Unsupervised, Fast and Precise Recognition of Digital Arcs in Noisy Images

T. P. NGUYEN, B. KERAUTRET, I. DEBLED-RENNESSON, J. O. LACHAUD

Équipe ADAGIO

LORIA
Campus Scientifique - BP 239
54506 Vandoeuvre-lès-Nancy Cedex, France

LAMA

Bâtiment Chablais, Campus Scientifique, 73376 Le Bourget-du-Lac Cedex, France

Outline

1. Introduction
2. Arc segmentation
3. Unsupervised Noise Detection
4. A framework for arc recognition along noisy curves
5. Experimentations
6. Conclusions and futur work

Outline

1 Introduction
2 Arc segmentation
3 Unsupervised Noise Detection
4 A framework for arc recognition along noisy curves
5 Experimentations
6 Conclusions and futur work

Introduction

Motivation

- Arc and circle are basic objects in discrete geometry.

⇒ The study of thes primitives are important.

- Arc and circle appear often also in images.
- Due to the effect of aquisition phase, there is often noise in images

⇒ The detection, recognition of these primitives in noisy condition are interesting topic in pattern recognition.

Reel image

Introduction

Motivation

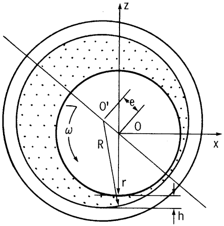
- Arc and circle are basic objects in discrete geometry.

⇒ The study of thes primitives are important.

- Arc and circle appear often also in images.
- Due to the effect of aquisition phase, there is often noise in images

⇒ The detection, recognition of these primitives in noisy condition are interesting topic in pattern recognition.

Document graphic



Discrete circle

Discrete circle

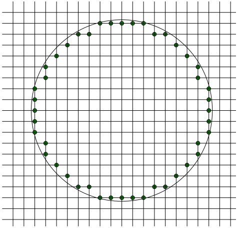
- Basic object in discrete geometry.
- Based on the discretization of a reel circle.

Existing definitions

- Kim's definition
- Nakamura's definition
- Andres' definition

Définition

A discrete circle ([Kim84]) is constructed from digital points that are are the most nearest and interior in a discrete circle.



C. E. Kim.
Digital disks.
Pattern Analysis and Machine Intelligence, IEEE Transactions on, PAMI-6(3) :372–374, May 1984.

Discrete circle

Discrete circle

- Basic object in discrete geometry.
- Based on the discretization of a reel circle.

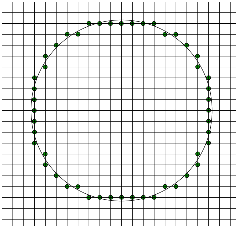
Existing definitions

- Kim's definition
- Nakamura's definition
- Andres' definition

A. Nakamura and K. Aizawa.
Digital circles.
Computer Vision, Graphics, and Image Processing, 26(2) :242–255, 1984.

Définition

A discrete circle ([Nakamura84]) is a sequenque of digital points that are nearest a discrete circle.



Discrete circle

Discrete circle

- Basic object in discrete geometry.
- Based on the discretization of a reel circle.

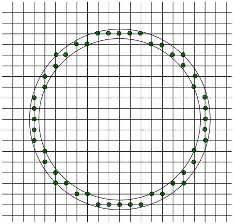
Existing definitions

- Kim's definition
- Nakamura's definition
- Andres' definition

E. Andres.
Discrete circles, rings and spheres.
Computers & Graphics, 18(5) :695–706, 1994.

Définition

A digital circle ([Andres95]) is a sequence of digital points that verifies :
$(R - \frac{w}{2})^2 \leq (x - x_0)^2 + (y - y_0)^2 < (R + \frac{w}{2})^2\}$



Outline

1 Introduction

2 Arc segmentation

3 Unsupervised Noise Detection

4 A framework for arc recognition along noisy curves

5 Experimentations

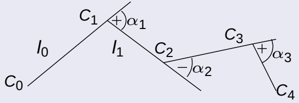
6 Conclusions and futur work

Tangent space representation [Arkin91], [Latecki00]

Input

$C = \{C_i\}_{i=0}^{n}$ is a polygonal curve with

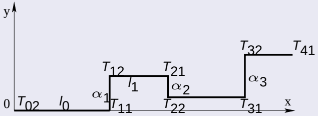
- $\alpha_i = \angle(\overrightarrow{C_{i-1}C_i}, \overrightarrow{C_iC_{i+1}})$
- l_i is the length of segment C_iC_{i+1}.
- $\alpha_i > 0$ if C_{i+1} is at the right side of $\overrightarrow{C_{i-1}C_i}$, $\alpha_i < 0$ otherwise.



Output

We consider the transform that associates polygon C of $\mathbb{Z}^2$ to a polygon of $\mathbb{R}^2$ constituted by the segments $T_{i2}T_{(i+1)1}, T_{(i+1)1}T_{(i+1)2}$ for i from 0 to $n-1$ width

- $T_{02} = (0, 0)$
- $T_{i1} = (T_{(i-1)2}.x + l_{i-1}, T_{(i-1)2}.y)$, pour i de 1 Ã n,
- $T_{i2} = (T_{i1}.x, T_{i1}.y + \alpha_i)$, pour i de 1 Ã $n-1$.



L. Latecki and R. Lakamper.

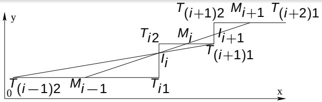
Property of an arc in tangent space

Principal result

Suppose that

- $C = \{C_i\}_{i=0}^{n}$ is a polygon with $\alpha_i = \angle(\overrightarrow{C_{i-1}C_i}, \overrightarrow{C_iC_{i+1}})$ such that $\sin \alpha_i \simeq \alpha_i$ for $i \in \{1, \ldots, n-1\}$
- $T(C)$ its representation in the tangent space, constituted by segments $T_{i2}T_{(i+1)1}, T_{(i+1)1}T_{(i+1)2}$ for i from 0 to $n-1$
- $\{M_i\}_{i=0}^{n-1}$ is a set of central point of $\{T_{i2}T_{(i+1)1}\}_{i=1}^{n-1}$.

Therefore, C is a polygon that approximates an arc of circle if and only if $\{M_i\}_{i=0}^{n-1}$ is a set of collinear points.

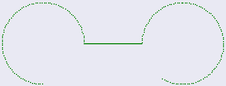


Consequence

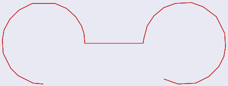
Interest of this result

Reconnaissance de cercle (arc) $\Longrightarrow$ Reconnaissance de droite

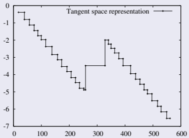
Example



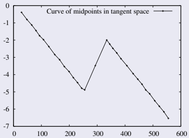
(a) Entry curve



(b) Approximated polygon



(c) Tangent space representation



(d) Central curve in the tangent space

Arc recognition and segmentation of a digital curve into arcs

Recognition of digital arc

1. Polygonalize the input curve
2. Transform this polygon to tangent space
3. Construct the middle curve in this tangent space
4. Verify the collinearity of points in this curve
   - A parameter to control the approximation error

Complexity

- Use [Debled et al. 06] for pour accomplishing steps 1 and 4 in linear time
- Step 2 and 3 are done in linear time

$\Rightarrow$ The proposed method is linear

Thanh Phuong Nguyen et Isabelle Debled-Rennesson :
Segmentation en arcs discrets en temps linéaire.
In RFIA, 2010.

Arc recognition and segmentation of a digital curve into arcs

Segmentation of a curve into arcs

1. Polygonalize the input curve
2. Transform this polygon to tangent space
3. Construct the middle curve in this tangent space
4. Polygonalize the middle curve in the tangent space
   - Utilize parameter α to verify detected arcs

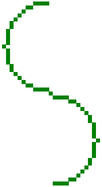
Complexity

- Use [Debled et al. 06] for pour accomplishing steps 1 and 4 in linear time
- Step 2 and 3 are done in linear time

$\Rightarrow$ The proposed method is linear

Thanh Phuong Nguyen et Isabelle Debled-Rennesson :
Segmentation en arcs discrets en temps linéaire.
In RFIA, 2010.

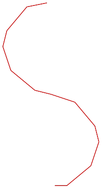
Experimentation on arc detection



Experimentation

- Input curve
- Polygonalization
- Representation in tangent space
- Middle curve in the tangent space
- Detect arcs by using blurred segment to verify the collinearity of the middle curve

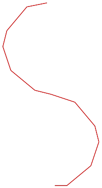
Experimentation on arc detection

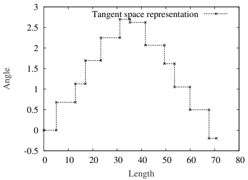


Experimentation

- Input curve
- Polygonalization
- Representation in tangent space
- Middle curve in the tangent space
- Detect arcs by using blurred segment to verify the collinearity of the middle curve

Experimentation on arc detection

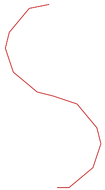


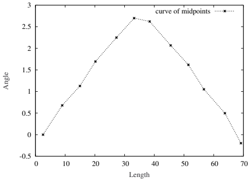


Experimentation

- Input curve
- Polygonalization
- Representation in tangent space
- Middle curve in the tangent space
- Detect arcs by using blurred segment to verify the collinearity of the middle curve

Experimentation on arc detection

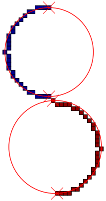


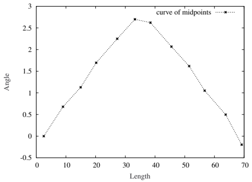


Experimentation

- Input curve
- Polygonalization
- Representation in tangent space
- Middle curve in the tangent space
- Detect arcs by using blurred segment to verify the collinearity of the middle curve

Experimentation on arc detection





Experimentation

- Input curve
- Polygonalization
- Representation in tangent space
- Middle curve in the tangent space
- Detect arcs by using blurred segment to verify the collinearity of the middle curve

Outline

1 Introduction

2 Arc segmentation

3 Unsupervised Noise Detection

4 A framework for arc recognition along noisy curves

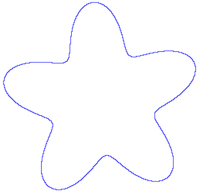
5 Experimentations

6 Conclusions and futur work

Automatic detection of significatif scales [KerLach09]

Principal idea

1. Exploit the asymtotic properties of perfect shape discretization.
2. Estimate these properties from multiscale represenatation.
3. Compare them to determine significatif scale.

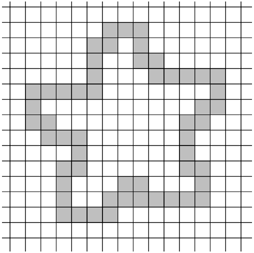


X

Automatic detection of significatif scales [KerLach09]

Principal idea

1. Exploit the asymtotic properties of perfect shape discretization.
2. Estimate these properties from multiscale represenatation.
3. Compare them to determine significatif scale.

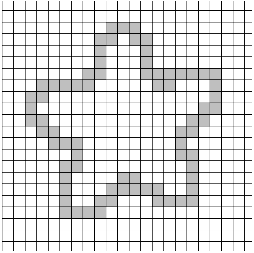


$Dig_{20}(X)$

Automatic detection of significatif scales [KerLach09]

Principal idea

1. Exploit the asymtotic properties of perfect shape discretization.
2. Estimate these properties from multiscale represenatation.
3. Compare them to determine significatif scale.

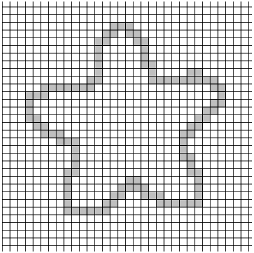


$Dig_{15}(X)$

Automatic detection of significatif scales [KerLach09]

Principal idea

1. Exploit the asymtotic properties of perfect shape discretization.
2. Estimate these properties from multiscale represenatation.
3. Compare them to determine significatif scale.

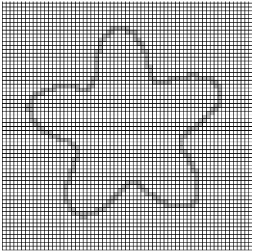


$Dig_{10}(X)$

Automatic detection of significatif scales [KerLach09]

Principal idea

1. Exploit the asymtotic properties of perfect shape discretization.
2. Estimate these properties from multiscale represenatation.
3. Compare them to determine significatif scale.

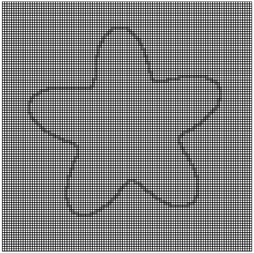


$Dig_5(X)$

Automatic detection of significatif scales [KerLach09]

Principal idea

1. Exploit the asymtotic properties of perfect shape discretization.
2. Estimate these properties from multiscale represenatation.
3. Compare them to determine significatif scale.

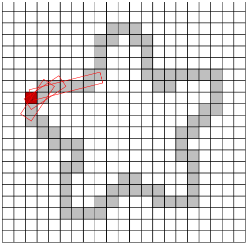


$Dig_3(X)$

Automatic detection of significatif scales [KerLach09]

Principal idea

1. Exploit the asymtotic properties of perfect shape discretization.
2. Estimate these properties from multiscale represenatation.
3. Compare them to determine significatif scale.



$Dig_{15}(X)$

Asymptotic properties of the length of maximal segments :

- Standard discrete line (discretizations 4-connexe)
- Segment of discrete line (SDL), a part of connected discrete line.
- Maximal segment of a contour C : SDL of C inextended neither to right side nor to left side.

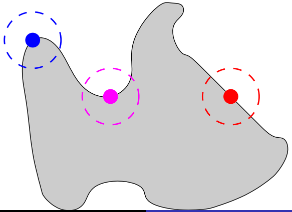
Asymtotic results of maximal segments

Theorem [Lachaud 06] : asymtotic behavior of length of maximal segments

- X simple connected shape in R^2 with the boundary ∂X with a piecewise boundary C^3,
- U an open connected neighborhood of $p \in \partial X$,
- (L_j^h) the digital lengths of the maximal segments covering p along the boundary of $Dig_h(X)$,

$$\text{if } U \text{ is strictly convex or concave, then } \Omega(1/h^{1/3}) \leq L_j^h \leq O(1/h^{1/2}) \quad (1)$$

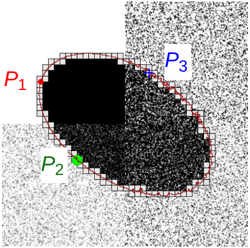
$$\text{if } U \text{ has null curvature everywhere, then } \Omega(1/h) \leq L_j^h \leq O(1/h) \quad (2)$$

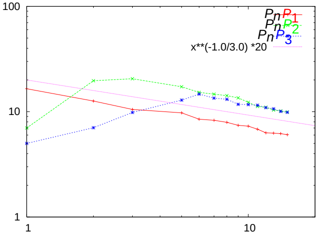


Multiscale profile

Multiscale profile of a point P on a discrete contour

- Multiscale profile : P_nP = sequence $(\log i, \log(E(L^{h_i})))_{i=1..n}$, with E mean operator, L^{h_i} are the digital lengths of of the maximal segments covering P sont les longueurs discrètes des segments forall of subsampling $i \times i$.





Meaningful scales and noise detection

Meaningful scales

A meaningful scale of a multiscale profile $(X_i, Y_i)_{1 \leq i \leq n}$ is then a pair (i_1, i_2) $1 \leq i_1 \leq i_2 \leq n$, such that for all i, $i_1 \leq i < i_2$,

$$\frac{Y_{i+1} - Y_i}{X_{i+1} - X_i} \leq t_m,$$

and not true for $i_1 - 1$ et i_2.
Parametert_m = threshold of noise level for separate noisy/non-noisy zones.

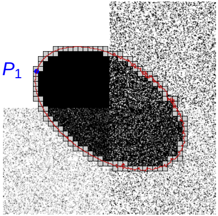
Meaningful scales and noise detection

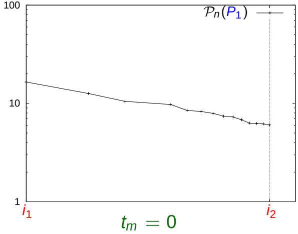
Meaningful scales

A meaningful scale of a multiscale profile $(X_i, Y_i)_{1 \leq i \leq n}$ is then a pair (i_1, i_2) $1 \leq i_1 \leq i_2 \leq n$, such that for all i, $i_1 \leq i < i_2$,

$$\frac{Y_{i+1} - Y_i}{X_{i+1} - X_i} \leq t_m,$$

and not true for $i_1 - 1$ et i_2.
Parametert_m = threshold of noise level for separate noisy/non-noisy zones.





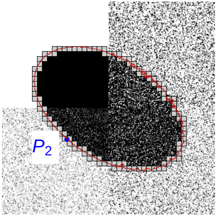
Meaningful scales and noise detection

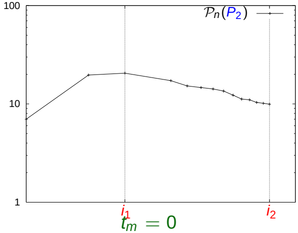
Meaningful scales

A meaningful scale of a multiscale profile $(X_i, Y_i)_{1 \leq i \leq n}$ is then a pair (i_1, i_2)
$1 \leq i_1 \leq i_2 \leq n$, such that for all i, $i_1 \leq i < i_2$,

$$\frac{Y_{i+1} - Y_i}{X_{i+1} - X_i} \leq t_m,$$

and not true for $i_1 - 1$ et i_2.
Parametert_m = threshold of noise level for separate noisy/non-noisy zones.





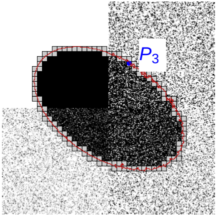
Meaningful scales and noise detection

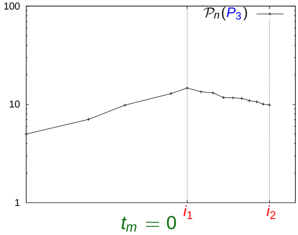
Meaningful scales

A meaningful scale of a multiscale profile $(X_i, Y_i)_{1 \leq i \leq n}$ is then a pair (i_1, i_2) $1 \leq i_1 \leq i_2 \leq n$, such that for all i, $i_1 \leq i < i_2$,

$$\frac{Y_{i+1} - Y_i}{X_{i+1} - X_i} \leq t_m,$$

and not true for $i_1 - 1$ et i_2.
Parametert_m = threshold of noise level for separate noisy/non-noisy zones.





Meaningful scales and noise detection

Meaningful scales

A meaningful scale of a multiscale profile $(X_i, Y_i)_{1 \leq i \leq n}$ is then a pair (i_1, i_2) $1 \leq i_1 \leq i_2 \leq n$, such that for all i, $i_1 \leq i < i_2$,

$$\frac{Y_{i+1} - Y_i}{X_{i+1} - X_i} \leq t_m,$$

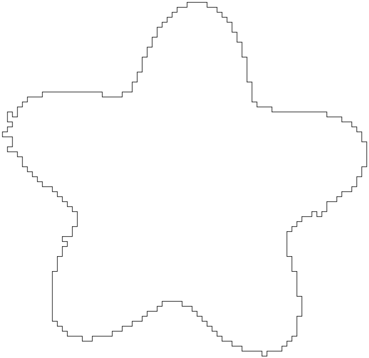
and not true for $i_1 - 1$ et i_2.
Parametert_m = threshold of noise level for separate noisy/non-noisy zones.

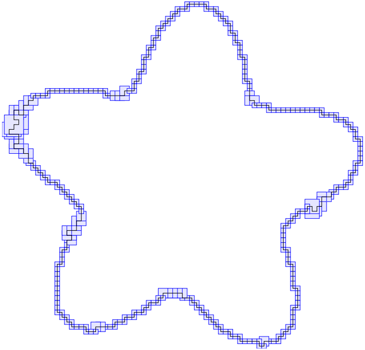
Noise level at a point P

If (i_1, i_2) is the first meaningful scale of point P, the noise level at P is $i_1 - 1$.

Experimentations on noise detection

Flower with local noise insertion

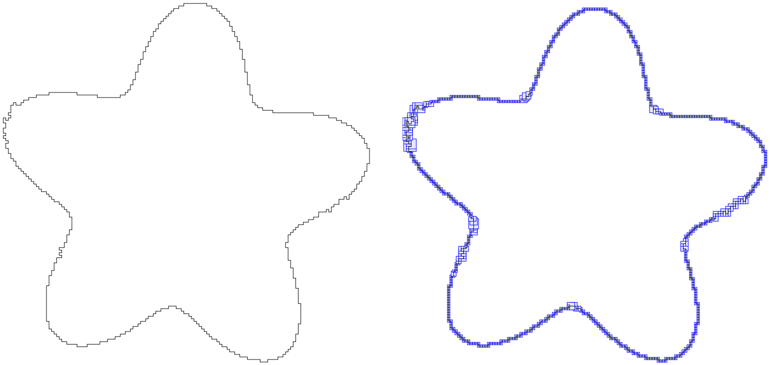




Local noise at résolution $R0$

Experimentations on noise detection

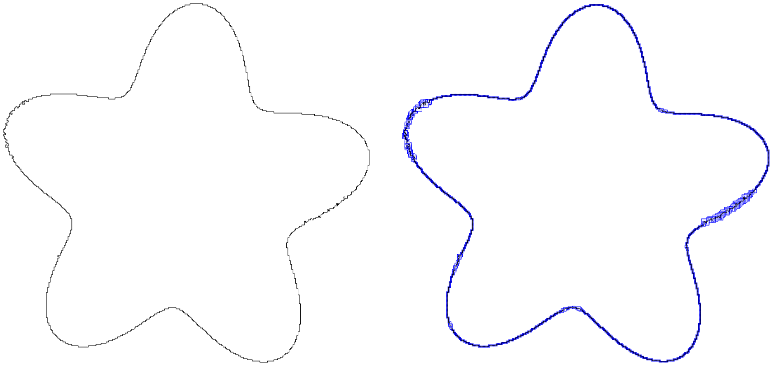
Flower with local noise insertion



Local noise at résolution $R1$

Experimentations on noise detection

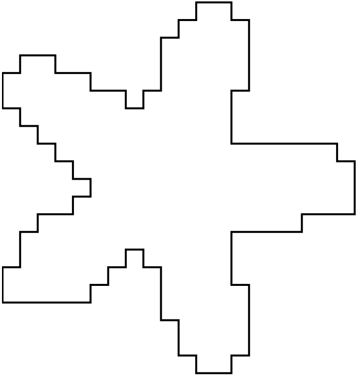
Flower with local noise insertion

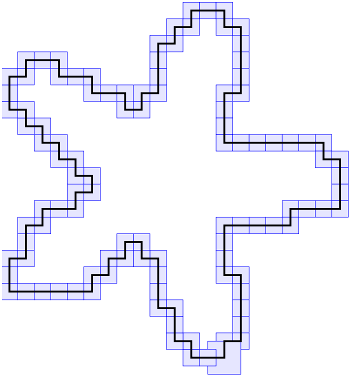


Local noise at résolution $R2$

Experimentations on noise detection

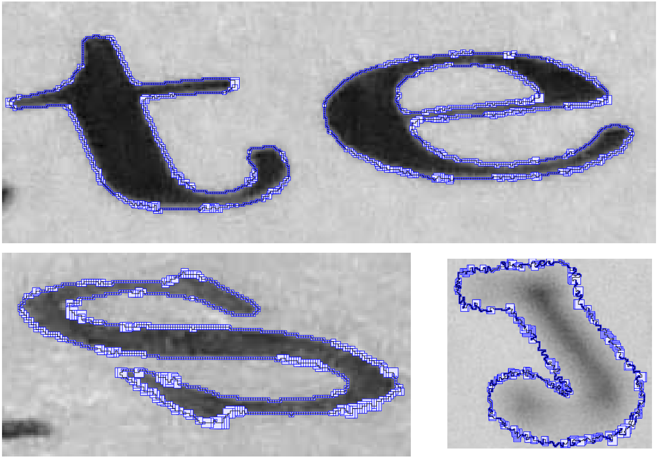
Flower at low resolution without noise





Noise detection on real images

Noise detection on real images



Outline

1 Introduction

2 Arc segmentation

3 Unsupervised Noise Detection

4 A framework for arc recognition along noisy curves

5 Experimentations

6 Conclusions and futur work

Problem of arc detection on noisy curves

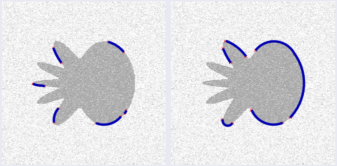
Remarks concerning the arc detection algorithm

- A parameter ν_1 to take into account the amount of noise in the polygonalization step
- This parameter is adjusted manually

$\Rightarrow$ For each noisy curve, how can we choose the value of ν_1 to obtain the best result ?

Our proposed solution

- Use [KerautretLauchaud09] to determine noise level of the noisy curve
- Construct approximated polygon based on this noise information



(e) Width=2 (f) Width=3

Polygonalization adapted to noisy curves

Proposed solution

- Two solutions for taking into account the noise of discrete contour
- The first one considers the hypothesis of uniform distribution
- The second one considers the hypothesis of non-uniform distribution

Algorithme 1 : Polygonalization based on unsupervised noise detection.

Data : $C = \{C_i\}_{i=0}^{n}$ digital curve, $\nu = \{\nu_i\}_{i=0}^{n}$ noise information, *uniformNoise- true* if uniform noise distribution, *false* otherwise
Result : P-approximated polygon
begin
    b $\leftarrow$ 0 ; Add C_b to P;
    if *!uniformNoise* **then**
        while $b < n$ **do**
            Use [DEB05] to recognize $\{C_b, \ldots, C_e\}$ as blurred segment of width ν_b;
            Add C_b to P ; b $\leftarrow$ e;
    else
        $\bar{\nu} \leftarrow$ mean value of $\nu = \{\nu_i\}_{i=0}^{n}$;
        while $b < n$ **do**
            Use [DEB05] to recognize $\{C_b, \ldots, C_e\}$ as blurred segment of width $\bar{\nu}$;
            Add C_b to P ; b $\leftarrow$ e;
end

Arc recognition along noisy curves

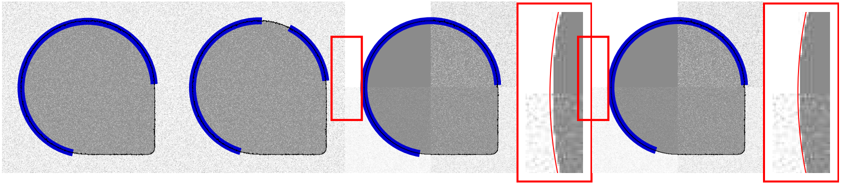
Algorithme 2 : Arc segmentation along a noisy digital curve

Data : $C = \{C_i\}_{i=0}^{n}$ noisy digital curve
Result : ARC- sequence of extracted arcs
begin
  $N \leftarrow \{N_i\}_{i=0}^{n}$ noise information determined by [1] (see Section **??**);
  $ARC \leftarrow \emptyset$; Use Algorithm 1 to polygonalize C in $P = \{P\}_{i=0}^{m}$;
  Represent P in the tangent space by $T(P)$ (see Section **??**);
  Determine the midpoint set $MpC = \{M_i\}_{i=1}^{n}$ (see Section **??**);
  Use [DEB05] to polygonalize MpC into a sequence $S = \{S\}_{i=0}^{k}$ of blurred segments of width 0.25;
  for i ***from*** 0 **to** $k - 1$ **do**
    $\{M_j\}_{j=b}^{e}$: sequence of points of MpC that corresponds to S_iS_{i+1};
    C' : part of C that corresponds to S_iS_{i+1};
    $isArc \leftarrow true$;
    for i ***from*** b **to** $e - 1$ **do**
      if $M_{i+1}.y - M_i.y > \frac{\pi}{4}$ **then** $isArc \leftarrow false$
    if $isArc$ **then** Add C' to ARC
end

Outline

1 Introduction
2 Arc segmentation
3 Unsupervised Noise Detection
4 A framework for arc recognition along noisy curves
5 Experimentations
6 Conclusions and futur work

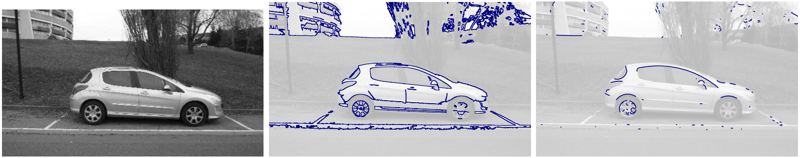
Experimentation



(g) global 1.07s 2228 points (h) adaptive 0.98s 2228 points (i) global 0.96s 1926 points (j) (k) adaptive 0.88s 1926 points (l)

FIGURE: Arcs detection from the global noise based approach (a,d) and the adaptive approach (b,e) (image size 512x512). (d,f) close-up view of (c,e).

Experimentation



(a) source image (b) contours (c) result (uniform noise)

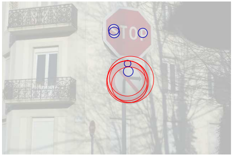
FIGURE: Arc detection with our method on an image of a car (size 4000x2672 pixels).

Experimentation

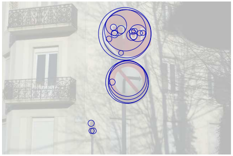
(a) Source

(b) Global : 6.57s, 12126 pts

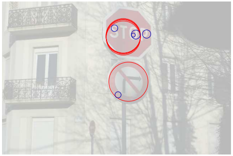
(c) Adaptif : 6s, 12126 pts



(d) CHT (Kimme1975) (1024x684)



(e) MHT (Rad2003) (1024x684)



(f) FHT (Dav1984) (4000x2672)

FIGURE: Application of our method on a real picture (size 4000x2672 pixels) with the possible values for *uniformNoise* (a-c), and comparison with three methods based on Hough transform (d-f). The corresponding parametres : (d) - $\mu_C = (70, 2, 25)$ 1m19s $\mu_C = (5, 1, 20)$ 1m0s, (e)- $\mu_M = (10, 190)$ 2.0s, (f)- $\mu_F = (200, 330, 100)$1m27s $\mu_F = (170, 50, 100)$ 4m26s

Outline

1. Introduction
2. Arc segmentation
3. Unsupervised Noise Detection
4. A framework for arc recognition along noisy curves
5. Experimentations
6. Conclusions and futur work

Conclusions

Conclusions

- A new approach for arc segmentation of digital curves in noisy images
- Combination between arc detection method and an unsupervised noise detector

$\Rightarrow$ an efficient arc detector in images. Our method

  - is better than methods based on the Hough transform which require both large memory and execution time
  - is not dependent to the need to set a specific parameter

Futur work

We plan to integrate the detection of curved zone in noisy curves of [Kerautret-Lachaud09] as a preprocessing step to enhance the robustness of the arc detector.

References

[Kimme1975] Carolyn Kimme and Dana Ballard and Jack Sklansky
Finding Circles by an Array of Accumulators
Short Communications Graphics and Image Processing **18** (1975) 120–122

[Rad03] A. A. Rad and K. Faez and N. Qaragozlou
Fast circle detection using gradient pair vectors
Digital Image Comp. : Techniques and Applications (2003), 879–887

[E.R Davies84] E.R Davies
A modified Hough scheme for general circle location
Pattern Recognition Letters **(7)** (1984), 37–43

[Debled06] Debled-Rennesson, I. ; Feschet, F. ; Rouyer-Degli
Optimal Blurred Segments Decomposition of Noisy Shapes in Linear Times
Comp. & Graphics **30** (2006) 30–36

[NguyenDebled10] T. P. Nguyen et I. Debled-Rennesson
A linear method for segmentation of digital arcs
Technical report. 2010.
`http://www.loria.fr/~nguyentp/pubs/techreport_arcsegmentation.pdf`

[KerLach09] Kerautret, B. ; Lachaud, J.-O.
Multi-scale Analysis of Discrete Contours for Unsupervised Noise Detection.