A Technique for Computerised Brushwork Analysis

Dmitry Murashov[1], Alexey Berezin[2] and Ekaterina Ivanova[2]
[1]Dorodnicyn Computing Centre of RAS, Vavilov st. 40, 119333, Moscow, Russian Federation
[2]State Historical Museum, Red Square, 1, 109012, Moscow, Russian Federation

Keywords: Attribution of Paintings, Images of Paintings, Brushwork, Image Ridges, Structure Tensor.

Abstract: In this work, the problem of computer-assisted attribution of fine-art paintings based on image analysis methods is considered. A technique for comparing artistic styles is proposed. Textural features represented by histograms of brushstroke ridge orientation and local neighborhood orientation are used in this work to characterize painter's artistic style. The procedures for feature extraction are developed and the parameters are chosen. The paintings are compared using three informative fragments segmented in a particular image. Selected image fragments are compared by information-theoretical dissimilarity measure. The technique is tested on images of portraits created in 17-19th centuries. The preliminary results of the experiments showed that the difference between portraits painted by the same artist is substantially smaller than one between portraits painted by different authors. The proposed technique may be used as a part of technological description of fine art paintings for attribution. The unsolved problems are pointed out and the directions of further research are outlined.

1 INTRODUCTION

The paper is devoted to the problem of developing image analysis techniques for computer-assisted attribution of fine-art paintings. In the glossary of the National Gallery, attribution is defined as an assessment of who was responsible for creating a particular work. Sometimes the term "attribution" is interpreted more widely and includes also an assessment of art school, time, country, etc. (Obukhov, 1959). One of the trends in attribution today is related to the analysis of digital images of paintings and called as “Computer-assisted Connoisseurship” (Stone, 2010). The idea of applying image analysis in attribution is that to compare images of authentic and studied paintings by features characterizing individuality of an artist. This idea is based on the concepts of Giovanni Morelli, who laid foundations of the method for comparative analysis in fine arts (Morelli, 1900), and his followers (Berenson, 1903), (Ignatova, 1994). With the individuality of artist the experts associate features of brushstrokes that are forming a painted surface.

In the studies related to the tasks of attribution, the feature sets that allow capturing appearance of individual painting techniques, or unconscious rhythm that distinguishes manner of an artist, are extracted from the images. When developing methods for attribution of paintings, the researchers analyze geometry and texture of individual strokes, configurations of groups of strokes, spatial frequencies, and other properties of the paint layer texture. As the tools, they use a variety of methods for image analysis created in the last few decades. In many papers the low-level texture features are extracted from coefficients of wavelet transform and values of Gabor filters responses.

In publications of different research groups, two main approaches to the task have been proposed. The first is based on the exhaustive comparison of square image fragments of the researched images (Johnson, 2008). The features are usually derived from the coefficients of the orthogonal transforms (in particular, wavelet transform). This approach is of high computational complexity and is sensitive to conditions of image acquisition and hardware parameters (Polatkan, 2009).

The second approach provides features computed from the segmented brushstrokes (Lettner, 2005), (Shahram, 2008), (Li, 2012). But one can find too few paintings with a sufficient number of distinguishable brushstrokes that can be successfully segmented in automatic mode, or even manually. It

Murashov D., Berezin A. and Ivanova E..
A Technique for Computerised Brushwork Analysis.
DOI: 10.5220/0005362302210226
In *Proceedings of the 10th International Conference on Computer Vision Theory and Applications* (VISAPP-2015), pages 221-226
ISBN: 978-989-758-091-8

can be done, for example, in images of paintings by van Gogh, P.J. Pollock and some others. Therefore, it is preferable to use features that can be computed directly from images, but not from the segmented brushstrokes.

In this paper, a technique for comparing artistic styles is proposed. Following recommendations of art experts (Ignatova, 1994), we propose to use for comparing paintings a group of brushstrokes that form homotypic details of these paintings. In (Sablatnig, 1998) for attribution of portrait miniatures, the homotypic details of the human faces were compared. The fragments were segmented using geometric model of face. In this work, we use images of the homotypic informative face details: forehead, nose, and cheek. It should be noticed that the size of paintings and, respectively, of images in current research is much larger than in (Sablatnig, 1998), and selected image samples differ from those in (Sablatnig, 1998). Three types of informative face fragments used in this work are shown in Figure 1. In the current research we use features that capture directions of artist's brush. Procedures for feature extraction are developed. Selected image fragments are compared using information-theoretical dissimilarity measure based on Kullback-Leibler divergence. The technique is tested on 11 images of portraits created in 17th-19th centuries. The preliminary results of the experiments showed that the difference between portraits painted by the same artist is substantially smaller than one between portraits painted by different authors, and these groups of paintings can be separated.

The paper is organized in the following way. In the next section the formal problem formulation is given. In sections 5 and 6 we describe the analyzed images of paintings and textural features capturing artistic manner. Feature extraction procedures are proposed. Then we introduce a technique for comparing images of portraits represented by extracted features. In two last sections we present the results of computing experiments and make conclusions.

2 PROBLEM FORMULATION

The problem is formulated as follows. Let U_j be images of paintings by J authors, $j = 1, 2, \ldots, J$; $U : R^2 \to R$. Let $u_j^i : \Omega \to R$, $\Omega \subset R^2$ be an informative sample of type i taken from image U_j, $i = 1, 2, \ldots, I$. Fragment u_j^i is characterized by a feature vector $\mathbf{x}_j^i = \left[x_j^{i1}, x_j^{i2}, \ldots x_j^{is}, \ldots, x_j^{iS} \right]^T$, $x_j^{is} = \gamma_s(u_j^i)$, $\gamma_s : R^2 \times R \to R$, $s = 1, 2, \ldots, S$. The difference between two samples u_j^i and u_k^i of type i of images U_j and U_k we define as

$$D_{jk}^i = \sqrt{\sum_{s=1}^{S} \left(d\,(x_j^{is}, x_k^{is}) \right)^2}\,, \qquad (1)$$

where $d\,(x_j^{is}, x_k^{is})$ is a measure of difference between the features of type s extracted from these two image samples. The difference D_{jk} between the images U_j and U_k is calculated from differences between corresponding informative samples as follows:

$$D_{jk} = \sqrt{\sum_{i=1}^{I} \left(D_{jk}^i \right)^2}\,. \qquad (2)$$

Let U_l be an image with unknown attribution, $l = J + 1$. It is necessary to find image U_m (and the author of the painting) providing minimum of distance D_{ml} .

In the next section, the properties of the analyzed images are described.

3 IMAGE DATA

The data used in the research are the image fragments of artworks painted in 17 – 19th centuries by different authors. The images are fixed by a digital camera. The size of the images is about 4270x2850 pixels. The distortions conditioned by acquisition process are compensated and images are uniformly oriented. The size of informative fragments varies from 990x814 to 1800x1000 pixels. Resolution of fragments is about 200 dots per cm that corresponds to the quality of the data used in the analogous studies. For example, Johnson et al. (Johnson, 2008), Polatkan et al. (Polatkan, 2009), and Li et al. (Li, 2012) analyzed images obtained at resolution of 196 dots per inch.

Some of the paintings have retouched and repainted areas. The features should be extracted only from areas with original brushwork. Thereby, retouched and repainted areas should be excluded during feature extraction. A technique developed in (Murashov, 2014) is used for localizing damaged paint layer areas.

In the next section, feature description of informative samples of images of paintings is given.

(a) (b) (c)

Figure 1: Informative fragments of portraits: (a) “forehead”; (b) “nose”; (c) “cheek”.

4 BRUSHWORK FEATURES

Taking into account complexity of brushstroke segmentation, it is preferable to use image features that do not need segmentation of a single brushstroke. The features will be extracted only from the areas containing maximum information about the artistic manner of the painter. In this work, histograms of brushstroke ridge orientation and local neighborhood orientation are considered as the features of a brushstroke group that describe the individual artistic manner, specific to a particular detail of a painting.

Image ridges are localized by modified technique described in (Eberly, 1996). A set of points forming a ridge of an object in grayscale image is extended by including parabolic and umbilic points of a grayscale image relief.

Let the grayscale image relief be a function $f \in C^2(R^2, R)$. It is assumed that $Df \neq 0$, $Df = \left(f_x, f_y\right)^T$. We denote $N = Df/|Df|$, $T = Df^{\perp}/|Df|$, and $Df^{\perp} = \left(-f_y, f_x\right)^T$, where N is a normal and T is a tangent to level lines (isophotes) of image f. The following expression based on Hessian describes the local properties of function f:

$$-\frac{1}{|Df|}\begin{bmatrix} N^T D^2 fN & N^T D^2 fT \\ T^T D^2 fN & T^T D^2 fT \end{bmatrix} = \begin{bmatrix} g & \mu \\ \mu & k \end{bmatrix}, \qquad (3)$$

where $k = -T^T\left(D^2 f/|Df|\right)T$ is an isophote curvature; $\mu = -T^T(D^2 f/|Df|)N$ is a gradient flowline curvature; $g = -N^T(D^2 f/|Df|)N$ is a measure of gradient variation along the flowlines. At ridge points of f the following conditions are taking place: $\mu = 0$ and $k > \max\{0, g\}$. We also consider the points of f where one or both eigenvalues of matrix (3) are zero. For obtaining ridge orientation histogram, orientation angle of the inertia axes of ridge connected components is calculated (Jähne, 2005):

$$\theta = \frac{1}{2}\arctan\frac{2\mu_{1,1}}{\mu_{2,0} - \mu_{0,2}}, \qquad (4)$$

where $\mu_{i,j}$ are the elements of inertia tensor:

$$\mathrm{M} = \begin{bmatrix} \mu_{2,0} & -\mu_{1,1} \\ -\mu_{1,1} & \mu_{0,2} \end{bmatrix}.$$

For computing direction histogram, length (in pixels) of ridge connected components is taken into account.

Another feature describing local orientation of painting texture is based on the notion of structure tensor, or the second moment matrix at a point x weighted by a window function:

$$\mu_f(x) = \int_{p \in R^2} (Df(p)(Df(p))^T w(x-p)dp, \qquad (5)$$

where $w(x-p)$ is a window Gaussian function (Lindeberg, 1994). The angle of simple neighborhood orientation φ is determined as:

$$\varphi = \frac{\pi}{2} + \frac{1}{2}\arctan\frac{2\mu_{f1,1}}{\mu_{f2,0} - \mu_{f0,2}}, \qquad (6)$$

where $\mu_{fi,j}$ are the components of the structure tensor (5). The proposed feature description of artistic manner is illustrated in Figure 2. In Figure 2 (a) – (c), the images of a human face detail "cheek", taken from three portraits, are shown. The portraits (a) and (b) are created by F. Rokotov, portrait (c) is painted by another artist. In Figure 2 (d) – (f), corresponding ridge orientation histograms are given, and in Figure 2 (g) – (i), simple neighborhood orientation histograms, obtained from images (a) – (c), are depicted.

The procedures for computing described above features are developed. For obtaining histogram of orientation angles of grayscale image ridges, the following operations are performed: (a) image rotation and scaling; (b) extension of image dynamic range; (c) creating a mask of informative fragment; (d) creating masks of craquelure and damages; (e) combining masks; (f) image masking; (g) Gaussian blurring; (h) localizing ridges of grayscale image relief; (i) defragmenting obtained image ridges; (j) filtering connected components of ridges by size; (k) computing orientation angle values and building a histogram. For extracting the second feature, firstly the image is downsampled with a factor equal to 2. Then the operations (a)-(g) listed above are performed, and histogram of simple neighborhood orientation is obtained. The procedure for creating a craquelure mask includes operations of "black top-hat", adaptive thresholding, interactive selection of connected components, morphological opening and dilation. The next section deals with description of a difference measure that is used for comparing images of details of paintings.

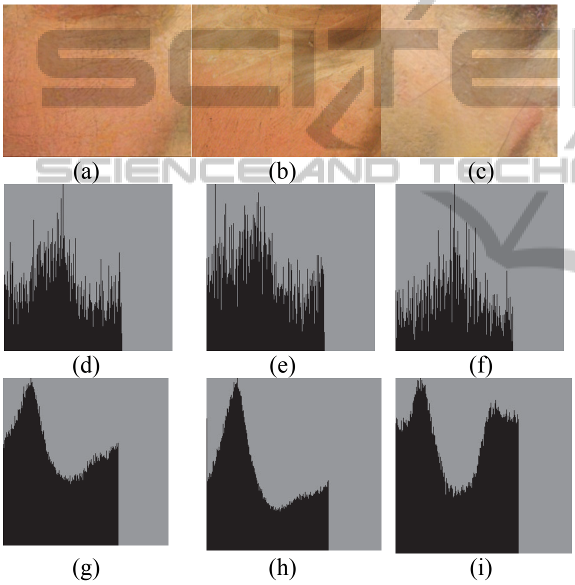

Figure 2: Illustration of a brushwork feature description: (a) – (c) are the images of a human face detail "cheek"; (d) – (f) are the ridge orientation histograms obtained from images (a) – (c); (g) – (i) are the corresponding simple neighborhood orientation histograms.

5 MEASURE OF IMAGE DIFFERENCE

For comparing fragments of artworks, statistical tests (Li, 2012), cluster analysis, and classification techniques (Johnson, 2008), (Polatkan, 2009) are used. In this paper, the image samples are compared using information-theoretical measure of difference, because this measure fits the features represented by distributions. The measure is constructed on the basis of Kullback-Leibler divergence as follows (Escolano, 2009):

$$d\left(x_j^{is}, x_k^{is}\right) = \frac{1}{2}\left[\sum_{\varphi\in H} p_\Phi(\varphi)\log\frac{p_\Phi(\varphi)}{q_\Phi(\varphi)} - \sum_{\varphi\in H} q_\Phi(\varphi)\log\frac{q_\Phi(\varphi)}{p_\Phi(\varphi)}\right] \tag{7}$$

where $p_\Phi(\varphi)$ and $q_\Phi(\varphi)$ are the probabilities of the event, when orientation angle values in samples u_j^i and u_k^i are equal to φ; H is the alphabet of random variable Φ representing the orientation angle. The measure $d\left(x_j^{is}, x_k^{is}\right)$ is non-negative and symmetric. Firstly, according to the procedure proposed above, we create craquelure masks for specified portrait regions (forehead, nose, and cheek, see Figure 1). We apply created masks to image patches at the step of computing features. Using the developed feature extraction procedures, we obtain histograms of orientation angles defined by expressions (4) and (6). After that, using measure of difference (7) and expression (1), the distances D_{jk}^i between fragments of type i in portraits j and k are computed. At the next step, as defined by expression (2), we aggregate computed distances D_{jk}^i between corresponding portrait regions into the values of distances D_{jk} between portraits j and k.

6 PRELIMINARY RESULTS

Computing experiment was carried out for choosing parameters of feature extraction procedures and testing the proposed features for applicability to attribution tasks. In the experiment we use images of three portraits by F. Rokotov and eight portraits by other artists dated to 17-19th centuries.

For choosing parameters of feature extraction procedures we computed distances

$$D_{jk}^s = \sqrt{\sum_{i=1}^{I}\left(d(x_j^{is}, x_k^{is})\right)^2}$$

between images represented by a particular feature s at different values of parameters. The first parameter under consideration is the lower bound b of the size of ridge connected components. Distances D_{jk}^s between portraits for values of b equal to 8 and 12 pixels were computed. Histograms of distances between images of paintings, represented by orientation angle of ridge connected components at $b = 8$ and $b = 12$, are shown in Figure 3. Here, the distances between three portraits by F. Rokotov are denoted as "own" and distances between portraits by different artists are denoted as "alien".

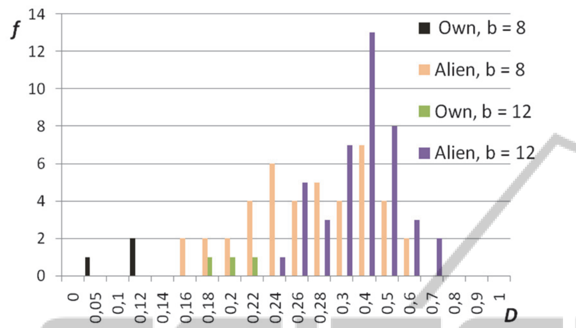

Figure 3: Histograms of distances between images of paintings, represented by orientation angle of ridge connected components at $b = 8$ and $b = 12$; f is a frequency of a distance value D.

The second parameter is the size of the window function w in (5). Distances D^s_{jk} between portraits for values of window function size a equal to 3, 5, 7, and 11 pixels were computed. Averages and standard deviations found from histograms of distances between "own" and "alien" images of paintings represented by angle of simple neighborhood orientation φ at different values of a are presented in Figure 4. The point at $a = 3$ corresponds to noise components of painting's texture. Other values of window function size produce distances that are revealing different components of brushwork texture characterized by different spatial frequencies.

The results of comparing images using features (3) and (5), extracted from the homotypic regions (forehead, nose, and cheek, see Figure 1) of three portraits by F. Rokotov and eight portraits by other artists are obtained and presented in Figure 5. Here, a histogram of distances D_{jk} between paintings by F. Rokotov is denoted as "own". Histogram of distances between paintings created by different artists is denoted as "alien". It follows from Figure 5 that distance between paintings created by the same artist is less than the distance between any two paintings created by different authors. This result fits the following description of brushworks made by the art experts that show the difference of the styles. The portraits by F. Rokotov are characterized by an arrangement of strait brushstrokes of various length, producing zigzag patterns. In the female portrait by V. Tropinin the embossed brushstrokes are weakly expressed and variously oriented. The portrait by P. D. de Rij is characterized by the accurate brushstrokes that creating the form of face details. In the portrait by A. Kharlamov, short, narrow-meshed, variously oriented, and intersecting brushstrokes create illusion of three-dimensionality. V.Lik's style of brushing is considered to be rather chaotic. The peculiarities of the artistic style of I. Ligotsky are conditioned by a uniform texture without any diversity of paint layer relief. Dense long brushstrokes reflect the structure of facial muscles. In the male portrait by F. Riss some of the short embossed strokes are visible in bright white regions of paint layer. The brushstrokes are mainly long and waved, exactly and firmly follow face details.

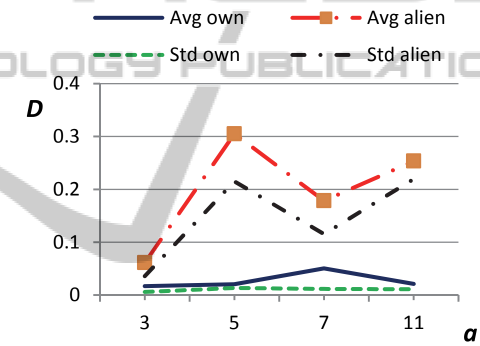

Figure 4: Averages and standard deviations found from histograms of distances between "own" and "alien" paintings at different values of window function size a.

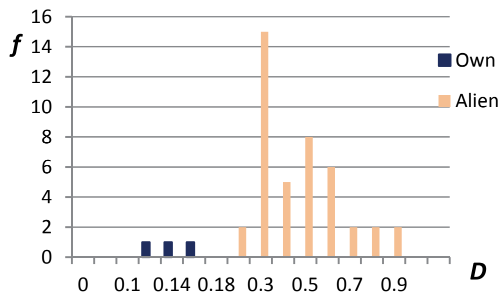

Figure 5: Histograms of distances between paintings created by the same artist ("own") and different artists ("alien").

So, “own” and “alien” paintings, represented by feature description that we proposed in this work, can be separated, and a threshold value for attribution decision can be chosen.

7 CONCLUSIONS

The problem of computer-assisted attribution of fine-art paintings based on image analysis methods is considered. A feature description of artistic brushwork based on textural characteristics of paintings is proposed. Selected image features in the form of orientation angle distributions give quantitative description of painter's artistic style and provide suitable accuracy of features computation. Feature evaluation does not require segmentation of a single brushstroke and is not sensitive to image acquisition conditions as opposed to the conventional techniques. The results of computing experiments showed the efficiency of the proposed features for comparing artistic styles. The proposed feature set may be used as a part of technological description of fine art paintings for restoration and attribution. The future research will be aimed at the problems, remained untouched in the current research. Firstly, as the art experts pay attention to the geometry of the brushes used by the artists, the research will be aimed on the frequency analysis of the images. Secondly, the results of the experiment presented above, showed that different values of the feature extraction procedures provide capturing different components of the painting's texture. So, another aim of the research will be concerned with multiscale feature description of paintings. Next, in the presented research we tested the proposed feature space and procedures on a limited number of paintings. In particular, we invoked in experiments only three paintings created by the same artist (F. Rokotov) and eight portraits by other artists. In order to obtain more accurate experimental results, we are planning to extend our image dataset. It is important to represent each artist in the dataset by a few artworks. And at last, it is necessary to develop a procedure for making decisions on similarity of brushwork techniques and artistic styles.

ACKNOWLEDGEMENTS

This work is supported by the RFBR grants No 12-07-00668 and No 15-07-09324.

REFERENCES

Obukhov, G., 1959. *A brief glossary of fine art*. Moscow, The soviet painter. (In Russian).

Stone, D., Stork, D., 2010. Computer-assisted Connoisseurship: The Interdisciplinary Science of Computer Vision and Image Analysis in the Study of Art, *IP4AI3, Museum of Modern Art*, New York, May 27, pp. 9-10.

Morelli, G., 1900. *Italian Painters. Critical Studies of Their Works*. John Murray, London.

Berenson. B., 1903. *The Study and Criticism of Italian Art*. George Bell and sons, London.

Ignatova, N, 1994. Analysis of oil painting textures. In *Fundamentals of Oil painting Examination. The guidelines*, Moscow, Grabar restoration Centre, vol. 1.

Johnson, C. R., Hendriks, E., Berezhnoy, I.J., Brevdo, E., Hughes, S.M., Daubechies, I., Li, J., Postma, E., Wang, J.Z., 2008. Image processing for artist identification (Computerized analysis of Vincent van Gogh's painting brushstrokes). *Signal Processing Magazine*, IEEE. Vol. 25, No 4. - P. 37-48.

Polatkan, G., Jafarpour, S., Brasoveanu, A., Hughes, S., Daubechies, I., 2009. Detection of forgery in paintings using supervised learning. *ICIP2009*, IEEE. P. 2921-2924.

Lettner, M., M. Sablatnig, M., 2005. Texture Analysis for Stroke Classification in Infrared Reflectogramms. H. Kalviainen et al. Eds., SCIA 2005, Springer-Verlag Berlin-Heidelberg, LNCS. Vol. 3540. - P. 459-469.

Shahram, M., Stork, D.G., Donoho, D., 2008. Recovering layers of brush strokes through statistical analysis of color and shape: an application to van Gogh's Self portrait with grey felt hat. *Computer Image Analysis in the Study of Art*. D. Stork, J. Coddington, Eds.: Proc. of the SPIE. Vol. 6810. - P. 68100D-1 - 68100D-8.

Li, J., Yao, L., Hendriks, E., Wang, J. Z., 2012. Rhythmic brushstrokes distinguish van Gogh from his contemporaries: findings via automated brushstroke extraction. *IEEE TPAMI*. Vol. 34, No 6. - P. 1159-1176.

Sablatnig, R., Kammerer, P., Zolda, E., 1998. Structural Analysis of Paintings Based on Brush Strokes. *Proc. of SPIE Scientic Detection of Fakery in Art*. SPIE. Vol.. 3315. – P. 87–98.

Murashov, D., 2014. Localization of differences between multimodal images on the basis of an information-theoretical measure, *Pattern Recognition and Image Analysis*. Springer, Vol. 24, No 1. - P. 133-143.

Escolano, F., Suau, P., Bonev, B., 2009. *Information Theory in Computer Vision and Pattern Recognition*. – London, Springer Verlag.

Eberly, D., 1996. *Ridges in Image and Data Analysis*. Klewer Academic Publishers.

Lindeberg, T., 1994. *Scale-space Theory in Computer Vision*. Kluwer Academic Publishers.

Jähne, B. 2005. *Digital Image Processing. 6th ed.* Springer.