Application of the Fuzzy Logic in Content Based Image Retrieval Using Color Feature

Dr. Hameed Abdul-Kareem .Younis

hameedalkinani2004@yahoo.com

Aqeel M. Humadi

aqeelm16@yahoo.com

Computer Science Dept., College of Science, University of Basrah, Basrah, Iraq.

Abstract

Content based image retrieval (CBIR) is a set of techniques for retrieving semantically-relevant images from an image database based on automatically-derived image features. Generally, in CBIR systems, the visual features (color, texture, and shape) are represented at low-level. They are just rigid mathematical measures that can't deal with the inherent subjectivity and fuzziness of people understandings and perceptions (different people would have different understandings and descriptions of the same visual content). As a result, there is a gap between low-level features and high-level semantics.

To overcome this problem, we introduce a new system of visual features extraction and matching using Fuzzy Logic (FL) which is a powerful tool that deals with reasoning algorithms used to emulate human thinking and decision making in machines.

Specifically, color feature is widely used in content-based image retrieval because of its low computational cost and invariance to scaling, translation, and rotation. The classic system of color histogram creation results in very large three-dimensional histograms with large variations between neighboring bins. Thus, small changes in the image might result in great changes in the histogram. Manipulating and comparing 3-D histograms is a complicated and computationally expensive procedure. To overcome these problems, a new fuzzy system of color histogram creation, based on the L*a*b* color space, is proposed, which links the three components of L*a*b* color space using fuzzy inference system and provides one-dimensional histogram which contains only 15 bins.

الخلاصة

نظام استرجاع الصور حسب محتوياتها المرئية (CBIR) هو عبارة عن مجموعة من التقنيات اللازمة لاسترجاع الصور المتشابهة من قاعدة صور اعتماداً على خصائصها المرئية المستخرجة آلياً.

في هذا النظام يتم تمثيل الخصائص المرئية (اللون، والنسيج، والشكل) على شكل واصفات رقمية واطئة المستوى، وهي بدورها تعتبر مقاييس رياضية صارمة ليس بإمكانها التعامل مع الذاتية والضبابية الكائنتين في فهم الناس وإدراكهم (تعدد الأشخاص يعني تعدد الإدراكات والمفاهيم لنفس المحتوى اللوني للصورة).

للتخلص من هذه المشكلة، نقدم طريقة جديدة لاستخراج الخصائص المرئية ومطابقتها باستخدام المنطق المضبب، وهو بدوره يمثل أداة قوية تتعامل مع خوارزميات الاستنتاج المستخدمة لمحاكاة التفكير البشري وصنع القرار في الآلة.

تستخدم خاصية اللون على نطاق واسع في نظام استرجاع الصور حسب محتوياتها اللونية، لأنها قليلة الكلفة الحسابية، وثابتة تجاه تغير المقياس والإنتقال والتدوير. إن الطريقة القديمة لاستخراج هستوكَرام الألوان تُنتج هستوكَراماً ثلاثي الأبعاد وكبير الحجم مع تغيرات كبيرة بين مجموعاته المتجاورة، لذلك فإن أي تغيّر بسيط في الصورة يؤدي إلى تغير كبير في هستوكَرام الألوان. بالإضافة إلى ذلك، فإن معالجة ومقارنة هستوكَرام ثلاثي الأبعاد معقدة ومكلفة حسابياً. للتغلب على هذه المشاكل، اقترحت طريقة مضببة جديدة لاستخراج هستوكَرام الألوان. تعتمد هذه الطريقة على الفضاء اللوني (L*a*b*)، إذ تربط مكوناته الثلاثة باستخدام نظام الإستنتاج المضبب، وتقدم هستوكَرام ألوان أحادي البعد مؤلف من 15 مجموعة فقط.

1. Introduction

Very large collections of images are growing rapidly due to the advent of cheaper storage devices and the Internet.

Finding an image from a large set of images is an extremely difficult problem. One solution is to label images manually, but this is very expensive, time consuming and infeasible for many applications. Furthermore, the labeling process depends on the semantic accuracy in describing the image. Therefore, many content based image retrieval systems are developed to extract low levels features for describing the image content [1].

A typical content-based retrieval system is divided into off-line feature extraction and on-line image retrieval [2]. In off-line stage, the system automatically extracts visual attributes of each image in the database based on its pixel values and stores them in a different database within the system called *a feature database*. In on-line image retrieval, the user can submit a query example to the retrieval system. The system represents this example with a feature vector. The distances (i.e., similarities) between the feature vectors of the query example and those of the media in the feature database are then computed and ranked. The system ranks the search results and then returns the results that are most similar to the query examples.
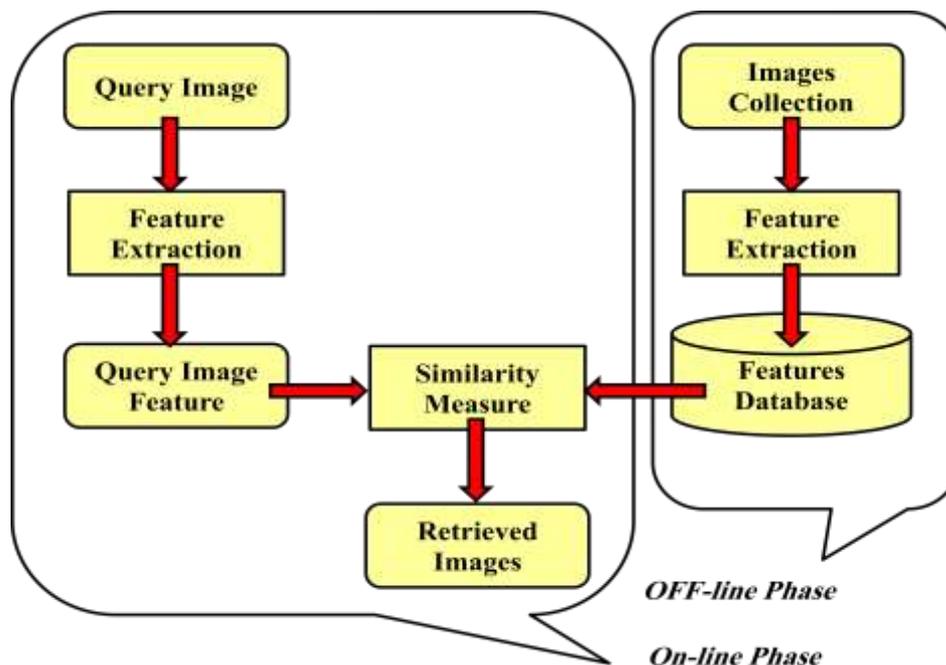

Figure (1): CBIR system.

Image data is fuzzy in nature and in content-based retrieval this property creates some problems such as [3]:

1. Descriptions of image contents usually involve inexact and subjective concepts.

2. Usually imprecision and vagueness exist in descriptions of the images and in some of the visual features.

3. User's needs to image retrieval may be naturally fuzzy.

To overcome these problems, it is needed to introduce a score, and quantify the degree of truth, by which the available description permits a decision about a given query.

FL is used in CBIR system because it is the nature of image data, and the nature of human perception and thinking process, so it can minimize semantic gap between high level semantic and

low level image features. Also, it is robust to the noise and intensity change in the images. Finally, the users are interested in results according to similarity (closeness) rather than equality (exactness).

In [4], a color histogram representation, called fuzzy color histogram (FCH), is presented by considering the color similarity of each pixel's color associated to all the histogram bins through fuzzy-set membership function. An approach for computing the membership values based on fuzzy-means algorithm is developed. The proposed FCH is further exploited in the application of image indexing and retrieval. Konstantinidis, Gasteratos and Andreadis [5] propose a fuzzy linking system for color histogram creation in L*a*b* color space. It contains 10 bins, and 27 rules used to derive the final histogram. Kucuktunc, and Zamalieva [6] propose a fuzzy linking system for color histogram creation in L*a*b* color space. It contains 15 bins, and 27 rules used to derive the final histogram.

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

The rest of the paper is organized as follows: The proposed CBIR system is described in section 2, the experimental results are illustrated in section 3, and finally, the conclusion is given in section 3.

2. The Proposed CBIR System

Firstly, we've to select the appropriate color space for CBIR system. The color space used for CBIR system must own two important aspects [1]:

a. **Device independency**: It means that the color space is never affected by display devices, i.e., it requires a *device-independent color space*.

b. **Perceptual uniformity**: It means that the resulting mathematical distance between colors is proportional to the perceived difference between them by human eyes.

Most color spaces (e.g., RGB, CMY (K), and HSI family) are device-dependent and not perceptually uniform, but L*a*b* color space stays at the safe side away from these two problems. So, among all color spaces, L*a*b* color space was selected because it is device-independent and perceptually uniform color space which approximates the way that humans perceive color [1].

Secondly, we've to build a fuzzy inference system, and then we create the required algorithms for relevant images retrieval.

1.1 Fuzzy Inference System (FIS) for Color Feature Extraction

In L*a*b* color space, L* stands for luminance, a* represents relative greenness-redness and b* represents relative blueness-yellowness.

Building fuzzy inference system for extracting fuzzy color histogram (FCH), as shown in Figure (7), is achieved by the following steps:

Step 1: After separating the three triplets of L*a*b* color space, as shown in Figure (2), each one is fuzzified as an input to the fuzzy inference system.

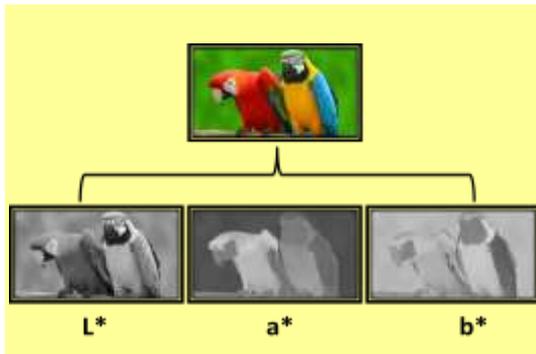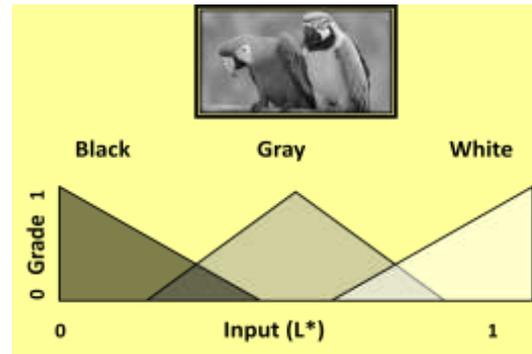Figure (2): Three triplets of L*a*b* color space.

Figure (3): Fuzzification of L* component.

L* component does not contribute in providing any unique color but for shades of colors, white, black, and grey. Thus, the L* component receives a lower weight with respect to the other two components of the triplet. For this reason, we subdivided L* component into only three triangular-shaped fuzzy sets: (Black, Gray and White), as shown in Figure (3).

In order for CBIR to work effectively, a* and b* are subdivided into five triangular-shaped fuzzy sets, as depicted in Figures (4 and 5). For a*, we have: (Green, Greenish, Middle, Reddish, and Red). For b*, we have: (Blue, Bluish, Middle, Yellowish, and Yellow). The reason for which the middle MF exists both in a* and b*, is that in order to represent black, grey and white as seen in L*, then a* and b* must be very close to the middle of their regions; this is a well-known fact about the L*a*b* space.
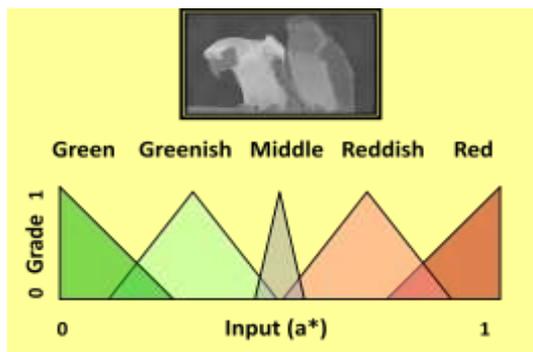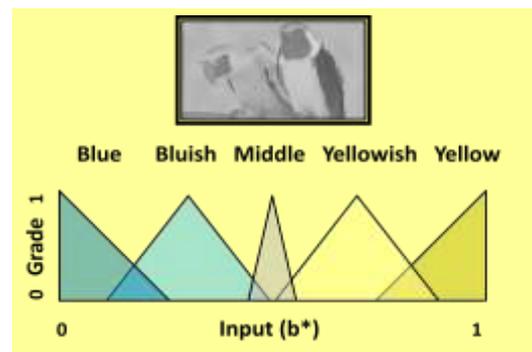

Figure (4): Fuzzification of a* component.

Figure (5): Fuzzification of b* component.

Step 2: The output of the system, which represent our fuzzy color histogram, is divided into 15 equally divided trapezoidal-shaped fuzzy sets, as shown in Figure (6). So, the final FCH consists of only 15 bins approximately representing the following colors: (Black, Gray, Red, Red-Orange, Orange, Yellow-Orange, Yellow, Yellow-Green, Green, Blue-Green, Blue, Blue-Violet, Violet, Red-Violet, and White).

Step 3: Creating a knowledge base (fuzzy IF-THEN rules) used for mapping from three fuzzy inputs (L*, a*, and b*) to one fuzzy output (FCH). Our proposed fuzzy inference system has 75 rules established through empirical conclusion. For example:

IF (L is *Black*) and (a is *Middle*) and (b is *Middle*) THEN (FCH is *Black*).
IF (L is *Gray*) and (a is *Red*) and (b is *Middle*) THEN (FCH is *Red*).
IF (L is *White*) and (a is *Green*) and (b is *Blue*) THEN (FCH is *Cyan*).
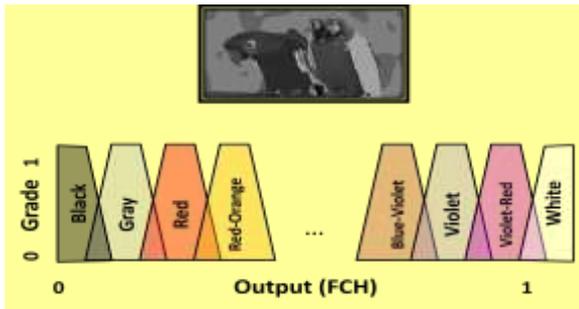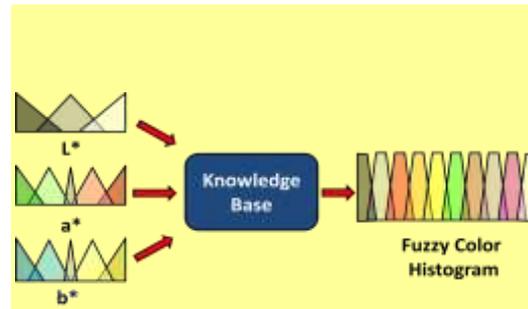.
.
.

Figure (6): Fuzzy Color Histogram.

Figure (7): Fuzzy Inference System for FCH extraction.

This representation takes into account the uncertainty presents in the extraction process of features and consequently, increases the precision rate in the image retrieval process.

1.2   Off-line Feature Extraction Algorithm

From given an image, FCH can be extracted using the algorithm illustrated in Figure (8). In this algorithm, given an image is read, and then resized to 50×50 pixels (aspect ratio saved). After that, it's converted from the default RGB color space to a color space appropriate for CBIR system (L*a*b* color space). Then, it's normalized and entered to the previously built fuzzy inference system (FIS) for extracting the FCH. The output of the fuzzy inference system is 2-D fuzzy colored image. The FCH is calculated from this 2-D fuzzy colored image by subdividing it into 15 bins.

1.3   2-D Fuzzy Colored Image Calculation Algorithm

The 3-D image is read by the fuzzy inference system, and then the three triplets of each pixel are fuzzified. These fuzzified triplets are entered into the fuzzy inference engine for computing fuzzy IF-THEN rules resident in the knowledge base. The three crisp components of each pixel in the input 3-D color image are converted into one crisp component in the output 2-D fuzzy colored image. This algorithm is illustrated in Figure (9).
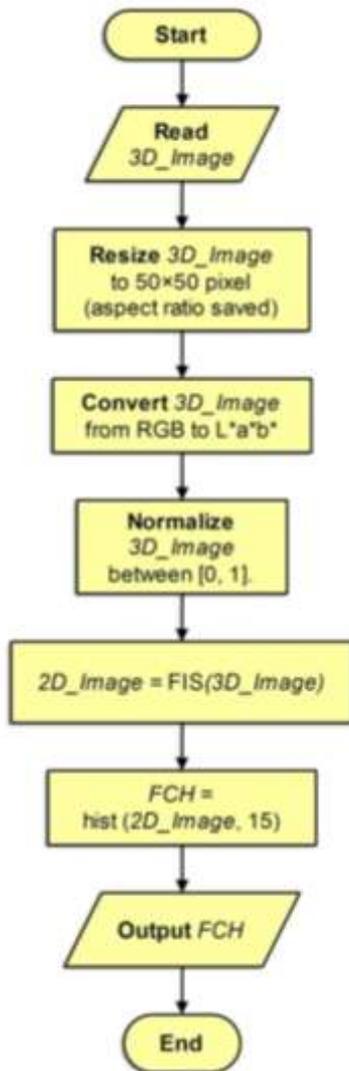
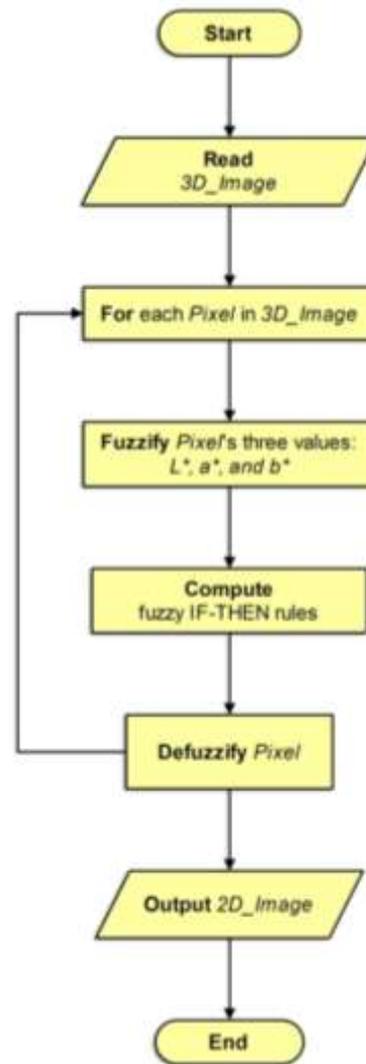Figure (8): A flow chart for illustrating the steps of extracting the FCH.

Figure (9): A flow chart illustrating the steps of converting a 3-D color image to 2-D fuzzy colored image using the proposed fuzzy inference system (FIS).

1.4 On-line Fuzzy Features Matching Algorithm

After obtaining the fuzzy color histogram as a visual feature of the query image using our proposed fuzzy inference system described previously, we need to compare it with the FCHs of all images in the image database to specify the degree of similarity, and then retrieve the most relevant (similar) images to the user.

There are many fuzzy similarity measures, the similarity measures used in our proposed system is called *Min-max ratio*. The similarity *(S(A,B))* between two fuzzy sets is given by [7]:

$$S(A,B) = \frac{\sum_{i=1}^{N} min(u_A(i), u_B(i))}{\sum_{i=1}^{N} max(u_A(i), u_B(i))} \qquad \dots (1),$$

where $u_A(i)$ and $u_B(i)$ are the membership values of the ith bin of histograms H_A and H_B, respectively. For an identical pair of fuzzy sets, the memberships are equal and the similarity value will be equal to 1.

The similarity algorithm starts with extracting the FCH from the query image, and then it's compared with the FCHs of all images in the image database. Then, the ranked similarities are

sorted descending, and the top nine images are retrieved to the user as the most relevant images, as shown in Figure (10).
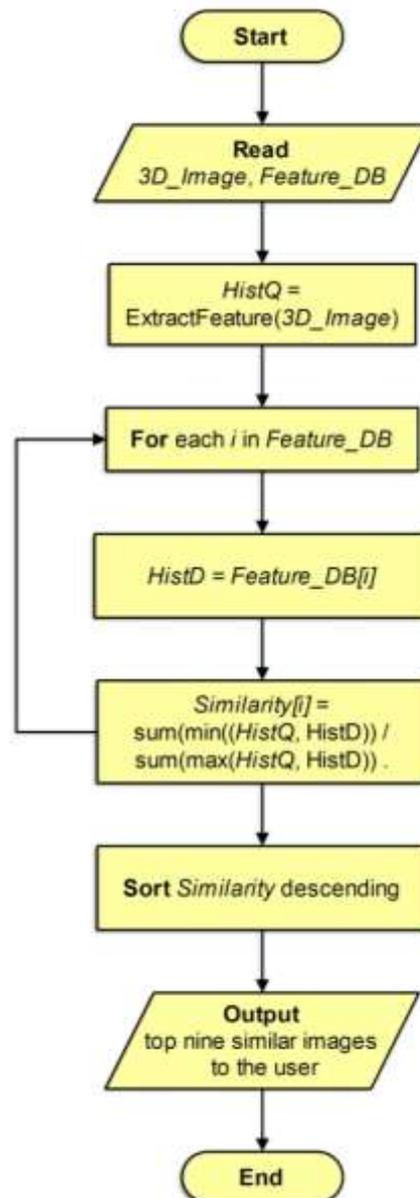
Figure (10): A flow chart illustrating the steps of on-line FCH matching algorithm.

1.5 Relevance Feedback

As mentioned previously, there is a large gap between low level visual features and image semantic. Therefore, relevance feedback is used in CBIR systems to manipulate with this problem. Many complicated techniques of relevance feedback are available, but it's time consuming and computationally expensive.

In our proposed system, the use of fuzzy logic technique has minimized this gap by applying human thinking process in the CBIR system. But, the problem hasn't totally eliminated (the gap is still existing although it has been minimized).

To tackle this problem, the proposed CBIR system has been provided with another technique which is called *relevance feedback*.

Fuzzy logic application in the CBIR system has made a relevance feedback process very simple. The extracted FCH is very easy for the user to understand; therefore a specialized graphical

interface is created to provide him/her with an editable FCH of the submitted query image. After extracting the color feature of the query image, the resulting FCH is retrieved to the user. Now, the user can modify the FCH of the query image and then resubmit the modified FCH to the proposed CBIR system as relevance feedback.

3. Experimental Results

The proposed system has been implemented using Matlab R2012a (7.14), and tested on a subset of 500 images of a general-purpose WANG [8] database which form 5 classes of 100 images each. The WANG database is a subset of 1000 images of the Corel stock photo database, in JPEG format of size 384×256 and 256×386.

3.1 Robustness to Noise

The conventional systems used for extracting 3-D color histograms are very sensitive to even very small noise in the perceptually relevant images and considers them as irrelevant, so the noise is reflected on the color histograms as a very large distance measure between them. Therefore, the performance of the CBIR decreases into the minimum.

In the proposed system, each bin in the FCH is represented by a fuzzy membership function, so the movement from one bin to the neighboring ones occurs gradually (not suddenly as in classic systems). Moreover, each pixel in given an image has a membership degree to multiple bins of the FCH ranges between [0, 1]. Therefore, any change in pixel's triplet values is slightly reflected on multiple bins. This technique guarantees the retrieval of relevant images to the query image, despite the presence of the noise.

We've proven it practically by adding (15%) of noise to a *bus-1* image, then computing the similarity measure between it and its noisy copy. In Figure (11), we used a conventional system for extracting a 3-D color histogram from these two images, then computing the degree of similarity between them using histogram intersection metric. Perceptually, these two images are identical, but statistically the similarity between them has never exceeded (59%)!
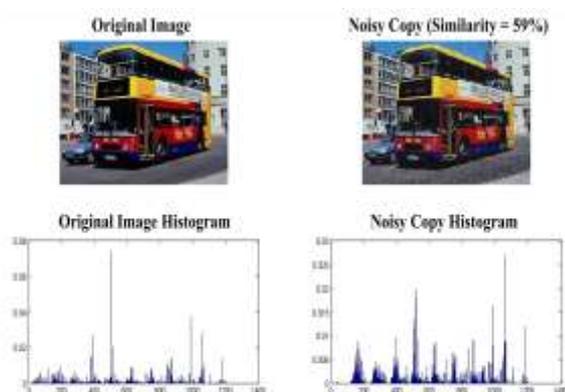

Figure (11): Similarity between *bus-1* image. and its noisy copy using classic color histogram
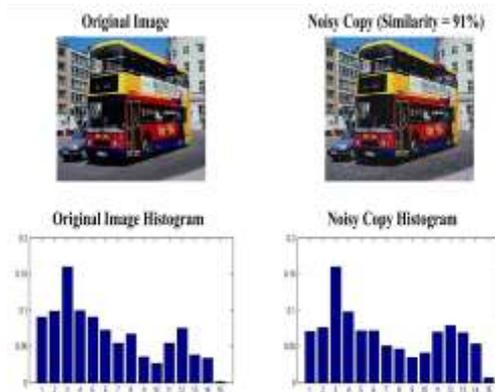
Figure (12): Similarity between *bus-1* image and its noisy copy using Fuzzy Color Histogram.

But, when we applied the proposed system, the results were proportional to human perception. For the *bus-1* image, the similarity degree was (91%), as shown in Figure (12).

3.2 Robustness to Illumination Change

The classic color histogram is three dimensional. One of these dimensions is reserved for illumination graduation. Moreover, the classic color histogram is computed using statistical system, where the movement from one bin to the neighboring one occurs suddenly. Therefore, any small change in illumination results in a large change in this part of color histogram, as shown in Figure (13). Therefore, the performance of the CBIR system will decrease to the minimum.

There is no existence of this problem in fuzzy color histogram, because it doesn't care of illumination change (all intensities of colors are represented by only one bin using fuzzy membership function), as shown in Figure (14).

We can summarize the comparison results between classic and fuzzy systems of extracting the color histogram to show their different sensitivities to the noise and illumination changes in the matching phase in Table (1).
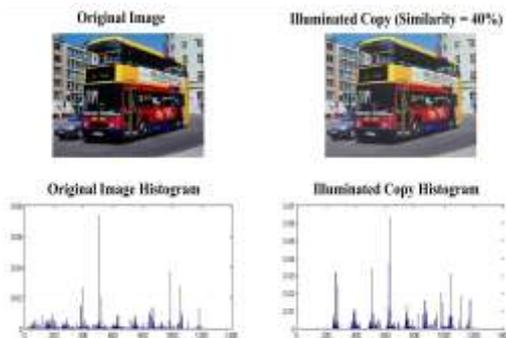
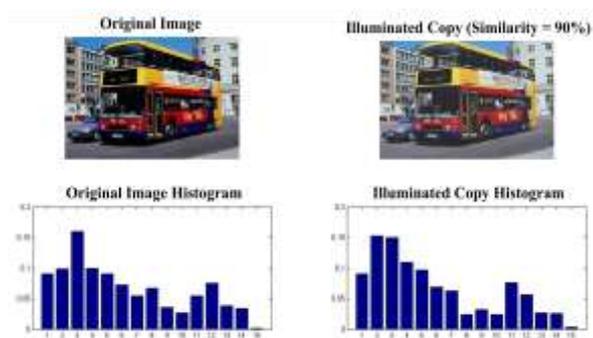|	
Figure (13): Similarity between *bus-1* image. and its illuminated copy using classic color histogram	Figure (14): Similarity between *bus-1* image and its illuminated copy using FCH.

Table (1): Sensitivity comparison of fuzzy and classic systems to noise and illumination changes.

Original Image	Similarity of Noisy Copy		Similarity of Illuminated Copy	
	Proposed Fuzzy System	Classic System	Fuzzy System	Classic System
	91%	59%	90%	40%
	96%	68%	68%	27%
	83%	64%	79%	20%

3.3 Performance of the Proposed CBIR System

The images perceptually highly relevant to the submitted query image must have very small average of distance measures (very high average of similarity degrees) between them and the query image. Also, these distance measures between them mustn't suffer from variation (dispersion).

The average of similarity degrees is computed using the mean (μ), as follows [9]:

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i \qquad \dots (2),$$

where N is the number of retrieved images, and x_i is a FCH of i-th image.

The dispersion is computed by the standard deviation (σ) which shows how much variation or dispersion from the average exists, as follows [9]:

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2} \qquad \dots (3),$$

where N is the number of retrieved images, x_i is a FCH of i-th image, and μ is the mean.

The conventional 3-D color histogram suffers from large distances between perceptually very similar images, and also suffers from dispersion. For example, the top nine images relevant to *rose-1* image have only 55% of mean, and 17% of standard deviation. So, if we assigned a threshold of 80%, which indicates to very similar images, the number of relevant images retrieved is only one! , as shown in Figure (15). Suppose that the number of relevant images is X, then the recall measure, which is the fraction of relevant images returned by the query, will be *1/X* (a very small ratio). As a result, the performance of the conventional system isn't good.

Our proposed system doesn't have the previously discussed problem, i.e., the distance measures are proportional to the perceptual similarity of the relevant images, and there is no dispersion exists. So, if we assigned a threshold of 80%, which indicates to very similar images, the number of relevant images retrieved is seven images, as shown in Figure (15). Suppose that the number of relevant images is X, then the recall measure will be *7/X* (a good ratio). Intuitively, *7/X* recall measure of fuzzy system is larger than *1/X* recall measure of the conventional system; therefore, we can deduce that the fuzzy system has much better performance than the conventional system.

Practically, we've proven that using multiple experiments applied on several images of WANG database, as shown in Table (2).
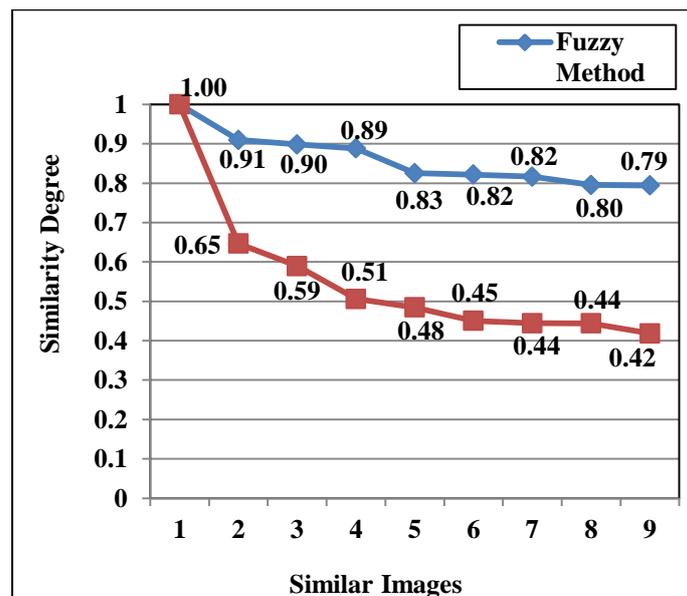

Figure (15): A difference in similarity degrees between classic and fuzzy systems in retrieving top nine images relevant to a *rose-1* image.

Table (2): Mean and standard deviation comparison between fuzzy and classic systems.

Original Image	Mean of similarity degrees		Standard deviation of similarity degrees	
	Proposed Fuzzy System	**Classic System**	**Fuzzy System**	**Classic System**
	87%	46%	5%	19%
	88%	68%	5%	13%
	85%	57%	7%	16%

4. Conclusions

From large variety of experiments applied on 500 images of WANG database, we've concluded the following results:

1. The FCH is robust to the noise and illumination changes in the images. As a result, it guarantees the retrieval of the images relevant to the query image despite the presence of the noise and the change of the illumination, as proven practically in Figures (12 and 14) and Table (1). Therefore, the recall measure interestingly increases.

2. Even though the FCH is a vector of only 15 elements, it has improved the CBIR system performance, because it's computed logically (human perception and thinking) not statistically (rigid measures), as shown in Figure (15) and Table (2).

3. The FCH minimizes the size of the features database and decreases the computational cost, because it is one-dimensional descriptor with only 15 bins. In the conventional system, the color histogram is three-dimensional with more than 1000 bins. So, the size of the fuzzy color histogram is smaller than the color histogram of the conventional system at ration of (0.015), as shown.

4. The perceptually relevant images have very small distance measures (high similarity degrees) between them and the query image, and they don't suffer from dispersion, because features extraction depends on perception (fuzzy) not on measure (crisp), as shown in Figure (15) and Table (2).

5. It's easy for users of the CBIR system to understand and directly modify the FCH of the query image, then submit the modified FCH to the CBIR system again as feedback, because the human thinking process is applied in the FCH extraction. Therefore, the FCH seems very easy for users to understand and modify.

5. References

[1]   V. Castelli, and L. Bergman, "Image Databases: Search and Retrieval of Digital Imagery", Wiley-Interscience, USA, 2002.

[2]   F. Long, H. Zhang, H. Dagan, and D. Feng, "Fundamentals of Content Based Image Retrieval", Springer-Verlag, Berlin Heidelberg New York, 2003.

[3]   L. Yan, and Z. Ma, "Intelligent Multimedia Databases and Information Retrieval: Advancing Applications and Technologies", September - 2011.

[4]   Han, J., & Ma, K. K. (2002). Fuzzy color histogram and its use in color image retrieval. IEEE Transactions on Image Processing, 11(8), 944–952. doi:10.1109/TIP.2002.801585

[5]   K. Konstantinidis, A. Gasteratos, I. Andreadis, "Image Retrieval Based on Fuzzy Color Histogram Processing", Optics Communications, vol.248, Issues 4-6, pp.375-386, 2005.

[6]   O. Kucuktunc, and D. Zamalieva, "Fuzzy Color Histogram-based CBIR System", March - 2009.

[7]   X. Shaoping, L.Chunquan, J. Shunliang, "Similarity measures for content-based image retrieval based on intuitionistic fuzzy set theory", ACADEMY PUBLISHER, July - 2012.

[8]   http://savvash.blogspot.com/2008/12/benchmark-databases-for-cbir.html

[9]   S. Ross, "Introduction to Probability and Statistics for Engineers and Scientists", Academic Press, Fourth Edition, USA, February – 2009.