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Retrieving images in fuzzy object-relational databases using dominant color descriptors☆

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Abstract

In this paper a fuzzy approach for image retrieval on the basis of color features is presented. The proposal deals with vagueness in the color description and introduces the use of fuzzy database models to store and retrieve imprecise data. To face the color description, the concept of dominant fuzzy color is proposed, using linguistic labels for representing the color information in terms of hue, saturation and intensity. To deal with fuzzy data in our database model, we use a general approach which can support the manipulation of fuzzy objects in an object-relational database system. This allows the retrieval of images by performing flexible queries on the database.

Keywords: Image retrieval; Fuzzy color descriptor; Dominant fuzzy colors; Fuzzy databases

1. Introduction

Multimedia libraries are, actually, very large databases used concurrently by many users, managing a great amount of data, and requiring fast query resolution. This fact has motivated an increment of the research about techniques for storing, indexing and retrieving visual information. Many practical applications, such as picture archiving [2], medical databases management or multimedia search engines on the Web [5], make this research field grow in an impressive way [12,25].

One of the first approaches to image retrieval was based on captions and textual descriptors performed by humans [13]. Although this is a useful way to describe images, its main drawback is the requirement of a person who makes the description (subjective, in any case).

The current image retrieval systems improve the textual-based ones by means of features, such as color, texture or shape, which are automatically extracted from images [3,7]. In these systems, images are represented by vectors of

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features, queries are defined as an image or sketch, and the matching between them is performed by measuring the similarity of the corresponding vectors.

In this framework, a very important point to take into account is the imprecision in the features descriptions, as well as the store and retrieval of that imprecise data. To deal with this vagueness, some interesting approaches introduce the use of fuzzy logic in the feature representation and in the retrieval process [9,10,23,27,29]. These fuzzy approaches also allow to perform queries on the basis of linguistic terms, avoiding one of the drawbacks of the classical image retrieval systems, where the queries have to be defined on the basis of images or sketches similar to the one we are searching for.

In this paper, images will be described in terms of their colors; concretely, a representation based on dominant colors, corresponding to the most representative colors in the image, will be used [6,14,15,20,26,30]. To deal with the problem of imprecision, novel definitions of fuzzy color and fuzzy HSI color space will be introduced to describe the dominant colors in terms of linguistic labels. Each label will be related to concepts used by humans in the perception of colors (hue, saturation and intensity), allowing for queries in terms of color components. The methodology proposed in this paper to extract dominant fuzzy colors from images consists of two stages: firstly, the dominant colors are extracted using a crisp approach (Section 2); then, each color calculated in the previous stage is employed in order to obtain the set of dominant fuzzy colors (Section 3).

On the other hand, in Section 4 we introduce an efficient solution to store, index and retrieve fuzzy data (in our case, dominant fuzzy colors). There is a wide variety of proposals for fuzzy data handling in databases [8,17,18,21,28,32] but in general these models and/or implementations do not have enough modeling power and performance for image indexing applications. For these kind of applications we propose to use the fuzzy object-relational database systems (FORDBMS) model introduced in [4]. This model evolves classic fuzzy databases models to incorporate object-oriented features for a powerful representation and handling of data, fuzzy or not. This paper shows how this FORDBMS is suitable for easy image representation and retrieval, using the fuzzy descriptors obtained by means of the algorithm also presented in this paper. Examples of queries are presented in Section 5 and, finally, the main conclusions and future works are summarized in Section 6.

2. Dominant colors

In this section a methodology to extract dominant crisp colors from images is presented (Section 2.2) using the color space described in Section 2.1. The notion of fuzzy degree of dominance is finally introduced in Section 2.3.

2.1. Color space

Although the RGB is the most used model to acquire digital images, it is well known that it is not adequate for color image analysis. Instead, other color spaces based on human perception (HSI, HSV or HSL) seem to be a better choice for this purpose [1,22,31]. In these spaces, hue (H) represents the color tone (for example, red or blue), saturation (S) is the amount of color (for example, bright red or pale red) and the third component (called intensity, value or lightness) is the amount of light (it allows the distinction between a dark color and a light color).

In this paper, the HSI color space will be used. Geometrically it can be represented as a cone, in which the axis of the cone is the gray scale progression from black to white, distance from the central axis is the saturation, and the direction is the hue (Fig. 1). In addition to its goodness for color image analysis, the HSI space is employed due to the semantics of the three components that define the space are those employed usually by humans in the description of colors, making easier to define meaningful linguistic labels on them.

However, the HSI representation has two well known problems: the non-representativity of the hue when the intensity or the saturation are small, and the non-representativity of saturation under low levels of intensity. An often practical solution to solve this problem in crisp approaches is to perform a partition of the color space based on the chromaticity degree of each point. Following this idea, here we propose to split the HSI space into three regions: *chromatic*, *semi-chromatic* and *achromatic* (Fig. 1) on the basis of thresholds T_I and T_S on the components I and S, respectively. A color $\mathbf{c} = [h, s, i]$ will be *achromatic* if $i \leqslant T_I$ (black zone in Fig. 1), *semi-chromatic* if $i > T_I$ and $s \leqslant T_S$ (gray zone in Fig. 1), and *chromatic* if $i > T_I$ and $s > T_S$ (white zone in Fig. 1). Let us remark that another solution to this problem, based on a fuzzy approach, will be introduced later in this paper.

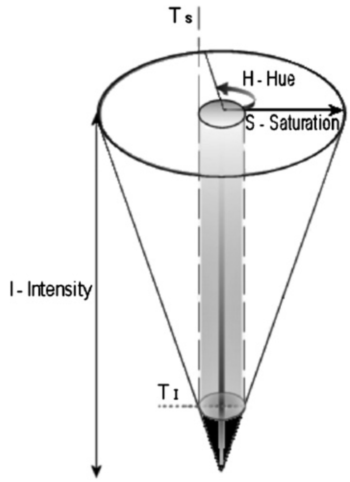

Fig. 1. HSI color space.

The problem described above has to be taken into account when we define a distance in the HSI space. This distance between two color stimuli $\mathbf{c}_1 = [h_1, s_1, i_1]$ and $\mathbf{c}_2 = [h_2, s_2, i_2]$ can be defined on the basis of the differences between its components:

$$\begin{aligned} \triangle_H(\mathbf{c}_1, \mathbf{c}_2) &= \begin{cases} \dfrac{|h_1 - h_2|}{\pi} & \text{if} |h_1 - h_2| \leqslant \pi, \\ \dfrac{2\pi - |h_1 - h_2|}{\pi} & \text{otherwise}, \end{cases} \\ \triangle_S(\mathbf{c}_1, \mathbf{c}_2) &= |s_1 - s_2|, \\ \triangle_I(\mathbf{c}_1, \mathbf{c}_2) &= \frac{|i_1 - i_2|}{MAXI}. \end{aligned} \tag{1}$$

Let us remark that $\triangle_H, \triangle_S, \triangle_I \in [0, 1]$. Based on the previous distances, Eq. (3) will be used to measure the difference between colors (for the sake of simplicity, we have removed the parameters $(\mathbf{c}_1, \mathbf{c}_2)$ in the notation $\triangle_H$, $\triangle_S$ and $\triangle_I$). This equation is defined by parts in order to avoid the use of non-representative components. Notice that $\triangle C(\mathbf{c}_1, \mathbf{c}_2) \in [0, 1]$.

To calculate the HSI values from the RGB coordinates, the following transformation is applied:

$$\begin{aligned} H &= \arctan\left(\frac{\sqrt{3}(G + B)}{2R - G - B}\right), \\ S &= 1 - \min\{R, G, B\}/I, \\ I &= (R + G + B)/3, \end{aligned} \tag{2}$$

$$\triangle C(\mathbf{c}_1, \mathbf{c}_2) = \begin{cases} \triangle_I & \text{if } c_i \text{ or } c_j \text{ are achromatic}, \\ \dfrac{1}{\sqrt{3}}[\triangle_I^2 + \triangle_S^2 + \triangle_H^2]^{1/2} & \text{if } c_i \text{ and } c_j \text{ are chromatic}, \\ \dfrac{1}{\sqrt{2}}[\triangle_I{}^2 + \triangle_S{}^2]^{1/2} & \text{otherwise}, \end{cases} \tag{3}$$

with R, G and $B \in [0, 1]$.

2.2. *Dominant crisp color extraction*

Dominant colors provide a powerful tool for describing the representative colors in an image, allowing for efficient indexing of large databases. Many crisp approaches to dominant color extraction have been proposed in the literature, for example those based on histogram analysis or clustering techniques [1].

In this paper we will perform a clustering approach using the Batchelor and Wilking algorithm [11], where the number of clusters is unknown a priori. To face the problem of non-representativity in the HSI color space, we propose to perform the clustering procedure separately for the chromatic, semichromatic and achromatic areas. Thus, for each zone, the clustering method is initialized with one cluster consisting of all pixels and then an iterative split procedure is performed until a stopping criterion is met. This stopping criterion is based on a parameter $\theta \in [0, 1]$ related to the maximum distance to be achieved between points within each cluster (in this paper we have fixed $\theta = 0.3$). To measure the distance between points, Eq. (3) is used. As a result, we obtain a set of $N = N_c + N_s + N_a$ clusters (with N_c, N_s and N_a being the number of clusters generated for the chromatic, semichromatic and achromatic areas respectively) where the centroid of each cluster, calculated as the mean value, defines a dominant color. To avoid noisy or less relevant colors, we will discard those clusters with a number of points less than a threshold T_d.

In the following, the set of dominant colors will be noted as *DCS*, with

$$DCS = \{\mathbf{dc}_1, \mathbf{dc}_2, \ldots, \mathbf{dc}_N\} \tag{4}$$

and $\mathbf{dc}_k = [h_k, s_k, i_k]$ being a dominant crisp color represented in the HSI color space.

2.3. Degree of dominance

Intuitively, a color is dominant to the extent it appears frequently in a given image. Since *frequent* is an imprecise concept, dominance also is, i.e., it is possible in general to find colors that are clearly dominant, colors that are clearly not dominant, and colors that are dominant to a certain degree, that depends on the percentage of pixels where the color appears.

It seems natural to model the idea of frequent apparition by means of a fuzzy set over the percentages, i.e., a fuzzy subset of the real interval [0, 1]. Hence, we define the fuzzy subset *Dominant of colors* as follows:

$$Dom(\mathbf{c}) = \begin{cases} 0 & fr(\mathbf{c}) \leqslant u_1, \\ \dfrac{fr(\mathbf{c}) - u_1}{u_2 - u_1} & u_1 \leqslant fr(\mathbf{c}) \leqslant u_2, \\ 1 & fr(\mathbf{c}) \geqslant u_2, \end{cases} \tag{5}$$

where $fr(c)$ is the percentage of pixels with color $\mathbf{c}$ in the image under consideration, and u_1 and u_2 are two parameters such that $0 \leqslant u_1 < u_2 \leqslant 1$.

3. Extraction of dominant fuzzy colors

In this section, a set of dominant fuzzy colors is obtained taking as starting point the set of dominant crisp colors extracted in the previous one. Let us remark that the use of fuzzy sets, and the associated linguistic labels, allows to represent the dominant colors in the same way that humans do, that is, using concepts like hue, saturation, and intensity.

3.1. Fuzzy HSI color space

We introduce the following definitions:

Definition 1. A fuzzy HSI color $\widetilde{C}$ is a linguistic label whose semantic is represented by a fuzzy subset of $[0, 2\pi] \times [0, 1] \times [0, 1]$.

Definition 2. A fuzzy HSI color space $\widetilde{\mathrm{HSI}}$ is a set of fuzzy HSI colors that defines a partition of $[0, 2\pi] \times [0, 1] \times [0, 1]$.

A very convenient way of defining and representing a fuzzy HSI color space is to employ a fuzzy hue space, a fuzzy saturation space and a fuzzy intensity space, consisting of fuzzy hues, fuzzy saturations and fuzzy intensities, respectively. We introduce these concepts in the following definitions:

Definition 3. A fuzzy hue (resp. saturation, intensity) is a linguistic label whose semantic is represented by a fuzzy subset of $[0, 2\pi]$ (resp. $[0, 1]$, $[0, 1]$).

Definition 4. A fuzzy hue (resp. saturation, intensity) space is a set of fuzzy hues (resp. saturations, intensities) that defines a partition of $[0, 2\pi]$ (resp. $[0, 1]$, $[0, 1]$).

By using these concepts, a fuzzy HSI color $\widetilde{C}$ can be defined and represented in practice by a triple $[\widetilde{C}_H, \widetilde{C}_S, \widetilde{C}_I]$, where $\widetilde{C}_H$, $\widetilde{C}_S$, and $\widetilde{C}_I$ are a fuzzy hue, a fuzzy saturation and a fuzzy intensity, respectively. In this way, the fuzzy sets representing the fuzzy HSI colors that form a fuzzy HSI color space can be obtained by combining the corresponding fuzzy sets representing fuzzy hues, saturations and intensities in a suitable way. For the sake of simplicity, we shall employ the name of the linguistic label to name also the corresponding fuzzy set.

This procedure has several advantages. First, less linguistic labels have to be defined. Second, we can represent and work with every component of the fuzzy HSI color individually (for example, we could query for colors with red hue). Finally, the linguistic labels associated to fuzzy HSI colors can be obtained by combining the corresponding linguistic labels associated to fuzzy hues, intensities and saturations.

In general, the representation of $\widetilde{C}$ as a fuzzy subset of $[0, 2\pi] \times [0, 1] \times [0, 1]$ can be obtained as follows:

$$\widetilde{C}(h, s, i) = \min\{\widetilde{C}_H(h), \widetilde{C}_S(s), \widetilde{C}_I(i)\}. \tag{6}$$

In the previous equation, the problem of non-representativity in semichromatic (undefined hue) and achromatic (undefined hue and saturation) zones should be taken into account. The definition of these zones in a fuzzy HSI color space will depend on the linguistic labels defined for saturation and intensity. In this work we have employed the fuzzy spaces for hue, saturation, and intensity that are shown in Fig. 2. Specifically, we have used as reference the Munsell color space [24] which divided in 10, 9 and 7 intervals the hue, intensity and saturation respectively. Each of these intervals are fuzzified using a trapezoidal function to define the fuzzy sets memberships. As result we obtain a fuzzy partition in the sense of Ruspini.

With these fuzzy spaces, the achromatic (resp. semichromatic) zone in the corresponding fuzzy HSI color space will correspond to fuzzy colors $\widetilde{C}$ verifying $\widetilde{C}_I =$"dark" (resp. $\widetilde{C}_S =$"very low saturated" and $\widetilde{C}_I \neq$"dark").

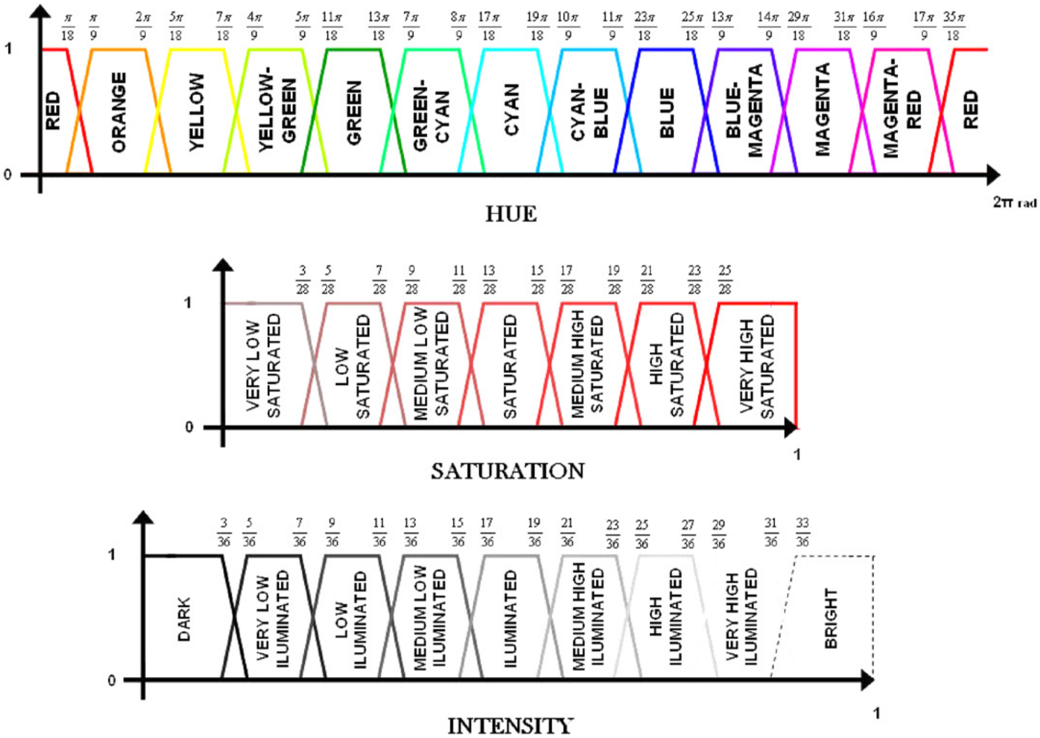

Fig. 2. Fuzzy HSI color space.

In order to deal with the problem of non-representativity in semichromatic and achromatic zones, we introduce "undefined" as a linguistic label for both the fuzzy hue and fuzzy saturation spaces, represented by the fuzzy sets $[0, 2\pi]$ and $[0, 1]$ respectively. Then, Eq. (6) will be adapted as shown in Eq. (7), and the corresponding representation of $\widetilde{C}$ via a triple of fuzzy hue, fuzzy saturation and fuzzy intensity will have the label "undefined" for hue in the semichromatic and achromatic zones, and also for saturation in the achromatic zone.

$$\widetilde{C}(h, s, i) = \begin{cases} \widetilde{C}_I(i) & \text{if } \widetilde{C} \text{ is achromatic,} \\ \min\{\widetilde{C}_S(s), \widetilde{C}_I(i)\} & \text{if } \widetilde{C} \text{ is semichromatic,} \\ \min\{\widetilde{C}_H(h), \widetilde{C}_S(s), \widetilde{C}_I(i)\} & \text{if } \widetilde{C} \text{ is chromatic.} \end{cases} \tag{7}$$

3.2. Possibility distribution of fuzzy colors

Since a crisp color can accomplish with several fuzzy colors, when going from a crisp color space to a fuzzy one, we obtain possibility distributions of fuzzy colors. Let us note Π^c the distribution associated to a crisp HSI color c = [h, s, i], i.e., $\Pi^c = \sum_{\widetilde{C}\in\widetilde{HSI}} \widetilde{C}(h, s, i)/\widetilde{C}$. Notice that these are special distributions, since they verify that the intersection of the support of all the fuzzy colors whose possibility degree is greater than 0 is not empty, since they are obtained by calculating the accomplishment degree between the crisp color c and the fuzzy HSI colors.

This kind of possibility distributions in a fuzzy HSI color space can be represented by three possibility distributions, in the corresponding hue, saturation and intensity spaces. In particular, Π^c can be represented by the three distributions $\Pi^c_H = \sum_{\tilde{h}\in\widetilde{H}} \tilde{h}(h)/\tilde{h}$, $\Pi^c_S = \sum_{\tilde{s}\in\widetilde{S}} \tilde{s}(s)/\tilde{s}$, and $\Pi^c_I = \sum_{\tilde{i}\in\widetilde{I}} \tilde{i}(i)/\tilde{i}$. Π^c can be obtained from them as follows: each triple $[\tilde{h}, \tilde{s}, \tilde{i}]$ of labels appearing in the respective distributions Π^c_H, Π^c_S, and Π^c_I with degree greater than 0, defines a fuzzy color $\widetilde{C}$ such that $\widetilde{C}_H = \tilde{h}$, $\widetilde{C}_S = \tilde{s}$, and $\widetilde{C}_I = \tilde{i}$. Then Π^c can be obtained using equation 7 since $\Pi^c(\widetilde{C}) = \widetilde{C}(h, s, i)$, $\widetilde{C}_H(h) = \Pi^c_H(\tilde{h})$, $\widetilde{C}_S(s) = \Pi^c_S(\tilde{s})$, and $\widetilde{C}_I(i) = \Pi^c_I(\tilde{i})$.

3.3. Dominant fuzzy colors

On the basis of the fuzzy HSI color space defined in the previous section, we introduce the concept of dominant fuzzy color in an image as follows:

Definition 5. A dominant fuzzy color is a fuzzy HSI color that appears frequently in the image.

As in the case of dominant crisp colors, this definition is imprecise in nature, i.e., "dominant" is an imprecise concept defined on the set of fuzzy colors.

Many approaches are possible to calculate how dominant is a fuzzy color in an image. One possible approach is to calculate the frequency with which each fuzzy color appears in the image, by using some fuzzy cardinality measure. This will be discussed in future papers.

The alternative approach we adopt in this paper is to obtain the fuzzy subset of dominant fuzzy colors from the set of crisp dominant colors. Assuming that a crisp dominant color will be a color that appears frequently in the image, we shall consider that a fuzzy color is dominant to the extent that it matches a dominant crisp color. This leads to the following definition:

Definition 6. Let $DCS = \{\mathbf{dc}_1, \ldots, \mathbf{dc}_N\}$ be the set of dominant crisp colors where $\mathbf{dc}_k = [h_k, s_k, i_k]$. The fuzzy subset of dominant fuzzy colors for an image will be

$$\widetilde{DCS} = \bigcup_{k\in\{1,\ldots,N\}} \widetilde{DCS}_k, \tag{8}$$

where

$$\widetilde{DCS}_k = \sum_{\widetilde{C}\in\widetilde{HSI}} (\widetilde{C}(\mathbf{dc}_k) \otimes Dom(\mathbf{dc}_k))/\widetilde{C} \tag{9}$$

with $\otimes$ being a t-norm (we use the minimum in this paper) and where $\widetilde{C}$ is a fuzzy color of the fuzzy HSI color space $\widetilde{HSI}$, $\widetilde{C}(\mathbf{dc}_k)$ is calculated according to Eq. (7), and the union is performed using the maximum.

Hence, for each dominant crisp color $\mathbf{dc}_k$, we obtain the possibility distribution given by Eq. (9), where the degree of dominance associated to each $\widetilde{C}$ is calculated as the minimum between the membership degree of $\mathbf{dc}_k$ to $\widetilde{C}$ and the dominant degree of $\mathbf{dc}_k$. If a fuzzy color $\widetilde{C}$ is compatible with several dominant crisp colors, then different degree of dominance will be obtained for $\widetilde{C}$ corresponding to each crisp color compatible with it; in this case, the maximum of these degrees will be selected as the final degree of dominance of $\widetilde{C}$ as Eq. (8) shows.

4. Fuzzy object-relational database system

The recent emerging of large image databases leads to the need for database management systems (DBMS), applied to multimedia libraries management, to ensure high performance, scalability, availability with fault tolerance and distribution.

Nowadays, market leader DBMSs offer these required features transparently. However, the database models implemented by them, generally the relational model, are not suitable to manage fuzzy data, which is necessary for this kind of image description algorithms. In order to solve this drawback, some database models and DBMSs implementing them have been proposed. Nevertheless, the existing fuzzy DBMSs are in general research prototypes which do not match the high performance and other necessary requirements for this kind of applications.

The strategy of implementation of our FORDMS model [4] is based on the extension of a market leader O-RDBMS (Oracle) by using its advanced object-relational features. This strategy let us take full advantage of the host O-RDBMS features (high performance, scalability, etc.) and the ability for representing and handling fuzzy data provided by our extension, making this FORDBMS very convenient for support systems for flexible content based retrieval of images.

4.1. Fuzzy datatype support

Our FORDBMS is able to handle and represent a wide variety of fuzzy datatypes, which allows to model any sort of fuzzy data easily. These types of fuzzy data are the following:

- Atomic fuzzy types (AFT), represented as possibility distributions over ordered (OAFT) or non ordered (NOAFT) domains.
- Fuzzy collections (FC), represented as fuzzy sets of objects with conjunctive (CFC) or disjunctive (DFC) semantics.
- Fuzzy objects (FO), whose attribute types could be crisp or fuzzy, and where each attribute is associated with a degree to measure its importance in object comparison.

There is a wide variety of associated operators, for all previous datatypes, to ease the creation, storage, manipulation, and flexible condition definition on them.

4.2. Database modelling of image characterization

Since the retrieval system is supported by a database, a specific database datatype is needed to enable easy storage, handling, and condition definition mechanisms for the image descriptors defined in this article. As it will be shown, the basic fuzzy datatypes introduced earlier are very useful for modeling this datatype, because of its flexible modeling capabilities, data handling mechanisms, and flexible condition operators.

The image descriptor datatype, whose name is *DominantColorSet*, is modeled as shown in Fig. 3. In this figure, the classes whose background color is dark gray corresponds to the basic fuzzy datatypes provided by the described FORDBMS, and the classes with light gray background correspond to the basic typed provided by the host ORDBMS on which the FORDMBS is defined. All other classes, with white background, correspond to the classes defined to represent the image descriptor datatype. Let us depict the *DominantColorSet* datatype definition using a *bottom to top* approach.

As it has been proposed in previous sections, the basis of a fuzzy color are the linguistics labels, defined in Fig. 2, which are represented by trapezoidal possibility distributions defined over hue, saturation and intensity domains. These linguistic labels are modeled using an OAFT derived datatype for each HSI color component, creating the datatypes *FHue*, *FSaturation* and *FIntensity*. These datatypes represent the fuzzy hue ($\widetilde{H}$), saturation ($\widetilde{S}$) and intensity ($\widetilde{I}$) spaces respectively. A value of these datatypes is able to represent a linguistic label.

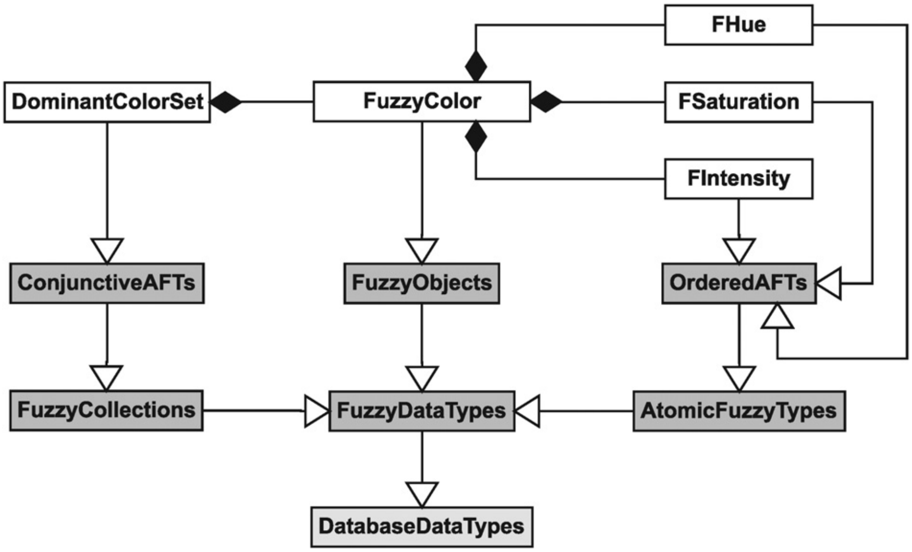

Fig. 3. UML diagram for DominantColorSet datatype.

A fuzzy color, based on previous definitions, can be represented as a triple $[\widetilde{H}, \widetilde{S}, \widetilde{I}]$. In other words, a fuzzy color is the composition of three linguistic labels defined in fuzzy hue, saturation and intensity spaces. A fuzzy color in the database is represented by the datatype *FuzzyColor*, which is defined by composing three values of *FHue*, *FSaturation* and *FIntensity*, in the same way that a fuzzy color is composed. In fact, the *FuzzyColor* datatype is a FO derived datatype with three attributes of the datatypes *FHue*, *FSaturation* and *FIntensity*, respectively.

Finally, in order to represent the fuzzy subset of dominant colors $\widetilde{DCS}$ the *DominantColorSet* datatype is created. $\widetilde{DCS}$ is a fuzzy subset of fuzzy colors, as defined in Eq. (8), whose membership degrees correspond to their degree of dominance, calculated as shown in Eq. (9). Taking into account the fuzzy nature of fuzzy colors, and the conjunctive semantics of the $\widetilde{DCS}$ definition, the datatype *DominantColorSet* must be a CFC whose elements are values of the *FuzzyColor* datatype.

4.3. Fuzzy datatype operators

The current section describes the most significant operators for the defined fuzzy datatypes, which are used to define conditions based on dominant color presence in image retrieval queries.

4.3.1. Fuzzy inclusion operator

The operator `FInclusion(A,B)` calculates the inclusion degree $A \subseteq B$, where A and B are instances of CFC. The calculus is done using a modification of the *Resemblance Driven Inclusion Degree* introduced in [16], which computes the inclusion degree of two fuzzy sets whose elements are imprecise.

Definition 7 (*Resemblance driven inclusion degree*). Let A and B be two fuzzy sets defined over a finite reference universe $\mathscr{U}$, μ_A and μ_B the membership functions of these fuzzy sets, S the resemblance relation defined over the elements of $\mathscr{U}$, $\otimes$ be a t-norm, and I an implication operator. The inclusion degree of A in B driven by the resemblance relation S is calculated as follows:

$$\Theta_S(B|A) = \min_{x \in \mathscr{U}} \max_{y \in \mathscr{U}} \theta_{A,B,S}(x, y), \tag{10}$$

where

$$\theta_{A,B,S}(x, y) = \otimes(I(\mu_A(x), \mu_B(y)), \mu_S(x, y)). \tag{11}$$

We propose a modification that substitutes the minimum aggregation operator in Eq. (10) by a weighted mean aggregation operator, whose weight values are the membership degrees in A of the elements of $\mathscr{U}$, divided by the cardinal of A. This modification is made in order to obtain a less extreme resemblance inclusion degree, since it takes into account the importance of each included element. The *Modified Resemblance Inclusion Degree* is defined in Eq. (12).

$$\Theta_S(B|A) = \sum_{x\in\mathscr{U}} \frac{\mu_A(x)}{|A|} \cdot \max_{y\in\mathscr{U}} \theta_{A,B,S}(x, y) \tag{12}$$

with $|A| = \sum_{x\in\mathscr{U}} \mu_A(x)$. Our implementation of `FInclusion(A,B)` uses the minimum as t-norm, and as implication operator the Gaines fuzzy inclusion operator [19] defined in Eq. (13):

$$I(x, y) = \begin{cases} 1 & \text{if } x \leqslant y, \\ y/x & \text{otherwise.} \end{cases} \tag{13}$$

4.3.2. Fuzzy equality operator

The operator `FEQ(A,B)` calculates the resemblance degree between two instances of a fuzzy datatype.

When `A` and `B` are two instances of CFC, this resemblance degree is calculated by means of the *generalized resemblance between fuzzy sets* proposed in [16], which is based on the concept of double inclusion.

Definition 8 (*Generalized resemblance between fuzzy sets*). Let A and B be two fuzzy sets defined over a finite reference universe $\mathscr{U}$, over which a resemblance relation S is defined, and $\otimes$ be a t-norm. The generalized resemblance degree between A and B restricted by $\otimes$ is calculated by means of the following formulation:

$$\beth_{S,\otimes}(A, B) = \otimes(\Theta_S(B|A), \Theta_S(A|B)). \tag{14}$$

Therefore, the implementation of the operator `FEQ(A,B)`, when A and B are instances of CFC, aggregates the results of `FInclusion(A,B)` and `FInclusion(B,A)` using a t-norm. However, we substitute the t-norm by the arithmetic mean aggregation operator in order to get a more flexible comparison.

If the operator `FEQ(A,B)` is applied when `A` and `B` are instances of the class *FuzzyColor*, then the resemblance degree between these objects is calculated as the average of the resemblance degree of their attribute values.

Definition 9 (*Object resemblance degree*). Let o_1 and o_2 be two objects of the class C, $obj.a_i$ the value of the ith attribute of the object obj, n the number of attributes defined in the class C, and FEQ the resemblance operator.

$$OR(o_1, o_2) = \frac{1}{n} \sum_{i\in\mathscr{A}}^{n} FEQ(o1.a_i, o2.a_i). \tag{15}$$

5. Retrieving images by dominant color criteria

The described framework makes database systems able to answer queries based on the set of dominant colors within an image, so users can define queries containing dominant color based conditions. These sentences can be expressed as simple and standard SQL sentences which can be processed directly by the DBMS.

Dominant color based conditions are, in fact, fuzzy conditions defined on the fuzzy set of dominant colors used as a descriptor for the images in a database. These conditions are based on the *fuzzy inclusion operator* and/or *fuzzy equality operator for CFC* defined before.

Therefore, the user can define a fuzzy set of fuzzy colors which must be included in, or resemble to, the descriptor of each image in the database. Each fuzzy color in the fuzzy set can be defined by using the linguistic labels defined for each *HSI* color component, which makes possible to define queries using natural language color descriptors. Also, this way of dominant color definition makes possible the definition of different conditions over each HSI color component, or avoiding any restriction on a color component by using the linguistic label *unknown*.

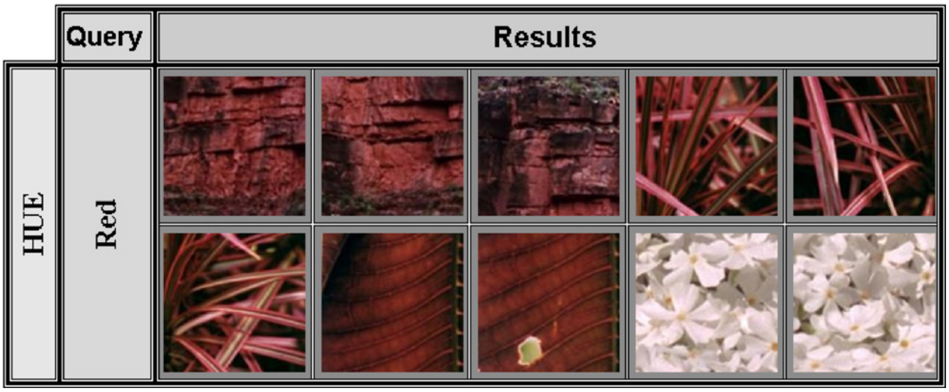

Fig. 4. Color inclusion query results using only the hue component.

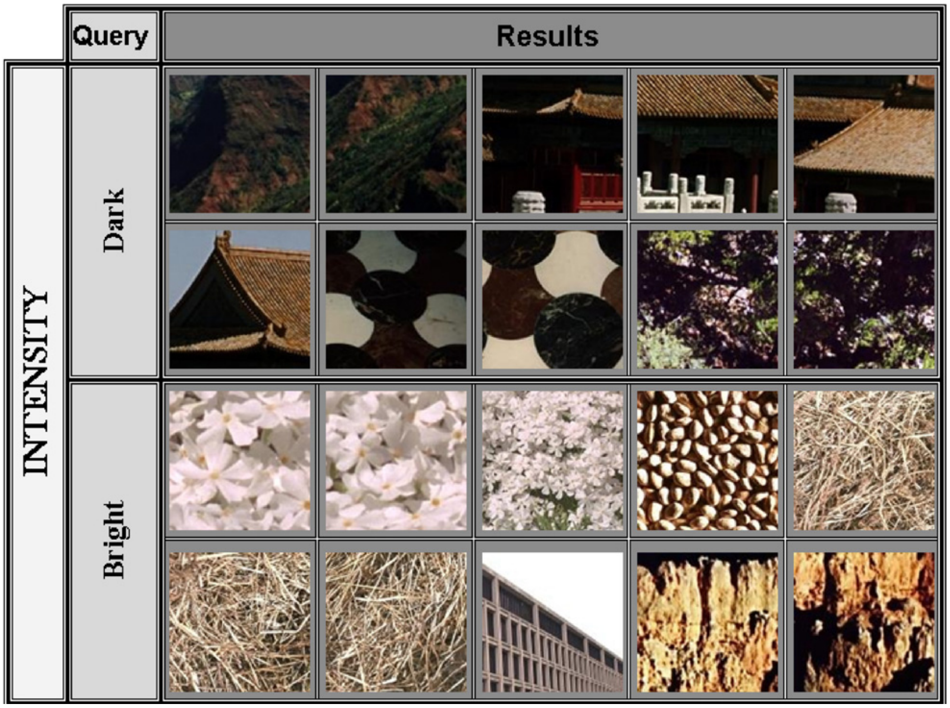

Fig. 5. Color inclusion query results using only the intensity component.

5.1. Query examples

The described query definition mechanism of dominant color based conditions makes it possible to express different queries based on the inclusion, or resemblance, of fuzzy sets of dominant colors.

In our experiments we have empirically fixed T_d to 2%, μ_1 to 0.05 and μ_2 to 0.2. Parameters T_S and T_I have been set to $\frac{1}{7}$ (the highest value of the support of the fuzzy set $VeryLowSaturated$) and $\frac{1}{9}$ (the highest value of the support of the fuzzy set *Dark*), respectively.

5.1.1. Dominant color inclusion query

For instance, we want to obtain from a database the images *including any kind of red hue*, which includes *pale dark red*, *light bright red*, etc. The previous condition is defined by applying the inclusion operator on the image descriptor

Fig. 6. Color inclusion query results using hue and intensity components.

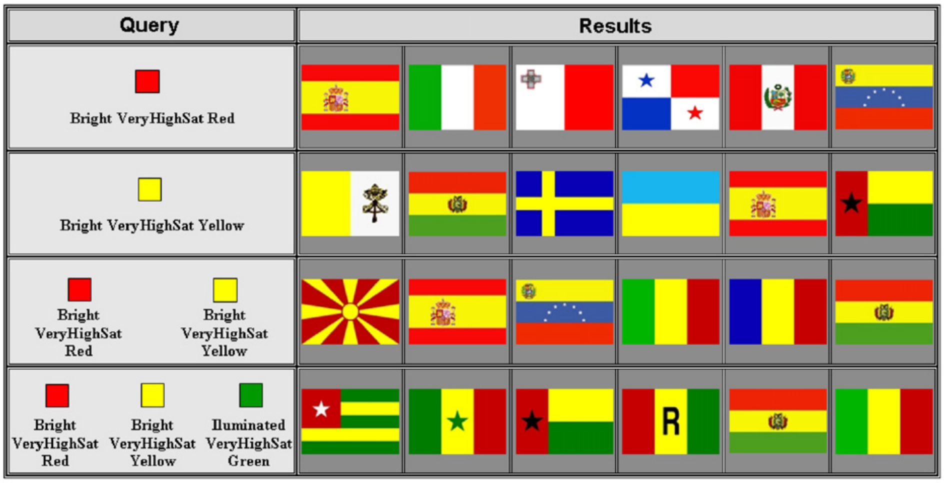

Fig. 7. Color inclusion query results using all the color components.

and a fuzzy set of dominant colors, which includes only one fuzzy color defined using the linguistic label *red* for the hue component, and the linguistic label *unknown* for the saturation and intensity components.

The results of this query applied on a database containing about 700 color images, are shown in Fig. 4 ordered by relevance. The system recovers a set of images including pale red images (the first ones) and bright red images (the last ones). A similar example, using only the intensity component, is shown in Fig. 5. In this case we are interested in dark images, independently of the hue or saturation; hence, we perform the query with the labels [*unknown*, *unknown*, *dark*] and we obtain as result the images on the top of Fig. 5 (on the bottom, results corresponding to "bright images" are shown).

Fig. 6 shows an example of searching for bright red images. In this case, we use the hue and the intensity components, performing the query with the labels [*red*, *unknown*, *bright*] (let us remark that the result of this query is a subset of the images obtained in the case of Fig. 4).

Results on a flag database containing 160 images are shown in Fig. 7. The queries performed in this example use all the color components. The first column shows the fuzzy color (linguistic labels) of the query and a representative crisp color which accomplishes with this fuzzy color. On the left, Fig. 7 shows the query results corresponding to flag images containing the query color.

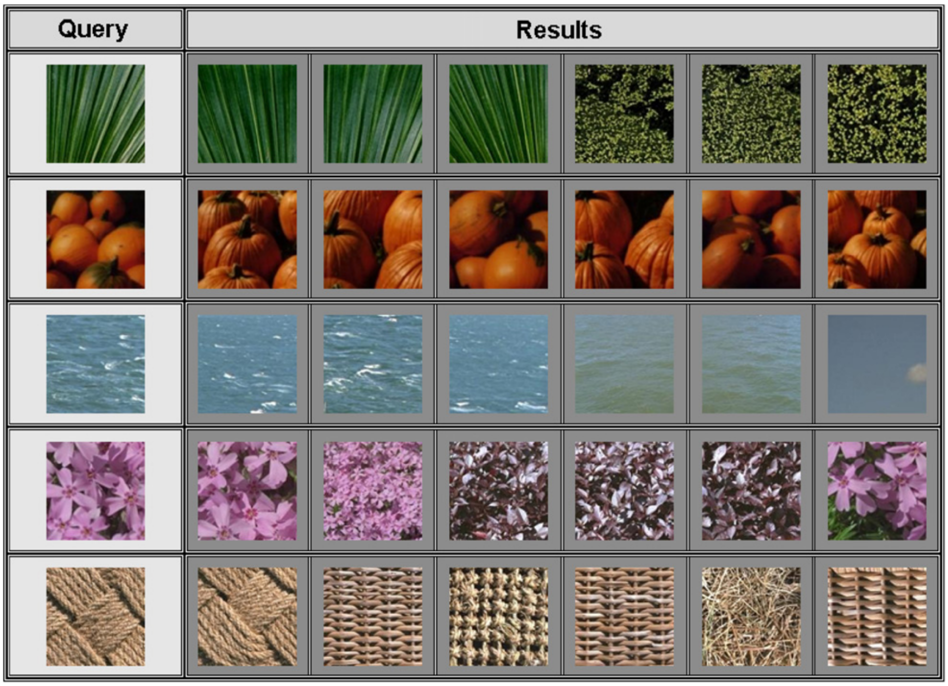

Fig. 8. Image resemblance query results.

5.1.2. Dominant color resemblance query

Also, we would be interested in getting images with a dominant color pattern similar to the one associated with a sample image. This condition can be defined by using the *fuzzy equality operator for CFC* to compute the resemblance degree between the fuzzy set of dominant colors which describes each image in the database and the one which describes the example image.

Fig. 8 shows an example applied on a database containing about 700 color images. In this case, we are interested in getting images with colors similar to the one showed in the first column. For each image, the query results are shown on the left ordered by relevance.

6. Concluding remarks and future works

In this paper we have proposed a novel approach for retrieving images based on fuzzy databases using color information. It has been shown that the extraction of dominant color descriptors from images using a fuzzy approach, combined with the ability of a FORDBMS to represent and handle of complex fuzzy data, provides a powerful platform for content based image retrieval.

Future works will lead to incorporate new fuzzy features, such as texture or shape, for image description. In the field of FORDMS, new methods for fuzzy data indexing, atomic or not, based on the extension of traditional indexing mechanisms will be studied, in order to increase query processing performance. Furthermore, flexible query optimization, and flexible query parallelization using FDBMS clusters will be taken into account. These future works will lead to extraordinarily improvement of the query processing performance in image retrieval applications in real world environments, and making possible parallel query processing an therefore the scalability of this kind of retrieval systems.

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