

SYSTEM ANALYSIS OF THE PROBLEM OF ESTABLISHING THE AUTHENTICITY AND AUTHORITY OF PAINTING WORKS

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Abstract. Cultural values have long been the objects of crimes, among which the export from the state stands out. Falsification hides artworks from customs control and its detection requires a long examination using a variety of methods of analysis. This article discusses the task of verifying painting's authenticity during customs inspection. A two-stage procedure is proposed, which includes a quick check based on the analysis of painting's images and a longer museum expertise. To implement the image analysis, it is proposed to use an intelligent decision-making system, which is based on a classifier that implements the k -nearest neighbors algorithm. A set of features to describe painting's properties is formed, metrics for calculating the similarity measure on objects in the course of classification is proposed. To train an algorithm, a dataset is proposed, which includes paintings by world and European artists, as well as Ukrainian painters from different centuries.

Keywords: intelligent decision-making system, automatic classification, k -nearest neighbors, customs examination, paintings.

INTRODUCTION

The rapid rates of art market growth and constantly increasing demand for works of fine art have led to the fact that the problem of authenticating works of art has become extremely urgent for all market participants: art museums and galleries, auctions, collectors and individuals, and for states customs services.

Works of fine art have long ceased to be just an expression of the artist's ideas and intentions; they often function as payment means and objects for profitable investments. For this reason, the paintings of famous masters have become associated with criminal activities — forgeries, embezzlements, illegal transportation across state borders. The canvases of famous artists are especially widely falsified. Falsifiers not only inflict enormous material damage on states, paintings owners, but also spiritually devalue the works of great masters of painting, which poses a threat to the economic security of states [1]. Falsification of works of fine art means the production of counterfeit painting objects and their sale to obtain material benefits. Depending on forger qualifications, used techniques, technical means and materials in painting, there are fakes of different complexity — from simple (copying) to super forgeries, to establish which authenticity is extremely difficult even for specialists.

Expertize procedures are used to establish the paintings authenticity, or at least to determine the degree to which they are classified as “cultural value” or “national wealth”. There are two types of expertise — customs and museum ex-

expertise [2]. The purpose of the customs examination is to ensure economic security in the country. Customs expertise is strictly structured and has a hierarchy of goals, where dating is at the top, and rest of data obtained is additional and basic for the conclusion whether this work belongs to the appropriate category.

The ultimate goal of museum expertise is to establish the authenticity and authorship of a painting. Currently, four main methods of authenticating pictures are used: forensic, attributive, technological, complex [3].

The forensic method includes: studies of author's signature on the picture; examinations of painting author fingerprints; research of handwritten notes, signatures, imprints of seals (stamps) on reverse side of the picture; analysis of provenance reliability (the work ownership history from creation moment to present). Currently, the concept of provenance has expanded: it also includes a list of checks or invoices proving the fact of purchasing an item for a certain amount, expert assessments, history of participation in auctions, reproductions in books and catalogs, participation in exhibitions, as well as any references in relevant literature.

The attributional method consists in studying the art form details to find out the specifics of master individual style.

The technological method is implemented using various technical means of analysis: microscopic, X-ray spectral, macrophotography, as well as photography in ultraviolet and reflected infrared rays, etc. In the technological method of research, all elements of picture are analyzed: base, soil, paint layer, etc. From the obtained data, it is established that at various stages of his career, what certain primers, paints, varnishes, brushes the artist used. The results show that each artist has his own manner of "painting", his own special technique, and style. To increase reliability of making a decision on the paintings authenticity, a complex forensic, technological and art history expertise is used [4]. The practical use of complex examinations for paintings authentication requires not only involvement of highly qualified experts groups equipped with the necessary technical means, but also significant financial and time costs. A systematic solution to this problem is possible based on intelligent video analytics, machine learning methods and computational intelligence.

Taking into account the effect of time factor, we can say that the customs examination should be more efficient to ensure a quick decision on the possibility of exporting art object outside the state. Museum expertise is not so strictly limited in time, since it is not performed at border crossing points. Obviously, for customs examination, the choice of methods used is rather limited in terms of speed: these are variants of technological method based on photographing works of art in different lighting conditions (studio, infrared, ultraviolet, X-ray), macro photography. The rest of technological methods, as well as forensic, art history and attributive expertise cannot be promptly performed under conditions of customs control. Therefore, a two-stage procedure for establishing the authenticity and authorship of paintings is proposed (Fig. 1).

In this work, the first stage of the examination will be considered — the customs one, which is proposed to be implemented using one of technological methods, namely, photographing works of painting with high resolution under studio lighting conditions.

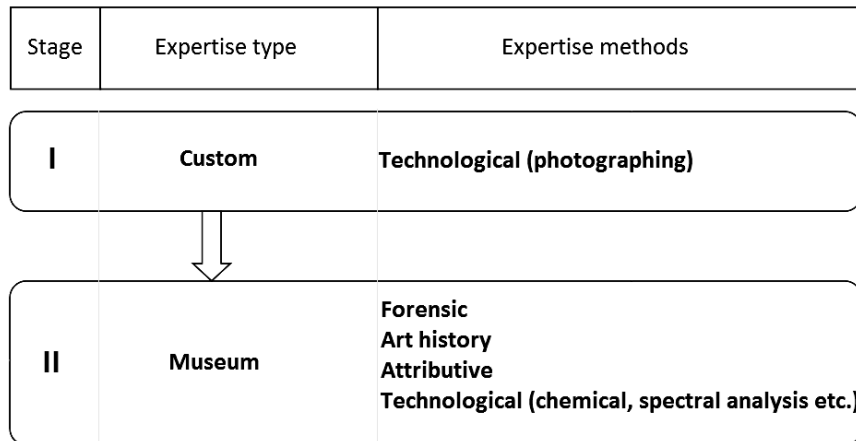


Fig. 1. Scheme of a two-stage expertise procedure for establishing the authenticity and authorship of paintings

ANALYSIS OF AREAS OF RESEARCH AND STATEMENT OF THE PROBLEM

Currently, research in this area is carried out in several directions. One direction is more focused on the creation of new and improvement of existing devices that allow the analysis of materials and substances that forms an object of art [1–6].

Another area is directly related to technologies of image digitization and their analysis using statistics, signal processing, machine learning [7–10].

Deep neural networks, which have recently become popular, have also not remained outside the attention of scientists who are developing means for comparing, identifying, and authenticating pictures. The most effective were convolutional neural networks due to their ability to distinguish a large number of heterogeneous features in images [11–14]. A number of interesting solutions were found during the use of generative networks [15–18].

This work is devoted to the problem of automatic identification of cultural values, in particular, paintings using the intelligent decision support system (IDSS) [19]. A system oriented to work in real time must have high speed and high accuracy in solving the classification problem. For this, an approach based on the weighted *k*-nearest neighbour’s algorithm is proposed, since for deep learning networks it is necessary to re-train if the value database is replenished by at least one object.

METHODOLOGY

Formally, the classification problem can be presented as follows. There is a set of *n* objects

$$I = \{i_1, i_2, \dots, i_l, \dots, i_n\}, \quad l = \overline{1, n},$$

each of them is characterized by a set of *m* features

$$F = \{f_1, f_2, \dots, f_q, \dots, f_m\}, \quad q = \overline{1, m}.$$

Features take values from a certain set

$$C^{[f_q]} = \{c_1^{[f_q]}, c_2^{[f_q]}, \dots, c_h^{[f_q]}, \dots, c_p^{[f_q]}\}, \quad h = 1, \dots, p,$$

where p is the number of possible discrete values of each feature.

One feature f_T is the target, its values for an objects set I make up a vector $C^{[f_T]} = C_T$. The classifier G learns by examples to establish relationships of the form

$$G(F(I)) = C_T,$$

calculating the approximated values of the target feature \hat{C}_T such that the difference between the specified and approximated values will be minimal:

$$d(C_T, \hat{C}_T) \rightarrow \min .$$

A trained classifier allows calculating target attribute values for new objects $I_{new} = \{i_{n+1}, i_{n+2}, \dots\}$ in this way:

$$G(F(I_{new})) = C_{TNew} .$$

When identifying works of painting, the classification problem can be solved for several target attributes [11]:

- determination of painting artistic style with target attribute C_{TStyle} ;
- determination of picture genre with target attribute C_{TGenre} ;
- defining the author with target attribute $C_{TArtist}$;
- determination of picture creation time with target attribute C_{TTime} .

Obviously, the dataset used to solve the problem must include the appropriate attributes. If the artist's name is an attribute required for such datasets, then defining and marking up an art style requires the participation of highly qualified art historians. The markup of the painting genre is an even more difficult problem, so this attribute may not be present in all datasets, what should be taken into account when developing an intelligent decision-making system.

In this paper, it is proposed to solve the problem of classifying paintings by the attribute of creation time C_{TTime} (Fig. 2).

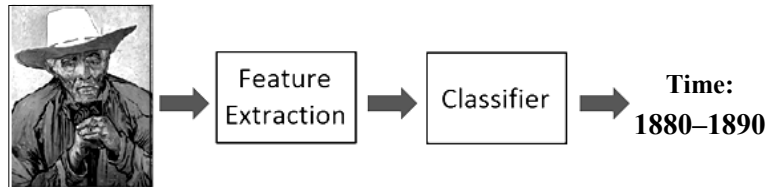


Fig. 2. Illustration of a painting classification system

As noted in [8], when marking up data, art critics often use information about the author's belonging to a particular artistic style — this increases the accuracy of identification. Therefore, it is possible to single out global and local characteristic features necessary to recognize the painting author and, accordingly, the time of the painting (Fig. 3).



Fig. 3. Scheme of paintings classification based on global and local features

During their creative activity, many artists have changed the artistic manner of writing, moved from one style to another, so the use of signs that can characterize the artistic style will be useful. In the datasets that are currently used in the development of automatic classification systems, the following styles are most often considered: abstract expressionism, baroque, constructivism, cubism, impressionism, neo-classical, pop art, post-impressionism, realism, renaissance, romanticism, surrealism, symbolism [8]. In this work, the artistic style will be considered as one of the auxiliary attributes.

FEATURE EXTRACTION

To describe the general properties of a painting, data on color and structural properties inherent in the entire image are most often used. To form sets of such data, many different algorithms and descriptors are used: wavelet transforms, Radon, Hough, Fourier, Chebyshev transforms and their combinations [7]; Gabor filters; Local Binary Patterns (LBP); SIFT detectors [20]; textural features; first 4 moments; multidimensional histograms; edge statistics features, etc. [8]. In particular, it is by the first 4 moments and by edges, the Impressionists's works can be classified unambiguously. Contour markers convey information about brush strokes style that is specific to each artist, which makes Impressionism, stand out in comparison with other styles.

Surrealist paintings can be described more informatively with the help of contour and object statistics, which reflects the presence of significant "empty" areas in their works.

In [7] it is noted that the use of color data in descriptors compilation increases the classification accuracy by 18,1%. However, researchers most often work with color data in RGB representation, since this color space describes signals from image capture and displaying devices. In this work, it is also proposed to use the CIELab color space [21], since it is focused on the unambiguous description of visual stimuli in accordance with human vision.

Thus, the following set of global picture descriptors is proposed:

1. Local Binary Patterns (LBP) [22] for describing texture properties. In this work, an LBP implementation is used within a neighborhood of 20 pixels and with a radius of 2 pixels.
2. Color modification of LBP to describe the color properties of the texture. LBPs are calculated in R, G, B and CIEL, CIEa, CIEb color channels. The results are combined using concatenation to form a multivariate histogram for each image.
3. The first 4 points — mean, standard deviation, skewness, and kurtosis, calculated in the directions of 0, 45, 90, 135 degrees. Moments are calculated along the "stripes" in the image in several specified directions. A 3-bin histogram is plotted for each obtained data vector.
4. Tamura's textural features are roughness, contrast, directionality, linearity, roughness and regularity.

The texture roughness characterizes main details dimensions that form the image. Its estimate is based on average values calculation within neighborhood of pixels:

$$A_k(x, y) = \sum_i \sum_j \frac{b(i, j)}{2^{2k}},$$

where $b(i, j)$ is brightness of pixel with i, j coordinates; k is neighborhood size; the texture roughness is then

$$E_k(x, y) = A_k(x, y) - A_k(x', y), \quad x' \neq x.$$

The texture contrast is estimated based on fourth moment μ_4 relative to mathematical expectation and variance σ^2 within neighborhood:

$$C_k(x, y) = \frac{\sigma}{(\alpha_4)^{0,25}},$$

where $\alpha_4 = \frac{\mu_4}{\sigma^4}$ — kurtosis.

The texture directivity is estimated based on quantized edge directions histogram $H_{dir}(a)$:

$$D_k(x, y) = 1 - r n_{peaks} \sum_p \sum_{a \in w_p} (a - a_p)^2 H_{dir}(a),$$

where n_{peaks} is peaks number; a_p — peak angular direction; r — coefficient that depends on quantization of angles levels a_p ; $a_p = \arctan \frac{\Delta x}{\Delta y}$ calculated with

Pruitt contour detector.

Linear similarity $L_k(x, y)$ is evaluated as average coincidence of edge directions that match in pixels pairs separated by a distance along the edge direction in each pixel.

Texture regularity is a generalized feature defined as

$$R_k(x, y) = 1 - r(\sigma_{coarseness} + \sigma_{contrast} + \sigma_{directionality} + \sigma_{linelikeness}),$$

where $\sigma_{coarseness}, \sigma_{contrast}, \sigma_{directionality}, \sigma_{linelikeness}$ are standard deviations for each feature.

Roughness summarizes contrast and roughness of texture as follows:

$$Roughness_k(x, y) = E_k(x, y) + C_k(x, y).$$

5. Radon transform features, calculated for angles of 0, 45, 90, 135 degrees and then combined into 5-pocket histograms.

6. Haralik's textural features — contrast, correlation, entropy, energy and homogeneity. They are calculated based on the contingency matrix

$$P(i, j) = \frac{\neq [(p_1, p_2) \in I | (p_1 = i) \wedge (p_2 = j)]}{\neq I},$$

where p_1, p_2 are pixels belonging to image.

Then contrast will be defined as

$$C_H(x, y) = \sum_{i, j} (i - j)^2 p(i, j);$$

the correlation is as follows:

$$Corr_H(x, y) = \sum_{i, j} \frac{(i - \mu_i)(j - \mu_j)p(i, j)}{\sigma_i \sigma_j},$$

entropy:

$$Entropy_H(x, y) = \sum_i \sum_j p(i, j) \log_2 p(i, j),$$

energy:

$$Energy_H(x, y) = \sum_i \sum_j p(i, j)^2.$$

7. Palette redundancy [9]:

$$M_B = \frac{H_{\max} - H_{RGB}}{H_{\max}},$$

where H_{\max} is maximum image entropy, which for 8-bit color coding is $8 \times 3 = 24$; H_{RGB} — entropy calculated for individual R, G, B channels.

It is proposed to describe features of individual areas of image, individual details using local descriptors, which include:

- 1) euler's number, minimum, maximum, median, mathematical expectation, variance for each object;
- 2) SIFT descriptor, built for gray level images, and images in RGB and CIE Lab color spaces.

The result of local features selection are descriptors in form of multidimensional vectors.

CLASSIFICATION OF PICTURES IMAGES

A wide variety of artistic techniques, styles, colors that artists use when creating paintings, leads, when developing an intelligent decision-making system, to the need to implement such a classifier that will be highly adaptable as new samples become available, and will also allow objects to be compared using a large set very dissimilar features. In [7], a comparison of such classification methods as weighted k -nearest neighbors method and SVM was made. The comparison showed that weighted k -nearest neighbors method provides an increase in classification accuracy by about 15–20% compared to SVM.

Weights determination

To calculate weights, it is proposed to use two basic approaches:

1. Assigning weights in accordance with information gain criterion, which is calculated on class-based entropy basis for attribute values:

$$W_E(f_i) = -\sum_{c=1}^C p_c \log_2(p_c),$$

where p_c is number of objects with a feature value f_i and that belonging to class c .

2. Assignment of weights in accordance with the Fischer method:

$$W_F = \frac{\sum_{c=1}^C p_c (\mu_c - \mu)^2}{\sum_{c=1}^C p_c \sigma_c^2},$$

where μ_c , σ_c^2 is mathematical expectation and standard deviation of data points belonging to class c for a specific attribute; μ is global mathematical expectation for all data points for a particular attribute.

Metrics used

To build a classifier, can use a variety of metrics, for example, Euclidean distance, Hamming distance, Mahalanobis, Minkowski, or Chebyshev distances. However, the use of each metric is associated with peculiarities of internal data structure or algorithm properties. These factors can lead to a significant decrease in classification accuracy. The Chebyshev metric will be more useful when comparing objects by the same attribute. To determine Mahalanobis distance, it is necessary to calculate observations covariance matrix, which for considered problem becomes is a laborious task. In addition, due to significant patterns data heterogeneity, the Mahalanobis metric will reduce classification accuracy due to covariance matrix “blurring” over entire data volume.

Thus, in this problem of classifying pictures using weighted k -nearest neighbors algorithm, it is proposed to use Euclidean distance

$$d(f_i, f_j) = \sqrt{(f_{i1} - f_{j1})^2 + \dots + (f_{in} - f_{jn})^2} = \|f_i - f_j\|,$$

weighted Euclidean distance

$$d(f_i, f_j) = \sqrt{\lambda_1(f_{i1} - f_{j1})^2 + \dots + \lambda_n(f_{in} - f_{jn})^2}.$$

Hamming distance

$$d(f_i, f_j) = \sum_{l=1}^n |f_{il} - f_{jl}|$$

and the Minkowski distance

$$d(f_i, f_j) = \left(\sum_{l=1}^n |f_{il} - f_{jl}|^p \right)^{1/p},$$

where f_i, f_j are vectors of attribute values for compared objects i, j ; f_{il}, f_{jl} — values of l -th attribute for objects i, j being matched.

Obviously, all attribute values must first be normalized so that the condition

$$f_{il} \in [0, 1], \quad i = 1, \dots, n; \quad l = 1, \dots, m$$

now for each object i_p , which is characterized by a vector of features f_i , the degree of similarity with a certain class c_T is calculated in accordance with equation

$$M_{i,c_T} = \frac{1}{\min(d_{i,c_T}) \sum_{i=1}^n \frac{1}{\min(d_{i,c_T})}}.$$

Dataset for experimental research

The activities of many museums now also include the digitization of stored valuables to provide wider user access. Therefore, number of art databases now totals dozens, each with thousands of images [11, 23–28]. There are databases contain-

ing mainly classical works. Others, on the contrary, are focused on contemporary art. Still others represent different eras and artistic styles.

In this work, it is proposed to use a small-sized dataset [29] with open access. This set contains works by 50 artists who worked at different times — from the 15th to the 20th century. Their works are ranked among a variety of artistic styles: Impressionism, Post-Impressionism, Northern Renaissance, Baroque, Romanticism, Symbolism, Realism, Surrealism, Byzantine art, etc.

When studying the possibility of automatic identification of art values in our country, it is important to take into account the historical context. It so happened that for a long time access to works of world-famous artists was closed to Ukraine, here it is much more likely that you can find paintings by Russian and Ukrainian masters who worked in the 18–20 century in the appropriate artistic style. Therefore, the set [29] was supplemented with images of paintings by Russian artists of the 17–19th century in the styles of romanticism, classicism, realism [30]. These images were obtained from the official portal of the Hermitage Museum, and data on the artists — in Wikipedia. It is important to note that a considerable number of paintings are not attributed by author, but they also have art value and may be subject to identification by style.

In addition, dataset also includes paintings by Ukrainian artists of the 19th and 20th centuries, obtained from the portal of the National Art Museum of Ukraine [31].

CONCLUSIONS

The paper considers the problem of paintings automatic identification using an intelligent decision support system (IDSS). The authors proposed a solution in the form of a classifier based on a weighted k -nearest neighbor's algorithm.

The paper proposes a set of local and global features can be used to attribute objects to be classified. The set of features includes color, texture, statistical and other characteristics.

To calculate weights for k -nearest neighbors algorithm implementation, it is proposed to use the Fisher method, as well as information gain criterion. In the algorithm for similarity measure calculating, authors proposes to use several metrics: Euclidean, weighted Euclidean metrics, Minkowski and Hamming metrics.

As a dataset for experimental research, it was proposed to use a set includes works by famous world and European artists, as well as supplemented by paintings by Russian and Ukrainian masters.

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СИСТЕМНИЙ АНАЛІЗ ПРОБЛЕМИ ВСТАНОВЛЕННЯ СПРАВЖНОСТІ Й АВТОРСТВА ТВОРІВ ЖИВОПИСУ / А.А. Мартиненко, А.Д. Тевяшев, Н.Є. Кулішова, Б.І. Мороз

Анотація. Культурні цінності давно є об'єктами злочинів, зокрема вивезення їх із держави. Фальсифікація приховує твори живопису від митного контролю; її виявлення потребує тривалої експертизи з використанням різноманітних методів аналізу. Розглянуто завдання встановлення справжності картин під час митної перевірки. Запропоновано двоетапну процедуру, яка передбачає швидку перевірку на основі аналізу фотографій творів живопису та більш тривалу музейну експертизу. Для реалізації аналізу фотографій запропоновано використовувати інтелектуальну систему прийняття рішень, дія якої базується на класифікаторі, що реалізовує алгоритм k -найближчих сусідів. Сформовано набір ознак опису властивостей творів живопису, запропоновано метрики для обчислення міри подібності об'єктів під час класифікації. Для навчання алгоритму пропонується набір даних, що включає картини світових, європейських художників та українських майстрів різних століть.

Ключові слова: інтелектуальна система прийняття рішень, автоматична класифікація, k -найближчих сусідів, митна експертиза, твори живопису.

СИСТЕМНЫЙ АНАЛИЗ ПРОБЛЕМЫ УСТАНОВЛЕНИЯ ПОДЛИННОСТИ И АВТОРСТВА ПРОИЗВЕДЕНИЙ ЖИВОПИСИ / А.А. Мартыненко, А.Д. Тевяшев, Н.Е. Кулишова, Б.И. Мороз

Аннотация. Культурные ценности давно являются объектами преступлений, в частности их вывоз из государства. Фальсификация укрывает произведения живописи от таможенного контроля; для ее обнаружения необходима длительная экспертиза с использованием разнообразных методов анализа. Рассмотрена задача установления подлинности картин в ходе таможенной проверки. Предложена двухэтапная процедура, которая предполагает быструю проверку на основе анализа фотографий произведений живописи и более длительную музейную экспертизу. Для реализации анализа фотографий предложено использовать интеллектуальную систему принятия решений, действие которой базируется на классификаторе, реализующем алгоритм k -ближайших соседей. Сформирован набор признаков для описания свойств произведений живописи, предложены метрики для вычисления меры сходства объектов в ходе классификации. Для обучения алгоритма предлагается набор данных, который включает картины мировых, европейских художников, а также украинских мастеров разных столетий.

Ключевые слова: интеллектуальная система принятия решений, автоматическая классификация, k -ближайших соседей, таможенная экспертиза, произведения живописи.