HELMHOLTZ AI | ARTIFICIAL INTELLIGENCE COOPERATION UNIT

Cell Segmentation with Uncertainty-Aware Contour Proposal Networks

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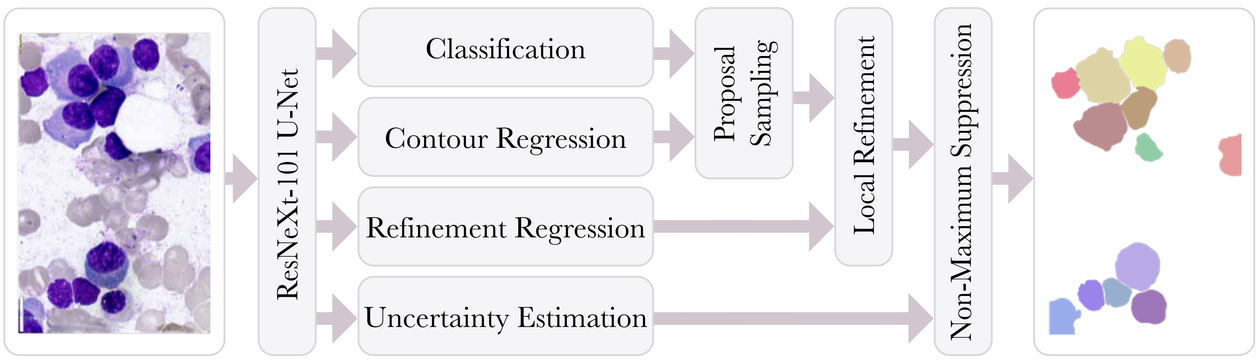
INTRODUCTION

- Automated analysis of neuronal cell properties is paramount for studying brain architecture
- Algorithms need high efficiency at high throughput, and good reliability
- Challenging to assess the quality or certainty of individual segmentations during inference
- The Uncertainty-Aware Contour Proposal Network (UA-CPN) [1] extends the CPN [2]
- Includes uncertainty estimation, without sacrificing efficiency
- Method is trained to introspect by predicting four estimates per object
- Valuable information for downstream tasks, quality control and data selection

METHOD

Uncertainty-Aware Contour Proposal Network

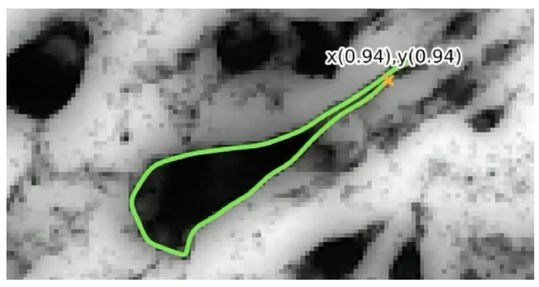


Contours Regression

- Contours are represented as vectors
- Sine and cosine transform maps to coordinates
- Predict coefficients a, b, c, d:

$$x_n(t) = a_0 + \sum_{n=1}^{N}\left(a_n \sin\left(\frac{2n\pi t}{T}\right) + b_n \cos\left(\frac{2n\pi t}{T}\right)\right)$$

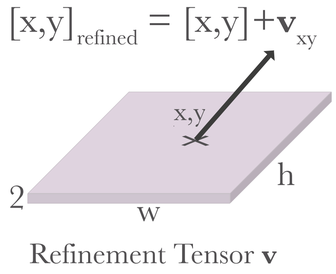
$$y_n(t) = c_0 + \sum_{n=1}^{N}\left(c_n \sin\left(\frac{2n\pi t}{T}\right) + d_n \cos\left(\frac{2n\pi t}{T}\right)\right)$$



Contour Refinement

- Improves pixel precision
- Implicitly learned self-correction

$$[x,y]_{refined} = [x,y] + \mathbf{v}_{xy}$$

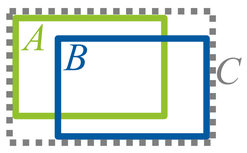


Refinement Tensor $\mathbf{v}$

Boundary Supervision

- Allows supervision with bounding boxes
- Allows for mixed-annotation training
- Generalized Intersection over Union [3]

$$GIoU = IoU - \frac{|C \setminus (A \cup B)|}{|C|}$$



Localization Uncertainty Estimation

- Goal: Efficiently provide uncertainty estimates for segmented object boundaries
- Model estimates four boundary localization uncertainties: top right, bottom, left
- Learns to introspect based on systemic errors made during training
- Trained with negative power log-likelihood loss [4]:

$$\mathcal{L}_{\text{uncertainty}} = \eta\left(\sum_i\left(\frac{(v_i - \hat{v}_i)^2}{2\delta^2} + \frac{1}{2}\log\delta_i^2\right) + 2\log 2\pi\right)$$

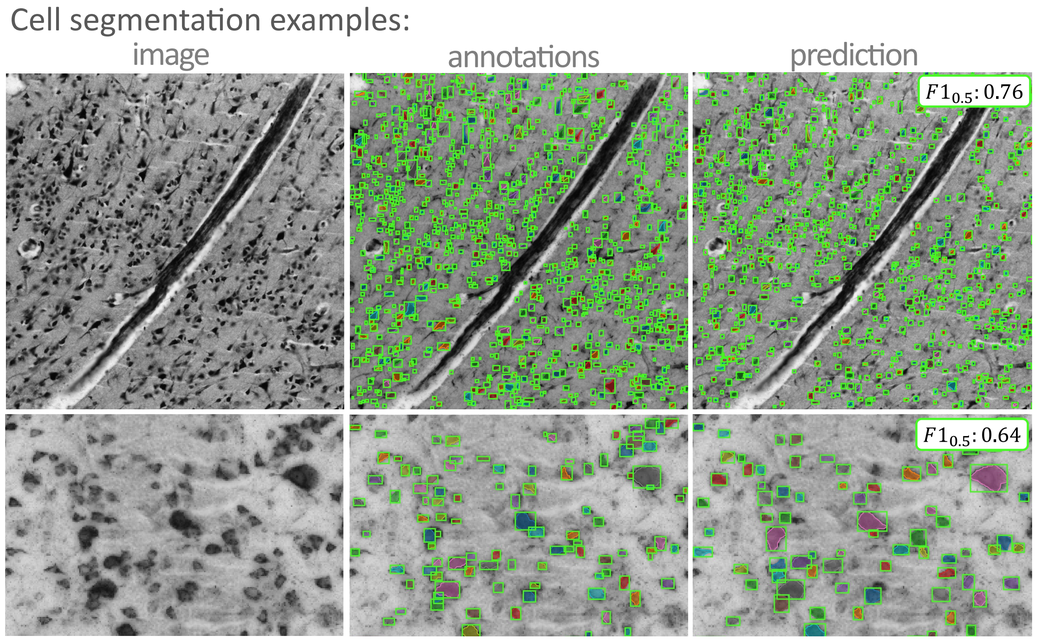
- η: IoU, δ_i: uncertainty estimate , v_i: Targeted boundary, $\hat{v}_i$: Predicted boundary
- Valuable information for downstream tasks, training data selection, quality control, …

EXPERIMENTS & RESULTS

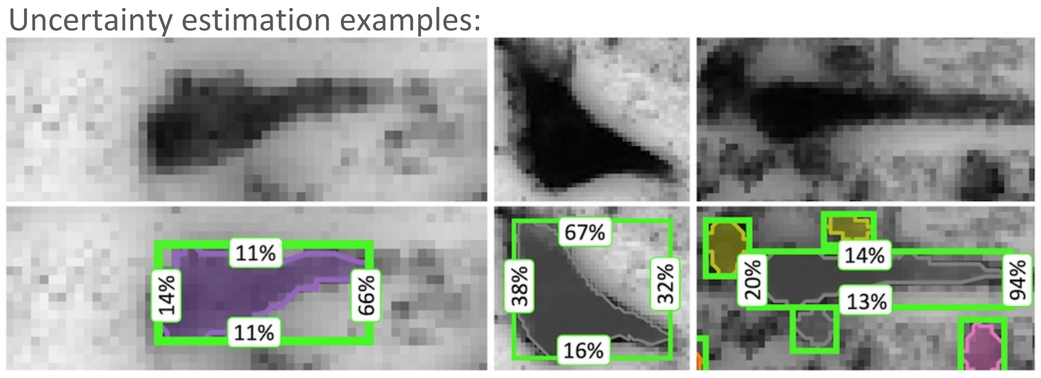
Neuronal cell bodies

- Test score of $0.48\ F1_{avg}$
- Among the correctly detected cells, 86% of the estimated uncertainties show a margin smaller than 25% to the optimal solution of NPLL for the measured test loss
- Uncertainty estimation also uncovers annotation inconsistencies

Cell segmentation examples:



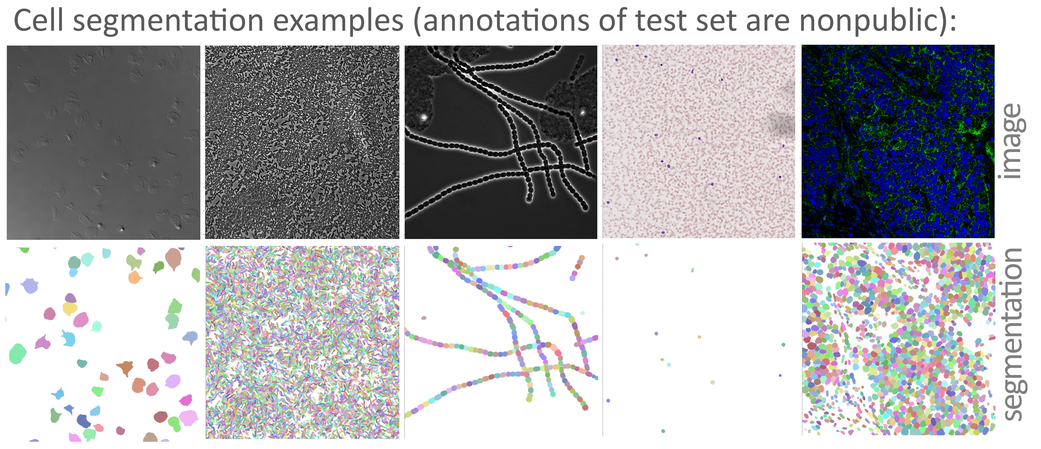
Uncertainty estimation examples:



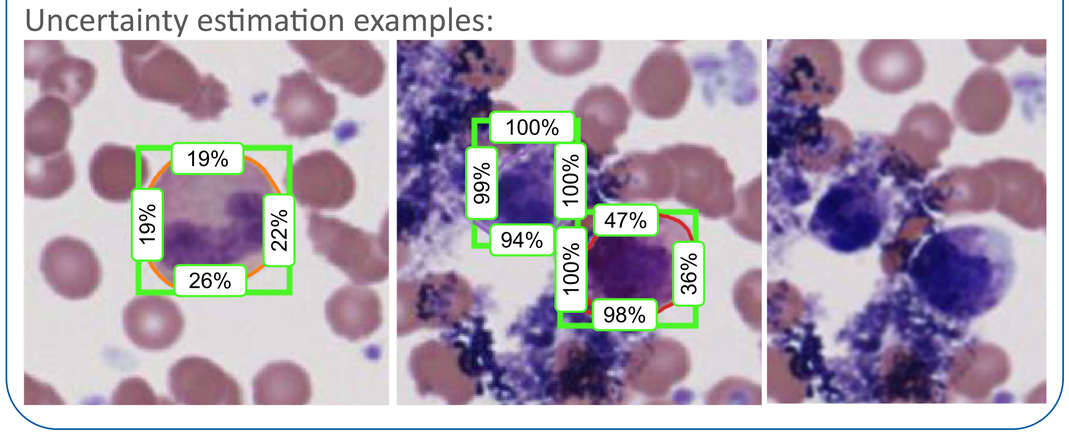
NeurIPS 22 Cell Segmentation Competition

- 2nd best mean F1 score (81.81), 3rd place in ranking

Cell segmentation examples (annotations of test set are nonpublic):



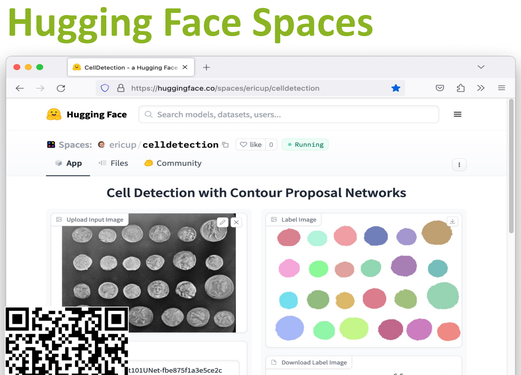
Uncertainty estimation examples:



TRY IT YOURSELF

Napari Plugin

Hugging Face Spaces

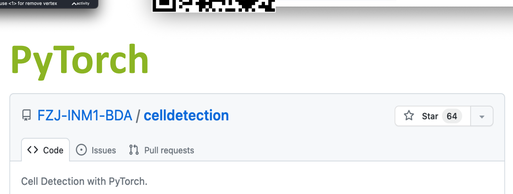


Hugging Face API

```
import requests

response = requests.post("https://ericup-celldetection.hf.space/run/predict", json={
  "data": [
    "",
    "ginozo_CpnResNeXt101UNet-fbe875f1a3e5ce2c",
  ]
}).json()

data = response["data"]
```

```
const response = await fetch("https://ericup-celldetection.hf.space/run/predict", {
  method: "POST",
  headers: { "Content-Type": "application/json" },
  body: JSON.stringify({
    data: [
      "",
      "ginozo_CpnResNeXt101UNet-fbe875f1a3e5ce2c",
    ]
  })
});

const data = await response.json();
```

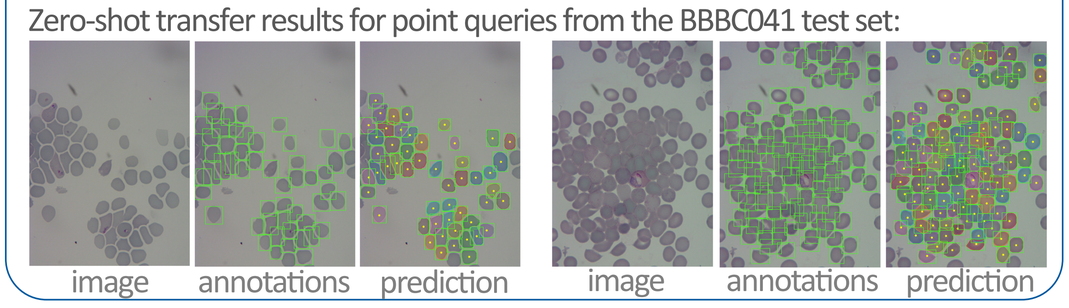
PyTorch



ONE CLICK, ONE CONTOUR – ZERO-SHOT TRANSFER

The **Contour Proposal Network** (CPN) can also produce high quality object contours and masks from input queries such as points or weak segmentations.

Zero-shot transfer results for point queries from the BBBC041 test set:



[1] Eric Upschulte, Stefan Harmeling, Katrin Amunts, and Timo Dickscheid. Uncertainty-Aware Contour Proposal Networks for Cell Segmentation in Multi-Modality High-Resolution Microscopy Images. OpenReview Preprint YtgRjBw-7GJ, 2022.
[2] Eric Upschulte, Stefan Harmeling, Katrin Amunts, and Timo Dickscheid. Contour proposal networks for biomedical instance segmentation. Medical Image Analysis, 77:102371, 2022.
[3] Hamid Rezatofighi, Nathan Tsoi, JunYoung Gwak, Amir Sadeghian, Ian Reid, and Silvio Savarese. Generalized intersection over union: A metric and a loss for bounding box regression. In 2019 IEEE/CVF CVPR, pages 658–666, 2019.
[4] Youngwan Lee, Joong-won Hwang, Hyungil Kim, Kimin Yun, and Jongyoul Park. Localization uncertainty estimation for anchor-free object detection. CoRR, abs/2006.15607, 2020.