An Improved Artificial Fish Swarm Algorithm in Image Segmentation Application

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ABSTRACT
This paper proposes an artificial fish swarm clustering algorithm based on dynamic niche (FSDN), and a dynamic identification of the niches is performed at each generation to automatically evolve the optimal number of clusters as well as the cluster centers of the image data set. The experimental results show that FSDN algorithm has good performance, effectiveness and flexibility.

Categories and Subject Descriptors
I.4.6 Segmentation: pixel classification

General Terms: Algorithms

Keywords: artificial fish swarm algorithm; niching; adaptive strategy; image segmentation

1. INTRODUCTION
Artificial fish swarm algorithm (AFSA) is one kind swarm intelligence optimization algorithm [1]. It is a random and parallel search optimization algorithm based on simulating fish's behaviors. Image segmentation is a first and key step for image analysis. It is a process of partitioning an image into different regions which are mutually non-overlapping. AFSA is suitable for complex problems unsolved by traditional methods. An improved artificial fish algorithm based on dynamic niche is given here.

2. THE OBJECTIVE FUNCTION
With the objective function, the traditional image segmentation problem based on clustering algorithm can be transformed into an extremum questioning process of multi-peak function. The peak number of the objective function is the one of regions to the segmentation problem. The variable values corresponding to the peaks are the regional centers of the segmentation problem.

Let $\mathbf{X} = \{\mathbf{x}_1, \mathbf{x}_2, \cdots, \mathbf{x}_n\}$ be a finite subset of a N-dimensional space, *K* be the number of clusters. Our clustering goal is to find $\mathbf{c}_i$ to maximize the total similarity measure $J_s(\mathbf{z})$ with

$$J_s(\mathbf{z}) = \max \sum_{j=1}^{K} \sum_{i=1}^{n} \left(\exp\left(-\frac{\left\| \mathbf{x}_i - \mathbf{z}_j \right\|^2}{\beta} \right) \right)^{\gamma} \quad (1)$$

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where $\mathbf{z} = (\mathbf{z}_1, \mathbf{z}_2, \cdots, \mathbf{z}_K)$ and β can be defined by

$$\beta = \frac{\sum_{j=1}^{n} \left\| \mathrm{x}_j - \bar{\mathrm{x}} \right\|^2}{n}, \text{ where } \bar{\mathrm{x}} = \frac{\sum_{j=1}^{n} \mathrm{x}_j}{n}$$

According to the analysis of γ, we know that γ can determine the location of peaks in $J_s(\mathbf{z}_j)$. Let $\tilde{J}_s(\mathrm{x}_k)$ be the total similarity of xk to all data points with

$$\tilde{J}_s(\mathrm{x}_k) = \sum_{j=1}^{n} \left(\exp\left(-\frac{\left\| \mathbf{x}_j - \mathbf{x}_k \right\|^2}{\beta} \right) \right)^{\gamma}, k = 1, 2, \cdots, n \quad (2)$$

This function can be seen closely related to the density shape of the data points in the neighborhood of x_k. A large value for $\tilde{J}_s(\mathrm{x}_k)$ means that x_k is close to some cluster centers and has many data points around it. A good estimation of γ can give a good estimation of the peak of $\tilde{J}_s(\mathrm{x}_k)$. The CCA algorithm [10] is used to estimate γ. After getting the estimation of γ, $\tilde{J}_s(\mathrm{x}_k)$ becomes a multimodal function, and the number of peaks is equal to the number of clusters.

3. THE FSDN ALGORITHM
3.1 Description of the Algorithm
Each chromosome represents one cluster center and is evaluated by using the fitness function described in Section 2. The niches are identified by the dynamic niche algorithm at each generation and the most fit niche masters are conserved. The individuals are evolved through prey behavior, swarm behavior or follow behavior. The process terminates after some number of generations, fixed either by the user or determined dynamically by the program itself, and the niche masters obtained are taken to be the solutions. The algorithm is as follows: 1) Initialize a group of artificial fishes with size of *P*. 2) Evaluate the food concentration of each artificial fish. 3) Apply the dynamic niching algorithm and apply the species conservation. Copy the conserved masters in a separate location. 4) If the termination condition is not reached, go to Step 5. Otherwise, select the conserved masters from the population as the final cluster centers. 5) Apply the follow behavior, swarm behavior and prey behavior. 6) Evaluate the newly generated candidates. 7) Go back to Step 3.

3.2 Individual Representation
Here, real-valued representation is used. An AF corresponds to a cluster center. Each AF is described by a sequence of *M* real-

valued numbers where M is the dimension of the feature space. That is to say, the AF of the algorithm is written as

$$c = [c_1, c_2, \cdots, c_M] \quad (3)$$

An initial fish swarm of size P for FSDN algorithm is usually chosen at random. In this paper, P points are randomly selected from the data set but on the condition that there are no identical points to initialize the P fishes.

3.3 BEHAVIORS OF AFSA

The basic idea of AFSA is to imitate the fish behaviors such as praying, swarming and following behaviors with local searching of individual fish for reaching the global optimum. The AF can be expressed as the state vector $\mathbf{X} = \{x_1, x_2, \cdots, x_M\}$, where M is the dimension of the feature space. AF food concentration on the current location is expressed as $y = f(X)$, where $f(X)$ is the objective function. *Visual* and *Step* are stand the visual distance of AF and the distance that the AF can mover for each step, respectively. δ is the crowded degree factor and N is the number of AF. The typical behaviors are given in the ref.1.

3.4 Adaptive Dynamic Niche

In order to preserve the population diversity which prevents AFS being trapped by a single local optimum, a dynamic niche with species conservation method is proposed and is presented in Tab I.

TABLE I. THE DYNAMIC NICHING ALGORITHM

Input: Pop_t the AF at generation t; σ, the niche radius; P, the size of fish population.
Sort the current population according to their fitness. $u(t) = 0$ (the number of niche master candidates) $v(t) = 0$ (the number of true niche master)

For i = 1 to P do
If the i th individual is not marked then
$u(t) = u(t) + 1$
$N(u(t)) = 1$ (number of individuals in the $u(t)$ th niche candidate)
For $j = i + 1$ to P do
If ($d(i, j) < \sigma$) and ($u(t)$ th individual not marked)
insert the j th individual into the $u(t)$ th niche
$N(u(t)) = N(u(t)) + 1$
End If
End For
If ($N(u(t)) > 1$)
$v(t) = v(t) + 1$
End If
End If
End For

After the dynamic identification of the niches of the Pop_t, the individuals belonging to the same niche can be defined as a subset $S_t^i \neq \emptyset$ in Pop_t which have a distance from the master less than the niche radius and do not belong to other niches. The single individual in the subset is considered as an isolated individual and all the isolated individuals form the subset S_t^*. Then, the population Pop_t is partitioned into $v(t)$ populations as $S_t^1, S_t^2, \ldots, S_t^{v(t)}$, and S_t^* represents the set of all the isolated individuals

$$Pop_t = \left(\bigcup_{i \in \{1,2,\cdots,v(t)\}} S_t^i \right) \cup S_t^* \quad (5)$$

3.5 Fish iterative optimization

Each individual make iterative optimization with the given number of iterations. After each iteration, repeats dynamic niching division, and the individual of real niche representatives is the regional center of the segmentation problem. With the increase of the iterations number, the resulting number of niche accepted is the total areas of the image segmentation. The representing niche individual is the center of the region segmentation.

4. EXPERIMENT RESULTS

We have performed a set of experiments with color images taken from the Berkeley segmentation dataset and the segmentation result obtained through the grouping of the pixels. For the purpose of comparison, we have also executed Fuzzy C-means and K-means on the test images with K is set as the actual number of clusters present in the image. Several statistical validity functions [2] have to be used to evaluate the segmentation results. $F(I)$, F' and $Q(I)$ are used to evaluate the results. Here, the smaller the values of these functions the better the segmentation result should be. The quantitative evaluation on segmentation results are tabulated in Table II. All of the evaluation functions have favored segmentation by the FSDN algorithm by giving relatively small values for these three evaluation functions.

TABLE II. QUANTITATIVE EVALUATION ON SEGMENTATION OF SELECTED IMAGES.

Algorithm	Images	$F(I)$	F'	$Q(I)$
FCM	Plane	0.2115	0.0299	0.06265
	Church	0.0100	0.0028	0.0071
K-means	Plane	0.2283	0.0323	0.6769
	Church	0.3018	0.0523	0.6863
FSDN	Plane	0.0032	0.0005	0.0029
	Church	0.0224	0.0039	0.0265

5. CONCLUSIONS

This paper proposes a dynamic artificial fish swarm clustering algorithm based on niche technology for image segmentation, which has been developed for clustering problem with unknown cluster number. Each chromosome is encoded a center of a cluster by a real-valued vector. The dynamic niching is accomplished without assuming any a priori knowledge on the number of niches.

6. REFERENCES

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