Content-Based Access to Art Paintings

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Abstract—**This paper introduces ArtHistorian, a content-based classification and indexing system that represents the visual content of art paintings by a six-dimensional feature set. The introduced feature set 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 and painting styles. A hybrid classifier that combines PCA representation of paintings with the SVM classification is also exploited. It is shown that ArtHistorian is capable of classifying art paintings based on painters as well as art movements with an accuracy of greater than 90% and its false alarm ratio is very small. The developed system enables the user to run content-based queries and to retrieve from painting databases created in XML format.**

Keywords-Web museums,content classification, art paintings.

I. Introduction

Lately, several museums use the Web for presenting their large painting collections to the public. This requires a dynamic Web site topology which is adapting to the visitor's preferences. This is achieved by providing content-based access to paintings that allows the user to dynamically create presentations containing paintings which satisfy a selected similarity criteria, i.e., same art movement, same painter, same century, same visual content, etc. 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 classification and indexing system, that corporate automatically extracted low-level visual features in content-based classification for generating hypermedia presentations.

The developed system enables the user to run queries and search for a given painting in the database. When the user runs a query, the system looks through the paintings in the database and retrieves the best five matching record 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 stored in the database are in XML format, which is also the base language of MPEG-7 [2, 3]. Details of query and retrieval can be found in [4]. In this paper, we focus on the content representation and classification performance of ArtHistorian.

While designing an image indexing system, it is reasonable to expect that art paintings with similar visual content will be almost equally interesting to users. The visual characteristics of paintings are determined by the painter and the specific art movement that these paintings belong to. Several researches are focused on the identification of painters or painting styles, and offered indexing and retrieval schemes that can be exploited for artistic paintings [5, 6, 7]. The essential difference between the existing approaches and our method is the feature set used for content representation. We propose a novel six-dimensional content-representative feature set that enables to reflect characteristics of different art movements as well as the painters. Preliminary version of the feature set is presented in [8]. Another contribution of this paper is the use of a nonlinear SVM (Support Vector Machine) classifier [9] instead of neural networks or linear classifiers [6, 7, 8]. We have also combined representative methods by discriminative classifiers, and explored its effects on the system performance. The combination is achieved by applying PCA (Principal Component Analysis) to the extracted 6-D feature vectors followed by SVM training. Consequently, the classification is performed in the transformed feature space.

II. Extraction of Feature Vectors

Extraction of features representing the visual content of paintings is crucial in the design of an automatic classification and indexing system.

In this study, 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. Let the luminance component of a color image defined in RGB space is represented with 8 bits (256 grey level) and the pixels whose luminance value corresponds to [0,64] range are considered as dark pixels. Equation (1) defines μ_1 and μ_2.

$$\mu_1 = \frac{\text{Number of dark pixels}}{\text{Number of all pixels}},$$

$$\mu_2 = \text{Normalized}\left(\sum_{i=1}^{r}\sum_{j=1}^{c}\sqrt{(f_{ij})_x^2 + (f_{ij})_y^2}\right), \qquad (1)$$

where r and c are the number of rows and columns of the image, respectively, and $(f_{ij})_x$ and $(f_{ij})_y$ are the first order derivation of the image's (i,j) pixels in x and y directions, respectively.

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. However, these two dimensional feature vectors, alone, are insufficient for classification of other art movements, i.e., impressionism.

The classification performances of paintings that belong to impressionism and classicism movements are augmented by the inclusion of two extra features, defined as:

$$\mu_3 = \text{number}\Big(H(i) > thr\Big), \tag{2}$$

where *thr* is the threshold value determined to correspond the histogram to a maximum, and,

$$\mu_4 = \arg\max_i H(i), \quad i = 0, 1,.., 255, \tag{3}$$

where *H(i)* is the value of the histogram for i^{th} grey level.

As described in (2), 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. Main reason of defining these features is the discrimination of impressionist and classicist paintings from the other movements. 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 eliminate this drawback. The first one is μ_5, "Standard Deviation of Mean", described as in (4);

$$\mu_5 = \sum_{i=1}^{9}(mean_i - mean), \quad mean = \frac{1}{rc}\sum_{i=1}^{r}\sum_{j=1}^{c} f_{ij} \tag{4}$$

where $mean_i$ represents average luminance value of the i^{th} block, and *mean* is the average luminance value of the entire image. In the computation of μ_5, paintings in the training set are partitioned into 9 identical sub-blocks each of which preserves the original painting's aspect ratio. For each sub-block, average colour value is calculated in grey level. The deviation of these 9 values from the average colour value calculated for entire image gives out the μ_5. As μ_5 is the criterion for deviation of average grey levels of sub-blocks from the entire image, its value 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, and is calculated as in (5).

$$\mu_6 = \frac{1}{rc}\sum_{i=1}^{r}\sum_{j=1}^{c}\left(f_{ij} - mean/\sigma\right)^3, \tag{5}$$

where σ is defined in (6).

$$\sigma = \frac{1}{rc-1}\sqrt{\sum_{i=1}^{r}\sum_{j=1}^{c}\left(f_{ij} - mean\right)^2}. \tag{6}$$

"Skewness" attribute preserves its value, even when the brightness is harshly increased. It helps to successfully model the condition in classicist and expressionist movements, where colour distribution displays a different characteristic than that of the Gaussian distribution. Paintings of cubist and surrealist movements, generally, demonstrate a characteristic that matches the Gaussian distribution. However, in impressionism, the distribution slightly loses this property and it disappears considerably in the classicist movement.

III. CONTENT-BASED CLASSIFICATION

In this study, classification of artistic paintings based on art movements and painters is performed using six different classifiers, including Bayesian classifier, k-NN classifier, K-means clustering, fuzzy C-means clustering and Support Vector Machines (SVMs) [9]. A hybrid classifier that combines PCA representations with the SVM based discrimination is also evaluated. In the following, the design of SVM and hybrid classifiers will be briefly described.

A. SVM Classifiers for discrimination of painting styles

In this work, it is shown that SVMs have significantly better performances to discriminate the content of art paintings than comparative classification methods. SVM classifiers are originally designed for two-class classification. Since we deal with a M class classification, one-against-one method is used to transform it to (M-1)M/2 binary classification problems [9].

Given *n* observations each described by a feature vector $\boldsymbol{\mu}^i$, ϵ R^d, i=1,…,n, d=6, and the associated class label $y_i\epsilon\{$*Set of Art Movements*$\}$ for art-movement-based classification and $y_i\epsilon\{$*Set of Painters*$\}$ for painter-based classification, the hyperplane that separates the data satisfies: $\mathbf{w}\,\boldsymbol{\mu} + b = 0$, where $\mathbf{w}$ is the weight vector and normal to the hyperplane, b is the margin, and $|b|/|\mathbf{w}|$ is the perpendicular distance from the decision hyperplane to the origin. The parameters $\mathbf{w}$ and b are determined by training the SVM. The optimization of the margin can be achieved by using Lagrange multipliers function described in (7).

$$L(\boldsymbol{\lambda}) = \sum_{i=1}^{n}\lambda_i y_i K(\boldsymbol{\mu}, \boldsymbol{\mu}^i) + b\,. \tag{7}$$

where λ_i's are the Lagrange multipliers and $K(\boldsymbol{\mu}, \boldsymbol{\mu}^i)$ is the Kernel function specified by the user. In this work, since the RBF has the advantage of non-linear mapping into a higher dimensional space, a non-linear Gaussian RBF kernel is used thus $K(\boldsymbol{\mu}, \boldsymbol{\mu}^i)=\exp(-\gamma \parallel \boldsymbol{\mu} - \boldsymbol{\mu}^i \parallel^2)$, $\gamma>0$. To obtain a feasible solution for non-separable data and to manage the tradeoff between the margin and misclassification, the optimization constraints are relaxed and a cost parameter C >0 is defined. The optimal value of C is determined by the grid search method under the constraint $0< \lambda_i <C$. Among *n* training

vectors, $l < n$ support vectors are specified by the SVM training and used for the classification [9].

B. Hybrid Classification

The proposed hybrid classifier first transforms the extracted feature vectors into a new feature space by using PCA representation, then, performs SVM classification in the transformed domain. The idea behind integrating a data representative method with a data discriminative method is to improve the classification performance, especially in reduced dimensions. Dimension reduction is also important to decrease the computational complexity. After specifying the reduced dimension, the corresponding eigenvectors are used for the projection of both the training and test data sets into the new feature space. This is followed by the SVM training and classification steps, as described in sub section III. *A*.

IV. User Interface and Querying

ArtHistorian enables content browsing with a classification based indexing and query method implemented from the art historians' perspective. ArtHistorian's user interface includes a query formulation part. One way is to specify a query in terms of art movements and browse through the database. In this case, user shows a query example to ArtHistorian and asks other paintings of the same art movements. 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. After the classification, user can add the classified painting into the database and review or delete the existing records. Creation of a new class is also possible. Another way of posing a query is to make a query based database browsing in terms of a specific painter. In this case, ArtHistorian automatically specifies the painter of the query example and brings the best five matching of the paintings painted by the same artist. Yet another way is combination of these two querying into one scheme. A number of high-level conceptual information are also associated with a retrieved painting such as date of painting, title of painting, etc. and thus enabling the user to pose more specialized queries.

V. Results

Performance of the classification is crucial for content-based access to data. In order to evaluate the performance of six 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 art movements, i.e., classicism, cubism or impressionism, 9 from each class (8 different painters) [10]. For each painting, a 6-D feature vector is extracted and scaled to the range [0,1] in order to improve the performance of classification.

First, two test sets are designed to evaluate the classification performance of ArtHistorian. Test Set 1 includes 31 original paintings (12 classic, 9 cubic, 10 impressionist) from 9 different painters. Test Set 2 collects 124 paintings (48 classic, 36 cubic, 40 impressionist) from 9 different painters. Members of the 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 non of the training samples used in the training set are included in the test set. In the SVM training, the best values of the parameters γ and C for the RBF are determined by the grid search method as 1000 and 10, respectively.

Test results are presented in Table.I through Table.IV. Table I presents the 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 then 10% which is very low. The overall performance of Hybrid classifier is very close to the SVM classifier.

Table II reports the classification accuracy under different lighting conditions at different scales. Scale changes are simply generated by reducing the size of the original paintings. On the other hand, illumination changes are simulated by changing the brightness and contrast of the original paintings stored in the Test Set 1. The mean performances obtained by taking the arithmetic average of the overall values given in the first two tables are reported at the last row of Table I (Mean Ov.). For each of the three art movements, an overall classification accuracy higher than 90% is achieved by the SVM classifier. Thus it outperforms the rest of the classifiers. The hybrid classifier has the second highest score and its accuracy slightly drops under illumination changes.

Table III reports ArtHistorian's performance in 6, 4 and 2 dimensional feature spaces. Since the SVM and hybrid classifiers provided the highest performances, we only consider these two classifiers. For the SVM classifier, the dimension of feature vectors is reduced from 6 to 4, by eliminating the last two feature components. Similarly, the 2D feature vectors are obtained by eliminating the μ_3 and μ_4. This decision is made by applying the Forward Feature Selection algorithm [9].

TABLE I. Classification Performance in 6-D.

Art Mov.	TEST SET 1 – 6D					
	Bayesian	k-NN k=7	K means	Fuzzy C-means	SVM	Hybrid
Class.	92	92	75	75	92	92
Cub.	89	89	67	100	100	89
Imp.	90	70	100	100	100	100
Overall	**90**	**84**	**81**	**90**	**97**	**94**
Mean Ov.	**83**	**78**	**83**	**87**	**93**	**90**

TABLE II. Robustness to Scale and Lighting Changes.

Art Mov.	TEST SET 2 – 6D 25% Changes in Lighting					
	Bayesian	k-NN k=7	K means	Fuzzy C-means	SVM	Hybrid
Class.	90	77	88	84	94	92
Cub.	72	75	78	86	89	81
Imp.	74	75	85	85	90	90
Overall	**79**	**76**	**84**	**85**	**91**	**88**

For the hybrid classifier, the highest 4 and 2 eigen-values are used in the transformation to the 4-D and 2-D feature spaces, respectively. It is observed that the SVM classifier outperforms the hybrid classifier in 6-D and 4-D, however the hybrid classifier provides higher than 80% accuracy even in the 2-D feature space, in which SVM's performance remains less than 60%. It might be expected that the combination of PCA with SVM should increase the performance, however, in our case, this is only valid in 2-D, as shown in Table III. This is mainly because of PCA transformation is not scale and illumination invariant. Note that six of the feature components are required for an accurate classification.

In order to test the classification capability of ArtHistorian for M=5 different art movements, including classicism, cubism, impressionism, expressionism, and surrealism, Test Set 3 is designed by collecting 290 original paintings from 12 painters [10]. Note that Test Set 3 includes paintings in different resolutions, sizes, and aspect ratios. Table IV reports the results. 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. Therefore, the decrease in its performance is because of the increase of M from 3 to 5. On the other hand, both the SVM and Hybrid classifiers achieve 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. Note that, when the dimension of the feature space is reduced, the Hybrid classifier outperforms the SVM classifier.

In order to evaluate the painter-based classification performance of ArtHistorian, Test Set 3 is used for a M=12 class classification test. Table V reports the percentage of correctly classified painters by the Bayesian, SVM and Hybrid classifiers. It is observed that the performance of Bayesian classifier is still lower than the rest, however, it is capable of discriminate painters with a higher accuracy than the art-movements. The SVM and Hybrid classifiers provide 100% accuracy for this test case. Obviously, accuracy of the SVM and Hybrid classifiers may drop for a larger test set, however, it is almost always possible to increase the performance of the SVM based procedures by a longer training. Penalty is the increased computational complexity.

VI. CONCLUSIONS

ArtHistorian, a prototype system is developed for the classification and indexing of paintings based on their painters and art movements. Currently, ArtHistorian considers five fundamental art movements, however, the introduced content representative feature set is also capable of discriminating more than five classes. The system is robust to changes in scale and lighting conditions, and allows to create multimedia presentations based on the visual preferences of an individual user. Future work will focus on testing ArtHistorian's performance by improving its learning capability of new art styles.

TABLE III. OVERALL PERFORMANCE IN 6, 4, AND 2-D FEATURE SPACES.

	6D		**4D**		**2D**	
Test Data	**SVM**	**Hybrid**	**SVM**	**Hybrid**	**SVM**	**Hybrid**
Original	97	94	94	87	**Less Than 60%**	84
Changes in lighting	91	88	90	82		80
Overall	**93**	**90**	**91**	**83**		**81**

TABLE IV. FIVE-CLASS ART-MOVEMENT BASED CLASSIFICATION.

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

TABLE V. TWELVE-CLASS PAINTER BASED CLASSIFICATION.

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

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