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Accurate Junction Detection and Reconstruction in Line-Drawing Images

The-Anh Pham, Mathieu Delalandre, Sabine Barrat and Jean-Yves Ramel
Laboratory of Computer Science (LI), François Rabelais University, Tours city, France
phamtheanh@hdu.edu.vn, {mathieu.delalandre, sabine.barrat, jean-yves.ramel}@univ-tours.fr

Abstract

In this paper, we present an approach for junction detection and reconstruction in line-drawing images. Our approach is shifted to a problem of high curvature point detection from the skeleton of image. Like this, it is independent of any vectorization process and parameter free. The junction reconstruction stage takes benefit of the reliable skeleton segments and their topological relations to reconstruct junctions and make their positions accurate. The experimental results show that the proposed method is competitive with other baseline methods and can achieve accurate junction detection with some pixel errors.

1. Introduction

This work is related to the problem of keypoint detection in images. Keypoint detection is an important topic of the Computer Vision field, since keypoints are regarded as useful features to address the problems of indexing, recognition or spotting. In this paper, we are interested in a particular problem of keypoint detection: the detection of junctions in document images. Most of the techniques proposed in the Computer Vision field to detect junctions are not adapted to the document images [5] as they are dedicated to gray level images where intensity variability plays an important role in the detector accuracy. For this reason, dedicated methods have been proposed in the Document Image Analysis field where the junction detection problem has been mainly considered as a post-processing of the vectorization step.

In [2], the authors proposed an approach for junction reconstruction based on topological correction of vectorization results. This work, as discussed by the authors themselves, were subjected to several weaknesses being time-consuming, sensitiveness to interrupted patterns, the ambiguous step of merging junction points. The work in [2] has been further developed in [3] where its main improvements rely on the process of junction optimization by generating the hypothesis of two joint primitives. This approach requires traversing all possible paths starting from a long primitive and leading to either another long one or an end of a chain of short primitives and thus is subjected to the problem of combinational explosion. The work [6] reported the junction detection problem as an identification of relations (crossing, parallelism, *etc.*) between contour primitives (*i.e.* quadrilaterals). A last approach is related to the direct vectorization methods [7]. In this method, the junction detection is driven by a tracking process of the different lines in the image to generate hypothesis about junction position and configuration.

However, it is difficult to judge about performance of these different methods for junction detection, as their evaluation has been mainly driven at the vectorization level. In addition, these methods rely on vectorization, known to be sensitive to setting parameters, and presenting difficulties when heterogeneous primitives (straight lines, arcs, curves and circles) appear within a same document [7]. Knowledge about the document content must be included, making the systems less adaptable to heterogeneous corpus.

In this paper we present a new method for accurate junction detection and reconstruction in line drawing images. Our approach is shifted to a problem of high curvature point detection from the skeleton of image following a process of junction reconstruction. The experimental results prove that our approach is robust and accurate, parameter free and can be applied to heterogeneous documents composed of various graphical primitives. The rest of this paper is organized as follows. The proposed approach is described in Section 2. Then, experimental results are discussed in Section 3. Some key conclusions and future work are given in Section 4.

2. The proposed approach

The proposed approach is briefly outlined in Figure 1 including three stages of skeletonization, high curvature point detection and junction reconstruction. Two main challenges are identified in this work: accurate determination of support region in high curvature point detection and skeleton distortion. The former is addressed by using the linear least square (*LLS*) line fitting technique. The later is treated in the junction reconstruction stage. We will detail now the different stages in the next subsections 2.1, 2.2 and 2.3.

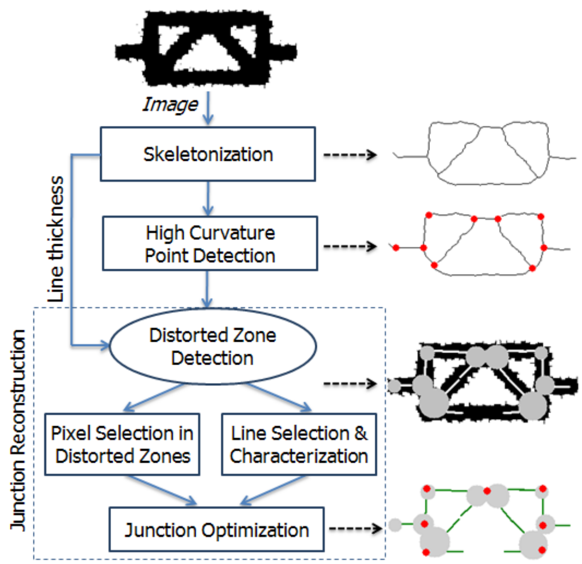

Figure 1. Overview of the proposed approach.

2.1 Skeletonization

Our method has to be applied to binary images. These images could be obtained following some enhancement processes such as noise filtering, binarization, *etc.* These operations depend on specific applications. After that, the skeleton of the input image is extracted based on the technique of G.S. di Baja [1] for the following advantages: stability, the well-shaped obtained skeleton and its computation efficiency. Starting from the skeleton chaining, all skeleton branches are extracted and become the inputs for the next stage.

2.2 High curvature point detection

As discussed in [8], one major challenge of many dominant point detection algorithms has been known as determination of the support region in which each dominant point of the curve should have its own view that makes sense to recognize this point from the others. Even though the method proposed by Teh-Chin [8] showed good results in this field, the step of determination of support region in this method is objected to several weaknesses (*i.e.* poor results in the presence of circles, sensitive to digitalization effect, *etc.*). To overcome these weaknesses, the *LLS* line fitting technique has been employed to automatically determine the support region of each point. Particularly, the support region of each point is estimated as the shorter length of two straight line segments fitted by the *LLS* technique on the leading and trailing parts at this point. Note that the use of *LLS* has been investigated in [2, 3] for the purpose of skeleton segmentation, not the same as our purpose of determination of the support region. Once the support region is precisely determined, the step of dominant point detection could be done using any one of the standard techniques as presented in [8]. The detected points, in combination with crossing-points (*i.e.* the skeleton points that have at least three 8-connected neighbors), are treated as the candidate junctions and will be used to detect distorted zones in the next stage.

2.3 Junction reconstruction

Our algorithm of junction reconstruction is composed of several steps: distorted zone detection, local topological configuration extraction and junction optimization. These three steps are detailed now in correspondence with an example in Figure 2.

Distorted Zone Detection: The distorted zones are detected based on two following observations: The source of distorted zones is due to the skeletonization process when applying to *thickened* objects and the distorted zones have taken place at the junction points. Consequently, a distorted zone Z_J, for a given candidate junction point J, is defined as the area constructed by a circle centered at J with a diameter of local line thickness at J. Several distorted zones could intersect together resulting in a Connected Component Distorted Zone (*CCDZ*). The pixels located inside each *CCDZ* are then recorded to be used as searching area for the further step of junction optimization (*e.g.* the gray areas in Figure 2(a)). At the same time, all the skeleton pixels located inside *CCDZ*(s) are removed remaining "not-distorted" or *reliable* skeleton segments.

Local Topological Configuration Extraction: A local topological configuration at each *CCDZ* is defined as the set of straight line segments, $\{P_iQ_i\}_{i=1,\ldots,n}$, stemming from this *CCDZ*. That is, for each reliable skeleton segment stemming from a *CCDZ*, we characterize it by a straight line segment originating from the extremity P_i linked to this *CCDZ* (*e.g.* Figure 2(b)). Each line segment P_iQ_i is then associated with an uncertain domain which is defined as the zone constructed by two rays, $P_{i1}Q_i$ and $P_{i2}Q_i$, originating from a common point Q_i and each ray will form an included angle of τ_i (in degrees) with P_iQ_i (*e.g.* Figure 2(c)).

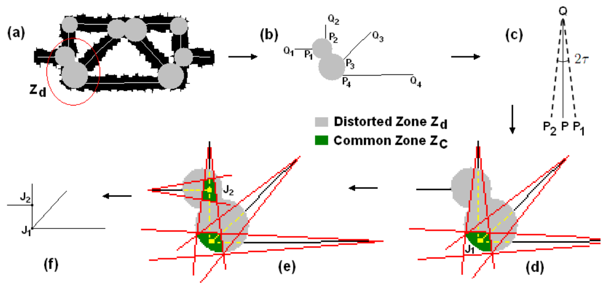

Figure 2. (a) Reliable line segments and distorted zones (*e.g.* Z_d) detected for an image; (b) local topological configuration extracted for the zone Z_d in (a); (c) the uncertain domain defined for a line segment; (d) the 1^{st} iteration: the segments $\{P_iQ_i\}_{i=2,3,4}$ are clustered into one group resulting in a new junction point J_1; (e) the 2^{nd} iteration: the segments $\{P_iQ_i\}_{i=1,2}$ are clustered in one group resulting in a new junction point J_2; (f) final topological skeleton and junction points.

Junction Optimization: The main idea of our junction optimization step is that the segments $\{P_iQ_i\}_{i=1,...,n}$ of a given *CCDZ* (*e.g.* Zd) will be clustered into different groups so that the segments of each group are then merged together to form a junction point. Concerning this problem of clustering segments, the authors in [2] described a solution where they calculated intersection zones constructed from the uncertain domains of different primitives. This approach is subjected to one constraint that each primitive is allowed to be clustered in only one group and thus gives a rise of several drawbacks as discussed before. Another approach to perform segment grouping is presented in [5] by using an EM-like algorithm subjected to one assumption that each neighborhood contains one junction point only. This situation is not our case since each distorted zone could include several junction points, and, more importantly, these junction points could be connected together. Therefore, we develop, below, a solution to address the problem of line segment clustering in the case of multiple junctions.

- Step 1: Initiate a searching zone: $Z_D = Z_d$.
- Step 2: Search for a junction point $J \in Z_D$ by maximizing an objective function $F(J)$ as follows:

$$F(J) = \sum_{i=1}^{n} \delta_i(J)(1 + \exp(-d_i(J)^2) * W(J))$$

  where $d_i(J)$ is the distance from J to the line segment P_iQ_i, and $\delta_i(J)$ is equal to either 1 or 0 depending on if J is located inside the uncertain domain of P_iQ_i or not. The weighted function $W(J) = \prod_{k=1}^{n} \theta(w_k)$ where the weights $\{w_k\}$ are first initiated as the distances between J and every extremity point P_k if $\delta_k(J) = 1$ and 0 otherwise. Then, all these weights $\{w_k\}$ are normalized to be unit length (*i.e.* $\sum_{k=1}^{n} w_k = 1$). The function $\theta(w_k) = w_k$ if $w_k \neq 0$ and 1 otherwise.
- Step 3: Determine the line segments whose the uncertain domains include the junction point J. A new group is then created for these line segments (*e.g.* Figure 2(d)). Let Z_C be the *common zone* defined as the overlapping area between the uncertain domains of the line segments linked to the new group and the zone Z_D. The distorted zone Z_D is then updated as $Z_D = Z_D \setminus Z_C$. Repeat Step 2 until every line segment is clustered into some group (*e.g.* Figure 2(e)).
- Step 4: For each line segment P_iQ_i that participates in more than one group, if there is at least one ray P_iX belonging to the uncertain domain of P_iQ_i which does intersect the common zones of *all* these groups, the line segment P_iQ_i is retained as it is; otherwise (*i.e.* this is the case of topological inconsistency), the uncertain domain of P_iQ_i is updated with a new angle $\tau_i = \tau_i - 1$. Repeat Step 1 until there is no presence of topological inconsistency among the obtained groups (*e.g.* Figure 2(f) illustrates final detected junctions).

It is noted that we have designed the objective function $F(J)$ in a specific way that it meets the three properties: (a) it tends to group as many line segments together as possible; (b) the optimal junction point J will be the point that minimizes the amount of bending energy of the line segments in each group and (c) the obtained junction point should be located in the *central zone* of all line segments in each group.

3. Experimental results

In this section, our junction detection method is evaluated based on repeatability criteria. In fact, this criteria is a standard for performance characterization of keypoint detection methods in the literature [9]. Given a reference image I_{ref} and a test image I_{test} taken under different distortions (*e.g.* noising, rotation, scaling) from I_{ref}, the repeatability indicates that local features detected in I_{ref} should be repeated in I_{test} with some small error ϵ in location ($\epsilon = 5$ in our experiment).

We have compared the results of the proposed approach with those of two baseline methods: a vectorization-based system in [3] and fork point detector of K. Liu [4]. All these detectors have been applied on the final recognition datasets (*i.e.* setA, setB, setC, and setD) from the Symbol Recognition and Spotting Contest in GREC2011 [10]. These datasets contain 2500, 5000, 7500, and 1800 test images, respectively. The first three datasets were distorted by Kanungo noises and geometric transformations (*i.e.* scaling and rotation) whereas the last dataset was disturbed by context noises (*i.e.* symbols cropped from full line-drawing images).

The repeatability scores of three junction detectors are shown in Table 1. As we can see, the proposed approach shows much better results than the ones obtained by all other detectors. Particularly, we have achieved rather high repeatability scores for the first three datasets but the performance of all detectors are significantly reduced for the last dataset. This point could be explained by the fact that the setA, setB and setC are composed of isolated symbols (*e.g.* the top row in Figure 3) while the setD is mixed with other context noises resulting in many false alarms detected in this dataset (*e.g.* the last row in Figure 3).

Table 1. Repeatability scores (%).

	setA	setB	setC	setD
Our method	77.57	78.97	80.04	19.44
Hilaire06	58.45	59.56	59.80	15.43
Liu99	59.31	59.51	59.01	15.79

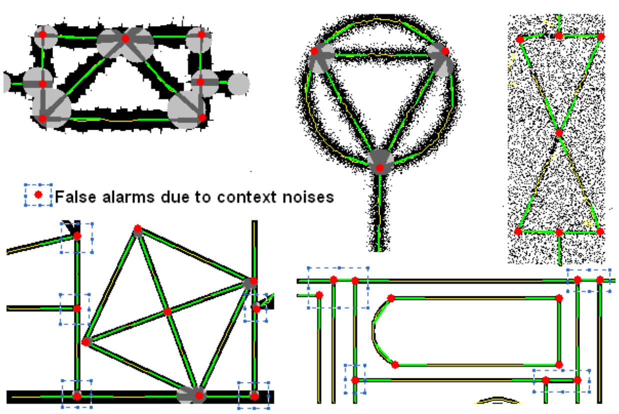

Figure 3. Few results of detected junctions (in red).

4 Conclusions and future work

In this paper, an approach for junction detection and reconstruction in line-drawing images has been presented. The first challenge consisting of the determination of support region has been addressed by using the *LLS* technique, that makes it robust to digitization effects. The other challenge of skeleton distortion has been treated by exploiting the useful information from reliable skeleton segments and taking into account the advantages of topological analysis and optimization. The experimental results show that the proposed method is robust and accurate, parameter free and competitive with other baseline methods. More experiments on different datasets with different kind of noises will be investigated in future work. In addition, using new evaluation metric instead of repeatability score has been also planned in the future.

Acknowledgment

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References

[1] G. S. di Baja. Well-shaped, stable, and reversible skeletons from the (3,4)-distance transform. *Journal of Visual Communication and Image Representation*, 5:107–115, 1994.

[2] X. Hilaire and K. Tombre. Improving the accuracy of skeleton-based vectorization. In *Proceedings of GREC'01*, pages 273–288, 2002.

[3] X. Hilaire and K. Tombre. Robust and accurate vectorization of line drawings. *IEEE Trans. Pattern Anal. Mach. Intell.*, 28(6):890–904, 2006.

[4] K. Liu, Y. Huang, and C. Y. Suen. Identification of fork points on the skeletons of handwritten chinese characters. *IEEE Trans. Pattern Anal. Mach. Intell.*, 21(10):1095–1100, Oct. 1999.

[5] M. Maire, P. Arbelaez, C. Fowlkes, and J. Malik. Using contours to detect and localize junctions in natural images. In *Proc. of CVPR*, pages 1–8, 2008.

[6] J.-Y. Ramel, N. Vincent, and H. Emptoz. A structural representation for understanding line-drawing images. *IJDAR*, 3(2):58–66, 2000.

[7] J. Song, F. Su, C. L. Tai, and S. Cai. An object-oriented progressive-simplification-based vectorization system for engineering drawings: Model, algorithm, and performance. *IEEE Trans. Pattern Anal. Mach. Intell.*, 24(8):1048–1060, 2002.

[8] C. H. Teh and R. T. Chin. On the detection of dominant points on digital curves. *IEEE Trans. Pattern Anal. Mach. Intell.*, 11(8):859–872, 1989.

[9] T. Tuytelaars and K. Mikolajczyk. Local invariant feature detectors: A survey. *Foundations and Trends in Computer Graphics and Vision*, 3(3):177–280, 2007.

[10] E. Valveny, M. Delalandre, R. Raveaux, and B. Lamiroy. Report on the symbol recognition and spotting contest. *Proceedings of GREC'11, LNCS*, 7423, 2011.