Automated Stroke Ending Analysis for Drawing Tool Classification

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Abstract

This paper proposes a drawing tool recognition method based on features calculated from the shape of stroke endings. The application for this method is to help art historians to identify the drawing tool used for a drawing. Since the style of a drawing depends on the drawing tool used, drawing tool recognition is an important step toward a style analysis. A dominant feature of a drawn stroke is its ending. Several features regarding curvature, proportions etc. are calculated out of the shape of the endings. These features are then used to classify stroke endings with a SVM classifier.

1 Introduction

Every drawing consists of an assemblage of strokes which can be arranged in different ways. They can form hatches, shapes or curves [12]. The analysis of strokes in drawings is an interdisciplinary field which unites Art History and Computer Science.[1]

Eight different drawing tools have been examined in this paper. These tools have been selected because they were the tools most used in making drawings since antiquity [12]. They are divided into dry and transferential drawing tools. The latter serve as carrier for a fluid drawing medium [1, 12]. The drawing tools examined in this paper are

- Dry Drawing Tools: Black chalk, charcoal, graphite.
- Transferential Drawing Tools: Reed pen (reed, juniper), goose quill, brush, metal nib pen.

The shapes of stroke endings drawn with these tools are used to recognize the drawing tool. Figure 1 shows the endings of strokes drawn with these tools (from left to right: black chalk, charcoal, graphite, brush, juniper, goose quill, metal nib and reed pen). Drawings were

Figure 1. Stroke endings of 8 drawing tools.

preparatory steps of paintings since the early Renaissance: sketches, to record an idea, to compose a drawing, to try out a different combination of elements and to study poses, proportions and arrangements [12]. Therefore they show the artistic development of the master in a way that changes in the style can be tracked and used for dating purposes or to ensure or discard an attribution. Autonomous drawings came up in the Renaissance area [12]. Even if they are not preliminary stages of a painting, their expressivity allows the same insights into an artist's work as drafts and sketches [12].

Drawing tool classification has been proposed by [9]. They use two approaches, one is based on stroke contour analysis and the other on stroke texture analysis.

Section 2 shows a method to cut off endings from a stroke. The features used to characterize an endings shape are listed in Section 3. Section 4 shows the results of the experiments made, while conclusions are drawn in Section 5.

2 Ending Extraction

To achieve a first segmentation, a thresholding algorithm is applied on a grayscale stroke image to divide the image into strokes and background. The thresholding algorithm proposed by Otsu [16] was used for our test strokes. This global threshold selection method has

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the advantage of being unparameterized and unsupervized [7].

Thresholding the image results in a binary representation of the strokes. Since the stroke contours are discretized, a snake [10] is applied on them to achieve a smooth contour. Snakes have the advantage that grayscale information can be introduced as a force to draw the snake toward the true contour. This means that the contour derived from the binarized image can be corrected with the snake.

To extract stroke segments from a stroke formation the parallel thinning algorithm by Zhang and Suen [18] is applied. This algorithm was examined by Lam and Suen [13] in their comparative paper about character skeletonization algorithms and showed good performance and results.

Skeletons show spurious branches and split-up junctions. These branches are produced by non-uniformities in the strokes [11] e.g. a rough outer contour of dry drawing tools or irregular ink flow of transferential drawing tools. When two strokes cross at a sharp angle, skeletonization methods produce two vertices connecting three skeleton segments rather than a vertex connecting four segments. The skeleton restructuring method presented by Kégl and Krzyzak [11] is applied to overcome these inconsistencies. They require a graph representation $G_{V,S}$ of the skeleton.

The skeleton is used to extract stroke segments from an stroke formation. The meeting point of the skeleton and the stroke border is the endpoint of the stroke. If there is no meeting point, the skeleton branches are extended until they meet with the stroke border.

A tessellation as proposed by [11] is computed to partition a stroke formation. It consists in calculating the distance of each point to the skeleton graph $G_{V,S}$. Then the shape is partitioned into nearest-neighbor regions. Each region contains the points x_{v_i} of a shape where the distance to a vertex $\Delta(v_i)$ is less than the distance to all other vertices V or x_{s_i}, where the distance to a edge $\Delta(s_i)$ is less than the distance to all other edges S.,

The skeleton is divided up into branches, which either go from an endpoint to the nearest junction on the path or consist of paths between junctions. A stroke segment is defined as all nearest neighbor sets which belong to vertices or edges of a skeleton branch.

Figure 2. Illustration of a stroke.

A stroke segment can be open, half-open or closed. An open stroke consists of a body connecting two endings, delimited by endpoints. Figure 2 shows a schematic stroke with body and endings (highlighted). These endings are distinguished from their body by their decreasing width toward the endpoints. A half-open stroke has one free ending. The other part of the stroke joins either another stroke at some angle or an area or a shadow. A closed stroke has both endings covered. Since endings are visible only on open and half-open strokes, only these types of strokes are considered.

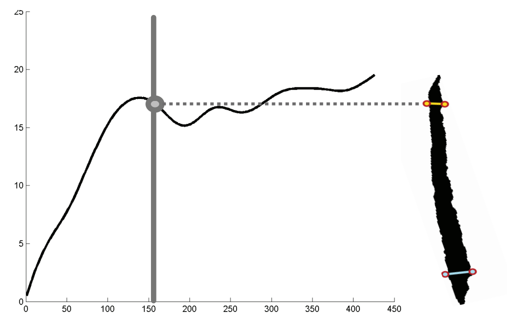

Figure 3. Ending extraction of a chalk stroke.

To find out the transition point between ending and body, the distance w between both sides of a stroke is calculated. This distance is regarded as a function with a limit at the mean width of the body which marks the transition between ending and body. There, the ending is cut from the body. The contour of the ending is used for further processing. Figure 3 shows this procedure. A chalk stroke is depicted with marks where the endings are cut off. The corresponding function of the upper ending is shown at the right side. The y-axis represents the distance between each opposed contour point (x-axis).

3 Features

This section describes the features used to characterize the shape of stroke endings.

3.1 Statistical Features

These features deal with statistical properties of shape [5].

Distance from Centroid: The distances Δ_x from every contour point x to the centroid are calculated and serve a representation of a shape. The following statistical terms calculated from Δ_x serve as features: Minimum, maximum, mean, standard deviation, skewness and kurtosis. These features describe the structure of an ending [5].

Moments: Chen and Tsai introduce seven moment invariants in [2] based on Hu-Moments. These Chen-Moments are defined for boundaries and are invariant under translation, rotation and scaling.

3.2 Curvature Based Features

It can be observed in Figure 1 that the drawing tools exhibit different curvature patterns at the endings. The curvature is calculated according to [5]. They use a multiscale approach, the so called *curvegram*. The increasing scale parameter causes the curvegram to be less sensitive to high frequency noise and fine details. The shape tends toward a shape with low positive curvature; it reflects its global structure.

Bending Energy: The mean bending energy, also known as boundary energy, is defined as [5]

$$\bar{B} = \frac{1}{N} \sum_{n=0}^{N-1} c\left(n\right)^2 \tag{1}$$

where c is the curvature at a point on the curve and N the number of points. Since the mean bending energy of the original shape is subject to noise, the bending energy of the low-pass filtered curve is also considered. This feature is a measure for shape complexity.

Standard Deviation: This feature is the ratio of the standard deviation of the original curvature and the smoothed curvature.

Curvature Development: The feature examines the relation between the curvature at 50% of the curve length and the mean curvature at 25%, respectively 75% of the curve length. It compares the curvature at the endpoint to the mean of the curvatures at half way through the ending. It distinguishes endings with a high curvature at the endpoint and low curvature at midway (pointed) and endings with low curvature at the endpoint and higher curvature at midway (angular).

Maximal Curvature: This feature introduces the relation between the maximum curvature of the original curve and the one of the smoothed curve.

3.3 Structural Features

These features describe the structure, i.e. the roughness and the width evolution of an ending.

Area to Perimeter Ratio: denotes the relation between the area which includes the ending and its perimeter [5].

Rectangularity: is the ratio between the ending and its rectangular bounding box [5].

Distance Relation: Let dw be the distance of the open ends of the stroke ending boundary (e.g. approximately the width of the stroke body) and dn be the distance between the point at 25% and the one at 75% of the curve length. The relationship $\frac{dn}{dw}$ is used as feature. This feature relates the thickness of the stroke to the thickness of the ending at midway. It can distinguish pointed or blunt endings.

Temperature: The temperature $Temp$ of a contour is defined on a thermodynamics formalism and has a strong relationship to the fractal dimension [5, 8]. It is defined as follows

$$Temp = \left(\log_2\left(\frac{2P}{P-H}\right)\right)^{-1} \tag{2}$$

P is the perimeter of an ending and H its convex hull.

Triangularity: This feature is inspired by the work of Shen et al. in [17]. A triangle is fitted into an ending. The three points defining it are the endpoint of the stroke and the open endpoints of the stroke ending. The area of this triangle A_{TR} is compared to the area A_{xy} of the stroke ending: $Triang = \frac{A_{TR}}{A_{xy}}$

Convex Hull Area Measure: This feature A_{AH} compares the area of the ending to the area of its convex hull A_H. It is defined as follows [6]:

$$A_{AH} = \frac{A_H - A_{xy}}{A_H} \tag{3}$$

4 Experiments and Results

To classify the the stroke endings, Support Vector Machines (SVM) are used [4]. The overall classification rate reached 70.6%. The evaluation was performed on a set of 468 stroke endings with leave-one-out-cross-validation.

Table 4 shows the results of the classification of the drawing tools. The performance of the algorithm is over 72% for all transferential drawing tools. In contrast, the recognition of dry drawing tools reached between 37% and 56%.

Other drawing tool classification systems used different tools and different numbers of classes. In [14] the classification of strokes into dry and fluid drawing media gained between 65% and 90%. In [9] the classification was done between three drawing tools (brush, black chalk and graphite). They reached a correct classification rate of 89% with combined boundary and texture features. [15] classified six classes of drawing tools with texture features and a classification rate of about 75%.

Another test performed on the strokes divides all strokes into two classes, one for the dry drawing tools and the other for the transferential tools. The overall classification rate reached 89.04%. Here again, the classification worked better for transferential tools: They

Drawing tool	%
Black Chalk	55.53
Charcoal	37.77
Graphite	56.25
Brush	89.09
Juniper	72.58
Metal Nib	82.75
Goose Quill	83.33
Reed Pen	87.52
Overall	**70.60**

Table 1. Percentage of correctly classified strokes per class.

reached about 96.38% while the dry drawing tools were classified in 81.70% of the cases in the right way, as shown in Table 2.

Class	All features	Reduced set
Trans.	96.38%	97.03%
Dry	81.70%	75.60%
Total	**89.04%**	**86.31%**

Table 2. Results of the classification into two classes of all 468 stroke endings.

We found a subset of features which reached a comparable result. This subset are the best three features according to the F-score [3] which tests for linear separability of features:

1. Distance from Centroid: Minimum
2. Distance from Centroid: Mean
3. Convex Hull Area Measure

The majority of the features are derived from the distance from the centroid. Table 2 shows the results. The overall classification rate decreased of 2.73%, the classification rate for the transferential tools increased of 0.65% and the classification rate for the dry drawing tools dropped of about 6.10%.

5 Conclusion

The classification was tested with drawn strokes. As the results show, transferential drawing tools are better recognized than dry drawing tools. This origins in the defined cut of the nib, which results in a low variance between stroke endings of one class. The inner-class variance of endings drawn with dry drawing tools is larger, because the ending shape depends more on factors like pressure, or more generally, on the individual style of the artist.

Future work includes the search for features which are better suited for dry drawing tools. Ending shape analysis can also be combined with stroke texture and boundary analysis. Since segmentation was not the main task of this thesis, here better results could be gained with a better segmentation method.

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