Robust Color Classification Using Fuzzy Reasoning and Genetic Algorithms in RoboCup Soccer Leagues

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Abstract. Color segmentation is typically the first step of vision processing for a robot operating in a color coded environment, like RoboCup soccer, and many object recognition modules rely on that, in this paper we present a method for color segmentation that is based on fuzzy logic. Fuzzy sets are defined on the H, S and L components of the HSL color space and provide a fuzzy logic model that aims to follow the human intuition of color classification. The membership functions used for the fuzzy inference are optimized by genetic algorithms. The method requires the setting of only a few parameters and has been proved to be very robust to noise and light variations, allowing for setting parameters only once. The approach has been implemented on MRL middle size robots, and successfully experimented in the numbers of the friendly matches of the Middle size in the 2006's games.

Keywords: Color classification, Image segmentation, fuzzy classification, Genetic Algorithms, Soccer robot.

1 Introduction

Many color vision systems require the first step of classifying pixels in a given image into a discrete set of color classes. This early vision step plays an important role in soccer robot because RoboCup soccer is a color-coded environment, where colors are used to define principal objects introducing specific concepts for robots. Recognition and positioning of colored beacons and goals in the field are used for self-localization and reactive behaviors, while the recognition of the orange ball feeds behaviors and coordination tasks.

Good color segmentation allows for easy implementation of object recognition and localization, most of the robot vision systems are based on fast and accurate implementation of such process. Most of the teams recognize and locate objects from a rough segmentation (e.g. [1]), applying more sophisticated recognition techniques (e.g., region growing) at a later stage. However, this second approach may be less

reliable or require more computational resources. According to [2], fuzzy approaches for image segmentation can be categorized into four classes: segmentation via thresholding, segmentation via clustering, supervised segmentation, and rule-based segmentation. Among these categories, rule-based approaches are able to take advantage of application dependent heuristic knowledge, and model them in the form of fuzzy rules. In [3], a set of fuzzy rules are established based on fuzzy variables, which are associated with the membership values of pixels obtained by the fuzzy c-mean clustering approach (FCM) [4] and the possibilistic c-mean clustering approach (PCM) [5], to construct a correction matrix for modifying the fuzzy partition matrix. In [6], a fuzzy reasoning method in conjunction with genetic algorithms is employed for color image segmentation through region merging.

In this paper we present an approach to color segmentation that has been used for RoboCup soccer in the Middle size league (also applicable for other usages). The aim of our work is to retrieve images according to their dominant(s) color(s) expressed through linguistic expressions and implementing in our vision system. In this paper a Genetic Algorithms for an automatic production of the optimized fuzzy rules has been employed. The results of performing this method on experimental data have demonstrated the efficiency of the method.

2 Color Spaces

MRL robots have many limitations that must be considered in the development of their vision system: low computational power and low quality of the color image. Therefore, many of the state-of-the-art segmentation techniques in the literature cannot be implemented in real-time application and do not have optimal results.

HSL space (Hue, Lightness and Saturation) is a space that characterizes the color directly thanks to its hue. In this space saturation corresponds to the quantity of "white" in the color and lightness corresponds to the light intensity of the color. Thus, the identification of color is made in two steps: first H, then L and S. the HSL space can be represented through a cylinder or a bi-cone (figure 1). The hue H is an angle, it means that its definition interval loops (0 and 255 are the same points). The "pure" red ((255,0,0) in RGB space) corresponds to an angle equal to 0 for h , a saturation s equal to 255 and a lightness l equal to 128.

Fig. 1. The HSL space (wikipedia.org)

In our work, we limit ourselves to the nine fundamental colors defined by the set T representing a good sample of colors (dimension H):

$$T = (\text{red}, \text{orange}, \text{yellow}, \text{green}, \text{cyan}, \text{blue}, \text{purple}, \text{magenta}, \text{pink})$$

T corresponds to the seven colors of Newton [7] to which we have added color pink and color cyan, that are included in the rainbow color set.

3 Color Representation

Another important point about spaces is the problem of uniformity of the scale. HSL space is quite convenient for our problem but it is a non UCS (uniform color scale) space [8]. Indeed our eyes don't perceive small variations of hue when color is green ($h = \pm 85$) or blue ($h = \pm 170$) while they perceive it very well with orange ($h = \pm 21$) for example. Thus to model the fact that the distribution of colors is not uniform on the circle of hues, Truck *et al.* propose to represent them with trapezoidal or triangular fuzzy subsets [9]. Several other works have been done in the field of none uniformly distributed scales: for example, Herrera and Martinez use fuzzy linguistic hierarchies with more or less labels, depending on the desired granularity [10].

Similarly, [9] associate colors with fuzzy sets. Indeed, for each color of T they built a membership function varying from 0 to 1 (f_t with $t \in T$). If this function is equal to 1, the corresponding color is a "true color" (cf. figure 2).

For each fundamental color, the associated interval is defined according to linguistic names of colors. For some colors, we obtain a wide interval. It is the case for the colors "green" and "blue" which are represented by trapezoidal fuzzy subsets.

Fig. 2. The dimension H

Fig. 3. Trapezoidal fuzzy subset

A trapezoidal fuzzy subset is usually denoted $(a; b; \alpha; \beta)$ (cf. figure 3) and when the kernel is reduced to one point, it is a triangular subset denoted by $(a; \alpha; \beta)$ since $a = b$ [11].

To complete the model, it is necessary to take into account the two other dimensions (L and S). Each colorimetric qualifier is associated to one or both dimension(s). To facilitate the process, each dimension interval is divided into three sub-intervals: *low value*, *average value* and *strong value*. Thus, we obtain six "one dimension-dependent" qualifiers and nine "two dimension-dependent" qualifiers [12] denoted by Q .

$$Q = \{\text{somber, dark, deep, gray, medium, bright, pale, light, luminous}\}.$$

Figure 4 shows the nine "two dimension-dependent" qualifiers.

Fig. 4. Fundamental color qualifiers

Each qualifier of Q is associated to a membership function varying between 0 and 1 ($\tilde{f}_q$ with $q \in 2 Q$). Every function is represented through the 3 dimension-set $(a; b; c; d; \alpha; \beta; \gamma; \delta)$ (cf. figure 5) As for the hues, the intersection point value of these functions is also supposed equal to 1/2 (cf. figure 6).

Fig. 5. Trapezoidal 3-D fuzzy subset

Fig. 6. Dimensions L and S

The membership function of any qualifier q is defined below:

$$\forall q \in Q, \tilde{f}_q(l, s) = \begin{cases} 1 & \text{if } a \leq s \leq b \text{ and } c \leq l \leq d \\ 0 & \text{if } s \leq a - \alpha \text{ or } s \geq b + \beta \\ & \text{or } l \leq c - \lambda \text{ or } l \geq d + \delta \\ \frac{l - (c - \lambda)}{\lambda} & \text{if } c - \gamma < l < c \text{ and } \alpha l - \gamma s \leq \alpha c - \gamma a \\ & \text{and } \beta l + \gamma s \leq \beta c + \gamma b \\ \frac{(d + \delta) - l}{\delta} & \text{if } d < l < d + \delta \text{ and } \beta l - \delta s > \beta d - \delta b \\ & \text{and } \alpha l + \delta s > \alpha d + \delta a \\ \frac{s - (a - \alpha)}{\alpha} & \text{if } a - \alpha < s < a \text{ and } \alpha l - \gamma s > \alpha c - \gamma a \\ & \text{and } \alpha l + \delta s \leq \alpha d + \delta a \\ \frac{(b + \beta) - s}{\beta} & \text{if } b < s < b + \beta \text{ and } \beta l + \gamma s > \beta c + \gamma b \\ & \text{and } \beta l - \delta s \leq \beta d - \delta b \end{cases} \quad (1)$$

4 Optimization of Membership Functions by Genetic Algorithms

In this section, we explain the method of optimizing the membership functions by genetic algorithms. Since the parameters of fuzzy membership function has a great effect on performance of our classification thus by using genetic algorithms we can optimize fuzzy parameters to minimize the error in fuzzy classification.

Genetic algorithms are search algorithms based on the mechanics of natural selection and natural genetics [13]. Genetic algorithms have three operations: a) crossover operation, b) mutation operation, c) selection operation.

Each membership function of H, S and L forms a trapezoid in this method. One of the membership functions is encoded to the three real numbers defined by the trapezoid. We regard these real numbers as a gene. Figure 7 shows the encoding of the membership functions. Because three membership functions are required by each reference vector in HSL space, the number of genes needed to express the classification rule is three times the number of vector in HSL space. The classification rule is encoded as a string using these genes. First, the string shoving random genotypes are taken as the initial population. In the crossover operation, some pairs of strings are selected as parents. One of the parents is selected according to its classification abilities, and another is selected at random. A crossover position is randomly selected on each pair of strings. Two new offspring strings are made by swapping real numbers after that position. In the mutation operation, each gene of the offspring is changed for a random real number with an occurrence probability. Before the selection operation, the strings are evaluated with the training samples. Evaluation is done using an objective function called

Fig. 7. Encoding of the membership function

The fitness function:

$$f(k) = W_0 E_{0k} + W_1 E_{1k} + W_2 E_{2k} + W_3 E_{3k} \quad (2)$$

Where $F(k)$ is fitness value of the k -th string; E_{0k} is the classification rate, E_{1k} is average of the difference from μ for the correct color to the other μ ; E_{2k} is the average of the difference from the membership value for the correct color of each parameter to the same value for the other colors; E_{3k} is the average width of the membership function; W_0, W_1, W_2 and W_3 are the weight for each parameter.

In the selection operation, the strings are selected according to their fitness values. Some strings whose fitness value is low are removed from the population. This operation keeps the size of the population constant. This method requires a search of a wide solution space because a real number is used as a gene. Therefore, we use the random search operation with the three operations; each string can search the narrow space around itself before the selection operation. The number of searching trials and the size of the Space searched are kept constant when a string finds a string more suitable than itself; the genes of the string are changed to these of the more suitable string. This operation makes it possible to search a wide space in detail without a large size of the population. Simulations of classification were performed using data measured by a prototype color sensor-whose measuring geometries were 0 illuminated and 45 received. Optimization was performed for classification of the dealt colors. Classification rate: 100%, where output fluctuation: ± 0.2 the same simulations were performed with the conventional method using permissible ranges. As result classification rate: 88.4% from the comparison of these results, we confirmed the effectiveness of this method.

5 Experimental Result

The Training Data have been captured from colorful images of middle size robots in 9 color sets (Red, Orange, Yellow, Green, Cyan, Blue, Purple, Magenta and Pink), under various lights intensities in our lab. The goal was to make this segmentation resistant in different lights and make sure that this segmentation is still performed correctly in variation of light.

Fuzzy system had three inputs each representing one of the dimensions of HSL. For the dimension H, 10 membership functions, for L and S, 3 and for the output 9 permanent membership functions were considered. Experimental results of some of test images are reported. In order to show the effectiveness of this method to object classification in field of MSL matches, we compared the classification ability of this method with that of the conventional one. The colors of object to be classified were relatively analogous. When objects contain different substances, they must be separated. In the case of highly analogously colored object, the classification is difficult because of the color and light non-uniformities.

The causes of the non-uniformity of the GA's parameters were as follows: population size was 100; number of offspring created by crossover operation was 50 for each generation; and occurrence probability of mutation was 5%. The classification rule that had a maximum fitness value at the 100th generation was evaluated for its classification ability. In the simulations 100 datum for each color were classified.

The same simulations were performed by the conventional method. In this method, the permissible ranges were obtained from a minimum and a maximum value of some classification trials. Therefore, the permissible ranges were yielded by the training samples used for this method. The simulation results were compared with those of this method. The results show that the proposed method is more robust against color non-uniformity and light illuminating non-uniformity. When color and light fluctuations were 5 % and 15 %, respectively, the classification rates in this method were 100% and 96.3 %, respectively; the rates in the conventional method were 91.4 % and 78.3%, respectively.

Fig. 8. Sample of color classification by this method in MRL

6 Conclusion

We have developed a robust vision for MRL robots with use of fuzzy sets and GA. This improved vision would help our Behavior Management System the possibility to work with hierarchies of informed behaviors, improved coordination mechanism, improved self-localization and improved color classification to solve the problem of shadow blades on the field.

Effectiveness of this method compared to the conventional method is clear. When color and light fluctuations were 5 % and 15%, the classification rates in this method were 100% and 96.3 %, respectively; the rates in the conventional method were 91.4% and 78.3%, respectively. Thus, changing the color or light of robots surrounding environment can be a possible threat for its rival. Color calibration can be undertaken more quickly, as the calibration method encourages the human trainer to identify all possible pixel values for each color of interest, rather than avoiding those that may cause misclassification (e.g. those that occur in shadow or on the borders of different objects within the image). Recently, object recognition has also improved, not only due to image segmentation performance, but because of object recognition routines which can result in recognition of different levels of color uncertainty indicated by core colors, maybe colors, and unknown colors.

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