Fuzzy Color Histogram-based CBIR System

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Abstract—**In this work we propose a fuzzy color histogram construction method for content-based image retrieval. Our algorithm links colors from *L*a*b** color space to fuzzy color histogram bins by using a Mamdani-style fuzzy inference system. First *L*a*b** color space is explored to specify significant colors that will correspond to fuzzy color histogram bins. Accordingly, we define membership functions and fuzzy rules. Fuzzy approach makes color histogram-based methods more robust and less sensitive to illumination changes and quantization errors. Output of our system consists of 15 colors; therefore it has a computational advantage in histogram comparison. We test the proposed method for matching images under varying illuminations. Experiments on a popular image dataset show that fuzzy color histogram approach performs better than conventional methods.**

I. Introduction

Searching and browsing image collections have become important and active research fields in the last decade. Querying by image content is one of most promising search techniques where users try to find relevant images based on the given query image. Color, texture, and shape are the low-level features that are usually preferred in content-based image retrieval (CBIR) systems. Among these methods, color histogram is the simplest, yet an effective visual feature commonly used in color image retrieval.

The aim of query-by-color is to find images, whose color features are similar to the color features of query image. After Swain and Ballard [10] presented that color can be an important identifying feature for color image retrieval, it became even popular. Various color spaces, quantizers, and similarity measures were compared by Smith in [11].

Although color histograms are commonly used in computer vision and have the computational advantages, it is a fact that they are also very sensitive to small illumination changes and quantization errors. Similar colors can be quantized into different bins, because conventional methods assign each pixel into exactly one bin. However, fuzzy approach can overcome this issue by assigning a pixel into each histogram bin with a definite degree of association via fuzzy-set membership functions.

Our aim in this work is to propose a fuzzy color histogram method that outperforms conventional methods for color image retrieval under varying illumination changes.

The rest of the paper is organized as follows: related work is given in Section II. Proposed method is described in Section III. Experiments and evaluation of their results are presented in Seciton IV. Finally conclusions and future work is discussed in Section V.

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II. Related Work

Fuzzy logic introduced by Zadeh [1] is being used in many applications related to image processing, such as shot-boundary detection, query by image content, object tracking, etc. Chung and Fung [4] introduce a fuzzy color quantization technique to color histogram construction, and evaluated its performance in video scene change detection in a very limited video dataset. Similarly, Das, Sural and Majumdar [7] define a unified interval type-2 fuzzy rule based model using fuzzy histogram and fuzzy co-occurrence matrix to detect cuts and various types of gradual transitions for shot-boundary detection. In [6], histogram differences of consecutive frames are characterized as fuzzy terms like small, significant, large, etc., and fuzzy rules for detecting abrupt and gradual transitions are formulized in a fuzzy-logic-based framework for segmentation of video sequences. Fang, Jiang and Feng [5] propose a fuzzy logic approach for temporal segmentation of videos, where color histogram intersection, motion compensation, texture change and edge variances are integrated for cut detection. Wang *et al.* proposes a robust kernel tracking method using fuzzy color histogram in [8]. By employing fuzzy approach on kernel tracking problem, mean shift-tracking scheme becomes more robust under different illuminations. Chuang *et al.* [9] presents a ratio histogram based on fuzzy color histogram to detect suspicious objects in an abnormal event.

There are some notable studies on fuzzy color histogram and its application to content-based image retrieval. Han and Ma introduce a fast approach for computing fuzzy color histogram using fuzzy c-means algorithm in [3]. They find a correspondence between conventional color histogram (CCH) and fuzzy color histogram (FCH), and compute the FCH of an image without dealing with membership functions. It is claimed that FCH improves robustness, efficiency, and computation. Konstantinidis, Gasteratos and Andreadis [2] propose a fuzzy linking method for color histogram creation in *L*a*b** color space. They evaluated their method on a limited dataset, and achieve higher accuracy values for several image retrieval tests. Compared to our work, fuzzy color histogram of [2] contains 10 bins. We extracted new colors and find fuzzy rules. Our experiments also focus on retrieving the original image, whereas they evaluate the relevancy of retrieved images.

III. Fuzzy Color Histogram

We use a color histogram-based method generated with the fuzzy linking method on $L^*a^*b^*$ color space. In this section, we explore $L^*a^*b^*$ color space to specify colors that will correspond to fuzzy color histogram bins, then give the details of fuzzy inference system with membership-functions and rules.

A. *Color Selection*

We have selected popular colors, and experimented with their values in $L^*a^*b^*$ color space.

$L^*a^*b^*$ is commonly preferred over *RGB* or other color spaces, because it is one of the perceptually uniform color spaces which approximates the way that human perceive color. In $L^*a^*b^*$ color space, L^* represents luminance, a^* represents greenness-redness, and b^* represents blueness-yellowness.

a^* and b^* components have more weights than L^* component. Therefore the fuzzy linking method in [2] subdivides L^* into 3 (dark, dim, and bright), a^* into 5 (green, greenish, middle, reddish, and red), and b^* into 5 (blue, bluish, middle, yellow, and yellowish) regions.

Range of $L^*a^*b^*$ color space is important for the fuzzy membership functions. L^* coordinate ranges from 0 to 100. The possible range of a^* and b^* coordinates depends on the color space that one is converting from. When converting from RGB, a^* coordinate range is between [-86.1813, 98.2352], and b^* coordinate range is between [-107.8617, 94.4758].

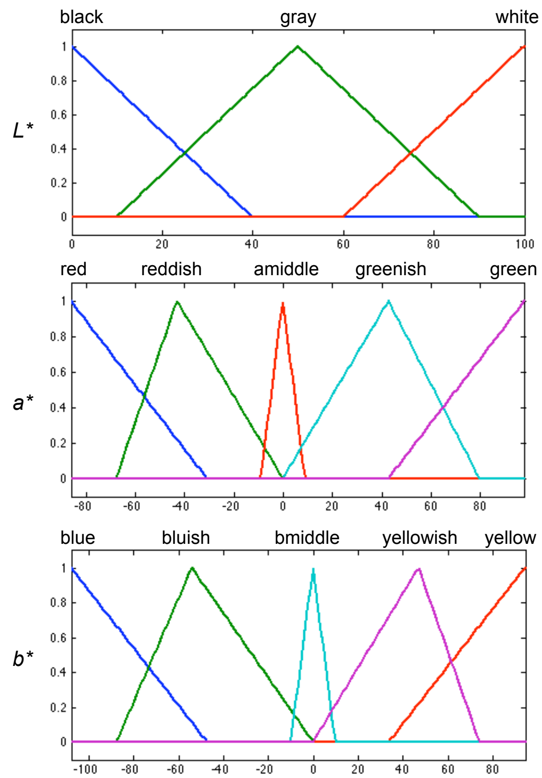
TABLE I. *Colors and fuzzy correspondences*

Name	L*	a*	b*	fuzzy L*	fuzzy a*	fuzzy b*
Black	0	0	0	black	amiddle	bmiddle
Blue	32.30	79.19	-107.86	black~grey	red	blue
Brown	64.60	10.22	69.09	grey	amiddle	yellowish
Cyan	91.11	-48.09	-14.13	white	greenish	bmiddle
Magenta	60.32	98.24	-60.83	grey	red	bluish
Lime	87.74	-86.18	83.18	white	green	yellow
Grey	76.19	0	0	grey	amiddle	bmiddle
Maroon	39.03	63.65	53.41	grey	reddish	yellowish
Navy	22.38	62.93	-85.72	black	reddish	blue~ish
Green	66.44	-68.49	66.10	grey	green	yellow~ish
Olive	73.92	-17.13	75.08	grey~white	greenish	yellow
Orange	83.91	3.43	82.63	white	amiddle	yellow
Pink	92.07	11.20	1.05	white	reddish	bmiddle
Purple	44.66	78.07	-48.34	grey	red	bluish
Red	53.24	80.09	67.20	grey	red	yellow~ish
Silver	89.53	0	0	white	amiddle	bmiddle
Teal	69.13	-38.22	-11.23	grey~white	greenish	bmiddle
Violet	50.46	89.85	-77.24	grey	green	blue
White	100	0	0	white	amiddle	bmiddle
Yellow	97.14	-21.55	94.48	white	greenish	yellow

We have selected 20 colors from List of Colors[1]. Table I shows L^*, a^*, b^* values, as well as their fuzzy correspondences for each color.

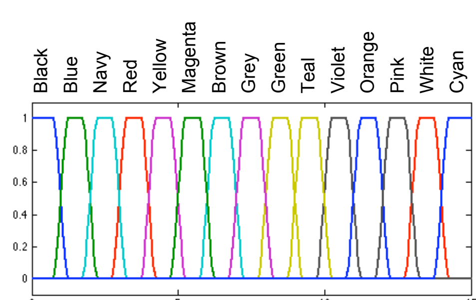
B. *Fuzzy Inference System*

Fuzzification of the inputs is achieved by using triangular membership functions for each component. Membership functions are shown in Figure 1.



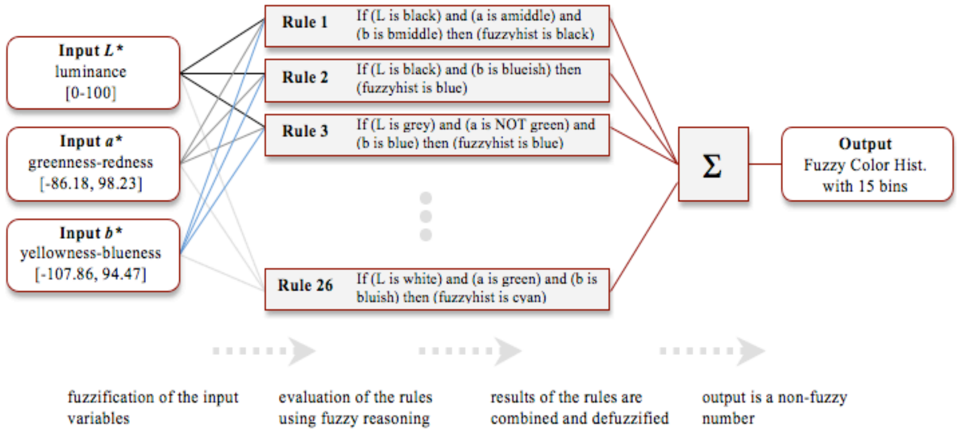
1. Fuzzy membership functions of the inputs

Three components are linked in a Mamdani-style fuzzy inference system, according to 26 fuzzy rules (see Appendix A). Generation of the final color histogram is performed using 15 trapezoidal membership functions, for each bin of output color histogram. Because some colors (olive, purple, silver, lime, maroon) reside very close to others in 3-d $L^*a^*b^*$ space, we selected the remaining 15 colors out of 20. Therefore, the final fuzzy color histogram contains 15 bins (see Figure 2).



2. Fuzzy membership function of the output

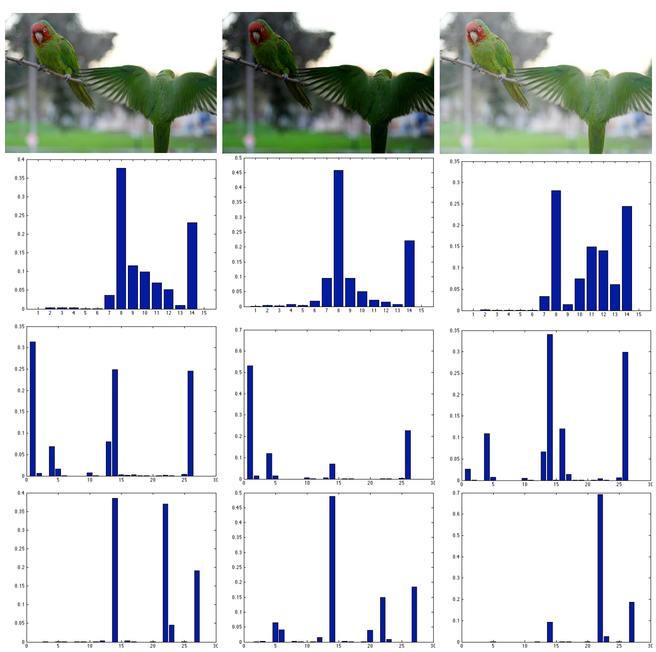
[1] http://en.wikipedia.org/wiki/List_of_colors



3. Structure of fuzzy color histogram

Overview of the proposed fuzzy inference system is shown in Figure 3. Degree of membership to fuzzy sets are calculated for each input, which is an image pixel in $L^*a^*b^*$ color space, according to fuzzy membership functions shown in Figure 1. Then the fuzzy rules are evaluated and their outputs are combined by MAX aggregation operator. After that the resulting fuzzy set is defuzzified to produce the crisp decision value, which is the final output of the system.

The main advantage of the proposed fuzzy color histogram over a conventional color histogram is its accuracy. Since the system is less sensitive and more robust to illumination changes and quantization errors, it performs better on image retrieval. A sample image with different illuminations achieved through gamma correction and corresponding color histograms are shown in Figure 4.



4. Image from the dataset and its color features. Original image and images generated by gamma correction (*first row*), corresponding fuzzy color histograms (*second row*), *RBG* color histograms (*third row*), and $L^*a^*b^*$ color histograms (*last row*)

It is clear from Figure 4 that color quantization output of *RGB* and $L^*a^*b^*$ color spaces has drastically changed with a slight change in illumination. On the other hand, fuzzy color histogram was more robust to the same changes.

IV. Evaluation

A. Dataset

We evaluated our fuzzy color histogram-based method on a popular image dataset, PASCAL Visual Object Classes [12]. We used training/validation data, which consists of 5096 images of different scenes and objects.

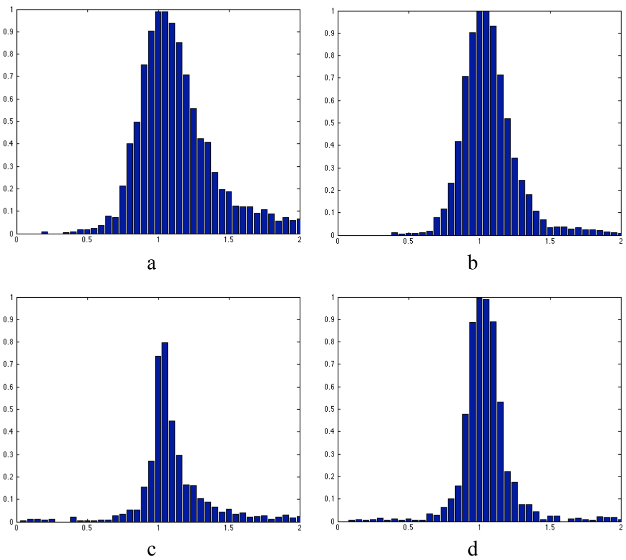
We expanded this dataset by creating one darker and one brighter alternative of each image by using gamma correction. The gamma value were chosen randomly from the interval [0,1] to produce brighter images, and from [1,2] to produce darker images. We used these altered images as queries, and tried to find the original correspondent from the original dataset.

B. Experimental Results

In order to evaluate the performance of fuzzy color histograms, we compared the results of image retrieval with *RGB* color histogram, $L^*a^*b^*$ color histogram, and intensity histogram. Similarity calculations for all cases were based on Euclidean (L_2) distance measure.

For each query image $I_i \in \{I_q\}$ selected from the query image collection of 10192 images $\{I_q\}$, we calculate the Euclidean distance d_{ij} between I_i and each original image $I_j \in \{I_o\}$ in original dataset $\{I_o\}$. Then we sort images in original dataset according to the calculated d_i values. If the original image of the query was found within the top n retrieved images, we consider this as a hit.

Figure 5 shows the average accuracy of each method for different gamma values varying from 0 to 2. Note that gamma correction with a value near to 1 results in minor changes of image illumination. As gamma correction parameter approaches 0 or 2 in our implementation, the changes become more significant.



5. Plot of average accuracy vs. gamma correction value for fuzzy color histogram (a), *RGB* color histogram (b), *L*a*b** color histogram (c), and intensity histogram (d) for *n*=10.

Plots on Figure 5 show that each visual feature can achieve high performance when the illumination change is minor (~0.05). However, as the change in illumination increases, conventional methods fail to retrieve the original image. The retrieval performances of different visual features are compared with fuzzy color histogram in Table II. ε corresponds to the range of gamma correction value. When ε=0.15, gamma value is in range [0.85, 1.15].

TABLE II. ***Retrieval performance (Accuracy) of visual features for different gamma correction values***

	n=10, ε=0.15		n=10, ε=0.25	
	Acc_B	Acc_D	Acc_B	Acc_D
RGB CH	87.26	88.17	66.25	71.41
*L*a*b** CH	39.24	51.24	26.26	38.24
Intensity histogram	79.24	80.36	53.94	57.84
Fuzzy CH	88.41	92.59	71.77	81.62

V. CONCLUSIONS

We proposed a fuzzy color histogram method for content-based image retrieval. Our method is more robust and less sensitive to illumination changes and quantization errors, which are in fact the major disadvantages of conventional color histogram methods. We experimented in *L*a*b** color space, identified output color histogram bins, and defined our fuzzy inference system accordingly. Experiments with images for different illumination settings showed that fuzzy color histograms are more stable than other color-based methods.

As a future work, the performance of proposed fuzzy method can be evaluated in different fields of computer vision, such as shot-boundary detection, kernel tracking, etc.

APPENDIX A – FUZZY RULES

26 fuzzy rules of the fuzzy inference system are listed below.

If (L is black) and (a is amiddle) and (b is bmiddle) then (fuzzyhist is black)
If (L is black) and (b is blueish) then (fuzzyhist is blue)
If (L is grey) and (a is NOT green) and (b is blue) then (fuzzyhist is blue)
If (L is white) and (a is amiddle) and (b is blueish) then (fuzzyhist is blue)
If (L is white) and (a is greenish) and (b is blueish) then (fuzzyhist is blue)
If (L is black) and (a is reddish) and (b is blue) then (fuzzyhist is navy)
If (L is grey) and (a is red) and (b is NOT blue) then (fuzzyhist is red)
If (L is grey) and (a is reddish) and (b is bmiddle) then (fuzzyhist is red)
If (L is black) and (a is reddish) and (b is yellowish) then (fuzzyhist is red)
If (L is grey) and (a is reddish) and (b is yellow) then (fuzzyhist is yellow)
If (L is white) and (a is amiddle) and (b is yellow) then (fuzzyhist is yellow)
If (L is white) and (a is greenish) and (b is yellow) then (fuzzyhist is yellow)
If (L is grey) and (a is reddish) and (b is blueish) then (fuzzyhist is magenta)
If (L is white) and (a is reddish) and (b is blueish) then (fuzzyhist is magenta)
If (L is grey) and (a is amidle) and (b is yellowish) then (fuzzyhist is brown)
If (L is white) and (a is reddish) and (b is yellow) then (fuzzyhist is brown)
If (L is grey) and (a is amiddle) and (b is bmiddle) then (fuzzyhist is grey)
If (L is grey) and (a is greenish) and (b is yellow) then (fuzzyhist is green)
If (L is white) and (a is green) and (b is yellowish) then (fuzzyhist is green)
If (L is grey) and (a is greenish) and (b is bmiddle) then (fuzzyhist is teal)
If (L is grey) and (a is green) and (b is blue) then (fuzzyhist is violet)
If (L is white) and (a is red) and (b is yellow) then (fuzzyhist is orange)
If (L is white) and (a is reddish) and (b is bmiddle) then (fuzzyhist is pink)
If (L is white) and (a is amiddle) and (b is bmiddle) then (fuzzyhist is white)
If (L is white) and (a is greenish) and (b is bmiddle) then (fuzzyhist is cyan)
If (L is white) and (a is green) and (b is bluish) then (fuzzyhist is cyan)

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