Human Perception-based Color Segmentation Using Fuzzy Logic

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Abstract

Many color vision systems require a first step of classifying pixels in a given image into a discrete set of color classes. In this paper we describe a human perception-based approach to pixel color segmentation. Fuzzy sets are defined on the H, S and V components of the HSV color space and provide a fuzzy logic model that aims to follow the human intuition of color classification. Experiments suggest that the classification performed by the proposed algorithm introduces an improvement over some other basic color classification techniques, especially in outdoor natural scenes, which are considered more challenging to color segmentation methods. 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 makes the proposed method suitable for applications where efficiency is a primary issue.

Key words: Color segmentation, Fuzzy Logic.

1 Introduction

Many color vision systems require a 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 computer vision applications, as error in this process will be propagated further [11]. However, while humans can easily classify colors in the spectrum visible to the human eye, machines find this task more challenging. Although many color segmentation methods have been proposed [8, 3, 4, 9, 10, 16, 18], no algorithm has been proven to provide an optimal solution, and research efforts are being continued.

Basic approaches to this problem include color space thresholding, linear color thresholding and nearest neighbor classification. The approach of color space thresholding is based on partitioning the color space into a fixed number of rectangular blocks [3]. Although having a clear advantage in terms of computational complexity, partitioning the color space into a relatively small number of rectangular segments usually do not provide an optimal solution to the problem.

A more accurate approach is linear thresholding, which partitions the color space into segments with linear boundaries. Any given pixel is then classified according to the segments it lies in. This technique provides better performance, but the more complex partitioning slows down the algorithm and introduces the problem of choosing the optimal color space segmentation, usually solved using machine learning techniques such as artificial neural networks.

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. Like color space thresholding, nearest neighbor classification is also limited by the cluster shapes, which are determined by the distribution of the samples in the training set. In order to provide good performance, nearest neighbor classification should use a relatively large number of samples, which slows down the algorithm and may prevent it from providing practical real-time performance [4].

Several data-driven methods that are based on the human perception of color have been proposed, such as region growing segmentation [16] and human perception-based texture analysis [8]. In this paper, a knowledge-driven approach that follows the human perception of color segmentation is described. 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. In Section 2 the fuzzy logic model is described and in Section 3 experimental results are discussed.

2 Fuzzy logic modeling of colors

The proposed method is based on segmentation of the HSV color space using a fuzzy logic model that follows a human intuition of color classification. While some common approaches are based on sampling HSV triples using fixed-size bins [1], the method described in this paper predefines the segments using a fuzzy logic model, and divides the color space into segments based on linguistic terms. This approach is different than some data-driven approaches such as nearest neighbor classification, in which the shapes of the segments are determined by the distribution of the samples in the training-set, or basic approaches such as color space thresholding, that defines the segment shapes based on the data structures used by the algorithm.

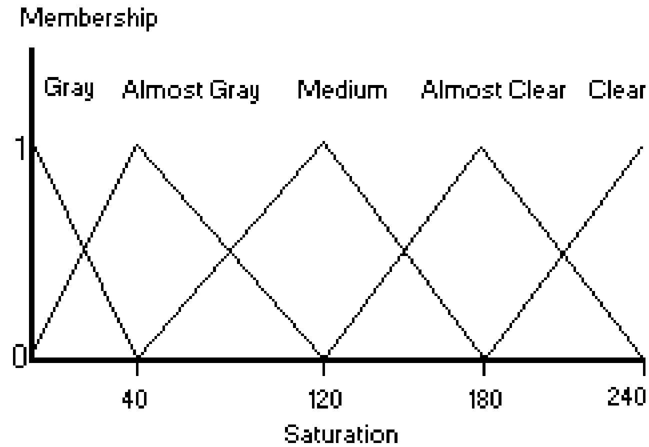

Figure 2: The fuzzy sets defined on *Saturation*.

2.1 Fuzzy sets

Fuzzy Logic is often used as an interface between logic and human perception [5, 20, 21]. The presented method is based on fuzzy logic modeling of the HSV color space, which is more intuitive and closer to the human perception of color than the RGB space [12]. Since in HSV color space each color is defined by three values (H, S and V), the fuzzy logic model has three antecedent variables (*Hue*, *Saturation* and *Value*) and one consequent variable, which is a color class ID. The domain of the variables *Hue*, *Saturation* and *Value* is the interval (0,240). The domain of the consequent variable is discrete, and depends on the number of the predefined color classes.

In the model presented in this paper there are 10 fuzzy sets for *Hue*, 5 fuzzy sets for *Saturation* and 4 fuzzy sets for *Value*. All membership functions are in the form of a *triangular* function [19].

The fuzzy sets of the antecedent fuzzy variable *Hue* are defined based on 10 basic hues distributed over the 0 – 240 spectrum. As described in Fig. 1, the hues are *Red*, *Dark Orange*, *Light Orange*, *Yellow*, *Light Green*, *Dark Green*, *Aqua*, *Blue*, *Dark Purple*, *Light Purple*. The point of maximum of each membership function is determined based on the visual color spectrum described in [7], normalized to the (0,240) interval. The membership functions are described in Fig. 1.

Saturation is defined using the five fuzzy sets *Gray*, *Almost Gray*, *Medium*, *Almost Clear*, *Clear*, as shown in Fig. 2.

Value is defined using the four fuzzy sets *Dark*, *Medium Dark*, *Medium Bright* and *Bright* as described in Fig. 3.

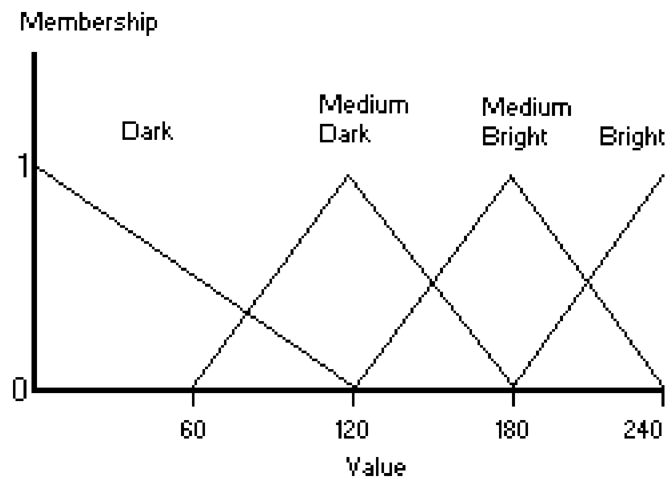

Figure 3: The fuzzy sets defined on *Value*.

2.2 Fuzzy rules

The fuzzy rules in this model are defined based on human observations. For example, the rule "*Dark Orange* $\wedge$ *Medium* $\wedge$ *Medium Dark* $\longmapsto$ *Dark Brown*" is defined by manually classifying the color produced by the HSV triple such that the values of *H*, *S* and *V* are the points of maximum of the membership functions associated with the fuzzy sets *Dark Orange*, *Medium* and *Medium Dark*. Based on the membership functions described in Fig. 1, 2 and 3, in this case the values are $H = 20$, $S = 120$ and $V = 120$. The color produced by this HSV 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 *Medium* and the value

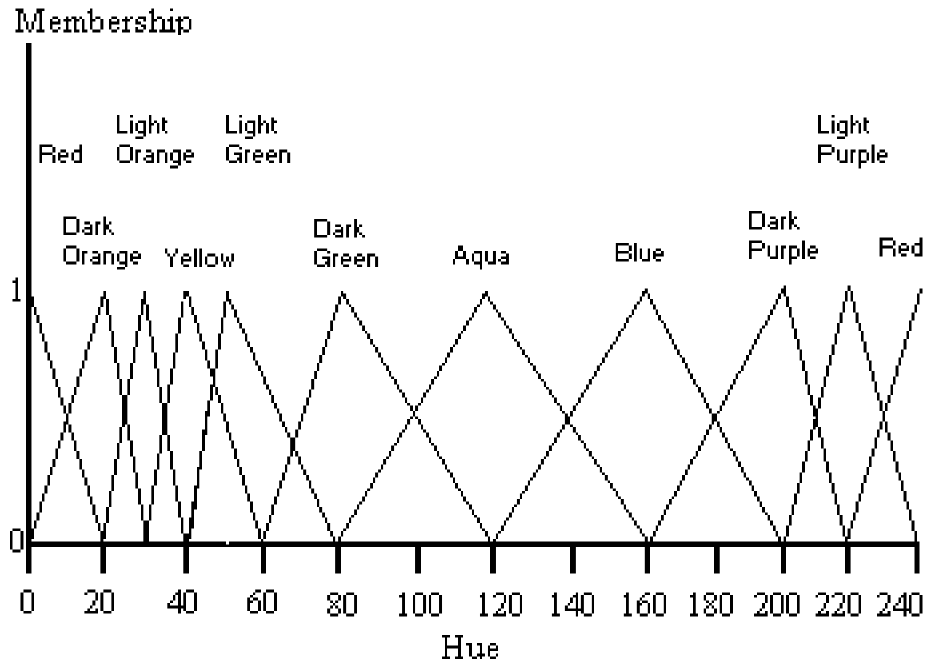

Figure 1: The fuzzy sets defined on *Hue*.

is *Medium Dark* then the color is *Dark Brown*".

The reasoning procedure is based on a zero-order Takagi-Sugeno model [14, 15], so that the consequent part of each fuzzy rule is a crisp discrete value of the set {*Black*, *White*, *Red*, *Orange*, *Yellow*, *Dark Gray*, *Light Gray*, *Pink*, *Light Brown*, *Dark Brown*, *Aqua*, *Blue*, *Olive*, *Light Green*, *Dark Green*, *Purple*}. The set of fuzzy rules includes rules such as:

Red $\wedge$ Gray $\wedge$ Bright $\longmapsto$ white
Red $\wedge$ Almost_Gray $\wedge$ Dark $\longmapsto$ black
Red $\wedge$ Almost_Gray $\wedge$ Medium_Dark $\longmapsto$ dark_gray
Red $\wedge$ Almost_Gray $\wedge$ Bright $\longmapsto$ pink
Red $\wedge$ Medium $\wedge$ Medium_Dark $\longmapsto$ dark_brown
Red $\wedge$ Almost_Clear $\wedge$ Medium_Bright $\longmapsto$ red
Dark_Green $\wedge$ Medium $\wedge$ Bright $\longmapsto$ light_green
Dark_Green $\wedge$ Almost_Clear $\wedge$ Dark $\longmapsto$ black
Dark_Green $\wedge$ Almost_Clear $\wedge$ Medium_Dark $\longmapsto$ dark_green

Since this model has 10 fuzzy sets for *Hue*, 5 for *Saturation* and 4 for *Value*, the total number of rules required for this model is 10×5×4=200.

2.3 The computation process

The computation process classifies any given HSV triple to a known predefined color. In the fuzzification stage the *Hue* component of the HSV triple is fuzzified using the *hue* fuzzy sets described in Fig. 1, the *Saturation* component is fuzzified using the *saturation* fuzzy sets described in Fig. 2 and the *Value* component is fuzzified using the *value* fuzzy sets described in Fig. 3. Rule evaluation is performed using the *product* inferencing method.

Since the domain of the consequent variable is a set of discrete values, continuous defuzzification methods cannot be used. One possible defuzzification method in this case is to simply select the consequent part of the rule that has the maximal strength. I.e., the output value is the consequent part of the rule such that the product of the memberships of *H*, *S* and *V* to the fuzzy sets of the rule's antecedent part is maximal comparing to all other rules. However, since the same consequent part can be common to more than one fuzzy rule, considering only the fuzzy rule with the maximal strength can lead to a false conclusion since another consequent part may be supported by several rules, which are, together, stronger. For instance, if three fuzzy rules R_1, R_2 and R_3 have strengths of 0.2, 0.21 and 0.23 respectively (while the strength of all other rules is 0), it may be reasonable to use the consequent part of R_3 as the output value. However, if the consequent parts of R_1 and R_2 are identical, choosing the consequent part of R_1 and R_2 should be considered. Therefore, the defuzzification is performed in three stages. In the first stage, all fuzzy rules are grouped by their consequent parts. In the second stage, each group of fuzzy rules is assigned with a value that is the sum of the strengths of its contained rules. In the third stage, the group that has the maximal sum of strengths is selected, and the consequent part of its fuzzy rules is assigned to the consequent fuzzy variable.

3 Experimental results

We chose to test the algorithm using outdoor natural scenes, which are sometimes considered more challenging to color segmentation methods [6]. Fig. 4 is an example of a true-color image and its transformation such that each pixel is classified and assigned with the color that corresponds to the classification. The classification methods tested are color space thresholding, nearest neighbor using uniformly distributed 200 color samples and the proposed fuzzy logic-based method described in Section 2.

Although the nearest neighbor classification and the fuzzy logic-based classification use the same number of color samples (200), the comparison shows that the performance of the nearest neighbor color classification is inferior to that of the proposed fuzzy logic-based method. Color space thresholding lost most of the color information. The advantage of the proposed classification method is that the segments provided by the fuzzy logic modeling are shaped based on the dependencies between the dimensions of the color space, while the shapes of the segments of color space thresholding are based on the data structures used by the algorithm, and segments created by the nearest neighbor method are determined by the distribution of the samples in the training set.

Fig. 5 shows another comparison of the three color segmentation methods in a similar fashion used in Fig. 4. An eyeball comparison of the images suggests that the proposed fuzzy logic-based method provides a more accurate color classification than color space thresholding and nearest neighbor classification.

Color segmentation is often used in the field of remote sensing and GIS (Geographic Information Systems) [13, 17]. Fig. 6 shows a satellite image of New York area and the color classification using the three methods. Comparing the images, the proposed fuzzy logic-based approach provided the most accurate detection of water, vegetation and urban areas. For instance, the color space thresholding method produced an image in which the entire Long Island area is colored in gray, while the nearest neighbor classification did not detect Great South Bay and covered urban areas in yellow instead of gray.

Another important advantage of the proposed approach is its low computational complexity. Since the total number of rules in the model is constant, the classification of each pixel is performed in constant complexity. Practically, a system with an Intel Pentium IV processor at 2.66 MHZ and 512 MB of RAM processes the 150×225 image of Fig. 4 in $\sim$0.35 seconds.

4 Conclusion

In this paper, a fuzzy logic based method of color segmentation was 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. Experimental results suggest that the classification performed by the presented algorithm provides better accuracy than some other basic color classification techniques. 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.

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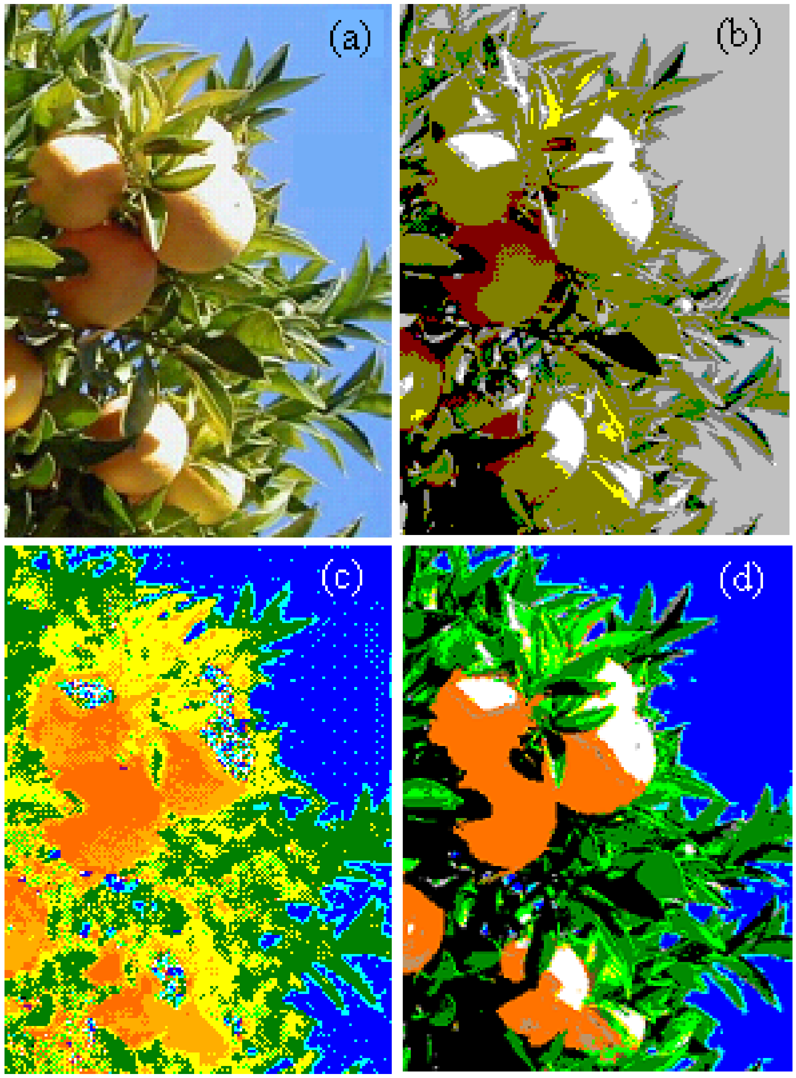

Figure 4: Color segmentation of the original image (a) using color space thresholding (b), nearest neighbor (c) and the proposed fuzzy logic-based method (d).

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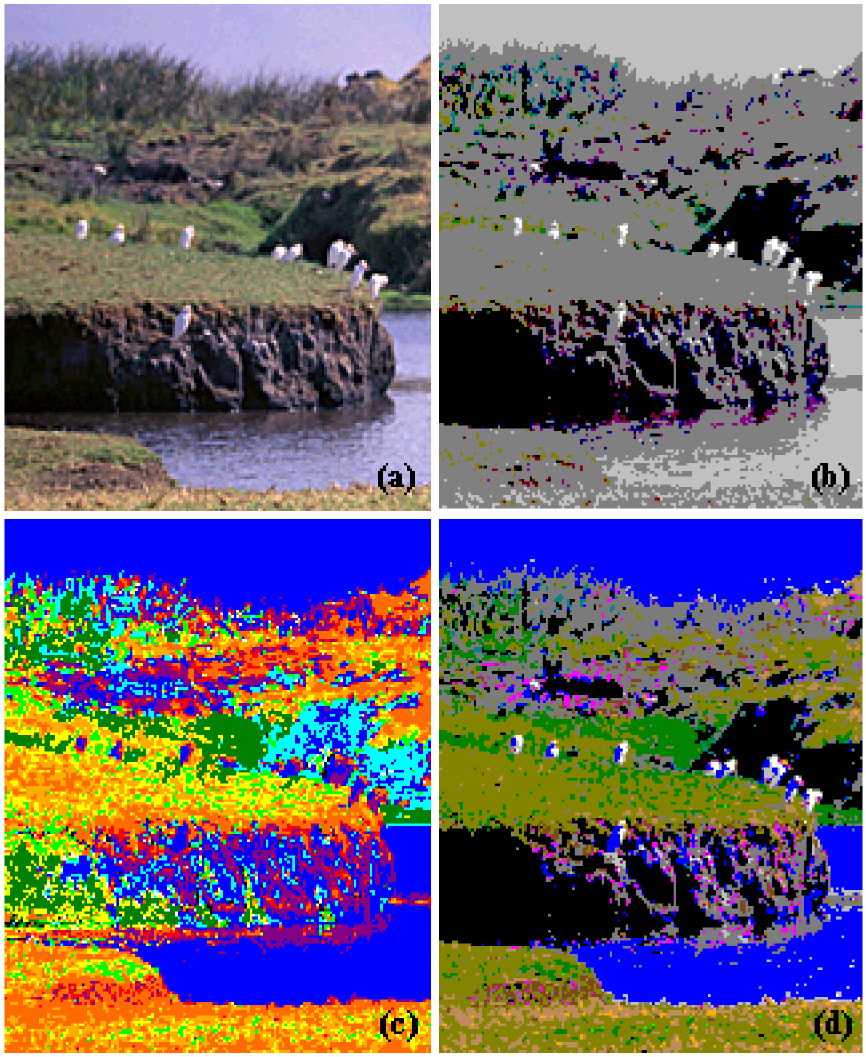

Figure 5: Color segmentation of the original image (a) using color space thresholding (b), nearest neighbor (c) and the proposed fuzzy logic-based method (d).

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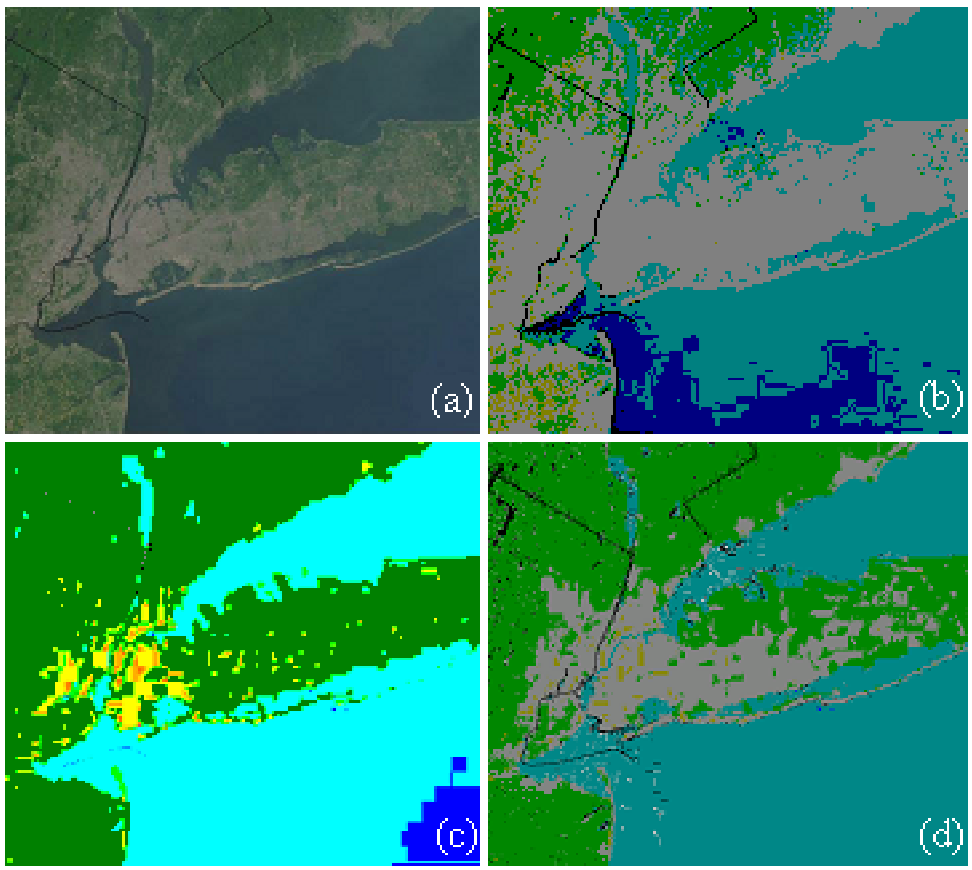

Figure 6: Color segmentation of New York area satellite image (a) using color space thresholding (b), nearest neighbor (c) and the proposed fuzzy logic-based method (d).