

Deep Extreme Level Set Evolution



DELSE combines powerful CNN image feature extraction with Level Set Evolution. It is end-to-end differentiable, and produces "well behaved" object contours.

Level Set Formulation

Level Set Representation

- Implicit curve with level set function ϕ $C = \{ (x, y) | \phi(x, y) = 0 \}$ Foreground: $\{(x,y) \in \Omega_I | \phi(x,y) > 0\}$ Background: $\{(x,y) \in \Omega_I | \phi(x,y) < 0\}$
- Curve evolution with level sets

$$\frac{\partial C(s,t)}{\partial t} = V\vec{N} \Leftrightarrow \frac{\partial \phi}{\partial t} = -V|\nabla \phi|$$
$$\phi_{i+1}(x,y) = \phi_i(x,y) + \Delta t \frac{\partial \phi_i}{\partial t}$$

Level Set Energy Design

• *Motion Term*: determines the motion of level set evolution. DELSE predicts a vector field \vec{V}_{θ} with motion branch and evolve with

$$\left[\frac{\partial \phi_i}{\partial t}\right]_{\text{motion}} = -\langle \vec{V_{\theta}}, \nabla \phi_i \rangle$$

• *Curvature Term*: To make the curve's shape generally well behaved, DELSE regularize the predicted curve by moving it in the direction of its curvature. This term is selective with a learned modulation function m_{θ} .

$$\frac{\partial \phi_i}{\partial t}\Big]_{\text{curvature}} = m_\theta \,\kappa |\nabla \phi_i| = m_\theta \,|\nabla \phi_i| \,\operatorname{div}\Big(\frac{\nabla \phi_i}{|\nabla \phi_i|}\Big)$$

• *Regularization Term*: To maintain a desirable shape of LSF, DELSE regularize $|\nabla \phi|$ to be either close to 0 or 1 with

$$\left[\frac{\partial \phi_i}{\partial t}\right]_{\text{reg}} = \operatorname{div}\left(p'(|\nabla \phi_i|) \frac{\nabla \phi_i}{|\nabla \phi_i|}\right)$$

Object Instance Annotation with Deep Extreme Level Set Evolution Zian Wang¹, David Acuna^{*2,3,4}, Huan Ling^{*2,3}, Amlan Kar^{2,3}, Sanja Fidler^{2,3,4} Tsinghua University¹, University of Toronto², Vector Institute³, NVIDIA⁴

Model Architecture



Architecture of DELSE: Extreme points are encoded as a heat map and concatenated with the image, which are then passed to the encoder CNN. A multi-branch architecture is used to predict the initial curve and parameters used in level set evolution.

Results

Model	Bicycle	Bus	Person	Train	Truck	Motorcycle	Car	Rider	mIoU	F mean(1 pix)	F mean(2 pix)
DEXTR*	71.92	87.42	78.36	78.11	84.88	72.41	84.62	75.18	79.11	54.00	68.60
DELSE*	74.32	88.85	80.14	80.35	86.05	74.10	86.35	76.74	80.86	60.29	74.40
DEXTR [29]	76.36	88.58	82.44	76.40	87.53	75.20	87.17	79.06	81.59	60.65	73.85
Level Set Regression	76.05	88.21	82.40	78.69	86.50	74.31	87.17	78.99	81.54	58.87	72.08
DELSE	77.83	89.56	83.42	82.45	88.11	77.16	88.29	79.98	83.35	64.35	77.62

Quantitative Evaluation on Cityscapes. mIoU for region similarity and F metric for boundary.

Model	J mean	J recall	F mean	F recall
DEXTR	82.4	94.2	84.5	93.5
Level Set Regression	81.7	90.9	83.4	91.4
+ Motion Term	84.0	94.9	84.7	94.0
+ Modulation Term	84.8	95.0	87.5	95.1
+ Skip Features	85.6	95.1	87.8	94.8







Interactive correction on Cityscapes. Corrections are used with DELSE*, which is trained on 10 out of 16 cities.

Multi-scale boundary evaluation on DAVIS.







	mIOU	F mean
Full data)	83.35	77.62
10 of 16 cities)	82.45	75.85
liting Clicks	mIOU	F mean
	84.73	79.64
	85.97	81.34
	86.83	82.52
oints Clicks	mIOU	F mean
	83.60	78.27
	84.49	79.67
	84.94	80.53







Visualization of CNN branches outputs.

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Qualitative Results

Qualitative results on Cityscapes. Note that our model takes ground-truth boxes as input, following the setting of Polygon-RNN.

Qualitative results for occluded objects on Cityscapes. **Top row**: ground-truth, **Bottom row**: DELSE

Visualization of Level Set Evolution through time.





