A graphical user interface for a fine-art painting image retrieval system

Conference Paper · January 2004

DOI: 10.1145/1026711.1026729 · Source: DBLP

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A Graphical User Interface for a Fine-Art Painting Image Retrieval System

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ABSTRACT

For describing and analyzing digital images of paintings we propose a model to serve as the basis for an interactive image retrieval system. The model defines two types of features: palette and canvas features. Palette features are those related to the set of colors in a painting while canvas features relate to the frequency and spatial distribution of those colors. The image retrieval system differs from previous retrieval systems for paintings in that it does not rely on image or color segmentation. The features specified in the model can be extracted from any image and stored in a database with other control information. Users select a sample image and the system returns the ten closest images as determined by calculating the Euclidean distance between feature sets. The system was tested with an initial dataset of 100 images (training set) and 90 sample images (testing set). In 81 percent of test cases, the system retrieved at least one painting by the same artist suggesting that the model is sufficient for the interactive classification of paintings by artist. Future studies aim to expand and refine the model for the classification of artwork according to artist and period style.

Categories and Subject Descriptors:

H. INFORMATION SYSTEMS H.3. INFORMATION STORAGE AND RETRIEVAL H.3.3. Information Search and Retrieval *Retrieval Model*

General Terms: Measurement

Keywords: Image retrieval, painting classification

1. INTRODUCTION

The growth of online databases for artwork demonstrates a need for new approaches to storing and retrieving digital images of art [1]. Computer archiving and retrieval applications for paintings tend to prefer precision to general applicability and flexibility. A great deal of work, for example, focuses on automatically authenticating and classifying fine art [2,3,4]. Applications of this nature require high resolution images, preprocessing modules, and specifically engineered feature sets to support their accuracy requirements. The growth of online databases of artwork suggests that there is a need for general purpose and flexible approaches to archiving, analyzing, and retrieving digital images of art that sacrifice precision for the sake of more general utility. A general and flexible painting retrieval system would provide students, teachers, and researchers with an effective tool for learning, teaching, and thinking about painting.

A fine-art indexing and image retrieval (IIR) system designed for educational purposes should support three tasks required of all art students: formal analysis, comparison of the formal aspects of paintings, and the classification of style[5]. Every student in college-level art history classes is required to analyze the formal aspects of a painting including the identification and interpretation of elements such as color, line, shape, and texture. In many cases, formal analysis involves a comparison of two or more paintings. As students improve their abilities, they are asked not only to compare and contrast specific works but also to classify paintings based on their knowledge of artist and period styles. Analysis, comparison, and classification therefore are among the primary tasks to learn by those studying art.

In this paper, we propose an IIR system to support the efforts of college-level art students to analyze, compare, and classify paintings. The system is based on a general model for describing and analyzing digitally scanned images of paintings. Based on the artistic act of creating a painting, the model defines two types of features: palette and canvas features [6]. Palette features are those related to the unique set of colors in a painting while canvas features relate to the frequency and spatial distribution of those colors. In accordance with the model, a preliminary feature set is defined comprising one palette feature and fifteen canvas features. We demonstrate that the preliminary feature set is sufficient to support the analysis, comparison, and classification of paintings in an interactive IIR system with a small dataset.

The paper is organized into five sections each describing a different aspect of the IIR system. After a survey of previous work in Section 2, Section 3 describes the structure and organization of the fine-art painting image database with a discussion of the preliminary feature set. In section 4, the graphical user interface is discussed in the context of supporting student activities. The image retrieval experimental results are examined in section 5. Section 6 concludes the paper with some future extensions to the system and some general remarks.

MIR'04, October 15–16, 2004, New York, New York, USA.

2. PREVIOUS WORK

The present work draws on developments in the fields of image retrieval, computer vision, and pattern recognition. The solutions to effective classification of artwork are as varied as the fields from which these solutions originate. Kröner and Lattner [7] trained a naïve Bayes classifier to distinguish free hand drawings of Eugene Delacroix from those of comparable artists with only five features – three measured the ratio of black and white pixels and two measured stroke direction – and their experiments yielded an overall accuracy rate of 87% with some results as high as 90%. Researchers working with a collection of 600 Austrian portrait miniatures [3, 4, 8, 9] used brush stroke detection techniques to identify the structural signature of an artist's personal style. In a more recent study, Keren [10] proposed a framework for the classification of paintings based on local features derived from discrete cosine transform (DCT) 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 technique produced an 86% success rate on a testing set comprising works of Rembrandt, Van Gogh, Picasso, Magritte, and Dali.

The image retrieval research associated with fine art has concentrated on closing the semantic gap between the user and image retrieval systems [1, 11]. Hachimura [12] described a method for indexing and retrieving paintings based on the extraction of principal and background color segments. Another group of researchers has concentrated on the application of Johannes Itten's color theory to image retrieval problems developing both a visual language for color description [13] and an image retrieval system for painting [14]. Itten proposed a 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..

This paper aims to synthesize the approaches and techniques of these research communities for the purpose of developing a general purpose academic IIR system. Most of the painting classification systems proposed thus far [3, 4, 7, 8, 9] have achieved highly accurate results on reasonably narrow testing sets focusing on particular artists (Delacroix) or particular subjects (Portraits miniatures). The classification system with the broadest applicability [10] relies on local features calculated from DCT coefficients. While such features work well for the classification of paintings based on artistic style, these features offer little of analytical value to students of art. The goal of the IIR system therefore is to develop an interactive indexing and image retrieval system that can classify artistic style with a semantically relevant feature set, i.e., one that is useful for the analysis and comparison of works of art.

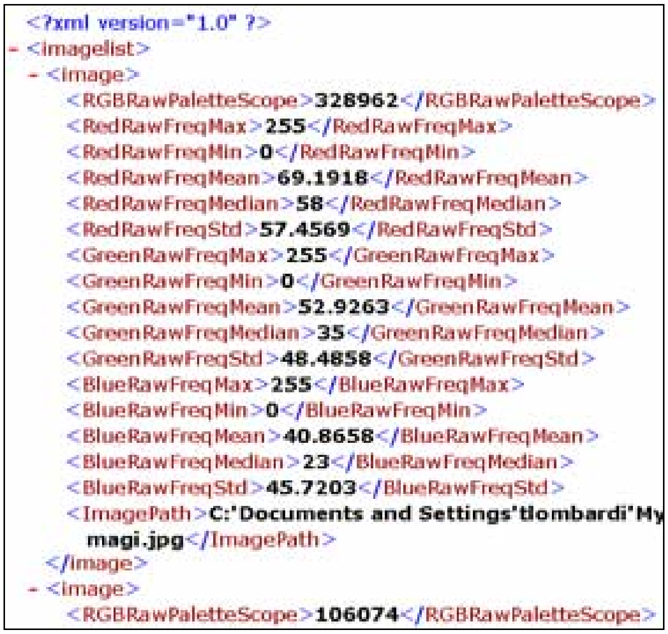
3. DATABASE CONSTRUCTION

The IIR database was designed to emphasize simplicity and portability. The database consists of two main components: a directory structure and an index file. Figure 1 shows the top level of the directory structure that contains three folders: thumbs, train, and xml. The thumbs and train directories each contain one folder per artist. Every image added to the database is copied into the appropriate artist subfolder in the train directory and a resized small version of the file is copied into the artist's thumbs directory. The xml directory contains the index files required to maintain the integrity of the directory structure and to manage the data extracted from the images. The design supports student needs for simple access to data and ease of data distribution.

Figure 1. Directory structure for IIR system database.

When an image is added to the database, features are extracted from the image and stored in an index file in the xml directory of the database. As stated earlier, a preliminary feature set was defined in accordance with a general model for describing and analyzing digital images of paintings. The model defines palette and canvas features as a taxonomic principle for features related to fine-art paintings. The palette features capture information regarding the unique set of colors used to make a painting, and they are derived from the color map of an image. The canvas features capture the frequency and spatial distribution of the colors in an image, and these features correspond to those extracted from an M x N image index.

The preliminary feature set used for the IIR system comprises one palette feature and fifteen canvas features. The preliminary palette feature is the palette scope which measures the total number of unique RGB triples found in an image. The preliminary canvas features are the max, min, mean, median, and standard deviation from each of the red, green, and blue color channels. Figure 2 shows an example of the resulting sixteen extracted features and the path to the image as stored in the XML index file. The XML index file contributes to the design goals of simplicity and portability by allowing easy access to the underlying data.



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<?xml version="1.0" ?>
- <imagelist>
  - <image>
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      <RedRawFreqMax>255</RedRawFreqMax>
      <RedRawFreqMin>0</RedRawFreqMin>
      <RedRawFreqMean>69.1918</RedRawFreqMean>
      <RedRawFreqMedian>58</RedRawFreqMedian>
      <RedRawFreqStd>57.4569</RedRawFreqStd>
      <GreenRawFreqMax>255</GreenRawFreqMax>
      <GreenRawFreqMin>0</GreenRawFreqMin>
      <GreenRawFreqMean>52.9263</GreenRawFreqMean>
      <GreenRawFreqMedian>35</GreenRawFreqMedian>
      <GreenRawFreqStd>48.4858</GreenRawFreqStd>
      <BlueRawFreqMax>255</BlueRawFreqMax>
      <BlueRawFreqMin>0</BlueRawFreqMin>
      <BlueRawFreqMean>40.8658</BlueRawFreqMean>
      <BlueRawFreqMedian>23</BlueRawFreqMedian>
      <BlueRawFreqStd>45.7203</BlueRawFreqStd>
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        magi.jpg</ImagePath>
    </image>
  - <image>
      <RGBRawPaletteScope>106074</RGBRawPaletteScope>
```


Figure 2. XML index file for IIR system database.

4. GRAPHICAL USER INTERFACE

The graphical user interface was designed to facilitate the analysis, comparison, and classification of paintings. The screen is divided into three main sections: an image frame, a feature frame, and a comparison frame. Figure 3 shows the image frame that includes an image window for displaying sample and test images, a *Select Painting* button, an *Add Painting* button, and a *Compare Painting* button. When a student wants to view and analyze an image, the student clicks the *Select Painting* button and then browses for the desired file. The image is loaded into the display area and the sixteen features are extracted and displayed in the feature frame (Figure 4).

The functionality associated with the image and feature frames is sufficient for analyzing and comparing the extracted color features of any image on a user's system. The system allows users to ask and to provide tentative answers to questions like: How blue are the paintings from Picasso's Blue Period? How did Van Gogh's use of color change over time? If a user finds a particularly important image, that image can be added to the database permanently for future review and comparison by clicking the *Add Painting* button.

The *Compare Painting* button allows the user to compare the image in the image frame to all of the images in the database. The system calculates the Euclidean distance between the feature vector of the test image and the feature vectors of the images in the database. The results are sorted and the ten closest images are displayed in the comparison frame. In addition to functioning as a comparison tool, the results in the comparison frame serve as a simple classification tool for artist identification by narrowing the selection of possible artists. Users browsing images of paintings can use this functionality as a study aid for learning artist and period styles.

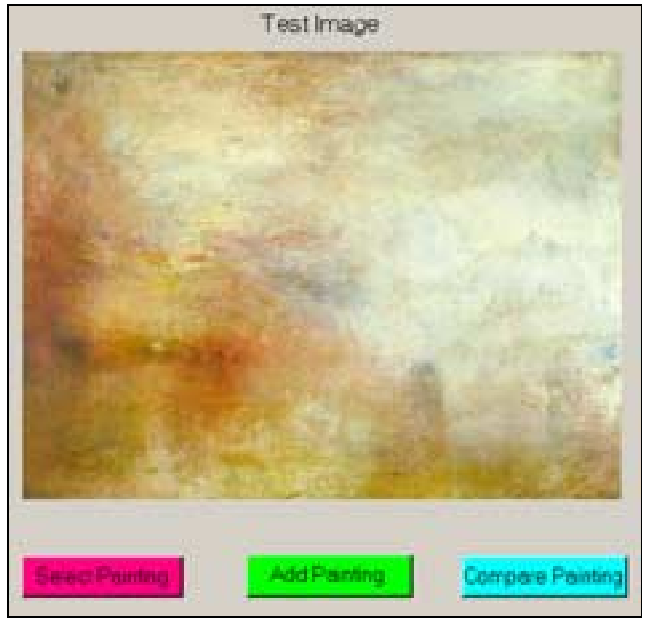

Figure 3: The image frame of the IIR GUI.

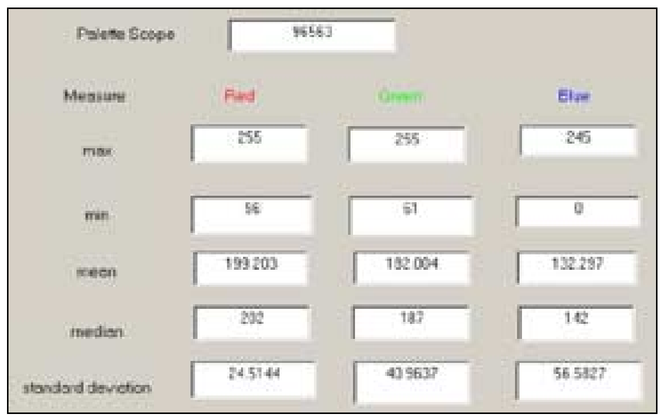

Figure 4: The feature frame of the IIR GUI.

5. IMAGE RETRIEVAL TEST RESULTS

The system was tested in two different ways. First, the feature set was tested to identify the degree to which it could distinguish between artists. Second, the system was tested interactively to identify how useful the system might be for someone learning to distinguish the works of individual painters.

The test of the feature set demonstrates that these features are sufficient to distinguish between the styles of two artists. In three separate experiments, summarized in Table 1, a nearest neighbor classifier reliably distinguished between the work of Picasso and Van Gogh with accuracies varying from 83 to 94%.

Table 1. Feature set experimental results.

Training Set	Testing Set	Percent Correct
36	36	94
200	200	88
200	200	83

The first interactive portion of the testing was based on a database of 100 training images: ten images from the corpus of each of the following ten artists: Braque, Cezanne, De Chirico, El Greco, Gauguin, Modigliani, Mondrian, Picasso, Rembrandt, and Van Gogh. The results of the initial interactive experiment are summarized in Table 2. The testing set included 90 images chosen at random from the work of the same ten artists. The application proved useful for classifying paintings by artist even with a small dataset and minimal training. In 81% of test cases, the system retrieved at least one painting by the same artist suggesting that the model is effective for interactive classification of paintings by artist.

Table 2. Initial interactive experimental results.

Training Set	Testing Set	Percent Correct
100	90	81

The second and more challenging interactive test was based on a database of 500 images drawn from the Web Museum (http://www.ibiblio.org/wm/paint/auth/). The database included 10 images from each of fifty artists. Although the overall retrieval rate was only 49.2%, Table 3 shows that the system performed particularly well with respect to certain artists. For instance, the system retrieved paintings by Rembrandt at a rate of 71.9%. Furthermore, an analysis of the mistakes made in classification reveals that the system is effectively classifying artistic style even when it fails to classify the artist correctly. Table 4 lists the most common mistakes made when classifying images of Rembrandt. The test images of Rembrandt are most often confused with the works of Caravaggio, Rembrandt's great artistic influence, and those of Ast and Vermeer, two of Rembrandt's Dutch contemporaries [15]. Moreover, of the 305 erroneous results, the system never retrieves the work of Bacon, Cassatt, Davis, Hockney, Malevich, Monet, Morisot, Pollock, Sisley, or Turner.

Table 3. Web Museum interactive experimental results.

Artist	Training Set	Queries	Success	Percent
Aertsen	9	8	7	87.5
El Greco	10	8	4	50.0
Hopper	10	8	1	12.5
Malevich	10	11	6	54.5
Monet	10	10	6	60.0
Morisot	10	11	5	45.5
Rembrandt	10	32	23	71.9
Renoir	10	38	12	31.6
Turner	10	10	3	30.0
Velazquez	10	8	7	87.5
Overall	*500*	*299*	*147*	*49.2*

Table 4. Analysis of misclassifications of Rembrandt.

Artist	Number of Images	Percent
Caravaggio	31	10.16
Ast	22	7.21
Vermeer	21	6.89
Delacroix	20	6.56
Rubens	16	5.25
Durer	14	4.59
Klimt	14	4.59
Velazquez	14	4.59
Chase	12	3.93
Bassano	11	3.61
Greco	11	3.61
Aertsen	11	3.61
Memling	10	3.28
Toulouse-Lautrec	10	3.28
Bouguereau	9	2.95
Altdorfer	8	2.62
Cezanne	8	2.62
Daumier	7	2.23
Bruegel	6	1.97
Gauguin	5	1.64
Van Gogh	5	1.64
Whistler	5	1.64
Baldung	4	1.31
Ingres	4	1.31
Modigliani	4	1.31
Kiefer	3	0.98
Bosch	2	0.66
Hopper	2	0.66
Kandinsky	2	0.66
Matisse	2	0.66
Watteau	2	0.66
Weyden	2	0.66
Cranach	1	0.33
Degas	1	0.33
Manet	1	0.33
Munch	1	0.33
Piero	1	0.33
Redon	1	0.33
Renoir	1	0.33
Seurat	1	0.33

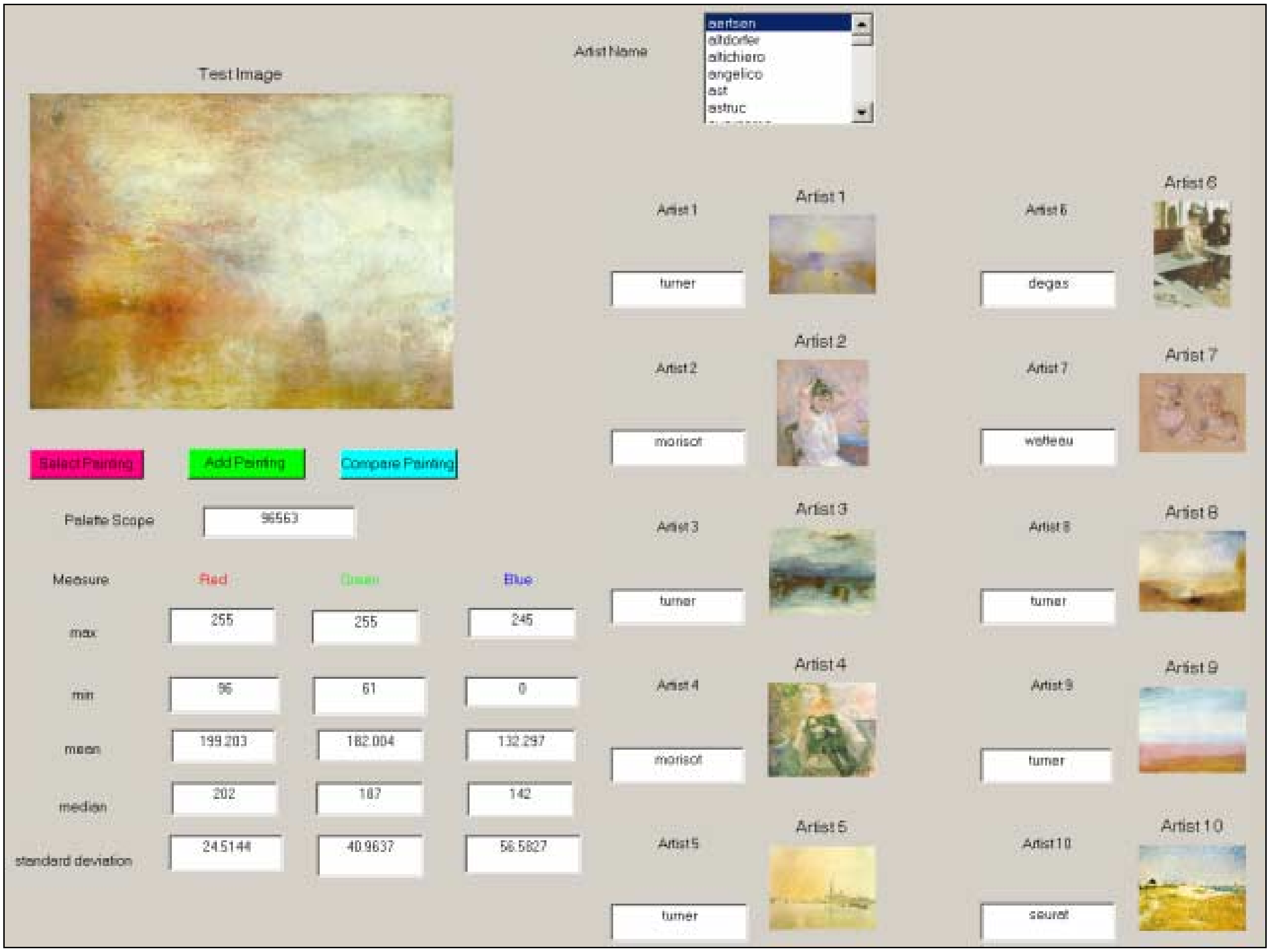

Figure 5: The Fine-art Painting Image Retrieval System

6. CONCLUSIONS

Our research demonstrates that a simple feature set based on color is sufficient for the development of an IIR system for fine-art paintings. The primary beneficiaries of such a system are college students learning to identify the work of artists. The system supports the three primary learning tasks of students of art: analysis, comparison, and classification. The interactive, portable, and flexible nature of the system allows students and teachers to adapt the system to specific goals and needs.

Experimental results confirm that the system works best for a small number of artists and images. More extensive testing on larger datasets revealed that although the system did not reliably distinguish between the works of specific artists, it did reliably retrieve stylistically similar works of art. In order for the system to scale properly, both the number of features and the number of training images per artist must be increased.

In addition to its reasonable accuracy, the feature set has several advantages. First, the features are not specific to an artist or even a medium. The feature set should work equally well on paintings in oil or water color for example. Second, neither special photography nor high resolution images are required to extract the features. Third, the feature extraction process requires no preprocessing such as image segmentation, size modification, or orientation correction.

Future research aims to expand and refine the feature set and the IIR system. The feature model will be expanded to include a more robust feature set. Moreover, the IIR system will be expanded to incorporate several types of classification related to artist and period style. The primary goal of the research is to develop techniques and applications appropriate for educational environments.

7. ACKNOWLEDGMENTS

We would like to thank the administrators of the following Websites for their generous permission to study their images:

The Artchive, http://www.artchive.com,

Olga's Gallery, http://www.abcgallery.com,

The WebMuseum, http://www.ibiblio.org/wm/paint/,

The Online Picasso Project, http://www.tamu.edu/mocl/picasso/,

The Van Gogh Gallery, http://www.vangoghgallery.com/

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