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Some Issues in the Art Image Database Systems

Peter L. Stanchev
Kettering University, pstanche@kettering.edu

David Green Jr.
Kettering University, dgreen@kettering.edu

Boyan N. Dimitrov
Kettering University, bdimitro@kettering.edu

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Peter L. Stanchev[1,2], David Green Jr.[1], Boyan Dimitrov[1]
[1]Kettering University, Flint, MI 48504
USA
[2]IMI - BAS, Sofia, 1113, Bulgaria.
{pstanche, dgreen, bdimitro}@kettering.edu

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ABSTRACT*: In this paper we illustrate several aspects of art databases, such as: the spread of the multimedia art images; the main characteristics of art images; main art images search models; unique characteristics for art image retrieval; the importance of the sensory and semantic gaps. In addition, we present several interesting features of an art image database, such as: image indexing; feature extraction; analysis on various levels of precision; style classification. We stress color features and their base, painting analysis and painting styles. We study also which MPEG-7 descriptors are best for fine painting images retrieval. An experimental system is developed to see how these descriptors work on 900 art images from several remarkable art periods. On the base of our experiments some suggestions for improving the process of searching and analysis of fine art images are given.*

Categories and Subject Descriptors
I.4 [Image Processing and Computer Vision]; **H.2.8** [Database applications]: Image databases; **H 3.1** [Content analysis and indexing]

General Terms
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1. Introduction

There are millions of art images available on the web in many image and multimedia databases. Some of them [5] are in: The Library of Congress: [http://www.loc.gov/rr/print/catalog.html], [http://memory.loc.gov], [http://international.loc.gov] and [http://www.loc.gov/exhibits/]; New York Public Library's NYPL Digital Gallery [http://www.nypl.org/digital/digitalgallery.cfm], [http://digital.nypl.org/mmpco/]; the Thinker Image Base, Fine Arts Museums of San Francisco [http://www.thinker.org/fam/about/imagebase/index.asp]; the Cleveland Museum of Art's [http://library.clevelandart.org/public/copyright.html]; the Los Angeles County Museum of Art (LACMA) Collections Online [http://collectionsonline.lacma.org]; the Boston Museum of Fine Arts Collections Database [http://www.mfa.org/artemis/collections/index.htm]; the National Gallery of Art [http://www.nga.gov]; the Smithsonian's American Museum of Art [http://americanart.si.edu/search/search_artworks.cfm]; the Seattle Art Museum [http://www.seattleartmuseum.org]; the Metropolitan Museum of Art (New York) [http://www.metmuseum.org]; the Minneapolis Institute of Arts [http://www.artsmia.org/collection/]; Albright-Knox Art Gallery [http://www.albrightknox.org]; Currier Museum of Art [http://209.187.119.118/]; Olga's Gallery [http://www.abcgallery.com]; a Virtual Art Museum [http://cgfa.sunsite.dk/index.html]; the database of European painting and sculpture of the Gothic, Renaissance and Baroque periods (1100-1850) [http://www.wga.hu/index.html], and many more. An interesting project in this area is ARTISTE, EC project aims to develop an Integrated Art Analysis and Navigation Environment hosted on a distributed database and accessed via the World Wide Web. Reproductions and posters are now available from many sides such as: AllPosters.com, the World's Largest Poster and Print Store, ocensbridge.com, brushstrokesdirect.com, and many other sites.

In art painting, the real space is converted into 2D space according to the articst perception. Summers [35] describes this conversion process. Special analysis of semantic notation and retrieval in art and architecture image collections were implemented in [34]. A fine-art indexing and image retrieval system usually has at least three components: formal analysis, comparison of the formal aspects of paintings, and the classification of style. The book of Barnet [1] is a comprehensive survey for analyzing art. He looks not only into illuminates on an individual painting, but also defines in his book the meaning of terms such as "iconography", "value", "saturation," "composition", "description" and "formal analysis." The Taylor's guide [36] provides a comprehensive view of art, moving from the analytical study of specific works to a consideration of broad principles and technical matters. Taylor's thoughtful discussion of pure forms and our response to them gives the reader a useful starting point for looking at art that does not reproduce nature, and for understanding the distance between contemporary figurative art and reality. In typical library systems such as [28], the following fields are used for describing contents of art painting: (1) Item number; (2) Artist - the name of the artist; (3) Life dates - the birth and death dates of the artist; (4) Nationality - the nationality of the artist; (5) Title - the title as it appears on the frame or accompanying material; (6) Century - the century with which the artist is associated; (7) Date of work - the year(s) artist devoted to that particular work; (8) Movement - the movement with which the artist is primarily associated; (9) Sub-movement - limits movement; (10) Category - painting, sculpture, architecture, minor arts; (11) Object class - stained glass, mobile, pottery, fresco, engraving, etc.; (12) Medium - material used; (13) Location - city in which the original artwork may be viewed; (14) Site - place within the city where the work is located. Recently a new standard emerges - the Encoded Archival Description (EAD) [7]. It is a community-driven standard maintained by the Network Development and MARC standards office of the Library of Congress in partnership with the Society of American Archivists. The EAD is an XML DTD based and electronically encodes finding aids, inventories, and guides to collections of primary artifacts. The guide is structured hierarchically, so that at the top you identify and describe the entire collection, then as you move down, you describe sub-groups of objects, and list individual object records.

There are various recommended search models for art images. Some of them [9] are:

- ***Search by association***. This is to browse through a large set of images with similarity to a given image or sketch. It often implies iterative refinement of the search.
- ***Targeted search.*** The purpose is to find a specific image. The search may be for a precise copy of the image in mind. Target search may also be for another image of the same object the user has an image of. For instance another painting of the series of the water lily pond at Giverny by Claude Monet. An example for such as search is given in Fig. 1. These systems are suited to search for paintings, textile patterns, and catalogues in general.
- ***Category search.*** The aim is to find an arbitrary image representative for a specific class. In category search, the user may have available a group of images and the search is for additional images of the same class. For instance searching other paintings by the same artist.

From a technical point of view, Art Image Retrieval [39] encounters many challenges that are also common in content based image retrieval, like high-dimension feature space, nonlinear distributions, insufficient training examples and the gap between low-level features and high-level contents. Moreover, there are some other unique characteristics coming with any art retrieval:

  

Figure 1. The targeted image and the retrieved images from the series of the water lily pond at Giverny by Claude Monet

- ***A Profile-Driven Process***. The query concept is replaced by the user profile, which is governing the entire retrieval process. The user may just implicitly keep a query in mind "return some nice images to decorate my house".
- ***A New Gap.*** There is another gap between the low-level visual features and the higher-level abstract properties, e.g. painting styles and expressed feelings or emotions. In some sense, this gap might be more important since the higher-level abstract properties are always more indicative for the expression of art images.
- ***Diversity of User Preferences.*** The user's interests in art images are typically diverse. One may love different styles of paintings in a meanwhile.
- ***Uncertainty of User Preferences.*** The people are always not sufficiently confident with their preferences for art images.

Working with art images, two main gaps appear: sensory gap and content gap.

- ***The Sensory Gap.*** This is the gap between the object in the world and what is in the canvas [8]. It arrives from the fact that there are many techniques and ways associated with the human observer. Differences in lightning, scene or shadow make no difference in the interpretation for humans. The pictures of arts are always recorded in frontal view with white-light illumination. Examination if an artist in detail draws the shadows and highlights may be assessed by evaluation of the painted colors to conform to the physical laws of light reflection. Edge classification based on the physical laws of light reflection highlights realistic shadow edges. To reduce this gap technical and software tools can be used. The VASARI project developed a colorimetric scanner system for direct digital imaging of paintings. It provides higher color accuracy than conventional film and high resolution, so it can be used to replace film photography (http://www.ecs.soton.ac.uk/~km/projs/vasari/). Concerning image quality improvement ArtShop [2] offers two technical tools: vector median filtering and scanner. To crack restoration, the system has detected the crack by the help of the user. The user can decide to erase it by applying an interpolation algorithm.
- ***The Semantic Gap.*** The semantic gap is the 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 [30]. The semantic gap deals with the pictorial contents of an image by a set of lingual codes such as ICONCLASS [37]. It can be approached by a combination of top-down term translation and bottom-up feature description. The top-down part represents the index terms describing the contents of an image in ontology's. The bottom-up is interpreted by complete feature sets characterizing the picture.

Other issues for the art images are the protection of artwork digital reproductions through digital watermarking [38]. The art image copyright in U.S.A. is described in Copyright & Art Issues [http://uoregon.edu/~csundt/copyweb/]. More information can be found in VRA Intellectual Property Rights Committee [http://www.arthist.umn.edu/slides/IPR] and IFLANET's (International Federation of Library Associations and Institutions) Information Policy: Copyright and Intellectual Property [http://www.ifla.org/II/cpyright.htm].

The rest of the paper is organized in the following way. Section two present some fine art systems and their main characteristics. Section three is devoted to present a method for searching the best MPEG-7 descriptor for art paintings. In section four experimental results are discused.

2. Fine art systems

In this section some art image data bases systems with interesting features are analyzed. These systems take in account the specific of the art images.

A lightweight image retrieval system for paintings [21]. The image indexing features in use are divided into three groups:

- canvas features: max, min, mean, median, and standard deviation from each of the red, green, and blue color channels;
- color features: intensity mean (measures the global brightness of a grayscale image), color frequency distribution (measures the degree of disorder found in the frequency distribution of colors in a painting);
- edge characteristics: line count (uses the Sobel edge detector to identify lines in the image).

Art historian system [14]. The system is robust to changes in illumination as well as resolution. It contains an automatic extraction of features of paintings' art movements such classification and indexing of paintings based on their art movements. A six dimensional as classicism, impressionism and cubism; and introduces a system developed for the feature set is proposed for the representation of content. It is shown that the feature set enables one to highlight art movements efficiently. In the classifier design, statistical pattern recognition approach is exploited using Bayesian, k-NN and SVM classifiers. The system also offers a quick query based database search by indexing the paintings with their six dimensional feature vectors. In this study, it has been shown that the art movements of paintings can be indexed by exploiting six different features:

- Percentage of dark colors.
- Gradient coefficient calculated from the gradient map of the painting image.
- Number of local and global maximum in the luminance histogram.
- Color range that the peak point of the luminance histogram corresponds.
- After the partition of the painting image into identical blocks, the deviation of average grey level acquired within each block from the average grey level acquired within an entire image.
- "Skew," the deviation of grey level distribution from Gauss distribution.

The pictorial portrait database [29]. The system uses a hierarchical database indexing method based on Principal Component Analysis. The description incorporates the eyes, as the most salient region in the portraits. The algorithm has been tested on 600 portrait miniatures of the Austrian National Library.

PICASSO system [6]. The system hurdle a multiple descriptions of each data set, each one covering a different level of precision. Images are analyzed at several levels of resolution in order to obtain a pyramidal segmentation of color patches. Each region at level *n* is obtained by clustering adjacent regions at level *n-1*. Region energy measure is associated to each region. This energy is obtained as a weighted sum of three entries: (1) the area, (2) the color uniformity, and (3) the color contrast.

ArtHistorian [12]. The system enables content browsing with a classification based indexing and query method implemented from the art historians' perspective. The system automatically classifies the art movement that the query example belongs to, and brings the best matching paintings belonging to the same movement in a ranked order. A number of other information is also associated with a retrieved painting such as date of painting, title of painting, etc.

Free hand drawings of Eugene Delacroix system [19]. Kröner and Lattner trained a naive Bayes classifier to distinguish from those of comparable artists with using only five features: three measured the ratio of black and white pixels and two measured stroke direction.

Painting classification system. D. Keren [17] proposed a framework for classification of paintings based on local features derived from discrete cosine transform coefficients. After calculating the local features, each pixel was classified and the overall classification of the image was determined from a majority vote of the pixel values. The testing set comprising works of Rembrandt, Van Gogh, Picasso, Magritte, and Dali.

Different tools are used to analyze the art images in order to enhance their search. Usually a set of ontologies, including the Art and Architecture Thesaurus [26], AAT, WordNet and IconClass are used. The knowledge is represented in RDF Schema, a W3C standard for semantic annotation. The ontologies are represented as a subclass hierarchy of RDFS classes.

2.1. Color features

The color is one of the most widely used image retrieval feature in art systems. The fundamentals of color were established by Newton in his Opticks [24] in 1704. Albert Munsell [23] provided the theoretical basis on which most painters derived their notations about color ordering. The emotion and psychological influence of color has been studied by Goethe [11]. The influence of the color was studded from Hegel, Descartes, Schopenhauer and many others.

The MPEG-7 standard includes five color descriptors which represents different aspects of the color and includes color distribution, spatial layout, and spatial structure of the color. The histogram descriptors capture the global distribution of colors. The dominant color descriptor represents the dominant colors used. The color layout descriptor captures the spatial distribution or layout of the colors in a compact representation. While MPEG-7 standards [22] accommodate different color spaces, most of the color descriptors are constrained to one or a limited number of color spaces for ensuring inter-operability. The two important criteria for color feature detectors according to [10] are: (1) ***Repeatability***, they should be invariant under varying viewing conditions, such as illumination, shading, and highlights; (2) ***Distinctiveness***, they should have high discriminative power.

In [13] Hachimura described a method for indexing and retrieving paintings based on the extraction of principal and background color segments. Lewis, Dupplaw, and Martinez [20] have developed an approach to sub-image matching which uses a pyramid of color coherence vectors and which can locate details of high resolution art images in large collections of such images. They have developed the idea of a multimedia thesaurus in their MAVIS 2 multimedia information system as an attempt to bridge the semantic gap.

Another group of researchers has concentrated on the application of Johannes Itten's color theory [15] to image retrieval problems developing both a visual language for color description [3] and an image retrieval system for painting [4]. Itten proposed taxonomy of colors based on hue, luminance, and saturation that provided the basis for his color theory. Researchers are interested in this theory because it is particularly well-suited to describing the human experience of color (warm, cold, contrast, harmony) and therefore the theory provides a foundation for formalizing high-level semantic information about images. In this theory color aesthetics may be approached from impression (visually), expression (emotionally) and construction (symbolically).

In [32] image retrieval is based on high level color properties. Six different types of contrasts are identified: Contrast of hue, Light–dark contrast, Warm–cold contrast, Complementary contrast, Simultaneous contrast, and Contrast of saturation.

2.2. Painting analysis

Description of different painting analysis is given in [27]. It includes phases such as:

· **Color classification**: Artist classification by art historians is based on color impression. This term describes the overall color perception of the painted face - its color tone.

· **Color space transformation**: A color space transformation is used since true color image processing is time-consuming and there is a lack of feasible methods of color feature.

· **Face extraction**: When dealing with portraits, face extraction is easier than conventional face detection since artists paint a person with a standard "creation model" in mind.

· **Shape classification**: Portraits are compared on a region by region basis, since artists tend to use a rather schematic than realistic way of modeling face details.

· **Stroke detection and analysis**: In order to compare the segmented regions not only by shape but also by the brush strokes used to paint them, the stroke detector is applied in specific regions. The stroke segments are grouped into strokes by matching similar curvatures and orientations of neighboring stroke segments.

· **Stroke classification**: The structure of the detected stroke segments allows a classification of the miniatures since it is similar to the basic elements of art historical classification. [18] presents a content-based and collaborative filtering. The objects are selected for particular user preferences.

2.3. Painting styles

Painting styles are often analyzed. For instance bright colors and smooth transitions that hide the sharp edges are some of the determining features of "impressionist" art movement. "Cubism" movement generated paintings reflecting different perspectives and involving analytic. Most impressionist works are heavily textured. The distinctive edges and, the high contrast are some of the determining features of impression art movement. An other example is that the painters of classicism preferred dark colors in their paintings and tried to draw the objects as real as possible.

Another type of retrieval in art systems is retrieval by painting styles [16]. Jia Li and James Wang use a mixture of stochastic models. The 2-D multi-resolution hidden Markov model (MHMM) is used in the experiment. These models form an artist's distinct digital signature. For certain types of paintings, only strokes provide reliable information to distinguish artists. Chinese ink paintings are a prime example of the above phenomenon. They do not have colors or even tones. The 2-D MHMM analyzes relatively large regions in an image, which in turn makes it more likely to capture properties of the painting strokes.

3. MPEG-7 descriptors analysis for art painting

Due to the availability of specific image features used in the MPEG-7 standard [22], we base our evaluation on them. An example of applying MPEG-7 descriptors for indexing and retrieval of video is the IBM MARVEL system [31]. Several visual descriptors exist for representing the physical content of images, as for instance color histograms, textures, shapes, regions, etc. Depending on the specific characteristics of a data set, some features can be more effective than others can, when performing similarity search. Descriptors based on color representation might result not to be efficient with a data set containing mainly black and white images. In [33] we have proposed a methodology for predicting the effectiveness of a visual descriptor on a target data set. The technique is based on statistical analysis of the data set and queries. Experiments, where we assessed the quality of the visual descriptor from a user perspective have demonstrated the reliability of our approach. The experiments were conducted with a large number of users to guarantee the soundness of the analysis of results. We use the following six MPEG-7 visual descriptors: (1) Scalable Color (SC), based on the color histogram in HSV color space encoded by a Haar transform. We used the 64 coefficients form; (2) Dominant Color (DC), presents a set of dominant colors taking in considerations their spatial coherency, the percentage and color variance of the color in the image. We used the complete form; (3) Color Layout (CL), based on spatial distribution of colors. It is obtained applying the DCT transformation. We used 12 coefficients; (4) Color Structure (CS), based on color distribution and local spatial structure of the color. We used the 64 coefficients form; (5) Edge Histogram (EH) based on spatial distribution of edges (80 fixed coefficients); and (6) Homogeneous Texture (HT) based on the mean energy and the energy deviation from a set of frequency channels. We used the complex form.

Let us consider a data set composed of *N* images $(I_1,\ldots,I_N)$, and let us indicate the query as Q. For a specific visual descriptor *vd* the distance between image I_i and the query is defined as. This distance function is an evaluation of the dissimilarity between the images. The similarity function can be obtained in different ways from a distance function (e.g. $s = 1 - d$ if d is in the range [0, 1]). All images in the data set can be ranked according to the distance measure with respect the query. We obtain an ordered list of pairs, where if proceeds in the list. Let us consider that a generic query returns to the user *k* images, ordered in increasing distance $d_{vd}(Q,I)$ (decreasing similarity) with respect to *Q*. We found that the following measure is appropriate to predict the retrieval effectiveness of a given visual descriptor *vd*:

$$R_k = \frac{avg_Q(Q,I_{Q,k+1}) - avg_Q(Q,I_{Q,1})}{D}$$

where $avg_Q(Q,I_{Q,1})$ is the average distance between the queries and the most similar image (not considering the query image itself). Similarly we define $avg_Q(Q,I_{Q,k+1})$ where $I_{Q,k+1}$ is the (*k+1*)-th image ranked for the given query image Q. D is the average distance between all images in the data set. This measure depends on *k* (the size of the retrieved set), but from the experimental evaluation we found that for typical values of *k* (between 10 and 50) R_k does not varies significantly. This measure is related to the difference between the average distances of the first retrieved image and of the *(k+1)*-th nearest image. Higher values of R_k are expected to provide a good “distinction” among the retrieved images, so that the visual descriptor *vd* is expected to provide good retrieval effectiveness.

We conducted our experiments on the following data sets: (1) 21,980 key frames extracted from the TREC2002 video collection (68.45 hrs MPEG-1); (2) A subset of the image collection of the Department of Water Resources in California. It is available from UC Berkeley (removing B&W and animals we used 11,519 images); and (3) 1,224 photos from the University of Washington (UW), Seattle. We found that the Color Structure (CS) was always the best descriptor.

4. The experiment

We used 900 art images from over than 200 artists from 19 century presenting the neoclassicism, romantics, realism, impressionism and symbolism; from 18 century; from 15-17 century presenting renaissance and baroque; from middle ages presenting Byzantium, Islam and Gothic; from ancient art presenting near East, Egypt, Greece and Rome; and from prehistory. Making the statistical analysis we found the following ranking of the descriptors: SC, CL, DC, CS, HT and EH. A very interesting founding is that CS comes in last place for art images and was the best descriptor for all other data sets which we tried. The result is given in Fig. 2. In Fig. 3, 4 and 5 we show the search in the developed system using the best color descriptor – CS, using linear combination of all color descriptors, using texture descriptors, using linear combination of color and texture descriptors. We found that using different color descriptors we obtain different resulting set. This is because the colors are the most impressive feature in the art images. Something which was not obvious is that only textures descriptors find most of the images if we try color and texture descriptors together.

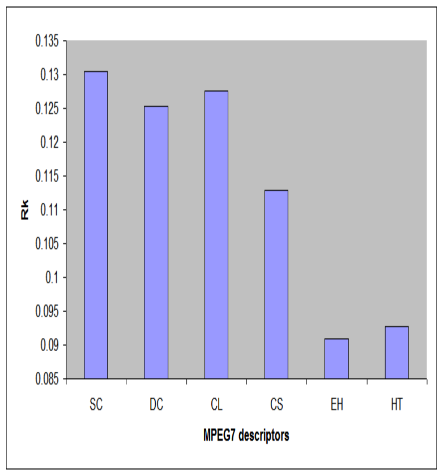

Figure 2. Experimental results

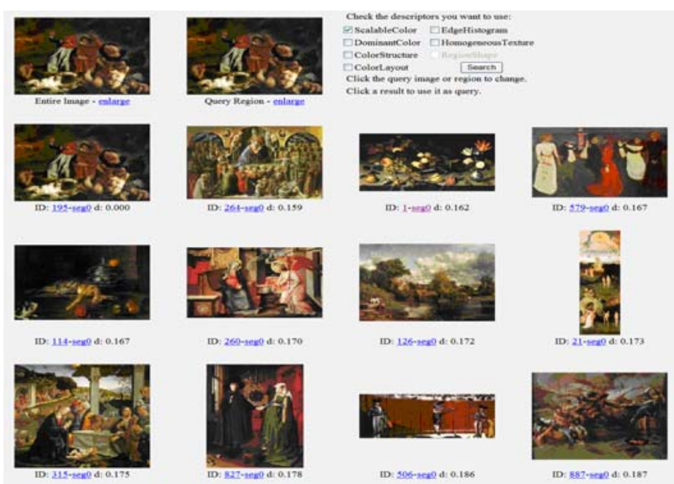

Figure 4. Search using the all MPEG-7 color descriptors

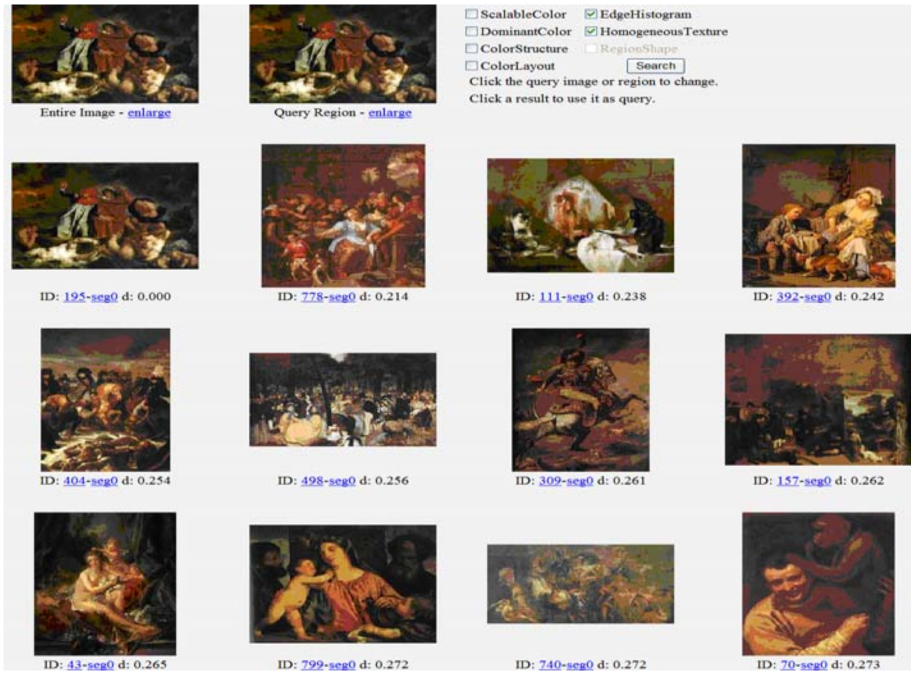

Figure 5. Search using the MPEG-7 textual descriptors

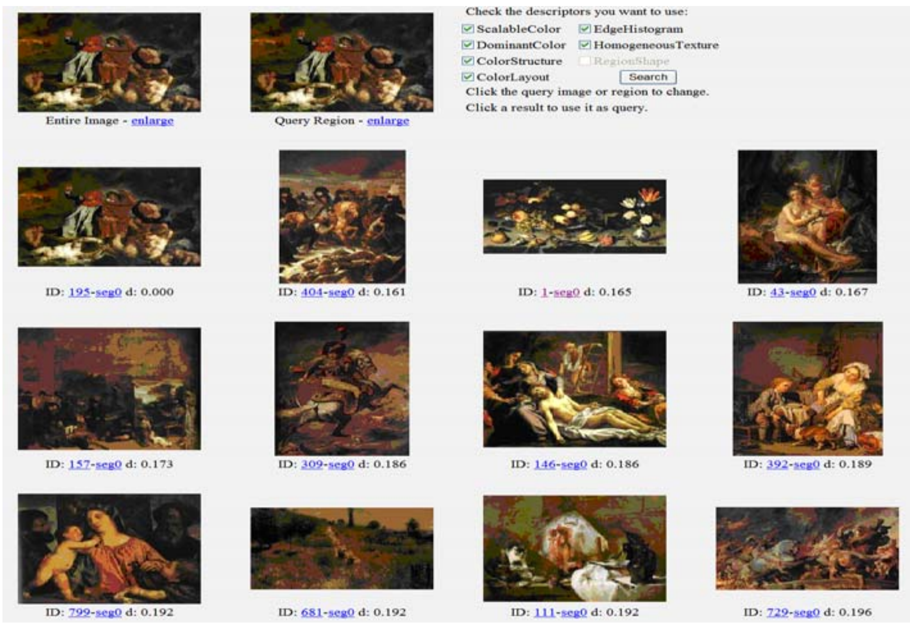

Figure 6. Search using MPEG-7 color and textual descriptors

5. Conclusion

In the paper we have illustrated several aspects of the fine art databases. We showed that MPEG-7 descriptors can be used, but they give different results. The use of the Color Structure descriptor only produces sufficiently efficient results in the query search. More experiments will be conducted to find the best combination of descriptors for such kind of images. The new generation Semantic Web languages, such as RDF(S) and OWL [25] will play a major role. The integration of semantic understanding of pictures with personalized delivery raises new questions. The query language for this type of system is not yet standatized but we hope that an emerging standard will come soon.

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Peter L. Stanchev

Professor Peter L. Stanchev received his Ph.D. from Sofia University. He has couple of books and more than 150 research papers in Image Processing, Medical Informatics, and Image Database Systems. He is presently department chair in the Institute of Mathematics and Computer Science, Bulgarian Academy of Sciences, Sofia, Bulgaria and Professor of Computer Science at Kettering University, Flint, Michigan, USA.

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Professor Dr David Green, Jr. received his PhD from Michigan State University. His primary area of research is in Differential Equations, Image Data Processing, Mathematical Modeling of physical phenomena and stochastic processes. He is presently department head of the Science and mathematics department at Kettering University, Flint, Michigan.

Professor Boyan Dimitrov, PhD of the Moscow State University (1971), Dr of Math. Sciences, Sofia, Bulgaria (1986). He works in the field of Applied Probability and statistics (queering models, reliability, warranty, age determination, image processing, and related areas). He works at the Science and Math Department of Kettering University in Flint, Michigan.