darwinian swarms simply peak and then die. It is possible that the Darwinian swarms were not given ample time to search the fitness landscape. Since the number of swarms in the population at any given instant is controlled by, in addition to the fitness landscape, the parameter P introduced adaptation of the parameter P would be beneficial. Since the computing demands of this algorithm are higher than a pre-engineered single swarm algorithm, a high-performance computing platform is desirable. The Darwinian PSO algorithm can be parallelized at two levels. The individual swarms particles could be distributed across a cluster, which is beneficial when the fitness computation is lengthy. Second, the swarms could be distributed as well. The high Computational demands of the algorithm motivated our choice for a lower number of Trials (15 per test function).

SUGGESTION

In this paper we are using ant colony algorithm for optimization and also how it is differentiated from DPSO. Instead of using ant colony algorithm, for beneficial purpose suggested that bee colony algorithm, bacteria colony algorithm, canalized Fuzzy c- means algorithm. It may give the efficient optimized results.

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