International Journal of Soft Computing and Engineering (IJSCE)
ISSN: 2231-2307, Volume-1, Issue-3, July 2011

Segmentation and Classification using Heuristic HRSPSO

H.S. Behera

***Abstract*—In this paper, a Heuristic Hybrid Rough Set Particle Swarm optimization (HRSPSO) Algorithm is proposed for partitioning a digital image into different segments that is more meaningful and easier to analyze segmentation and Classification. The heuristic HRSPSO algorithm has been implemented with a novel method in MATLAB platform considering 50 iterations and 20 particles. The experimental study and performance evaluation show that Heuristic HRSPSO optimization Algorithm is observed to be having optimal solution with smallest DB (Davies-Bouldin) index and it converges after fifteenth iterations.**

***Index Terms*—Image Processing, Clustering, Image Segmentation, Classification, Davies-Bouldin index, Rough Set, Particle Swarm Optimization, Hybrid Rough Set Theory, Image Pixel Classification, Fuzzy C- Means (FCM).**

I. INTRODUCTION

Image segmentation refers to the process of partitioning a digital image to multiple segments or set of pixels. The goal of segmentation is to simplify the representation of an image into different segments that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries in images. It is also 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. Image segmentation is nothing but the process of dividing an image into disjoint homogenous regions [7]. These regions usually contain similar objects of interest. The homogeneity of the segmented regions can be measured using pixel intensity. Some of the practical applications of image segmentation are Medical Imaging, Locate objects in satellite images (roads, forests, etc.), Face recognition, Fingerprint recognition, Traffic control systems, and Machine vision.

A Several general-purpose algorithms and techniques have been developed for image classification [9]. Since there is no general solution to the image segmentation problem, these techniques often have to be combined with domain knowledge in order to effectively solve an image segmentation problem for a problem domain.

Manuscript received June 13, 2011
H.S. Behera, Faculty in Dept. of Computer Science and Engineering, Veer Surendra Sai University of Technology (VSSUT), Burla, Orissa, India.

(Email: hsbehera_india@yahoo.com).

II. PRELIMINARIES

Clustering can be defined as the optimal partitioning of a given set of n data points into c subgroups, such that data points belonging to the same group are as similar to each other as possible [6]. The data points from two different groups share the maximum difference. Image segmentation is also considered as a clustering problem where the features describing each pixel correspond to a pattern, and each image region corresponds to a cluster. Many clustering algorithms have widely been used to solve the segmentation problem like K-means [6][10], FCM etc. Some hard clustering approaches do not consider overlapping of classes which occur in many practical image segmentation problems.

A. Rough Set Theory (RST)

The rough set theory, pioneered by Pawlak [1] in mid 1980's, has emerged as a promising mathematical tool for extracting knowledge from datasets which contain imperfection, such as noise, unknown values or errors due to inaccurate measuring equipment. Rough set theory plays an important role for discovering patterns in hidden data and thus has extensive applications in data mining task. RST can be considered sets with fuzzy boundaries. Recently it has been emerged as a major mathematical tool for managing uncertainty that arises from granularity in the domain of discourse—that is, from the indiscernibility between objects in a set. The intention is to approximate a rough (imprecise) concept in the domain of discourse by a pair of exact concepts, called the lower and upper approximations. Many different problems can be addressed by RST, with many different areas of research. RST has also been used for knowledge representation and for analyzing attributes dependencies.

B. Hybrid Rough Set Particle Swarm Optimization

Particle swarm optimization (PSO) is a swarm intelligence based algorithm to find a solution to an optimization problem in a search space, or model and predict social behaviour in the presence of objectives. It is a population based stochastic optimization technique developed by Eberhart et. al. [3][5] in 1995, inspired by social behaviour of bird flocking or fish schooling.PSO is similar to a genetic algorithm (GA) in that the system is initialized with a population of random solutions.Compared to GA, the advantages of PSO are that PSO is easy to implement and there are few parameters to adjust. PSO has been successfully applied in many areas: function optimization, artificial neural network training, fuzzy system control, and other areas where GA can be applied. It is unlike a GA, however, in that each potential

solution is also assigned a randomized velocity, and the potential solutions, called particles, are then "flown" through the problem space.

Each particle keeps track of its coordinates in the problem space which are associated with the best solution (fitness) it has achieved so far. This value is called pbest. Another "best" value that is tracked by the global version of the particle swarm optimizer is the overall best value, and its location, obtained so far by any particle in the population. This location is called gbest. The particle swarm optimization concept consists of, at each time step, changing the velocity each particle toward its pbest and gbest locations. Acceleration is weighted by a random term, with separate random numbers being generated for acceleration toward pbest and gbest locations. There is also a local version of PSO in which, in addition to pbest, each particle keeps track of the best solution, called /best, attained within a local topological neighborhood of particles.

The Hybrid Rough Set Particle Swarm Optimization technique [4] has been used for grouping the pixels of an image in its intensity space. Medical and remote sensing satellite images become corrupted with noise very often. Fast and efficient segmentation of such noisy images has remained a challenging problem for many years. In this work, image segmentation is treated as a clustering problem. Each cluster is modeled with a rough set. PSO is employed to tune the threshold and relative importance of upper and lower approximations of the rough sets. Davies–Bouldin [2] clustering validity index is used as the fitness function, which is minimized while arriving at an optimal partitioning.

PSO, which gained huge popularity as a naturally inspired optimization tool [4] in recent times, is used. to tune the threshold, and relative importance of upper and lower approximation parameters of the sets. The Davies–Bouldin[2] clustering validity index is used as the fitness function of the PSO, that is minimized.

The PSO algorithm, as first described by Eberhart and Kennedy [3] is reminiscent of the behavior of flock of birds or the sociological behavior of a group of people. In PSO[4], a population of articles is initialized with random positions:

$$\vec{Z}_i(t) = [\vec{Z}_{i,1}(t), \vec{Z}_{i,2}(t), \dots \vec{Z}_{i,j}(t)]$$

and velocities:

$$\vec{v}_i(t) = [\vec{v}_{i,1}(t), \vec{v}_{i,2}(t), \dots \vec{v}_{i,d}(t)]$$

in d-dimensional space. A fitness function, f is evaluated, using the particle's positional coordinates as input values. Positions and velocities are adjusted, and the function is evaluated with the new coordinates at each time-step. The velocity and position update equations for the pth dimension of the ith particle in the swarm may be given as follows:

$$v_{ip}(t+1) = \omega . v_{ip}(t) + C_1 . \varphi_1 . (P_{lip} - Z_{ip}(t)) + C_2 . \varphi_2 . (P_{gp} - Z_{ip}(t))$$

$$Z_{ip}(t+1) = Z_{ip}(t) + v_{ip}(t+1) \quad (1)$$

The variables Φ1 and Φ2 are random positive numbers, drawn from a uniform distribution, and with an upper limit Φmax, which is a parameter of the system. C1 and C2 are called acceleration constants, and ω is the inertia weight. Pli is the best solution found so far by an individual particle, while Pg represents the fittest particle found so far in the entire community.

C. Rough C-Means Algorithm

In rough c-means (RCM) algorithm, the concept of c-means clustering[10][4] is extended by viewing each cluster as an interval or rough set. A rough set Y is characterized by its lower and upper approximations RL (Y) and RU (Y) respectively. This permits overlaps between clusters. Here an object Xi can be part of at most one lower approximation. If X k Є R1(Y) of cluster Y , then simultaneously X k Є R2(Y) .If Xi is not a part of any lower approximation, then it belongs to two or more upper approximations. Here the cluster center Zi of cluster Ci is computed [4] as:

$$\overrightarrow{Z_i} = w_{low} \frac{\sum_{\vec{X}_k \epsilon R_1(Y)} \vec{X}_k}{|R_1(Y)|} + w_{up} \frac{\sum_{\vec{X}_k \epsilon [R_2(Y) - [R_1(Y)]} \vec{X}_k}{|R_2(Y) - R_1(Y)|}$$

If $R_2(A) - R_1(A) \neq \emptyset$

$$= w_{low} \frac{\sum_{\vec{X}_k \epsilon R_1(Y)} \vec{X}_k}{|R_1(Y)|} \quad (2)$$

where the parameters Wlow and Wup correspond to the relative importance of the lower and upper approximations respectively. Here |R1(Y)| indicates the number of pattern points in the lower approximation of cluster Y, while |R2(Y)-R1(Y)|is the number of elements in the rough boundary lying between the two approximations. In RCM (Rough c-means)[4], a threshold parameter needs special mention. If the difference of distances (Euclidean usually) of an object Xk from two cluster centers Zi and Zj of clusters Ci and Cj respectively, is lesser than some threshold δ, then Xk Є R2(Cj) and Xk Є R2(Ci) and Xk cannot be a member of any lower approximation. Else, Xk Є R1(Cj) such that distance d(Xk,Zi) is minimum over the c clusters.

D. Role of Choice of Parameters on RCM

It is observed that the performance of the algorithm [4] is dependent on the choice of Wlow, Wup and threshold δ. Wlow = 1− Wup , 0.5 < Wlow < 1 and 0 < δ < 0.5 is allowed. It is to be noted that the parameter threshold measures the relative distance of an object Xk from a pair of clusters having centroids Zi and Zj. The smaller the value of threshold, the more likely is Xk to lie within the rough boundary (between upper and lower approximations) of a cluster. This implies that only those points which definitely belong to a cluster (lie close to the centroid) occur within the lower approximation. A large value of threshold implies a relaxation of this criterion, such that more patterns are allowed to belong to any of the lower approximations. The parameter Wlow controls the importance of the objects lying within the lower approximation of a cluster in determining its centroid. A lower Wlow implies a higher Wup, and hence an increased importance of patterns located in the rough boundary of a cluster towards the positioning of its centroid.

E. Tuning the Cluster Validity Index with PSO

In this work a PSO algorithm is proposed to determine the optimal values of the parameters Wlow and δ for each c (number of clusters). For the fitness

function of the PSO, a statistical mathematical function is choosen, also called a cluster validity index, well known as Davies-Bouldin (DB) index [2][4] . This measure is a function of the ratio of the sum of within-cluster scatter to between-cluster separation, and it uses both the clusters and their sample means. Firstly, the within i-th cluster scatter and the between i-th and j-th cluster distance defined as [4] as,

$$S_{i,q} = \left[\frac{1}{N}\sum_{\vec{X}\epsilon C_i}\left\|\vec{X}-\vec{Z}_i\right\|_2^q\right]^{1/q}$$

$$d_{ij,t} = \left\{\sum_{p=1}^{d}|Z_{i,p}-Z_{j,p}|^t\right\}^{1/t} = \left\|\vec{Z}_i-\vec{Z}_j\right\|_t$$

where q, t >= 1, q is an integer and q, t can be selected independently. Ni is the number of elements in the i-th cluster Ci. Next Ri,qt is defined as,

$$R_{i,qt} = max_{j\epsilon K, j\neq i}\left\{\frac{S_{i,q}+S_{j,q}}{d_{ij,t}}\right\}$$

$$DB(c) = \frac{1}{c}\sum_{i=1}^{c}R_{i,qt}$$

Finally, the DB measure defined as,

The smallest DB(c) indicates a valid optimal partition.

III. HERISTIC HRSPSO ALGORITHM

First all the pixels of an input image is treated as as data points. The grey scale intensity of each pixel serves as a single feature. Although the data points are single dimensional, the number of data items is as high as 65, 636 for a 250X250 grey image. Then a Rough C-Means (RCM) algorithm on the image pixel data has run. Parameters of the RCM are evolved by employing a PSO algorithm. We find that this results into an excellent image segmentation algorithm having two advantages. It removes noisy spots and it is less sensitive to noise than other techniques.

A. Steps of the Heuristic HRSPSO Optimization: Algorithm

1. Choose the initial mean Z_i for the clusters.
2. Initialize a population (array) of particles with random positions and velocities on ***d*** dimensions in the problem space.
3. For each particle, evaluate the desired optimization fitness function in d variables.
4. Compare particle's fitness evaluation with particle's pbest. If current value is better than pbest, then set pbest value equal to the current value, and the pbest location equal to the current location in d-dimensional space.
5. Compare fitness evaluation with the population's overall previous best. If current value is better than gbest, then reset gbest to the current particle's array index and value.
6. Change the velocity and position of the particle according to equations **(1)** and *(2)*, respectively:
   a. Yid = Vid + CI * rand0 * *(Pid-xld)* + *cz* * Rand0 * *L& -xid)* (1)
   b. xld= Xid + Vid (2)
7. Loop to step (2) until a criterion is met, usually a sufficiently good fitness or a maximum number of iterations (generations).

B. Pseudo Code

For each particle
  Initialize particle
  END
Do
  For each particle
  Calculate fitness value
  If the fitness value is better than the best fitness value (p_{Best}) in history
    set current value as the new p_{Best}
End
Choose the particle with the best fitness value of all the particles as the g_{Best}
For each particle
  Calculate particle velocity according equation (a)
  Update particle position according equation (b)
End

IV. EXPERIMENTAL STUDY

A. Implementation

The Hybrid Rough Set - PSO algorithm for image pixel classification is implemented. First of all, a noisy image is taken as input and converted into a gray scale image. The image pixels are classified using the K-means clustering algorithm, which gives the initial means and their respective positions in the clusters for the required number of clusters. After obtaining the initial values for the cluster centers, the upper and the lower bounds of each cluster are calculated and the respective cluster centers are upgraded using the Rough C-means algorithm. The threshold parameter (δ) and the other parameters Wlow and Wup are tuned using the Particle Swarm Optimization technique. A statistical mathematical function, called the Davies-Bouldin (DB) index[2] is used as the fitness function of the PSO. Finally, the smallest DB index is obtained which is observed to be the optimal solution. The convergence of the solution is plotted against the number of iterations.

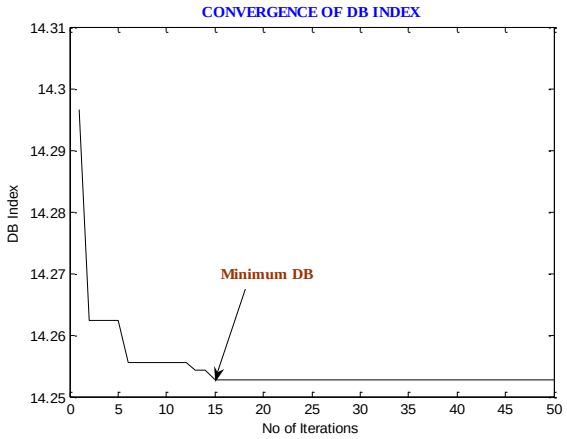
B. Results

No of Iterations = 50. No of Particles = 20.

No. of Iterations	Threshold value(δ)	Parameter w_{low}	Minimum DB Index
1	1.0000e-003	0.6889	$14.2967x10^{-3}$
2	0.0013	0.6389	$14.2623x10^{-3}$
3	0.0050	0.6000	$14.2623x10^{-3}$
4	0.0033	0.6000	$14.2623 x10^{-3}$
5	0.0036	0.6000	$14.2623 x10^{-3}$
6	0.0022	0.6000	$14.2556 x10^{-3}$
7	0.0029	0.6000	$14.2556 x10^{-3}$
8	0.0037	0.6000	$14.2556 x10^{-3}$
9	0.0028	0.6000	$14.2556 x10^{-3}$
10	0.0035	0.6000	$14.2556 x10^{-3}$
11	0.0040	0.6000	$14.2556 x10^{-3}$
12	0.0037	0.6000	$14.2556 x10^{-3}$
13	0.0028	0.6000	$14.2544 x10^{-3}$
14	0.0028	0.6000	$14.2544 x10^{-3}$

15	0.0038	0.6000	14.2527 x10^{-3}
16	0.0038	0.6000	14.2527 x10^{-3}
17	0.0031	0.6000	14.2527 x10^{-3}
18	0.0030	0.6000	14.2527 x10^{-3}
19	0.0030	0.6000	14.2527 x10^{-3}
20	0.0042	0.6000	14.2527 x10^{-3}
21	0.0028	0.6000	14.2527 x10^{-3}
22	0.0037	0.6000	14.2527 x10^{-3}
23	0.0036	0.6000	14.2527 x10^{-3}
24	0.0040	0.6000	14.2527 x10^{-3}
25	0.0029	0.6000	14.2527 x10^{-3}
26	0.0042	0.6000	14.2527 x10^{-3}
27	0.0030	0.6000	14.2527 x10^{-3}
28	0.0036	0.6000	14.2527 x10^{-3}
29	0.0039	0.6000	14.2527 x10^{-3}
30	0.0037	0.6000	14.2527 x10^{-3}
31	0.0035	0.6000	14.2527 x10^{-3}
32	0.0035	0.6000	14.2527 x10^{-3}
33	0.0036	0.6000	14.2527 x10^{-3}
34	0.0035	0.6000	14.2527 x10^{-3}
35	0.0036	0.6000	14.2527 x10^{-3}
36	0.0036	0.6000	14.2527 x10^{-3}
37	0.0036	0.6000	14.2527 x10^{-3}
38	0.0035	0.6000	14.2527 x10^{-3}
39	0.0035	0.6000	14.2527 x10^{-3}
40	0.0035	0.6000	14.2527 x10^{-3}
41	0.0035	0.6000	14.2527 x10^{-3}
42	0.0035	0.6000	14.2527 x10^{-3}
43	0.0035	0.6000	14.2527 x10^{-3}
44	0.0036	0.6000	14.2527 x10^{-3}
45	0.0035	0.6000	14.2527 x10^{-3}
46	0.0035	0.6000	14.2527x10^{-3}
47	0.0035	0.6000	14.2527 x10^{-3}
48	0.0036	0.6000	14.2527 x10^{-3}
49	0.0036	0.6000	14.2527 x10^{-3}
50	0.0036	0.6000	14.2527 x10^{-3}

MINIMUM DB INDEX= 0.0142527≈0.0143



V. CONCLUSION

Comprehensive study has been made on Heuristic HRSPSO algorithm after implementation with considering 50 iteration and 20 particles. The experimental results and performance evaluation show that Heuristic HRSPSO optimization Algorithm is observed to be having good performance and optimal.

VI. ACKNOWLEDGEMENT

I would like to gratefully acknowledge the support of the research work done by Swagatam Das et.al. on particle swarm for image pixel classification.

REFERENCES

[1] Pawlak, Z., Rough Sets, Theoretical Aspects of Reasoning about Data. Kluwer Academic, Dordrecht, 1991.
[2] Davies, D.L., Bouldin, D.W., A cluster separation measure, IEEE Transactions on Pattern Analysis and Machine Intelligence 1, 224–227, 1979.
[3] Eberhart, R. C., Shi, Y.: Particle swarm optimization: Developments, applns and resources, In Proceedings of IEEE International Conference on Evolutionary Computation, vol. 1,81-86, 2001.
[4] Swagatam Das[1], Ajith Abraham[2] and Subir Kumar Sarkar[1] "A Hybrid Rough Particle Swarm Algorithm for Image Pixel Clasification"
[5] Kennedy, J, Eberhart R. Particle swarm optimization, In Proceedings of IEEE International Conference on Neural Networks, (1995) 1942-1948.
[6] Jain, A.K., Murty M.N., and Flynn P.J. (1999): Data Clustering: A Review, ACM Computing Surveys, Vol 31, No. 3, 264-323.
[7] Trivedi M. M, Bezdek J. C, Low-level segmentation of aerial images with fuzzy clustering, IEEE Trans.on Systems, Man and Cybernetics, Volume 16, Issue 4 July, 1986.
[8] L.O. Hall, I.B. Özyurt, J.C. Bezdek, Clustering with a genetically optimized approach, IEEE Trans. Evo Comp. 3 (2)(1999) 103–112.
[9] Bandyopadhyay, S., and Maulik, U., (2002) Genetic clustering for automatic evolution of clusters and application to image classification, Pattern Recognition, 35, 1197-1208.
[10] Lingras, P., West, C., Interval set clustering of Web users with rough k-means. Technical Report No. 2002-002, Department of Mathematics and Computer Science, St. Mary's University, Halifax, Canada, 2002.