Active Learning and Focused Proofreading for Delineation

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Linear Structures



~200µm





~20 µm

~1mm



Graph-based Reconstruction











Image

Overcomplete graph Weighted graph after edge classification

Initial reconstruction -MinSubGraph Final result after proofreading



How much time do we save with automation?

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Proofreading To reconstruct (supervised) 25 out of 70 000 000 20 Reconstruction neurons in the mouse brain we need*: Annotation Time[h] (supervised) 10 0 Manual Automated Automated with our speed-ups



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Our Contribution

Accelerating 3 steps of reconstruction

Geometry-based AL strategy



Efficient MIP formulation



Proofreading



Active Learning for Faster Annotation

Goal: reduce the annotation effort by labelling only the most informative examples





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Active Learning for Faster Annotation

Question: how to select informative samples?

- 1. Uncertainty-based Sampling
- 2. Density-based Sampling
- 3. Expected Error Reduction

BUT most methods do not take geometry into account.



Exploiting Geometry to Speed Up Annotation

Alter the weight of one edge at a time and see how the reconstruction changes.



Select the sample that causes the greatest improvement in reconstruction.



Exploiting Geometry to Speed Up Annotation

Improvement measured by the change in cost: $\Delta c = c(R^*) - c(R')$



Intuition: if after changing the edge's weight the cost decreases, then the edge might have been misclassified.



Exploiting Geometry to Speed Up Annotation

Sometimes random annotation performs better than Active Learning strategies...





But exploiting geometry helps to avoid some common pitfalls



Focused Proofreading



Favor samples that not only decrease the cost, but also change the topology.

Combine cost and topology and score edges by:

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\frac{c(R^*) - c(R')}{DIADEM(R^*, R')}
```

DIADEM score captures similarity between two graphs



Combining Active Learning and Proofreading

50 samples to train classifier (AL) and 25 to fast-proofread the reconstruction





Efficient MIP Formulation

Turetken et al. PAMI'16: $O(|V||\mathcal{E}|)$ size Our equivalent formulation: $O(|\mathcal{E}|)$ size

	Axons1	Axons2	Axons3	Axons4	Axons 5	Axons6
# edges	164	223	224	265	932	2638
MIP [3]	0.91	1.04	1.19	1.45	78.3	393.7
MIP ours	0.03	0.10	0.04	0.23	0.10	5.23
speedup	26.1x	10.1x	27.3x	6.3x	743.5x	75.2x

	BFN euron 1	BFNeuron2	OPF1	OPF2	BFN euron 3	BFNeuron4
# edges	120	338	363	380	645	2826
MIP [3]	0.48	2.25	1.53	1.65	2.13	308.23
\mathbf{MIP} ours	0.02	0.12	0.05	0.08	0.26	2.30
speedup	18.2x	17.7x	29.4x	19.9x	$8.1 \mathrm{x}$	134.0x



Conclusion

- Reduction in annotation and proofreading effort by employing geometry-based strategy
- Efficient formulation of optimization problem that allows for interactive applications
- Next steps:
 - edge sampling strategies
 - other definitions of change in reconstruction

