ARTHISTORIAN: AN INTEGRATED INDEXING AND PERSONALIZED BROWSING SYSTEM FOR ART PAINTINGS

Oguz Icoglu[+]*, Bilge Gunsel, and Sanem Sariel*

Multimedia Signal Processing and Pattern Recognition Lab.
Electrical-Electronics Eng. Faculty. Istanbul Technical University 34469, Maslak - Istanbul, Turkey
email: oguz.icoglu@tuwien.ac.at, bgunsel@ehb.itu.edu.tr, sariel@cs.itu.edu.tr
web: http://www.ehb.itu.edu.tr/~bgunsel/mspr

ABSTRACT

This paper introduces ArtHistorian, an art painting indexing system designed for automatic generation of dynamic painting presentations. The developed system aims personalized content browsing with a classification based indexing and query method implemented from the art historians' perspective. ArtHistorian represents the visual content of paintings by a 6-D feature vector that is robust to scale changes and can handle variations in lighting conditions. A nonlinear SVM classifier included in the system learns the characteristics of fundamental art movements, painters and painting styles. Automatically generating indexes based on the classification results, the system creates an efficient storage environment that enables the user to run content-based queries and to retrieve materials from extensive painting records. Thus, it is very suitable for Internet art collections and active Web museums.

1. INTRODUCTION

Recently, several museums use the Web for presenting their large painting collections to the public. The main advantage of presenting a museum's painting collections through the Web is making it feasible to rearrange the collection for each individual visitor. For example, the visitor, after viewing one painting, might want to view paintings that are similar. In contrast to most of the existing static Web sites in which the hypertext structure linking the objects has been defined once to all, and is the same for all users, these type of queries require a dynamic topology which is adapting to the visitor's test and choices. This is achieved by providing some functionalities which allow the user to dynamically create presentations of paintings that satisfy a selected similarity criteria, i.e., same art movement, same painter, same century, etc. In image indexing, it is reasonable to expect that art paintings with similar content will be almost equally interesting to users.

Two fundamental problems in content-based access to paintings/images are extraction of content representative features (indexes) and specification of similarity measures [1]. This paper introduces ArtHistorian, an art painting indexing system, that corporate automatically extracted low-level visual features in content-based classification for generating hypermedia presentations.

Visual characteristics of the paintings are determined by the painter and the specific art movement that these paintings belong to. Moreover, philosophical approaches, common understandings and technical possibilities of an era determine the features of art movements. Several studies are focused on the identification of painters or painting styles, and offer indexing and retrieval schemes that can be exploited for artistic paintings [2, 3, 4]. The essential difference between the existing approaches and our method is the feature set used for content representation. We employ a six dimensional content-representative feature set that enables the reflection of different art movement and painting characteristics [5]. Preliminary version of the feature set is presented in [6]. Another contribution of this paper is the use of a nonlinear SVM (Support Vector Machine) classifier [7] instead of neural networks or linear classifiers [3, 4, 6].

Based on the results of the classifications, ArtHistorian arranges the fundamental indexes and enables the user to run queries in terms of art movement or painter and to search for a given painting in the database. When the user runs a query, the system looks through the paintings in the repository filtered from the overall database, and retrieves the best five matching

[+] O. Icoglu is currently working in Vienna University of Technology, Department of Building Physics and Building Ecology.

records together with their conceptual information like the name of the painter, art movement, creation year, etc. Currently five art movements are considered: classicism, impressionism, cubism, expressionism and surrealism. All painting data [8] stored in the database are in XML format, which is also the base language of MPEG-7 [9].

2. ARTHISTORIAN

ArtHistorian is intended to constitute a feasible infrastructure for the tomorrow's Web museums, where the visitors will be granted fast access to demanded materials without losing time within the static links of irrelevant records. Towards this end, the concept of active Web museums is born where dynamic environments are presented that can response to user preferences. However, the realization of active Web museums requires the implementation of a powerful content-based filtering technology in order to identify the relevant items for each user. Therefore, the content analysis of the materials should be performed and linked with the user preferences. From the art historians' perspective, movements and painters are two of the most important attributes of the content that constitute the users' interest scope.

ArtHistorian models the paintings by utilizing a novel six dimensional vector used as the determining feature set for each art movement and painter. The proposed feature set considers philosophical approaches that determined the visual content and features of art paintings. For example, in "classicism" movement, born in Italy and widely accepted between 1400-1600, realism, harmony and simplicity were determining factors that reflected the Roman and Greek philosophy. Painters of classicism preferred dark colours in their paintings and tried to draw the objects as real as possible because of the lack of technologies like photograph cameras. In contrast, "expressionism", born in early 20th century, was a style of painting in which the intention was not to reproduce a subject accurately, but instead to portray it in such a way as to express the inner state of the artist. On the other hand, "impressionism", born in France in late 19th century, was focused on natural paintings and light-colour changes. Bright colours and smooth transitions that hide the sharp edges were some of the determining features of impressionist art movement. "Cubism" movement, emerged in the beginning of 20th century, generated paintings that reflected different perspectives and involved analytic, visual-based features. The ratio of dark and bright colours used in the paintings possesses no determining power for cubist movement. However, the distinctive edges and, consequently, the high contrast are some of the determining features of this art movement. "Surrealism" was one of the leading influences of the 20th century and surrealist paintings exhibit free form objects and great variety of content.

After applying classification on each input, ArtHistorian indexes the paintings in the database with respect to their classification results, namely with respect to their art movements and painters. The extraction of the determining features and details of the classification are explained in [5] and are summarized in the third and fourth section, respectively. Fifth section gives detailed information about the database structure, and the query and filtering mechanism in ArtHistorian. Consequently, the classification and query performances are reported in the sixth section followed by the conclusion.

3. CONTENT-BASED INDEXING

The design of an automatic painting classifier requires the mathematical modeling of the visual clarities as determining features. In this paper, the features that distinguish the five fundamental art movements, namely, classicism, impressionism, cubism, expressionism and surrealism, are defined. However, the same feature set can be effectively used for more than five classes.

In [5], it has been shown that the content of paintings can be indexed by exploiting six different features. Suppose μ_i refers to i^{th} individual entity of the feature vector $\boldsymbol{\mu}$ for i=1,2,.,6. Physically, μ_1 is the percentage of dark colors. On the other hand, μ_2 is calculated from the gradient map of the painting image, and referred as "gradient coefficient". Especially, the "classicism" and "cubism" movements, and thereby, "classicist" and "cubist" painters can be classified quite accurately by using these two features. Classification performances of surrealist and expressionist paintings are augmented by μ_2.

The classification performances of paintings that belong to impressionism and classicism movements are augmented by the inclusion of two extra features: μ_3 is the number of local and global maxima in the luminance histogram. Moreover, μ_4 specifies the color range that corresponds to the peak point of the luminance histogram. Impressionist paintings generate one maxima in the bright regions of the luminance histogram, whereas classicist paintings generate a maximum point in dark regions. In cubist, expressionist and surrealist paintings, more than one maximum point occur in variable regions of the histogram.

Additionally, changing lighting conditions and the resolution of the painting images may cause false classification. Two more features are included to preserve the system performance against changing lighting conditions and scale changes. The first one, μ_5, is the standard deviation of average grey levels of sub-blocks from the entire image. Sub-blocks are chosen as non-overlapped equal-sized blocks and the value of μ_5 is not affected by scale changes. While, in impressionist or classicist paintings, this feature gives high values because of local brightness or semantic colour changes (human face, sky, etc.), it does not exceed a specific value for cubist paintings since each sub-block does not demonstrate a big deviation from the overall average value.

The colour distribution of paintings completely changes because of the variation in the lighting condition. However, the deviation of grey level distribution from Gauss is not affected with this art-effect. Therefore, "skewness", the criterion for deviation grey level distribution of the image from Gauss, is selected as the sixth feature, μ_6. Detailed mathematical definitions of the content-representative feature vector can be found in [5].

4. CLASSIFICATION OF ART MOVEMENTS AND PAINTERS

In this study, statistical pattern classification approach is used and the classification of artistic painting movements is performed using five different classifiers, including Bayesian parametric classifier, k-NN classifier, K-means clustering, fuzzy C-means clustering and Support Vector Machines (SVMs). Since they are well-known, we are not presenting details of the first four classification schemes [7]. In the following, the design of SVM classifier will be briefly described.

SVMs have been shown to have equivalent or significantly better performances than comparative classification methods. In this work, it is demonstrated that the SVM classifier is a suitable tool to discriminate the content of art paintings. Given n training observations each described by a feature vector $\boldsymbol{\mu}_i \in R^d$, i=1,…,n, where d=6 and the associated class label $y_i \in$ {*Set of Art Movements*} for art-movement-based classification and $y_i \in$ {*Set of Painters*} for painter-based classification, the hyperplane that separates the data satisfies: $\mathbf{w}\,\boldsymbol{\mu} + b = 0$, where **w** is the weight vector and normal to the decision hyperplane, b is the margin, and $|b|/|\mathbf{w}|$ is the perpendicular distance from the hyperplane to the origin.

The optimal SVM classifier that maximizes b is designed by maximizing the Wolfe dual of the Lagrange functional given in Eq.(1),

$$\max_{\alpha} L(\boldsymbol{\alpha}) = \sum_{i=1}^{n} \alpha_i - \max_{\alpha} \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j \mathrm{K}(\boldsymbol{\mu}_i \cdot \boldsymbol{\mu}_j), \quad (1)$$

subject to constraints

$$\sum_{i=1}^{n} \alpha_i y_i = 0, \quad 0 \le \alpha_i \le C(\xi_i = 0), \quad i = 1,\dots,n,$$

where α_i is the i^{th} Lagrange multiplier corresponding to the i^{th} training vector. If the training set is not separable, deviations of the misclassified samples from the decision boundary is controlled by a slack variable ξ_i, and the misclassification cost C defines an upper bound for the Lagrange multiplier, α_i, i = 1,…,n. The optimal value of C is determined by the grid search. [7].

In this work, because of the nonlinear separable nature of the feature vectors, a nonlinear SVM classifier is designed by using a Gaussian Radial Basis Function (RBF) kernel. The Gaussian RBF kernel is defined as $K(\mu_i, \mu_j) = e^{-\|\mu_i - \mu_j\|^2 / 2\sigma^2}$, where σ is the global basis function width.

ArtHistorian models the classification of art paintings as a M dimensional classification problem, where M denotes the number of art movements/the number of painters. Since the SVM classifier is originally designed for two-class classification, when M>2, ArtHistorian transforms the problem into $(M-1)M/2$ binary classification based on the one-against-one method [7]. For each class pair, the SVM classifier is trained and the hyperplane parameters **w** and b, that determine the decision surface, and the support vectors μ_s, $s = 1, 2, \dots, l$, that correspond to $\alpha_s > 0$, (where $l \le n$) are obtained. Then, the trained SVM classifier is used for the M class classification of query examples.

5. QUERY AND FILTERING

ArtHistorian enables content-based access to art paintings concurrently aiming to filter its database with respect to user preferences. Towards this end, classification is crucial for minimizing the database to a painting repository and for enabling fast and efficient query through a personalized collection set. Figure 1 displays how the data storage and query mechanisms work in ArtHistorian. Firstly, feature extraction and classification is applied to the input painting where the art movement and painter information are extracted together with the representational 6-D feature set. Additionally, some textual information, like title, creation date/place and description, are also associated with the content data (Figure 2). Through an indexing function, the input data is consequently added to the database with respect to its art movement and painter. Figure 3 shows the structure of the database formed in XML format, where the material data are placed in hierarchical levels enabling the fast query activities. Platform independency also makes XML a feasible data environment for Internet applications.

Data query is performed through the same mechanism given in Figure 1, where the database is filtered to a painting repository. The repository stores records of the paintings that belong to the art movement and painter focused by the user.

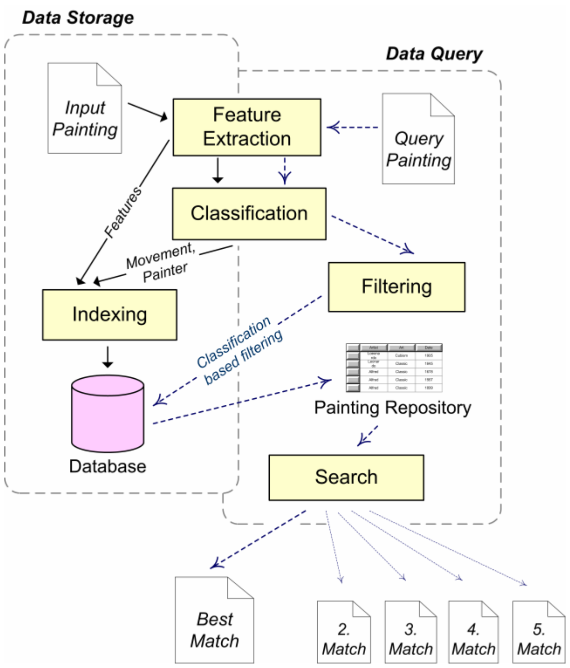

Figure 1. Query and data storage structure in ArtHistorian.

The queries are executed within the painting repository. This prevents the scanning of the extensive database and gives the relevant search results based on the user preferences. The painting repository is dynamically formed in the memory.

This formation enables the queries to be performed on either the art movement level where best five matching paintings that belong to the same movement are brought, or the painter level where best five matching paintings painted by the same artist are given. The queries can also be executed on both levels that generate more precise results based on the user interests (Figure 4).

6. RESULTS

6.1. Classification Results

Performance of the classification is crucial for the content-based data browsing proposed in ArtHistorian. Towards this end, ArtHistorian is designed in a flexible structure that enables the declaration of new classes, utilization of distinct classifiers, and employment of different feature sets. This section first reports the art-movement based classification performance of ArtHistorian, then, the results obtained for the painter-based classification.

In order to evaluate the performance of five different classifiers and robustness to the changes in the lighting conditions as well as the scale, a training set is constructed by collecting 27 original paintings from three fundamental art movements, i.e., classicism, cubism and impressionism, 9 from each class, 8 different painters [8]. The training set is formed by assigning the class labels to each training vector, and the training vectors are scaled to the range [0,1], in order to improve the performance of classification.

Two test sets are designed to evaluate the classification performance achieved by different classifiers. Test Set 1 includes 31 original paintings (12 classic, 9 cubic, 10 impressionist) of nine different painters. Test Set 2 collects 124 paintings (48 classic, 36 cubic, 40 impressionist) of nine different painters. Members of Test Set 2 are generated by changing the lighting conditions and scales of the paintings stored in the Test Set 1. Members of the test sets are also scaled. Note that none of the training samples used in the training set are included in the test sets. In the SVM classification, the best values of the parameters σ and C for the RBF are determined by the grid search method as 0.022 and 10, respectively.

Test results are presented in Table 1 through Table 4. Table 1 reports the art-movement based classification performance of ArtHistorian for Test Set 1. It is shown that the classification accuracy achieved by the SVM classifier outperforms the rest of the classifiers for each art movements as well as in overall. The overall success ratio is greater than 90% and the false alarm ratio is less than 10%, which is very low.

In order to evaluate robustness to scale and illumination changes, scale changes are simply generated by reducing the size of the original paintings. On the other hand, illumination changes are simulated by changing the

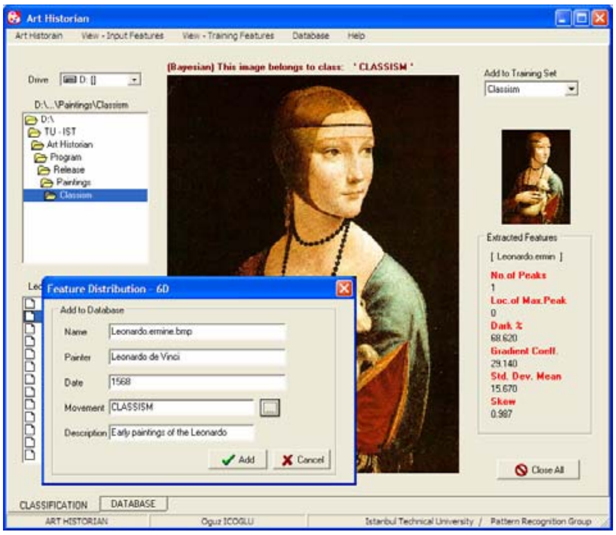

Figure 2. Adding a new input painting to database through the ArtHistorian's user interface.

```
<?xml version="1.0" standalone="yes" ?>
<DATAPACKET Version="2.0">
 <METADATA>
   <FIELDS>
     <FIELD attrname="TITLE" fieldtype="string"/>
     <FIELD attrname="PAINTER" fieldtype="string"/>
     <FIELD attrname="DATE" fieldtype="string"/>
     <FIELD attrname="MOVEMENT" fieldtype="string"/>
     <FIELD attrname="DESCRIPTION" fieldtype="string"/>
     <FIELD attrname="LOCATION" fieldtype="string"/>
   </FIELDS>
 </METADATA>
 <ROWDATA>
   <MOVEMENT attrname="CLASSICISM">
     <PAINTER attrname="Leonardo de Vinci">
       <TITLE attrname="Leonardo.ermine.bmp" />
       <DATE attrname="1568" />
       <DESCRIPTION attrname="Early paintings of.." />
       <LOCATION attrname="//Paintings/Leonar..bmp" />
       <FETURES peakcount="1.00" peakloc="0.00"
                blackper="68.62" grad="29.14"
                sdmean="15.67" skew="0.98" />
     </PAINTER>
        <… Other painters …>
   </MOVEMENT>
       <… Other movements …>
 </ROWDATA>
</DATAPACKET>
```

Figure 3. Database structure in XML format.

brightness and contrast of the original paintings stored in the Test Set 1. Classification accuracy obtained at 25% lower/higher brightness levels and at 25% lower/higher contrast levels are reported in Table 2 and Table 3, respectively. The mean performances obtained by taking the arithmetic average of the overall values given in the first three tables are reported at the last row of Table 1 (Mean Ov.). For each of the art movements, an overall classification accuracy higher than 90% is achieved by the SVM classifier. Thus it outperforms the rest of the classifiers.

We have also tested the performance of ArtHistorian for M=5 different art movements, including classicism, cubism, impressionism, expressionism, and surrealism. Therefore, Test Set 3 is designed by collecting 290 original paintings from 12 painters [8]. Note that Test Set 3 includes paintings in different resolutions, sizes, and aspect ratios. Table 4 reports the classification accuracy obtained by the Bayesian and SVM classifiers. As it is observed, the classification accuracy of Bayesian classifier radically decreases, when the number of classes are 5 (around 70%). Note that for the same test set, if we eliminate the paintings belonging to expressionist and surrealist movements, Bayesian classifier provides 100% accuracy (when M= 3: classicism, cubism, expressionism). Therefore, the decrease in its performance is because of the increase of M from 3 to 5. On the other hand, the SVM classifier achieves 100% accurate classification. In order to increase accuracy from around 90% to 100%, the number of training vectors, *l* is selected as almost ten times higher than the previous test set. It can be concluded that the proposed 6-D feature set with a SVM-based classification scheme is adequate to discriminate 5 different art movements. Note that the design of ArtHistorian is flexible, and users can simply declare a new class through its interface.

Art Movement	**TEST SET 1 – 6D**				
	Bayesian	k-NN k=7	K means	Fuzzy C-means	SVM
Class.	92	92	75	75	92
Cub.	89	89	67	100	100
Imp.	90	70	100	100	100
Overall	90	84	81	90	97
Mean Ov.	**83**	**78**	**83**	**87**	**93**

Table 1. Classification performance in 6-D.

Art Movement	**TEST SET 2 – 6D 25% Brightness Changes**				
	Bayesian	k-NN k=7	K means	Fuzzy C-means	SVM
Classicism	87	79	88	88	92
Cubism	83	83	72	83	89
Imp.	73	80	90	90	90
Overall	**81**	**81**	**83**	**87**	**90**

Table 2. Robustness to brightness and scale changes.

Art Movement	**TEST SET 2 – 6D 25% Contrast Changes**				
	Bayesian	k-NN k=7	K means	Fuzzy C-means	SVM
Classicism	96	75	88	79	96
Cubism	61	67	83	89	89
Imp.	75	70	80	80	90
Overall	**77**	**71**	**84**	**83**	**91**

Table 3. Robustness to contrast and scale changes.

Classifier / **Art Movement**	**Bayesian**	**SVM**
Classicism	94.53	100
Cubism	63.27	100
Impressionism	93.52	100
Surrealism	44.74	100
Expressionism	63.34	100
Overall	**71.88**	**100**

Table 4. 5-class art-movement based classification accuracy.

Classifier / Painter	Bayesian	SVM
Raphael	100	100
Sisley	92.6	100
Gris	93.55	100
Cezanne	88.58	100
Monet	89.48	100
Picasso	92.6	100
Leonardo	90.63	100
Rembrandt	100	100
Miro	64.71	100
Grozs	68.43	100
Dali	66.67	100
Kandinsky	90.91	100
Overall	**86.51**	**100**

Table 5. 12-class painter based classification accuracy.

In order to evaluate the painter-based classification performance of ArtHistorian, Test Set 3 is used for a M=12 class classification test. Table 5 reports the percentage of correctly classified art paintings by the Bayesian and SVM classifiers. It is observed that the performance of Bayesian classifier is still lower than the SVM, however, it is capable of discriminate painters with a higher accuracy than the art-movements. Even though the number of classes increased from 5 to 12, the accuracy of Bayesian classifier is higher than 85%, which is about 15% higher than its art movement discrimination capability. The SVM classifier provides 100% accuracy for this test case. Recall that the performance remains around 90% when the number of support vectors is small. Obviously, accuracy of the SVM classifier may drop for a large test set, however, it is almost always possible to increase the performance of SVM based procedures by a longer training. Penalty is the increased computational complexity.

6.2. Query Results

The retrieval results of ArtHistorian provide a degree of satisfaction. 290 paintings of 12 painters collected in the Test Set 3 are used for querying, where the brightness of the query paintings are modified, and the resolutions are changed. As it is described in the previous sections, ArtHistorian allows personalized browsing. Therefore, the user is capable of personalizing her/his query with respect to the art movements or painters. Browsing through the entire database without any personalization is also possible.

ArtHistorian offers two different search methods. First is based on Mahalanobis distance metric [7], where the distances between query painting and the records in the repository are calculated taking the dominant features of the query image's class into account. Therefore, the features are individually weighted with respect to their determining capability. The determining capability of features for each class is computed with Covariance Estimation performed over the samples in the training set. The second method is based on Euclidean distance metric [7], where features of the class are not weighted, as if all features equally possess the same determining capability.

For a painter-based retrieval from a database collecting the paintings of Test Set 3, 290 of the query examples were retrieved as the first best match, mainly because of the errorless classification performance of the SVM classifier. Obviously, this performance will be lower when the size of the database is extended without training the SVM classifier for the extended database.

It is observed that, when the classification accuracy is high, both Mahalanobis and Euclidean distance metrics retrieve the query example as the first best match, if it is stored in the database. However, their 2^{nd}, 3^{rd}, 4^{th} and 5^{th} matches are almost always different. Figure 4 illustrates the results of a query run over painter-based filtering. A query example of “Mona Lisa” with 25% contrast change (shown at the upper right side) is browsed. Figure 4(a) and (b) illustrate the paintings that ArtHistorian brings by using Mahalanobis metric and Euclidean metric, respectively. Note that the original of query example was retrieved as the first best match for both of the metrics. However, 2^{nd}, 3^{rd}, and 5^{th} best matches are different.

Another test has been performed on the paintings stored in the Test Set 2. 24 paintings apart from the training set are used for querying, where the brightness of the original paintings are modified by ±40% to ±60%, and the resolutions are reduced by 40%. When the Mahalanobis distance is used to express similarity, 13 of the query examples were retrieved as the first best match while 21 of them were in the best five matches. These numbers were changed to 9 and 21, respectively, when the similarity measure is Euclidean distance.

7. CONCLUSIONS

ArtHistorian, a prototype system, is developed for the classification and indexing of paintings based on their painters and art movements. We believe that the system provides a feasible structure that can be adapted by Internet art collections and Web museums. Moreover, ArtHistorain forms a potential infrastructure on personalized content browsing for tomorrow's prospective active Web museums. Currently, ArtHistorian considers five fundamental art movements, however, the used content representative feature set is also capable of discriminating more than five movements. Current work is focus on increasing ArtHistorian's browsing performance by improving its learning capability of user preferences.

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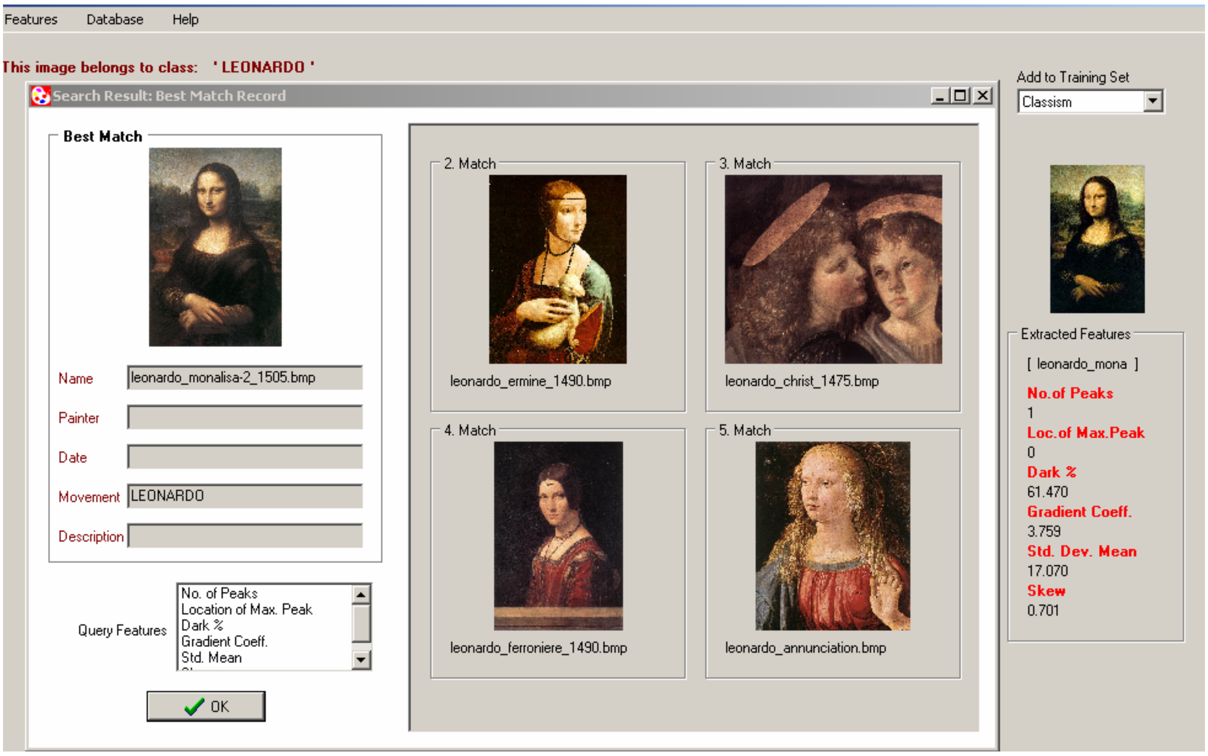
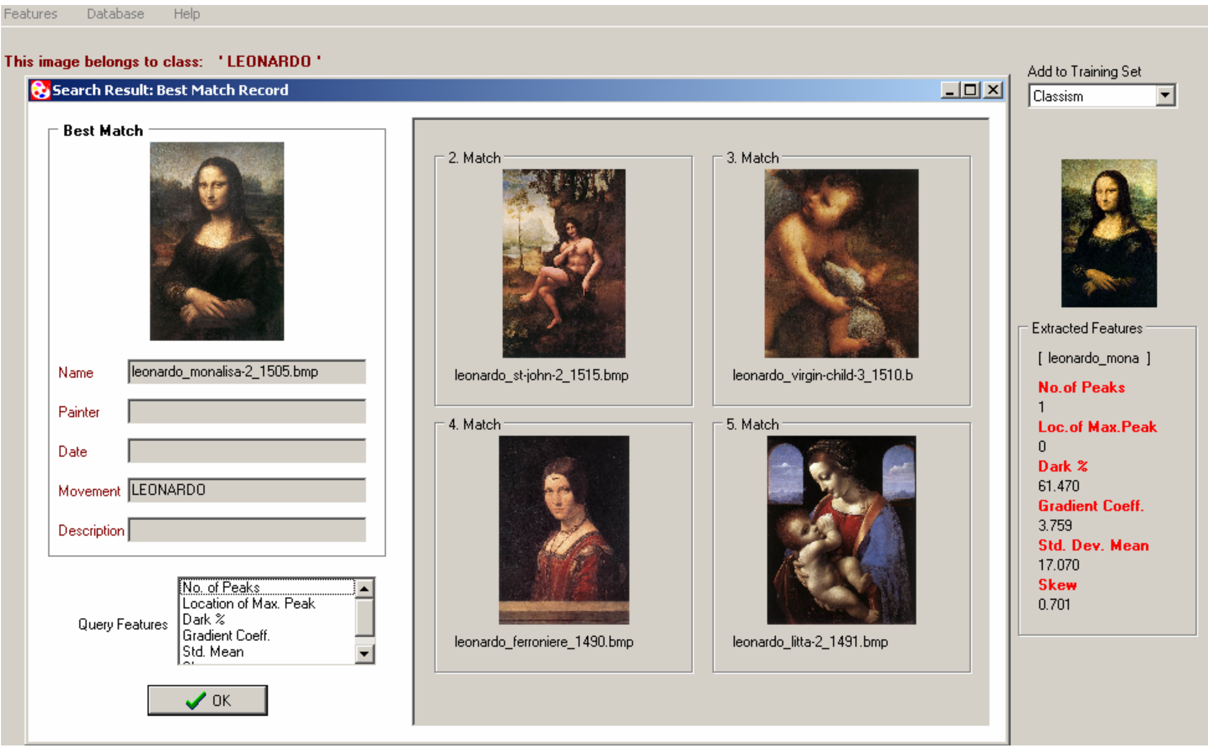


(a)



(b)

Figure 4. Results of a query run over painter-based filtering. A sample of "Mona Lisa" with 25% contrast change is browsed. ArtHistorian brings the correct painting together with similar paintings from "Leonardo" (a) by using Mahalanobis distance metric, (b) by using Euclidean distance metric.