# Fuzzy Color Space Segmentation to Identify the Same Dominant Colors as Users

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## Abstract

*In this paper we propose a solution for the identification of the dominant colors in pictures taking into account the way people perceive them. To that end we developed an algorithm based on a reduced palette of 12 colors and on a non-uniform segmentation of the HSV color space using fuzzy membership functions. Experimental results from an evaluation with users, showed that our algorithm based on the fuzzy histogram is able to identify the same three dominant colors as users in 50% of the cases, while the classic histogram is only able to identify 43%.*

## 1. Introduction

In the last years, due to the massive volume of images collected everyday, efficient, effective and easy to use systems for exploration, organization and retrieval of images are needed. In general, color is one of the most visually distinguishable characteristics, causing that the majority of the existing solutions take advantage of that and use the dominant colors (DCs) to describe the image content.

However, most solutions for dominant color identification use an algorithm-centered approach, rather than looking at how people perceive the DCs. In general, these solutions are only concerned with some system-centered measures, and do not consider the DCs that the users see on the images. Additionally, most of the existing works consider too many colors as possible DCs, making the enumeration and specification of colors by the users an almost impossible task, when they want to explore or retrieve images.

In this paper we present a new method for the identification of the dominant colors in images, which was built around the following three principles: i) a palette of only 12 colors, that all cultures are able to enumerate; ii) a non-uniform segmentation of the HSV (Hue, Saturation and Value) color space to better reflect the "size" of each color; iii) the use of fuzzy membership functions [3] to convey the ambiguity that is present in some regions of the color space.

With this approach we want to foster the creation of retrieval and exploration systems able to identify the real DCs that people see when looking at a picture, and where users could easily enumerate the DCs that they want to find in the images, using for instance textual queries, natural language or sketches of color blobs.

We performed an experimental evaluation with users, where we compared the DCs identified by users with the DCs identified by our algorithm and by the classic histogram, using two sets of pictures. Results showed that our algorithm was able to identify the same three DCs as the users in 50% of the times.

In the remainder of this paper we analyze some solutions for the identification of the DCs, present our fuzzy segmentation of the HSV color space and describe our algorithm for the DCs identification. To conclude the paper, we present the main results from the evaluation with users and provide some conclusions.

## 2. Related Work

Along the years several solutions for the identification of the DCs in images have been developed. Here we describe some of them, ranging from histogram, segmentation, correlogram and statistical based approaches.

One of the first segmentation based methods for the identification of DCs was developed by Smith et al. [16]. The authors used the HSV color space and a palette of 18 different hues, to identify a maximum of five dominant colors per region. Their method was based on the uniform segmentation of the color space and in the application of a color median filter.

The MPEG-7 standard [14] also has a descriptor for the dominant colors, called Dominant Color Descriptor (DCD), which extracts the distribution of dominant colors in images, using clustering and color quantization. The descriptor contains the dominant colors, their percentages, variances and their spatial coherency.

Yang et al. developed a new algorithm [18] based on MPEG-7, which uses the modified Generalized Lloyd Algorithm (GLA) to obtain a small number of representative colors and their percentages. Authors divided the RGB color space in eight equal regions, and selected the centroid of each block as its quantized color by averaging the color distribution. Their algorithm identifies four to five dominant colors.

Liu et al. [13] developed a region-based image retrieval system with high-level concepts obtained from colored region features. The authors, first segmented each image into homogeneous regions and then defined a DC for each region and assigned a semantic name.

In [8] Huang et al. introduced an algorithm for extracting DCs in the CIELab color space, using an Ant Colony Clustering algorithm. The authors tried to address the two known issues of the classic GLA quantization schemes: avoid the clustering to get into local optimality and the sensibility to initial clustering centers.

Younes et al. proposed a fuzzy approach to segment the HLS color space, using a palette of nine colors [19]. Their main goal was to create a solution where users could retrieve images according to their DCs, expressed through fuzzy linguistic expressions.

In [5] Chamorro-Martínez et al. presented an approach where the HSI color space is divided in three zones: chromatic, semi-chromatic (gray) and achromatic (black). The chromatic zones is then divided using fuzzy membership functions for the Hue, Saturation and Intensity. In combination with the fuzzy logic, authors used also a clustering algorithm to identify the DCs.

Kiranyaz et al. addressed the DC extraction as a dynamic clustering problem [10]. The authors used techniques based on Particle Swarm Optimization to find the optimal number of DCs in the HSV color space. Their algorithm looked for the best solution between a range of dimensions related with the number of dominant colors. The algorithm is very computationally demanding and there is no guarantee that the solution will not converge to a local minimum, due to over- or under-clustering.

In [11] Lézoray et al. introduced an unsupervised morphological clustering on 2D histograms. These 2D histograms are pair-wise associations of the RGB color space, namely Red-Green, Red-Blue and Green-Blue. After the independent clustering on each of these three pair-wise histograms, a region merging is performed with the help of a Minimum Spanning Tree based algorithm. The DCs correspond to the maximums (centroids) in the 2D histograms.

Bhoyar et al. proposed another system for color histogram computation, based on fuzzy logic [4]. Authors used a palette of 11 colors and fuzzy if-then rules to decide the color of a pixel from its RGB components. A color histogram with 11 bins is then computed for each image, and used as the color descriptor.

In [9] Kiranyaz et al. presented a color descriptor which represents DCs both in spatial and color domains. The DCs are extracted using a quad-tree decomposition to partition the image, and recursively subdivide each cluster into four quadrants. The authors used a clustering method that iterates until reaching a maximum number of clusters, which correspond to the DCs.

Almost all of the previously described works, do not consider the perception that users have of the DCs in pictures. None of them performed tests with users to verify which DCs and how many DCs people see in common pictures. Moreover, the segmentation of the color space is often made with empirical rules and using the RGB color space, which is not the best to separate the chromatic, from the concentration or the brightness. Finally, in general the methods for DCs identification only take into account the Precision and Recall measures or the Averaged Normalized Modified Retrieval Rate (ANMRR), putting all the evaluation focus on the system and forgetting the users.

In our algorithm, we took a different approach by putting the users in the center of the development cycle, to create a solution that will identify the DCs perceived by humans.

## 3. Fuzzy Segmentation of the Color Space

It is relatively unanimous among various authors, like for instance [19, 5, 12, 1, 4, 20, 10], that the use of fuzzy logic applies well to the segmentation of the HSV color space, because the Hue circle has a subtle continuous variation of colors. For the case of far apart pure hues, such as red (HSV: 0,1,1) or cyan (HSV: 180,1,1), we almost never have doubts, but for any two pure consecutive hues, like for instance yellow and green, it is difficult for a person to see the boundaries. With the fuzzy approach we can have a variable grade from two adjacent hues and gently combine these hues with a proportional weight. For example, we are able to say that a pixel is 0.6 green and 0.4 yellow.

In this section we describe our proposal for the segmentation of the HSV color space using fuzzy logic and a palette of 12 colors. Contrary to other authors [5, 13, 15, 18] that first divide the color space and then assign names to the resulting “slices” of color, we first selected the color palette, and only after we divided the color space.

### 3.1. The 12 Colors Palette

As we have seen in the related work section, there is no consensus in the number of colors to use in the quantization process or in the segmentation of the color space. Some authors use few colors to get a short processing time, but with the disadvantage of diverging from the original colors, while others use more colors, resembling the original colors found in the pictures, but achieving more colors than the human eye can distinguish.

In the last decade various authors [6, 1, 4] adopted the set of 11 colors identified by Berlin et al. [2] in 1969 (red, brown, orange, yellow, green, blue, purple, pink, black, gray and white). This set, which contains the colors that can be named by all cultures, was coined by Chang et al. [6] in 2000 as the "Just Not the Same" colors (JNS), because any two colors from this set are perceived as JNS.

In our work we decided to use an extended version of this set, introduced by Ware in the scope of an application for nominal information coding [17]. This palette has 12 colors, and is composed by the JNS colors plus the cyan. We opted for this palette because it is reacher than the JNS, but still does not contain too many colors, and especially, because it contains colors whose names people can easily enumerate, enabling them to specify colors using various modalities, such as speech, writing or sketches. This same set of 12 colors is also used by Google Images.

### 3.2. The Achromatic Colors

Our approach performs the segmentation of the HSV color space in two steps. First, we consider the achromatic colors and only after we isolate the chromatic ones.

Taking into consideration that the HSV color space has two particularities: i) the Hues of colors with small Values or small Saturations are not representative; ii) the Saturation of colors with low levels of Value is not representative; we identified three zones in the color space for the achromatic colors (black, gray and white), based on the brightness degree of each point. While Chamorro-Martínez et al. [5] opted only for two zones (black and gray), we decided to include a third zone for white, because when we have a high Value (for certain Saturation) from the user point of view it is white. We confirmed this by doing some informal tests with users.

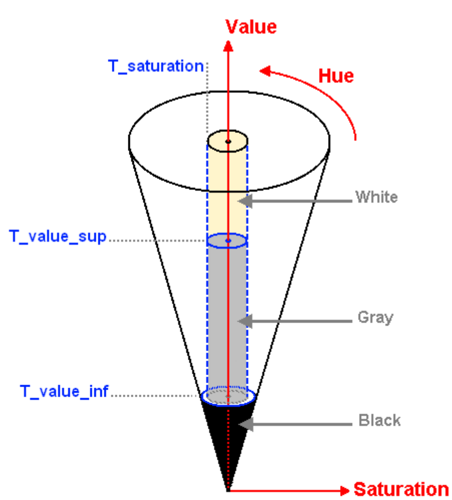


**Figure 1. The three achromatic colors (black, gray and white) of the HSV color space.**

Figure 1, represents the HSV color space with the three achromatic zones. In summary, a color in HSV is black if its Value component is less than $T\_value\_inf$. A color is gray if its Value component is delimited between $T\_value\_inf$ and $T\_value\_sup$, and at the same time its Saturation component is less than $T\_saturation$. A color is white if its Value is greater than $T\_value\_sup$ and its Saturation is less than $T\_saturation$. The values for these thresholds were defined based on the intervals defined by Chamorro-Martínez et al. [5], namely for $T\_value\_inf = 0.19$ we considered the intervals `Dark` and `Very Low Illuminated`; for $T\_value\_sup = 0.81$ we considered the intervals `Very High Illuminated` and `Bright`; and finally for $T\_saturation = 0.14$ we considered the interval `Very Low Saturated`.

### 3.3. The Chromatic Fuzzy Membership Functions

While most authors [5, 15] segmented the Hue dimension in equal intervals and then assigned a name to each, in our approach we first identified the colors and only after we defined the size of the intervals for each color.

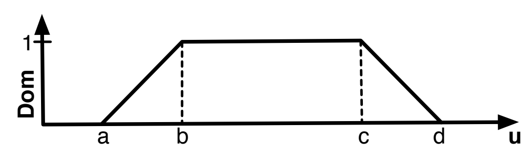


**Figure 2. Definition of a fuzzy set with a trapezoidal-shaped membership function.**

We use trapezoidal-shaped membership functions (see Figure 2), because according to Benavente et al. [1] there are no worth gain comparatively to Gaussian-shaped functions. To define the four values for the Hue of the 9 chromatic colors (see Figure 3), we applied the following rules:

1. The central hue of each trapezoidal membership function is the one defined by the Color Module of the last CSS3 specification, published by W3C (http://www.w3.org/TR/2011/REC-css3-color-20110607).
2. The kernel[1] size of each membership function is 10° for brown and orange, 20° for red, yellow, purple and pink, and 40° for green, cyan and blue;
3. Two membership functions always cross at the 0.5 degree of membership (dom);

[1]The kernel of a fuzzy membership function is where its degree of membership is equal to 1.

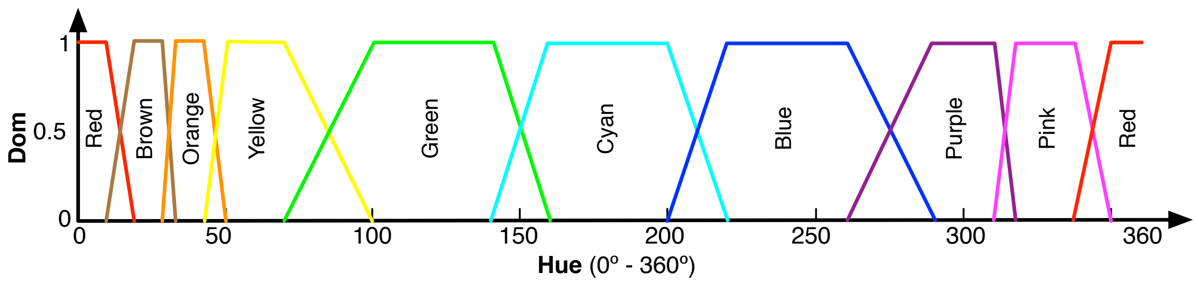


**Figure 3. Membership functions for the Hue of the 9 chromatic colors.**

4. The right slope of one trapezoidal-shaped membership function is equal to the left slope of the adjacent membership function (and vice versa);

5. Three different membership functions never overlap;

We also defined membership functions for the Saturation and Value components of the HSV color space. Similarly to Younes et al. [19] we defined three membership functions for Saturation and three for Value: low ($< 0.25$), mid ($> 0.25$ & $< 0.75$ ) and high ($> 0.75$).

These membership functions are used only to separate brown and pink from their neighbors in the color space, because they are non pure-hue colors (the Hue component alone is not enough to completely define them). Brown, for instance has a Hue of 24°, a Saturation of 0.86 and a Value of 0.54. Based on this, to completely define brown, orange, pink and purple, we considered not only their Hues but also their Saturation and/or Value components.

A orange Hue with mid or low value (dark orange) is considered brown, and a low saturated bright orange (beige) is also considered brown. On the other hand, a brown Hue with high Saturation and high Value (saturated bright brown) is considered orange.

When a color has red or brown Hue and has mid or low Saturation and high Value (skin color), then it is considered pink. It is also considered pink when we have purple Hue with high Value (bright purple). Finally, a dark pink (pink Hue with mid or low Value) is considered purple.

## 4. Fuzzy Histogram for DC Identification

A 'normal' histogram is created by dividing the color space into a set of bins and then by counting the number of pixels of the image that belong to each bin. For a space of N colors, the histogram is an N-dimensional vector $(h_1, ..., h_N)$, where each element $h_i$ represents the portion of pixels of color $i$ in the image.

In our solution, for each pixel of the image we evaluated the degree of membership for its Hue and assign it to the correspondent bin of the fuzzy histogram, according to the following rules:

1. If the pixel color has a hue with a single dom we add one to the correspondent bin;

2. When a color has a hue with two degrees of membership, then we evaluate the dom for each hue, and add it to the respective bin.

For example, a pixel with a Hue of 75 will have a dom of 0.83 for yellow and a dom of 0.17 for green. It means that we will add 0.83 to the yellow bin of the histogram and 0.17 to the green bin. The achromatic colors (black, gray and white) are always processed before the chromatic ones. A pixel classified as achromatic does not enter into the chromatic tests.

After processing the complete image, each of the 12 bins of the fuzzy histogram will have the sum of the doms for their Hues. Finally, we normalize the values (0-1) of the bins to make the comparison easier.

To identify the dominant colors, we order the bins according to its value and select the biggest ones as the dominant colors. All bins with values below 0.1 are not consider for being a dominant color.

## 5. Experimental Evaluation

To address the problem of identifying the dominant colors in images from the human point of view, we performed a study with users to identify the **name** of the colors that users know, **how many** dominant colors do users perceive on typical images, like for instance photos, and **what** dominant colors do they identify on each image.

The collected results were used to validate the 12 colors palette and to evaluate and compare our fuzzy histogram with the classic histogram.

### 5.1. Procedure of the Study

The study was done using an on-line survey composed of four parts. The first part was used to collect information about the users, such as the age, sex and if they wear glasses or contact lenses. The second part was used to test the color blindness of the subjects. To that end we used three pictures from the Ishihara test [7].

In the third part we presented five images to the users (one at a time) and asked them to write freely the name of the dominant colors that they perceive in the pictures, using their mother language. Finally, in the fourth part we showed 20 images to the users (one at a time) complemented with a palette of 12 colors and a five levels Likert scale (with 1 meaning *Completely Disagree* and 5 meaning *Completely Agree* that this color is dominant), for users to express their level of agreement with each of the 12 colors, relatively to the corresponding picture.

Intentionally we did not provide a definition of "dominant color" nor mentioned the "correct" number of dominant colors to identify, to avoid affecting the choices of the inquired subjects.

The 25 pictures were chosen from the Stock.xchng (www.sxc.hu) website, taking into account that they should be representative of what a normal user will have in his/her personal photo collection and that they should be filter-free. Pictures main topics go from close portraits, to wide nature landscapes, sport scenes, Venice gondolas or even a crowded street of New York. The 25 images were randomly assigned to the third and fourth part of the survey.

### 5.2. Results from the Study

We collected 39 valid surveys, 14 from females and 25 from males, with half of them belonging to the 18–29 age group. Half of the participants (19) wear glasses or contact lenses and none of them had color blindness problems. We did not encounter any relation between age, sex or the use of glasses/contact lenses and the given answers.

For the first set of five pictures, participants enumerated on average 1.94 ($SD = 0.36$) dominant colors per image, and the most frequent number of DCs written per image (the mode) was one. In the second set of 20 pictures the average number of DCs identified per image was 3.39 ($SD = 0.49$), and the most frequent number of DCs selected per image (the mode) was three.

From the obtained results and also from some informal conversations with users, after they answered the survey, we can conclude that when users have the color palette available or know the name and number of colors that they can use, they enumerate more DCs per image.

We also counted the names of the colors written by the users, for the group of five pictures, that belonged to the 12 colors palette, and we observed that 94.6% of the names written by the users belonged to it. From this, we can conclude that the color palette that we adopted is appropriated for the identification of dominant colors, when users have to write or mention the name of a color.

### 5.3. Comparative Evaluation

To evaluate our algorithm for DCs identification based on the fuzzy segmentation of the color space, we decided to compare it with the classic histogram, which is a mere count of pixels, collected on each respective bin. Although the majority of the algorithms that compute the classic histogram to identify the DCs, do a uniform segmentation of the color space, we used the same palette of 12 colors and our non-uniform segmentation of the HSV color space, to make the comparison fair. However, in this case we used a strict non-fuzzy segmentation of the color space, with the limits for each Hue in the values where it has a dom of 0.5.

The DCs identified by our algorithm using fuzzy histograms and the classic histogram were compared with the DCs enumerated by the users in the study. To perform the comparison, we considered the three most dominant colors from each image, and we analyzed the set of five images and the set of 20 images separately.

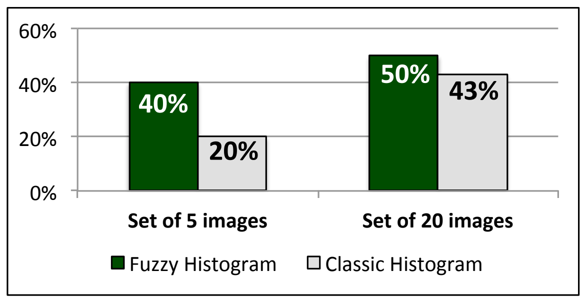


**Figure 4. Percentage of three DCs identified by the algorithms equal to those enumerated by the users.**

From Figure 4 we can see that in both cases, the fuzzy histogram identifies more colors similar to those enumerated by users than the classic histogram.

In the case of the set of five images, we have for the fuzzy histogram an average of 40.0% ($SD = 14.9$) of the DCs equal to those identified by the users, while for the classic histogram we have only 20% ($SD = 18.3$). The pairwise t-test shows that the average percentage of equal DCs for each image is significantly bigger on our algorithm than on the classic histogram, with a value of $p < 0.07$.

In the case of the set of 20 images, we have for the fuzzy histogram an average of 50.0% ($SD = 22.9$) of the DCs equal to those identified by the users, while for the classic histogram we have 43.3% ($SD = 21.9$). The pairwise t-test shows that the average percentage of equal DCs for each image is significantly bigger on our algorithm than on the classic histogram, with a value of $p < 0.04$.

Although the classic histogram had inherited a great advantage from our approach - the non-uniform segmentation of the color space - from the experimental results we can state, with at least 97% certainty, that our approach is better than the classic histogram, in identifying the three DCs that users perceive from images.

## 6. Conclusions

We presented in this paper a new algorithm for the identification of the DCs in images, based on fuzzy logic and on a non-uniform segmentation of the HSV color space. Moreover, and contrary to other approaches, we first defined the color palette and only after we segmented the color space. We selected a palette of 12 colors, which includes only colors that can be enumerated by all cultures.

To identify the DCs in an image, we first create a fuzzy histogram by adding the degrees of membership associated to the color of each pixel in the image. The colors with the highest values are considered the DCs.

To evaluate our solution we followed a different path from other researchers, by performing tests with users. With these, we wanted to know how many and what DCs users saw on the images, and verify if our algorithm was identifying the same DCs as users.

Experimental results revealed that the 12 colors palette was a correct choice, since almost 95% of the colors enumerated by the users belonged to it. We also found that the majority of the users identified only three DCs on each picture, contrary to some authors who claimed that common users can distinguish up to 256 or 512 different DCs.

Finally, the comparison of our fuzzy histogram with the classic histogram, showed that our algorithm for the identification of the dominant colors presents results more similar to those produced by users.

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