Shahrood University of Technology

Journal of Artificial Intelligence and Data Mining (JAIDM)
Journal homepage: http://jad.shahroodut.ac.ir

Research paper

Image Retrieval based on Multi-features using Fuzzy Set

Monireh Azimi Hemat[1] and Fatemeh Shams Ezat[2] and Marjan Kuchaki Rafsanjani[3*]

1. Department of Computer Engineering and Information Technology, Payame Noor University, Iran.
2. Department of Computer Science, Faculty of Mathematics and Computer, Fasa University, Fasa, Iran.
3. Department of Computer Science, Faculty of Mathematics and Computer, Shahid Bahonar University of Kerman, Kerman, Iran .

Article Info

Article History:
Received 16 May 2022
Revised 01 July 2022
Accepted 06 September 2022

DOI:10.22044/jadm.2022.11876.2337

Keywords:
Image retrieval, feature extraction, fuzzy color histogram, image edges, spatial dependency of pixels.

**Corresponding author: kuchaki@uk.ac.ir(M. Kuchaki Rafsanjani).*

Abstract

In content-based image retrieval (CBIR), the visual features of the database images are extracted, and the visual feature database is assessed in order to find the images closest to the query image. Increasing the efficiency and decreasing both the time and storage space of indexed images is the priority in developing the image retrieval systems. In this research work, an efficient system is proposed for image retrieval by applying fuzzy techniques, which are advantageous in increasing the efficiency and decreasing the length of the feature vector and storage space. The effect of increasing the considered content features' count is assessed to enhance the image retrieval efficiency. The fuzzy features consist of color, statistical information related to the spatial dependency of the pixels on each other, and the position of image edges. These features are indexed in fuzzy vector format 16, 3, and 16 lengths. The extracted vectors are compared through the fuzzy similarity measures, where the most similar images are retrieved. In order to evaluate the proposed system's performance, this system and three other non-fuzzy systems where fewer features are of concern are implemented. These four systems are tested on a database containing 1000 images, and the results obtained indicate improvement in the retrieval precision and storage space.

1. Introduction

The rapid advances in hardware technology next to the growth in computer capabilities make it possible to store a large volume of multi-media information. The image databases are applied in medicine, telecommunications, and the industry. Searching for images and information in these databases is complicated and time-consuming, which lead to the emergence of an active research field named image retrieval.

In this field, the two approaches context-based image retrieval and content-based image retrieval are of concern, and the critical features of the image are extracted by both in the indexing phase. In the first approach, indexing is manual, and in the second is automatic. When a considerable volume of visual information is at hand, context image retrieval encounters two major challenges: individual perceptions from images and timing [1, 2]. These two challenges push image retrieval forward based on content, which indexes images based on their visual content rather than applying the keywords.

Content-based image retrieval (CBIR), performs in two indexing and searching phases. In the first phase, for each image in database, the features are extracted and stored in the visual features database. In the search phase, when the user requires a similar image for a query image, the features of this image are extracted. These extracted features are compared with all features in the features database by applying a similarity measure. The images that are most similar to the query image are extracted and returned to the user.

In each CBIR system, the images are indexed through the visual features like color, shape, and texture [3]. Since the beginning of studies run on CBIR, color has been of concern. Usually, in some systems, the color histograms are applied to index this feature. The color histogram represents only the overall distribution of the image, and other visual image features, like shape and texture, are not considered; therefore, this practical information is lost. This disadvantage becomes even more pronounced in large databases, with multiple images having the same color distribution. Recently, in many studies, information about the shape, texture or spatial relationships of the image with the color histogram are combined to overcome this drawback.

Although the fuzzy sets have the flexibility and power to express ambiguity in color, they are also contributive in image processing [4]. The researchers in [5] were the ones who first applied the fuzzy sets in image processing; the researchers in [6] introduced the fuzzy similarity measures for image retrieval.

The fuzzy sets and similarity measures are applied to index images and calculate their similarities. The positive effect of the multiplicity of feature extraction and applying the fuzzy sets increase the efficiency of image retrieval systems and encourage the authors here to propose a fuzzy image retrieval system based on more features. The fuzzy features of concern here are the color, statistical information related to the spatial dependence of pixels on each other, and the image edge position. The focus is on fuzzification and developing the non-fuzzy system provided by [7]. They designed a system with an acceptable performance by combining color and image edge features. In their study, upon blocking the image, the extracted homogeneous and non-homogeneous blocks identify the image edges and combine them with the information obtained from the color of the image blocks to determine the similarity of the images possible.

In this paper, the feature extraction process phases are fuzzed, and the spatial dependency of image pixels that complements the information on the image edges is added to the features of the image. Despite the increase in the image features, because of applying the fuzzy methods, the dimensions of the feature vector decrease by one-fifth compared to the previous system [7].

Therefore, considering an additional feature and applying the fuzzy sets in the proposed system improved the performance of the image retrieval system significantly next to reducing storage space.

This article is organized as what follows. The literature is reviewed in Section 2; the proposed system is explained in Section 3; the implimentation results are presented in Section 4, and the article concludes in Section 5.

2. Literature Review

In preliminary researches in the CBIR field, one feature is used to retrieve images. However, the findings were weak because images often contained several content aspects [8]. The researchers integrate two or more features to achieve a better retrieve efficiency. This action is commonly known as a feature combination or feature fusion.

In research [9], a system based on combining color and texture features for content-based image retrieval has been proposed. The authors used HSV color space and extracted the color histogram and texture features based on a concurrency matrix. These matrices form the feature vectors. The combination of global color histogram, local color histogram, and texture features has been analyzed and the results show the superiority of this method over the methods that use only one feature. In [10], the authors proposed a method that used a combination of three features of color, shape, and texture to retrieve the image based on the content. In this article, HSV color space is used and a better retrieve result is obtained. Also to increase the retrieval speed based on the shape, the approximate shape has been considered instead of the exact shape, and the grey level co-occurrence matrix has been used to extract the texture features of the images. The similarity measure used is the Canberra distance.

In another research work, a CBIR system is proposed with a forward feed structure with three steps for image retrieval [11]. In the first step, the appropriate N images were retrieved from the data set images based on color characteristics, which included M images. They used the color histogram to calculate the color features. In the next step, by calculating the Gabor filter to calculate the texture feature, the P-related images are obtained from the N image subset based on the texture feature.

Finally, to retrieve K-related images from P-images, the Fourier descriptor is calculated and used as the shape feature. In this way, the values of N, K, and P can be changed so that the relevant feedback can be used to improve accuracy.

However, one of the disadvantages of this system is that it does not have a step for classifying images based on spatial information.

The researchers in [12] have developed a new CBIR system that works based on the color and texture features. They integrated the mean k-clustering algorithm with particle swarm optimization (PSO). The system was performed on the 1000 images in 10 classes from WANG dataset. The efficiency is improved except in two architecture and buses classes compared to the previuos advanced techniques. In addition, the proposed system did not take into account the shape feature when calculating the similarity.

Ponomarev *et al*. have proposed a new image retrieval system using the integration of color, shape, and texture [13]. To extract these three features, automatic color correlation, Gabor transforms, and wavelet transform was used. Manhattan distance is the measure used to calculate the similarity between the data set images and the query image. The mean values for the Corel, Li, and Caltech 101 datasets were 0.8300, 0.8800, and 0.7000, respectively. The system also had drawbacks including increased computational complexity due to the combination of several features.

Local structure descriptors are provided in CBIR to illustrate the local spatial structure of information that makes these descriptors more semantic. MTSD is one of the new descriptions in this field that uses local and multi- trend structures [14]. This paper is based on the integration of edge, color, and intensity information, and uses several trends to identify low-level features and information on local spatial structure. The authors tested this descriptor on the Caltech and Corel datasets (1K, 5K, and 10K), and the results show that the proposed descriptor performs much better than many advanced descriptors.

Image analysis at a resolution level may lose valuable detail. Therefore, a new system was proposed in [15]. This system is based on the texture and shape features, in which a local binary pattern descriptor is used to extract the texture features, and Legendre moments are used to extract the shape features. Although local binary pattern is used to extract local attributes, combining the local attributes with global attributes create an effective attribute vector. Their system was tested on five datasets, which improved accuracy and sensitivity. The disadvantage of this system is that achieved higher resolution with increasing computational cost due to multi-analysis.

The researchers in [16] have proposed an invariant CBIR system for color change and texture rotation. This proposed system is based on fusing textures and colors to cunstract a 360-lenght feature vector. The extraction of color features is done by converting images to HSV color space and quantizing through the color histogram.

One of problems in image retrieval are the illumination changes. Using only Hue and Saturation channels are the solution to solve this problem. Rotate local binary pattern (RLBP) extracts the fixed texture features. Their system is evaluated through implementation on the Zurich (ZB) building, 1K Corel and 10K Corel.

A multi-stage CBIR technique was introduced in [17]. In the first step, the color moment was used to extract the color feature, which reduces the cost of calculations. In next step, the edge and texture features are extracted from the images in the new dataset created from the first step. To extract texture information, LBP was used, while the Canny Edge Detector extracted edge information. Although this system improves performance and increasing accuracy and decreasing runtime, the runtime required depends on the number of data set images.

They also presented a method for color-based dominant image retrieval [18]. Four image datasets were used in the experiments to evaluate their dominant color descriptor. To improve the new system, it should be combined with other feature extraction methods as texture and shape to reduce the semantic gap.

The presented image retrieval system in [19] extracts global and local texture and colour information in two spatial and frequency domains. In this system, image is filtered by Gaussian filter, then co-occurrence matrices are made in different directions, and the statistical features are extracted. This information and Gabor filter banks are used to extract local texture features.

A subjective approach to the CBIR system based on a combination of low-level features such as texture and color was developed [20]. For extract color features, the color moments in the HSV color space are used, and to extract texture features DWT and Gabor wavelets are utilized. In this paper, a specific technique about the color features and combined features (hybrid techniques) between color and shape features is described [21]. In [22], the authors discussed about the general architecture, various functional components, and techniques of image retrieval systems. Image retrieval techniques such as CBIR using color, using texture, and using shape

features are discussed in this paper. The comparison study about features such as color, texture, shape, and combined features in terms of several are described in this paper. The discussed parameters are recall, precision, and response time.
The disadvantage of this descriptor is that it does not describe the correlation between local spatial information, texture, intensity, and color [23]. The summarized literature on multi-feature-based systems is shown in Table 1.

Table 1. Summary of literature on multi- feature-based systems.

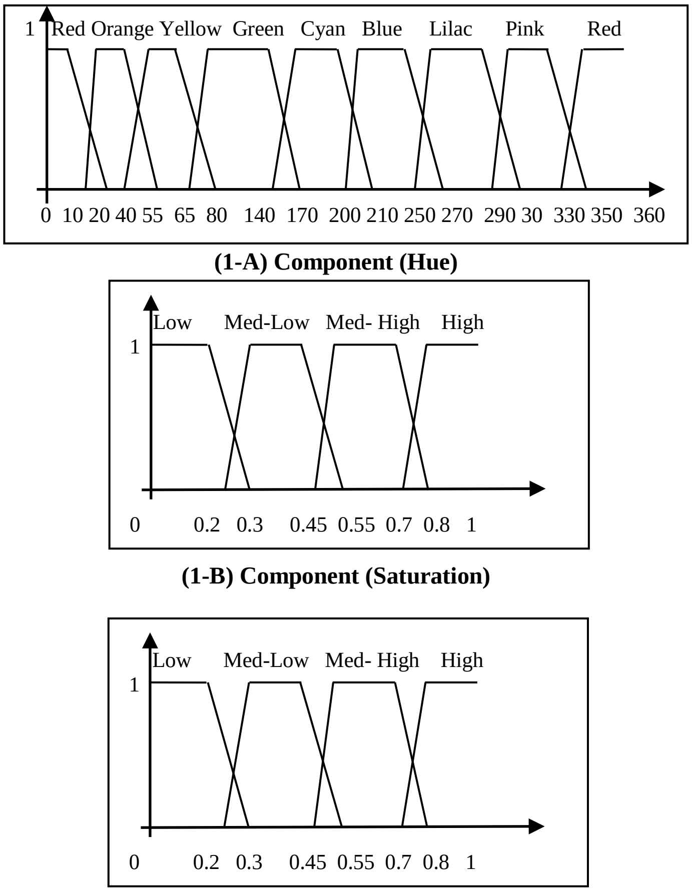
Ref.	Features	Dataset	Accuracy
[7]	Color Shape	Corel	0.6450
[8]	Color Texture	Corel VisTex	0.750 0.8550
[9]	Color Texture	NA	0.750
[10]	Color Texture Shape	Corel	0.8767
[11]	Color Texture Shape	Corel CIFAR	0.7690 0.8590
[12]	Color Texture	Wang	0.7352
[13]	Color Texture Shape	Corel Li	0.8300 0.8800
[14]	Color Texture Shape	Wang	0.9050
[15]	Texture Shape	Corel 1K Corel 5K	0.9995 0.5676
[16]	Color Texture	Corel 1K Corel 10K	0.8770
[17]	Color Texture Shape	Wang Corel 5K	0.8325 0.6860
[18]	color	Wang Corel 10K	0.7534 0.4136
[19]	Color Texture	Corel	0.7627
[20]	Color Texture	Corel 1K Corel 1.5K	0.8750 0.8633
Proposed system	Color Texture Shape	Corel	0.800

3. Proposed System

A fuzzy indexing method based on some visual features of the image is proposed. The fuzzy features consist of color, statistical information related to the spatial dependence of pixels to one another, and the image edge position.

3.1. Fuzzy color feature extraction

Considering the advantages of fuzzy sets in modeling vague concepts, they are applied to extract the feature vector and calculate the similarity of the image color content. One of the color spaces for indexing is HSV. In this space, Hue is used to distinguish colors, Saturation is the percentage of white light added to pure color, and Value refers to the perceived light intensity. In the HSV space, each color is represented by a 3D vector '(H, S, V)', where $H \in [0,360]$ is Hue, and $S \in [0,1]$ and $V \in [0,1]$ are the Saturation and Value, respectively. The components of this HSV color space are divided by the trapezoidal fuzzy functions into 8, 4, and 4 sections, with the membership function (Figure 1).
In this modeling, the trapezoidal fuzzy numbers are used.



(1-A) Component (Hue)

(1-B) Component (Saturation)

(1-C) Component (Value)

Figure 1. Trapezoidal membership functions of HSV color space components.

The membership function of these numbers is expressed through (1). The trapezoidal numbers depend on the four numerical a, b, c, and d parameters [24].

$$A(x;a,b,c,d)=\begin{cases} 0 & if \quad x \le a, \\ \dfrac{x-a}{b-a} & if \quad a < x < b, \\ 1 & if \quad b \le x \le c, \\ \dfrac{d-x}{d-c} & if \quad c < x < d, \\ 0 & if \quad d \le x, \end{cases} \qquad (1)$$

To compute the Hue image feature vector, according to Figure (1-A), the membership degree of all image pixels is obtained. For an image A_j and a pixel *p* this fuzzy number is symbolized as $\mu_{A_j}^{p} = (c_1.c_2.c_3.c_4.c_5.c_6.c_7.c_8)$, where each numerical c_i in [0, 1] is the membership degree of pixel *p* in the H segment, where i = 1 to 8. As observed in Figure (1-A), the color red is of two ranges; if the value of H in one pixel is in one of these red ranges, then the value of other rang is zero and is not considered; consequently, there exists a fuzzy vector with length 8.

The average of these fuzzy numbers is a fuzzy number symbolized as $\mu_{A_j}^{H}$, the Hue feature vector.

To extract the feature vector of the Saturation and Value components of the image, the membership degree of each pixel in the 4 functions is obtained, Figure (1-B and 1-C).

The calculation of H, S, and V are made in a similar manner. For an image A_j and a saturation S, the obtained fuzzy numbers are symbolized as $\mu_{A_j}^{S}$. For an image A_j and a Value V, the obtained fuzzy numbers are symbolized as $\mu_{A_j}^{V}$. As a result, a 16-fuzzy vector is obtained (8 for H, 4 for S, and 4 for V).

3.2 Extracting fuzzy sets related to spatial dependency of image pixels

The 8 neighbors of each pixel are shown in Figure 2. The neighboring pixels count of each center pixel of similar H color is within the 0 to 8 range.

1	2	3
4		5
6	7	8

Figure 2. 8 neighbors of center pixel or block.

This range can be modeled by applying the trapezoidal fuzzy numbers shown in Figure 3. If the count of the pixels in the same color cluster as the central pixels is low, then the spatial dependency state is Low, and the same holds for the medium and higher count, dependencies, the Med, and the High, respectively.

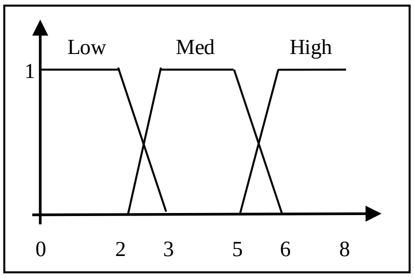


Figure 3. Membership function of positioning a pixel alongside eight neighbors in terms of pixel color.

Therefore, for the image A_j and each pixel *p* the fuzzy number $\mu_{A_j}^{p} = (n_1.n_2.n_3)$ is obtained, where each n_i is a number within [0, 1] as for membership degree of pixel *p* in *i*- spatial dependency level, i = 1 to 3.

The average of these fuzzy numbers is a fuzzy number symbolized as $\mu_{A_j}^{D}$, the spatial dependency feature vector.

3.3 Extraction of fuzzy sets of statistical characteristics related to homogeneous regions and image edges

To extract this feature, the image is first converted into an equivalent grayscale image and then divided into 8 × 8 blocks, followed by the gradient magnitude calculated for each block *b* according to (2) [7].

$$|\nabla_b| = \sqrt{\Delta x^2 + \Delta y^2} \qquad (2)$$

To obtain Δx for block *b*, first, each block is divded into left and right half-block 8 × 4, and next, the average grayscale of these two half-blocks is calculated as x_L and x_R. The average grayscale is obtained by calculating its average Value of 32 (8 × 4) pixels. The difference between these two values is Δx.

To calculate Δy, each block is divided into upper and lower half-blocks of 4 × 8, with the average grayscale of y_u and y_L and a difference of Δy.

After calculating $|\nabla_b|$ for each block, the blocks with gradient magnitude lower than a threshold 13 are known as homogeneous; otherwise, non-homogeneous [7].

After determining the homogeneous or non-homogeneous blocks, the following steps must be of concern:

1- Assign a code to 8 neighbors of each block according to Figure 2.

2- For each block, form an 8-digit vector of 0 and 1 numbers. To determine each digit *i*, if the central block and its i-neighboring block are in the same homogeneous state, the digit *i* is 1; otherwise, 0

3- The sum of these vectors is obtained for homogeneous and non-homogeneous blocks separately.

4- By dividing these two vectors by their maximum values, they become fuzzy vectors with all fractures within [0, 1].

An 8-digit fuzzy feature vector is extracted for homogeneous blocks and an 8-digit fuzzy feature vector for non-homogeneous blocks (a total of 16) by following the four steps. Finally, for each image A_j, a 16-member fuzzy set μ_{A_j} is obtained.

The block diagram of this proposed feature extraction process is shown in Figure 4.

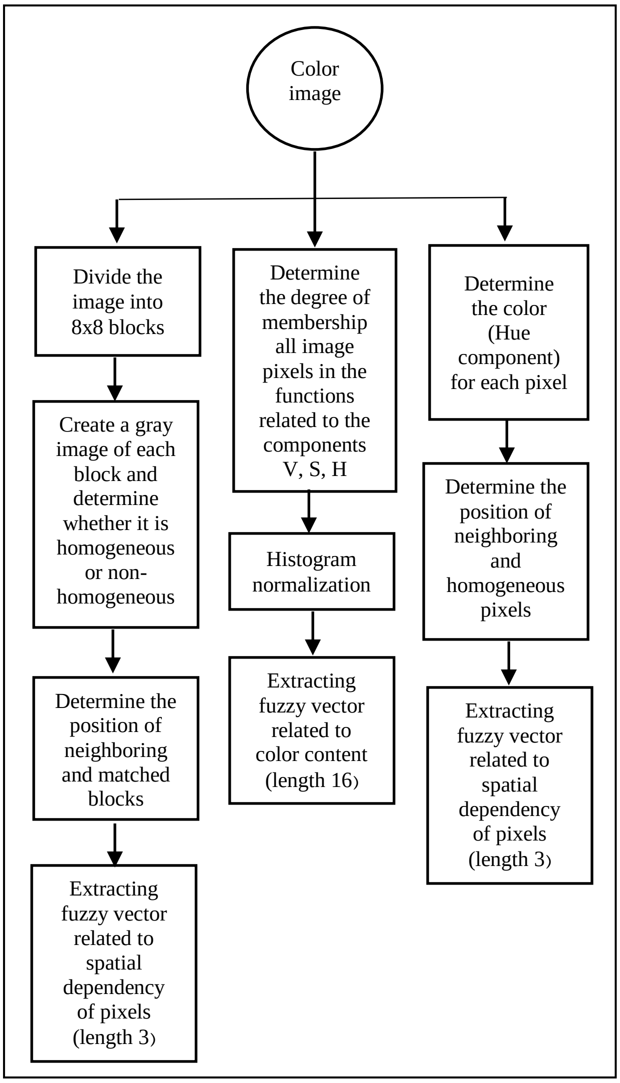


Figure 4. Block diagram of feature vector extraction section.

3.4. Fuzzy retrieval (determining similarity of two images)

In the indexing phase, a fuzzy feature vector of 35 (8 + 4 + 4 + 3 + 16) length is extracted for each image. In the retrieval step, the main problem is determining the similarity of the two images (two feature vectors). In this process, a fuzzy similarity measure is applied to retrieve the most similar database images to query. The descriptions and types of fuzzy similarities are mentioned in [25]. Here, the similarity is measured separately for each feature, and finally, the results are combined to calculate the overall similarity of the two images.

To calculate the similarity in H through (3), the two images A_0 and A_j are applied in color c:

$$S\left(\mu^{c}_{A_0},\mu^{c}_{A_j}\right)=\frac{\left|\mu^{c}_{A_0}\cap\mu^{c}_{A_j}\right|}{\left|\mu^{c}_{A_0}\cup\mu^{c}_{A_j}\right|}=\frac{\sum_{x\in S_c}\min\left(\mu^{c}_{A_0}(x),\mu^{c}_{A_j}(x)\right)}{\sum_{x\in S_c}\max\left(\mu^{c}_{A_0}(x),\mu^{c}_{A_j}(x)\right)} \tag{3}$$

where A_0 is the query image, and A_j is an image in the dataset.

In this context, S_c is the same fuzzy function range for the color c.

As to H, the average similarity rate in 8 colors is symbolized as $S\left(\mu^{H}_{A_0}.\mu^{H}_{A_j}\right)$.

The average similarity of two images A_0 and A_j in S and V is $S\left(\mu^{S}_{A_0}.\mu^{S}_{A_j}\right)$ and $S\left(\mu^{V}_{A_0}.\mu^{V}_{A_j}\right)$ respectively, calculated through (3).

For images A_0 and A_j, the similarity of the two images in terms of the spatial dependency of the image pixels is expressed as $S\left(\mu^{D}_{A_0}.\mu^{D}_{A_j}\right)$. This average is obtained by inserting three values of D, which is the degree of membership of each pixel in the three dependency states, using (3).

To calculate the similarity of two images A_0 and A_j for the edges, after extracting the 16-feature vectors for each image, the similarity measure shown in (3) is applied, and $S\left(\mu_{A_0}.\mu_{A_j}\right)$ is obtained.

To combine the amounts mentioned in the previous sections and determine the final similarity of the two images A_0 and A_j, (4) is applied [7].

$$S_{total} = \alpha\left(\frac{s\left(\mu_{A_0}^{H},\mu_{A_j}^{H}\right)+s\left(\mu_{A_0}^{S},\mu_{A_j}^{S}\right)+s\left(\mu_{A_0}^{V},\mu_{A_j}^{V}\right)}{3}\right) +\beta\left(s\left(\mu_{A_0}^{D},\mu_{A_j}^{D}\right)\right)+\gamma\left(s\left(\mu_{A_0},\mu_{A_0}\right)\right) \quad (4)$$

where α, β, and γ are the constant coefficients that determine the effect of each feature on the final similarity value of S_{total}, where α + β + γ = 1. The experimental values of α = 0.45 and β = 0.15 and γ = 0.40 are applied according to the trial and error method.

4. Experimental Results

To compare this proposed system with the four systems, all are implemented and tested on a database of 1000 images taken from the Corel collection. These images are arranged in 10 different semantic groups: woman, lion, elephant, horse, flower, fish, mountain, balloon, modern, and bus. 100 images were selected from each group [26].

Some of the compared systems are applied only on two or three image content features [7, 9, 19, 10].

The systems are developed in MATLAB 6.5 using a Pentium PC, 2 GHz. To measure the performance of each system, all 1000 selected Corel database images are indexed. In the retrieval phase, the images are randomly selected as the query images, and similar images are retrieved. The query images are the same for comparing all four image retrieval systems.

4.1. Performance evaluation

The most common evaluation measures are different types of precision and recall. In some researches, The effectiveness of the extracted features has been measured by these parameters [27]. In this paper, we used the efficiency measure presented in [28]. If the number of images retrieved is lower than the number of relevant images, retrieval efficiency represents the precision; otherwise, the recall (5).

$$\left(\begin{matrix}Retrieval\\ Efficiency\end{matrix}\right) = \begin{cases}\dfrac{No,\ of\ \ relevant\ \ images\ \ retrieved}{Total\ \ no,\ of\ \ images\ \ retrieved} & if\ \ condition\\[2ex] \dfrac{No,\ of\ \ relevant\ \ images\ \ retrieved}{Total\ \ no,\ of\ \ relevant\ \ images} & Otherwise\end{cases} \quad (5)$$

which condition is: [No.of retrieved images < No.of relevant images].

The considered query set includes 500 images of 10 various groups. In order to test the proposed system, it is compared with four other systems. The obtained results are tabulated in Table 2 and graphed in Figure 5, where the average retrieval efficiencies, for 500 queries, for the 1, 5, 10, 20, 30, 40, 50, 60, 70, 80, 90, and 100 first retrieved images are reported. Figure 5 shows that the proposed system makes better results than other systems. The retrieval results for two sample query images are shown in Figure 6, where the most similar retrieved images are presented.

Table 2. Average retrieval efficiency versus number of images retrieved, computed over 500 queries.

Number of retrieved images	Color and shape [7]	Color and texture [9]	Color, Shape, and texture [10]	Color and texture [19]	Proposed system
1	0.791	0.823	0.901	0.909	0.920
5	0.753	0.801	0.873	0.900	0.912
10	0.733	0.789	0.832	0.874	0.901
20	0.680	0.734	0.801	0.825	0.887
30	0.654	0.705	0.770	0.796	0.843
40	0.649	0.687	0.760	0.789	0.812
50	0.609	0.659	0.712	0.763	0.800
60	0.587	0.636	0.684	0.691	0.785
70	0.550	0.611	0.645	0.673	0.743
80	0.539	0.588	0.612	0.666	0.729
90	0.490	0.579	0.601	0.619	0.703
100	0.478	0.550	0.587	0.602	0.690

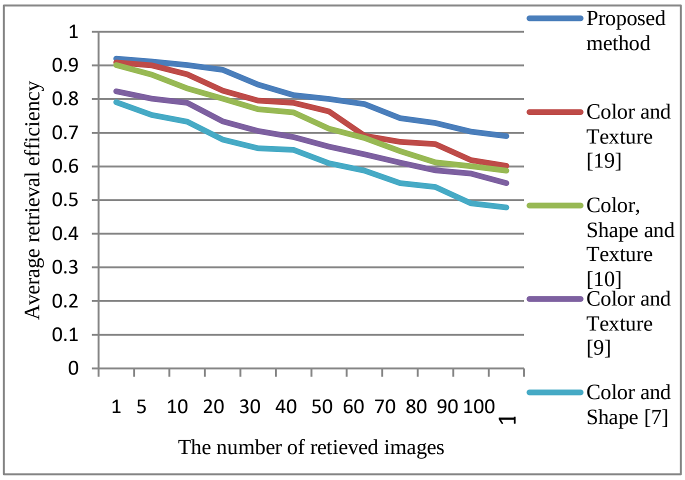


Figure 5. Efficiency graph in terms of number of retrieved images for 5 systems examined.

Figure 6. Two sample retrieval results: images in place 1 are query images. Images in place 2 to 45 are retrieved images.

4.2. Comparison of system storage space

As to the performance of the retrieval systems, the storage space for the feature vectors is of concern. When all images in a dataset are indexed, the extracted feature vectors should be stored in a separate database. One of the advantages of indexing images in the form of fuzzy sets is a significant decrease in the dimension of the feature vector. The lengths of the extracted vectors of the five systems are tabulated in Table 3, where although the suggested system has three content features, it requires less storage space than the other systems. When the count of the images in the database is high, the value of this reduction will be greater as well.

Table 3. Lengths of extracted feature vectors in 5 systems examined.

Image retrieval system	Feature vector length
Color, shape, and texture system (non-fuzzy) [10]	288
Color-shape system (non-fuzzy) [7]	124
Color-texture system (non-fuzzy) [19]	68
Color-texture system (non-fuzzy) [9]	64
Proposed system (fuzzy)	35

4.3. Comparison of system run time

the CBIR feature extraction phase is executed offline for database images. Therefore, usually only the extraction phase of the query image and the similarity matching phase are performed online. In another experiment, the run time of the proposed system is compared with 4 mentioned systems. In this section, the average run time of the feature extraction phase for 100 random images is measured from the same database of 1000 images taken from the Corel collection and it is reported in milliseconds in Table 4. As shown in Table 4, the run time of the proposed system is higher than [7] and [19]. The reason for this is in the amount of calculations to extract feature vectors. In [7], only the color histogram and edge information is used and, in [19] three texture analysis operator along with a colour histogram, is used to extract the feature vector. Despite this, the run time of the proposed system is within the usual range of CBIR systems, and also the precision of the proposed system is higher than other 4 systems, which shows its efficiency.

Table 4. Running time (in milliseconds) of 5 systems examined.

Image retrieval system	Run time (ms)
Colorshape system (non-fuzzy) [7]	90
Color-texture system (non-fuzzy) [19]	105
Proposed system (fuzzy)	118
Color-texture system (non-fuzzy) [9]	129
Color, shape, and texture system (non-fuzzy) [10]	146

5. Conclusion

Due to the vague and ambiguous nature of the color images' content, fuzzy techniques have been and are being applied in indexing and retrieving the images. The positive effect of increasing the considered features of the image on the image retrieval efficiency is assessed. Color properties, the spatial dependency of pixels, and image edge information are different aspects of the images assessed in this article. The results indicate that the performance of the image retrieval system can improve by considering more features of image content.

Indexing images in the form of fuzzy sets, rather than improving the image retrieval efficiency (precision and recall), reduce the length of the feature vectors extracted from the images. It can be deduced that applying correct fuzzy sets and techniques in other image retrieval systems will end in better performance and less storage space. The long processing time is one of the issues when increasing the calculated visual aspects of the image. Because our method divids the images into same blocks, resizing the image has no effect on the retrieval results. The run time of the proposed system is within the usual range of CBIR systems; consequently, the authors here seek to concentrate on reducing the consumed time of image retrieval systems by applying the multi-agent and distributed systems next to parallel processing methods as their future work. Also investigation of the system on other color quantizations and in terms of effectiveness to altere resolution and applying filters on images can be done in future works.

References

[1] Y. Rui, T. S. Huang, and S.-F. Chang, "Image retrieval: current techniques, promising directions, and open issues," *Journal of Visual Communication and Image Representation*, vol. 10, no. 1, pp. 39-62, 1999.

[2] I. K. Sethi, I. L. Coman, and D. Stan, "Mining association rules between low-level image features and high-level concepts", *Aerospace/Defense Sensing, Simulation, and Controls*. SPIE, 2001.

[3] S. Chang and S. Liu, "Picture indexing and abstraction techniques for pictorial databases," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. PAMI-6, no. 4, pp. 475-484, 1984.

[4] J. M. Prewitt, "Object enhancement and extraction," *Picture processing and Psychopictorics*, vol. 10, no. 1, pp. 15-19, 1970.

[5] H. Frigui, "Interactive image retrieval using fuzzy sets," *Pattern Recognition Letters*, vol. 22, no. 9, pp. 1021-1031, 2001.

[6] C. Vertan and N. Boujemaa, "Using fuzzy histograms and distances for color image retrieval," in *Proceedings of the Challenge of Image Retrieval*, vol. 6, 2000.

[7] H. Nezamabadi-Pour, A. Kabir, and S. Saryazdi, "Image retrieval using color and edge," in *Proceedings of the second Conference on Machine Vision, Image Processing & Applications*, Tehran-Feb. 2003.

[8] Y. D. Chun, N. C. Kim, and I. H. Jang, "Content-based image retrieval using multiresolution color and texture features", *IEEE Transactions on Multimedia*, vol. 10, no. 6, pp.1073–1084, 2008.

[9] Y. Jun, Z. Li, L. Liu, and Z. Fu, "Content-based image retrieval using color and texture fused features", *Mathematical and Computer Modelling*, vol. 54, pp. 1121–1127, 2011.

[10] R. K., Lingadalli and N., Ramesh, "Content-based image retrieval using color, shape and texture", *International Advanced Research Journal in Science, Engineering and Technology*, vol. 2, no. 6, June 2015.

[11] N. Shrivastava and V. Tyagi, "An efficient technique for retrieval of color images in large databases", *Computers & Electrical Engineering*, vol. *46*, pp. 314–327, 2015.

[12] Z. S. Younus, D. Mohamad, T. Saba, H. M. Alkawaz, A. Rehman, M. Al-Rodhaan, and A. Al-Dhelaan, "Content-based image retrieval using PSO and k-means clustering algorithm", *Arabic Journal Geoscience*, vol. 8, no. 8, pp. 6211–6224, 2015.

[13] A. Ponomarev, H. S. Nalamwar, I. Babakov, C. S. Parkhi, and G. Buddhawar, "Content-based image retrieval using color, texture and shape features", *Key Engineering Materials*, vol. 685, pp. 872–876, 2016.

[14] M. Zhao, H. Zhang, and J. Sun, "A novel image retrieval method based on multi-trend structure descriptor", *Journal of Visual Communication and Image Representation*, vol. 38, pp. 73–81, 2016.

[15] P. Srivastava and A. Khare, "Integration of wavelet transform, local binary patterns and moments for content-based image retrieval", *Journal of Visual Communication and Image Representation*, vol. 42, pp. 78–103, 2017.

[16] M. Sajjad, A. Ullah, J. Ahmad, N. Abbas, S. Rho, and S. W. Baik, "Integrating salient colors with rotational invariant texture features for image representation in retrieval systems", *Multimedia Tools and Applications*, vol. 77, no. 4, pp. 4769–4789, 2018.

[17] L. K. Pavithra and T. S.Sharmila, "An efficient framework for image retrieval using color, texture and edge features", *Computers & Electrical Engineering*, vol. 70, pp. 580–593, 2018.

[18] L. K. Pavithra and T. Sree Sharmila, "An efficient seed points selection approach in dominant color descriptors (DCD)", *Cluster Computing*, vol. 22, no. 4, pp. 1225–1240, 2019.

[19] N. T. Bani and SH. Fekri-Ershad, "Content-based image retrieval based on combination of texture and colour information extracted in spatial and frequency domains ", *The Electronic Library*, vol. 37, no. 4, pp. 650-666, 2019.

[20] R. Ashraf, M. Ahmed, U. Ahmad, M. A. Habib, S. Jabbar, and K. Naseer, "MDCBIR-MF: Multimedia data for content-based image retrieval by using multiple features", *Multimedia Tools and Applications*, vol. 79, pp. 8553–8579, 2020.

[21] M. N. Abdullah, M. A. M. Shukran, M. R. M. Isa, N. S. M. Ahmad, M. A. Khairuddin, M. S. F. M. Yunus, and F. Ahmad, "Colour features extraction techniques and approaches for content-based image retrieval (CBIR) system", *Journal of Materials Science and Chemical Engineering*, vol. 9, pp. 29-34, 2021.

[22] M. Shukran, M. Abdullah, and M. Yunus, "New approach on the techniques of content-based image retrieval (CBIR) using color, texture and shape features", *Journal of Materials Science and Chemical Engineering*, vol. 9, pp. 51-57, 2021.

[23] A. Raza, H. Dawood, H., Dawood, S., Shabbir, R., Mehboob, and A., Banjar, "Correlated primary visual text on histogram features for content base image retrieval", *IEEE Access*, vol. 6, pp. 46595–46616, 2018.

[24] R. Fullér, "On product-sum of triangular fuzzy numbers," *Fuzzy Sets and Systems*, vol. 41, no. 1, pp. 83-87, 1991.

[25] D. Van der Weken, M. Nachtegael, and E. Kerre, "Using similarity measures for histogram comparison," *in Proceedings of the International Fuzzy Systems Association World Congress*, 2003, pp. 396-403.

[26]https://github.com/lforg37/mdb_corel10k/blob/master/corel-10k.7z

[27] H. Mohamadi , A. Shahbahrami and J. Akbari, "Image retrieval using the combination of text-based and content-based algorithms", *Journal of Artificial Intelligence and Data Mining*, vol. 1, no. 1, pp. 27-34, 2013.

[28] B. M. Mehtre, M.S. Kankanhalli, A.D., Narasimhalu, and G.C. Man, "Color matching for image retrieval", *Pattern Recognition Letters*, vol. 16, pp. 325-331, 1995.

بازیابی تصویر بر اساس چندویژگی با استفاده از مجموعه های فازی

منیره عظیمی‌همت[۱]، فاطمه شمس‌عزت[۲] و مرجان کوچکی رفسنجانی[۳*]

[۱] گروه آموزشی مهندسی کامپیوتر و فناوری اطلاعات، دانشگاه پیام نور، ایران.

[۲] بخش علوم کامپیوتر، دانشکده ریاضی و کامپیوتر، دانشگاه فسا، فسا، ایران.

[۳] بخش علوم کامپیوتر، دانشکده ریاضی و کامپیوتر، دانشگاه شهید باهنر کرمان، کرمان، ایران.

ارسال ۲۰۲۲/۰۵/۱۶؛ بازنگری ۲۰۲۲/۰۷/۰۱؛ پذیرش ۲۰۲۲/۰۹/۰۶

چکیده:

در بازیابی تصویر مبتنی بر محتوی، ویژگی‌های بصری تصاویر پایگاه داده استخراج می‌گردند و پایگاه داده ویژگی‌های بصری به منظور یافتن نزدیک‌ترین تصاویر به تصویر پرس و جو بررسی می‌شود. افزایش کارایی و کاهش زمان و فضای ذخیره سازی تصاویر نمایه شده در طراحی سیستم‌های بازیابی تصویر دارای اهمیت است. در این پژوهش، یک سیستم کارآمد برای بازیابی تصویر با استفاده از تکنیک‌های فازی پیشنهاد شده است که در افزایش کارایی و کاهش طول بردار ویژگی و فضای ذخیره‌سازی کارآمد است. همچنین اثر افزایش تعداد ویژگی‌های محتوایی درنظر گرفته شده، در افزایش کارایی بازیابی تصویر بررسی می‌شود. ویژگی‌های فازی شامل رنگ، اطلاعات آماری مربوط به وابستگی فضایی پیکسل‌ها به یکدیگر و موقعیت لبه‌های تصویر است. این ویژگی‌ها در قالب بردارهای فازی با طول ۱۶، ۳ و ۱۶ نمایه شده‌اند. بردارهای استخراج شده از طریق معیار شباهت‌های فازی مقایسه شده و مشابه‌ترین تصاویر بازیابی می‌شوند. به منظور ارزیابی عملکرد سیستم پیشنهادی، این سیستم و سه سیستم غیرفازی دیگر که ویژگی‌های کمتری استفاده کرده‌اند، پیاده‌سازی می‌شوند. این چهار سیستم بر روی یک پایگاه داده حاوی ۱۰۰۰ تصویر آزمایش شده‌اند و نتایج به دست آمده نشان دهنده بهبود در دقت بازیابی و فضای ذخیره‌سازی است.

کلمات کلیدی: بازیابی تصویر، استخراج ویژگی، هیستوگرام رنگ فازی، لبه های تصویر، وابستگی فضایی پیکسل‌ها.