Texture Analysis of Painted Strokes[1)]

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Abstract:
The following work presents a study of stroke classification in which two classes of strokes are identified: fluid and dry strokes. The discrimination is done with a feature vector which is extracted from the image texture from some test samples of strokes drawn in different fluid and dry materials. To find an adequate texture analysis method especially for this application, three different texture analysis methods are executed on test images from painted strokes. The methods applied are based on statistical features of first and second order and on the discrete wavelet transformation, where the statistical features of second order are extracted from the co-occurrence matrix. The classification results obtained are compared and discussed.

1 Introduction

The recognition of painted strokes is an important step in analyzing painted works of art like panel paintings, independent drawings and underdrawings. But even for art experts it is difficult to recognize all drawing tools and materials used for the creation of the strokes. The use of computer-based imaging technologies brings a new and objective analysis method and assists the art expert in analyzing paintings.
Painted strokes can be painted either in dry or fluid drawing materials. Chalk and graphite are examples of dry materials and paint or ink applied by pen or brush are examples of fluid drawing materials. The discrimination of the texture from these two classes is as follows: the texture from dry drawing materials is coarse with a variety of gray levels and the texture from fluid drawing materials is more homogeneous and fine.
The boundary characteristics of painted strokes have been used to recognize them [5]. This work deals with the analysis of the stroke texture in order to recognize strokes and their underlying drawing material. The strokes are classified into two classes: one for strokes drawn in dry painting materials and the other for strokes drawn in fluid painting materials.
Texture classification is performed based on features extracted from the image texture. To find an

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adequate texture analysis method for the stroke application three different texture analysis methods are applied and compared. The first method is based on first order statistical features. The second one is based on the co-occurrence matrix and the third one is based on the discrete wavelet transformation. The test samples for the strokes considered are extracted from test panels which are prepared by a restorer.

The organization of this paper is as follows. Section 2 describes the strokes used for this work. Section 3 covers the texture analysis methods used. Experimental results are given in Section 4 and finally Section 5 gives a summary and conclusions.

2 The Strokes

The experiments are performed on four different test panels with strokes applied with different drawing tools and materials which are prepared by an art expert. The four panels are prepared with different groundings and the following types of strokes are considered in this work: graphite, black chalk and silver point are the representatives for the dry strokes and ink applied by brush, quill or reed pen are the considered fluid strokes. The test panels are digitized using a flat-bed scanner with an optical resolution of 1200 dpi. Figure 1 shows examples for the strokes. The stroke texture from the fluid materials, see Figure 1(c), (d) and (e), is more homogeneous in comparison to the texture from the dry drawing materials in Figure 1(a), (b) and (f) which is rather coarse and rough.

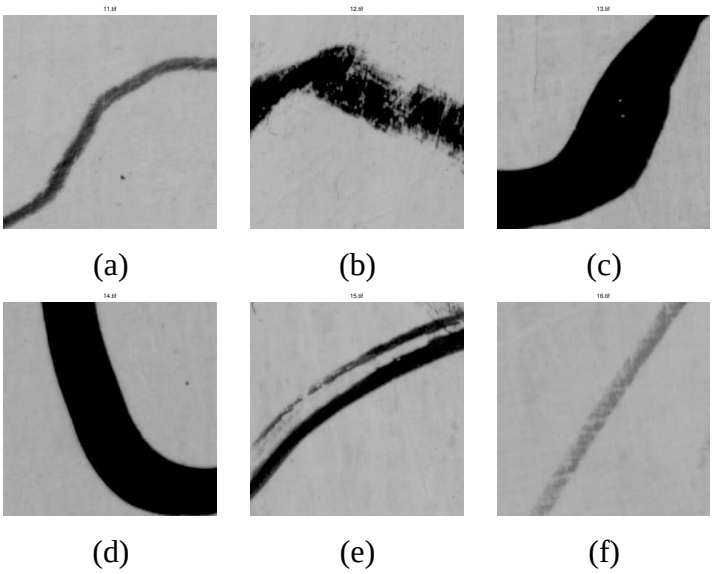


Figure 1: Examples of the strokes on the test panels. (a) is a stroke applied by graphite, (b) shows a black chalk stroke, (c) a brush stroke, (d) a stroke from a quill, (e) a reed pen stroke and (f) shows a stroke painted by a silver point. The size of the windows constitutes 300×300 **pixels.**

The roughness of the texture from the dry drawing materials depends on the groundings of the panels. The more plain the underground, the finer is the texture from the strokes. A characteristic from strokes applied by quill and reed pen are the irregularities in the surface and thus in the texture. These irregularities are caused through the different groundings on the panels. Some fluid drawing

materials are not accepted similarly on the different groundings and this brings discontinuities into the surface. This condition can be seen in Figure 1(e) where the background interfuses the stroke. Because of the differences between the strokes on the four test panels strokes from different panels are not compared.

3 The Texture Analysis Methods

To get a comparative study and to find a practicable texture analysis method for the stroke application three different simple texture analysis methods are performed in this work. The first method extracts statistical features of first order from the test samples which are further used for the classification process. The gray level co-occurrence matrix (GLCM) is used by the second method. Previous investigations showed that this method outperforms the others in comparative studies [2], [10]. The third method is based on the discrete wavelet transformation, which also shows good results in comparative studies [8], [9].
The rest of this section gives a brief overview of the texture analysis performed in this work.

3.1 Statistical Features of First Order

Statistical features of first order take into account the individual gray values from the pixels in a $n \times m$ matrix $\mathbf{R}$ but the spatial arrangement is not considered, i.e. different textures can have the same gray level histogram.
To get a two dimensional feature vector for the test samples with statistical features of first order the mean and standard deviation were calculated from the test samples.

3.2 The Co-occurrence Matrix

The co-occurrence matrix is a very popular tool for texture analysis. It was presented in 1973 by Haralick, Shanmugam and Dinstein [3]. The $N \times N$ co-occurrence matrix describes the spatial alignment and the spatial dependency of the different gray levels, whereas N is the number of gray levels in the original image. The co-occurrence matrix $P_{\phi,d}(i,j)$ is defined as follows. The entry (i,j) of $P_{\phi,d}$ is the number of occurrences of the pair of gray levels i and j at inter-pixel distance d and the direction angle ϕ. The considered direction angles are $0°$, $45°$, $90°$ and $135°$ and the inter-pixel distance d is 1 [3].
To get textural features to describe the image texture Haralick suggested 14 features which are extracted from the co-occurrence matrix. For this work the four most popular features used in literature are chosen [4]: the Angular Second Moment (=Energy), Contrast, Inverse Difference Moment and the Entropy. These four features extracted from the co-occurrence matrix result in a four dimensional feature vector which is further used for texture classification.

3.3 The Discrete Wavelet Transformation

The discrete wavelet transformation (DWT) [6] decomposes an original signal $f(x)$ with a family of basis functions $\psi_{m,n}(x)$, which are dilations and translations of a single prototype wavelet function known as the mother wavelet $\psi(x)$:

$$f(x) = \sum_{n=0}^{\infty} \sum_{m=0}^{\infty} c_{m,n} \psi_{m,n}(x) \ . \tag{1}$$

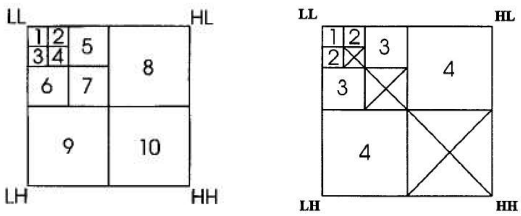
$c_{m,n}$ constitutes the DWT coefficients where m and n are integers and referred to as the dilation and translation parameters.
An efficient way to implement this scheme using filters was developed by Mallat [6]. The 2D DWT is computed by a pyramid transform scheme using filter banks. The filter banks are composed of a low pass and a high pass filter and each filter bank is then sampled down at a half rate of the previous frequency. The input image is convolved by a high pass filter and a low pass filter in horizontal direction (rows). After this step another convolution in vertical direction (columns) is performed with a high and a low pass filter. Thus the original image is transformed into four sub images after each decomposition step:

- LL sub image: Horizontal and vertical directions have low frequencies. The corresponding sub image is an approximation of the input image
- LH sub image: The horizontal direction has low frequencies and the vertical one has high frequencies
- HL sub image: The horizontal direction has high frequencies and the vertical one has low frequencies
- HH sub image: The horizontal and vertical directions have high frequencies.

A three level decomposition results in 10 sub images, see Figure 2(a) whereas the approximation image is the input image for the next level.
Statistical information calculated from the resulting sub images can be used as the texture features. Here the mean of the coefficient magnitudes is used to build a four dimensional feature vector which is built up as follows: the HL and LH sub images from each channel are combined and the HH sub images are not considered because they tend to contain the majority of noise [7], see Figure 2(b).

4 Experiments and Results

The classification of the feature vectors was done using the k-means algorithm. To find a practicable window size for this application four different matrix sizes were tested. The experiments were executed with matrix sizes 20×20, 25×25, 32×32 and 50×50 with 50 test samples per panel



(a) (b)

Figure 2: (a) 10 channels of a three level wavelet decomposition of an image. (b) Grouping of wavelet channels to form 4 bands to calculate the features [7]

and matrix size. Previous work performed their analysis with matrix sizes varying from 8×8 to 64×64 windows [1], [3]. However a major problem in this application is the tiny width of the silver point and graphite strokes. Thus the silver point stroke is not considered because of its narrow width. 32×32 and 50×50 matrices which do not only cover the stroke but also the background are also not considered for the classification process. On the other hand small matrix sizes are also not applicable, because of the roughness from the texture of dry strokes and the loss of texture information by decreasing the window size.
To test the algorithms 880 test images were generated with the following feature vectors for each image:

1. a two dimensional vector with statistical features of first order

2. a four dimensional feature vector calculated from the co-occurrence matrix which contents the energy, inertia, entropy and homogeneity

3. a four dimensional feature vector with the mean magnitudes calculated from the grouped sub images from the discrete wavelet transformation.

Table 1 shows the correct classification rate in percent for the individual strokes after division into two classes: one for dry strokes (graphite and black chalk) and one for fluid strokes (brush, quill and reed pen). The results are given for all matrix sizes from one of the four panels for the three methods performed.
The recognition of the black chalk and the brush stroke showed the best results because the texture is homogeneous over the whole stroke surface. In contrast the texture from the quill and reed pen stroke shows some discontinuities in the surface and thus limits the classification. There are only results for the graphite stroke with matrix size 20×20 and 25×25 because of the tiny width (bigger matrices are marked by an x in the table). The recognition of this type of stroke is good but the classification is bad for the wavelet based features. This effect results from the k-means algorithm.
Generally the percentage of correct classification is better for larger matrices but the matrix size is limited by the width of the strokes. The mean recognition rate from the three methods for a matrix ranges from 81,3% for the 20×20 matrices to 90% for the 32×32 matrices. This mean value is

	Graphite	Bl. Chalk	Brush	Quill	Reed Pen	Total	Mean
20×20							
Statistical features	100	10	70	60	100	68	
Co-occurrence features	50	100	90	100	60	80	
Wavelet based features	100	100	100	100	80	96	81,3
25×25							
Statistical features	100	10	60	40	100	62	
Co-occurrence features	100	100	90	20	30	68	
Wavelet based features	0	100	100	70	60	66	65,3
32×32, 1. Attempt							
Statistical features	x	100	100	100	70	92,5	
Co-occurrence features	x	100	100	90	60	87,5	
Wavelet based features	x	100	100	100	60	90	90
32×32, 2. Attempt							
Statistical features	x	100	100	80	90	92,5	
Co-occurrence features	x	100	100	80	40	80	
Wavelet based features	x	100	100	90	100	97,5	90
50×50							
Statistical features	x	100	100	60	80	85	
Co-occurrence features	x	100	100	60	80	85	
Wavelet based features	x	60	100	70	80	77,5	82,8

Table 1: Percentage of correct classification for the individual strokes from one panel after division into two classes: one for dry and one for fluid strokes. The results are shown for the three methods performed and all matrix sizes. Column *Total* shows the percentage of correct classification for the individual methods and column *Mean* shows the mean value from the three individual methods for the individual matrix size.

annoted in the last column of Table 1. The best classification rate was obtained with the feature vector from the DWT (using the Daubechies (6) mother wavelet) and the matrix sizes 32×32 and 50×50. The classification rate of the statistical features of first order was almost as high as the DWT features. The co-occurrence method only performed well for large matrices, but the results are not constant for all four panels.

The discrimination of the fluid strokes (brush and quill) showed the best classification rate for all methods because of their homogeneous texture. The recognition of the black chalk strokes showed good results for large matrices but the rough texture of the black chalk gets lost for smaller matrices and thus the discrimination rate decreases.

Figure 3 shows the results of classification using the statistical features of first order, the co-occurrence features and the features from the DWT. The horizontal axis shows the different matrix sizes 20×20, 25×25, 32×32 and 50×50 for the four panels (indicated in brackets) and the y-axis shows the percentage of correctly classified strokes. It can be seen that the results are generally better for large

matrix sizes. However the DWT features (the dark gray line with squares) show a good discrimination rate even for small matrices.

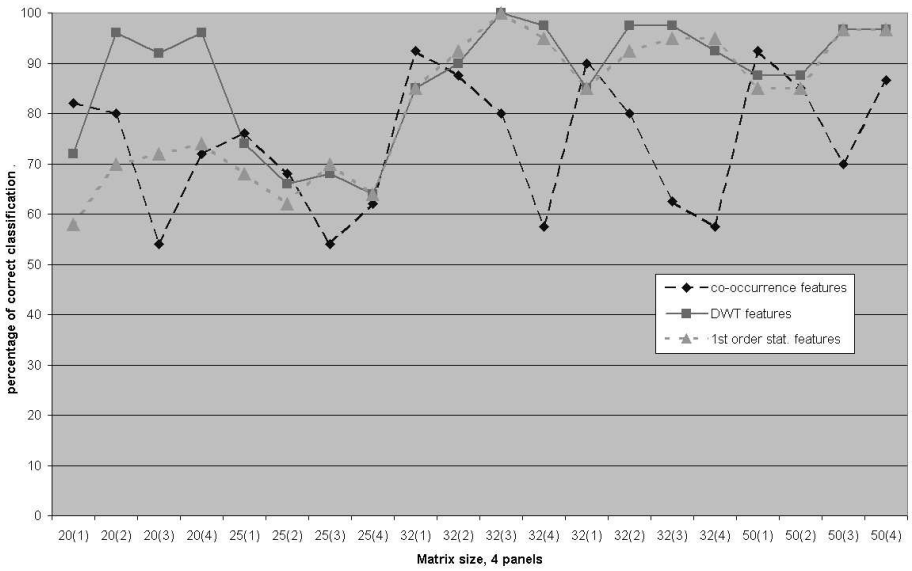


Figure 3: Classification results.

5 Summary and Conclusions

The work presented has focused on the identification of different stroke textures which are significant for the recognition of the underlying drawing material. The wavelet transform provides an efficient tool for texture analysis for this application. The discrimination showed good results even for small test matrices of size 20×20. The discrimination with first order statistical features showed similar results for large test matrices and the co-occurrence method produced sub-optimal results.
The work showed that a discrimination between dry and fluid strokes is possible. A distinction between fluid or dry strokes e.g. between brush and quill, is not possible yet. Several other features like boundary characteristics have to be added to achieve a finer distinction. An analysis of the strokes in painting direction will also bring better results, because the texture depends on the painting direction. Also an improvement of the texture analysis, e.g. the combination of different methods (DWT and co-occurrence method) can bring better results.

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