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Research paper

Applying Intuitionistic Fuzzy Sets to Improve Fuzzy Content-based Image Retrieval Systems

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Abstract

Visual features extracted from images in content-based image retrieval systems are inherently ambiguous. Consequently, applying fuzzy sets for image indexing in image retrieval systems has improved efficiency. In this article, the intuitionistic fuzzy sets are used to enhance the performance of the Fuzzy Content-Based Image Retrieval (F-CBIR) system. To this aim, an Intuitionistic Fuzzy Content-Based Image Retrieval (IF-CBIR) is proposed by applying intuitionistic fuzzy generators on fuzzy sets. Due to the diversity of the intuitionistic fuzzy distance measure, several are assessed in IF-CBIR; in these assessments, the measure with higher performance is identified. Finally, the proposed IF-CBIR and the existing crisp CBIR and F-CBIR simulate on Corel 5K and Corel 10K databases. The results show that our proposed method has higher (10-15%) precision compared to the mentioned methods.

1. Introduction

The rapid advance of computer technology in recent years has led to a generation of sizable multi-media databases. The attempts to manage image retrieval from these databases began in the 1970s. The researchers sought human coding, which, due to diverse personal interpretations of an image and being time-consuming, was deemed inefficient [1]. To overcome these drawbacks, Content-Based Image Retrieval (CBIR) is proposed, where image retrieval systems are based on image feature information like image content, edge pattern, color, texture, target area spatial arrangement, and object shape [2]. According to [3], CBIR is defined as the problem of searching for identical images based on their visual contents from large image repositories. The process of CBIR is to retrieve images associated with a specified inquiry from sizable image databases based on two prominent main steps, where, first, the images are identified through a class of features (indexing step) and, then those similar to the inquiry are retrieved (searching step).

Researchers in [4] initiated the CBIR field, after which the color segment gained momentum. By applying only color content, the other information in the images will not be of concern; consequently, researchers have to consider this element with other features of an image simultaneously [5–8]. In this context, researchers in [5] developed a system that achieved satisfactory results by considering color and image edge features. By partitioning the image into blocks, the homogeneous and non-homogeneous blocks are extracted to detect image edges. These edges were then combined with color information from the image blocks to assess similar images.

Fuzzy sets are powerful tools for representing ambiguity in images, making them valuable in image processing [9]. Their introduction to this field can be traced back to researchers in [10], while [11] pioneered the use of fuzzy similarity measures in image retrieval.

The Intuitionistic Fuzzy Sets (IFS)s were presented in 1986 as a more general and comprehensive extension of FSs [12]. Intuitionistic fuzzy sets model uncertainties in the real world better than conventional fuzzy sets. Since these sets consider the degree of non-membership in addition to the degree of membership, they show the uncertainty of an object better. To date, many of these sets are applied in image processing and retrieval [13]. Among the higher-order fuzzy set concepts, intuitionistic fuzzy sets (IFSs) provide a robust and flexible mathematical framework. IFSs address not only vagueness but also hesitancy arising from incomplete or imprecise information. IFSs better reflect human behavior, as individuals who express the degree of membership of an element in a set often do not provide a complementary degree of non-membership that sums to one. As a result, IFSs allow for a more nuanced representation of knowledge by incorporating both membership and non-membership degrees, making them highly suitable for applications such as image processing. This uncertainty stems from the intrinsic imprecision or vagueness in pixel-color values and human perception. It seems that the IFSs are more adequate than FSs in image retrieval. subsequently, an Intuitionistic Fuzzy CBIR system (IF-CBIR) based on Fuzzy CBIR systems (F-CBIR) is being proposed here with the following primary contributions:

• The IF-CBIR systems are suggested based on F-CBIR and different IFS generators.

• The effect of the three common IFS generators on retrieval efficiency becomes evident.

• Some intuitionistic fuzzy distance measures have been evaluated to identify the most effective one.

• The positive effect of applying IFS instead of FS, in CBIR on Corel-5k and Corel-10k datasets becomes evident. The article is organized in the following way: Section 2 presents a summary of previous research; the preliminaries are discussed in Section 3; the intuitionistic fuzzy image retrieval is described in Section 4; the findings from the experiment can be found in Section 5 and the article is concluded with suggestions for further studies in Section 6.

2. Literature review

There are many studies on applying different FSs in image processing and retrieval fields [14–16]. Researchers in the study [14] employed a fuzzy approach to image retrieval, aiming to decrease the computational time required for affine invariant feature extraction. Their approach utilizes fuzzy sets to address the issue of high dimensionality. Each pixel's color contribution is linked to all histogram bins, incorporating fuzzy set membership functions. Finally, the fuzzy color histogram, with its quick results and compact memory size, outperforms traditional color histograms in image retrieval. Regarding the color and texture-based image retrieval system, researchers in reference [15] utilized the global color histogram and the gray level co-occurrence matrix as color and texture features [15]. They introduced a novel similarity measurement technique that combines the k-Nearest Neighbors (kNN) algorithm with a fuzzy mathematical approach called SBkNNF. In reference [16], a group of researchers introduced a proficient image retrieval system utilizing fuzzy models. This system incorporates fuzzy features, including color, statistical data regarding the spatial relationships of pixels, and edge positions within the image. These features are represented as fuzzy vectors with lengths of 16, 3, and 16, respectively. The fuzzy similarity measures are applied to compare the extracted vectors and retrieve the most similar images.

Researchers in [14–16] by applying different content of images for the indexing phase, proposed the three F-CBIRs, which are selected in this study to assess and introduce equivalent IF-CBIR.

Researchers in studies [14–16] explored the use of various image content for indexing, leading to the development of three F-CBIR systems. These F-CBIR systems were chosen in this research to evaluate and propose an equivalent IF-CBIR system.

The application of IFS in image retrieval is proposed in [17, 18]. These sets have been used to enhance image processing systems [19, 20].

3. Preliminary

In this Section, we briefly explain the primary notations and definitions on FSs and IFSs and image retrieval. Due to completeness, we first remind the FS definition.

Definition 1. *[9] Let X be a nonempty set, then the fuzzy set is defined as* $A = \{(x, \mu_A(x)): x \in X\}$ *where,* $\mu_A(x): X \to [0, 1]$ *is named membership function.*

IFSs provide a more flexible mathematical framework than FSs to deal with the uncertainty and vagueness in the images.

IFSs both consider uncertainty on membership degree and hesitance in implying membership value.

Definition 2. *[12] An intuitionistic fuzzy set A on X is defined as* $A = \{(x, \mu_A(x), \nu_A(x)): x \in X\}$ *where,* $\mu_A(x): X \to [0, 1]$ *and* $\nu_A(x): X \to [0, 1]$ *are the membership and non-membership functions of A, respectively, in the sense that* $0 \le \mu_A(x) + \nu_A(x) \le 1$ *for each* $x \in X$ *and* $\pi_A(x) = 1 - \mu_A(x) - \nu_A(x)$ *is named intuitionistic or the hesitance index.*

3.1 Constructing intuitionistic fuzzy set through a fuzzy set

This subsection presents the construction methods of IFS. We can convert FS into IFS by two main methods:

Method A: jurio et al. [21] presented a new method to generate an IFS:
Let A_F be an FS on universal set X, and δ, π: X → [0, 1], be two mappings, then the IFS A_{IF} is as follows:
A_{IF} = {(x, F (μ_{AF} (x), π(x), δ(x)) |x ∈ X} where, F (x, y, z) = (x (1 − yz), 1 − x (1 − yz) − yz).

Method B: Bustince et al. [22] developed a new IF-generator where the non-membership value is as follows:
$N(\mu(x)) = g^{-1}(g(1) - g(\mu(x)))$ where, N is a negation and $g: [0, 1] \rightarrow [0, 1]$ is an increasing function. Yager and Sugeno are two common increasing functions that are applied in IF-generators to generate the IFS A_{IF} as follows [23, 24]:

(I) IFS generated through Yager's intuitionistic fuzzy Negation:

$$A_{IF} = \{x, \mu_A(x), (1-\mu_A(x)^{\lambda})^{\frac{1}{\lambda}} \mid x \in X, \lambda > 1\} \quad (1)$$

(II) IFS generated through Sugeno's intuitionistic fuzzy Negation:

$$A_{IF} = \{x, \mu_A(x), \frac{1-\mu_A(x)}{1+\lambda\mu_A(x)} \mid x \in X, \lambda \geq 0\}$$

Each of these generators in IF-CBIR produces different results, which are expressed in the implementation. In practice, various generators can be evaluated through a trial-and-error approach within the CBIR system.

3.2. Intuitionistic fuzzy distance measures

The similarity or dissimilarity measures define the resemblance of two samples or objects. The distance measures of IFSs for retrieval systems are applied in this article. According to [25], the properties of IF-distance measures are defined as:

Definition 3. *Let d be a mapping,* $d: IFSs \times IFSs \rightarrow [0,1]$. *If d(X, Y) satisfies the following properties, then d(X, Y) is named a distance measure:*

I. $0 \leq d(X,Y) \leq 1$

II. $d(X,Y) = d(Y,X)$,

III. $d(X,Y) = 0$ *iff* $X = Y$,

IV. *If* $X \subseteq Y \subseteq Z$, *then* $d(X,Z) \geq d(X,Y)$ *and* $d(X,Z) \geq d(Y,Z)$,

Where X, Y, and Z are the given IFSs.

Some common distance measures on IFSs defined on a limited set of objects are tabulated in Table 1.

3.3. Image retrieval concepts

The CBIR system identifies the key visual characteristics of an image to search and compare with other images. The indexing and searching steps constitute a regular CBIR system:
Indexing step: Extracts the proper feature vectors from images and saves them in the image database.
Searching step: Computes the feature vector of a query image and compares it to all image feature vectors in the database.
By applying these steps, the CBIR system finds images similar to the user's query image. The architecture of a CBIR system is presented in Figure 1.
Color is a common feature in most color-based image retrieval systems. A color space is a coordinate system that allows colors to be measured and specified quantitatively [33]. The red, green, and blue (RGB) and hue, saturation, and value (HSV) systems are vivid examples of color space representations. Most image processing tasks consider an image as a collection of pixels in RGB values. Humans cannot perceive colors by combining the different values of RGB. Colors are perceived in terms of HSV, Figure 2. In the most available systems, the HSV color space is of concern. The correlations among the colors are determined through HSV, which improves the RGB color model.

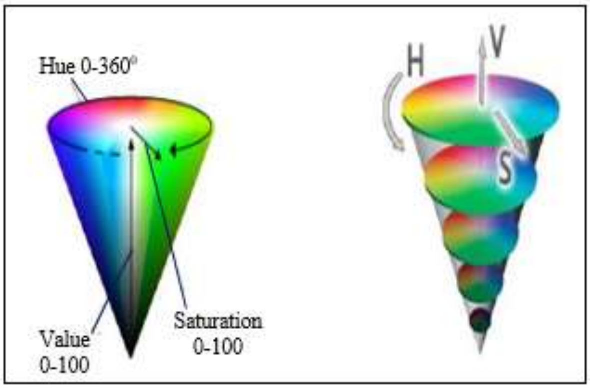

Figure2. HSV Color space.

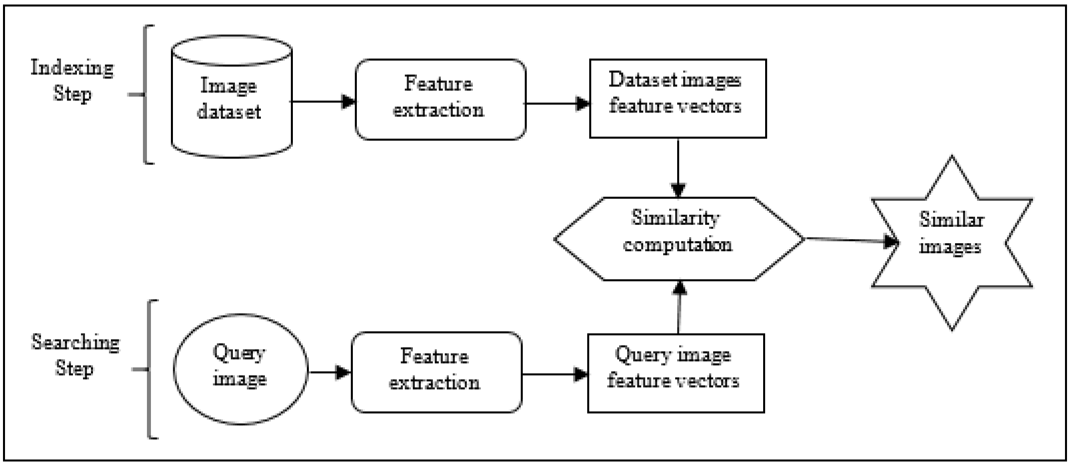

Figure 1. Architecture of a content-based image retrieval system.

Table 1. Some distance measures on IFSs.

ID	IFS distance measure	Ref.
Dist. 1	$d_{Ham}(A,B)=\frac{1}{2n}\sum_{i=1}^{n}(\lvert\mu_A(x_i)-\mu_B(x_i)\rvert+\lvert\nu_A(x_i)-\nu_B(x_i)\rvert)$	[26]
Dist. 2	$d^{*}_{Ham}(A,B)=\frac{1}{2n}\sum_{i=1}^{n}(\lvert\mu_A(x_i)-\mu_B(x_i)\rvert+\lvert\nu_A(x_i)-\nu_B(x_i)\rvert+\lvert\pi_A(x_i)-\pi_B(x_i)\rvert)$	[27]
Dist. 3	$d^{M}_{Ejc}(A,B)=\sqrt{(\frac{1}{3n}\sum_{i=1}^{n}((\mu_A(x_i)-\mu_B(x_i))^2+(\nu_A(x_i)-\nu_B(x_i))^2+(\pi_A(x_i)-\pi_B(x_i))^2)}$	[28]
Dist. 4	$d_{EA}(A,B)=1-\frac{1}{n}\sum_{i=1}^{n}(\sqrt{\mu_A(x_i)\mu_B(x_i)}+\sqrt{\nu_A(x_i)\nu_B(x_i)}+\sqrt{\pi_A(x_i)\pi_B(x_i)})$	[29]
Dist. 5	$d_{Hau}(A,B)=\frac{1}{n}\sum_{i=1}^{n}\max(\lvert\mu_A(x_i)-\mu_B(x_i)\rvert,\lvert\nu_A(x_i)-\nu_B(x_i)\rvert)$	[30]
Dist. 6	$d_{mpm}(A,B)=\frac{1}{n}\sum_{i=1}^{n}\frac{\lvert\mu_A(x_i)-\mu_B(x_i)\rvert+\lvert\nu_A(x_i)-\nu_B(x_i)\rvert}{\mu_A(x_i)+\mu_B(x_i)+\nu_A(x_i)+\nu_B(x_i)}$	[31]
Dist. 7	$d_{Hh}(A,B)=\frac{1}{2n}\sum_{i=1}^{n}\left((\lvert\mu_A(x_i)-\mu_B(x_i)\rvert+\lvert\nu_A(x_i)-\nu_B(x_i)\rvert)\times(1-\frac{1}{2}\lvert\pi_A(x_i)-\pi_B(x_i)\rvert)\right)$	[32]
Dist. 8	$d_{Hc}(A,B)=\frac{1}{2n}\sum_{i=1}^{n}\left((\lvert\mu_A(x_i)-\mu_B(x_i)\rvert+\lvert\nu_A(x_i)-\nu_B(x_i)\rvert)\times\cos(\frac{\pi}{6}\lvert\pi_A(x_i)-\pi_B(x_i)\rvert)\right)$	[32]

The HSV color space represents color in a three-dimensional space, where the central axis ranges from white at the top to black at the bottom, with various neutral colors in between. Hue (H) is determined by the angle from the axis, saturation (S) by the distance from the axis, and value (V) by the distance along the axis.

4. Intuitionistic fuzzy image retrieval (our proposed method)

The application of IFS can improve the F-CBIR performance is revealed in this article. Suggested IF-CBIR retrieves similar images through the following steps:

- **IF-Indexing step:** the IF-feature vectors, initially extracted in fuzzy form, are transformed into IFS and stored.
- **IF-Searching step:** the IF-distance measures help identify images that closely resemble the query image.

4.1. IF-Indexing step

Since we aim to improve F-CBIR through IFS, the three examined fuzzy methods are selected as the IFS feature production base [14–16]; We use the extracted fuzzy features to generate intuitionistic fuzzy features. These F-CBIR methods represent various approaches to combining image content features.

4.1.1. Description of the three fuzzy indexing methods

One common method for feature vector extraction is based on the histogram of image content. An essential step in F-CBIR is the fuzzification of feature vectors. To achieve this, the feature vectors are converted into fuzzy vectors by applying triangular and trapezoidal fuzzy numbers [34]. These fuzzy vectors have a length significantly less than the number of pixels in the image. Using fuzzy numbers substantially reduces the size of feature vectors. For instance, Figure 3 shows a fuzzification model of the HSV color space saturation component by trapezoidal membership functions. For each pixel of an image, according to the amount of its saturation, a fuzzy vector with length four is obtained. The average of these vectors for all pixels constructs the fuzzy saturation feature vector of the image.

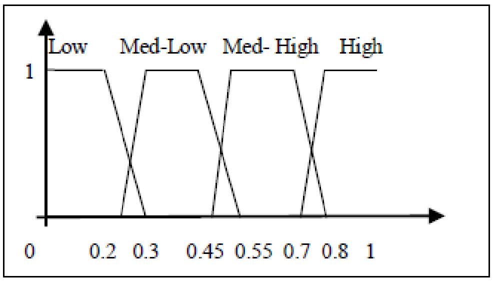

Figure 3. Trapezoidal membership functions of HSV color space saturation component.

In what follows, three F-CBIR systems are disrobed:

Method I: Fuzzy feature extraction based on color content [14]:

According to [14], each pixel value is quantified into 6 (H) × 3 (S) × 1 (V) to generate 18 bin values. In situations where the hue value (H) is undefined, three grayscale values are used to calculate the signature from the RGB histogram. The membership functions are treated as triangular fuzzy numbers. Therefore, for each pixel, a 21-dimensional vector is computed, containing (6×3×1=18+3=21) membership values. The average of these vectors for all pixels is considered a fuzzy color feature vector.

Method II: Fuzzy feature extraction based on color and texture [15]:

This method is based on two features of image content, which are discussed separately.

Color feature extraction:

The Global Color Histogram (GCH) uses the HSV color space by first converting the image from RGB to HSV. Then, the HSV color space is quantified into a histogram: 16 bins for H, 4 bins for S, and 4 bins for V. The resulting 256-dimensional (16x4x4=256) color feature vector C is extracted corresponding to the image as:

$C = [c_1, c_2, ..., c_{256}]$.

Texture feature extraction:

The Gray Level Co-occurrence Matrix (GLCM) method is used to analyze the texture of an image by extracting 15 different features. These features include small and large gradient advantages, inhomogeneity of gray and gradient distribution, energy, mean gray level, gradient average, gray and gradient mean square deviation, correlation, gray and gradient level entropy, hybrid entropy, inertia, and inverse difference moment. The texture feature vector T is described based on these features as:

$$T = [t_1, t_2, ..., t_{15}]$$

The color and texture feature vectors are enhanced for better effectiveness and representation by applying a fuzzy mathematical algorithm to blur them. By merging the fuzzy color feature vector $\tilde{C}$ and fuzzy texture feature vector $\tilde{T}$, a larger, 271-dimensional feature vector $\tilde{Z}$ is created that combines both aspects. The relationship between these vectors is described by their correlation as:

$$\tilde{Z} = [0.5\tilde{C}, 0.5\tilde{T}].$$

Method III: Fuzzy feature extraction based on color, spatial dependency, and edge [16]:

This method is based on three features of image content, which are discussed separately.

Color feature extraction: This multi-feature-based system indexes images using HSV color space, which breaks down colors into Hue, Saturation, and Value. It then represents these components using trapezoidal fuzzy numbers, dividing the HSV space into 16 sections (8 values for H, 4 for S, and 4 for V). Therefore, for each image, the system creates a 16-dimensional vector.

Spatial dependency feature extraction: For each pixel, its eight neighbors are considered according to Figure 4. The number of neighbors of each pixel that have the same H is counted. The number of these similar neighbors is an integer number within the [0,8] range. This similarity is further refined using three trapezoidal fuzzy numbers, which generate a 3-dimensional vector representing fuzzy membership values. Averaging these vectors across all pixels produces a "spatial dependency feature vector".

1	2	3
4		5
6	7	8

Figure 4. The eight neighbors of the central pixel or block.

Edge feature extraction: This step involves converting the image into grayscale and dividing it into 8x8 blocks, then calculating the gradient magnitude for each block b as follows [5]:

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

This gradient is applied to determine the homogeneous and nonhomogeneous blocks for which an 8-digit binary vector is made. To determine digit i, $(1 \leq i \leq 8)$, digit *i* is assigned a value of 1 if the central block and its *i-th* corresponding neighboring block are in the same homogeneous state. Otherwise, the digit is assigned a value of 0.

This process is run separately for homogeneous and non-homogeneous blocks. The average of all homogeneous and non-homogeneous blocks is computed separately, and a 16-dimensional vector of fuzzy membership values is extracted. For every image, the linear combination of three extracted features is calculated by applying the following coefficients:

Image feature = 0.45 × color feature + 0.15 × spatial feature + 0.40 × edge feature.

4.1.2. Converting fuzzy features into intuitionistic

For each of the three mentioned methods in Section 4.1.1, after extracting the fuzzy feature vectors, the intuitionistic fuzzy feature vectors are obtained by using the constructing methods in Section 3-2, indicating that the indexing step of the intuitionistic fuzzy method is taken.

Example 1. Table 2 presents an illustration of IF-indexing, utilizing the fuzzy method III and the Sugeno-based generator (method B-II). This example involves an image of a flower with dimensions of 80x360 pixels, which is indexed to IF-feature vectors.

Table 2. The IF membership and non-membership values extracted for a sample image.

Feature Vector	Membership value			
H	0.8870	0.0829	0.0122	0.3643
	1.0000	0.0630	0.0100	0.2015
S	0.1436	0.7296	1.0000	0.2480
V	0.6654	1.0000	0.5375	0.3997
Place	0.8000	0.1552	0.0326	
Homogenous	0.9636	1.0000	0.8909	0.9273
	0.9273	0.9091	0.9818	0.9818
Non-Homogenous	0.3455	0.4727	0.3455	0.3273
	0.3636	0.3273	0.4364	0.4000

Feature Vector	Non-membership value			
H	0.0407	0.7867	0.9643	0.3678
	0.0000	0.8320	0.9707	0.5691
S	0.6653	0.1099	0.0000	0.5026
V	0.1435	0.0000	0.2229	0.3336
Place	0.1200	0.6446	0.9082	
Homogenous	0.0124	0.0000	0.0392	0.0255
	0.0255	0.0323	0.0061	0.0061
Non-Homogenous	0.3871	0.2710	0.3871	0.4066
	0.3684	0.4066	0.3010	0.3333

As observed in this table, an image with 28800 pixels (80×360) is indexed with 70 numbers, leading to a substantial reduction in the usage memory, which is an advantage of IF-CBIR.

4.2. IF-search step

Here, for each query image, an IF-indexing step is first applied to extract the IF-feature vector. Next, by applying an intuitionistic distance measure, as mentioned in Section 3.3, the similarity of each dataset image with the query image is calculated.

5. Experimental Results

To understand how IF-CBIR systems operate, the Corel-5k and Corel-10k image datasets are of concern. These data sets are widely applied for evaluating the CBIR systems performance, Table *3*

Table 3. The feature of Corel-5k and Corel-10k data sets.

Database	Corel-5k	Corel-10k
Type of image	color image	color image
The number of semantic categories	50	100
The number of images in each category	100	100
The number of images	5000	10000

The balloon, bus, elephant, fish, flower, horse, lion, modern, mountain, and woman categories are selected from each data set.

The experiments in this study are evaluated through the following efficiency metric [35]:

$$\text{Retrieval efficiency} = \begin{cases} \dfrac{\text{No.of relevant images retrieved}}{\text{Total No.of images retrieved}} & \text{if No.of retrieved images} < \text{No.of relevant images} \\[2ex] \dfrac{\text{No.of relevant images retrieved}}{\text{Total No.of relevant images}} & \text{Otherwise} \end{cases}$$

Retrieval efficiency is measured by precision when the number of retrieved images is less than the number of relevant images, while recall is the appropriate metric when the number of retrieved images exceeds the number of relevant images. In this study, 50 random images were selected from each of the 10 specified categories as query images to compare the performance of all methods. Given that each category contains 100 images, precision is the metric used for evaluation in this paper.

The average retrieval efficiency for these 500 (50×10) images is of concern. The performance of IF-CBIR systems is compared with F-CBIR and crisp-CBIR systems. The details of the overall performance of IF-CBIR systems concerning the fuzzy and crisp CBIR systems are tabulated in Table 4. These results are obtained through the most efficient IF-generator and IF-distance measure and for 50 retrieved images in this experiment.

Table 4. The average precision for crisp-CBIR, F-CBIR, and IF-CBIR in the Corel 5K and Corel 10K data set.

Data set	IF-CBIR precision	F-CBIR precision	Crisp-CBIR precision
Corel 5K	**0.636**	0.543	0.501
Corel 10K	**0.596**	0.506	0.461

To compute the content of Table 4, two scenarios are of concern:

5.1. Scenario I- Finding the most efficient IF-generator (IF construction method):

Here, the eight distance measures are applied in all explained IF methods, and the average is considered to find the best generator. This procedure is run separately for each of the three fuzzy systems [14–16], and Tables 5, 6, and 7 are then applied.

Table 5. The average precision of applying three IFS generators for converting the F-CBIR system [14].

IF construction method	Average efficiency for Corel 5 K		Average efficiency for Corel 10 K	
	IF-CBIR	**F-CBIR**	**IF-CBIR**	**F-CBIR**
Method A	0.57		0.53	
Method B-I (Yager based generator)	0.52	0.52	0.49	0.48
Method B-II (Sugeno based generator)	**0.61**		**0.58**	

Table 6. The average precision of applying three IFS generators for converting the F-CBIR system [15].

IF construction method	Average efficiency for Corel 5 K		Average efficiency for Corel 10 K	
	IF-CBIR	**F-CBIR**	**IF-CBIR**	**F-CBIR**
Method A	0.64		0.60	
Method B-I (Yager based generator)	0.57	0.57	0.53	0.53
Method B-II (Sugeno based generator)	**0.66**		**0.62**	

Table 7. The average precision of applying three IFS generators for converting the F-CBIR system [16].

IF construction method	Average efficiency for Corel 5 K		Average efficiency for Corel 10 K	
	IF-CBIR	**F-CBIR**	**IF-CBIR**	**F-CBIR**
Method A	0.59		0.55	
Method B-I (Yager based generator)	0.55	0.54	0.51	0.51
Method B-II (Sugeno based generator)	**0.64**		**0.59**	

As observed in Tables 5-7, applying the Yager-based generator leads to similar results with F-CBIR systems. The Sugeno-based generator yields the best results; therefore, we select it to construct the IFS in the rest of the experiment.

5.2. Scenario II. Finding the most efficient IF-distance measure:
Here, by applying the Sugeno generator, 3 IF-CBIRs are constructed from 3 F-CBIRs [14–16], and the effect of distance measures is assessed. In this process, 50 query images from each of the 10 image categories are chosen to compute their average efficiency based on each of the eight distance measures for every category. The overall results by averaging the 3 IF-CBIR systems on Corel 5K and Corel 10K are tabulated in Tables 8 and 9.

Table 8. The average efficiency of the three IF-CBIR for ten categories in the Core 5K data set using various distance measures.

Category	F-CBIR	Dist. 1	Dist. 2	Dist. 3	Dist. 4	Dist. 5	Dist. 6	Dist. 7	Dist. 8
Balloon	0.42	0.46	0.45	0.47	0.45	0.48	0.47	0.49	0.49
Bus	0.72	0.76	0.74	0.76	0.72	0.78	0.73	0.81	0.79
Elephant	0.22	0.25	0.25	0.26	0.24	0.30	0.28	0.34	0.35
Fish	0.33	0.37	0.38	0.40	0.36	0.42	0.42	0.47	0.46
Flower	0.60	0.63	0.61	0.64	0.62	0.66	0.65	0.68	0.68
Horse	0.78	0.83	0.83	0.84	0.81	0.85	0.85	0.86	0.87
Lion	0.58	0.64	0.62	0.64	0.62	0.65	0.65	0.68	0.66
Modern	0.53	0.57	0.57	0.58	0.56	0.59	0.58	0.60	0.61
Mountain	0.62	0.67	0.66	0.68	0.65	0.73	0.70	0.72	0.73
Woman	0.63	0.67	0.67	0.68	0.66	0.69	0.67	0.71	0.69
Average	0.543	0.585	0.578	0.595	0.569	0.615	0.600	**0.636**	0.633

Table 9. The average efficiency of the three IF-CBIR for ten categories in the Core 10K data set using various distance measures.

Category	F-CBIR	Dist. 1	Dist. 2	Dist. 3	Dist. 4	Dist. 5	Dist. 6	Dist. 7	Dist. 8
Balloon	0.38	0.43	0.42	0.46	0.42	0.45	0.44	0.46	0.44
Bus	0.68	0.72	0.70	0.75	0.70	0.71	0.70	0.77	0.75
Elephant	0.20	0.22	0.23	0.20	0.21	0.25	0.25	0.30	0.31
Fish	0.31	0.34	0.35	0.36	0.34	0.39	0.40	0.43	0.41
Flower	0.55	0.60	0.58	0.60	0.60	0.62	0.61	0.64	0.64
Horse	0.73	0.79	0.80	0.82	0.77	0.82	0.81	0.82	0.81
Lion	0.55	0.61	0.59	0.62	0.59	0.61	0.62	0.62	0.61
Modern	0.49	0.54	0.55	0.55	0.52	0.56	0.55	0.56	0.59
Mountain	0.59	0.64	0.62	0.64	0.61	0.67	0.67	0.69	0.70
Woman	0.58	0.63	0.62	0.65	0.62	0.62	0.64	0.67	0.66
Average	0.506	0.552	0.546	0.565	0.538	0.570	0.569	**0.596**	0.592

5.3. Computational complexity for some methods

We select one of the three described methods (method III [16]) to evaluate crisp and IF-CBIR systems in terms of computational complexity. To evaluate the running times, we measured the required time for extracting feature vectors in both crisp and IF-CBIR systems. For this purpose, the average runtime of the indexing step for 100 random images from the Corel 5K dataset is measured and reported in milliseconds in Table 10. As shown in this table, the runtime of the IF-CBIR system is higher than that of the crisp system. This is due to the additional computation required for fuzzification of the extracted feature vectors. It is important to highlight that the indexing step is executed only once for each image in the dataset, whereas the searching step is performed multiple times across the dataset, making it a more critical process as discussed below.

Assessing storage requirements involves examining the length of the feature vectors. Once all images in a dataset are indexed, the extracted feature vectors must be stored in a dedicated database. A notable benefit of representing images as fuzzy sets is the significant reduction in feature vector dimensions [16, 36, 37]. Table 10 summarizes the lengths of crisp and IF-CBIR feature vectors. As shown, the dimensions of the intuitionistic fuzzy feature vectors are considerably smaller than those of the crisp vectors. This reduction becomes increasingly advantageous as the number of images in the database grows.

Table 10. The computational complexity (for method III [16]).

	Run time (ms)	Feature vector length
Crisp-CBIR	55	124
IF-CBIR	69	70

Example 2. The top 50 ranked retrieved images, retrieved by IF-CBIR using the Sugeno generator and the most efficient distance measure (Dist. 7) on the Corel 5K dataset, are shown in Figure 5. In this example, the precision is 0.82.

6. Conclusion

This article reveals the positive effects of applying intuitionistic fuzzy sets to model image features in CBIR systems. In this endeavor, the Sugeno-based generator was selected as the best for the indexing step after evaluating several IF-generators. Next, in the searching step, the most effective of the eight distance measures was selected. Experimental results obtained using the most efficient generator and IF-distance measure indicate a precision improvement of approximately 10% for F-CBIR systems and approximately 15% for crisp CBIR.

Given that CBIR involves two fundamental steps, potential improvements in each step can enhance the quality of image retrieval. For instance, in the feature extraction stage, deep learning-based methods can be employed. These algorithms generate high-quality features but also increase computational complexity. In the retrieval phase, exploring other types of similarity measures may lead to improved results. Additionally, considering the variety of methods for constructing Intuitionistic Fuzzy Sets, it is possible to identify alternative functions through trial and error that may perform better in the context of image retrieval.

Figure 5. A sample retrieval results: image 1 in the frame is the query image, and image from 2 to 50 are the retrieved images from Corel 5.

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استفاده از مجموعه‌های فازی شهودی برای بهبود سیستم‌های بازیابی تصویر مبتنی بر محتوای فازی

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چکیده:

در سیستم‌های بازیابی تصویر مبتنی بر محتوا، ویژگی‌های بصری استخراج‌شده از تصاویر به طور ذاتی مبهم هستند. از این رو، استفاده از مجموعه‌های فازی برای مدل سازی تصاویر در این سیستم‌ها به بهبود کارایی آن‌ها کمک کرده است. در این مقاله، از مجموعه‌های فازی شهودی برای ارتقای عملکرد سیستم بازیابی تصویر مبتنی بر محتوا فازی (F-CBIR) استفاده می‌شود. به این منظور، یک سیستم بازیابی تصویر مبتنی بر محتوا با استفاده از مجموعه‌های فازی شهودی (IF-CBIR) معرفی شده است. در این سیستم، از تولیدکننده‌های فازی شهودی برای بهبود مجموعه‌های فازی استفاده می‌شود. به دلیل تنوع در معیارهای فاصله فازی شهودی، این معیار ها در IF-CBIR مورد ارزیابی قرار می‌گیرند و بهترین آن‌ها از نظر عملکرد شناسایی می شود. در نهایت، سیستم IF-CBIR پیشنهادی و سیستم‌های موجود CBIR و F-CBIR بر روی پایگاه‌های داده Corel 5K و Corel 10K مورد شبیه سازی قرار گرفته اند. نتایج نشان می‌دهند که روش پیشنهادی ما دارای دقتی بالاتر (۱۰ تا ۱۵ درصد) نسبت به سایر روش‌های ذکر شده است.

کلمات کلیدی: بازیابی تصویر، استخراج ویژگی، بازیابی تصویر فازی، بازیابی تصویر فازی شهودی، فضای رنگ HSV.