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Human Perception-based Color Image Segmentation Using Comprehensive Learning Particle Swarm Optimization

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Abstract. *In computer vision, image processing is any form of signal processing for which the input is an image, such as photographs or frames of videos. The output of image processing can be either an image or a set of characteristics or parameters related to image.The color vision systems require a first step of classifying pixels in a given image into a discrete set of color classes. The aim is to produce a fuzzy system for color classification and image segmentation with least number of rules and minimum error rate. Fuzzy sets are defined on the H, S and L components of the HSL color. Particle swarm optimization algorithm is a recent metaheuristic that has been inspired from social behavior of fishes, bees, birds, etc, that live together in colonies. During the search process, a population member tries to maximize a fitness criterion, which is here high classification rate and small number of rules. Finally, particle with the highest fitness value is selected as the best set of fuzzy rules for image segmentation. In Comprehensive learning, particle Swarm optimization specific weight is assigned to each color for obtaining high classification rate.*
Keywords: CLPSO, Color Classification, Fuzzy Logic, Image Segmentation

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1. **Introduction.** In computer vision, image processing is any form of signal processing for which the input is an image, such as photographs or frames of videos. The output of image processing can be either an image or a set of characteristics or parameters related to image. The image processing involves techniques like image restoration, image enhancement, image segmentation etc.

The image segmentation refers to the process of partitioning an image into multiple segments based on selected image features (sets of pixels). The goal of segmentation is to simplify and change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, it 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 process of partitioning a digital image into multiple regions (set of pixels) is called image segmentation. The partitions are different objects in image which have the same texture or color. The result of the image segmentation is a set of regions that collectively cover the entire image. All 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 characteristics. Some of practical applications of image segmentation are: image processing, computer vision, face recognition, medical imaging, digital libraries, image and video retrieval [2]. Image segmentation methods fall into five categories: Pixel based segmentation [2], Region based segmentation [3], Edge based segmentation [4 5], Edge and region Hybrid segmentation [6] and Clustering based segmentation [7 8 9]. Color image segmentation using fuzzy classification is a pixel based segmentation method. A pixel is assigned a specific color by the fuzzy system, which partitions the color space into segments with linear boundaries. Any given pixel is then classified according to the segments it lies in.

Another common approach is nearest neighbor classification. This method performs a search in a set of predefined classified color samples in order to find the K closest neighbors (usually in terms of Euclidean distance) to any given pixel. The pixel is then classified according to the most popular class among the K neighbors. [14].

Other 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 drawback of this method is that the process becomes very cumbersome and time consuming and also there is no guarantee that produced fuzzy rules are best possible ones. The method is proposed which produces smaller number of fuzzy rules while preserving low error rate. To that aim CLPSO is used to search for a set of fuzzy rules. The paper is organized as follows: in Section 2, fuzzy color classification is explained. An introduction to comprehensive learning particle swarm optimization is illustrated in Section 3. In Section 4, the details of fuzzy color image segmentation using CLPSO is proposed. The experimental setup and results are shown in Section 5. Finally, Conclusions and discussions are provided in Section 6.

2.

2.1. Fuzzy Color Classification.

Fuzzy c o l o r 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. The block diagram is shown in Figure.1

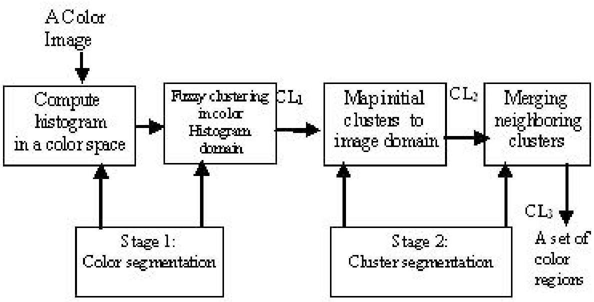

Figure 1. Block Diagram of Color Image Segmentation.

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 illustrated in Figure.2, 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.

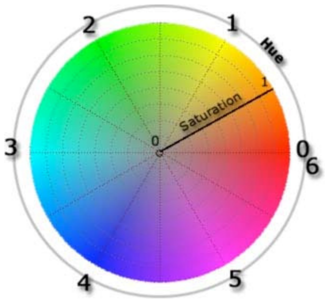

FIGURE 2. H and S dimensions.

In the model presented in this paper there are 10 fuzzy sets for Hue, 5 fuzzy sets for Saturation and 4 fuzzy sets for Luminance. All membership functions are in the form of a triangular function [15].

The fuzzy sets of the antecedent fuzzy variable Hue are defined based on 10 basic hues distributed over the 0 V 255 spectrum. As described in Figure. 3, the hues are Red, Dark Orange, Yellow, Green, Cyan, Blue, Purple, Light Purple, Magenta, Pink.

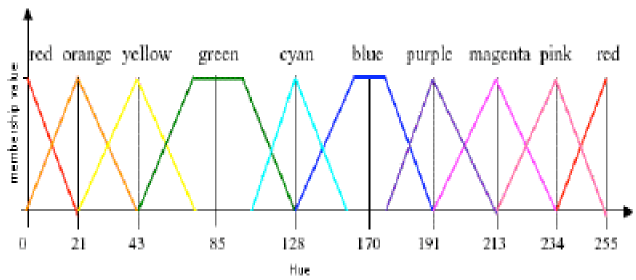

FIGURE 3. Partitioning H dimension with triangular membership function.

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.

Saturation is defined using the five fuzzy sets Somber, Gray, Pale, Dark, Deep as shown in Figure 4.

Lightness is defined using the four fuzzy sets Dark, Medium Dark, Medium Bright and Bright as described in Figure 5.

Combining these two dimensions nine regions for representing a color shown in Figure 6 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. Figure 7 illustrates this concept.

2.2. **Fuzzy Rules.** The fuzzy rules in this model are defined based on human observations. For example, the rule "Dark Orange Pale Luminance -¿ Dark Brown"' is defined

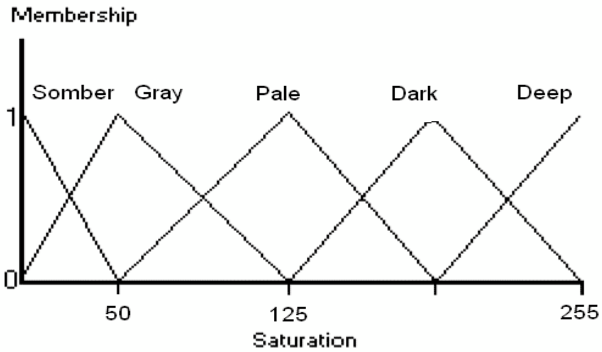

FIGURE 4. Saturation.

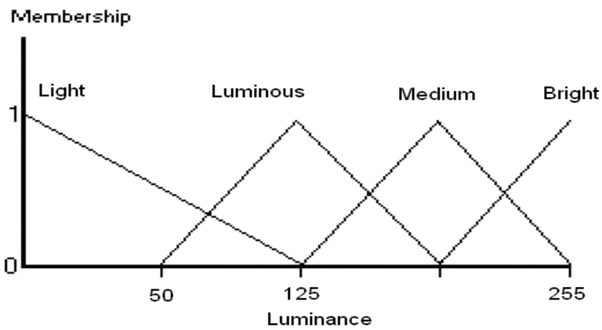

FIGURE 5. Lightness.

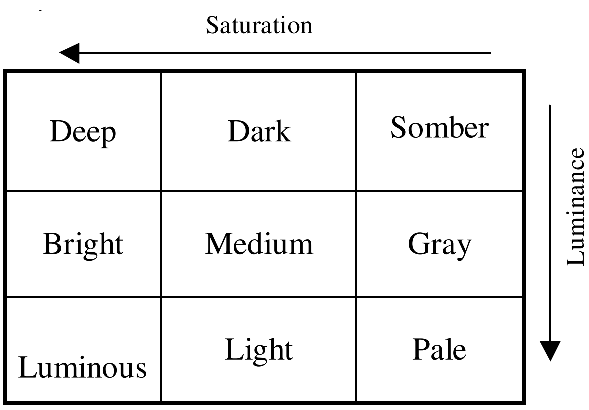

FIGURE 6. Color representation on S and L dimensions.

by manually classifying the color produced by the HSL triple such that the values of H, S and L are the points of maximum of the membership functions associated with the fuzzy sets Dark Orange, Pale and Lightness. Based on the membership functions described in Fig. 3, 4 and 5, in this case the values are H=21, S=125 and L=125.The color produced by this HSL triple would be classified by most human observers as Dark Brown. This corresponds to the natural language human perception-based rule if the hue is Dark Orange, the saturation is Pale and the Lightness is Luminance then the color is Dark Brown. The model has 10 fuzzy sets for Hue, 5 for Saturation and 4 for Lightness; the total number of rules required for this model is 10 x 5 x 4=200.

Each fuzzy rule is represented as follows: If the hue is Dark Orange, the saturation is Pale and the Lightness is Luminance then the color is Dark Brown. Example of set of

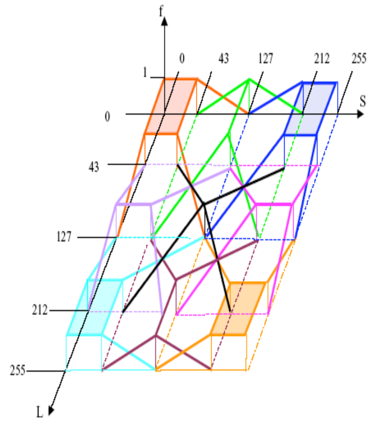

Figure 7. Fuzzy Membership on S and L.

the fuzzy rules include Red Δ Light Δ Deep-→White Red Δ Deep Δ Bright-→Black The above fuzzy rules are treated as j- rules and each jth rule is represented as follows:

j V th rule: if x1 is Aj1and x2 is Aj2 andKxm is Ajm then x = (x1, x2,K., xm) belongs to class Hj with CF=CFj j=1,2,K., R in which R is the number of fuzzy rules, m is the dimensionality of input vector, *H j {1,2,K.,M}* is output of the *j*th rule, M is the number of color classes, *CFj [0,1]* is the certainty factor of *j*th rule.

3. **Comprehensive Learning Particle Swarm Optimization Algorithm.** Particle Swarm Optimization (PSO) algorithm is motivated by social behavior of organisms such as bird flocking and fish schooling [10-11]. PSO as an optimization tool provides a population-based search procedure in which individuals called particles change their position (state) with time. The velocity Vid and Xid position of the ith particle are updated as follows:

$$V_i^d \quad V_i^d + c1 * rand1_i^d * (pbest_i^d - X_i^d) + c2 * rand2_i^d * (gbest_i^d - X_i^d) \tag{1}$$

$$X_i^d \quad X_i^d + V_i^d \tag{2}$$

Where Xi is the position and Vi is the velocity of the particle. pbest is the best previous position yielding the best fitness value for the *i*th particle and gbest is the best position discovered by the whole population. c1 and c2 are the acceleration constants reflecting the weighting of stochastic acceleration terms that pull each particle toward *pbest* and gbest positions respectively [16-17]. rand1_i^d and rand2_i^d are two random numbers in range of (0,1).

In PSO, individuals represent points in the ndimensional search space [12]. A particle represents a potential solution. The velocity *d* is the best position discovered by the whole population. pbest which is the previous best position and *gbest* is the best position positions respectively [13] are chosen Although there are numerous variants for the PSO, premature convergence when solving multimodal problems is still the main deficiency of the PSO. In the original PSO, each particle learns from its *pbest* and *gbest* simultaneously. Restricting the social learning aspect to only the *gbest* makes the original PSO converge fast. However, because all particles in the swarm learn from the *gbest* even if the current *gbest* is far from the global optimum, particles may easily be attracted to the *gbest* region and get trapped in a local optimum if the search environment is complex with numerous local solutions. CLPSO is a novel learning strategy that improves the original PSO, all particles' *pbest* are used to update the velocity of any one particle. CLPSO ensures that the diversity of the swarm is preserved to discourage premature convergence referred to learning probability, which is disadvantage in PSO, t h a t can take different values for different particles. Here the following velocity updating equation is used.[1]

$$V_i^d \qquad * V_i^d + c * rand_i^d * (pbest_i^d - X_i^d) \tag{3}$$

For each dimension of particle i , a random number is generated. If this random number is larger than i, the corresponding dimension will learn from its own *pbest*; otherwise it will learn from another particle's *pbest*. Selection procedure when the particle's dimension learns from another particle's *pbest* as follows:

1) Randomly choose two particles out of the population which excludes the particle whose velocity is updated.
2) Compare the fitness values of these two particles *pbest*s and select the better one.
3) Use the winner's *pbest* as the exemplar to learn from for that dimension. If all exemplars of a particle are its own *pbest*, randomly choose one dimension to learn from another particle's *pbest*'s corresponding dimension [13].

4. **CLPSO Based Fuzzy Classification.** Population P with L particles is represented as a vector to exemplify a fuzzy rule base. The parameter vector consists of the premise parameters of the candidate fuzzy rule. The other parameter include the membership functions of the j-th rule in which the number of input vectors are also coded. The other parameter gbest is used to update and reduce the number of fuzzy rules.

Algorithm:

Step 1) Initialize the CLPSO-based method and general parameters like population size, maximum number of fuzzy rules, maximum number of iterations.
Step 2) Select particle's neighbors.
Step 3) Update *pbest* and *gbest*
Step 4) Update velocity and position of each particle according to equations 1 and 2.
Step 5) Decay Velocities
Step 6) Check Stopping Criteria
Step 7) *Stop*: Report particle with the best fitness value as best rule base.

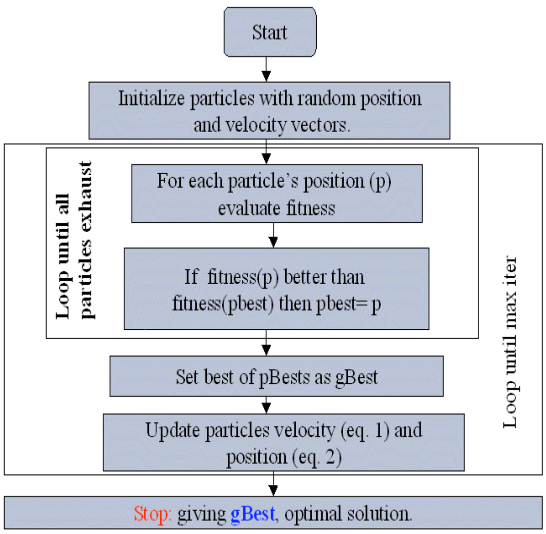

FIGURE 8. Flowchart of selecting pbest and gbest.

5. **Experimental Results.** In this Section, details of the implementation and experimental results are presented. The standard data base images of natural outdoor scenes, terrestrial and aerial views, satellite images are used. The methods tested are threholding based fuzzy logic method and CLPSO based fuzzy method. Figures 8 and 9 shows the original image and its HSL Conversion respectively. Figure 10 shows the segmentation of high intensity colors using Fuzzy CLPSO. Figure 11 shows the extraction of low intensity color. Thus the segmentation and salient region extraction is achieved with CLPSO based fuzzy with less computational time as stated in Table1.

TABLE 1. Comparison of Fuzzy and CLPSO.

Sr.No.	Method	Number of Rules	Execution Time (Sec)
1.	Fuzzy Clustering (Thresholding	200	167.1
2.	CLPSO based Fuzzy	90 (At random) and used 30.	2.125

FIGURE 9. Original Images.

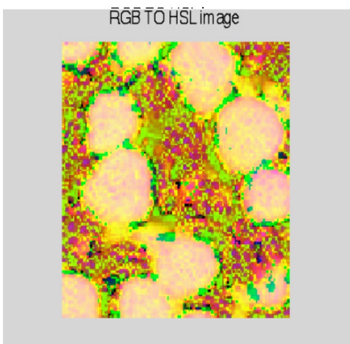

FIGURE 10. RGB to HSL Conversion of Image.

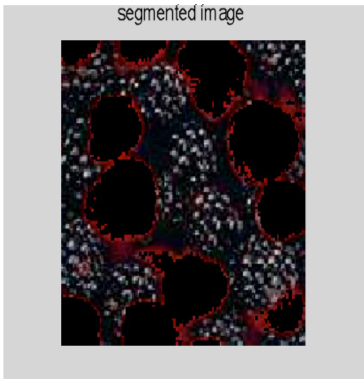

Figure 11. Segmented Image of high intensity.

Figure 12. Segmented Image of low intensity.

6. **Conclusions and Future Work.** A fuzzy logic based method of color segmentation using CLPSO is described. The presented approach aims to model the human perception of colors by using fuzzy logic. Due to the use of fuzzy logic, the clusters are not limited to rectangular or linear segments. A particle of the swarm codes for a set of fuzzy rules. A fitness function rates for the Optimality of each particle. During iterations, particles try to maximize fitness function by cooperatively working on search space. This process is continued until either maximum number of iteration is met or average velocity approaches zero. Finally, the rule base represented by the best particle is used for the task of image segmentation. Because of smaller number of rules generated by this method, it shows higher computation speed. Experimental results suggest that the classification performed by the presented algorithm provides better accuracy than some other basic color classification techniques like FCM and k-means. The knowledge-driven model allows simple modification of the classification based on the needs of a specific application, and the efficiency of the algorithm in terms of computational complexity allows practical use in a variety of real-life applications.

The image segmentation using Fuzzy and Particle swarm optimization should give the result in terms of accuracy in percentage in applications like lane departure warning system, remote sensing, microscopic images, feature.

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