A Fuzzy Approach for Retrieving Images in Databases using Dominant Color and Texture Descriptors

J. Chamorro-Martínez, P. Martínez-Jiménez, and J.M. Soto-Hidalgo

***Abstract*— In this paper, a fuzzy approach for image retrieval on the basis of color and texture features is presented. For this purpose, two new descriptors "*Fuzzy Dominant Color Descriptor*" and "*Fuzzy Dominant Texture Descriptor*" are proposed. Each descriptor will be defined as a fuzzy set over a finite universe of color/texture fuzzy sets (with membership degrees according to its dominance degrees). The color/texture fuzzy sets are defined taking into account the relationship between the computational feature and its human perception. In addition, fuzzy operators over the new descriptors are proposed to define conditions in image retrieval queries. The proposed framework makes database systems able to answer queries using color-based and texture-based linguistic labels in natural language.**

I. Introduction

In last years, large collections of digital images have been created. Many of these collections are used in practical applications, such as picture archiving [4], medical databases management or multimedia search engines on the Web [6]. Usually, the only way of searching these collections was by keyword indexing based on captions and textual descriptors performed by humans [11]. 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). This fact has motivated an increment of the research about techniques for storing, indexing and retrieving visual information.

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 [5], [7]. In these systems, images are represented by vectors of 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 feature 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 [8], [17]. In these fuzzy approaches the semantic data is managed by means of fuzzy sets, allowing to perform queries on the basis of linguistic terms.

J. Chamorro-Martínez and P. Martínez-Jiménez are with the Department of Computer Science and Artificial Intelligence, University of Granada, Spain. J.M. Soto-Hidalgo is with the Department of Computer Architecture, Electronics and Electronic Technology, University of Córdoba, Spain. email:{jesus,pedromartinez}@decsai.ugr.es, jmsoto@uco.es

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However, these approaches have two main drawbacks: (i) given a feature, the fuzzy sets are not obtained by considering the relationship between the computational feature and its human perception [13], [18], [3] so the linguistic labels related to these fuzzy sets do not necessarily match what a human would expect; and (ii), from our knowledge, none of these approaches proposes fuzzy descriptors of features for describing semantically an image [19], [12] so all imprecise information that fuzzy sets provides is not considered in the retrieval process.

In this paper, we face the previous questions introducing fuzzy descriptors for colors and textures. For color representation, the fuzzy color and fuzzy color space definitions we introduced in [2] will be used. Concretely, a color will be modelled by means of a fuzzy set (a fuzzy color) and a fuzzy partition will be defined in the color feature domain (a fuzzy color space). In this paper we propose to define this partition on the basis of the ISCC-NBS color naming system [9], [10], that is based on the human perception of color.

For texture representation, we will use the *coarseness/fineness* property, that is one of the most popular in image analysis. In fact, it is common to associate the presence of texture with the presence of fineness (let us remark that "coarseness" and "fineness" are opposite but related textural concepts). We propose to model the texture coarseness property by means of fuzzy sets. Concretely, fuzzy partitions on the domain of coarseness measures are proposed, where the number of linguistic labels and the parameters of the membership functions will be calculated relating representative coarseness measures (our reference set) with the human perception of this texture property.

Given an image, the dominance of each "color fuzzy set" and "texture fuzzy set" will be analyzed. On the basis of this dominance, two new descriptors "*Fuzzy Dominant Color Descriptor*" and "*Fuzzy Dominant Texture Descriptor*" are proposed in this paper. Each descriptor will be defined as a fuzzy set over the finite universe of color/texture fuzzy sets (with membership degrees according to its dominance degrees). Moreover, fuzzy operators over this descriptors are proposed to define conditions in image retrieval queries. In this paper, the fuzzy inclusion and resemblance operators will be used. The proposed framework makes database systems able to answer queries using color-based and texture-based linguistic labels in natural language.

The rest of the paper is organized as follows. In sections II and III the color and texture fuzzy modellings are presented. The dominance-based color and texture fuzzy descriptors are defined in section IV, and the fuzzy operators for image

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retrieval are described in section V. Results are shown in section VI, and the main conclusions and future work are summarized in section VII.

II. Fuzzy Modelling of Colors

In this section, the notions of fuzzy color (section II-A) and fuzzy color space (section II-B) we presented in a previous work [2] are summarized. Based on it, a fuzzy partition will be defined in the color feature domain (our fuzzy color space) according to the ISCC-NBS color naming system [10].

A. Fuzzy color

For representing colors, several color spaces can be used. In essence, a color space is a specification of a coordinate system and a subspace within that system where each color is represented by a single point. The most commonly used color space in practice is RGB because is the one employed in hardware devices (like monitors and digital cameras). It is based on a cartesian coordinate system, where each color consists of three components corresponding to the primary colors red, green, and blue. Other color spaces are also popular in the image processing field: linear combination of RGB (like CMY, YCbCr, or YUV), color spaces based on human color terms like hue or saturation (HSI, HSV or HSL), or perceptually uniform color spaces (like CIELa*b*, CIELuv, etc.).

In order to manage the imprecision in color description, we introduce the following definition of fuzzy color:

Definition 2.1: A fuzzy color $\widetilde{C}$ is a normalized fuzzy subset of colors.

As previously explained, colors can be represented as a triplet of real numbers corresponding to coordinates in a color space. Hence, a fuzzy color can be defined as a normalized fuzzy subset of points of a color space. From now on, we shall note XYZ a generic color space with components X, Y and Z[1], and we shall assume that a color space XYZ, with domains D_X, D_Y and D_Z of the corresponding color components is employed. This leads to the following more specific definition:

Definition 2.2: A fuzzy color $\widetilde{C}$ is a linguistic label whose semantics is represented in a color space XYZ by a normalized fuzzy subset of $D_X \times D_Y \times D_Z$.

Notice that the above definition implies that for each fuzzy color $\widetilde{C}$ there is at least one crisp color $\mathbf{r}$ such that $\widetilde{C}(\mathbf{r}) = 1$.

In this paper, and following [2], we will define the membership function of $\widetilde{C}$ as

$$\widetilde{C}(\mathbf{c}; \mathbf{r}, S, \Omega) = f\left(\left|\overrightarrow{\mathbf{rc}}\right|; t_1^c, \ldots, t_n^c\right) \qquad (1)$$

depending on there parameters: $S = \{S_1, \ldots, S_n\}$ a set of bounded surfaces in XYZ verifying $S_i \cap S_j = \emptyset$ $\forall i, j$ (i.e., pairwise disjoint) and such that $Volume(S_i) \subset Volume(S_{i+1})$; $\Omega = \{\alpha_1, \ldots, \alpha_n\} \subseteq (0, 1]$, with $1 = \alpha_1 > \alpha_2 > \cdots > \alpha_n = 0$, the membership degrees associated to S verifying $\widetilde{C}(\mathbf{s}; \mathbf{r}, S, \Omega) = \alpha_i$ $\forall \mathbf{s} \in S_i$; and $\mathbf{r}$ a point inside $Volume(S_1)$ that is assumed to be a crisp color representative of $\widetilde{C}$.

In Eq.1, $f : \mathbb{R} \to [0, 1]$ is a piecewise function with knots $\{t_1^c, \ldots, t_n^c\}$ verifying $f(t_i^c) = \alpha_i \in \Omega$, where these knots are calculated from the parameters $\mathbf{r}$, S and Ω as follows: $t_i^c = \left|\overrightarrow{\mathbf{rp}_i}\right|$ with $\mathbf{p}_i = S_i \cap \overline{\mathbf{rc}}$ being the intersection between the line $\overline{\mathbf{rc}}$ (straight line containing the points $\mathbf{r}$ and $\mathbf{c}$) and the surface S_i, and $\left|\overrightarrow{\mathbf{rp}_i}\right|$ the length of the vector $\overrightarrow{\mathbf{rp}_i}$.

B. Fuzzy color space

For extending the concept of color space to the case of fuzzy colors, and assuming a fixed color space XYZ, with D_X, D_Y and D_Z being the domains of the corresponding color components, the following definition is introduced:

Definition 2.3: A fuzzy color space $\widetilde{XYZ}$ is a set of fuzzy colors that define a partition of $D_X \times D_Y \times D_Z$.

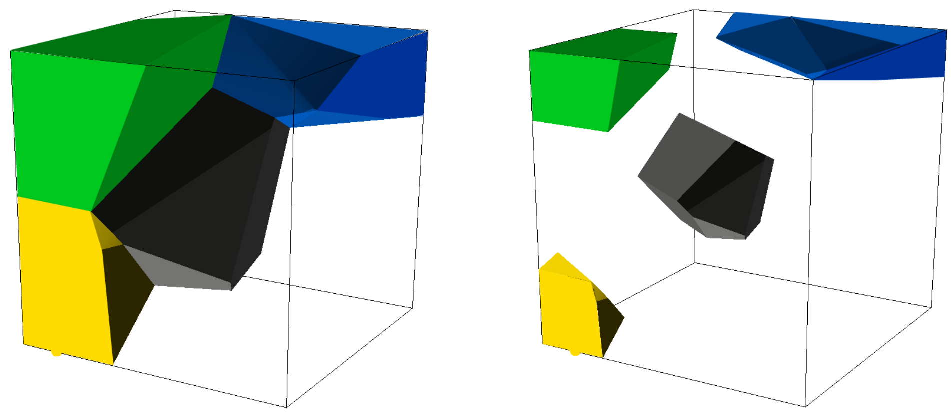
As we introduced in the previous section (see Eq.1), each fuzzy color $\widetilde{C}_i \in \widetilde{XYZ}$ will have associated a representative crisp color $\mathbf{r}_i$. Therefore, for defining our fuzzy color space, a set of representative crisp colors $R = \{\mathbf{r}_1, \ldots, \mathbf{r}_n\}$ is needed. In this paper we propose to use the color names (and color points) provided by the ISCC-NBS system [9], [10], witch is based on human tests about color perception. ISCC-NBS system defines a set of valid terms and modifiers which can be combined to obtain the final color name. The basic set is formed by 13 color names (10 hues -pink, red, orange, brown, olive, green, blue, violet, purple- and 3 achromatic colors -white, grey and black-), while the extended set is formed by 31 colors (the basic ones and some combination of them formed by adding the $-ish$ suffix -Brownish Orange, Purplish Blue among others-). In this paper, the extended set will be used (i.e, $R = \{\mathbf{r}_1, \ldots, \mathbf{r}_{31}\}$ with $\mathbf{r}_i$ a RGB color).

For defining each fuzzy color $\widetilde{C}_i \in \widetilde{XYZ}$, we also need to fix the set of surfaces S_i and the associated memberships degrees Ω_i (see Eq.1). In this paper, we have focused on the case of convex surfaces defined as a polyhedra (i.e, a set of faces). Concretely, three surfaces $S_i = \{S_1^i, S_2^i, S_3^i\}$ have been used for each fuzzy color $\widetilde{C}_i$ with $\Omega_i = \{1, 0.5, 0\} \forall i$.

To obtain $S_2^i \in S_i$ $\forall i$, a Voronoi diagram has been calculated [16] with R as centroid points . As results, a crisp partition of the color domain given by convex volumes is obtained (each volume will define a Voronoi cell). The surfaces of the Voronoi cells will define the surfaces $S_2^i \in S_i$ $\forall i$. Once S_2^i is obtained, the surface S_1^i (resp. S_3^i) is calculated as a scaled surface of S_2^i with scale factor of 0.5 (resp. 1.5). For more details about the parameter values which define each polyhedra, see [2].

Figure 1 shows the surfaces S_2^{yellow}, S_2^{blue}, S_2^{green} and S_2^{grey} (on the left), and S_1^{yellow}, S_1^{blue}, S_1^{green} and S_1^{grey} (on the rigth). The representative crisp values are $\mathbf{r}_{yellow} = [254, 220, 1]$, $\mathbf{r}_{blue} = [1, 90, 200]$, $\mathbf{r}_{green} = [1, 220, 30]$ and $\mathbf{r}_{gray} = [132, 132, 132]$.

[1]Although we are assuming a three dimensional color space, the proposal can be easily extended to color spaces with more components.



(a) (b)

Fig. 1. Some surfaces associated to the fuzzy color space. (a) S_2^i (b) S_1^i for $i = \{yellow, blue, green, grey\}$

III. Fuzzy Modelling of Textures

In this section, the fuzzy modelling of textures is presented. Given a texture property (coarseness, orientation, regularity, etc), let $\mathcal{M}$ be a measure of that property, let $\mathcal{M}(i)$ be the result of applying the measure $\mathcal{M}$ to a texture image, and let $\mathcal{D}_{\mathcal{M}}$ be the measure domain[2]. As in the case of the color modelling shown in section II, the notions of fuzzy texture and fuzzy texture space are introduced as follows:

Definition 3.1: A fuzzy texture $\widetilde{T}$ is a linguistic label whose semantics is represented by a normalized fuzzy subset of $\mathcal{D}_{\mathcal{M}}$.

Definition 3.2: A fuzzy texture space Π is a set of fuzzy textures that defines a partition of $\mathcal{D}_{\mathcal{M}}$.

By using these concepts, the fuzzy modelling of the coarseness property is described in the next section.

A. Fuzzy Modelling of Coarseness

As it was pointed, we propose to model the texture coarseness property by means of fuzzy sets. Concretely, fuzzy partitions on the domain of coarseness measures are proposed (our fuzzy texture space). From now on, we will note Π_k the partition defined on the domain of a given coarseness measure $\mathcal{M}_k$, N_k the number of fuzzy sets which compounds the partition Π_k, and $\widetilde{T}_k^i$ the i-th fuzzy set in Π_k.

In this paper, we propose to define the membership function $\widetilde{T}_k^i(x)$ for each fuzzy set $\widetilde{T}_k^i$ by using a trapezoidal function of the form

$$\widetilde{T}_k^i(x) = \begin{cases} 0 & x < a_k^i \quad or \quad x > d_k^i \\ \frac{x - a_k^i}{b_k^i - a_k^i} & a_k^i \le x \le b_k^i \\ 1 & b_k^i \le x \le c_k^i \\ \frac{d_k^i - x}{d_k^i - c_k^i} & c_k^i \le x \le d_k^i \end{cases} \tag{2}$$

[2]Usually, in most popular measures, $\mathcal{D}_{\mathcal{M}} = \mathbb{R}$

It should be noticed that $a_k^1 = b_k^1 = -\infty$ and $c_k^{N_k} = d_k^{N_k} = \infty$.

This way, two questions need to be faced in order to define the fuzzy partition Π_k,: (i) how many fuzzy sets will compound the partition, and (ii) how to obtain the parameter values of the membership function for each fuzzy set. In order to solve these questions, we propose a solution based on the study shown in [1].

With regard to the number of fuzzy sets which compounds the partition, we will analyze the ability of each measure to distinguish between different degrees of fineness. This analysis will be based on how the human perceives the fineness-coarseness. To get information about human perception of fineness, a set of images covering different degrees of fineness will be gathered. These images will be used to collect, by means of a pool, human assessments about the perceived fineness. Using the data about human perception, and the measure values obtained for each image, we will apply an iterative algorithm based on a set of multiple comparison tests, in order to obtain the number of classes (fineness degrees) that each measure can discriminate. Thus, we propose to set the number of fuzzy sets N_k in the partition Π_k as the number of classes that can be discriminated by the measure $\mathcal{M}_k$. The detailed description of the analyzed measures, the set of images, the pool and the iterative algorithm is shown in [1].

In addition, the information given by the tests, will be used to define the parameter values of the membership function $\widetilde{T}_k^i(x)$ for each fuzzy set $\widetilde{T}_k^i$. For each class obtained in the distinguishability analysis, we will compute its representative value as the mean of the measure values in the class. In our proposal, the center position of the kernel of the fuzzy set $\widetilde{T}_k^i$ will be established by the representative value of the corresponding i-th class given by the tests. The kernel size will be set as the size of the confidence interval around this representative value. Thus, since a fuzzy partition in the sense of Ruspini is proposed, all the parameter values are obtained.

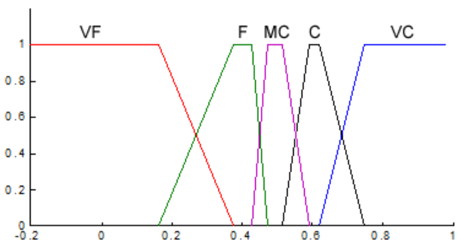


Fig. 2. Fuzzy partitions for the measure of Correlation. The linguistic labels are VC = very coarse, C = coarse, MC = medium coarse, F = fine, VF = very fine

TABLE I
PARAMETER VALUES THAT DEFINE THE MEMBERSHIP FUNCTIONS $\mathcal{T}_k^i(x)$ COMPOUNDING THE PARTITION FOR THE MEASURE OF CORRELATION

i	a_k^i	b_k^i	c_k^i	d_k^i
1	$-\infty$	$-\infty$	0.1600	0.3758
2	0.1600	0.3758	0.4302	0.4725
3	0.4302	0.4725	0.5175	0.5937
4	0.5175	0.5937	0.6203	0.7480
5	0.6203	0.7480	∞	∞

Figure 2 shows the fuzzy partition Π_k for the measure of *Correlation* (the one with higher capacity to discriminate fineness classes according to [1]). Table I shows the parameter values that define the membership function $\widetilde{T}_k^i(x)$ for each fuzzy set compounding this fuzzy partition.

IV. DOMINANCE-BASED COLOR AND TEXTURE FUZZY DESCRIPTORS

For describing semantically an image, the dominant colors and textures will be used. In this section, Fuzzy Descriptors for dominant colors and textures are proposed (section IV-B) on the basis of the dominance degree of a given color/texture (section IV-A).

A. Dominant Fuzzy Colors and Textures

Intuitively, a color (or a texture) is dominant to the extend it appears frequently in a given image. As it is well known in the computer vision field, the histogram is a powerful tool for measuring the frequency in which a property appears in an image. The histogram is a function $h(x) = n_x$ where x is a pixel property (grey level, color, texture value, etc.) and n_x is the number of pixels in the image having the property x. It is common to normalize a histogram by dividing each of its values by the total number of pixels, obtaining an estimate of the probability of occurrence of x.

Working with fuzzy properties suggests to extend the notion of histogram to ”fuzzy histogram”. In this sense, a fuzzy histogram will give us information about the frequency of each fuzzy property (color or texture in our case). In this paper, the counting will be performed by using the scalar sigma-count (i.e., the sum of membership degrees). Thus, for any fuzzy set F with membership function $F : X \to [0, 1]$, the fuzzy histogram is defined as

$$h(F) = \frac{1}{NP} \sum_{x \in X} F(x) \tag{3}$$

with NP being the number of pixels[3].

Using the information given by the histogram, we will measure the ”dominance” of a color/texture fuzzy set. Dominance is an imprecise concept, i.e., it is possible in general to find colors/textures that are clearly dominant, colors/textures that are clearly not dominant, and colors/textures that are dominant to a certain degree, that depends on the percentage of pixels where the color/texture appears.

It seems natural to model the idea of dominance by means of a fuzzy set over the percentages given by $h(F)$, i.e., a fuzzy subset of the real interval $[0, 1]$. Hence, we define the fuzzy subset ”Dominant”, noted as Dom, as follows:

$$Dom(F) = \begin{cases} 0 & h(F) \le u_1 \\ \frac{h(F) - u_1}{u_2 - u_1} & u_1 \le h(F) \le u_2 \\ 1 & h(F) \ge u_2 \end{cases} \tag{4}$$

where u_1 and u_2 are two parameters such that $0 \le u_1 < u_2 \le 1$, and $h(F)$ is calculated by means of Eq. 3.

B. Dominance-based fuzzy descriptors

On the basis of the dominance of colors and textures, two new image descriptors are proposed in this section. For a generic image property, we introduce de following definition of fuzzy descriptor:

Definition 4.1: Let $\mathscr{P}$ be a finite universe of fuzzy sets associated to a given image property[4]. A fuzzy descriptor is defined as a fuzzy set over the reference universe $\mathscr{P}$

In the case of the ”Color” property, we define the following fuzzy descriptor for dominant colors:

Definition 4.2: Let $\mathscr{C}$ a finite reference universe of color fuzzy sets. We define the *Fuzzy Dominant Color Descriptor* as the fuzzy set

$$FDCD = \sum_{C \in \mathscr{C}} Dom(C)/C \tag{5}$$

with $Dom(C)$ being the dominance degree of C given by Eq. 4.

In the case of the ”Texture Coarseness” property, we define the following fuzzy descriptor:

Definition 4.3: Let $\mathscr{T}$ a finite reference universe of texture fuzzy sets. We define the *Fuzzy Dominant Texture Descriptor* as the fuzzy set

$$FDTD = \sum_{T \in \mathscr{T}} Dom(T)/T \tag{6}$$

with $Dom(T)$ being the dominance degree of T given by Eq. 4.

[3]For texture properties, a window centered on each pixel will be used to calculate the measure value x.

[4]For example, the property ”Color” with $\mathscr{P}$ being a set of fuzzy colors.

V. Fuzzy operators for image retrieval

Fuzzy operators over fuzzy descriptors are needed to define conditions in image retrieval queries. In this section, a "Fuzzy inclusion operator" (section V-A) and a "Fuzzy resemblance operator" (section V-B) are proposed.

A. Fuzzy inclusion operator

Given two Fuzzy Descriptors, FD^i and FD^j, the operator presented in this section calculates the inclusion degree of FD^i in FD^j. The calculus is done using the *Resemblance Driven Inclusion Degree* introduced in [14], which computes the inclusion degree of two fuzzy sets whose elements are imprecise.

Definition 5.1: Let FD^i and FD^j be two Fuzzy Descriptors defined over a finite reference universe of fuzzy sets $\mathscr{P}$, $FD^i(x)$ and $FD^j(x)$ the membership functions of these fuzzy sets, S the resemblance relation defined over the elements of $\mathscr{P}$, $\otimes$ be a t-norm, and I an implication operator. The inclusion degree of FD^i in FD^j driven by the resemblance relation S is calculated as follows:

$$\Theta_S(FD^j|FD^i) = \min_{x\in\mathscr{P}} \max_{y\in\mathscr{P}} \theta_{i,j,S}(x,y) \quad (7)$$

where

$$\theta_{i,j,S}(x,y) = \otimes(I(FD^i(x), FD^j(y)), S(x,y)) \quad (8)$$

In this paper we use the minimum as t-norm, the compatibility as the resemblance relation S, and as implication operator the one defined in equation 9.

$$I(x,y) = \begin{cases} 1 & \text{if } x \le y \\ y/x & \text{otherwise} \end{cases} \quad (9)$$

B. Fuzzy resemblance operator

The operator presented in this section calculates the resemblance degree between two Fuzzy Descriptors, FD^i and FD^j. This resemblance degree is calculated by means of the *Generalized Resemblance between Fuzzy Sets* proposed in [14], which is based on the concept of double inclusion.

Definition 5.2: Let FD^i and FD^j be two Fuzzy Descriptors defined over a finite reference universe of fuzzy sets $\mathscr{P}$, over which a resemblance relation S is defined, and $\otimes$ be a t-norm. The generalized resemblance degree between FD^i and FD^j restricted by $\otimes$ is calculated by means of the following formulation:

$$\Lambda_{S,\otimes}(FD^i, FD^j) = \otimes(\Theta_S(FD^j|FD^i), \Theta_S(FD^i|FD^j)) \quad (10)$$

The described framework makes database systems able to answer queries based on the set of dominant color and textures within an image. Therefore, the user can define a fuzzy set of fuzzy colors/textures (i.e, a descriptor) which must be included in, or resemble to, the descriptor of each image in the database. Each fuzzy color or fuzzy texture in the fuzzy set can be defined by using the linguistic labels proposed in sections II (for colors) and III (for textures), which makes possible to define queries using natural language.

C. Fuzzy operators over sets of Fuzzy Descriptor

The operators presented in this section calculate the inclusion and the resemblance degrees between two sets of Fuzzy Descriptors, $FDS^i = \{FD^i_1, FD^i_2, \ldots, FD^i_n\}$ and $FDS^j = \{FD^j_1, FD^j_2, \ldots, FD^j_n\}$, with n being the number of Fuzzy Descriptors in each set.

The inclusion degree of FDS^i in FDS^j driven by the resemblance relation S is calculated as follows:

$$\hat{\Theta}_S(FDS^j|FDS^i) = \sum_{k=1}^{n} w_k \Theta_S(FD^j_k|FD^i_k) \quad (11)$$

with w_k being a weight verifying $\sum_{k=1}^{n} w_k = 1$.

The generalized resemblance degree between FDS^i and FDS^j restricted by $\otimes$ is calculated by means of the following formulation:

$$\hat{\Lambda}_{S,\otimes}(FDS^i, FDS^j) = \sum_{k=1}^{n} w_k \Lambda_{S,\otimes}(FD^i_k, FD^j_k) \quad (12)$$

with w_k being a weight verifying $\sum_{k=1}^{n} w_k = 1$.

It can be noticed that the values of the weights $w_k, k = 1, \ldots, n$ can be adjusted to give more or less importance to the different Fuzzy Descriptor.

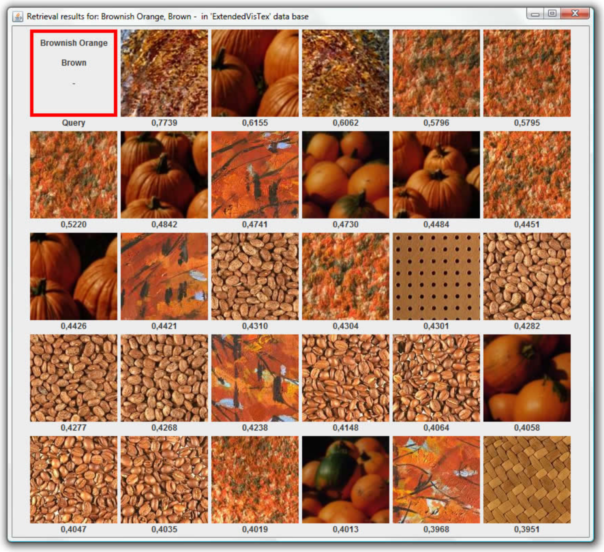
VI. Results

In this section, we will use the proposed dominance-based fuzzy descriptors FDCD and FDTD and the fuzzy inclusion and resemblance operators in a retrieval system. The database used in this retrieval system will be *VisTex* [15]. This database has been chosen because it is composed by a great variety of color texture images covering different presence degrees of coarseness. Moreover, the standard *VisTex* database has been extended to incorporate images with more variety of colors. In particular, the standard database is composed by 669 images of size 128×128, and it has been extended with 62 images of the same size.

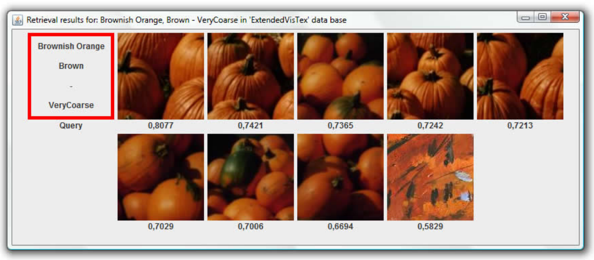
Three retrieval examples will be shown in order to illustrate the performance of the system. In the first two examples, linguistic labels will be used as query, whereas in the third example the query is specified as an image. In our experiments we have empirically fixed the parameters u_1 and u_2 in equation 4 to 0.05 and 0.25 in the case of color, and 0.2 and 0.4 in the case of texture, respectively.

In the first example, Figure 3(a) shows the retrieval results using only color information. The linguistic labels *Brownish Orange* and *Brown* have been used in this color inclusion query (specifically, the query descriptor will be $FDCD^{query} = 1/BrownishOrange + 1/Brown$). Retrieved images are shown in decreasing order of the resemblance degree, that is shown below each image. It can be noticed that images with the same dominant colors can be found in these results, including "pumpkins", "coffee grains", "paintings", etc..

Figure 3(b) shows the retrieval results combining color and texture information by using the set of fuzzy descriptors $FDS = \{FDCD, FDTD\}$. In this query, the same linguistic labels as in Figure 3(a) are used for color information

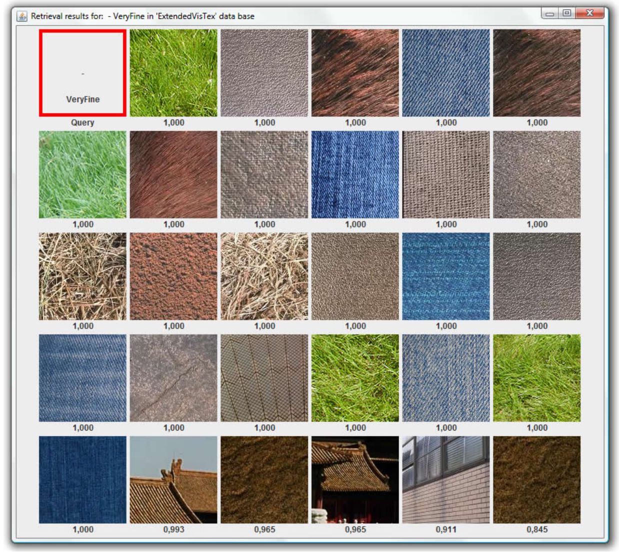


(a)

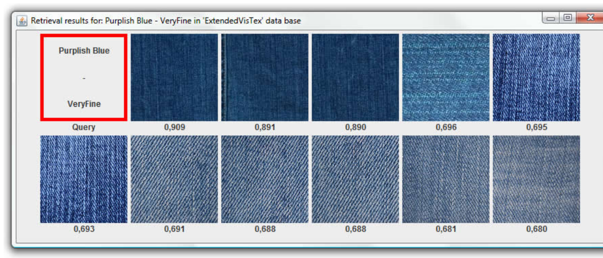


(b)

Fig. 3. Retrieval results on ExtendedVisTex database for (a) the color inclusion query with the labels *Brownish Orange* and *Brown*, and (b) the color and texture inclusion query with the labels *Brownish Orange*, *Brown* and *Very Coarse*.



(a)



(b)

Fig. 4. Retrieval results on ExtendedVisTex database for (a) the texture inclusion query with the label *Very Fine*, and (b) the color and texture inclusion query with the labels *Purplish Blue* and *Very Fine*.

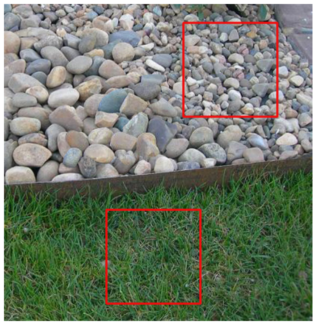
($FDCD^{query} = 1/BrownishOrange + 1/Brown$), and the linguistic label *Very Coarse* is used for texture information ($FDTD^{query} = 1/VeryCoarse$). The resemblance degree is calculated by using the fuzzy resemblance operator shown in section V-C with $w_1 = w_2 = 0.5$, i.e. giving equal importance to color and texture descriptors. It can be shown that in this case the "pumpkins" images are retrieved with the greatest resemblance degrees, because their textures are perceived as very coarse.

In the second example, Figure 4(a) shows the retrieval results using only texture information. The linguistic label *Very Fine* has been used as query ($FDTD^{query} = 1/VeryFine$), and it can be noticed that images with very fine textures have been retrieved, including grass, denim, fur, etc.. More specific retrieval results can be obtained by combining color and texture information, as it can be shown in Figure 4(b). In this case, the linguistic labels *Very Fine* and *Purplish Blue* has been used as query ($FDTD^{query} = 1/VeryFine$ and $FDCD^{query} = 1/PurplishBlue$). It can be noticed that "denim" images are retrieved with the greatest resemblance degree, because their textures are perceives as very fine and their dominant color is purplish blue.

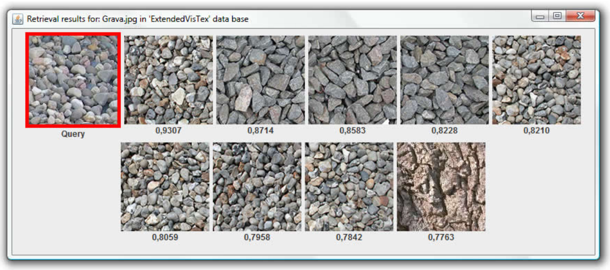
Also, we would be interested in getting images with similar patterns to the one associated with a sample image. This condition can be defined by using the fuzzy resemblance operator to compute the resemblance degrees between the set of fuzzy descriptors $FDS = \{FDCD, FDTD\}$ that describes the sample image and the corresponding set of each image in the database. Figure 5 shows an example where we are interested in getting images with similar colors and textures to the ones selected using a red square in Figure 5(a). In this case, each selected image has been used as query, and the retrieval results are shown in Figure 5(b) and 5(c). These results are ordered by its resemblance degree, giving equal importance to color and texture descriptors. It can be shown that "gravel" images and "grass" images are retrieved with the greatest resemblance degree in each query.

VII. Conclusions

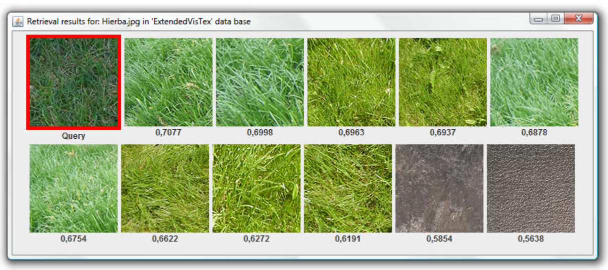
In this paper a fuzzy approach for image retrieval on the basis of color and texture features has been presented. The *Fuzzy Dominant Color Descriptor* and the *Fuzzy Dominant*



(a)



(b)



(c)

Fig. 5. Retrieval results on ExtendedVisTex database using the images selected in (a) as query. (b) Results for gravel image query, and (c) results for grass image query.

Texture Descriptor have been proposed. Fuzzy operators over the new descriptors have been defined to allow inclusion-based and resemblance-based conditions in image retrieval queries. Thus, the proposed framework has made our database system able to answer queries using color-based and texture-based linguistic labels in natural language. The system has been applied to texture image retrieval in order to analyze its performance, obtaining satisfactory results.

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