EFFICIENT COLOUR IMAGE SEGMENTATION USING MULTI-ELITIST- EXPONENTIAL PARTICLE SWARM OPTIMIZATION

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ABSTRACT

Multi-Elitist Particle Swarm Optimization Algorithm (MEPSO) for Image cluster classification and segmentation was proposed in [2]. It 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. This particle representation scheme has been adopted for selecting the optimal number of clusters from several possible choices. In [3] we proposed exponential particle swarm optimization (EPSO). EPSO has a great impact on global and local exploration it is supposed to bring out the search behaviour quickly and intelligently as it avoid the particles from stagnation of local optima by varying inertia weight exponentially, so that the movement of the particles will be faster and distant from each other. The aim of the above two enhanced Particle swarm techniques were to produce a fuzzy system for color classification and image segmentation with least number of rules and minimum error rate. The enhanced PSO techniques are used to find optimal fuzzy rules and membership functions. The best fuzzy rule is selected for image segmentation. The enhanced PSO techniques give best rule set than standard PSO.In this paper we combined both the technique to produce better result than the two individual techniques. We call this PSO as MEEPSO (Multi elitist exponential particle swarm optimization).We implement and evaluate the effectiveness of this new enhanced PSO techniques and prove that the proposed PSO technique is better than existing two enhanced PSO techniques.

Keywords: *PSO, EPSO, MEPSO, MEEPSO, Colour, fitness, Classification, Fuzzy Logic, Image Segmentation, fitness, global best, local best*

1. 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.[4] 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).[4].

Image segmentation methods are Pixel based segmentation [5], Region based segmentation [6], Edge based segmentation [7,8], Edge and region Hybrid segmentation [9] and Clustering based segmentation [10 11 12]. Color image segmentation using fuzzy classification is a pixel based segmentation method. A pixel is assigned 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.

The PSO is an evolutionary computation technique proposed by Kennedy and Eberhart [13,14]. 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 Exponential particle swarm optimization (MEEPSO) 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. The performance of MEEPSO is compared with EPSO and MEPSO.

2. PSO BASED FUZZY SYSTEM

A fuzzy set is fully defined by its membership functions [I5]. 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).

3. 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 around this circle, a fuzzy membership function can code for a color by giving it a range of hues each with different membership value.

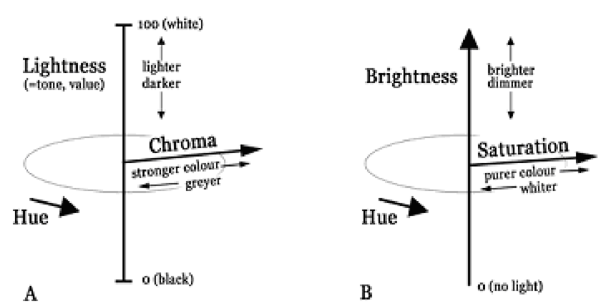

Figure 1 H and S dimensions with Brightness and Lightness

As an example, H dimension in Fig. 2 is partitioned into ten trapezoidal membership functions each one coding a different color [4].

Trapezoidal membership function showed in Fig. 3 needs four parameters to be specified [4].

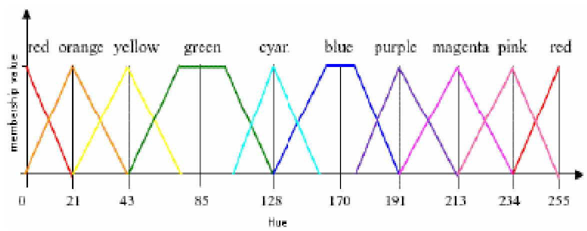

Fig. 2 - Partitioning H dimension with trapezoidal membership function

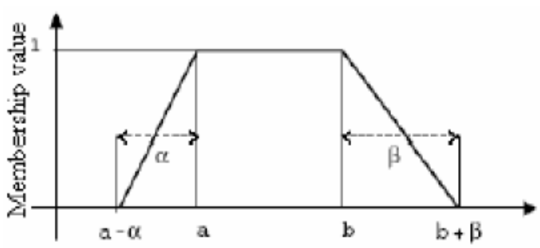

Fig. 3 - Trapezoidal Membership function

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.

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, CF_j ε [0,1] is the certainty factor of jth rule.

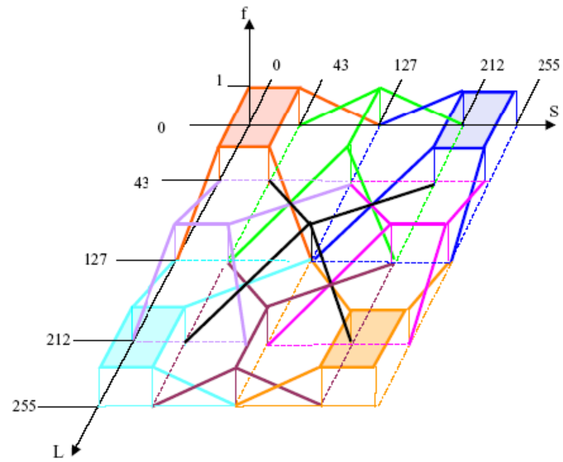

Fig. 4 - Fuzzy Membership on S and L

Saturation

Luminance

Deep	Dark	Somber
Bright	Medium	Gray
Luminous	Light	Pale

Fig.5-Color representation on S and L dimensions

4. EXPONENTIAL 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 [16]. An improvement to original PSO is constituted by the fact that w is not kept constant during execution; rather, starting from a maximal value, it is linearly decremented as the number of iterations increases down to a minimal value [17], initially set to 0.9, decreasing to 0.4 over the first 1500 iterations if the iterations are above 1500, and remaining 0.4 over the remainder of the run according to

w = (w - 0.4) (MAXITER − ITERATION/ MAXITER) + 0.4 -----(1)

MAXITER is the maximum number of iterations, and ITERATION represents the number of iterations.

EPSO has a great impact on global and local exploration it is supposed to bring out the search behavior quickly and intelligently as it avoid the particles from stagnation of local optima by varying this inertia weight exponentially, as given in equation (2), so that the movement of the particles will be more faster and distant from each other.

$w = (w - 0.4)\ e^{(MAXITER-\ ITERATION/\ MAXITER)-1} + 0.4$ ----(2)

5. MULTI-ELITIST PARTICLE SWARM OPTIMIZATION

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[18] 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 gbest 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 t^{th} and $(t+1)^{th}$ timestamp

Step2: If the fitness value of particle in t^{th} 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}.

6. MULTI-ELITISTEXPONENTIAL PARTICLE SWARM OPTIMIZATION

In Multi-Elitist Exponential particle swarm optimization PSO, we combine both the advantages of exponential particle swarm optimization and Multi – Elitist particle swarm. The same Steps of Multi-Elitist PSO is followed. Only new thing is simply adding the features of varying inertia weight exponentially. The elitist concept can prevent the swarm from tending to the global best too early in the searching process. EPSO has a great impact on global and local exploration it is supposed to bring out the search behavior quickly and intelligently as it avoid the particles from stagnation of local optima. So we get great improvement in the performance of Multi-Elitist PSO than the other two enhanced PSO techniques. We will show the performance of MEEPSO in experimental studies section.

7. EXPERIMENTAL STUDIES

The main purpose is to compare the quality of the EPSO, MEPSO and MEEPSO 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 EPSO, MEPSO and MEEPSO 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, Fig 7 and Fig 8 illustrate the convergence behavior of EPSO, MEPSO and MEEPSO algorithms for the classification problems. The linear PSO algorithm exhibited a faster, but premature convergence to a large quantization error, while the EPSO and MEPSO had a slower convergence, but to lower quantization error. MEEPSO is faster, non premature and slower convergence to very lower quantization error than other two algorithms.

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.

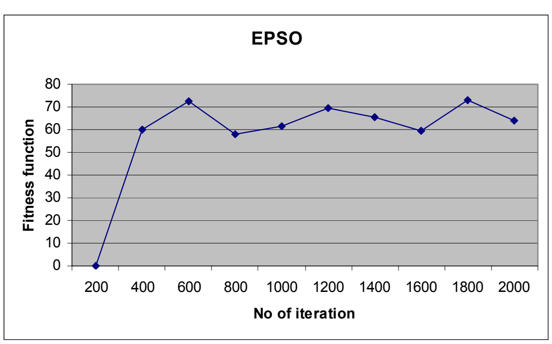

Fig. 6 Algorithms convergence EPSO

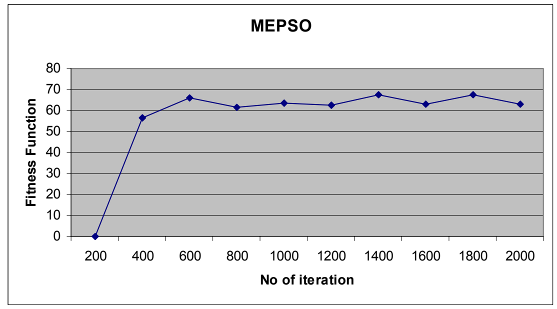

Fig. 7 Algorithms convergence MEPSO

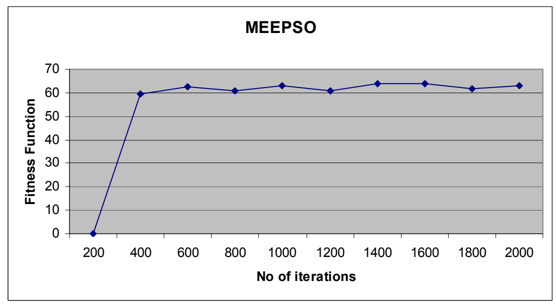

Fig. 8 Algorithms convergence MEEPSO

7. CONCLUSION AND FUTURE SCOPE

This paper investigated the application of the MEEPSO to Image segmentation. The MEEPSO algorithm was compared against the EPSO and MEPSO algorithms which showed that the MEPSO convergence slower to lower quantization error than other two enhanced PSOs, while the standard PSO convergence faster to a large quantization error. Also the proposed MEEPSO 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.

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