Stroke segmentation from livestock brand images

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Abstract. The detection and extraction of primitive curves is an important stage in line analysis systems used to handle considerable number of digital image processing problems. This article presents a stroke segmentation approach suitable to perform similarity measuring, using digital image processing techniques, in a cattle brand registration system. The skeletons of the brands are analyzed to detect and separate primary strokes at junction and intersection points. Primary strokes are then mapped into a three-dimensional orientation space to group them in the primitive continuous strokes. The results of a set of experiences are presented.

1 Introduction

The detection and extraction of continuous curves is an important stage in line analysis systems used to handle considerable number of digital image processing problems, like blood vessels in medical image analysis [1], strokes in handwritten text recognition [2, 3], roads and rivers and other curvilinear structures in satellite image analysis [4], detection of fractures in material and geological structural analysis by mean of images [5].

The identification of similarities in handwritten cattle brand registration is another application where the correct extraction of primitive strokes is crucial for successful brand similarity measuring. These brands are composed by one or more isolated draws: letter, number, symbol, etc.; most of the times these symbols appear overlapped. Each isolated draw is composed by connected primitive strokes.

In our search for a suitable method of stroke segmentation to perform similarity measuring in a cattle brand registration system, we have found several approaches that make use of certain line characteristics like curve width and orientation. In our particular case the cattle brand registration system requires these brands to be recorded as sketches handwritten on a digital table. With this digitalization mechanism, the width of the strokes is the same in all directions, so, it is not a predominant line feature. In such a situation the only informative feature that characterizes a curve is its orientation.

The techniques for the segmentation of isolated lines are trivial, but the methods of detection and separation of overlapping curves are not. In order to do so, we need to locally analyze the regions of the strokes and establish some criteria to determine the existence of X-like intersections and T-like junctions.

In the literature there exist several previous studies related to junction analysis [6–9]. Partial stroke grouping and line continuation also received a considerable number of studies [10–13].

Some successful methods of stroke segmentation allowing junction analysis and partial stroke grouping into primitive continuous strokes make use of the orientation space [14–16]. Nevertheless, there are certain conditions where these methods may fail to correctly segment a set of overlapping strokes, for instance, when junctions or intersections occur at very small angles or on a region with high curvature [15].

In this article we present an alternative stroke segmentation approach suitable for applications like cattle brand similarity measuring. Section 2 will describe the stages of the proposed methods, Section 3 will discuss our specific implementation, Section 4 will present some results, and finally Section 5 will conclude the article.

2 Stroke segmentation

The proposed method is divided in two main stages. First we proceed detecting junction and intersection points and extracting primary strokes by separating the brand curves at these points. In a second stage, those primary strokes will be grouped into continuous primitive strokes.

2.1 Junction and intersection detection

We can consider the whole brand logo image as a curvilinear region $\mathcal{B}$ in a 2-dimensional space. Each point $P \in \mathcal{B}$ could be classified, exclusively, as a regular point or as a singular point; these points usually appear grouped in regular and singular regions, respectively. Singular regions are made-up of points from strokes junctions and intersections. Regular regions are composed of connected terminal points and normal curve points. To properly identify to which kind of region a point P belongs, let define the degree of freedom $n(P)$ of point P as the number of directions toward which the brand curve can be traced starting from point P.

Figure 1 illustrates several types of points. Terminal points will be those for which $n(P) = 1$, since from a terminal point we can trace a curve in one direction, solely. Any point for which $n(P) = 2$ will be classified as a normal point of $\mathcal{B}$. Hence, regular regions will be any set $\{x_i \mid 0 < n(x_i) \leq 2\}$ of connected points x_i. Similarly, singular points, i.e., junction and intersection points, will be points for which $n(P) \geq 3$; singular regions are generally composed of isolated singular points. There may be points for which $n(P) = 0$, i.e., isolated dots; these will count as an isolated stroke.

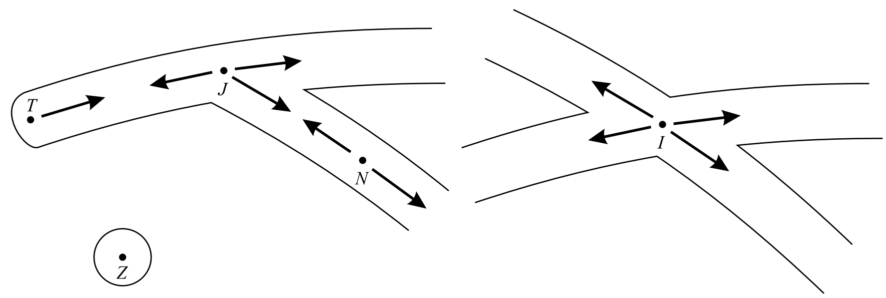

Fig. 1. Several kind of points: a terminal point, $n(P) = 1$ labeled T; a normal point, $n(P) = 2$ labeled N; a T-like junction point, $n(P) = 3$ labeled J; a X-like intersection point, $n(P) = 4$ labeled I; and an isolated dot, $n(P) = 0$ labeled Z.

2.2 Primary stroke extraction

Let define a primary stroke as the union of a regular region, as defined above, and its delimiting singular regions, if the latter exists. At this point we can face five scenarios, see Fig. 2:

1. isolated points, e.g., Z;
2. isolated strokes, which have terminal points in both of its ends, e.g., $\overline{IJK}$;
3. isolated closed loops, composed uniquely with normal points, for instance, an O shaped draw;
4. untied primary strokes, which have a terminal point in one of its ends, and a singular point in the other, e.g., $\overline{AB}$;
5. tied primary strokes, which have singular points in both ends, e.g., $\overline{BC}$.

Note that—defined this way—a regular region will belong to one, and only one, primary stroke. While a singular region, or just a singular point P, will belong to $n(P)$ primary strokes. Note also that a successful extraction of a primary stroke relies, primarily, on the correct identification of singular points.

Summarizing, to extract a primary stroke we proceed isolating each regular region together with each delimiting singular region, if any.

2.3 Primary stroke grouping

Let define what we understand by a primitive stroke using a practical example. A primitive stroke, in the scope of this work, is a curvilinear trace one can draw with a pen on a paper, from an initial point to a final point, which may or may not be the same initial point, without leaving the paper. Based on that analogy, isolated strokes—including isolated dots—and isolated closed loops are primitive strokes by themselves, for example, point Z and stroke $\overline{IJK}$ in Fig. 2. However, tied and untied primary strokes may or may not be part of a more complex primitive stroke, for instance, in Fig. 2, strokes $\overline{GC}$ and $\overline{CH}$ form a single primitive stroke $\overline{GCH}$, but if point H does not exists, the primary untied

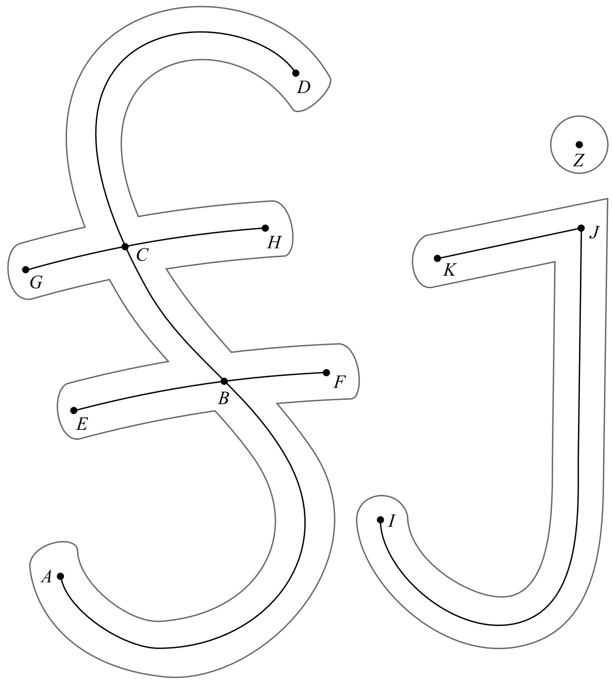

Fig. 2. Several types of primary strokes. An isolated dot, Z; an isolated stroke, $\overline{IJK}$; untied primary strokes, $\overline{AB}$, $\overline{CD}$, $\overline{EB}$, $\overline{BF}$, $\overline{GC}$, and $\overline{CH}$; and a tied primary stroke, $\overline{BC}$.

stroke $\overline{GC}$ would also be a primitive stroke. Analogously, if points A and D does not exist, the tied stroke $\overline{BC}$ would also be a primitive stroke as well as a primary stroke.

Alternatively we can give a more rigorous definition: A primitive stroke is the union of one or more primary strokes, provided that the resulting region determines a continuous 2-dimensional curve or a simple polygonal. This definition allows for two or more primary strokes joined by L-vertexes—e.g. point J in Fig. 2—to be treated as primitive strokes.

To determine which primary strokes are part of the same primitive stroke and group them together, we will proceed as follows. First we will construct a 3-dimensional orientation space, see Fig. 3, in which the x and y axes are the same axis determined by the image's reference frame, and the z axis is the line orientation parameter. Let $\zeta(P)$ represent the orientation of the tangent line at point $P \in \mathcal{B}$, measured with respect to the x axis in the 2-dimensional space containing $\mathcal{B}$. Each point $P(x, y)$ will be mapped to point $\bar{P}(x, y, z)$ in the orientation space setting $z = \zeta(P)$.

After mapping all points in $\mathcal{B}$, into the orientation space, every primary stroke will be connected to other primary strokes determining a continuous curve in the orientation space, the primitive stroke they conform. The only procedure that

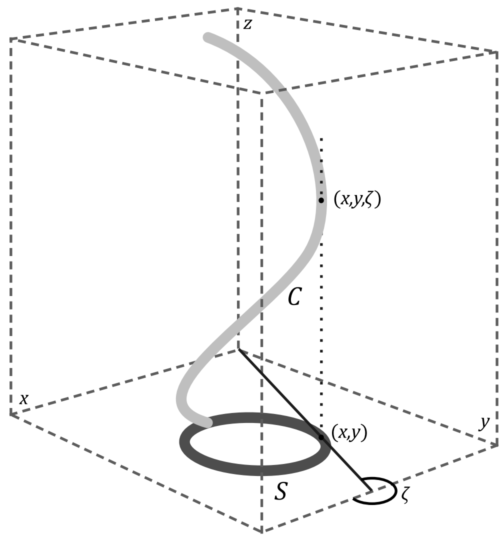

Fig. 3. Mapping a curve into the orientation space.

left to do is to project each primitive stroke back from the orientation space onto individual planes, see Fig. 4.

Note that this technique is not able to separate two tangent lines, since at the tangent point both lines will have the same x and y coordinate and the orientation of the tangent line at that point will be the same for both curves.

3 Implementation

Some methods allow the identification of line junctions and intersections working on thick lines [14, 16], our experiments with those techniques show that there are particular cases in which junctions and intersections are not handle properly. We propose to implement the line analysis on the skeletons of the brand strokes allowing us to detect the junction and intersection points. A suitable skeleton is required for this purpose. For suitable we understand a one pixel width skeleton without neither spurious nor redundant elements. There are many approaches to choose from [17–19] but in general the skeletonisation step should be followed by a normalization procedure. Normalization is required to cleanup spurious branches (line fuzz artifacts), to restore the loss of connectivity at intersection (necking artifacts) and junction (tailing artifacts) regions, and to remove redundant points ensuring a one pixel width skeleton. These kind of postprocessing are described in [18, 20, 21].

For our experiences we have chosen the Euclidean Distance Transform to find the medial axis of the brand strokes, which have been tuned to bring one pixel width skeletons. The only normalization step we have applied to the obtained skeleton is the staircase removal algorithm described in [18].

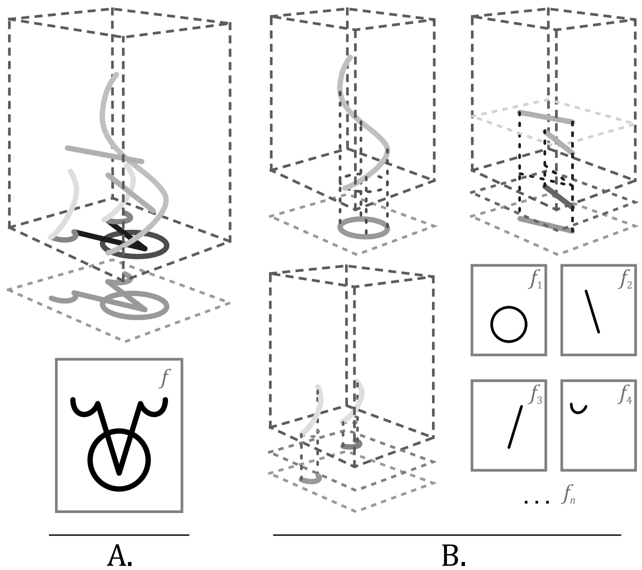

Fig. 4. Projecting the mapped continuous curves from the orientation space back onto individual planes will produce separated images for each stroke in the original image.

When we have achieved a suitable skeleton to work with, let take the degree of freedom $n(P)$ of each pixel P in the brand skeleton as the number of pixels in the 8-neighborhood of pixel P. As it has been said before, junction and intersection points are represented by pixels with $n(P) \geq 3$. Proceed labeling each pixel in the cattle brand skeleton with its degree of freedom. Once all singular points have been identified and labeled, perform the following algorithm to separate the primary strokes in the cattle brand skeleton:

1. Search the original image frame for a pixel P_0 with $n(P_0) = 2$. If any, create a new image frame and proceed with step 2.
2. Copy into the new image frame each 8-connected pixel P_i starting at P_0 for which $n(P_i) \leq 2$ and remove those pixels from the original image.
3. Whenever an 8-connected pixel P_m with $n(P_m) > 2$ stops the process from the previous step copy this pixel into the new image frame.
4. Repeat from step 1 until there remain no more pixel P for which $n(P) = 2$.
5. Copy any pixel P with $n(P) = 0$ each into an individual image frame until there are no more such pixels in the original image frame.

After we have obtained all primary strokes from the original image, each one of them is mapped into a 3-dimensional orientation space. Continuous strokes should occupy connected regions in the orientation space, this way, projecting back these connected regions onto individual planes should effectively group primary strokes to form the primitive strokes from the original cattle brand image. Note that it is not necessary to map the entire primary stroke, but only the singular regions belonging to them. Labeling the mapped voxels in the orientation space will help us to determine which primary strokes should be merged together. To measure the orientation of the tangent line passing each pixel we use the boundary-to-boundary orientation distance as described in [14, 15]. The only parameter that should be tuned is the orientation quantization which will determine the number of levels in the orientation space; we have set this value to 3°. Lower values will setup high orientation selectivity, but also will result in a low continuity sensitivity producing discontinuous lines if junctions or intersections occur at regions with high degrees of curvature. Similarly, higher values will group strokes when junctions or intersections occur at very small angles.

4 Experimental results

Table 1 summarizes the results of testing two stroke segmentation approaches on various test sets. The first approach use the method presented in [14, 15] which perform the line junction and intersection analysis on thick lines using the point-to-boundary orientation distance (PBOD) therein defined. The second approach use the skeletons of the cattle brand images to determine the junction and intersection points as described in Section 3. Both approaches use the orientation space technique to group primary strokes in continuous primitive strokes.

Several image test sets were synthesized by applying affine transformations to real cattle brand images: A) The displaced set contains images translated within the canvas a non integral amount of pixels; B) The rotation set contains images arbitrarily rotated in 3° steps; C) The scaling set contains images scaled slightly, expanding or shrinking the original images using random scale factors; D) The stretching set contains images scaled in only one direction, using a similar criteria to the scaling set; E) The shearing set contains images slightly slanted in one or two directions using randomly selected shearing factors.

Both approaches fail to separate or reconnect segments in some images, specially in variations in which the alteration of the orientation of the strokes plays a central role, as in rotation or shearing transformations. Just the alterations that exhibit the more severe errors as shown in Table 1.

	Junction analysis using	
Transformation	PBOD	Skeleton
Displacement	13.3%	8.3%
Rotation	18.1%	11.4%
Scaling	13.7%	9.0%
Stretching	14.9%	9.5%
Shearing	16.2%	10.7%
Mean Values	15.2%	9.8%

Table 1. Segmentation error rates for two stroke segmentation approaches.

Based on these results, the proposed method shows a slight improvement in the segmentation of the strokes in cattle brand images undergoing several kinds of transformations, promising better results for our cattle brand similarity measuring system.

5 Conclusion

We have presented a stroke segmentation algorithm suitable to perform similarity measuring of handwritten cattle brand images based on the comparison of local stroke shape features. The skeleton of the brand sketch is used to identify the strokes' junction and intersection points, and these points are used to determine the primary strokes that compose the cattle brand. An orientation space mapping technique is used to group these primary strokes in primitive strokes that will allow the local shape feature extraction needed to perform the similarity comparison.

A minor issue of this segmentation technique using the orientation space mapping method is the correct trade-off between the orientation selectivity and the continuity sensitivity, which is handled by properly selecting a suitable value for the quantization of the orientation parameter. A major problem that we have not solved yet is that the current method is not able to segment tangent lines.

The drawback with tangent lines is that both will occupy the same place in the space at the point of tangency. Namely, if curve S_1 and curve S_2 are tangents at point C, the slope of these curves—and therefore its orientation—at that point will be the same. Thus, point C will be mapped to the same point in the orientation space, and curves S_1 and S_2 will remain connected.

This limitation may be solved constructing a higher order space introducing another parameter like the line curvature, as suggested by [14], since such space will be able to represent not only more than one orientation at a single point, but even more than one curvature.

The results of our experiences show a slight improvement in the segmentation allowing better results in processes depending on this technique.

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