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Image Segmentation Using Glowworm Swarm Optimization for Finding Initial Seed

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Abstract: ***The segmentation is a challenging task in digital image processing. There are various methods available for performing segmentation. Clustering based image segmentation is an important technique in image segmentation scenarios. Under this Expectation-Maximization algorithm (GMM- EM) for image segmentation is taken here for analysis. This algorithm is a popular tool for estimating model parameters, especially mixture models and it is a hill-climbing approach. But Image segmentation using GMM-EM algorithm has several drawbacks, such as local maxima, plateau and ridges. The important drawbacks are local maxima which mean that it is sensitive to initialization. To overcome the problem of local maxima this paper proposes a new Glowworm swarm optimization (GSO) algorithm along with EM algorithm. In the initial stage, the GSO is executed for a short period for automatic clustering. The result from the GSO is used as the initial optimal seed of the EM algorithm. Compared to the existing method of segmentation using only with GMM, this paper GSO based EM gives better results with minimum time and errors.***

Keywords: segmentation, EM clustering, GSO

1. Introduction

The goal of segmentation is to simplify and change the representation of an image into something that is more meaningful and easier to analyze and to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics. The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image. Each of the pixels in a region is similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristics. There are various Clustering methods available using clustering concept. Among them model based clustering takes important role.

1.1 Model Based Clustering Algorithm

Model-based clustering uses a model which is often derived by a statistical distribution. Auto Class is the most popular example of this category. In the category of clustering, it belongs to the mixture densities-based clustering as well. In the probabilistic view, data points are assumed to be generated according to probability distributions. Combining it with clustering point of view, each cluster is represented with different probability distributions. The algorithms belonging to this category mostly use expectation-maximization (EM) approach[1,2]. It first initializes the parameters of each cluster. It computes the complete data log-likelihood in e-step and selects new parameters maximizing the likelihood [3] function. Auto Class considers a number of families of probability distributions including Gaussian, Poisson and Bermoulli, for different data types. A Bayesian approach is used in Auto Class to find out the optimal partition of the given data based on the prior probabilities [2].

1.2 E M Algorithm

An Expectation-Maximization (EM) algorithm [1,2] is used for finding maximum likelihood estimates of parameters in probabilistic models, where the model depends on unobserved latent variables. In order to find maximum likelihood estimate it is necessary find probability density function and log likelihood. The EM algorithm is an efficient iterative procedure to compute the Maximum Likelihood (ML) estimate in the presence of missing or hidden data. Each iteration of the EM algorithm consists of two processes:

E-step: In the expectation, or E-step, the missing data are estimated given the observed data and current estimate of the model parameters. This is achieved using the conditional expectation, explaining the choice of terminology.

M-step: In the M-step, the likelihood function is maximized under the assumption that the missing data are known. The estimates of the missing data from the E-step are used in lieu of the actual missing data.

2. Existing Mythology

In analyzing the images [3], accuracy and the result of segmentation become an important factor. According to the input image the accuracy and the result of segmentation to complete the process of segmentation may vary. There are many types segmentation methods are available but here use Expectation-Maximization (EM) algorithm with Gaussian Mixture Models (GMM) based on clustering methods.

The EM (Expectation-Maximization) algorithm is a very popular model based clustering algorithm in many areas of application, in particular for clustering problems, its practical usefulness is often limited by its computational efficiency. In fact, one of the common criticisms of the EM algorithm is, compared to other optimization methods that it converges only at a linear rate. The convergence can be especially slow if the proportion of unobserved to observe information is large. Another drawback [4] of EM is that, every iteration it passes through all of the available data. Thus, if the size of the data is very large, even one single iteration of EM can become computationally intense. Fitting parametric density models such as Gaussian mixture models (GMM) by using the Expectation-Maximization (EM) algorithm can be interpreted as model-based clustering methods where each mixture component is viewed as a cluster. Due to its capability of discovering clusters of arbitrary ellipsoidal shapes, the GMM-EM algorithm is a superior version of k-means. However, as the number of dimensions increases, significant difficulties arise in the estimation of covariance matrices for GMMs. Furthermore, due to their objective of interest being a non-convex optimization problem, k-means and GMM-EM easily get trapped in local minima, and are very sensitive to initializations. The common practice is to run these algorithms many times from different initial values and to employ several local search heuristics.

3. Proposed Methodology

GMM-EM algorithm may converge to a local maximum of the observed data likelihood function, depending on starting values. It is very sensitive to initialization. In order to eliminate local maxima problem of GMM-EM clustering the idea of proposed method using GSO (Glow swarm) Optimization is developed.

3.1 Glowworm Swarm Optimization Clustering Algorithm

Propose **Glowworm Swarm Optimization** (GSO) instead of GMM. In GSO, a swarm of agents are initially randomly distributed in the search space. The agents in GSO [5, 6, 7] are thought of as glowworms that carry a luminescence quantity called luciferin along with them. The glowworms emit a light whose intensity is proportional to the associated luciferin and interact with other agents within a variable neighborhood. The glowworm identifies its neighbors and computes its movements by exploiting an adaptive neighborhood, which is bounded above by its sensor range. Each glowworm selects, using a probabilistic mechanism, a neighbor that has a luciferin value higher than its own and moves toward it. These movements based only on local information and selective neighbor interactions enable the swarm of glowworms to partition into disjoint subgroups that converge on multiple optima of a given multimodal function.

It starts by placing a population of *n* glowworms randomly in the search space so that they are well dispersed. Initially, all the glowworms contain an equal quantity of luciferin l_0. Each iteration consists of a luciferin-update phase followed by a movement phase based on a transition rule. The choice of these parameters has some influence on the performance of the algorithm. In terms of the total number of peaks captured, they suggest the parameter selection as shown in Table 1. Thus, only *n* and r_s need to be selected. These parameters value brings more convenience to people to apply the GSO algorithm.

Table 1: The GSO algorithm parameter selection

Ρ	**Γ**	**Β**	n_t	**S**	l_0
0.4	0.6	0.08	5	0.03	5

GLOWWORM SWARM OPTIMIZATION (GSO) ALGORITHM

Set number of dimensions $= m$
Set number of glowworms $= n$
Let s be the step size
Let $x_i(t)$ be the location of glowworm i at time t
deploy_agents_randomly;
for $i = 1$ to n do $\ell_i(0) = \ell_0$
$r_d^i(0) = r_0$
set maximum iteration number $=$ *iter_max*;
set $t = 1$;
while ($t \leq iter\_max$) do:
{
for each glowworm i do: % Luciferin-update phase
$\ell_i(t) = (1-\rho)\ell_i(t-1) + \gamma J(x_i(t))$;

for each glowworm i do: % Movement-phase
{
$N_i(t) = \{j : d_{ij}(t) < r_d^i(t); \ell_i(t) < \ell_j(t)\}$;
for each glowworm $j \in N_i(t)$ do:
$p_{ij}(t) = \frac{\ell_j(t)-\ell_i(t)}{\sum_{k\in N_i(t)} \ell_k(t)-\ell_i(t)}$;
$j = select\_glowworm(\vec{p})$;
$x_i(t+1) = x_i(t) + s\left(\frac{x_j(t)-x_i(t)}{\|x_j(t)-x_i(t)\|}\right)$
$r_d^i(t+1) = \min\{r_s, \max\{0, r_d^i(t) + \beta(n_t - |N_i(t)|)\}\}$;
}
$t \leftarrow t+1$;
}

3.2 Algorithm Symbolic Description

$X_i(t)$ is the glowworm *i* in *t* iteration location; $l_i(t)$ is the luciferin of the glowworm *i* in *t* iteration; $N_i(t)$ is the neighbourhood set of glowworm *i* in *t* iteration; $r_d^i(t)$ is the dynamic decision domain radius of glowworm *i* in *t* iteration; r_s is the upper bound of the $r_d^i(t)$; p_{ij} (t) is the probability of glowworm *i* selects neighbour *j* ; n_t is the threshold of the number of agents include in the neighbourhood set; ρ is the evaporation rate of luciferin ; γ is the replacement rate of luciferin; β is the rate of change of the neighbourhood range. $J(x_i(t))$represents the value of the objective function at agent *i*'s location at time *t*.

The glowworms encode [8] the fitness of their current locations, evaluated using the objective function into a luciferin value that they broadcast to their neighbors. Enhance the GSO clustering by using the Schwefel Function as the objective function.

$$f(X) = \sum_{i=1}^{n} [-Xi \sin(\sqrt{|Xi|})] \quad \text{---------------(1)}$$

Movement phase:

$$p_{ij}(t) = \frac{\ell_j(t) - \ell_i(t)}{\sum_{k\in N_i(t)} \ell_k(t) - \ell_i(t)}, \quad \text{--------- (2)}$$

p_{ij} (t) is the probability of glowworm *i* selects neighbor *j*
$_i(t)$ is the neighborhood set of glowworm *i* in *t* iteration

$$x_i(t+1) = x_i(t) + s\left(\frac{x_j(t) - x_i(t)}{\left\| x_j(t) - x_i(t) \right\|}\right),$$

--------- (3)

3.3 Hybrid GSO with EM Clustering Algorithm

In the hybrid algorithm, the algorithm includes two segmentation process; the GSO and the EM based on clustering methods. In the initial stage, the GSO is executed for a short period for automatic clustering, forming spherical or close to spherical shape clusters. The result from the GSO is used as the initial seed of the EM algorithm. The EM algorithm will be applied for refining and generating the final result. The hybrid algorithm can be summarized as:

- Start the GSO clustering process until the maximum number of iterations is exceeded;
- Inherit clustering result from GSO as the initial seed of the EM algorithm;
- Start EM process until a stop criterion is met.

4. Results and Discussions

The proposed image segmentation technique is evaluated with the help of a Berkley's image data set. The comparison is carried out with image segmentation using standard GMM-EM, proposes Hybrid GSO +EM and semi supervised GSO+EM.

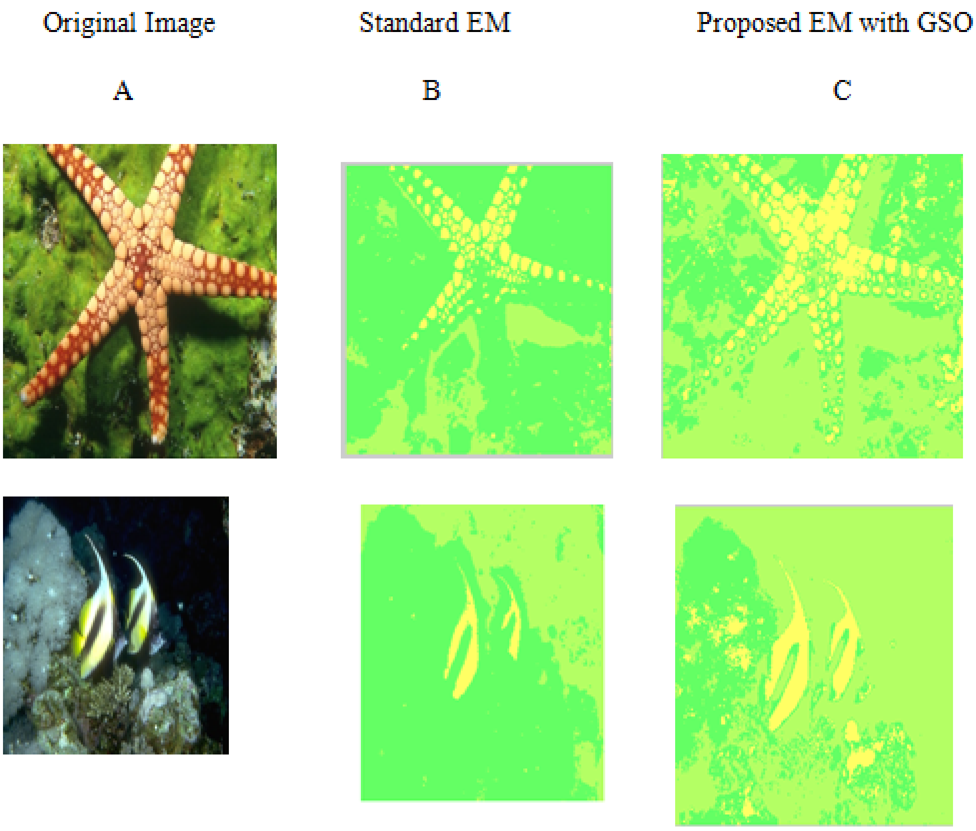

Figure 2: Original Input image

The first column A is the original images. The Colum B represents the result of Segmentation using standard EM algorithm. The column C shows the result segmentation using proposed idea with GSO EM algorithm. From the above figure it can be clearly observed that the GSO with EM algorithm results in better visual clarity (Column C) when compared to Standard EM algorithms (Column B).

4.1 Performance Measurement

The performance of image segmentation is measured by rand index measure and GCE (Global consistency Error). The following measurement is given for one sample image. The ground truth is given.

4.1.1 The Probabilistic Rand Index (PRI)

Rand Index is the function that converts the problem of comparing two partitions with possibly differing number of classes into a problem of computing pair wise label relationships. PRI counts the fraction of pairs of pixels whose labeling are consistent between the computed segmentation and the ground truth, averaging across multiple ground truth segmentations to account for scale variation in human perception. It is a measure that combines the desirable statistical properties of the Rand index with the ability to accommodate refinements appropriately. Since the latter property is relevant primarily when quantifying consistency of image segmentation results. The comparison is shown in figure 3.

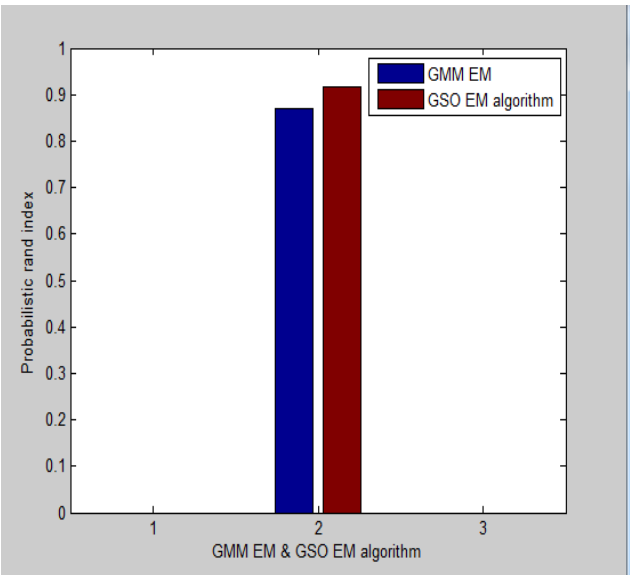

Figure 3: Performance Chart using PRI

4.1.2 Global Consistency Error

The first parameter used for evaluating the proposed segmentation technique is Global Consistency Error (GCE). This measure is a Region-based Segmentation Consistency which is computed to quantify the consistency among image segmentation of various granularities.

The comparison is shown in following Table.

Table 3: Performance Table

Performance	Algorithm	
	GMM-EM	GSO-EM
Probabilistic Rand Index	0.8734	0.9416
Global Consistency Error	1.0000	0.3051

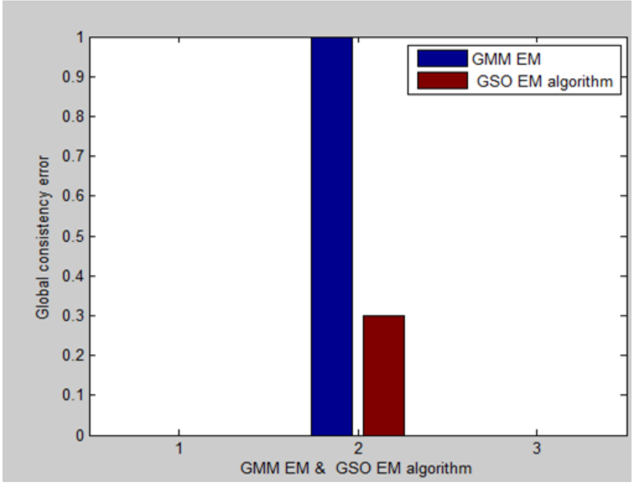

Figure 4: Performance chart using GCE

5. Future Enhancement

The proposed work will be extended for medical images and satellite images. In this analysis the text features are not considered. It will be extended for implementing texture features for finding initial centroids.

6. Conclusion

The standard GMM-EM algorithm may converge to a local maximum, depending on starting values. It is very sensitive to initialization. To overcome this problem the glowworm swarm optimization (GSO) using Schwefel Function along with EM method. This shows that better result when compared to the standard EM.

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