An Art Images Retrieval System Based On Similarity Descriptor

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ABSTRACT

Last decade Content Based Image Retrieval (CBIR) has captured attention due to the increase of knowledge of multimedia databases in the different areas. In this paper we present an image retrieval art system, which was developed to query and to explore a collection of art images by QBE, considering similarity criteria like: color palette, use of light and the technique used. These similarity criteria are analyzed by extracting low-level features such as color, texture and spatial relationships.

Keywords: CBIR, color histograms, Art databases

I. INTRODUCTION

Currently a number of museums and galleries have been incorporated into the web as a service to the public display of their collections. One of the advantages of having such tools would be the possibility that visitors to a museum and students of art history could have access to visit the collection considering their interests. Suppose, for example that a person after visiting a museum is interested in finding paintings similar to those seen during the course of a given exposure, this implies the existence of mechanisms that allow dynamic browsing consider the similarity criteria selected by the user i.e. same art movement, same artist, time, among others.

Therefore there are two fundamental problems when making content retrieval of images art: the extraction of representative features from the content and definition of a similarity measure. In this paper IMTHAC system is presented, which uses low-level features to extract content in images to determine the similarity between two pieces of pictorial art through color palette used, light inside the paints, lines, texture, composition and depth.

I.1 PICTORIAL FEATURES FROM THE ART HISTORY PERSPECTIVE

The formal approach assumes painting styles [1] [2] where the observer understands the art in formal terms of color, shape (linear or pictorial) and lighting, in addition to the iconographic content. Each of the formal elements for clarity in the explanation of the proposed approach corresponds to a category. Thus, four categories will be under analysis: Light, Line, Texture and Color. Categories like iconographic analysis are not considered, since this requires identification and connotation of the objects using a semantic interpretation is beyond the scope of this work.

The use of light in a painting is closely related to the color and composition, the degradation of light helps to create an atmosphere and depth effects. The use of light is an important feature by itself when classifying styles of painting in question, for instance lighting in *Impressionism* is considered as a protagonist. When speaking of paint composition and spatial organization is referred to the line but also the stroke, i.e. if the shapes that constitute the images created by the painter are produced by drawing or created by glazing such as Renaissance paint using the technique of *sfumato*.

Texture defines the quality of the surface in terms of its appearance; the actual texture refers to the physical characteristics of the stroke. The impasto is the application of pigment so little fluid creating a dense layer. A painting has also a virtual texture achieved by the impact made by the painter who can give the rough appearance being different from its actual texture. Finally, color is perhaps the best known formal element, when speaking of color it is considered three elements: hue, saturation and brightness or intensity. In painting it is common to speak of the color palette specially when it is related with an art movement because colors represent a distinctive pattern inside paintings, for example the color palette of Picasso and Braque *Cubist* painters have muted colors (ocher , dark green and gray variety).

Figure 1. Targeted search example, in this case the searched images are of same object with different color characteristics.

I.2 ART IMAGES RETRIEVAL SYSTEMS (AIR)

Retrieval systems for art images usually have at least three components: formal analysis, comparison of the paintings formal aspects and style classification. There are several documented search models for art images, some of them are: [13] [14]

I.2.1 Search by Association

For this model all the images in the database should be analyzed, whereas similarity criteria for a given image or sketch should be considered. This often involves iterative refinement of the search.

I.2.2 Targeted Search

The goal, in this type of search, is to find a specific image. The search can be for an exact copy of the image given as an example or target; it can also search for another image of the same object. Suppose a user has a specific image and wants to find images with the same objects such as another painting *Marylin* series of Andy Warhol (1962), an example of this type of search is shown in Figure 1. For targeted searches it should specify the target image's type by saying return exact image or object with chromaticity, texture, etc..

I.2.3Search by Category

The goal is to find an arbitrary representative corresponding to the specific class of the sample image. In the category search, the user may have available a set of images including additional images of the same class. For example, search for other paintings by the same artist or same style of painting.

Working with art images, we can also identify two types' intervals in the range of meanings: sensory gap and the range of content or meaning (semantic gap). Sensory Interval relates to diversity between the object in the real world and that seen in the paint under analysis [3]. For digital image analysis has to consider the use of color, the existence of edges, brightness and texture for it considering the statistical properties of images. For that matter, the range of content or meaning refers to difference between the immediate interpretation of pictorial information in all its different forms and the interpretation that follows from a formal description of the object [4].

In this paper, the sensory range to define the similarity criteria between images and the system developed using the search pattern by association is considered.

In subsequent sections we will first briefly review previous work related to the search patterns by association particularly those who consider the color as a criterion of similarity. After this, we describe our proposal considering as similarity elements the color palette, spatial distribution of color, texture and lighting. Finally, the results obtained to date and ongoing work is presented.

II. Related Work

There are basically two techniques for retrieval (indexing) images by color: (1) for the global distribution of color and (2) for local distribution or color regions. The relevant difference between the two techniques is by indexing global distribution can only make comparisons with overall image while local distribution enables the search for localized regions within the image. Both techniques have their advantages and they are designed to solve different types of queries. The overall indexing by color is more useful when the query comprises an image as an example.

Since 1980 several algorithms which use color extraction from images have been developed [8]. The most common methodology for comparing the contents of a query image with the rest of the images in a database is to compare their color histograms In [9], Jain and Vailaya considered color space RGB and obtained a histogram for each channel of the image, the similarity was measured using the Euclidean distance to compare each bin of the histograms. Jeong [10] instead of using three histograms for each of the RGB channels trying to create bins that contained the information of the three channels and therefore the number of bins was greater. Some tests were also carried out with the HSV model. Other two examples of systems using the global color distribution but focused on Art are QBIC [11] and PICASSO [12].

III. System Proposal

The following sections provide a brief overview of the work performed to support the selection of the methodology used to develop the search model implemented by association, considering elements of similarity such as the color palette, spatial distribution of color, lighting, and texture.

III.1 Extracting the Color Palette from Images

As the main similarity criterion of similarity the color palette used is considered. We understand the whole color palette of dominant colors in a painting that may be associated with age, author or style of painting. Histograms are used to extract the palette of color. The histogram of an image is defined by the probability mass function of the image intensities. This extends for color images to capture the joint probabilities of the intensities of the three color channels. Formally, a color histogram is defined in (1),

$H_{A,B,C}$ (a, b, c) = N * Prob (A=a, B=b, C=c) **(1)**

where A, B and C represent color channels (R, G, B ó H, S, V) and N, is the number of pixels in the image. Computationally, the color histogram is obtained by discretizing the colors of an image and the number of pixels of each color [15].

To generate the color histograms, a color space which describes mathematically how the colors can be represented, is needed. From existing color spaces just two of them were utilized in this work: the RGB color space, the most widely used by the vast majority of video and photographic cameras, and HSV resembles the way in which the human senses colors and how it is capable of separating color values. Given the characteristics of the images to be analyzed, HSV color space was chosen for this work. Additionally, since in the images analyzed, colors are generated by the juxtaposition of tones, quantization process is used to standardize the range of colors to be treated. The quantization process aims to reduce the number of different colors used in a visual image without losing information. Another advantage to reduce the number of colors is to improve the processing speed.

The quantization method proposed by Zhang Lei, Fuzong Lin and Zhang Bo [4] was modified, based on a quantization to 36 colors using non-uniform HSV color space. This quantization works well with everyday images, however the results of our images were not satisfactory so instead of making a non-uniform quantization, it was necessary to make a uniform quantization to 56 colors, as the color palette, which is handled in art. The change made was to consider only 12 colors instead of 7 colors, taking into account the color wheel used by artists. Once the images were quantized to 56 bins, their histograms were obtained. Comparisons measure between histograms is shown in (2),

$$\sum_i \sqrt{R_i S_i} \qquad (2)$$

where Ri and S_i are the color histograms and, i is the number of pixels in the image. Figure 2 shows the dynamics of the process done.

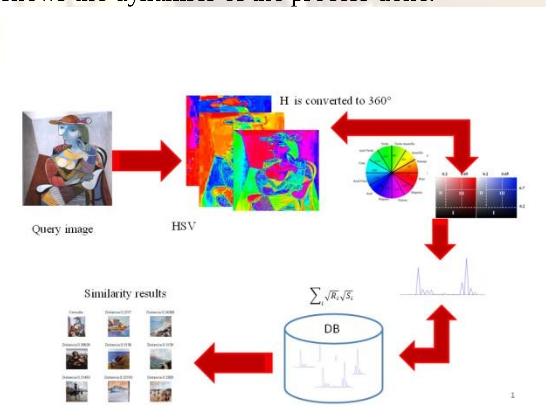

Figure 2. The query image in RGB space is converted to HSV space, then the HSV image is quantized to 56bins, its color histogram is extracted and compared with the histogram of the existing images in the database, returning the similar images in color, and allowing the user to determine the percentage of similarity.

III.2 Space-Color Algorithm

Spatial information was included in order to avoid losing image color distribution information in the image, and to avoid false positives. In particular, besides the color its position in the query image plane was added allowing the precision increases significantly.

Some improved techniques for color histograms including spatial characteristics are reported in the literature. One of these proposes the construction of the histogram by creating concentric circles in the image [6] to which is added a factor, considering the histogram of the first circle, which is the one corresponding to the center of the image as that of greater weight. Lei[5] proposes to determine for each color c_i, from the quantized color set C, the position of its center of mass normalized. They consider also, two weight coefficients α and β for the user's level of interest by color or spatial information. In [7] Cinque et al. present Spatial Chromatic Histograms (SCH), which combine information on the position (location) of the pixels of similar color and their arrangement within the image with the classic color histogram. For each color in the quantified image, the percentage of pixels having the same color is calculated, and spatial information summarized in the relative coordinate of the barycentre of the spatial distribution besides its corresponding standard deviation. Several experiments were carried out to test the algorithms behavior described in the preceding paragraphs when dealing with art images. These experiments allowed to decided whether include or not the barycentre of the different colors found in the image and its standard deviation.

The proposed algorithm is as follows:

For an image I already quantized to 56 bins,

$$P_k(I) := \{ (x,y) \in I : [x,y]=k \} \qquad (3)$$

as the set of pixels in I whose color is k. It is also calculated $h_I(k)$ corresponding to the percentage of pixels of color K that are in I,

$$h_I(k) = \frac{|P_k^I|}{n \times m} \qquad (4)$$

with nxm the total number of pixels of the image I, and compute for each color k its barycentre,,

$$\boldsymbol{b}_I(k) = (\bar{x}_k, \bar{y}_k)$$

where:

$$\bar{x}_k = \frac{1}{n}\frac{1}{|P_k|}\sum_{(x,y)\in P_k} x \qquad (5)$$

$$\bar{y}_k = \frac{1}{m}\frac{1}{|P_k|}\sum_{(x,y)\in P_k} y \qquad (6)$$

The barycentre gives an idea of the pixels' position having the same color; however it is still a rough approximation of the spatial properties of the image pixels. Since several pixels' arrangements of the same color can have closer barycentres, in order to improve information about the spatial properties and regions with higher concentration of pixels of one color, then the standard deviation of the pixels for Pk (I) is obtained. Let p be a pixel in any Pk (I) with relative coordinates (*xp*, *yp*) the standard deviation is then defined in (7),

$$\sigma_I = \sqrt{\frac{1}{|P_k|}\sum_{\boldsymbol{p}\in\boldsymbol{P}_k} d\left(\boldsymbol{p},\boldsymbol{b}_I(k)\right)^2} \qquad (7)$$

It requires a new function of similarity (8) between two images, as the function used in [7], if the barycentre and the standard deviation in the calculation of color histogram is included, with c

$$f_s(Q,I) = \sum_{i=1}^{c} \min\left(h_Q(i),h_I(i)\right) \times \left[\frac{\sqrt{2} - d\left(\boldsymbol{b}_Q(i),\boldsymbol{b}_I(i)\right)}{\sqrt{2}} + \frac{\min\left(\sigma_Q(i),\sigma_I(i)\right)}{\max\left(\sigma_Q(i),\sigma_I(i)\right)}\right] \qquad (8)$$

the number of bins resulting from the quantization, Q being the query image and R any other image that is in the database.

III.3 OTHER CHARACTERISTICS UNDER ANALYSIS

Other features that can improve the results of similarity between images were also considered as lightness component of color images, dark pixels and texture. For texture, the method of gray level difference [16, 17] (GLDM)) was implemented. The texture is used in combination with the color distribution. In Fig. 3, an implemented algorithm diagram for searching images by similarity in color and texture is shown.

IV. EXPERIMENTAL RESULTS

A database with 1300 art images from different painting styles: Renaissance, Classicist, Mannerist, Baroque, Impressionism, Post-Impressionism and Cubism was use to test the algorithms proposed. These images were classified by an expert. The results were evaluated by efficiency measure (Efficiency of Retrieval or Fill Ratio) defined by Methre et al. and they also were used for similarity in the color image retrieval by Barolo et al. [7]. This measure proposed to be S the number of relevant parts that the user wants to retrieve from an image given as example, IQR the total number of relevant images, and R^E_q the number of relevant images retrieved in the short list. The measure of effectiveness is given in (9),

$$\eta_S = \begin{cases} \dfrac{\left|\mathbf{R}^{\mathbf{I}}_q \cap \mathbf{R}^{\mathbf{E}}_q\right|}{\left|\mathbf{R}^{\mathbf{I}}_q\right|} & \text{if} \quad \left|\mathbf{R}^{\mathbf{I}}_q\right| \le S \\[2ex] \dfrac{\left|\mathbf{R}^{\mathbf{I}}_q \cap \mathbf{R}^{\mathbf{E}}_q\right|}{\left|\mathbf{R}^{\mathbf{E}}_q\right|} & \text{if} \quad \left|\mathbf{R}^{\mathbf{I}}_q\right| > S \end{cases} \qquad (9)$$

If $|R^I_q| \le S$, the efficiency is reduced as far as traditional *recall* whereas that $|R^E_q| \ge S$ efficiency corresponds to the *precision*.

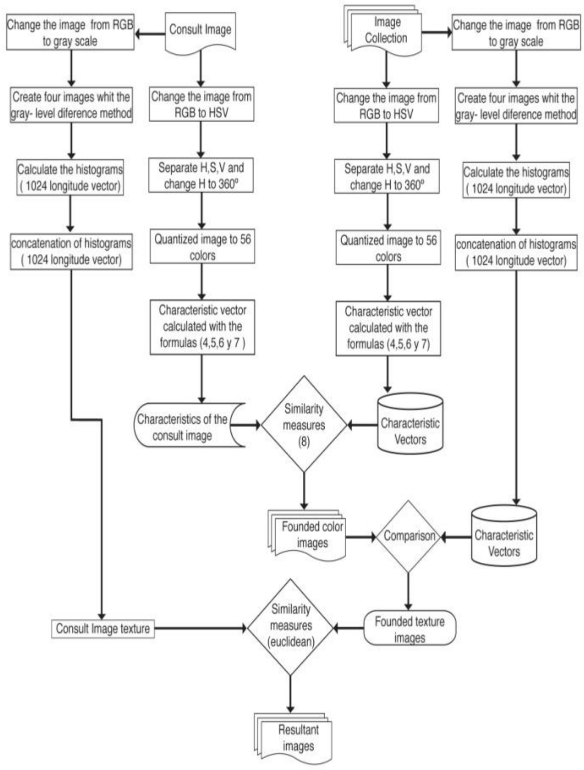

Figure 3. Diagram of color and texture distribution.

Figures 4, 5, 6 and 7, show system responses to search for similar images to the query image to each of the algorithms implemented for art image retrieval by association. For all cases the top ten most relevant images are shown besides the similarity percentage of each of the resulting images with the image query. In this case, a limit was established as much as 50% similarity reaching an efficiency of 81%. Additionally, the Fig. 8 presents the MAP (mean average precision) results from different tests performed on the images database grouped by the pictorial style of the desired image.

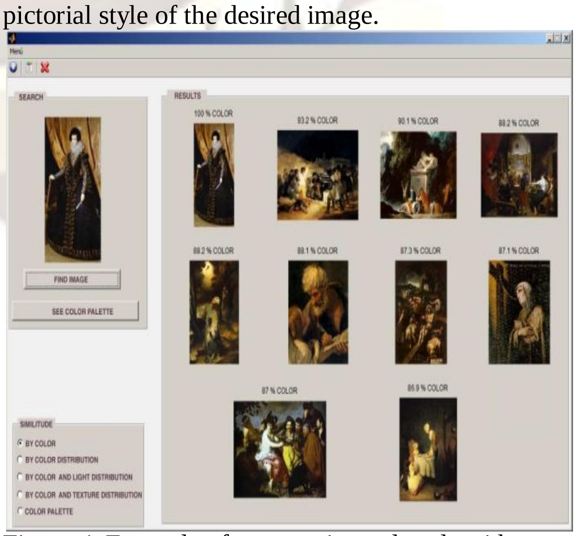

Figure 4. Example of query using color algorithm

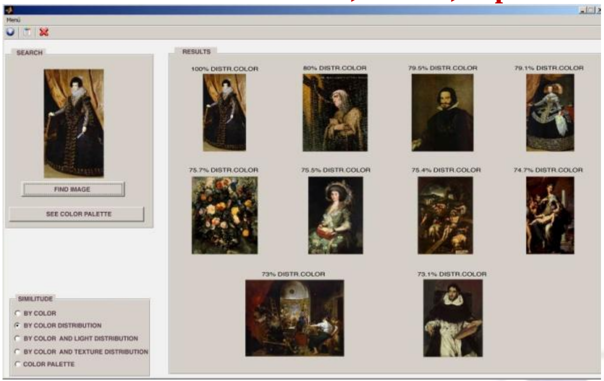

Figure 5. Example of query using color distribution algorithm

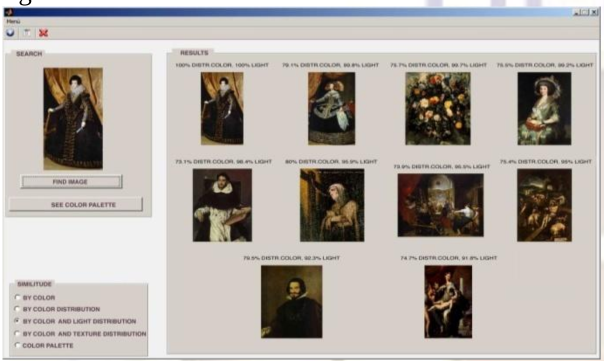

Figure 6. Example of query using color and light distribution algorithm.

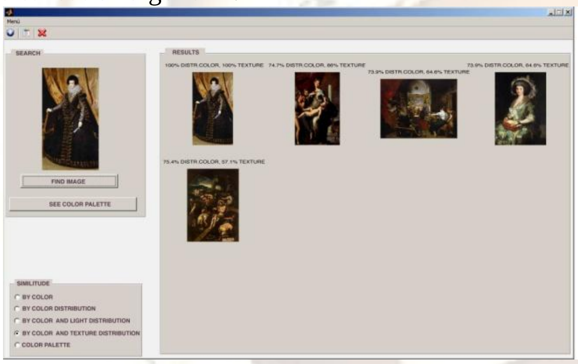

Figure 7 Example of query using color and texture distribution algorithm. This case only shows five results as they are the most similar to 50% similarity.

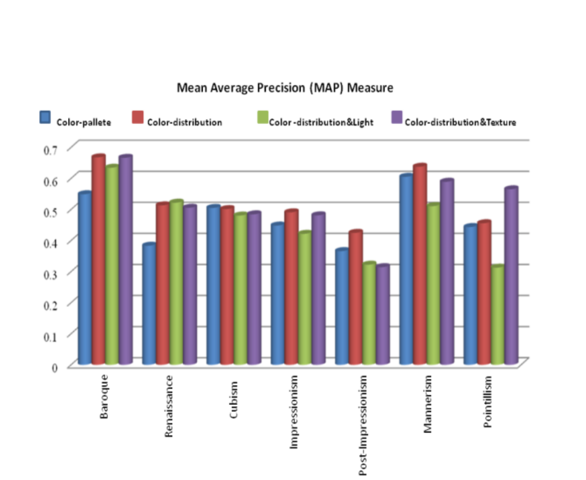

Figure 8. MAP measure results implemented in the seven classes.

V. CONCLUSIONS AND FUTURE WORK

The research presented focuses primarily on the color palette of art images being enriched with texture and brightness detected in them. It also considers the spatial distribution of color thereby allowing not only retrieve images that are similar in color palette and lighting but can additionally retrieve images similar in content. The results so far are encouraging and we plan to incorporate searching by category to enrich the search model. In particular, searching by a specific artist or images corresponding to a particular pictorial style is under consideration.

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