Efficient color image segmentation using Multi-Elitist Particle Swarm Optimization Algorithm

K.M.Murugesan† and Dr.S.Palaniswami††,

Anna University,Coimbatore,Tamil Nadu,India

Summary
Image color classification and Image segmentation using comprehensive learning particle swarm optimization (CLPSO) technique was developed by Parag Puranik, Dr. P.R. Bajaj, Prof. P.M. Palsodkar[1],The aim was to produce a fuzzy system for color classification and image segmentation with least number of rules and minimum error rate. In this paper we propose Multi-Elitist Particle Swarm Optimization Algorithm (MEPSO) for Image cluster classification and segmentation. The proposed method is based on a modified version of classical Particle Swarm Optimization (PSO) algorithm, known as the Multi-Elitist PSO (MEPSO) model. It also employs a kernel-induced similarity measure instead of the conventional sum-of-squares distance. Use of the kernel function makes it possible to cluster data that is linearly non-separable in the original input space into homogeneous groups in a transformed high-dimensional feature space. A new particle representation scheme has been adopted for selecting the optimal number of clusters from several possible choices. The MEPSO is used to find optimal fuzzy rules and membership functions. The best fuzzy rule is selected for image segmentation.MEPSO give best rule set than standard PSO.

Key Words:
PSO, MEPSO, Color, Classification, Fuzzy Logic, Image Segmentation, fitness, global best, local best.

I. Introduction

Image segmentation refers to the process of partitioning a digital image into multiple segments (sets of pixels) (Also known as super pixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze.[2] Image segmentation is typically used 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 (see edge detection). Each of the pixels in a region are 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 characteristic(s).[2].
Image segmentation methods are Pixel based segmentation [3], Region based segmentation [4], Edge based segmentation [5 6], Edge and region Hybrid segmentation [7] and Clustering based segmentation [8 9 10]. Color image segmentation using fuzzy classification is a pixel based segmentation method. A pixel is assigned around this circle, a fuzzy membership function can code for a color by giving it a range of hues each with different

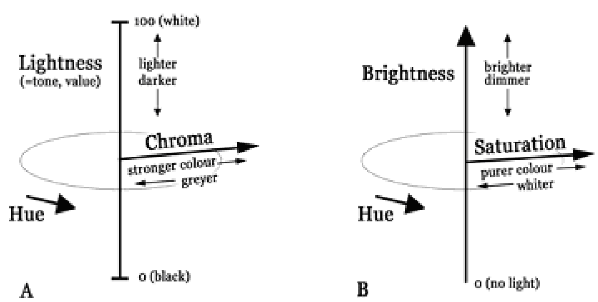

Figure 1 H and S dimensions with Brightness and Lightness

membership value. As an example, H dimension in Fig. 2 is partitioned into ten trapezoidal membership functions each one coding a different color. [2]

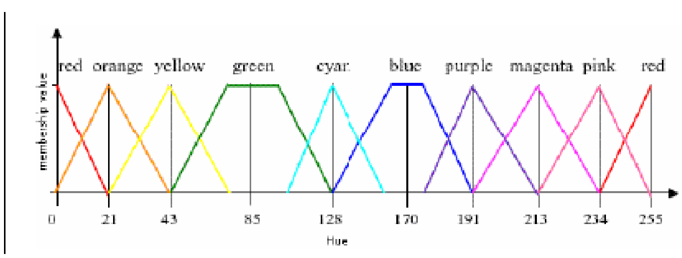

Fig. 2 – Partitioning H dimension with trapezoidal membership function

Trapezoidal membership function showed in Fig. 3 needs four parameters to be specified [2].

Manuscript received March 5, 2010
Manuscript revised March 20, 2010

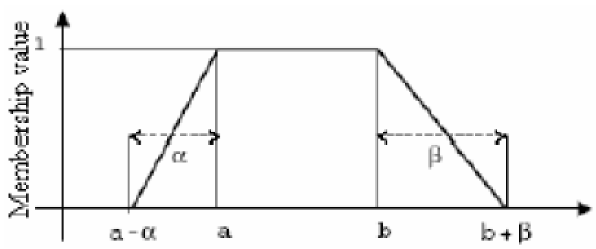

Fig. 3 – Trapezoidal Membership function

To represent two remaining dimensions of a color, because of their less importance for determining a color compared with Hue dimension, each dimension is divided into three parts: weak, medium and strong. Combining these two dimensions nine regions for representing a color shown in Fig. 4 are obtained. A two dimensional membership function is then placed on each region. In order to generate two dimensional membership functions, three 1D trapezoidal membership functions is placed over each dimension and then by multiplying these functions a set of nine 2D membership functions is generated. Fig. 5 illustrates above concept a specific color by the fuzzy system. One approach in designing such a fuzzy system is an expert to look at training data and try to manually develop a set of fuzzy rules.

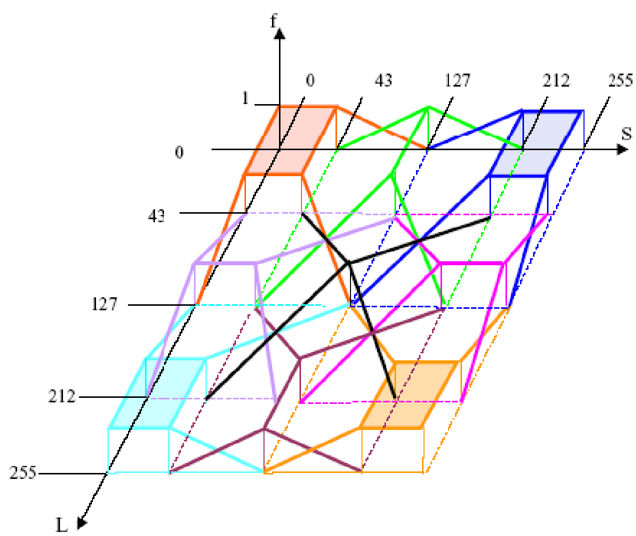

Fig. 4 – Fuzzy Membership on S and L

The PSO is an evolutionary computation technique proposed by Kennedy and Eberhart [12,13]. Its development was based on observations of the social behavior of animals such as bird flocking, fish schooling, and swarm theory. Like the GA, the PSO is initialized with a population of random solutions. It also requires only the information about the fitness values of the individuals in the population. This differs from many optimization methods requiring the derivation information or the complete knowledge of the problem structure and parameter. Compared with the GA, the PSO has memory so that the information of good solutions is retained by all individuals.

Furthermore, it has constructive cooperation between individuals, individuals in the population share information between them. In the PSO-based method, each individual is represented to determine a fuzzy classification system. The individual is used to partition the input space so that the rule number and the premise part of the generated fuzzy classification system are determined. Subsequently, the consequent parameters of the corresponding fuzzy system are obtained by the premise fuzzy sets of the generated fuzzy classification system.

The Multi-Elitist particle swarm optimization (MEPSO) technique is used to find optimal fuzzy rules and membership functions. Finally, particle with the highest fitness value is selected as the best set of fuzzy rules for image segmentation

II. PSO Based Fuzzy system

A fuzzy set is fully defined by its membership functions [I1]. For most application, the sets that have to be defined are easily identifiable. However, for other applications they have to be determined by knowledge acquisition from an expert or group of experts. Once the fuzzy sets have been established, one must consider their associated member functions. How best to determine the membership function is the first question that has to be tackled. This paper presents a classification method using fuzzy expert rules (FER) an approach using PSO to adjust the shape of membership functions for the FER.Behavior-based problems aforementioned based on Fuzzy Logic where the fuzzy parameters, e.g. Fuzzy Membership Functions and Fuzzy Rule Bases are tuned by PSO Algorithm (PSOs) known as PSOFuzzy System (PSOFS).

III. Fuzzy Color Classification

Fuzzy color classification is a supervised learning method for segmentation of color images. This method assigns a color class to each pixel of an input image by applying a set of fuzzy rules on it. A set of training image pixels, for which the colors are known, are used to train the fuzzy system.

Different color spaces like HSL, RGB, YIQ, etc. have been suggested in image processing, each suitable for different domains. HSL color space is used because a color in this space is represented in three dimensions: one which codes the color itself (H) and another two which explain details of the color, saturation (S) and lightness (L). As it can be seen in Fig.1, H dimension is shown in a circle with colors occupying a range of degrees around it. Instead of assigning a specific hue value to each color

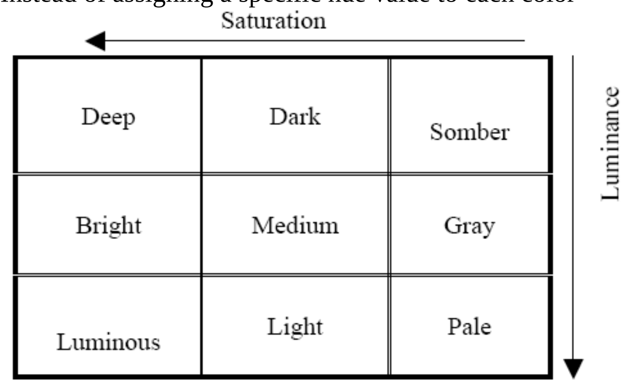

Fig. 5 —Color representation on S and L dimensions

Each fuzzy rule is represented as follows:
j – th rule:
if x_1 is $A_{j1}$and x_2 is A_{j2} and…x_m is A_{jm} then x = (x_1, x_2,…., x_m) belongs to class H_j with CF=CF_j j=1,2,…., R in which R is the number of fuzzy rules, m is the dimensionality of input vector, H j ε {1,2,….,M} is output of the jth rule, M is the number of color classes, CFj ε [0,1] is the certainty factor of jth rule.

IV. Multi-Elitist Particle Swarm Optimization

In linear PSO, the particles tend to fly towards the gbest position found so far for all particles. This social cooperation helps them to discover fairly good solutions rapidly. However, it is exactly this instant social collaboration that makes particles stagnate on local optima and fails to converge at global optimum. Once a new gbest is found, it spreads over particles immediately and so all particles are attracted to this position in the subsequent iterations until another better solution is found. Therefore, the stagnation of PSO is caused by the overall speed diffusion of newly found gbest [14].

In PSO, a population of conceptual 'particles' is initialized with random positions Zi and velocities Vi, and a function f, is evaluated using the particle's positional coordinates as input values. In an n-dimensional search space, $Z_i = (Z_{i1}, Z_{i2}, Z_{i3}, . . . , Z_{in})$ and $V_i =(V_{i1}, V_{i2}, V_{i3}, . . . , V_{in})$: Positions and velocities are adjusted, and the function is evaluated with the new coordinates at each time-step. The basic update equations for the dth dimension of the ith particle in PSO may be given as

$V_{id}(t+1)= ώ.V_{id}(t)+C1.\varphi_1.(P_{lid} - X_{id}(t))+C2\ \varphi_1.(P_{gid} - X_{id}(t))$,

$X_{id}(t+1)= (X_{id}(t)+ V_{id}(t +1)$ -------------(1)

The variables φ_1 and φ_2 are random positive numbers, drawn from a uniform distribution and defined by an upper limit /max, which is a parameter of the system. C1 and C2 are called acceleration coefficients whereas x is called inertia weight. P_l is the local best solution found so far by the ith particle, while P_g represents the positional coordinates of the fittest particle found so far in the entire community or in some neighborhood of the current particle. Once the iterations are terminated, most of the particles are expected to converge to a small radius surrounding the global optima of the search space.

In many occasions, the convergence is premature, especially if the swarm uses a small inertia weight ώ or constriction coefficient. As the global best found early in the searching process may be a poor local minima, Swagatam Das ,Ajith Abraham ,Amit Konar[16] proposed a multi-elitist strategy for searching the global best of the PSO. This new variant of PSO is called (Multi-Elitist Swarm Optimization) MEPSO.

When the fitness value of a particle at the tth iteration is higher than that of a particle at the (t + 1)th iteration, the b will be increased. After the local best of all particles are decided in each generation, the local best is moved, which has higher fitness value than the global best into the candidate area. Then the global best will be replaced by the local best with the highest growth rate b. The elitist concept can prevent the swarm from tending to the global best too early in the searching process. The MEPSO follows the g_best PSO topology in which the entire swarm is treated as a single neighborhood The algorithm steps of MEPSO is as follows:

step1: The fitness value of each particle is got for tth and (t+1) th timestamp

step2: If the fitness value of particle in tth timestep is greater than the fitness value of particle in (t-1)th timestep,then b(t) = j (t -1) + 1;

step3: Repeat step2 until swarm size is N

step4: Update Local best

step5: If the fitness of Local best is greater than the current Global best, then choose Local best of current particle and put into candidate area.

Step6: Calculate b of every candidate, and record the candidate of bmax.

Step7:Update the Global best to become the candidate of b_{max}.

Step8: If the fitness of Local best is not greater than the current Global best, then update the Global best to become the particle of highest fitness value.

Step9: Repeat step1 until t becomes t_{max}.

V. Experimental Studies

The main purpose is to compare the quality of the MEPSO and PSO base image segmentation , where the quality of the segmentations measured according to the quality of segmentation.

We used classification problems to compare the performance of the MEPSO and PSO algorithms. Practical data has been obtained from colored images of Middle Sized RoboCup soccer field. Data has classified into 10 different colors (*red, orange, yellow,green, cyan, blue, purple, magenta* and *pink*). 1200 samples were selected from each color class while 200 samples were randomly selected as test samples and 1000 samples as practical data. Totally, 10000 practical data samples and 2000 test samples have been used for all of the colors.

The system has 3 inputs for each of HSL dimensions. The number of membership functions for H, S&L inputs and one output are 11, 3, 3 and 10, respectively. Algorithm parameters were set as TABLE I.

TABLE I

Parameter Name	Symbol	Initial Value
Population size	L	1000
Number of particle	P	100
Max number of iterations	K	2000

Fig. 6 and Fig 7 illustrate the convergence behavior of the PSO and MEPSO algorithms for the classification problems. The linear PSO algorithm exhibited a faster, but premature convergence to a large quantization error, while the MEPSO had a slower convergence, but to higher quantization error. A fitness function rates for the Optimality of each particle. The particles try to maximize fitness function by cooperative working. This process is continued until either maximum number of iteration is met or average velocity approaches zero.

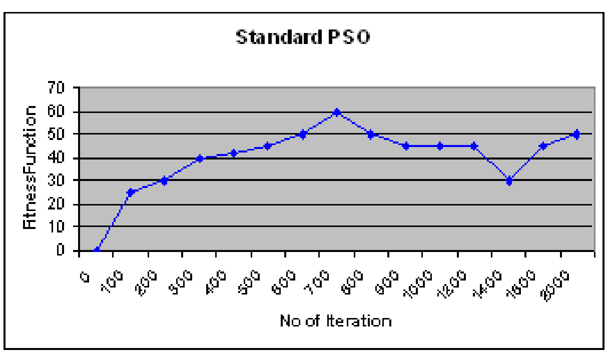

Fig. 6 Algorithms convergence PSO

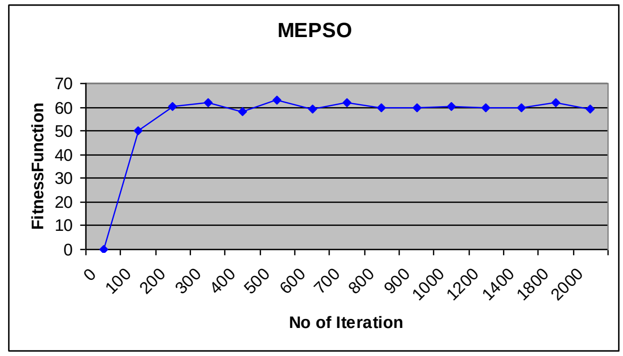

Fig. 7 Algorithms convergence MEPSO

VI. Conclusion and Future Scope

This paper investigated the application of the MEPSO to Image segmentation. The MEPSO algorithm was compared against the PSO clustering algorithm which showed that the MEPSO convergence slower to lower quantization error, while the PSO convergence faster to a large quantization error. Also the proposed MEPSO increases the possibility to find the optimal positions as it decrease the number of failure. Future scope includes applications like computer vision, medical imaging, face recognition, digital libraries and image and video retrieval.

References

[1] Parag Puranik, Dr. P.R. Bajaj, Prof. P.M. Palsodkar, Fuzzy based Color Image Segmentation using Comprehensive Learning Particle Swarm Optimization (CLPSO) – A Design Approach Proceedings of the International MultiConference of Engineers and Computer Scientists 2009 Vol I IMECS 2009, March 18 - 20, 2009, Hong Kong

[2] Linda G. Shapiro and George C. Stockman (2001): “Computer Vision”, pp 279-325, New Jersey, Prentice-Hall, ISBN 0-13-030796-3

[3] G.A. Ru z, P.A. Estévez, and C.A. Perez, “A NeurofuzzyColor Image segmentation Method for Wood SurfaceDefect Detection,” Forest Prod. J. 55 (4), 52-58, 2005.

[4] Moghaddamzadeh and N. Bourbakis, “A Fuzzy Region Growing Approach for Segmentation of Color Images,” Pattern Recognition, 30(6):867-881, 1997.

[5] G.S. Robinson, “Color Edge Detection,” Opt. Eng, 16(5): 479-484, 1977.

[6] J. Canny, “A Computational Approach to Edge Detection,” IEEE Trans. Pattern Anal. Mach. Intell, 8(6): 679-698, 1986.

[7] Shiji and N. Hamada, “Color Image Segmentation Method Using Watershed Algorithm and Contour Information,” Proc. Inter. Conf. on Image Processing,4:305-309, 1999.

[8] B. Zhang, “Generalized K-harmonic Means–boosting in Unsupervised Learning,” Technical report (HPL-2000–137), Hewlett-Packard Labs, 2000.

[9] J. Bezdek, “A Convergence Theorem for the Fuzzy ISODATA Clustering Algorithms,” IEEE Trans Pattern Anal Mach Intell, 2:1-8, 1980.

[10] K. Huang, "A Synergistic Automatic Clustering Technique (Syneract) for Multispectral Image Analysis," Photogrammetric Eng Remote Sens, 1(1):33–40, 200
[11] Chia-Chong Chen,Design of PSO-based Fuzzy Classification Systems, Tamkang Journal of Science and Engineering, Vol. 9, No 1, pp. 63_70 (2006)
[12] Eberhart, R. and Kennedy, J., "A New Optimizer Using Particle Swarm Theory," Proc. Int. Sym. Micro Machine and Human Science, Nagoya Japan, Oct., pp. 39-43 (1995).
[13] Kennedy, J. and Eberhart, R., "Particle Swarm Optimization," Proc. IEEE Int. Conf. Neural Networks, Perth, Australia, pp. 1942_1948 (1995).
[14] El-Desouky N., Ghali N., Zaki M., A New Approach to Weight Variation in Swarm Optimization, proceedings of Al-azhar Engineering, the 9th International Conference, April 12 - 14, 2007.
[15] Jain, A., Murty, M., Flynn, P., Data Clustering: A Review, ACM Computing Surveys, Vol. 31, No. 3, 1999
[16] Swagatam Das , Ajith Abraham, Amit Konar, Automatic kernel clustering with a Multi-Elitist Particle Swarm Optimization Algorithm, Science direct, Pattern Recognition Letters 29 (2008) 688–699

K.M.Murugesan received B.E degree in Electronics and Communication Engineering from University of Madras in 1981 and M.E degree in Applied Electronics from BharathiarUniversity in 1985, He is a Research Scholar of Department of Electrical and Electronics Engineering, Anna, University Coimbatore,Tamil Nadu,India

Dr.S.Palaniswami is working as Registrar in Anna University Coimbatore, Tamil Nadu, India