A Fuzzy logic-based Model in Image Processing

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Keywords: Computational Model, Fuzzy Sets, Munsell color space, Image processing

Abstract

Many works have been done to enable computer, as brain of robot, to learn color categorization, most of them rely on modeling of human color perception and mathematical complexities. This paper aims at developing the innate ability of the computer to learn the human-like color categorization.

1. Introduction

Many works have been done to enable computer, as brain of robot, to learn color categorization, most of them rely on modeling of human color perception and mathematical complexities [1, 2]. Human perceives color in categories, which may be identified using color name such as red, blue, etc. The categorization is unique for each human being. However despite the individual differences, the categorization is shared among members in society.

Theories of categorization in artificial intelligence, information retrieval, data mining, and other computational fields are no different in kind from theories that predate modern computers. The computer, however, introduces two important elements. It enables theories to be tested on large amounts of data, and it enforces precision, since no program running on a digital computer can ever be vague or ambiguous. Both elements can be helpful in formulating and testing theories, but neither can guarantee truth, relevance, or usefulness. This paper surveys a variety of computational methods that have been applied to categorization and related methods for reasoning with and about the categories. These methods can be used for three different purposes: Artificial intelligence, Intelligence enhancement and Hypothesis testing [3-5]. A computer, however, can analyze large volumes of realistic data and test hypotheses about causal mechanisms that could generate or interpret such data. These above approaches differ primarily in their goals, simulation, enhancement, or understanding of human cognition. Computational methods designed for any one of them can usually be adapted to the others.

The approach is based on fuzzy logic modeling of the HSV color space, and provides a fast, yet fairly accurate, color segmentation using natural language rules of human intuition that allow simple modification of the classification criteria. This work aims at developing the innate ability of the computer to learn the human-like color categorization and how it is built and developed without much mathematical complexity in HSV (Hue, Saturation and Value) color space, see fig. 1.

2. Experimental

Color categorization has been studied from different disciplines. For many years, biologists, philosophers, linguists, and anthropologists have worked on this topic, providing very different points of view about the problem. To understand the motivation of our work we summarize those works that are closer to our goal, that is, the computational automation of the color categorization task in the frame of computer vision applications. The basis of most of the works on color categorization has been the study of Berlin and Kay in which they stated the existence of a unique and common set of 11 basic color terms in different languages. In the way of explaining the color categorization process, Kay and McDaniel proposed a general model of color categorization that attempted to find the relationship between the neurophysiological mechanisms involved in color categorization and the semantic categories of basic color terms [5-9].

The model is based on fuzzy set theory where each color category has a characteristic function that defines a membership degree to the category. The most interesting aspect of the model is that it considers the color categorization problem as something more than the assignment of a color term to a stimulus, because the fuzzy approach takes into account the non discrete nature of the problem [7-10]. The final goal of this work is to build a computational model that allows defining a decision function that automatically performs the color categorization visual task.

Our model considers the color categorization task as a fuzzy decision. The best way to model mathematically this decision function is by considering the basis of the fuzzy set theory [8, 9]. A fuzzy set is described by its membership function, in color categorization, we can consider that any color category, C_k, is a fuzzy set with a membership function, f_{C_k}, which assigns to each color sample x a membership value $f_{C_k}(x)$ within the [0, 1] interval. This value represents the certainty we have about x has to be named with the linguistic term, t_k, corresponding to category C_k. From this point of view, the first step of any color categorization modeling process will be the definition of the membership functions for each color category, the reader recommend to consult with [2, 7-10] for more details.

Once these functions are defined, it will be possible to compute a color descriptor, CD(x), such as the following:

$CD(x) = (f_{C_1}(x), \ldots, f_{C_n}(x)) = (m_1, \ldots, m_n)$ (**1**)

where $\sum_k m_k = 1$ and $m_k \in [0, 1]$ for $k = 1, \ldots, n$. CD(x) describes the membership relation of x to each color category, m_k is the certainty value associated to x by f_{C_k} and n is the number of categories considered. In our case n = 11 and the categories considered in the model correspond to the 11 basic color terms proposed by Berlin and Kay [2], that is $t_k \in$ {white, black, red, green, yellow, blue, brown, purple, pink, orange, gray}.

The information contained by CD(x) can be used by a decision function N(x) that assigns to x one of the 11 color terms considered. At the moment, the decision function we have chosen assigns the color term that corresponds to the category C_k with the highest membership value m_k in CD(x) as follows:

$N(x) = t_k \mid m_k = \mathrm{Max}\ \{f_{C_i}(x)\}_i$ (**2**)

Therefore, the color descriptor CD(x) defined above is a vector of 11 components and the information contained in such descriptor can be used by a decision function to decide the color name of a given stimulus x. Human perceived color defines a three-dimensional color space, called HSV, which corresponds to two cylindrical cones joined at their base, as shown in Fig. 1.

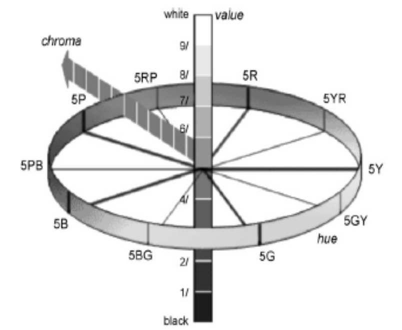

Fig. 1. The HSV color space

The Author has showed in [3] that for given set X of cardinality four, concluded Hue, Saturation and Value in the HSV color space and maximum mean value, respectively, one has determined the upper and lower approximation operators of a fuzzy approximation space (X, R), where R is a T-similarity relation on X and T is a continuous triangular norm on [0, 1]. Now, at first consider new fuzzy sets with characteristic functions in the main theorem of Ref. [3] and then, $m_M = 1 - (m_H + m_S + m_V)$ (**3**).

By the previous fuzzy sets and the following fuzzy logics, we are able to introduce a color categorization model:

Red $\wedge$ *Gray* $\wedge$ *Bright* $\rightarrow$ *white;*

Red $\wedge$ *Almost-Gray* $\wedge$ *Dark* $\rightarrow$ *black;*

Red $\wedge$ *Almost-Gray* $\wedge$ *Medium-Dark* $\rightarrow$ *dark-gray;*

Red $\wedge$ *Almost-Gray* $\wedge$ *Bright* $\rightarrow$ *pink;*

Red $\wedge$ *Medium* $\wedge$ *Medium-Dark* $\rightarrow$ *dark-brown;*

Red $\wedge$ *Almost-Clear* $\wedge$ *Medium-Bright* $\rightarrow$ *red;*

Dark-Green $\wedge$ *Medium* $\wedge$ *Bright* $\rightarrow$ *light-green;*

Dark-Green $\wedge$ *Almost-Clear* $\wedge$ *Dark* $\rightarrow$ *black;*

Dark-Green $\wedge$ *Almost-Clear* $\wedge$ *Medium-Dark* $\rightarrow$ *dark-green.*

3. Results and discussion

The data set provided in this article has been obtained from a color categorization experiment stored in: http://www.cvc.uab.es/color_naming, see [2].

The computations of color descriptors and decision functions were carried out with the aid of GAP SYSTEM (http://www.gap-system.org), a group theory software package which is free and extendable, as follows:

```
LogTo(" AutoColorCategorization.txt");
X:=[[43.23897,38.48174,10.41669],
  [50.7743,49.84015,18.75137],
     [54.18561,55.10332,11.37618],
        [62.66311,43.17296,10.56606],
[75.81799,20.52865,9.061852],
    [83.55142,11.26785,5.548528],
       [90.48829,0.797417,2.058837],
          [44.36732,34.63375,20.22493],
[50.70356,48.92746,26.26019],…,[49.54885,19.1151
1,33.38811],[62.21151,18.61525,45.65719],
[70.07564,15.13976,51.19732],[74.6292,11.91557,47
.05493],[81.33766,8.750131,29.49287],
       [88.64256,1.87269,7.786669]];
     C1:=COLORRED;
       C2:=COLORORANGE;
         C3:=COLORBROWN;
     C4:=COLORYELLOW;
       C5:=COLORGREEN;
         C6:=COLORBLUE;
           C7:=COLORPURPLE;
     C8:=COLORPINK;
       C9:=COLORWHITE;
         C10:=COLORGREY;
           C11:=COLORBLACK;
     Len:=Length(X);
       F:=fuzzyfuction;
         CD:=ColorDiscritor;
            for i in [1..11]do
     CD=Imagefuzzfuction(C1,C2,C3,C4,C5,C6,C7,
C8,C9,C10,C11);
     MAT:=[ ];
     od;
     N:=decisionfunction;
     for j in [1..Len]do
     if Max((F[j][1])) then Add(Mat,j);
     fi;
     od;
     v:=MatTom(Mat);
       N:=transporsed(v);
         Print("N");
           Print("CD");
             Returen;
               end;
                  LogTo();
```

Here we consider just the first 50 samples in http://www.cvc.uab.es/color_naming. All outputs of our model are coincided with color naming model in [2] with some exceptions which are stored in Table 1, where x_i is the i [th] sample in Benavente and et al's color naming model.

The extraction of high level color descriptors is an increasingly important problem, as these descriptions often provide link to image content. When combined with image segmentation color categorization can be used to select objects by color, describe the appearance of the image and even generate semantic annotations [1-4, 10-14], see fig. 2.

TABLE 1. Partial color naming by our model

x_i	H	V	S	our model	the model in [2]
x_{39}	5.49YR	5.89	8.46	red	orange
x_{65}	6.55Y	8.75	2.65	yellow	yellow
x_{215}	9.13BG	7.78	3.46	gray	blue
x_{261}	5.35BG	8.61	0.3	gray	gray
x_{334}	1.98R	6.54	7.86	white	pink
x_{338}	5.56GY	8.98	0.94	brown	brown

4. Summary

We extend the method and develop a scheme for extracting the color composition of a complex image.

The algorithm follows the relevant neurophysiological findings and studies on human color categorization.

In testing the method the known color regions in different color spaces were identified accurately, the color names assigned to randomly selected colors agreed with human judgments, and the color composition extracted from natural images was consistent with human observations, see [12-14].

5. Acknowledgment

The author is indebted to dear Dr. Steve Jones for his useful helps and partial supports.

Fig. 2. The original images (left) and Color segmentation of proposed fuzzy logic-based method (right) [2]

6. References

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