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ARTISTIC GENRE CLASSIFICATION FOR DIGITIZED PAINTING COLLECTIONS

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This paper presents an automatic digital image classification system for the recognition of the artistic genre of paintings represented in consumer-quality digital images. The system is developed as a tool that helps a better understanding of visual arts by untrained users and is a first step into an automatic art painting guide. The developed system is based on the classical feature space paradigm; for each painting image a set of 12 relevant, descriptive features are extracted and feed to a classifier. The paper presents the possible use of SVM, AdaBoost and Neural Networks. The experiments are performed onto an image database containing almost 5000 digital painting images from six different genres (Baroque, Renaissance, Rococo, Romanticism, Impressionism and Cubism). We claim that the proposed approach outperforms the reported state of the art, in terms of classification performance, speed and size of the tested database.

Keywords: Image Classification, Paintings, Artistic Genre Classification.

1. Introduction

For the entire human history, the art world was considered reserved to human beings, but with the late growth of computers usage in daily life and the development of image processing and machine learning algorithms, the intelligent systems began to play a more important role in this field. Automatic art classification can be useful for both art experts, for automatically creating and organizing content oriented databases, and for inexperienced users. Furthermore, while automatic painting recognition and analysis is limited to examples included in the training database, genre classification can provide a broader understanding together with more details about a work of art, in order to assure a better understanding of the subject.

Lately, considerable efforts were put into creating image processing solutions that facilitate a better understanding of art [1], [2]. Extensive research was made in obtaining high quality and fidelity digital versions of art paintings

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with an apex reached by the VASARI project [3]. Complementary work included image analysis and diagnostics or virtual restoration, by color rejuvenation, pigment analysis, brush stroke analysis, lightning incidence, perspective anomalies, three dimensional space recovery, indicating whether the artist used optical tools, craquelure analysis or painting authentication as discussed in [4]. However, while most of the previously enumerated tasks are of great help for art historians, a high fidelity representation of art work is needed [2].

Contrary to most of the existing work, our purpose is to extend the advantages provided by image processing techniques in understanding art toward the general audience. The envisaged use case relies on non-demanding image acquisition (and thus prone to low pixel or color resolution, noise or other image quality artifacts) and robust analysis for genre identification. It should be mentioned that the envisaged approach is rather automatic and opposite from any art understanding approach, as introduced for instance in [5].

Typical understanding of art comes by placing it into the appropriate context, which, in the case of paintings, means the artistic genre or art movement. Although clear borders cannot always be determined between different genres, the visual art creations are usually grouped by art historians based on common elements (painting technique and semantic aspect) used by the artists. Painters belonging to the same art movement rely mainly on the same painting technique (brush stroke style, color palette, edge softness etc.) and approach the same themes [6].

Although the semantics of the painting plays a very important role in understanding, this aspect is not the subject of the current work, which is dedicated to the development of a genre classification method based on low-level image features.

As per our best knowledge there are only few approaches known in literature that try to solve this same problem. Gunsel et al. [7] present a classification solution based on six basic features extracted only from the luminance image. The performance of five classifiers is analyzed for discriminating between three genres: Classicism, Cubism and Impressionism. The downside of the work comes from the low number (31) of paintings used to test the system.

Zujovic et al. [8] rely on a set of gray-level features for classification in five genres: Abstract Impressionism, Cubism, Impressionism, Pop Art and Realism. The performance of five classifiers is discussed and evaluated on a database with 353 paintings.

Culjak et al. [9] present a solution for the classification of paintings belonging to Realism, Impressionism, Cubism, Fauvism, Pointillism and Naive Art. A set of features describing the HSV histograms and the amount of edges in the image are extracted obtaining a total number of 68 features. A database containing 693 images was used in order to evaluate the performance of four classification algorithms.

The current work relies on a low cardinality set of features extracted from digitized paintings that are capable of offering high performance in real life scenarios (important number of examples, important number of artists). The resulted feature space is further divided in areas assigned to artistic genre within a supervised learning framework. Practically, the features are input data for a trained classifier, which is experimentally chosen from various possible models.

The descriptive features are presented in section 2; the data set and the classifier choice are presented in section 3. Finally, the results obtained with the proposed system are discussed in section 4, while the last section is dedicated to some conclusions.

2. Feature Extraction

Attempts to use image extracted feature for distinguishing among artistic genres do exist in the literature [7], [8], [9]. We use a rather similar approach: first a set of features is extracted from the image than supervised classification follows. Some of the features already proposed in the literature are used, as well as a set of new features that proved to offer separability between different genres. The set of used features can be divided in luminance features, edge (or texture) features and color distribution features, for a total of 12 components. The set of used features is presented in Table 1. While some of the features are straightforward, other will be detailed in the following paragraphs.

Table 1

Description of the used features. Luminance (Lum.) are features based on the luminance image, Edge are features that are either based on Canny processed luminance image either specific edge image and color features are based on the HSV color space.

Feature	Type	Description
μ_1	Lum.	Luminance mean value
μ_2	Lum.	Maximum value of the 10 bins luminance histogram
μ_3	Lum.	Number of maxima in the luminance histogram
μ_1	Edge	Percentage of edge pixels
μ_2	Edge	Length dispersion of the most important straight lines
μ_3	Edge	Number of corners
μ_2	Edge	Overall power of details
μ_3	Edge	Percentage of details in the central area of the image
μ_1	Color	Orange-ness normalized with cyan-ess
μ_2	Color	Variance of the color palette
μ_3	Color	Color distribution in large blocks
μ_1	Color	Color distribution in small blocks

2.1. Luminance features. The first three features (μ_1, μ_2, μ_3) offer information about the brightness of the painting (overall brightness level, variation of brightness level across the painting). The amount of object illumination in a painting is typically used by the artist to infer certain mood to observer, thus being significant in genre discrimination. However, the use of the average illumination implies some constraints related to the uniformity of the image acquisition procedure across the entire database.

2.2. Edge features. Edge features are either computed on the gradient of the luminance image (μ_4, μ_5, μ_6) or on a color gradient map (μ_7, μ_8).

The amount of edges can be related to the brush stroke technique and with the level of details; this is defined as the percentage of edge pixels (μ_4) detected by a Canny edge detector [10] set with fixed edge intensity threshold values.

The historical period of a painting is also described by the power of abstraction which can be measured up to a certain extent by the distribution of straight lines. The classical Hough line detector was used to obtain information about the lines within the image [11]. The previously obtained edge map is thus transformed into the Hough plane and the lines corresponding to the highest 10 points in the plane are selected. The length for each of the 10 segments is then computed, and the variance of the lengths is taken as feature (μ_5).

Also related to the above-mentioned abstraction power is the number of corners within the image (μ_6). The corners are extracted from the image luminance following the approach described by He et al. [12].

The power of details is also assessed using information about the image color gradients. Let $G_x^R, G_x^G, G_x^B, G_y^R, G_y^G$ and G_y^B be the horizontal and vertical gradients for each of the R, G and B planes. The color gradient map is computed as:

$$G = \max\left\{\left|G_x^R\right|, \left|G_x^G\right|, \left|G_x^B\right|\right\} + \max\left\{\left|G_y^R\right|, \left|G_y^G\right|, \left|G_y^B\right|\right\} \tag{1}$$

A 256-bin histogram H_G is computed for the gradient map and each bin is weighted such that the high gradients are given a higher weight. The final feature is computed as the sum of the weighted histogram's bins:

$$\mu_7 = \sum_{i=1}^{256} (i/256) \cdot H_G(i) \tag{2}$$

Since some art movements are characterized by uniform distribution of details across the whole painting, while others contain a greater amount of details in the central part of the painting, the gradient distribution across the image support was analyzed. The central area C is defined for each painting as a centered rectangle with the sizes equal to 0.6 of the corresponding image sizes. The last texture feature (μ_8) reflects the percentage of important details (that is pixels with gradient magnitude above a certain threshold) located in the central area:

$$\mu_8 = \frac{Card\left\{ \underset{u,v \in C}{G} (u,v) > T \right\}}{Card\left\{ G_{u,v=1}^{M,N} (u,v) > T \right\}} \tag{3}$$

2.3. Color features. Color distribution features are extracted from RGB and HSV image representations. As noted by Ivanova et al [13], it is typically for artistic paintings that a 12-bin histogram representation of the Hue plane, H_H , exhibits two important modes in the orange and orange-cyan ranges. Although the two modes are located on the same position, unrelated to the art movement the painting belongs to, the ratio of the two modes varies from one genre to another. The next feature, (μ_9), is defined as the ratio between the hue histogram's value for orange (the third bin) and the value corresponding to cyan (the eighth bin):

$$\mu_9 = \frac{H_H(3)}{H_H(8)} \tag{4}$$

In art history, the artistic movements are separated, among others, by their color palette. In order to assess the number of different colors used in a painting, the image is sub-quantized to a representation of 4 bits per color component. The three sub-quantized color planes are merged into a single channel by alternatively interleaving bits from the binary representation of each color, leading to a single 12 bits plane representation of the image. The color feature (μ_{10}) is the variance of the 1000 bins histogram of the derived image representation.

$$\mu_{10} = \text{var}\{H(i)\}, i = \overline{1,1000} \tag{5}$$

The last two features reflect the distribution of the number of colors used across the painting. The image is divided into adjacent, non-overlapping, equal blocks at two different sizes (80 × 80 and 20 × 20). For each such block k, the variance of its color histogram H_k is computed as for the previous feature, obtaining a vector of variances:

Table 2

Image database content

Genre	No. of paintings	No. of authors
Renaissance	1000	104
Baroque	1000	198
Rococo	869	234
Romanticism	900	252
Impressionism	1000	28
Cubism	1000	11
Total	5769	827

$$v_k = \mathrm{var}\{H_k(i)\}, i = \overline{1,1000} \tag{6}$$

Finally, the features μ_{11} and μ_{12} are computed as the variances of the vector of variances described in equation (6), for the case of large image blocks (80 × 80) and respectively small image blocks (20 × 20).

3. Database and Classifier Design

One of the biggest challenges was the lack of standard public paintings databases, issue well known in the literature [2]. The performance is evaluated on a database containing 5769 paintings belonging to six different art movements, from 826 authors. The six art movements studied are: Renaissance, Baroque, Rococo, Romanticism, Impressionism and Cubism. The genres were chosen such that they span typical cases of highly separable classes (genres that are very different and easily to discern, like Cubism versus Renaissance) and highly mixed classes (genres that are very similar, hard to separate like Baroque and Renaissance).

As the images were gathered from various Internet sources, the acquisition conditions and image resolutions or quality may vary within extreme boundaries, from controlled professional acquisition to amateur image capturing. In order to avoid the normalization issues related to image size, all images were scaled at 0.3 Megapixel resolution. A distribution of paintings and authors across genres is presented in Table 2.

The classification of artistic paintings into genres was tested for five popular classifiers, Linear SVM, Nonlinear SVM, AdaBoost, Modest AdaBoost and Multilayer Perceptron, all using the same input image features.

The parameters involved in the feature definition were tuned on a separate database containing a total of 568 images, uniformly distributed across all artistic genres.

Table 3

Detection rates for tested classifiers: Linear SVM, Non-Linear SVM, Real AdaBoost, Modest AdaBoost and Multi-Layer Perceptron

Classifier / Genre	Linear SVM	Non-linear SVM	Real AdaBoost	Modest AdaBoost	MLP
Renaissance	57.5	60.3	59.1	52.9	**61.7**
Baroque	34.8	32	35.7	26.1	**35.6**
Rococo	27.6	30.2	29.9	26.6	**31.4**
Romanticism	27.3	29.7	29.6	26.3	**31.1**
Impressionism	57.6	66.4	58.4	58.5	**71.3**
Cubism	49.5	63.8	64.5	60.6	**62.5**
Overall	42.4	47.1	46.2	41.9	**49**

In order to increase the classification performance, the feature vector computed for the entire image was supplemented with the feature vectors computed for each of the image quarters. The classification was performed independently on each of the five feature vectors and a voting procedure was applied for the final decision. For validation, a 10-fold cross validation technique was used, as described in [14].

Since the SVM and AdaBoost classifiers are designed for two-class problems, a classification tree was constructed in order to solve the multi-class problem. For the non-linear SVM the Gaussian Radial Basis Function was used as kernel function. The maximum number of iterations for AdaBoost classifiers was set to 200. The Multi-Layer Perceptron has 12 input neurons and a hidden layer consisting in 100 neurons. The output layer has a number of neurons equal to the number of classification classes. The classifiers were independently optimized and the best achieved performance is presented in Table 3. The Multi-Layer Perceptron, yielding the best overall performance will be further used in the classification experiments.

4. Results and discussions

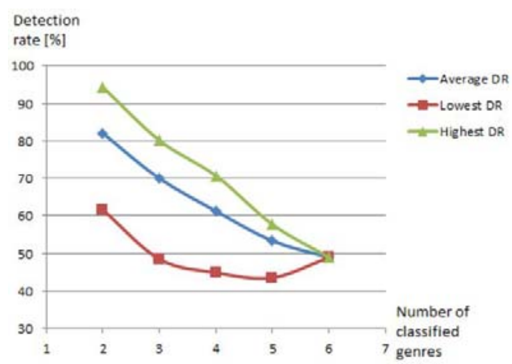
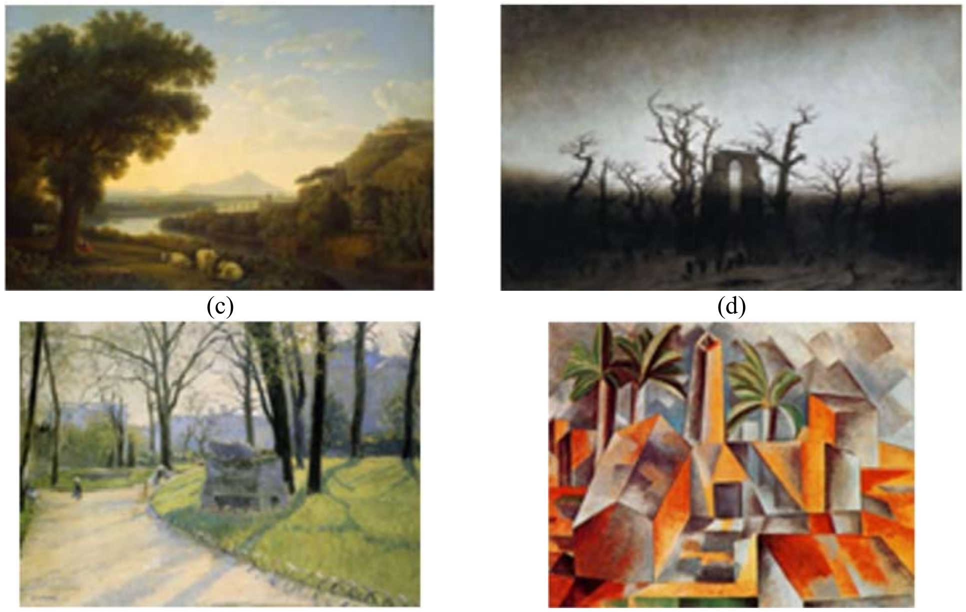


Fig. 1 Detection rate versus number of possible genres

(a)

(b)



(c) (d)

(e) (f)

Fig. 2 Examples of correctly classified paintings. (a) Renaissance: P. Lanciano “Madonna and Child with Saints” (b) Baroque: G. B. Viola "Penitent Magdalen in a Landscape" (c) Rococo: J.P. Hackert "Italian Landscape" (d) Romanticism: F.C. David "Italian Landscape" (e) Impressionism: G. Caillebotte "The Parc Monceau" (f) Cubism: P. Picasso "La fabrica de Horta d'Ebre"

All possible combinations of the following six genres were tested: Renaissance, Baroque, Rococo, Romanticism, Impressionism and Cubism. In Fig. 1, the average, the lowest and the highest detection rates are presented for each number of classes. For example, in the 4 classes case, the lowest detection rate of 44.87% is obtained when the Renaissance, Baroque, Rococo and Romanticism are tested. A low detection rate for this case is expectable, considering that the genres are very similar. On the other hand, the best result of 70.70% is obtained when Renaissance, Rococo, Impressionism and Cubism genres are selected.

An example of average detection rates obtained for multiple classes classification can be seen in Table 4. The used classes for each classification were: {Renaissance, Baroque, Rococo|Romanticism, Impressionism, Cubism} for 5 classes classification, {Renaissance, Baroque|Rococo|Romanticism, Impressionism, Cubism} for 4 classes, {Renaissance|Baroque|Rococo|Romanticism, Impressionism, Cubism} for 3 classes and {Renaissance|Baroque|Rococo|Romanticism, Impressionism|Cubism} for 2 classes classification. An example of correct classification is presented for each artistic genre in Fig. 2.

Table 4

Average Detection Rate for various number of classes

Number of Classes	**6**	**5**	**4**	**3**	**2**
Average DR [%]	49.0	55.9	65.6	76.9	88.8

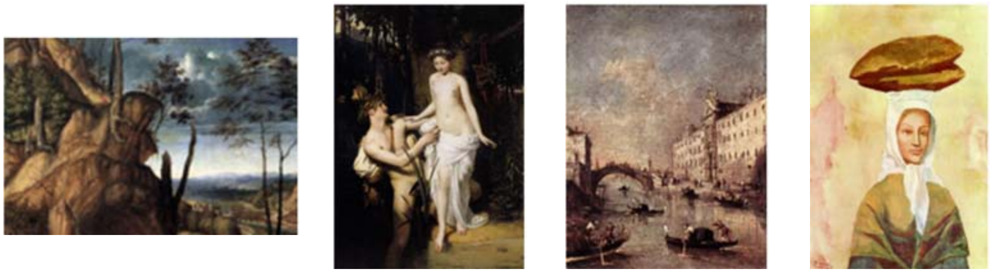
Table 5

Database content and Confusion matrix

	Images	Authors	**Ren**	**Bar**	**Roc**	**Rom**	**Imp**	**Cub**
Renaissance	1000	104	**617**	157	54	61	65	46
Baroque	1000	198	268	**356**	142	146	57	31
Rococo	869	234	168	157	**273**	158	70	43
Romanticism	900	252	156	189	141	**280**	97	37
Impressionism	1000	28	88	31	15	19	**713**	134
Cubism	1000	11	111	27	11	15	211	**625**
Total	5769	827	1000	1000	869	900	1000	1000

The similarities between different artistic genres can also be observed from the confusion matrix obtained for the classification with six classes, presented in Table 5. It can be observed that the highest confusion values occur between art movements that are harder to discriminate even for a human user if the semantic of the painting is not considered. Some examples of paintings misclassified by our solution and harder to discriminate without considering semantics can be seen in Fig. 3.

The main difficulty in comparing the proposed approach with similar implementations, such as presented in [7], [8], [9], is the rather impossible task of using the same image database. It should be mentioned that we are using a database that is 20 times bigger than the biggest database reported in the references above. Each author has used, apart the different number of image examples per class, different classes. Under these circumstances, we will chose the following comparison approach: we will globally compare the classification performance and the descriptor compactness for any reported approaches with more than 60 image examples per class; for smaller reported databases we will test the proposed features.



(a) (b) (c) (d)

Fig. 3 Examples of incorrectly classified paintings. (a) Renaissance as Rococo: L. Lotto "St. Jerome in the Desert" (b) Romanticism as Baroque: J.D. Court "Young Girl at the Scamander River" (c) Rococo as Romanticism: F. Guardi "Rio dei Mendicanti" (d) Cubism as Impressionism: P. Picasso "Woman with Loaves"

In [8], Zujovic et al. report results similar with us, with an overall detection rate of 68.3\%, but the evaluation was realized on smaller database (353 paintings), for five more clearly separable genres and using at least 26 features per image (as compared with 12 in the current proposed approach).

The solution presented by Gunsel [7] was implemented and tested. Upon testing the solution on our extensive database we were unable to confirm the very good results obtained by the authors on their original database (27 paintings used for training and 270 luminance-, contrast- and scale-modified versions used for testing). The larger database used in this work contains much more paintings, acquired with more variability. The results of the comparison are shown in Table 6, proving that, indeed, our solution outperforms the solution in [7].

5. Conclusions

This paper presents an effective method for painting classification based on artistic genres. A small but complete set of relevant features was developed. The performance of 5 classifiers is analyzed on an extensive database containing paintings from 6 different genres. The obtained results are comparable or better with state of the art and some of the art movements were analyzed for the first time, according to our best knowledge.

Although the achieved results are more than satisfactory being in the upper range of an inexperienced human, there still is a long way ahead until achieving results match the ones obtained by art experts. A 100% detection rate is practically impossible to achieve yet, as long as the separation between genres is not always very clear even for art historians and as long as the semantic of the painting is not taken into consideration.

Table 6

Detection rate comparison between the proposed solution and other similar solutions from recent literature; all tests are performed on the current 5769 image database

Genre	Gunsel et al. [7]	Our solution
Renaissance	47.2	*61.7*
Baroque	34.3	*35.6*
Rococo	13.8	*31.4*
Romanticism	20.3	*31.1*
Impressionism	49.2	*71.3*
Cubism	48.5	*62.5*
Overall	35.5	*49*

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R E F E R E N C E S

[1]. *M. Barni, A. Pelagotti and A. Piva*, "Image processing for the analysis and conservation of paintings: opportunities and challenges", in IEEE Signal Processing Magazine, **vol. 22**, no. 5, pp. 141-144, 2005

[2]. *B. Cornelis, A. Dooms, J. Cornelis, F. Leen and P. Schelkens,* "Digital Painting Analysis, At The Cross Section of Engineering, Mathematics and Culture", in Proc. of EUSIPCO, pp. 1254-1259, Barcelona, 2011.

[3]. *K. Martinez, J. Cupitt, D. Saunders and R. Pillay*, "Ten Years of Art Imaging Research", in Proceedings of the IEEE, **vol. 90**, no. 1, pp. 28-41, 2002.

[4]. *D. Stork*, "Computer Vision and Computer Graphics Analysis of Paintings and Drawings: An Introduction to the Literature", Computer Analysis of Images and Patterns, **vol. 5702**, pp. 9-24, 2009.

[5]. *J.A. Lay and L. Guan*, "Retrieval for Color Artistry Concepts", in IEEE Trans. on Image Processing, **vol. 13**, no. 3, pp. 125-129, 2004.

[6]. *L.S. Adams*, The Methodologies Of Art: An Introduction, Westview Press, 1996.

[7]. *B. Gunsel, S. Sariel and O. Icoglu*, "Content-based access to art paintings", in Proc. of ICIP, **vol. 2**, no. II, pp. 558-561, Genoa, Italy, 2005.

[8]. *J. Zujovic, L. Gandy, S. Friedman, B. Pardo and T.N. Pappas*, "Classifying paintings by artistic genre: An analysis of features & classifiers", Proc. of IEEE MMSP, pp. 1-5, Rio de Janeiro, Brazil, 2009.

[9]. *M. Culjak, B. Mikus, K. Jez and S. Hadjic*, "Classification of art paintings by genre", in Proc of The 34th MIPRO, pp. 1634-1639, Croatia, 2011.

[10]. *J. Canny*, "A Computational Approach to Edge Detection", in IEEE Trans. On PAMI, **vol. 8**, no. 6, pp. 679-698, 1986.
[11]. *P.V.C. Hough*, "Method and means for recognizing complex patterns", U.S. Patent, No. 3,069,654, 1962.
[12]. *X.C. He and N.H.C. Yung*, "Curvature scale space corner detector with adaptive threshold and dynamic region of support", Proc. of ICPR, **vol. 2**, pp. 791-794, 2004.
[13]. *K. Ivanova, P. Stanchev and B. Dimitrov*, "Analysis of the Distributions of Color Characteristics in Art Painting Images", in Serdica Journal of Computing, **vol. 2**, no. 2, pp. 111-136, 2008.
[14]. *P. Devijver and J. Kittler*, "Pattern Recognition: A Statistical Approach", Prentice Hall International, 1982.