Meaningful Thickness Detection on Polygonal Curve

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Meaningful Thickness Detection

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- Geometric estimator: best scale to analyze discrete shape.
- Algorithm parameter tuning.



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curvature estimator, scale: E=3



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Denoising approach [Hoang et al.,2011] (fidelity parameter $\epsilon = 50$)





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- based on perception principle from the Gestalt theory.
- False alarm probability based on curvature approximation.

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$$\{(x,y)\in\mathbb{Z}^2,\mu\leq ax-by<\mu+|a|+|b|\},$$

- Maximal straight segment:
 - 4-connected piece (denoted M) of DSL
 - No more a DSL by adding other contour points $C \setminus M$



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where (a, b, μ) are integers and gcd(a, b) = 1.

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 ⇒ Length (L) of maximal straight segments

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Experiments of asymptotic behaviour

Experiments from subsampling

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(2)

- Construction of a multiscale profile starting from initial resolution.
- Compare the multiscale profile to determine a local meaningful scale.
- Detect locally the amount of noise.
- Detect flat/curved parts.

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- α -Thick Blurred Segments [Faure et al., 2009, Debled-Rennesson et al., 2006]:
 - Defined with a thick parameter: t
 - maximal isothetic thickness of the convex hull.
 - $\Rightarrow (P_1, Q_1, Q_2, P_2, P_3)$
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2. Meaningful Thickness

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- Maximal *a*-Thick Blurred Segments.
- The multi scale behaviour is obtained from the *t* parameter.
 - \Rightarrow the *t* step *k* given from the mean distance between each consecutive contour point.



The plots of the lengths $\mathcal{L}_{j}^{t_{i}}/t_{i}$ in log-scale are approximately affine with negative slopes as specified besides:

	expected slope	
plot	curved part	flat part
$(\log(t_i),\log(\max_j \mathcal{L}_j^{t_i}/t_i))$	$pprox -rac{1}{2}$	pprox -1
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Multi-thickness criterion

The *multi-thickness profile* $\mathcal{P}_n(P)$ of a point P is defined as the graph $(\log(t_i), \log(\overline{\mathcal{L}}^{t_i}/t_i))_{i=1,...,n}$.

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 \Rightarrow From previous Property:

- if P is in flat zone: $\mu_n(P)$ should be around -1.
- if P is in strictly convex or concave zone: $\mu_n(P)$ should be within [-1/2, -1/3].













2. Meaningful Thickness

Illustration of multi-thickness profile (2)











Example obtained by adding noise:



 \Rightarrow Define a noise threshold T_m to discriminate the curved and noisy zone.

A *Meaningful thickness* of a multi-thickness profile $(X_i, Y_i)_{1 \le i \le n}$ is then a pair (i_1, i_2) , $1 \le i_1 < i_2 \le n$, such that for all $i, i_1 \le i < i_2$,

$$\frac{Y_{i+1}-Y_i}{X_{i+1}-X_i} \le T_m,$$

and the property is not true for $i_1 - 1$ and i_2 .



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3. Experiments

Experiments on polygonal shapes (1)



Experiments on polygonal shapes (1)



Experiments on polygonal shapes (2)



Stability from intern parameters



Stability from intern parameters



• Noise threshold T_m



Comparison with the Meaningful Scales [Kerautret&Lachaud,09]



Comparison with the Meaningful Scales [Kerautret&Lachaud,09]



Comparison with the Meaningful Scales (2) [Kerautret&Lachaud,09]



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Comparison with the Good Continuation approach [Cao 03]


- Extraction of all contours
- Apply meaningful thickness detection
- detection of straight parts.



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Meaningful Thickness Detection

ICPRAM 2012 21 / 25

- Applying an iterative process on contour points P_i.
- Each points are moved:
 - by a weighted average of its two neighbors.
 - from constraint defined from meaningful thickness.
- Constraints are also defined between polygon vertex by linear interpolation.



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B. Kerautret et al. (LORIA)

Meaningful Thickness Detection