From Neurons to Roads: Detection of Curvilinear Structures in Images

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Linear Structures

~1nm
Neuronal membranes

~1mm
Blood vessels

~10cm
Cracks

~10km
Roads
## Motivation

Brain connectivity  
Diagnostics  
Material properties  
Autonomous driving
Challenges

Requires large context
Challenges

Occlusions and noise
Challenges

Variability of appearances, presence of other linear structures
Detection Pipeline

Image
Segmentation
Final Graph
Current Approach – Pixelwise Loss

Encoder-decoder architecture trained using binary cross-entropy

\[ \mathcal{L}_{bce}(x, y, w) = - \sum_i [(1 - y_i) \cdot \log(1 - f_i(x, w)) + y_i \cdot \log f_i(x, w)]. \]

- \( x \) – input patch
- \( y \) – ground truth
- \( f \) – function parametrized by \( w \)
Topology Loss

Train using direct pixel-wise loss and topology loss that captures higher-level features

\[ \mathcal{L}_{\text{top}} = \frac{1}{M_n W_n H_n} \sum_{m=1}^{M} \left( l_m^n(y) - l_m^n(f(x, w)) \right)^2 \]

\( l_m^n \) — \( n^{th} \) channel of \( m^{th} \) layer of a pretrained VGG

\[ \mathcal{L} = \mathcal{L}_{\text{bce}} + \mu \mathcal{L}_{\text{top}} \]

Mosinska et al., CVPR 2018
Pixelwise vs. Topology Loss

Binary cross entropy is the same in every case, but topology loss differentiates between mistakes depending on how much they alter the geometry.

Ground truth \( L_{top} = 0.2858 \) \( L_{top} = 0.9979 \) \( L_{top} = 0.2279 \) \( L_{top} = 0.7795 \)
Activations

• Different filters are scale- and orientation-selective
• Some respond to long, smooth lines, while the others are activated by small background noise
Relation to Perceptual Loss

• Perceptual loss measures perceptual similarity between the original and generated images.
• Unlike in our application there is no defined ground truth for style transfer.
• Pre-trained VGG is applied here to natural images rather than binary masks.

[Diagram: Content + Style = Style-transferred image]
Results
Results

<table>
<thead>
<tr>
<th>Image</th>
<th>RegAC</th>
<th>BCE Loss</th>
<th>BCE and Topo Loss</th>
<th>Ground truth</th>
</tr>
</thead>
</table>

Table showing results of RegAC, BCE Loss, BCE and Topo Loss, and Ground truth.
Recursive Refinement

• Use the same network to progressively refine the results keeping the number of parameters constant.
Results

<table>
<thead>
<tr>
<th>Image</th>
<th>Iter 1</th>
<th>Iter 2</th>
<th>Iter 3</th>
<th>Ground truth</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1" alt="Image" />.png</td>
<td><img src="iter1.png" alt="Iter 1" /></td>
<td><img src="iter2.png" alt="Iter 2" /></td>
<td><img src="iter3.png" alt="Iter 3" /></td>
<td><img src="groundtruth.png" alt="Ground truth" /></td>
</tr>
<tr>
<td><img src="image2" alt="Image" />.png</td>
<td><img src="iter1.png" alt="Iter 1" /></td>
<td><img src="iter2.png" alt="Iter 2" /></td>
<td><img src="iter3.png" alt="Iter 3" /></td>
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</tr>
<tr>
<td><img src="image3" alt="Image" />.png</td>
<td><img src="iter1.png" alt="Iter 1" /></td>
<td><img src="iter2.png" alt="Iter 2" /></td>
<td><img src="iter3.png" alt="Iter 3" /></td>
<td><img src="groundtruth.png" alt="Ground truth" /></td>
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Inferring Connectivity
Inferring Connectivity

• Segmentation may still contain some mistakes – gaps or redundant predictions.

• It is not enough just to threshold it.

Should those road segments be connected? How are those neurons connected?

• We need to infer long-range relationships between the detected segments to recover the connectivity.
Path Classification

• Sample possible paths from the segmentation.
• For every candidate path extract HOG-like features that describe its curvature and neighbourhood.
• Train a classifier to assign probability to every path.
• The result is a weighted graph where weight is the cost of keeping path in the final solution

Turetken et al., PAMI 2014
Path Classification

Image

Segmentation

Sampled paths with overlaid probabilities

Corrected road fragment
Mixed Integer Program

In order to ensure connectivity and other constraints:

• Every path treated as a binary variable:
  • "1" – leave in the solution
  • "0" – discard it

• Find minimum cost subgraph subject to constraints:
  • Allow/disallow loops
  • Conservation of flow
  • Connection to the root

Turetken et al., PAMI 2014
From Segmentation to Large-scale Reconstruction

Path classification

Neighbourhood graph

Large-scale reconstruction
Conclusion

• Investigating larger context and higher-level features of linear structures is essential for effective delineation.

• Topology quality can be approximated by the features extracted using a pre-trained VGG.

• By reasoning about the long-range interactions between linear segments we can recover full connectivity of curvilinear structures.
Thank you for attention
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