Journal of AI and Data Mining
Vol. 2, No. 2, 2014, 167-179.

Modified CLPSO-based fuzzy classification system: Color image segmentation

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Received 6 August 2014; Accepted 23 December 2014
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Abstract
Fuzzy segmentation is an effective way of segmenting out objects in images containing varying illumination. In this paper, a modified method based on the Comprehensive Learning Particle Swarm Optimization (CLPSO) is proposed for pixel classification in HSI color space by selecting a fuzzy classification system with minimum number of fuzzy rules and minimum number of incorrectly classified patterns. In the CLPSO-based method, each individual of population is considered to automatically generate a fuzzy classification system. Afterwards, an individual member tries to maximize a fitness criterion which is high classification rate and small number of fuzzy rules. To reduce the multidimensional search space for an M-class classification problem, the centroid of each class is calculated and then fixed in membership function of fuzzy system. The performance of the proposed method is evaluated in terms of future classification within the RoboCup soccer environment with spatially varying illumination intensities on the scene. The results present 85.8% accuracy in terms of classification.

Keywords: *Comprehensive Learning Particle Swarm Optimization, Fuzzy Classification, Image Segmentation, Robotics, RoboCup, LUT Generation, Pattern Recognition.*

1. Introduction

The process of partitioning an image into regions is called image segmentation. The result of the image segmentation is a set of regions that cover the image. All of the pixels in a region are similar with respect to some characteristics, such as color, intensity, or texture. Image segmentation methods divided into five categories: pixel based segmentation [1,2], region based segmentation [3], edge based segmentation [4], edge and region hybrid segmentation [5], and clustering based segmentation [4,6,7]. Color image segmentation using fuzzy classification system is a pixel based segmentation method. A pixel is assigned to a specific color by the fuzzy system, which partitions the color space into segments. Any given pixel is then classified according to the segments it lies in.

Fuzzy rule-based systems applied to solve many classification problems. In many of them, fuzzy classification rules are derived from human experts. Because it is not easy to derive fuzzy rules from human experts, many approaches have been proposed to generate fuzzy rules automatically from the training patterns of the main classification problem [1,2,8,9,10,11].

Solving classification problems with high-dimensional pattern spaces has a significant shortcoming, the more the number of fuzzy rules are, the more the number of dimensions are and the learning time is too high. The Particle Swarm Optimizer (PSO) [12,13] is a computational method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality. Although PSO shares many similarities with evolutionary computation techniques, the standard PSO does not use evolution operators such as crossover and mutation.

PSO emulates the swarm behavior of insects, birds flocking, and fish schooling where these swarms search for food in a collaborative manner. Each member in the swarm adapts its search

patterns by learning from its own experience and other members' experiences.
In PSO, a member in the swarm represents a potential solution which is a point in the search space. The global optimum is regarded as the location of food. Each particle has a fitness value and a velocity to adjust its flying direction according to the best experiences of the swarm. The PSO algorithm is easy to implement and has been empirically shown to perform well on many optimization problems [14]. However, it may easily get trapped in a local optimum. In order to improve PSO's performance, we adopt the modified comprehensive learning particle swarm optimizer utilizing a new learning strategy.
In recent years, different methods have been proposed for tuning membership parameters and generating fuzzy rules such as genetic algorithm and PSO. Shamir [15] introduced a human perception based approach to pixel color segmentation using fuzzy systems. Fuzzy sets are defined on the H, S and V components of the HSV color space. The fuzzy rules in this model are defined based on human observations. Tuning fuzzy rules parameters by human expert, significantly affects the classification results and it is a time consuming problem. Marquesan et al. design a color classification system using CLPSO [16]. Image segmentation with the least number of rules and minimum error rate was the main purpose of his work. Enormous search space caused the learning process slow and also his proposed algorithm needed human supervision for defining output color classes. The similar approach using PSO variant algorithm was applied for color image segmentation in [1,2,8,13]. Casillas et al. presented a genetic feature selection process that can be integrated in multistage genetic learning method to obtain fuzzy rule based classification system. It composed a set of comprehensible fuzzy rules with high-classification ability [9]. Yuan et al. designed a fuzzy genetic algorithm to generate classification rules with several techniques such as multi-value logic coding, viability check and composite [10].
Although many color classification methods have been proposed using optimization technique [1,2,8,13,16] and many unsupervised methods for clustering introduced [6,7,17,18,19], no solution have an optimal solution for color image classification to have both high accuracy and time efficiency simultaneously.
In this paper, a modified method based on the Comprehensive Learning Particle Swarm Optimization (CLPSO) is implemented to select an appropriate fuzzy classification system with minimum number of incorrect classified patterns and minimum number of fuzzy rules. In this approach, Centroid of each class is calculated and then fixed in membership function of fuzzy system. As the consequence the search space reduces. Each individual in the population is considered to represent a fuzzy classification system. Then, a fitness function is used to guide the search procedure to select an appropriate fuzzy classification system.
The rest of this paper is organized as follows. Section 2 describes the structure of the fuzzy classification system. Section 3 proposes a modified CLPSO-based method to adjust the fuzzy classification system parameters for pixel classification problem. Section 4 considers classification problems of a humanoid robot vision data to illustrate the learning and the generalization ability of the proposed approach, respectively. Finally, section 5 demonstrates conclusions about the proposed method for solving the classification problem.

2. Fuzzy color classification system

Fuzzy color pixel classification is a supervised learning method for segmentation of color images. In this method, each pixel of an input image assigns to a color class by applying a set of fuzzy rules on it. A set of training pixels, for which the colors class are known, are used to train the fuzzy system.
Figure 1 shows a fuzzy classification system with color pixel on HSI color space as an input. Unlike RGB, HSI separates luminance, from Chroma. This is useful for robustness to lighting changes, or removing shadows.

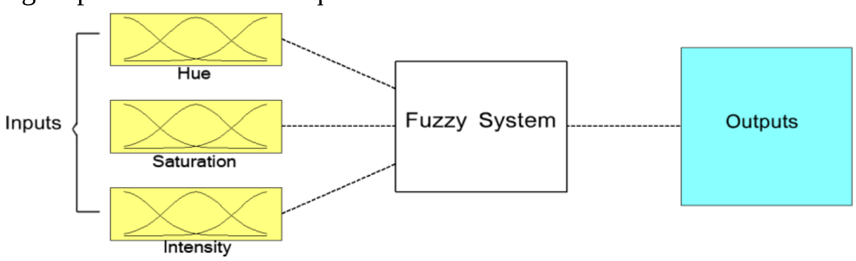


Figure 1. Fuzzy color pixel classification system.

For an M-class classification problem, a rule base of fuzzy classification system considered as follows [12]:

$$\begin{aligned}&\text{jth Rule:}\\&\text{if } x_1 \text{ is } A_{j1} \text{ and } x_2 \text{ is } A_{j2} \text{ and } \dots\\&\text{and } x_m \text{ is } A_{jm}\\&\text{then } \underline{x} = (x_1, x_2, \dots, x_m) \text{ belongs to}\\&\text{class } H_j \text{ with } CF = CF_j \quad j = 1,2,\dots,R\end{aligned} \tag{1}$$

Where R is the number of fuzzy rules and A_{ji} $i = 1,2,\dots,m$, are the premise fuzzy sets of the jth fuzzy rule, $H_j \epsilon \{1,2,\dots,M\}$, is the consequent class output of the jth fuzzy rule, and $CF_j \epsilon [0,1]$ is the grade of certainty of the jth fuzzy rule.

Fuzzy sets are defined on the H, S and I channels with Gaussian membership functions, which are described by (2):

$$\mu_{A_{ji}}(m_{(ji,1)}, m_{(ji,2)}, m_{(ji,3)}; x_i) = \begin{cases} \exp\left(-\left(\frac{x_i - m_{(ji,1)}}{m_{(ji,2)}}\right)^2\right), & \text{if } x_i \le m_{(ji,1)} \\ \exp\left(-\left(\frac{x_i - m_{(ji,1)}}{m_{(ji,3)}}\right)^2\right), & \text{if } x_i > m_{(ji,1)} \end{cases} \tag{2}$$

Where $m_{(ji,1)}$ determines the center position, $m_{(ji,2)}$ and $m_{(ji,3)}$ are the left and right width values of the membership function, respectively. Hence, the shape of membership function is defined by a parameter vector $\underline{m_{ji}} = [m_{(ji,1)}, m_{(ji,2)}, m_{(ji,3)}]$.

The jth rule is determined by a parameter vector $\underline{r}_j = [m_{j1}, m_{j2}, \dots, m_{jM}]$. Also, the set of parameters in the premise part of the rule base is defined as $r = [\underline{r}_1, \underline{r}_2, \dots, \underline{r}_R]$.

According to (1), the set of parameters in the consequent part of the rule is defined as $\underline{a} = [H_1, CF_1, H_2, CF_2, \dots, H_R, CF_R]$. When the input $x = (x_1, x_2, \dots, x_m)$ is given the premise of the jth rule is calculated by the (3).

The class output of the fuzzy classification system with respect to the input x can be determined by (4).

$$q_j(x) = \prod_{i=1}^{M} \mu_{A_{ji}}(x_i) \tag{3}$$

$$y = \arg \max_{j=1} q_j(x). CF_j \tag{4}$$

According to the above description, a fuzzy classification system determines by a set of premise and consequent parameters.

Different parameter sets determine different fuzzy classification systems and so the generated fuzzy classification systems have different performances.

The goal is to find an appropriate fuzzy classification system to have both minimum number of fuzzy rules and maximum number of correct classified pattern.

In the next section, to select an appropriate fuzzy classification system a modified CLPSO is applied.

3. Modified CLPSO-based fuzzy classification system

3.1. Particle swarm optimization

As mentioned before, PSO emulates a swarm behavior and each individual represents some points in the multi-dimensional search space. A particle is a potential solution.

The velocity V_i^d and position X_i^d of the dth dimension of the ith particle are updated as follows:

$$V_i^d \leftarrow V_i^d + c_1 * rand1_i^d * (pbest_i^d - X_i^d) + c_2 * rand2_i^d * (gbest_i^d - X_i^d) \tag{5}$$

$$X_i^d \leftarrow X_i^d + V_i^d \tag{6}$$

Where $X_i = (X_i^1, X_i^2, \dots, X_i^D)$ is the position of the ith particle, $V_i = (V_i^1, V_i^2, \dots, V_i^D)$ represents velocity of ith particle. $pbest_i = (pbest_i^1, pbest_i^2, \dots, pbest_i^D)$ is the best previous position yielding the best fitness value for the ith particle; and $gbest = (gbest^1, gbest^2, \dots, gbest^D)$ is the best position discovered by the whole population.

c_1 and c_2 are the acceleration constants reflecting the weighting of stochastic acceleration in terms that pull each particle toward pbest and gbest positions, respectively. $rand1_i^d$ and $rand2_i^d$ are two random numbers in the interval of [0, 1].

Although there are numerous variants for the PSO, premature convergence for multimodal problems is the main deficiency of the PSO.

In the original PSO, each particle learns from pbest and gbest simultaneously; restricting the social learning aspect to only to gbest, makes the original PSO converge fast.

Since all particles 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.

This matter is critical if the search environment is complex with numerous local solutions.

3.2. Comprehensive learning particle swarm optimization

In the CLPSO, velocity is updated according to (7):

$$V_i^d \leftarrow w * V_i^d + c * rand_i^d * \left(pbest_{fi(d)}^d - X_i^d\right) \quad (7)$$

Where $f_i = [f_i(1), f_i(2), \dots, f_i(D)]$ defines which particles' pbest, the particle i should follow. $\mathrm{pbest}_{\mathrm{fi(d)}}^{\mathrm{d}}$ can be the corresponding dimension of any particle's pbest including its own pbest, and the decision depends on probability P_{c_i}, referred to as the learning probability, which can take different values for different particles.

For each dimension of particle i, a random number is generated. If this random number is larger than P_{c_i}, the corresponding dimension will learn from its own pbest; otherwise, it will learn from another particles' pbest as follows:

1) First two particles randomly choose out of population.
2) The fitness of these two particles pbest are compared and the better one is selected. In CLPSO, the larger the fitness value is, the better the pbest is defined.

3) The winner's pbest is used as the exemplar to learn from that dimension. The details of choosing f_i are given in Figure 2.

4. Proposed modified CLPSO with fuzzy classification system

Training data contains a mapping from HIS color space $\mathbf{S}$ to a set of colors $\mathbf{M}$ which assigns a class label $\mathbf{m_i} \in \mathbf{M}$ to every point $\mathbf{s_j} \in \mathbf{S}$ in color space. If each channel is represented by an n-bit value and k = |M| represents the number of defined class labels, then $\mathbf{S} \rightarrow \mathbf{M}$, where $\mathbf{S} = \{\mathbf{0}, \mathbf{1}, \dots, \mathbf{2^n} - \mathbf{1}\}^{\mathbf{3}}$ **and** $\mathbf{M} = \{\mathbf{m_0}, \mathbf{m_1}, \dots, \mathbf{m_{k-1}}\}$. Assuming we have $\mathbf{M}$ cluster in data set, the centroid of each cluster $\mathbf{C}$ can be determined by the following equation:

$$C_x = \frac{1}{np} \sum_{j=1}^{n_p} s_{xj}, x \in \{H, S, I\} \quad (8)$$

Where n_p is the number of points in training set and s_{xj} represents the value of x-channel of the jth point in the training set. Using the cluster

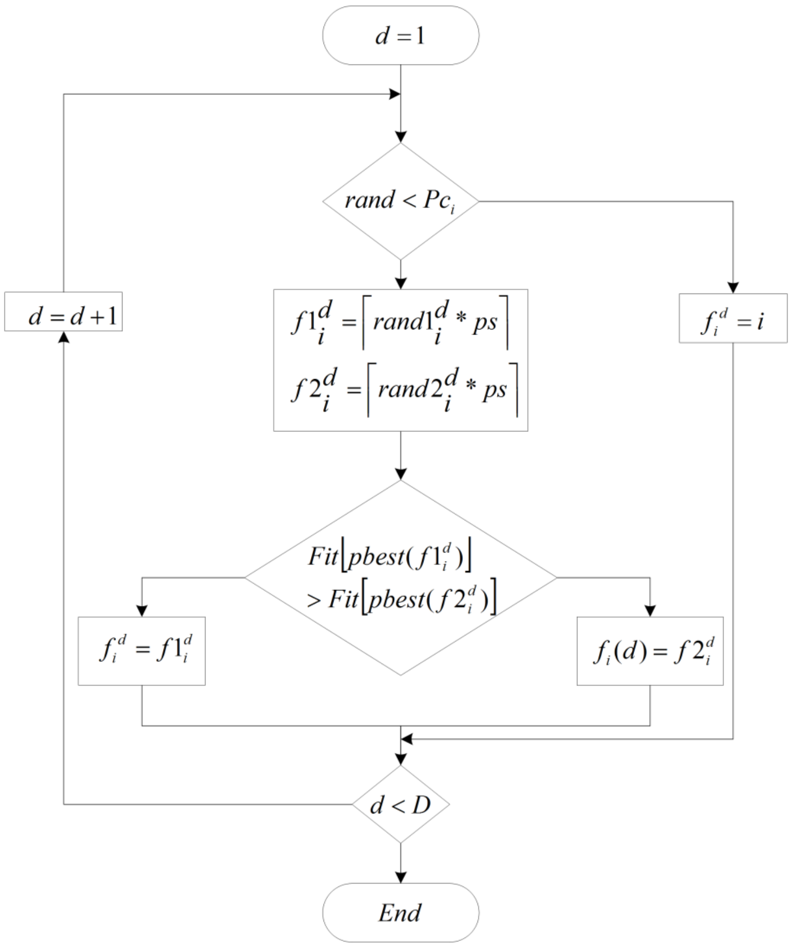


Figure 2. Selection of exemplar dimensions for particle i.

centroids, the center position of the Gaussian membership function of the fuzzy rule system, $m_{(ji,1)}$, can be fixed and therefore, we have a search space reduction. In addition, by having the number of clusters, minimum number of fuzzy rules is calculable and fitness function can be improved.

In the proposed 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.

A set of L individuals, P which is called population is expressed in the following:

$$\begin{bmatrix} \underline{P_1} \\ \underline{P_2} \\ \underline{P_3} \\ \vdots \\ \underline{P_h} \\ \vdots \\ \underline{P_L} \end{bmatrix} = \begin{bmatrix} \underline{r_1} & \underline{g_1} \\ \underline{r_2} & \underline{g_2} \\ \underline{r_3} & \underline{g_3} \\ & \vdots \\ \underline{r_h} & \underline{g_h} \\ & \vdots \\ \underline{r_L} & \underline{g_L} \end{bmatrix} \tag{9}$$

In order to evolutionarily determine the parameters of the fuzzy classification system, the individual $\underline{P_h}$ contains two parameter vectors: $\underline{r_h}$ and $\underline{g_h}$. The parameter vector $\underline{r_h} = [\underline{r_1^h}\ \underline{r_2^h} \cdots \underline{r_j^h} \cdots \underline{r_B^h}]$ consists of the premise parameters of the candidate fuzzy rules, where B is a positive integer to decide the maximum number of fuzzy rules in the rule base generated by the individual $\underline{P_h}$. B is all possible combination of clusters centroid for each channel which is $B = C_H \times C_S \times C_I$ where C_H, C_S, C_I is calculated by Eq.8. Likewise, the minimum number of fuzzy rules is equal to the number of main clusters, which is called Q.

Here, $\underline{r_j^h} = [m_{j1}^h\ m_{j2}^h \dots m_{ji}^h \dots m_{jM}^h]$ is the parameter vector to determine the membership functions of the jth fuzzy rule, where $\underline{m_{ij}^h} = [\underline{m_{(ji,1)}}\ \underline{\quad}_{(ji,2)}\ \underline{\quad}_{(ji,P)}^h]$ is the parameter vector to determine the membership function for the ith input variable.

The parameter vector $\underline{g_h} = [g_1^h\ g_2^h \dots g_j^h \dots g_B^h]$ is used to select the fuzzy rules from the candidate rules $\underline{r_h} = [\underline{r_1^h}\ \underline{r_2^h} \cdots \underline{r_j^h} \cdots \underline{r_B^h}]$ so that the fuzzy rule base is generated. $g_j^h \in [0,1]$ decides whether the jth candidate rule $\underline{r_j^h}$ is added to the rule base of the generated fuzzy system or not. If $g_j^h \geq 0.5$, then the jth candidate rule $\underline{r_j^h}$ is added to the rule base. Consequently, the total number of g_j^h $(j = 1,2,\dots,B)$ whose value is greater than or equal to 0.5 is the number of fuzzy rules in the generated rule base.

In order to generate the rule base, the index j of g_j^h $(j = 1,2,\dots,B)$ whose value is greater than or equal to 0.5 is defined as $I_r^h \in \{1,2,\dots,B\}$, $r = 1,2,\dots,r_h$ where r_h represents the number of the fuzzy rules in the generated rule base. $\{r_{I_1^h}^h, r_{I_2^h}\quad {}_h^h\}$ generates the premise part of the fuzzy rule base which is generated by the individual $\underline{P_h} = [\ \underline{r_h}\ \underline{g_h}]$.

For example, assume that $\underline{r_h}$ and $\underline{g_h}$ are denoted as $[\underline{r_1}\ \underline{r_2}\ \underline{r_3}\ \underline{r_4}\ \underline{r_5}\ \underline{r_6}]$ and $[0.12\ 0.72\ 0.82\ 0.35\ 0.29\ 0.8]$, respectively. According to $\underline{g_h}$, the generated rule base has three fuzzy rules $\{I_1^h, I_2^h, I_3^h\} = \{2,3,6\}$; therefore, $\{\underline{r_2}\ \underline{r_3}\ \underline{r_6}\}$ determines the premise part of the generated rule base.

The rule base of the generated fuzzy classification system is described as follows:

$$\begin{aligned} & rth\ Rule: \\ & if\ x_1 is\ A_{I_r^h 1}^h\ and\ x_2 is\ A_{I_r^h 2}^h\ and \dots \\ & and\ x_m is\ A_{I_r^h m}^h \\ & then\ \underline{x} = (x_1, x_2, \dots, x_m)\ belongs\ to \\ & class\ H_r\ with\ CF = CF_r \quad j = 1,2,\dots,r_h, \end{aligned} \tag{10}$$

Where $A_{I_r^h i}^h$, $i = 1,2,\dots,m$, are the fuzzy sets of the generated rth fuzzy rule. The membership function associated with the fuzzy set is described as follows:

$$\mu_{A_{I_r^h i}^h}\left(m_{(I_r^h i,1)}^h, m_{(I_r^h i,2)}^h, m_{(I_r^h i,3)}^h; x_i\right) = \begin{cases} exp\left(-\left(\dfrac{x_i - m_{(I_r^h i,1)}^h}{m_{(I_r^h i,2)}^h}\right)^2\right), if\ x_i \leq m_{(I_r^h i,1)}^h \\ exp\left(-\left(\dfrac{x_i - m_{(I_r^h i,1)}^h}{m_{(I_r^h i,3)}^h}\right)^2\right), if\ x_i > m_{(I_r^h i,1)}^h \end{cases} \tag{11}$$

Assume that N training patterns $(\underline{x_n}, y_n), n = 1,2,\dots,N$, are gathered from the observation of the considered M-class classification problem, where $\underline{x_n} = (x_{n1}, x_{n2}, \dots, x_{nm})$ is the input vector of the nth training pattern and $y_n \in \{1,2,\dots,M\}$, where M is the total number of classes, is the corresponding class output.

In order to determine the consequent parameters H_r and CF_r of the rth fuzzy rule, a procedure is proposed as follows [1]:

Step1. Calculate θ_t, $t = 1, 2, \dots, M$ for the rth fuzzy rule as follows:

$$\theta_t = \sum_{\underline{x}_p \in Class\ t} q_r(\underline{x}_p), \qquad t = 1,2,\dots,M. \tag{12}$$

Step2. Determine H_r for the rth fuzzy rule by:

$$H_r = arg \max_{t=1}^{M} \theta_t. \tag{13}$$

Step3. Determine the grade of certainty CF_r of the rth fuzzy rule by:

$$CF_r = \frac{\theta_{H_r} - \theta}{\sum_{t=1}^{M} \theta_t} \tag{14}$$

$$\theta = \sum_{\substack{t=1 \\ t \neq H_r}}^{M} \frac{\theta_t}{M-1} \tag{15}$$

In order to construct a fuzzy classification system which has an appropriate number of fuzzy rules and minimize incorrectly classified patterns simultaneously, the fitness function is defined as follows:

$$f_h = fit\left(\underline{p}_h\right) = g_1\left(\underline{p}_h\right) * g_2(\underline{p}_h) \tag{16}$$

$$g_1\left(\underline{p}_h\right) = \text{NCCP} \tag{17}$$

$$g_2\left(\underline{p}_h\right) = \begin{cases} \left(\dfrac{B - r_h}{B - Q}\right) & B \neq Q \\ \left(\dfrac{r_h}{B}\right) & B = Q \end{cases} \tag{18}$$

Where NCCP ($\underline{p}_h$) is the number of correctly classified patterns, r_h is the number of fuzzy rules in the rule base of the generated fuzzy classification system.
The fitness function is designed to maximize the number of correctly classified patterns and minimize the number of fuzzy rules.
In this way, as the fitness function value increases as much as possible, the fuzzy classification system corresponding to the individual will satisfy the desired objective as well as possible.
CLPSO-based method is proposed to find an appropriate individual so that the corresponding fuzzy classification system has the desired performance. The modified proposed procedure is described as follows:

Step1. Initialize the CLPSO-based method.
(a) Set the number of individuals (L), the maximum number of rules (B), the number of generations (K), and the constants for the PSO algorithm (ω_0, ω_1, c).

(b) Generate randomly initial population P. Each individual of the population is expressed as follows:

$$\begin{aligned} &\underline{p}_h = \left[\underline{r}_h\ \ \underline{g}_h\right] \\ &where \\ &\underline{r}_h = [m^h_{(11,1)}\ m^h_{(11,2)}\ m^h_{(11,3)} \cdots \\ &m^h_{(1m,1)}\ m^h_{(1m,2)}\ m^h_{(1m,3)} \cdots \\ &m^h_{(B1,1)}\ m^h_{(B1,2)}\ m^h_{(B1,3)} \cdots \\ &m^h_{(Bm,1)}\ m^h_{(Bm,2)}\ m^h_{(Bm,3)}] \\ &m^h_{(ji,k)}, j \in \{1,2,\dots,B\}, i \in \{1,2,\dots,M\}, \\ &k \in \{1,2,3\} \\ &and \\ &\underline{g}_h = \left[g^h_1\ g^h_2 \dots g^h_j \dots g^h_B\right].m^h_{(ji,k)}, \\ &\ j \in \{1,2,\dots,B\} \end{aligned} \tag{19}$$

$m^h_{(ji,k)}$ is randomly generated as follow:

$$m^h_{(ji,k)} = m^{min}_{(ji,k)} + \left(m^{max}_{(ji,k)} - m^{min}_{(ji,k)}\right) \times rand \tag{20}$$

Where the range of the parameter $m^h_{(ji,k)}$ is defined as $[m^{min}_{(ji,k)}, m^{max}_{(ji,k)}]$ and $rand$ is a uniformly distributed random numbers in [0,1], also g^h_j is randomly generated.

(c) Generate randomly initial velocity vectors $\underline{v}_h$, $h = 1, 2, \dots, L$. Each velocity vector is expressed as follows:

$$\begin{aligned} &\underline{v}_h = \left[\underline{\alpha}_h\ \ \underline{\beta}_h\right] \\ &where \\ &\underline{\alpha}_h = [\alpha^h_{(11,1)}\ \alpha^h_{(11,2)}\ \alpha^h_{(11,3)} \cdots \\ &\alpha^h_{(1m,1)}\ \alpha^h_{(1m,2)}\ \alpha^h_{(1m,3)} \cdots \\ &\alpha^h_{(B1,1)}\ \alpha^h_{(B1,2)}\ \alpha^h_{(B1,3)} \cdots \\ &\alpha^h_{(Bm,1)}\ \alpha^h_{(Bm,2)}\ \alpha^h_{(Bm,3)}] \\ &\alpha^h_{(ji,k)},\ j \in \{1,2,\dots,B\},\ i \in \{1,2,\dots,M\}, \\ &\ k \in \{1,2,3\}\ and \\ &\underline{\beta}_h = [\beta^h_1\ \beta^h_2 \dots \beta^h_B] \end{aligned} \tag{21}$$

$\alpha^h_{(ji,k)}$ is randomly generated as follows:

$$\alpha^h_{(ji,k)} = \frac{\left(\alpha^{max}_{(ji,k)} - \alpha^{min}_{(ji,k)}\right)}{20} \times rand \tag{22}$$

β^h_j is randomly generated as follows:

$$\beta^h_j = \frac{rand}{20} \tag{23}$$

(d) The fitness value for each particle of the population is calculated and saved. It is being noted that to calculate the fitness value, the fuzzy systems of each particle is tested with training data, individually.

Step2. Generate f_i for each particle as in.

Step3. Update the vector $\underline{g_h} = [g_1^h \ g_2^h \dots g_j^h \dots g_B^h]$, as follows:

$$g_{j^*}^h = 1 - g_{j^*}^h, \qquad j^* = rand([1, B]) \tag{24}$$

Where $rand$ generates an integer random number in interval of [1, B].

Step4. Update velocity and position of each particle according to (6 and 7).

Step5. Mutate the population randomly. At any stage an integer random number, called mutation indicator in range of $[1, L]$, is generated.

Particle associated with the selected indicator is selected and its $\underline{g_h}$ vector is replaced by Max-Score vector.

To obtain Max-Score, the total value of all existing rules regardless of $\underline{g_h}$ is achieved using fitness function. Since the fuzzy rules of each cluster is distinctive, the rule with maximum fitness value receives score 1 in Max-Score and the rest of the rules related to the cluster receive score 0. If the particle does not acquire a better fitness value after the mutation, $\underline{g_h}$ will be restored to the previous values before mutation.

Step6. If Max-gen > K then K = K+1 and go to step 2 or it; otherwise stops.

Step7. Based on the individual with the best fitness, the desired fuzzy classification system can be determined.

The flowchart of the modified-CLPSO is given in figure 3.

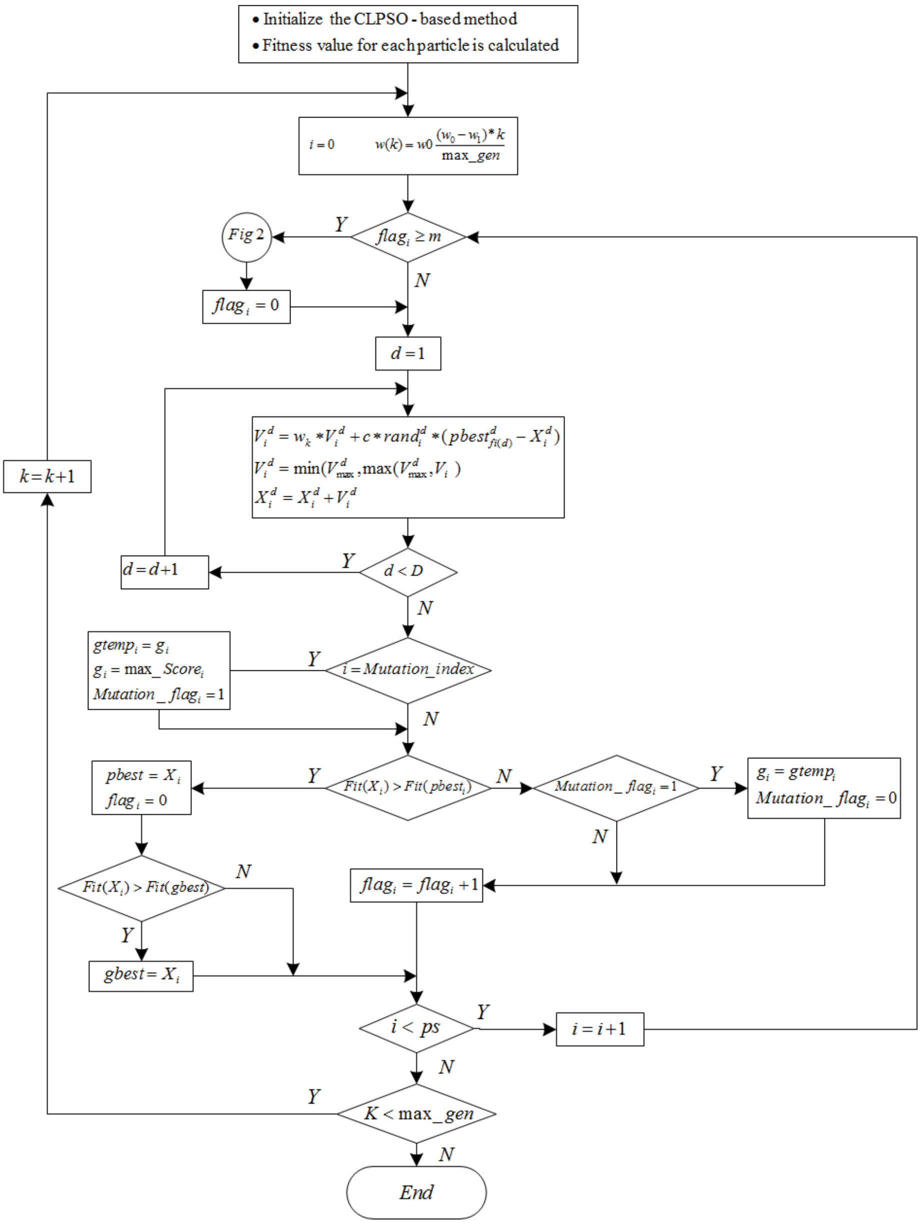


Figure 3. Flowchart of the modified CLPSO.

5. Experimental results

For evaluating the algorithm, one set of images (50 images) was obtained from reference [20] and also we obtain another set (117 images) in varying light condition to measure the robustness of the classifier against the light changes. In providing these images; fluorescent lights and also natural light of ambient without applying any filter were used. A lux-meter with 12 to 12000 lux sensitivity was used and ambient light level for each image was recorded. Light of obtained images was in the range of 100 to 1200 lux.

We implement our scheme on MATLAB R2013 installed on a computer with a Corei7 processor and 8GB RAM. The general parameters of the proposed CLPSO algorithm are listed in Table 1.

Table 1. Proposed method parameters.

Parameters	Symbol	Initialization value
Population size	L	30
Max number of rules	B	$C_{Hn} \times C_{Sn} \times C_{In}$
Min number of rules	Q	Variable
Max number of iterations	K	500
Constants of CLPSO	$(\omega_0, \omega_1, c, m)$	(0.9,0.4,1.49445,4)

For comparison and evaluation of fuzzy classification system, the first set of images was used. After training a fuzzy system with proposed method, its precision was evaluated; table 2 presents the results of this step and Table shows the result of fuzzy pixel classification on 7 samples of data set.

Table 2. Performance of the proposed classification system.

No.	No. of samples	Sensitivity	Specificity	Precision	Accuracy
1	50	0.7312	0.9644	0.6762	0.8582

5.1. Performance of the proposed fuzzy classification system against light changes

To evaluate the robustness of the proposed system against lights changes, set of 117 images in the range of 0 to 1000 lux were used (see Figure 4).

To train the system, a set of pixels in the range of 400 to 700 lux selected and the fuzzy system trained.

Numbers of obtained rules after training were 9 and general precision of classification system was 90%.

Figure 4. Five samples of increasing illumination recorded by lux meter.

To test the system, a set of pixels in the range of 0 to 1000 lux selected and system performance presented in table 4 according to the color and light.

The first column is standard colors defined by RoboCup; the second column is the range of light levels in which the images are taken, the next three columns are the minimum and maximum value of each channel of HSI color space, the result of classification with the proposed fuzzy system is shown in column six, last column shows increase or decrease in classification performance.

As shown in the table 4, in the range of 400 to 700 lux, the lowest classification precision related to green, orange and yellow, respectively.

In the range of 0-400 lux, the most decrease in classification precision related to cyan with 37.92 percent, yellow with 20.62 percent and orange with 7.68 percent, respectively.

In this range, it is noticeable that the classification precision for green color increased to 37.09 percent, because of light levels severely reduced in the range of 0-400 lux which places all the data in the correct class.

In the range of 700-1000 lux, classification precision of yellow, green, blue and cyan reduced to 18.33%, 7.5%, 19.58% and 1.2 %, respectively.

Therefore, the most robust color to the light changes is pink and the most sensitive color to the light changes is green.

The surveying colors according to robustness against the light changes are pink with 100%, blue with 92.63%, cyan with 86.96%, yellow with 84.92%, orange with 81.37% and green with77.35%.

Table 3. Result of fuzzy pixel classification tuned by proposed modified CLPSO algorithm.

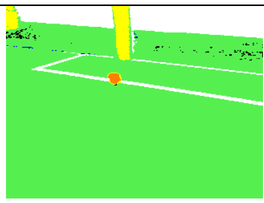
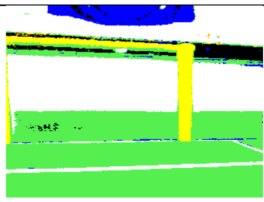
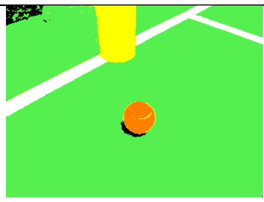
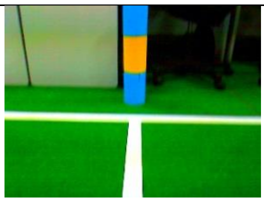
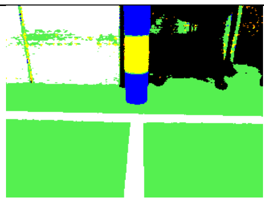
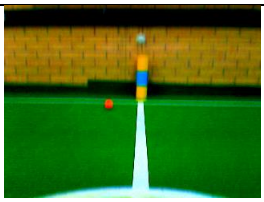
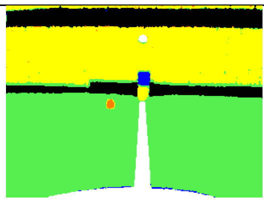
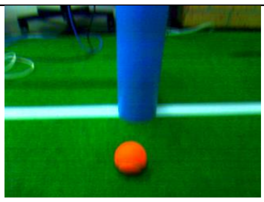
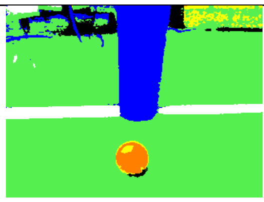
No.	Input Image	Fuzzy pixel classification output image	Sensitivity	Specificity	Precision	Accuracy
1			0.6099	0.9942	0.9562	0.9799
2			0.6044	0.9791	0.8821	0.8866
3			0.7224	0.9904	0.8997	0.9667
4			0.5949	0.9685	0.7217	0.7827
5			0.7229	0.9824	0.8375	0.8870
6			0.6440	0.9761	0.6629	0.8058
7			0.7747	0.9814	0.6821	0.9276

Table 4. The effect of light changes on system performance.

Color	Lux	Hue		Saturation		Intensity		Classification		Performance
		Min	Max	Min	Max	Min	Max	True	False	
Orange	400-0	3.78	19.27	191.56	232.02	120.00	230.00	75.62	24.37	-7.68
	700-400	7.57	30.47	189.01	234.18	140.00	238.00	83.3	16.6	0
	1000-700	15.14	39.77	76.26	230.44	140.00	243.00	85.20	14.79	+1.9
Yellow	400-0	29.30	42.50	154.06	218.51	116.00	226.00	77.29	22.70	-20.62
	700-400	34.99	43.50	190.85	219.71	153.00	234.00	97.91	2.08	0
	1000-700	36.21	43.86	119.22	219.71	180.00	236.00	79.58	20.41	-18.33
Green	400-0	70.26	108.15	130.00	217.00	84.00	171.00	100	0	+37.09
	700-400	79.90	109.51	107.05	221.45	152.00	212.00	62.91	37.09	0
	1000-700	75.65	111.25	95.21	225.32	163.00	235.00	69.16	30.83	-7.5
Blue	400-0	152.86	170.00	138.70	227.06	80.00	166.00	97.5	2.5	-2.5
	700-400	151.41	158.88	140.03	225.45	120.00	173.00	100	0	0
	1000-700	149.10	157.68	99.41	199.27	144.00	223.00	80.41	19.58	-19.58
Cyan	400-0	115.36	136.45	93.95	221.45	106.00	211.00	62.08	37.92	-37.92
	700-400	118.77	132.19	91.15	218.57	158.00	221.00	100	0	0
	1000-700	115.78	133.84	91.15	219.39	171.00	234.00	98.8	1.2	-1.2
Pink	400-0	229.35	251.7	151.17	221.00	73.00	172.00	100	0	0
	700-400	233.75	246.11	138.68	201.45	94.00	195.00	100	0	0
	1000-700	229.96	79.69	79.69	163.36	127.00	231.00	100	0	0

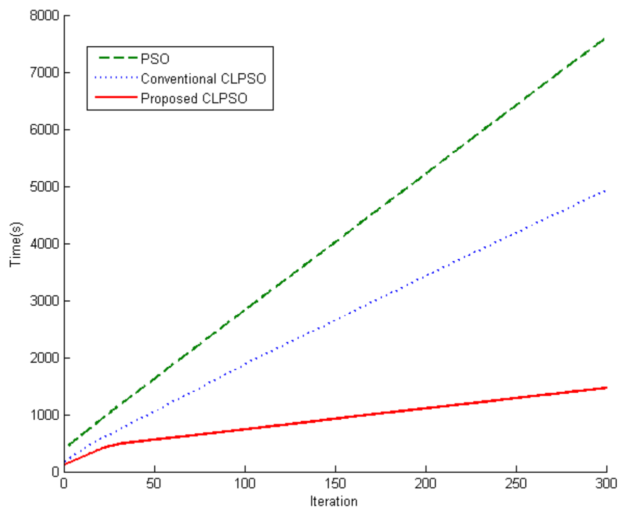


Figure 5. Consumed time graph of PSO, conventional CLPSO and proposed CLPSO methods.

6. Comparison of the proposed segmentation of the algorithm performance with the existing methods

One of the problems related to optimization techniques is that they are time-consuming. The proposed method has a higher speed compared with the conventional methods.
Figure 5 shows the iteration time table. Firstly, it is observed that all three slopes are approximately equal.
Due to iteration 20, mutations in the particles and the reduction of rules cause the decrease in the calculation complexity and the slope graph.
In figure 6, the overall precision of the existing methods is compared. For this comparison, the results of references [20,21,22] have been used.
In all methods, except for the reference method [20], an optimization algorithm is used to adjust the fuzzy classification system.

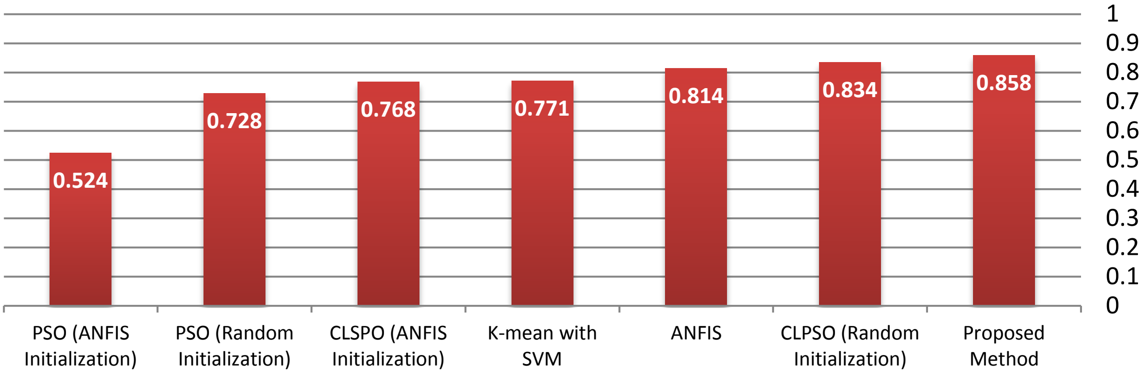


Figure 6. Accuracy of the existing methods.

In all methods, the Gaussian membership function is used, and the goal is to set up a classification system for Robocop competitions.

The main difference of the proposed method with the reference [21] is mainly the modified fitness function and the fixed centroids of the fuzzy membership function.

In [20], the overall precision of classification was not presented and the precision of positive and negative classes were used for expressing the results. For calculating the overall precision of this method, the following equation was used.

$$Balanced\ Accuracy = \frac{Sensitivity + Specificity}{2} \tag{25}$$

The proposed method with 0.858 precision for classifying 8 classes allocated the most precision method among the existing ones.

It is observed that the primary initialization has considerable effects on increasing the accuracy. In addition to the reported accuracy of different methods, the result of classification of each method is shown in figure 7.

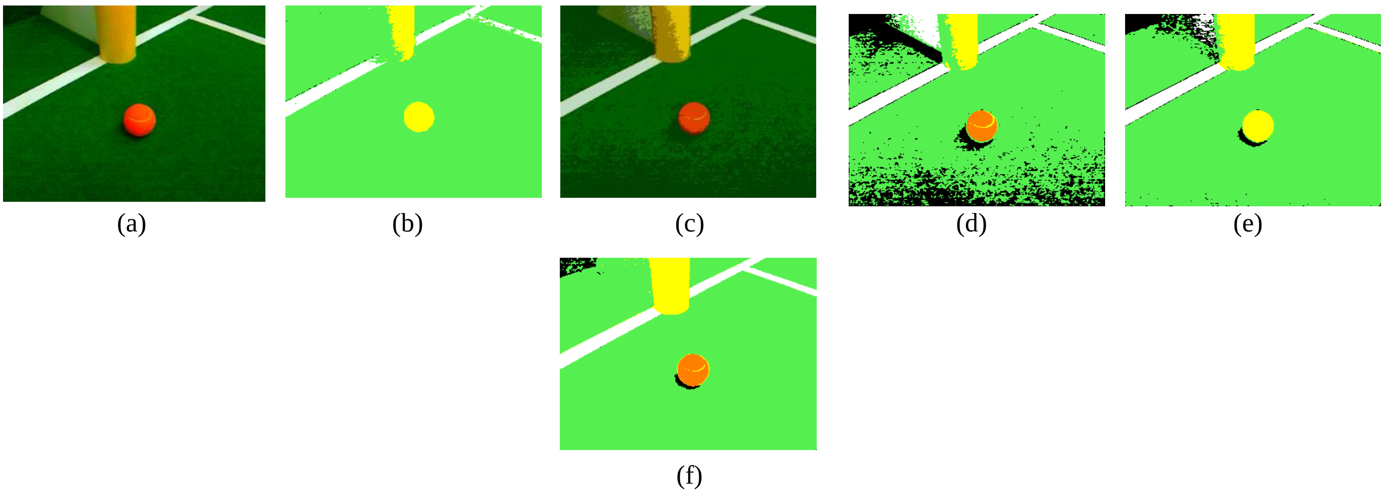


Figure 7. (a) original image, the rest are segmentation result of the test image produced by the following algorithms: (b) PSO random initialization, (c) k-mean with SVM, (d) ANFIS, (e) CLPSO random initialization, (f) proposed method.

One of the important parameters of fuzzy classification system is the number of rules.

As mentioned erliear, the reduction of rules in the fitness function has been taken into consideration and has been one of the main differences between the particle swarm optimization method and ANFIS. In figure 8, the number of obtained rules for various methods has been studied. Due to the lack of fuzzy methods in reference [20], this method has not been studied in figure 8. Calculations of the number and the cluster centers and using mutation in particles are the main reasons for the dramatic drop off in the number of proposed method rules.

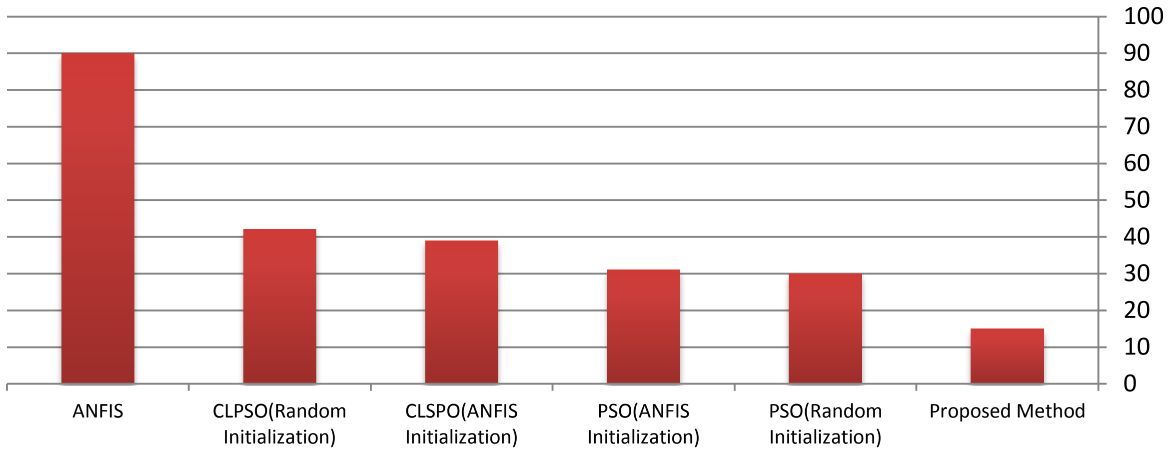


Figure 8. The number of fuzzy rules of the existing methods.

7. Conclusion

In this paper, a comprehensive learning particle swarm optimization (CLPSO) technique with some modifications was proposed to find optimal fuzzy rules and membership functions. Each particle of the swarm codes a set of fuzzy rules. During evolution, a population member tries to maximize a fitness criterion which is here high classification rate and small number of rules. The simulation results show that the selected fuzzy classification system not only has an appropriate number of rules for the considered classification problem but also has a low number of incorrectly classified patterns.

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نشریه هوش مصنوعی و داده کاوی

دانشگاه شاهرود

قطعه‌بندی تصاویر رنگی با استفاده از الگوریتم اصلاح‌شده بهینه-سازی ازدحام ذرات و منطق فازی

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ارسال ۲۰۱۴/۰۸/۰۶؛ پذیرش ۲۰۱۴/۱۲/۲۳

چکیده:

قطعه‌بندی فازی یک روش موثر در قطعه‌بندی تصاویر در شرایط نوری متغیر است. این پژوهش به معرفی یک روش ترکیبی بدون ناظر برای قطعه‌بندی برون خط تصاویر رنگی و ایجاد جدول مراجعه‌ای ایستا می‌پردازد که به بینایی ماشین توانایی کار در محیط‌هایی با ویژگی‌هایی رنگی می‌دهد. این روش به صورت خودکار با استفاده از الگوریتم بهینه‌سازی ذرات یک سیستم فازی برای طبقه‌بندی رنگ با حداقل قوانین و کم‌ترین خطا را تولید می‌کند. برای تنظیم پارامترهای سیستم فازی از یک الگوریتم اصلاح شده بهینه‌سازی ازدحام ذرات با یادگیری جامع بهره گرفته شده است که مانع از همگرایی زودرس می‌شود. هر ذره از جمعیت شامل مجموعه‌ای از قوانین فازی است که در حین تکامل یک عضو از جمعیت، سعی در افزایش برازندگی خود دارد. در این تحقیق نرخ طبقه‌بندی بالا و تعداد کم قوانین به عنوان برازندگی در نظر گرفته شده است. در پایان قوانین مربوط به ذره‌ای با بیش‌ترین میزان برازندگی جهت قطعه‌بندی فضای رنگ انتخاب می‌شود. در این روش در مراحل یادگیری به نظارت انسان نیازی نیست و کارایی روش پیشنهادی از نظر طبقه‌بندی در محیط ربوکاپ با شدت نور مختلف سنجیده شد که نتایج رضایت‌بخشی با دقت ۸۵/۸% برای قطعه‌بندی تصاویر رنگی ارائه داد.

کلمات کلیدی: بهینه‌سازی ازدحام ذرات با یادگیری جامع، طبقه‌بندی فازی، قطعه‌بندی تصویر، بینایی رنگی، ربوکاپ، شناسایی الگو.