Ranking Images Using Customized Fuzzy Dominant Color Descriptors

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Abstract. In this paper we describe an approach for defining customized color descriptors for image retrieval. In particular, a customized fuzzy dominant color descriptor is proposed on the basis of a finite collection of fuzzy colors designed specifically for a certain user. Fuzzy colors modeling the semantics of a color name are defined as fuzzy subsets of colors on an ordinary color space, filling the semantic gap between the color representation in computers and the subjective human perception. The design of fuzzy colors is based on a collection of color names and corresponding crisp representatives provided by the user. The descriptor is defined as a fuzzy set over the customized fuzzy colors (i.e. a level-2 fuzzy set), taking into account the imprecise concept that is modelled, in which membership degrees represent the dominance of each color. The dominance of each fuzzy color is calculated on the basis of a fuzzy quantifier representing the notion of dominance, and a fuzzy histogram representing as a fuzzy quantity the percentage of pixels that match each fuzzy color. The obtained descriptor can be employed in a large amount of applications. We illustrate the usefulness of the descriptor by a particular application in image retrieval.

Keywords: Customized Fuzzy Color, Dominant color descriptor, Fuzzy Quantification, Image retrieval.

1 Introduction

The use of visual descriptors, which describe the visual features of the contents in images, has been suggested for image retrieval purposes [9,13], among many other applications. These descriptors describe elementary characteristics such as color, texture and shape, which are automatically extracted from images [1,7]. Among these characteristics, color plays an important role because of its robustness and independence from image size and orientation [4,12,5].

In this paper we focus on the dominant color descriptor, one of the most important descriptors in the well-known MPEG-7 standard [15]. A dominant color descriptor must provide an effective, compact, and intuitive representation of the most representative colors presented in an image. In this context, many approaches to dominant color

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extraction have been proposed in the literature [16,6]. Our objective in this paper is to develop a dominant color descriptor able to cope with the following aspects:

1. to fill the semantic gap between the color representation in computers and its human perception, i.e., the color descriptors must be based on colors whose name and semantics, provided by (and understandable for) the users, is far from the set of colors represented by color spaces employed by computers, like RGB for instance.
2. the fuzziness of colors. Colors as perceived by humans correspond to subsets of those colors represented in computers. However, these perceived colors don't have clear, crisp, boundaries. Hence, perceived colors can be better modeled as fuzzy subsets of crisp colors.
3. the subjectivity in the set of colors. The collection of colors to be employed in the indexing of images is different for every user and/or application. We may also have a different number of colors, the same color may be given different names, and the same color name may have a different semantics, depending on the user and/or application. Hence, we need a *customized* set of colors, both in name and modeling, for each case.
4. the imprecision in the human's perception of dominance. It is usual to consider degrees of dominance, that is, colors can be clearly dominant, clearly not dominant, or can be dominant to a certain degree.

The first two requirements can be fulfilled by using the notions of *fuzzy color* and *fuzzy color space* [11]. In order to fulfil the third one, and to obtain customized fuzzy color spaces, we shall employ a methodology for developing a fuzzy color space on the basis of a collection of color names and corresponding crisp representatives, to be provided by the user for the specific application. Finally, in order to fulfil the fourth requirement, we introduce in this paper a fuzzy descriptor for dominant colors as a level-two fuzzy set on the fuzzy colors comprising the customized fuzzy color space modelling the imprecise concept of dominance.

In order to obtain this descriptor we use a histogram of fuzzy colors, as the dominance is related with the frequency of the colors in the image. The frequency will be represented by a fuzzy cardinality measure. A fuzzy quantifier will be employed in order to represent the semantics of *dominant* on the basis of the amount of pixels having a certain color, in a natural way. The final degree of dominance for a certain fuzzy color will be obtained as the accomplishment degree of a quantified sentence, calculated as the compatibility between the quantifier and the fuzzy cardinality of the set of pixels with the fuzzy color.

The rest of the paper is organized as follows. In section 2 the fuzzy color modelling is presented. The dominance-based color fuzzy descriptor is defined in section 3, and an inclusion fuzzy operator for image retrieval is described in section 4. Results are shown in section 5, and the main conclusions and future work are summarized in section 6.

2 Fuzzy Modelling of Colors

In this section, the notions of fuzzy color (section 2.1) and fuzzy color space (section 2.2) we presented in a previous work [11] are summarized.

2.1 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 term properties 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 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. *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 [11], we will define the membership function of $\widetilde{C}$ as

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

depending on three 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 $\overrightarrow{\mathbf{rp}_i}$.

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

2.2 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 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.

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 [10] 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 [11].

3 Dominance-Based Fuzzy Color Descriptor

For describing semantically an image, the dominant colors will be used. In this section, a Fuzzy Descriptor for dominant colors is proposed (section 3.2) on the basis of the dominance degree of a given color (section 3.1).

3.1 Dominant Fuzzy Colors

Intuitively, a color is dominant to the extent 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 color. In this paper, the cardinality $h(x)$ of the fuzzy subset of pixels having property x, P_x, will be measured by means of the fuzzy cardinality ED [2] divided by the number of pixels in the image, which is a fuzzy subset of $[0,1]$ calculated as follows:

$$h(x) = \sum_{\alpha_i \in \Lambda(P_x)} \frac{(\alpha_i - \alpha_{i+1})}{|(P_x)_{\alpha_i}|/N} \tag{2}$$

with $\Lambda(P_x) = \{1 = \alpha_1 > \alpha_2 > \cdots > \alpha_n > 0\}$ the level set of P_x union $\{1\}$ in case P_x is not normalized, and considering $\alpha_{n+1} = 0$.

Using the information given by the histogram, we will measure the "dominance" of a color fuzzy set. Dominance is an imprecise concept, 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. On the other hand, the degree of dominance depends on the percentage of pixels where the color appears. Hence, it seems natural to model the idea of dominance by means of a fuzzy set over the percentages, i.e., a fuzzy quantifier defined by a non-decreasing subset of the real interval $[0,1]$. More specifically, we define the fuzzy subset "Dominant", noted as *Dom*, as follows:

$$Dom(\alpha) = \begin{cases} 0 & \alpha \le u_1 \\ \frac{\alpha - u_1}{u_2 - u_1} & u_1 \le \alpha \le u_2 \\ 1 & \alpha \ge u_2 \end{cases} \tag{3}$$

for each $\alpha \in [0,1]$, where u_1 and u_2 are two parameters such that $0 \le u_1 < u_2 \le 1$.

Finally, in order to know whether a certain color is dominant in the image, we have to calculate the compatibility between its frequency and the quantifier defining the notion of "Dominant". For instance, in the case of a crisp color, its frequency is a crisp number x and its dominance is $Dom(x)$. In the case of a fuzzy color $\widetilde{C}$, its frequency is a fuzzy subset of the rational numbers calculated as in Eq. (2) and noted $h(\widetilde{C})$. In order to obtain the dominance of a fuzzy color $\widetilde{C}$ in an image the compatibility between the fuzzy cardinality of the fuzzy set of pixels $P_{\widetilde{C}}$ with color $\widetilde{C}$ in the image, and the quantifier *Dom*, corresponds to the evaluation of the quantified sentence "*Dom* of pixels in the image are $P_{\widetilde{C}}$". We shall use the method *GD* introduced in [3] as follows:

$$GD_{Dom}(P_{\widetilde{C}}) = \sum_{\alpha \in Supp(h(\widetilde{C}))} h(\widetilde{C})(\alpha) \times Dom(\alpha) \tag{4}$$

3.2 Dominance-Based Fuzzy Descriptors

On the basis of the dominance of colors, a new dominance image descriptor is proposed.

Definition 4. *Let $\mathscr{C}$ a finite reference universe of color fuzzy sets. We define the* Fuzzy Dominant Color Descriptor *as the fuzzy set*

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

with $GD_{Dom}(\widetilde{C})$ being the dominance degree of $\widetilde{C}$ given by Eq. 4.

4 Matching Operators

Fuzzy operators over fuzzy descriptors are needed in many practical applications. In this section, a "Fuzzy inclusion operator" (section 4.1) is proposed.

4.1 Fuzzy Inclusion Operator

Given two Fuzzy Dominant Color Descriptors, $FDCD^i$ and $FDCD^j$, the operator presented in this section calculates the inclusion degree of $FDCD^i$ in $FDCD^j$. The calculus is done using the *Resemblance Driven Inclusion Degree* introduced in [8], which computes the inclusion degree of two fuzzy sets whose elements are imprecise.

Definition 5. *Let $FDCD^i$ and $FDCD^j$ be two Fuzzy Dominant Color Descriptors defined over a finite reference universe of fuzzy sets $\mathscr{P}$, $FDCD^i(x)$ and $FDCD^j(x)$ 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 $FDCD^i$ in $FDCD^j$ driven by the resemblance relation S is calculated as follows:*

$$\Theta_S(FDCD^j|FDCD^i) = \min_{x\in\mathscr{P}} \max_{y\in\mathscr{P}} \theta_{i,j,S}(x,y) \tag{6}$$

where

$$\theta_{i,j,S}(x,y) = \otimes(I(FDCD^i(x), FDCD^j(y)), S(x,y)) \tag{7}$$

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 8.

$$I(x,y) = \begin{cases} 1 & \text{if } x \le y \\ y/x & \text{otherwise} \end{cases} \tag{8}$$

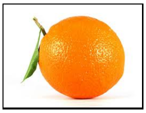
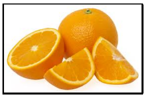
5 Results

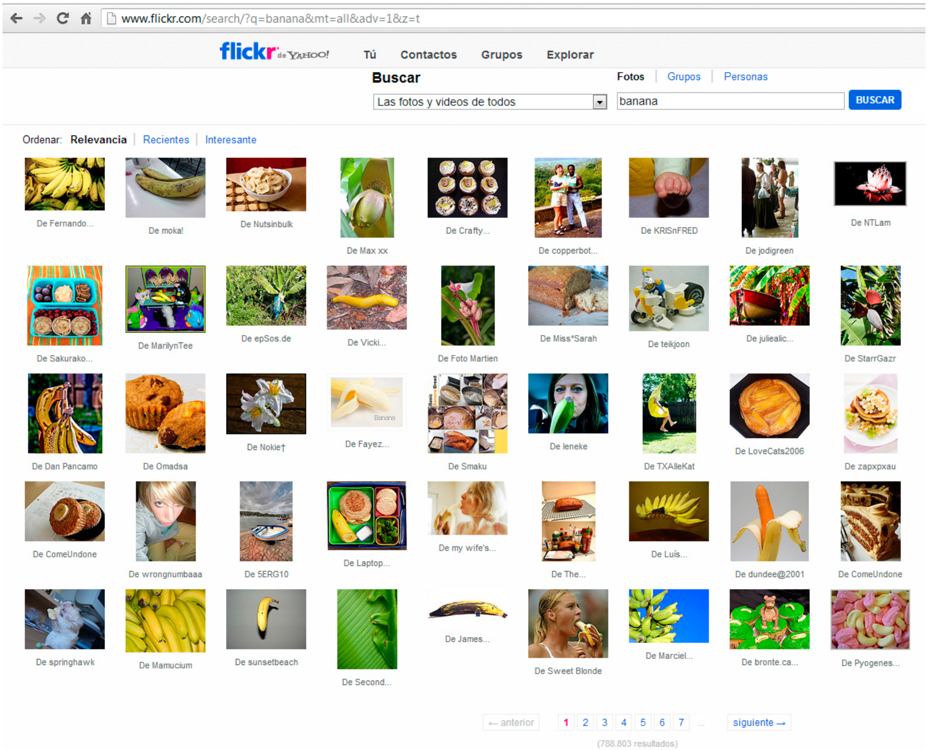
In this section, we will use the proposed Fuzzy Dominant Color Descriptor (FDCD) and the inclusion operator (section 4.1) in order to define image retrieval queries based on dominant colors. Specifically, query refinement on results provided by the *Flickr* system using FDCD over an user customized fuzzy color space.

5.1 Customized Color Space: An Example

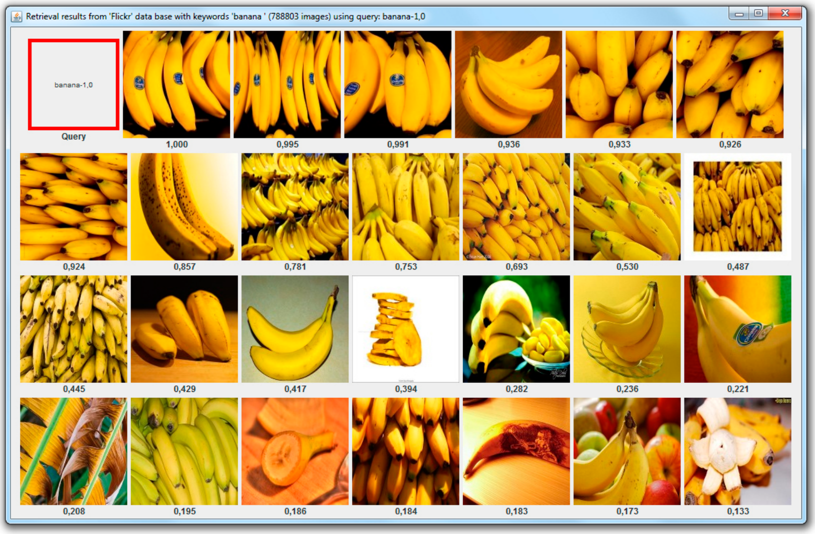
We have used an user customized fuzzy color space for fruit colors, designed on the basis of a collection of crisp colors and color names provided by the user, following the methodology described in section 2. A user outlined regions in several images and labeled each regions with the color name of a fruit. The crisp color corresponding to each region has been obtained as the centroid of all the colors in the corresponding regions in the RGB color space. For each fruit, 10 images have been used and one or more regions in each image considered as representative of each fruit have been outlined by the user. The results of this experiment are shown in table 1. (only two images for each fruit, not regions chosen by the user, are shown).

Table 1. Collection of images and corresponding representative colors. Selected regions for every image are not shown.

Color Name	**Images**	**Representative color**	**RGB**
banana	 		[254.0, 213.0, 0.0]
blackberry	 		[38.0, 42.0, 41.0]
green apple	 		[188.0, 227.0, 60.0]
lemon	 		[254.0, 234.0, 101.0]
orange	 		[255.0, 115.0, 1.0]
plum	 		[145.0, 145.0, 197.0]
raspberry	 		[253.0, 108.0, 128.0]
red apple	 		[162.0, 29.0, 34.0]
strawberry	 		[204.0, 12.0, 11.0]

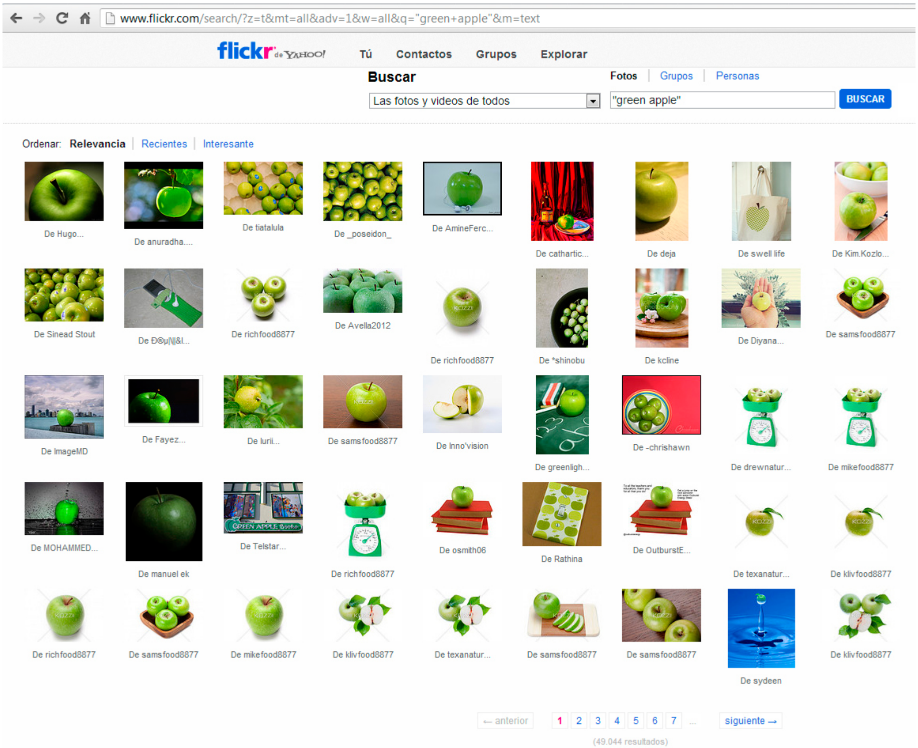


(a)

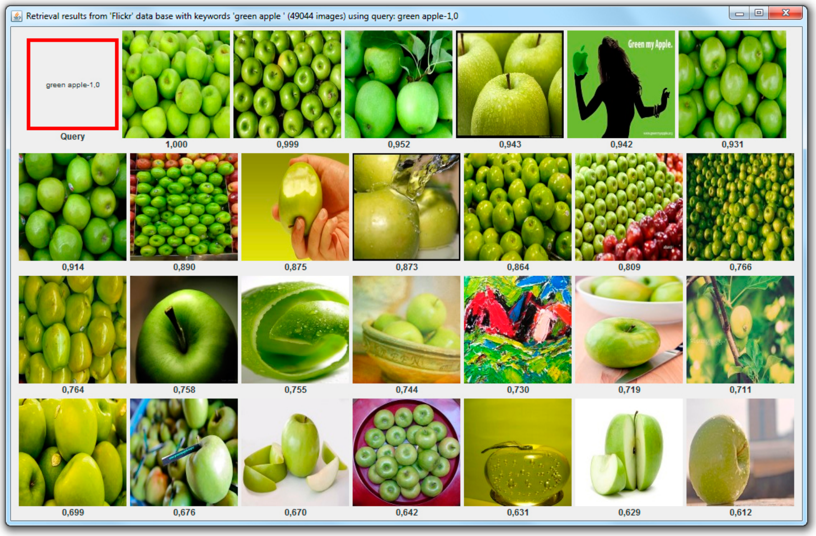


(b)

Fig. 1. Retrieval results on *Flickr* using keyword "banana": (a) results from Flickr only with keyword and (b) query refinement using $FDCD^{query} = 1/banana$



(a)



(b)

Fig. 2. Retrieval results on *Flickr* using keyword "green apple": (a) results from Flickr only with keyword and (b) query refinement using $FDCD^{query} = 1/greenapple$

5.2 Query Refinement Examples

In this illustrative application we have used the *Flickr* online image database. We have performed queries using color names as keywords. Then, we have refined the result of these queries using the Fuzzy Dominant Color Descriptor (FDCD) for each image and the fuzzy inclusion operator on the basis of the customized fuzzy color space just mentioned. Nowadays, there are more than 6 billion images hosted in *Flickr*, and our query has been applied to a collection of around 100000 images provided by the *Flickr* API [14] as the most interesting photos for a certain month.

Figure 1a shows the retrieval results for the query *banana*, ranked by relevance by *Flickr*. Figure 1b shows the result of the query refinement by ranking the previous result on the basis of our inclusion operator taking as criterion the dominance of the customized fuzzy color *banana* in the image. More specifically, we calculate the inclusion degree of the descriptor $1/banana$. This is equivalent in this particular case to calculate the degree of dominance of the color *banana* in the whole image. We have employed a definition of dominance based on a linguistic quantifier with parameters $u_1 = 0.1$ and $u_2 = 0.25$. Using this approach, the subjectivity of the color *banana* and the imprecision of the dominance in an image are considered and in our opinion, the refinement provides a better ranking of images.

A similar experiment has been performed using the color name *green apple*. Figure 2a shows the retrieval results for the query *green apple*, ranked by relevance by *Flickr*. Figure 2b shows the result of the query refinement using the dominance of the customized fuzzy color *green apple* in the image, using the same procedure employed for the previous case. Again, we consider that the refinement provides a better ranking of images than that of *Flickr*.

Please note that we do not claim that dominance of the previous customized fuzzy colors is enough on its own in order to recognize the presence of certain fruits in images. Other objects than bananas and/or green apples, but having the same colors, may be recognized when dominance is consider alone. However, they are very good for refining queries based on color labels, as those performed by *Flickr* and many other image retrieval systems.

6 Conclusions

In this paper, a new Fuzzy Dominant Color Descriptor has been proposed. This descriptor has been defined as a fuzzy set over a finite universe of fuzzy colors, in which membership degrees represent the dominance of each color. The color fuzzy sets have been defined taking into account the relationship between the color representation in computers and its human perception. In addition, fuzzy operators over the new descriptor have been proposed. We have illustrated the usefulness of our proposals with an application in image retrieval, specifically query refinement on results provided by the *Flickr* system.

Several future work related to this will be to apply the descriptor in the linguistic description of images, and the combination with other customized fuzzy concepts related to color as well as other basic features of images.

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