

# Automated Painter Recognition Based on Image Feature Extraction

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**Abstract** - This paper describes an approach to automated classification of paintings by artist. The individual style of an artist is recognized through specific elements of a painting which distinguishes the work of an individual from the works of others. The proposed method for automated painter recognition focuses on the measurable elements in a painting which are represented with a set of global image features. The set of computed image descriptors includes statistical features that describe the intensity of a grayscale image, features based on color and textural features obtained using different techniques. Several classifiers were tested and their performance was evaluated on a collection of 500 digitized images of paintings from 20 different artists, obtained from various Internet sources. Experimental results show overall classification accuracy of 75%.

**Keywords** – image feature extraction, painter recognition, painting classification, visual art

## I. INTRODUCTION

Art experts can easily identify the artist of a painting using not only their capability to recollect a particular artwork but also their whole visual art experience which enables them to link specific artistic features with their corresponding artist. The attempt at automating this task is based on imitating the cognitive process of artist identification. The main challenge in automatic painting classification is the process of mapping information from the domain of visual art perception, which is characterized by the intricacy of artistic expression and high complexity of cognitive tasks [1], into the domain of computer image processing, based entirely on the numerical representation of information.

Determining the identity of the artist usually implies recognizing the artist's personal style - a set of specific characteristics perceived through different aspects of painting. The best starting point for computational classification of paintings is focusing on the formal elements of style such as color, light, line, texture, composition, etc. [2]. Information contained in these elements is derived from extracting image features. After image feature extraction process, a painting is represented with a set of numerical descriptors. The cognitive process of learning and recognizing is achieved through the use of machine learning techniques, while the database containing digitized images of paintings, mimics the human visual art experience.

An overview of related work is given in the next section. The third section presents the image features used for describing characteristics of a painting. Implementation of the classification system is presented in the fourth section which includes the database description, image extraction details and information about used classifiers. Classification results are presented and analyzed in the fifth section, while the final conclusion is given in the sixth section.

## II. RELATED WORK

Extensive digitization of paintings and the ongoing development of image processing algorithms enabled new approaches to visual art analysis. This includes painter identification, painting authentication, classifying paintings by artist or schools of art, finding meaningful connections between artists etc.

Several researches focus on classification of paintings by artist. In [3] the authors present a model for an interactive image retrieval system based on color features, i.e. number of different RGB colors used in the image, as well as frequency and spatial distribution of colors. Database included ten images from fifty different artists and they obtained overall retrieval rate of 49.2%. In [4] the author proposes classification of paintings based on discrete cosine transform coefficients using naive Bayes classifier. They tested five painters and achieved an 86% success rate on a dataset of twenty to thirty paintings for each painter. Work [5] describes a method for automated recognition of nine artists representing three different schools of art using a large set of image features and image transforms. For classifying paintings by artist, authors use a dataset of 360 training images and 153 testing images and achieve a classification accuracy of 77%. Paper [6] presents ArtHistorian, a content-based classification and indexing system that represents paintings by a six-dimensional feature set which consist of simple global image statistics. In order to test the classification capability of their system, the authors use 290 paintings from 12 different painters. With such a simple model, the authors claim to obtain very good results: 86.51% precision rate using a simple Bayesian classifier and 100% using a support vector machine classifier. Work [7] gives a comparison of different approaches to artist identification and presents a framework for classical western paintings classification based on a large

image collection which consists of 1080 images from 25 different classical painters. Their classification framework relies on global color, texture and shape features and local texture features. The classification is done by a radial basis function neural network and an identification accuracy of 69.7% is obtained.

Analysis and visualization of similarities and influential links between painters was done in [8] for 34 and in [9] for 51 different painters. Also, the use of similar methodological principles as in the task of classifying paintings by artist can be found in a considerable number of researches, [10, 11, 12, 13], that are focused on classifying paintings by schools of art.

### III. IMAGE FEATURES

The main part of implementing a system that can process visual art is the transformation of painting characteristics into numerical descriptors. In solving this task, various approaches are possible and different types of image features can be extracted. Color, composition and brushstroke are considered to be the most relevant characteristics of paintings [14]. To retrieve this information, this paper combines features based on image intensity statistics, color distribution and texture analysis.

#### A. Image Intensity Statistics

To describe the intensity of a grayscale image, following statistical features were calculated: global mean, variance, standard deviation and range of intensity levels, histogram of intensity levels and histogram features such as mean, standard deviation, skewness, kurtosis, energy and entropy. The mean value of intensity levels is high for a bright image, while a dark image has a low mean value. Variance, standard deviation and range of intensity levels are measures of dispersion that describe the image contrast. An image with high contrast has a large range, variance and standard deviation, while an image with low contrast is characterized by small values of dispersion measures. The histogram models the probability distribution of intensity levels in the image and its shape and features provide information about image characteristics. For instance, a very narrow histogram implies a low contrast image. The histogram skew is positive when the tail of the histogram spreads out to the right, and negative when it spreads out to the left. Kurtosis shows the sharpness of the histogram; a normal distribution histogram will have zero kurtosis. High energy implies a low number of different intensity levels in the image, while entropy increases as the pixel values in the image are distributed among a larger number of intensity levels [15].

#### B. Color-based features

Color is probably the most noticeable part of information we obtain when observing a painting and therefore color-based features are important when building a system for automatic painting classification. Used images are registered in RGB color space. However, the HSV color model corresponds better with the human perception of color and should therefore be more suitable and semantically relevant. The HSV color model consists of three components: hue (color that can be plucked

out of the light spectrum), saturation (colorfulness) and value (relative lightness or darkness of a color). The extracted features include histograms of hue (Fig.1), saturation and value components and mean, variance, standard deviation, energy and entropy values calculated for each histogram.

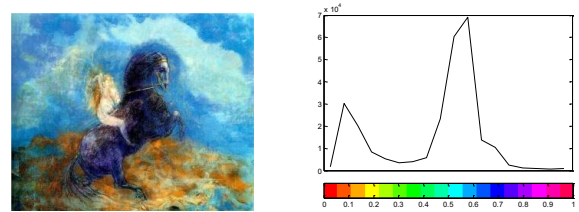


Figure 1. Example of a painting (Odilon Redon *Brunhild*) and its corresponding hue histogram

#### C. Texture based features

Visual texture of a painting is created with lines, shapes and brush strokes (Fig.2). In a digital image, texture can be seen as an image area containing repeated patterns of pixel intensities arranged in some structural way. [16] Although there is no formal and commonly accepted definition of image texture, there are various approaches for texture-based features extraction. In this paper, extraction of texture features was implemented in the spatial and spatial-frequency domains using three different methods: gray-level co-occurrence matrix [17], edge detection [15] and energy of discrete wavelet coefficients [18].



Figure 2. Examples of different textures in paintings

The gray-level co-occurrence matrix (GLCM), introduced by Haralick et al. [17], is a statistical approach that gives information about positions of pixels with similar gray level values. GLCM is defined by firstly specifying relative frequencies  $P(i, j, d, \theta)$  in which two pixels with gray levels  $i$  and  $j$ , separated by distance  $d$ , occur in a direction specified by angle  $\theta$ . In this study, the textural features were calculated from multiple GLCMs for values of angle  $\theta$  at  $0^\circ$ ,  $45^\circ$ ,  $90^\circ$  and  $135^\circ$  and for relative distance  $d$  of 1 pixel. From each computed GLCM four features were extracted: correlation (measure of how correlated a pixel is to its neighbor over the whole image), contrast (measure of intensity between a pixel and its neighbor over the whole image), energy (sum of squared elements in the GLCM) and homogeneity (value that measures the closeness of element distribution in the GLCM to the GLCM diagonal).

Edge detection is used to determine the amount of edges in an image. Relative frequency of edges within a painting can provide useful information considering that some artists, for instance Turner, typically paint soft and subtle edges, while

others, for example Malevich, paint clear and strongly marked edges. Extracted edge-based features include the ratios of edge pixels to size of image gained after applying Canny, Sobel and Roberts edge detectors and the ratios of horizontal and vertical edges calculated after detecting edges with the Sobel operator.

The two-dimensional discrete wavelet transformation (DWT) is an effective method for analyzing images in both spatial and frequency domains. To compute the wavelet features, Harr wavelet is calculated for the entire image and as a result the image is decomposed into four sub-bands. One sub-band corresponds to the approximation image, while other three sub-bands represent detail images [19]. The features obtained from these DWT transformed images include the percentage of energy corresponding to the approximation and percentages of energy corresponding to the horizontal, vertical and diagonal details.

#### IV. IMPLEMENTATION

##### A. Database

The image database includes paintings of twenty different artists from various historical art movements: Botticelli, Caravaggio, Rembrandt, Turner, Monet, Van Gogh, Waterhouse, Redon, Rousseau, Gauguin, Klimt, Mucha, Picasso, Dalí, Magritte, Kandinsky, Malevich, Pollock, Lichtenstein and Giger. Each artist was represented with a set of 25 images. The dataset of a particular artist was created with the intention to reflect the artist's unique characteristics and therefore it contains the most well-known and specific artworks. The images have been acquired through various websites and for this reason differ in quality and size. This might lead to inferior classification results but also minimize the source-dependency of images and enable the use of large databases that have not been collected under same conditions. In order to normalize all images into fixed dimensions, images were scaled to  $512 \times 512$  pixels.

##### B. Feature extraction

All features were extracted using Matlab. The complete system contains 111 features. This includes the 32-bin histogram of intensity levels, 18-bin hue histogram and 5-bin histograms of saturation and value components. Edges were found with Canny edge detector with thresholds 0.2, Sobel edge detector with threshold 0.1 and Roberts edge detector with threshold 0.6. The thresholds were chosen experimentally to select values that provide the most distinctly perceptible edges.

##### C. Classification

The classification of paintings by artist is performed using five different classifiers: multi-layer perceptron (MLP) [20] with one hidden layer, sequential minimal optimization for support vector machine (SMO) [21], Naive Bayes classifier [20], random forest [22] with 300 decision trees and AdaBoost M1 [23] with J48 as base classifier and 500 iteration. The classifiers were tested using Weka tool.

#### V. RESULTS

Evaluation of results was done by comparing classification results for different classifiers and analyzing how the use of different image feature types affects the classification performance. To validate the results of machine learning experiments, 10-fold cross validation was used. Classification accuracy is expressed using F1 measure which is a harmonic mean of precision (portion of the correctly classified images) and recall (portion of correctly assigned classes). Table 1. presents the results of classification for five different classifiers that were trained and tested using four different image features sets: the first column shows the results of classification when using only gray-level intensity statistical features (42 features), second column when using only color based features (37 features), third column when using only textural features (32 features) and the last column shows the results of classification when using all the extracted features (111 features).

TABLE I. PROPOSED FEATURES AND CLASSIFIERS (F1 MEASURE)

	Intensity features	Color features	Texture features	All features
MLP	0.459	0.479	0.597	0.753
SMO	0.430	0.519	0.538	0.745
Naive Bayes	0.411	0.496	0.516	0.651
Random forest	0.490	0.558	0.599	0.727
AdaBoost	0.486	0.549	0.624	0.752

Result analysis shows that the texture based features contribute the most to successful classification, while the image intensity statistics contribute the least. The reason is that texture based features include the most diverse types of image features. Also, textural features give the best information about lines, shapes and brush strokes which specify the style of a certain artist better than general image intensity or color.

The random forest classifier gives the best result for intensity and color feature sets; AdaBoost is best when using only texture based features and very good when using all extracted features, although in that case a slightly better performance is achieved with the multi-layer perceptron.

The overall true positive rate (the proportion of examples which were classified as class  $x$ , among all examples which truly have class  $x$ ) is 75%, whereas the result for a particular artist varies from 44% (Kandinsky) to 92% (Caravaggio and Lichtenstein). A more in-depth analysis of the results can be obtained by looking into the confusion matrix calculated from the MLP classification results, given in Table 2. Each column of the matrix represents the instances for a predicted class, while each row represents the instances for an actual class.

REFERENCES

TABLE II. CONFUSION MATRIX FOR MLP CLASSIFIER AND ALL FEATURES

	Bo	Ca	Re	Tu	Mo	VG	Wa	Re	Ro	Ga	Kl	Mu	Pi	Da	Ma	Ka	Ml	Po	Li	Gi
<b>Botticelli</b>	13	0	2	0	0	0	1	1	0	0	2	0	2	1	0	2	0	0	0	1
<b>Caravaggio</b>	1	23	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
<b>Rembrandt</b>	0	5	20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
<b>Turner</b>	0	0	0	20	1	0	1	1	0	0	0	0	0	0	2	0	0	0	0	0
<b>Monet</b>	0	0	0	2	17	1	0	2	0	1	0	0	0	1	1	0	0	0	0	0
<b>Van Gogh</b>	0	0	0	0	0	19	0	0	1	0	1	1	0	1	0	1	0	0	0	1
<b>Waterhouse</b>	1	0	0	0	0	0	21	0	0	0	2	0	0	0	0	0	0	0	0	1
<b>Redon</b>	0	0	0	1	1	0	0	20	0	2	0	0	0	1	0	0	0	0	0	0
<b>Rousseau</b>	1	1	0	0	0	2	0	0	17	0	1	0	0	1	1	0	0	0	0	1
<b>Gauguin</b>	0	0	0	0	1	0	0	1	0	19	1	0	0	2	0	1	0	0	0	0
<b>Klimt</b>	2	0	0	0	4	3	0	0	2	0	12	1	0	0	0	0	0	1	0	0
<b>Mucha</b>	1	0	0	0	0	0	0	0	0	0	1	22	0	1	0	0	0	0	0	0
<b>Picasso</b>	2	0	0	0	0	0	0	2	0	1	0	0	14	2	2	1	0	0	0	1
<b>Dali</b>	0	0	0	0	0	0	0	0	0	1	0	0	1	21	0	2	0	0	0	0
<b>Magritte</b>	0	0	0	1	1	0	0	1	0	0	0	0	1	0	20	1	0	0	0	0
<b>Kandinsky</b>	2	0	0	2	0	0	0	1	0	1	1	1	3	2	1	11	0	0	0	0
<b>Malevich</b>	0	0	1	0	0	0	0	0	0	0	0	0	1	0	1	1	21	0	0	0
<b>Pollock</b>	0	0	0	0	0	0	0	0	1	0	2	0	0	0	0	0	0	22	0	0
<b>Lichtenstein</b>	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	23
<b>Giger</b>	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0

Interpretation of the misclassified paintings might indicate general similarity between the works of different artists (e.g. Rembrandt and Caravaggio, as in [3]) and also point out artist whose work is more heterogeneous and therefore harder to classify correctly (e.g. Kandinsky or Klimt).

Comparison to the results of other painting classification approaches is difficult because this paper introduces several artists that have not been previously tested for automated painting classification, and due to the fact that image databases of existing classification methods vary highly in size and content.

CONCLUSION

This paper presents a simple and efficient approach to image feature extraction for the purpose of classifying paintings by artist. A set of global image features based on image intensity statistics, color distribution and texture analysis is calculated from digitized images of paintings which were obtained from different online sources. Considering that collected images were not uniform in quality or size, it might be expected that the described method would achieve better classification results using a more consistent database. On the other hand, this indicates that the system classification efficiency is not significantly impacted by changes to image quality and size. Future research is directed toward expanding the database of paintings by including a larger number of different artists. More importantly, future work aims to extend and refine the image feature set used for describing the characteristics of a painting.

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