MIPRO 2011, May 23-27, 2011, Opatija, Croatia

Classification of art paintings by genre

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***Abstract*—This paper offers an approach to automatic art genre classification of paintings. Development of machine learning algorithms and increase of overall computing power improved speed and efficiency of feature extraction from digital images and with it opened a whole new set of possibilities in classification of visual data such as paintings and other visual art. Automatic classification is useful in large database processing (e.g. museums) and could be used as a commercial application on mobile platforms. Six genres are classified in the paper: realism, impressionism, cubism, fauvism, pointilism and naïve art. Some of the genres have now been tested for the first time. Used features are described as well as a measure of their usefulness. Rate of success for different classifiers is given. Accomplished results are similar to related work results.**

I. Introduction

One of the tasks that people perform well is classification by type, e.g. classification of art works in genres, art movements or periods. However, it is not quite simple to describe the thought process of making a choice for a specific genre. Because of that, the task of painting classification into genres is traditionally entrusted to human experts.

Lately, along with development of machine learning algorithms and image processing, there have been attempts to perform this task automatically. Automatic computer classification is inspired by human perception of art and it is guided by art critics principles of distinguishing works of art. It has been shown that people perceive art genres through different elements of painting – colors, shapes, borders (e.g. motifs in painting, color palette, used techniques, brush stroke style, color mixing, edge softness etc.). There is no unique mechanism for visual art interpretation, therefore painting elements are interpreted separately [6]. Art genres often include a large number of painters, so a genre is distinguished from others by properties similar to some painters and different to other painters.

Related problems include painter identification, painting authentication, finding connections between painters etc. These problems have some similarities to the problem described in this paper, but they are basicaly different.

Classification in this paper will not consider semantics of a painting (i.e. the objects and motifs in painting, data about year of production and painter etc.) but only the painting technique. The following six genres are used: realism, impressionism, cubism, fauvism, pointilism and naïve art. Example of each genre is found on Figure 1.

In addition to art critics who can distinguish different artistic genres, there is a large number of people with limited knowledge of art who will potentially incorrectly classify similar genres. The assumption of this paper is that disagreements between people exist, considering classification in genres.

The next section gives an overview of related work. The third section describes the extraction of previously mentioned elements of the painting. Furthermore, the fourth section talks about tested methods of classification and the fifth section describes the final results. Conclusion and suggestions for future work on subject are given in the sixth section.

II. Related work

There are few works that focus on the classification of paintings by genre.

Article [3] describes the classification of five genres: classicism, impressionism, cubism, expressionism, surrealism. The used features in this work are information about "dark" pixels in the image (pixels whose RGB value lies in the interval [0,64]), information about the edges in the image (coefficient of gradient, i.e. Sobel's operator), luminance histograms (number of maxima in the histogram and the color of the histogram peak) and features that allow elimination of the influence of light conditions and image resolution, based on the gradient coefficients and luminance mean value. Selection of features is based on the idea that certain genres include much more dark pixels than other genres and reach different maxima in the luminance histogram.

Article [7] used a similar approach as in [3]. Features that were extracted on gray scale images are number of edges obtained by Canny edge detector and Gabor filters (the image is filtered several times with different parameters, and the mean value and variance of the sum of pixels is taken). Other features in this work are dealing with color in the image through histogram values for hue-saturation-value (HSV) color space. Used images have different resolutions and quality. They are obtained from the free art painting collection Artlex[1] and by using Google search engine. Classification of the following five genres is described: realism, impressionism, cubism, abstract expressionism, pop art. Large number of classifiers is tested in both works.

Article [5] uses a slightly different approach. Much more features are defined than in the previous two papers (various

[1] http://www.artlex.com

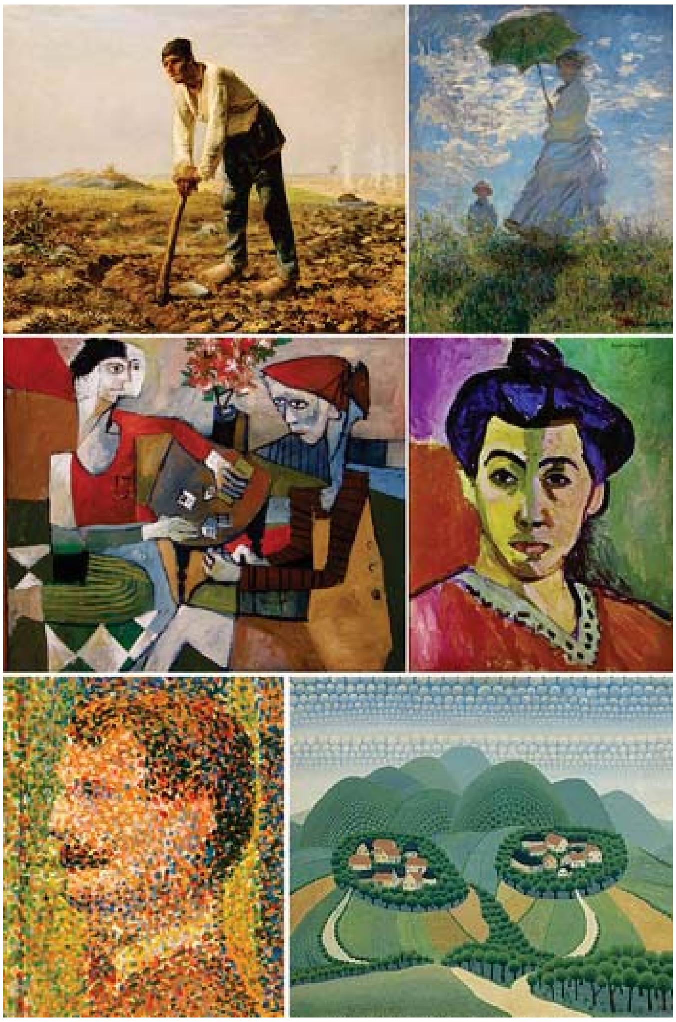

Fig. 1. Example paintings of used genres (shown in order): Realism, impressionism, cubism, fauvism, pointilism, naïve art.

edge statistics, object statistics, color histograms, Radon transformation etc.). Classification via Fisher discriminant analysis is then conducted, using the following three movements: impressionism, expressionism, surrealism. The paper achieves better results than other works, but this is partly expected due to smaller number of classes and possibly due to greater separability between them.

Our paper will use similar guidelines for feature extraction and some of the features described in these articles with moderate changes. Image database is obtained in the same way (images found by Google search engine, with variety in quality and size). Main difference from other papers is that they classify mostly the same genres that are usually very well mutually separable.

This work will, with the exception of already tested genres (impressionism, realism, cubism), introduce several new genres that haven't been yet tested as far as we know (fauvism, pointilism, naïve art). Some of the introduced genres partially overlap, which further complicates the correct classification.

Fig. 2. On the left is the original image, and on the right is the image after sharpening.

For some of these genres large databases could not be obtained.

III. Feature extraction

This paper is combining features recommended in related work as well as proposing some new features. Baseline idea is to find features that improve genre separability without considering the semantics of a painting. Features are based on color distribution or texture analysis since this is how humans perceive and classify art (before taking semantics into consideration). Genres were chosen in a manner that there are different and easily discerned genres and several similar genres that are hard to separate.

A. Image filtering

Image filtering is useful since it can reveal additional information hidden in poor image quality or large number of details in image. Most common filters convolve image elements with filter kernel. The following filters have been used: blur, sharpen and edge detection. Some features require several filters applied in a sequence. An example of a sharpen filter is given in Figure 2.

B. Color based features

Certain genres have mostly dark or mostly light paintings, some genres have a wide color palette while others use a specific color tone. Colors can be considered through several color models and this paper uses two models or color spaces: red-green-blue (RGB) and hue-saturation-value (HSV). Luminance component of color is calculated separately. Basic tool for color space analysis are histograms (an example histogram generated for the original image in Figure 2 can be seen in Figure 3). Histograms show color component distribution of an image.

Basic histogram feature is mean value for intervals of the normalized histogram. For a given interval k, mean μ_k^{color} is calculated as:

$$\mu_k^{color} = \frac{\sum_{i=k\cdot l}^{(k+1)\cdot l} H(i)}{l \cdot H_{max}} \quad (1)$$

where l is interval length, $H(i)$ is the normalized histogram value for value i of a color component. H_{max} is the maximum value in the normalized histogram. E.g. green color histogram in Figure 3 has the following mean values: 0.38, 0.83, 0.72, 0.55, 0.41, 0.31, 0.11 and 0.02 for $l = 32$. These eight values show that the first half of the histogram dominates and that tells us that green colors of the image in Figure 2 are mostly dark.

In similar manner as in [3], number of local maxima is considered on any given histogram (LM^{color}). E.g. luminance histogram in Figure 3 has 4 local maxima. Depending on the position of every maximum, a conclusion can be made on general image lightness. From this luminance histogram example, we can say that the image from Figure 2 is mostly dark or mildly light.

In addition to the number of local maxima we are also looking for the position of the highest value (i.e. peak). For the given example, luminance histogram has the value of $\varphi^{luminance} = 0.17$ for the highest local maximum. Value range is $[0, 1]$ with darker pictures closer to 0 and brighter pictures closer to 1.

It is also possible to count the number of pixel values in a given interval divided by the number of pixels in the image to get various pixel ratios. One possible use of this feature is counting pixels in luminance range of $[0, 64]$ (dark pixels) as in [3]. The result is a ratio of dark pixels in an image, i.e. "darkness" of the image.

Table I contains some of the values for one picture from each genre. Although generalization based on a single sample is inaccurate, it serves as an example of difference between genres based on color features and that those features could be important for classification. More on that in section V.

Main differences between genres are based on luminance. Fauvism, cubism, pointilism and naïve art use more transitions in intensity, while impressionism and realism use fine and even transitions. That results in reduced number of local maxima in luminance histograms for those two genres. Some genres have certain dominating colors. Naïve art mostly depicts natural motifs so green color is prevalent, while realist artists have darker pictures that lean toward red tones. Cubists like intensive colors and have high maxima for each color component and saturation values are high. In addition to numerical values in Table I those characteristics are easy to notice in Figure 1.

C. Features based on texture

Texture of a painting is characterized by brush strokes, shapes and general details. Sharpened image in Figure 2 shows that the artist uses very rough textures with more brush strokes than originally perceived. Some genres use rough painting style with visible edges, while others have smoother transitions. Excellent tools for extracting features based on texture are filters for edge detection and detail enhancement.

Main feature of a texture is the amount of edges in an image. Canny filtered image is black where there are no edges (example in Figure 4). By counting colored pixels and dividing by total number of pixels we get the ratio of edges in an image. For the given example using Canny edge filter we get

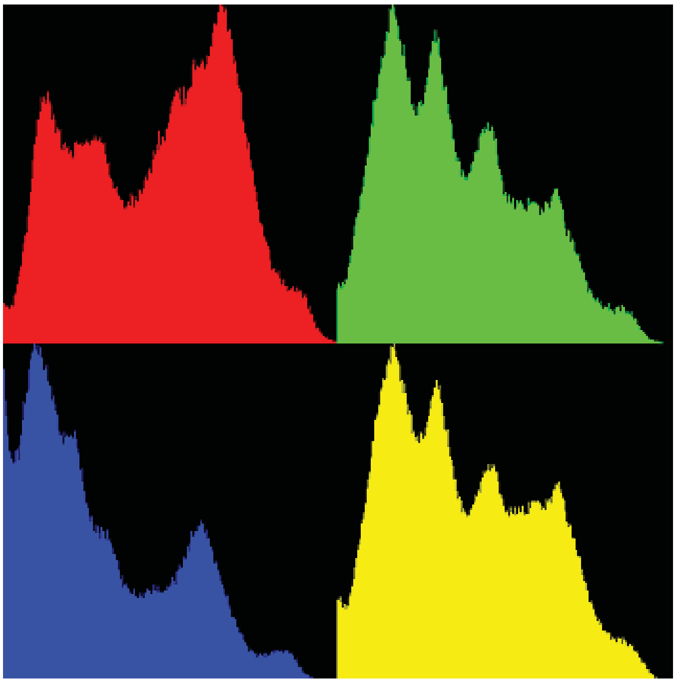

Fig. 3. Example of red, green and blue color and luminance histograms. On abscissæ are values of red, green, blue and luminance intensity in interval of $[0, 255]$, while ordinates have normalized histogram values in range of $[0, 1]$.

the ratio of 0.09. Canny filter thresholds are the same as in [2], as implemented in the *Java Image Processing Toolkit* library[2].

We extended edge detection with additional image preprocessing, such as sharpening or blurring. Sharpening distinguishes smaller – more detailed edges, while blurring removes them and leaves only more substantial edges. Using preprocessing on the given example we get 0.11 edge ratio for the sharpened image and 0.04 for the blurred image.

Blur and sharpen filters are also used to determine how sharp or blurry an actual image is. By using the filters, subtracting the original image and counting colored pixels it is possible to determine the sharpness of an image. Even though this feature is related to the edges, it looks at their surroundings rather than the edges themselves.

It is possible to combine filters, change their order and perform operations before and after filtering. Example of one such combination is filtering an image with two different sets of filters and calculating the ratio of differences between them. Interpretations of such combinations can be complicated, but they prove to be very useful in classification.

Some images are horizontally or vertically symmetric. Measure of symmetry is determined by subtracting images mirrored by a given axis. Counting dark elements on a filtered image gives a ratio of elements that are mirrored on the other side of an axis.

[2]http://sourceforge.net/projects/jipt/

TABLE I
SOME VALUES OF COLOR FEATURES.

Genre	$Max(\mu^{red})$	$Max(\mu^{green})$	$Max(\mu^{blue})$	LM^{lum}	φ^{lum}	φ^{hue}	φ^{sat}
Fauvism	0.61	0.68	0.72	4	0.08	0.04	0.61
Cubism	0.81	0.83	0.97	4	0.17	0.08	0.65
Impressionism	0.94	0.76	0.88	2	0.66	0.57	0.70
Realism	0.73	0.46	0.68	2	0.90	0.14	0.92
Pointilism	0.03	0.82	0.73	4	1.00	0.08	1.00
Naïve	0.47	0.54	0.69	6	0.07	0.46	0.07

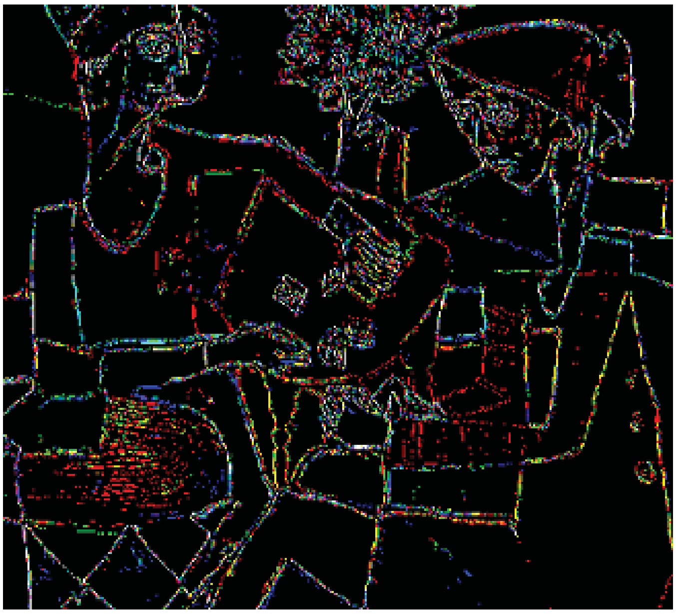

Fig. 4. Canny filter example

TABLE II
IMAGE DATABASE.

Genre	Number of images
Realism	166
Impressionism	165
Cubism	95
Fauvism	140
Pointilism	67
Naïve art	60
Total	693

IV. CLASSIFICATION

Several classifiers with different settings have been tested using Weka tool.[3] We used the following classifiers, chosen because of their speed and accuracy: artificial neural network (ANN), random forest [1], sequential minimal optimization for support vector machine (SMO) [4], k nearest neighbors (k-NN) and decision table.

V. RESULTS

Examples used for training and testing were obtained using Google search engine and Artlex image database. As genre labeling reference we were using Artlex database and Wikipedia. Number of images per genre (class) and overall number of images is shown in Table II. Due to time and memory requirements, large images were scaled so their larger side is equal to 1024 pixels (factor was 1024 by larger side).

It is quite possible that there is a certain number of images whose genre is not correctly determined at our sources (Artlex, Wikipedia), but this is expected and acceptable as determination of the genre of image is not unique. In addition, some of the genres partially overlap (e.g. impressionism vs. fauvism or pointilism as branches of neo-impressionism). Unfortunately, this problem will affect the test results. Selected examples vary in size and quality (most of images are lower quality), which contributes to the use of these methods in everyday life, such as photographing paintings using mobile phones.

For validation we have used 10-*fold* cross-validation, and *a priori* probability (probability that image from database belongs to class c which is equal to N_c/N, where N_c is number of images in class c and N is number of all images in database) as the reference method. Reason for that choice of reference method is the assumption that most people are not very good at recognizing the genre of a painting, so they will guess when genres overlap.

The results of the reference method range from 8.66% accuracy for naïve art as a genre with the lowest number of examples to 23.95% accuracy for realism, which has the largest number of examples.

The complete system contains 68 features:

1) mean values of histogram intervals for RGB and HSV color and luminance (50 features),
2) number of local maxima for the HSV color and luminance histograms (4 features),
3) positions of the peak for HSV color and luminance histogram (4 features),
4) ratio of dark pixels,
5) amount of edges extracted using Canny edge detector, with and without previous blurring/sharpening (4 features),
6) estimation of image sharpness (2 features),

[3]http://www.cs.waikato.ac.nz/ml/weka/

7) vertical and horizontal symmetry (2 features),
8) ratio of sharpened edges and real edges.

Overview of the classification performance using different classifiers and different combinations of features is shown in Table III. Classification performance is expressed using F_1 measure which is harmonic mean of precision (P) and recall (R):

$$F_1 = 2 \cdot \frac{P \cdot R}{P + R}, \tag{2}$$

while precision is defined as portion of the correctly classified images, and recall is the portion of the correctly assigned classes:

$$P = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}}, \tag{3}$$

$$R = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}, \tag{4}$$

where TP is number of images of class c that were classified as class c, FP is number of images which are not part of class c but they were classified as class c and FN is number of images of class c that were not classified as class c. Features connected with color are shown at the column labeled "Color," they were previously listed as 1st, 2nd, 3rd and 4th feature. Features associated with texture properties are shown in column "Texture," and are listed as 5th, 6th, 7th and 8th feature. Column "All" includes all listed features.

From result analysis it is clear that the features derived from texture, although their small number, contribute more to successful classification than features derived from color. The reason is the fact that genres do not differ greatly by color properties but more by ways of painting shapes and image semantic. Some paintings under the same genre may be predominantly green and bright, and some dark and red. On the other hand, strong edges are typical for cubism while lighter edges and mixing colors are more typical for impressionism. Use of the color based features could be more successful for other genres, like those listed on related works.

It is interesting to note that the performance of classifiers based on rules (decision tables), trees (random trees) and distance (k-NN) decreases when using all of the features. Further experiments have shown that the reduction of the number of features (e.g., removing color histograms) increases performance of those classifiers. This indicates that there is a problem with too large dimensionality of feature space. Although these classifiers have better performance on reduced feature set, they still do not surpass the ANN and the SMO classifiers.

Relationship between genres is shown in Table IV. Pointilism is a genre with the best separability. It is followed by cubism, naïve art and realism as satisfactory separable genres. Fauvism and impressionism have the worst statistics, which could be explained from the fact that those genres originate from approximately the same period and many artists who have represented one movement were connected with other movements. Fauvism is often mixed with cubism, and the reason for this is relative closeness of genres, which is visible at Figure 1 where both paintings are full of strong lines and large areas of various intensive colors. A lot of genres are classified as realism, which probably arises from the monotony of color and shape of that genre.

TABLE III
CLASSIFICATION RESULTS FOR ALL CHOSEN FEATURES, F_1 MEASURE IN PERCENTS.

Classifier	Color	Texture	All
ANN	37.7	55.0	56.6
RandomForest	38.2	53.2	50.7
SMO	42.5	52.1	60.2
k-NN (30)	38.8	52.9	46.4
DecisionTable	36.6	47.0	44.3

TABLE IV
CONFUSION MATRIX FOR SMO CLASSIFIER AND ALL FEATURES.

	C	F	I	N	P	R
Cubism	53	9	7	4	0	17
Fauvism	14	50	13	7	1	5
Impressionism	7	14	37	14	2	16
Naïve art	5	5	6	35	4	5
Pointilism	0	2	4	1	59	1
Realism	7	3	12	9	0	59

After removing impressionism from the system, SMO classifier achieved a success rate of 68%, while removing fauvism SMO achieves success rate of 64%. That indicates that impressionism may be too similar to other genres, therefore we need a feature or set of features that would improve separation of that genre from the others. Regarding the low performance of features based on color, it is more likely that such features could be found in the analysis of textures, edges and shapes.

In [7] maximum achieved accuracy is 68.3%. A maximum accuracy in [5] is 91%, but their method is tested on only 3 genres. In [3] maximum accuracy has reached over 90%, but [7] cites the same article and note that their maximum accuracy is only 49.8%. Therefore we can assume that there is a problem at comparing methods on different genres. The features can be highly dependent on the genre, so comparing different methods is problematic. With the achieved F_1 measure at amounts of 60.2%, 64% and 68%, we find our work commensurate with related works.

VI. CONCLUSION

This paper presents an effective approach to classification of paintings by art genre. The features are based on the color and texture of an image. Due to large number of genres, partly overlapping genres and low quality of examples, we can determine that it is possible to achieve better results by using better database or choosing other genres. In future work, it would be useful to develop new features describing the image texture.

We can conclude that computer's ability to analyze paintings raises important questions about the perception of applied arts.

We can ask ourselves could computer systems become art critics and could they do more than just evaluate art – could they create it?

ACKNOWLEDGMENT

We would like to thank Ivan Krišto for helping us in improving this paper.

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