Texture based Drawing Tool Classification in Infrared Reflectograms *

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Abstract

The recognition of painted strokes is an important step in analyzing painted works of art like paintings, 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. Thus the use of computer aided imaging technologies brings a new and objective analysis and assists the art expert in analyzing painted works of art. This work proposes a method to recognize strokes drawn by different drawing tools and materials. The method uses texture analysis algorithms performing along the drawing trace to distinguish between different types of strokes. The benefit of this method is the increased content of textural information within the stroke and simultaneously in the border region. We tested our algorithms on a set of six different types of strokes: 3 classes of fluid and 3 classes of dry drawing materials.

1 Introduction

In analyzing painted works of art the recognition of painted strokes is an important and adjuvant part of the art historian's work. The obtained knowledge achieves more insights into the painters work. But the recognition of the drawing tool and material of painted strokes is not always clear and unambiguously. Thus the help of computer aided systems can assist art experts in doing their work, comparable to the usage of computers in medical applications which are nowadays inconceivable without computers.
In this work we are going to develop an algorithm which detects underdrawing strokes from medieval painted work of art. Several work in this direction has been done before [6, 9]. Underdrawings constitutes the basic concept of an artist when he starts the creation of his work of

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art. Normally they are hidden by paint layers in the finished painting. With the help of infrared reflectography it is possible to view through the visible paint layers and thus make the underdrawings visible. The insights of underdrawings are considered by art experts and restorers in museums. One step towards to this challenge is the recognition of strokes in visible layers grabbed with scanners or normal cameras which is the concept of this work.

Bomford [1] specified typical fluid and dry drawing media used for the creation of underdrawings in medieval painted work of art. These tools will be examined and considered in this work. Painted strokes or lines can be painted either in dry or fluid drawing material. Chalk and graphite are examples for dry materials and paint or ink applied by pen or brush are examples for fluid painting materials. The appearance of the boundary characteristics, the texture, the stroke endings or the color variety can be used for the visual recognition of painted strokes.

Our method regards the stroke texture in order to recognize them. Texture analysis is a widespread research topic and is used and tested primarily for synthetic texture images like Brodatz [2], VisTex and MeasTex [16]. Practical applications are the detection of cloud types [3], rock texture [12] and texture classification or segmentation in SAR images [19]. An overview in texture analysis is given in [17].

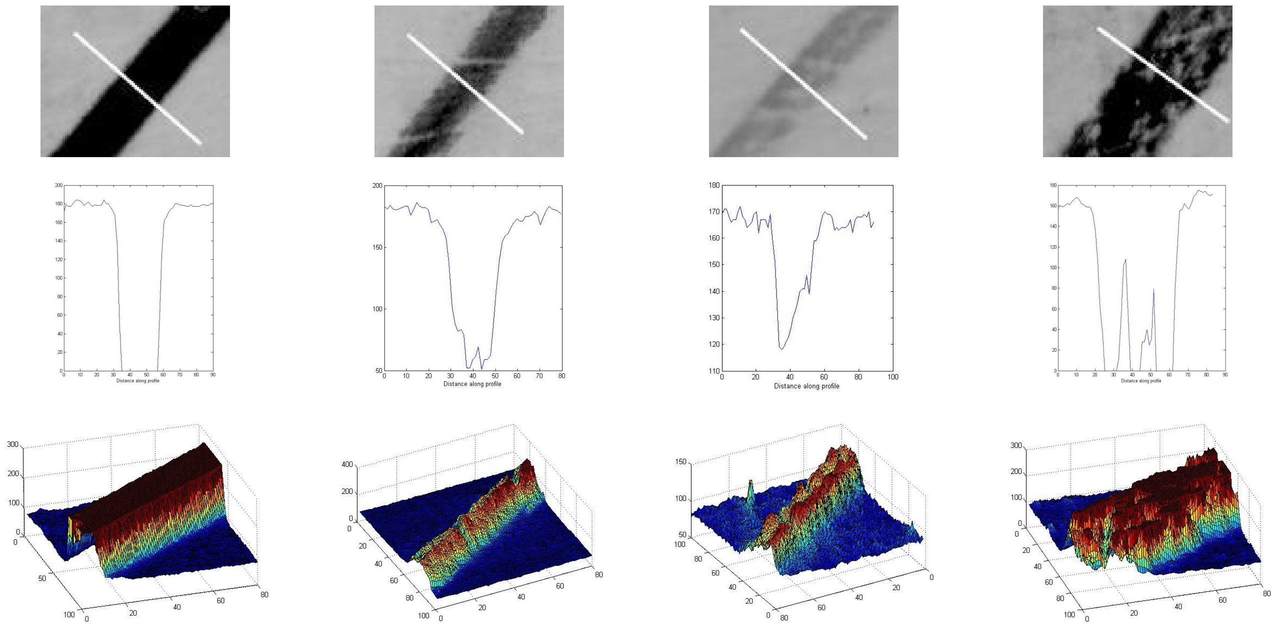
Franke et al. [4] analyzed the ink texture for writer identification. The work analyzed the texture of 62 different kinds of pens and refills which were subsequently classified into three different types of ink by an achieved recognition result up to 99,7%. A previous work from the author [9] examined the texture in strokes. Wirotius et al. [18] showed a differentiation in gray level distributions in writer identification. Unlike to [4] and [9] the calculation of the textural features will be aligned i. e. the window calculating the features moves along the stroke trace, parallel to the stroke boundary. So we can use bigger analysis windows in order to have more texture information and we have more texture information of the border region of the strokes which is fundamental to distinguish between them.

The organization of this paper is as follows. In the next section we show the data material used for our work. Section 3 covers our algorithm. In Section 4 experiments and results are given and the last two sections give a conclusion and cover the future work of our approach.

2 Data

The texture of painted strokes depends on the painting tool and material used, the underground (grounding), the drawing pressure, speed and angle. We will investigate the painting tool and material in our work. The effect of the background to the texture of the strokes will not be investigated in this work due to the fact that there is no information about the underground in real medival work of art. Also the influence of pressure, speed and angle is not investigated in this work.

The considered strokes used in the present study are applied on test panels prepared by a restorer. We examine the following strokes: 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 a resolution of 1200dpi. Figure 1 gives examples for dry and fluid drawing tools/materials. The first row shows a sample



(Brush) (Graphite) (Silver Point) (Black Chalk)

Figure 1: Considered strokes in this work.

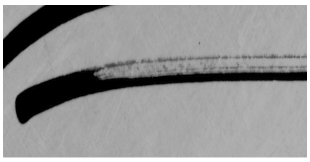


Figure 2: The reed pen stroke shows discontinuities along the stroke surface (texture).

window from the scanned image in the size of 100×80 pixels. Pixel-value cross-sections along the white line segments from this image can be seen in the second row. The image profile varies clearly between several strokes and main differences lie within the border regions of the profiles and thus in the border region of the strokes. The profile from the graphite and silver point stroke shows sloping borders and no black level pixel. The black chalk profile is very coarse with varying bottom. Profiles from fluid drawing materials like the brush stroke have sharp borders and a constant bottom. Hence important information lies within the border region of the strokes and thus even these regions have to be considered in the texture analysis. The third row shows a 3D view of the stroke surface. We used the reversed gray scale image were the z-axis gives the pixel value. The surface from the dry materials varies clearly and the surface from fluid drawing materials is nearby constant. Differences can be seen in the distribution of the texture over the whole stroke. The brush texture is nearby constant over the whole stroke. The texture from the quill stroke has some brighter areas and the surface from the reed pen shows discontinuities where the medial part of the stroke is sometimes brighter and has less drawing material than the border region. This incident can be seen in Figure 2.

3 Algorithm

Figure 3 gives an overview of the algorithm. The first task is the segmentation of the individual strokes to allow a particular texture analysis. Then the medial axis is calculated for each separated stroke to facilitate the texture analysis along the stroke trace in painting direction. The features calculated from the texture analysis are the input for the classifier which determines the painting tool and material used for the creation of the stroke. The following sections cover the individual tasks of segmentation and texture analysis.

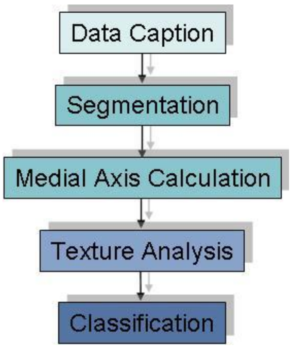


Figure 3: The overall algorithm for the recognition of painted strokes.

3.1 Segmentation

Through the similarities of our data and algorithm to applications in image document analysis we decided to choose a segmentation task adapted from document analysis. In document image analysis the input image is binarized and then the skeleton of the separated characters is calculated to get the overall shape for the proximate classification [7].
Leedham [8] found that a background subtraction by the help of the top-hat transformation with a proximate global threshold produced by Otsu's algorithm outperforms some other well known global and local thresholding algorithms for text/background segmentation in difficult document images. Morphological operations remove artifacts from the background and inside the strokes. To achieve the medial axis which is needed for the direction controlled texture analysis of the stroke, we calculate the skeleton from the individual strokes. The thinning algorithm from Zhang and Suen [20] is used therefore. Figure 4(a) shows the scanned input image. A detail from (a) after segmentation and thinning is shown in (b).

3.2 Texture Analysis

The primarily task in identifying the painted strokes is the extraction of the textural features. The benefit in this work is the direction controlled analysis. Standard texture classification algorithms perform parallel to the image boundaries. For the texture analysis for writer identification [4] a mask was generated to consider only regions belonging to the writing trace. In [9] the sample windows are extracted manually.
For the stroke application it is optimal to scan the textural features along the medial axis of the stroke trace. This condition can be seen in Figure 5 where the rotated sampling window

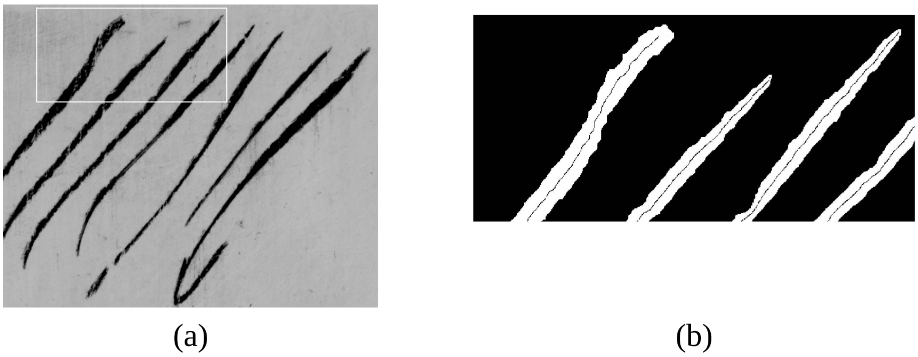


Figure 4: (a) Input image, (b) shows a detail from (a) after the segmentation and calculation of the medial axis.

(b) contains more texture information than the normal window (a). Through this innovation we have several advantages:

- Bigger sample windows can be adopted to gain the textural features for providing more texture information
- The windows include more border information of the strokes which is fundamental to distinguish between them (see Section 2)
- The recognition step can be automatized.

To gain the textural features we applied two different texture analysis methods. The requirements are analysis methods for irregular and coarse textures. A similar application area is the texture analysis of clouds [3]. The texture from clouds can be compared to our data because of the irregularity of the texture and the homogeneous case which means the clear case in the clouds application and the texture of fluid strokes in our application. The work from [3] uses 8 different texture analysis methods to build a feature vector of 55 elements. The first method for our work is the Gray Level Co Occurrence Method GLCM [5] which showed good results for the cloud texture analysis [3]. The second method is the Discrete Wavelet Transformation DWT [11] which also outperformed other methods in several comparative studies [15, 14].

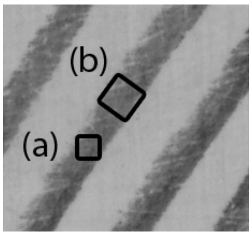


Figure 5: Sample windows to calculate textural features. (a) standard method, (b) proposed method.

3.2.1 Gray Level Co Occurrence Matrix

The co-occurrence matrix is a very popular tool in texture analysis. It has been presented in 1973 by Haralick, Shanmugam and Dinstein [5]. 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 $135°$.
We calculated the energy, inertia, entropy and the homogeneity to get an four dimensional feature vector which is further used for the classification.

3.2.2 Discrete Wavelet Transformation

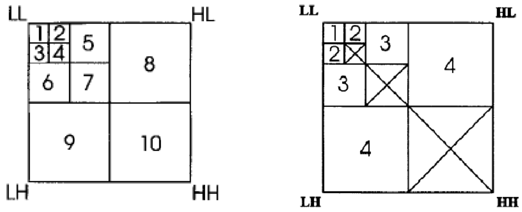
The discrete wavelet transformation (DWT) [11] decomposes an original signal $f(x)$ with a family of basis functions $\psi_{m,n}(x)$, which are dilations and translations of a single prototype wavelet function known as the mother wavelet $\psi(x)$:

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

$c_{m,n}$ 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 [11]. 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. A three level decomposition results in 10 sub images, see Figure 6(a) whereas the approximation image is the input image for the next level.
We calculate the energy of the coefficient magnitudes 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 [13], see Figure 6(b).

3.3 Texture Classification

The number of textural features per stroke depends on its length and the distance between placing the windows. We used a distance of 10 pixels to place the windows along the medial axis of the stroke. To limit the feature space we combined them by building the mean and standard deviation of the features. Thus we got 8 features for the GLCM method: the mean and standard deviation for the energy, inertia, entropy and homogeneity. And we got 8 DWT features: the mean and standard deviation from the energy in the four channels. The GLCM and DWT features are classified independently using the kNN classification algorithm.



(a) (b)

Figure 6: (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 [13].

4 Experiments and Results

We tested our method on a total set of 128 strokes. The features gained were classified using the kNN classifier and the leave-one-out method. Classification results are tabulated in Table 1. Best results were obtained with $k = 3$. The percentage of correct classified strokes constitutes 75.21% for the DWT features and 69.2% for the GLCM features. A combination of the features from both methods could not outperform this results. Here, the percentage of correct classified strokes constitutes 73.4% by a total number of 16 features.
To show the classification results for the several classes Table 2 tabulates the confusion matrix for the classification results from the DWT method. As seen in the tables, the reed pen stroke were most often misclassified by a percentage of correct classified strokes of 33.33%. This is due the fact that the texture from the reed pen is manifold, see Section 2. The highest percentage of correct classified strokes is within the silver point strokes. It constitutes 92.86%.
Figure 7 shows demonstrates the feature spaces. The x-axis shows the mean value of the energy in the first channel of the DWT method and the y-axis gives the standard deviation from the energy in the first DWT channel. It can be seen that all strokes show compact clusters for their features except the features for the reed pen (diamond) which are distributed over the whole feature space. Brush and Quill show low energy values. These two strokes differ by their standard deviation, whereas the brush has a higher standard deviation. Black chalk, graphite and silver point show increasing values for their energy and build up three clusters. As in agreement with the manual description of the strokes in Section 2 the fluid materials have low energy values for the mean energy value and the dry materials like chalk, graphite and silver point have higher energy values. The silver point has the highest energy values which is analog to Figure 1 where the 3D view from the silver point shows a fine texture with high frequencies.

Method	NoF	kNN (%)
DWT	8	75.21
GLCM	8	69.2
Combination	16	73.4

Table 1: Classification results: method, number of features and classification result.

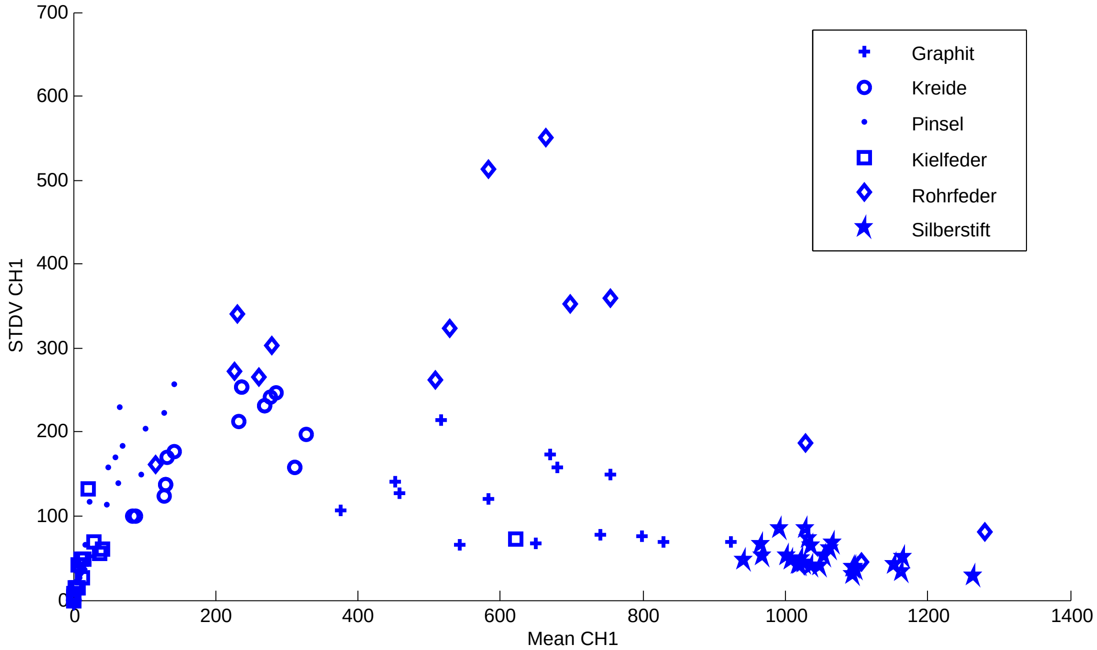


Figure 7: The feature space from the DWT features in Channel 1.

5 Conclusion

In this work a rotational alignment of texture analysis of painted strokes has been proven. The method developed was able to correctly classify up to 75% of painted strokes into a set of 6 predefined classes. We applied two different texture analysis methods, the Discrete Wavelet Transformation and the Gray Level Co Occurrence Matrix. The problems in analyzing the texture of painted strokes, the narrow width and the winding painting trace of the strokes, is avoided by an algorithm which performs along the drawing trace of the strokes to calculate the textural features. Through this enhancement we have three advantages in analyzing the stroke texture: first we have a maximum content of stroke texture, second we also have the maximum content of the border region of the strokes which is fundamental to distinguish between different types of painted strokes, and third the recognition can be automatized. The algorithm can be

stroke class	**classified as (%)**					
	Graphite	**Chalk**	**Brush**	**Quill**	**Reed Pen**	**Silver**
Graphite	85.71	7.14	0.00	0.00	0.00	7.14
Chalk	0.00	82.35	5.88	0.00	11.76	0.00
Brush	0.00	0.00	75.00	25.00	0.00	0.00
Quill	5.00	0.00	20.00	75.00	0.00	0.00
Reed Pen	5.56	22.22	5.56	16.67	33.33	16.67
Silver	0.00	0.00	0.00	0.00	7.14	92.86

Table 2: Confusion Matrix for the Classification results from the DWT features.

adopted to the identification of the different stroke types in painted work of art as well as the recognition of writing materials in handwritten documents.

6 Outlook

To improve the classification results we will add profile features to the textural features. Profile classification has been used in [18] where profiles have been described using 4 parameters: its length, the level of the darkest pixel, the skewness and the asymmetry coefficient. Furthermore we are going to test our method for the investigation of underdrawing strokes. Therefore the test panels will be covered by a painting layer and grabbed with an infrared camera to see the strokes under the covering layer. The paint layer consist of a pigment and a binder. Subject to the transparency of the paint layer to infrared radiation [10] we get more or less insight into the underdrawing in order to investigate the texture of these strokes. The experiences from these test series will be adopted to the investigation from infrared reflectogramms from real underdrawings of medieval painted work of art.

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