ETH zürich

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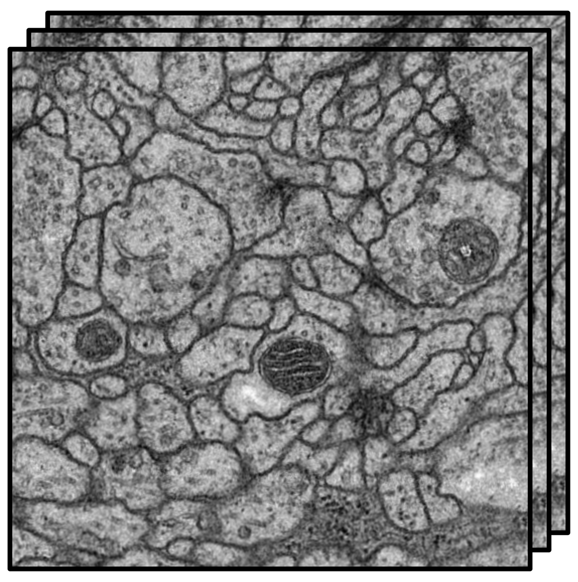
SuperSlicing Frame Restoration for Anisotropic ssTEM

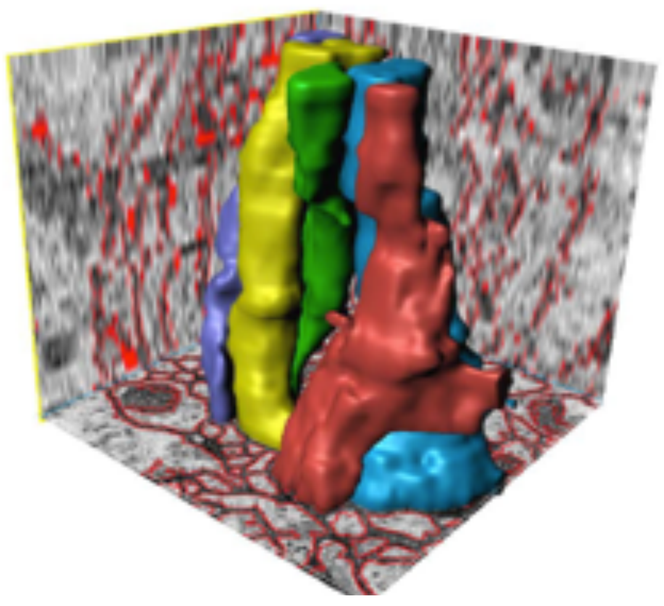
Dmitry Laptev, Alexander Vezhnevets, Joachim M. Buhmann,
Machine Learning Lab, ETH Zurich, Switzerland

1. Topology extraction

Task: Automatic reconstruction of Neuronal Structures from Serial Section Transmission Electron Microscopy (ssTEM)



Sections from ssTEM data set of the Drosophila first instar larva ventral nerve cord



Extracted Neuronal Topology

2. Anisotropic data

ssTEM imaging

- Slices 2μm ✕ 2μm ✕ 50nm
- Slice projection with EM
- Resolution: 4 ✕ 4 ✕ 50nm

=> highly anisotropic

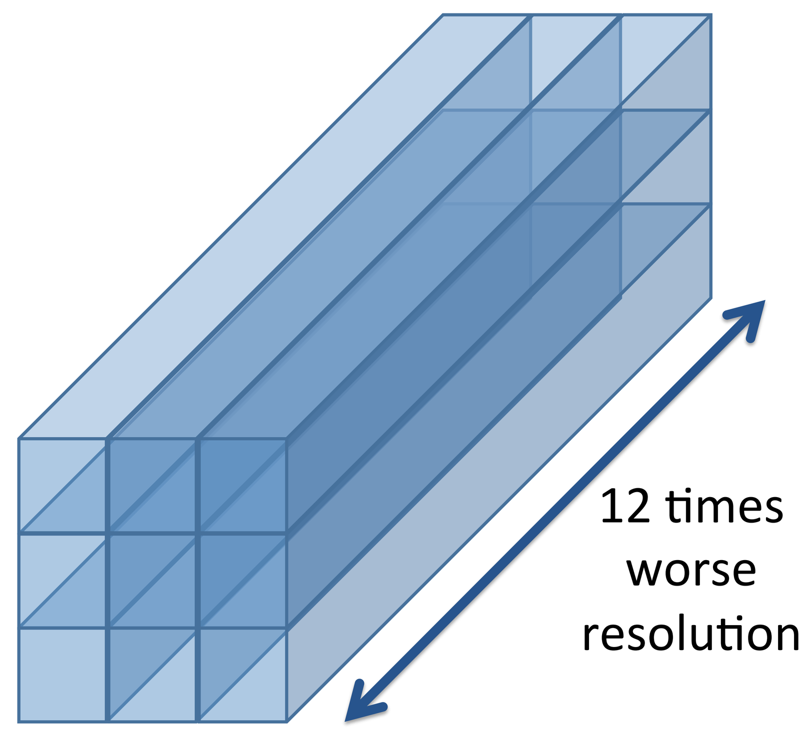
Problems:

- Blurred membranes

=> it is difficult to detect

- Slices sufficiently different

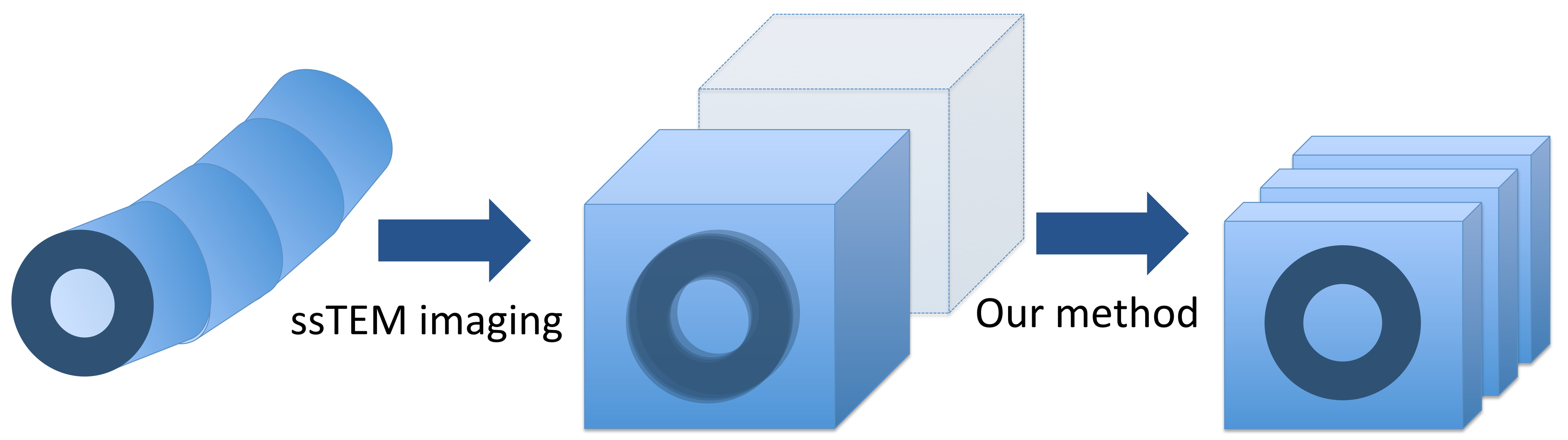
=> cannot use 3d



9 anisotropic voxels from ssTEM

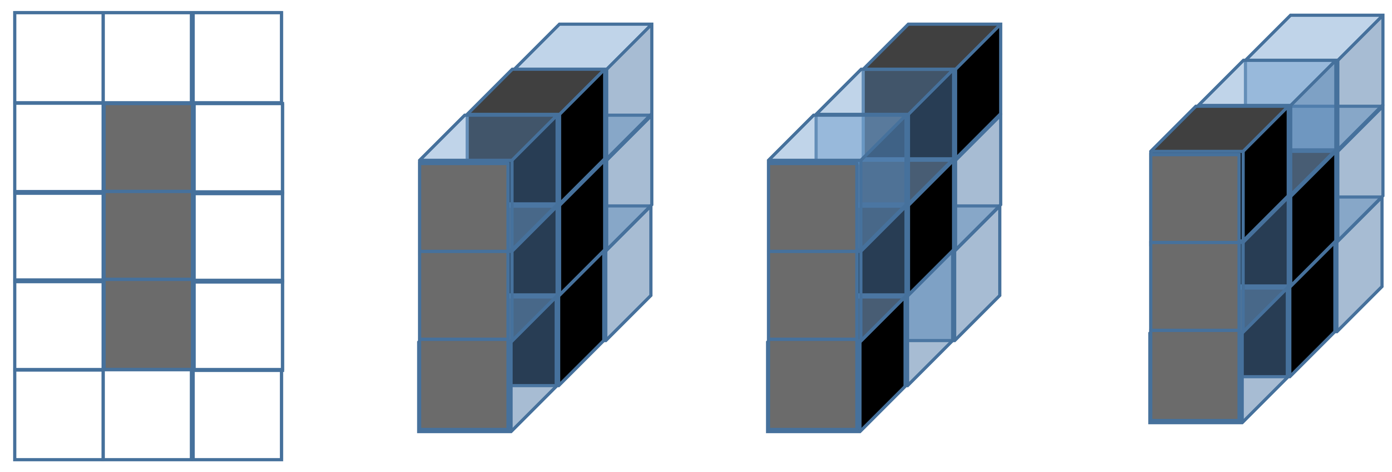
3. The idea of SuperSlicing

Idea: Decompose the observed frame into "hidden sub-frames"



Brain structures in 3d   Observed frames   Hidden sub-frames

Problem: very ill-posed task in general

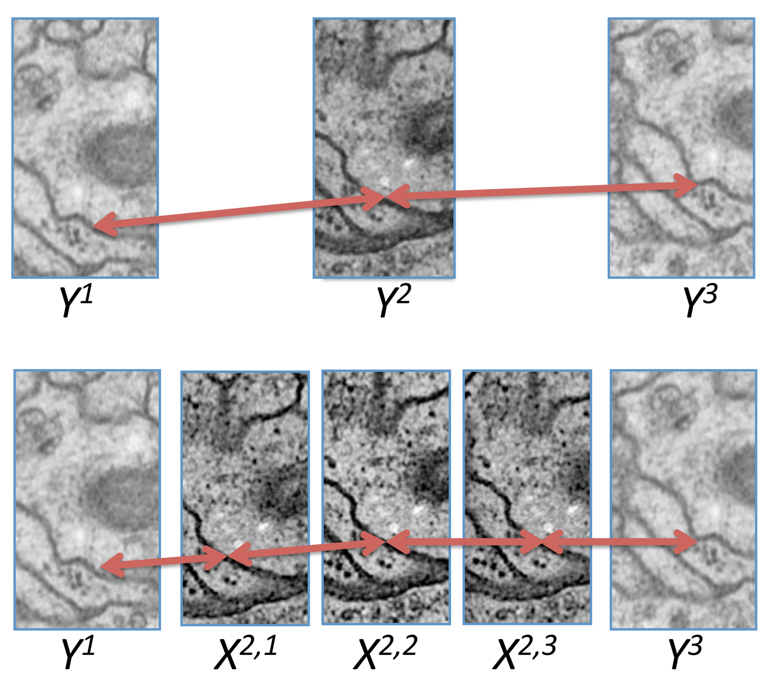


Observed frame   Three possible sub-frame decomposition

4. SuperSlicing with structural constraints

Structural constraints: interpolated smoothness between observed slices

- Y^n — observed frames, $n \in [1, \ldots, N]$,
- y_p^n — pixel p of the frame Y^n,
- $i(y_p^n)$ — the intensity of pixel y_p^n,
- $\epsilon(x_p^n)$ — a set of neighbors of pixel x_p^n,
- Ω — a set of given correspondences,
- $X^{n,l}$ — hidden sub-frames decomposition of Y^n, $l \in [1, \ldots, L]$.



An average of the hidden frames should give observed frame

$$E(X^{n,1}, \ldots, X^{n,L}) = \sum_{y \in Y^n} \Big(i(y) - \frac{1}{L} \sum_{l=1}^{L} i(x_p^{n,l}) \Big)^2$$

Smoothness across all the correspondences

$$+ \lambda \sum_{(\hat{x}_p^{n,l}, \hat{x}_q^{n,l+1}) \in \Omega} \Bigg(\sum_{x \in \epsilon(\hat{x}_p^{n,l})} w(x, \hat{x}_p^{n,l}) i(x) - \sum_{x \in \epsilon(\hat{x}_q^{n,l+1})} w(x, \hat{x}_q^{n,l+1}) i(x) \Bigg)^2$$

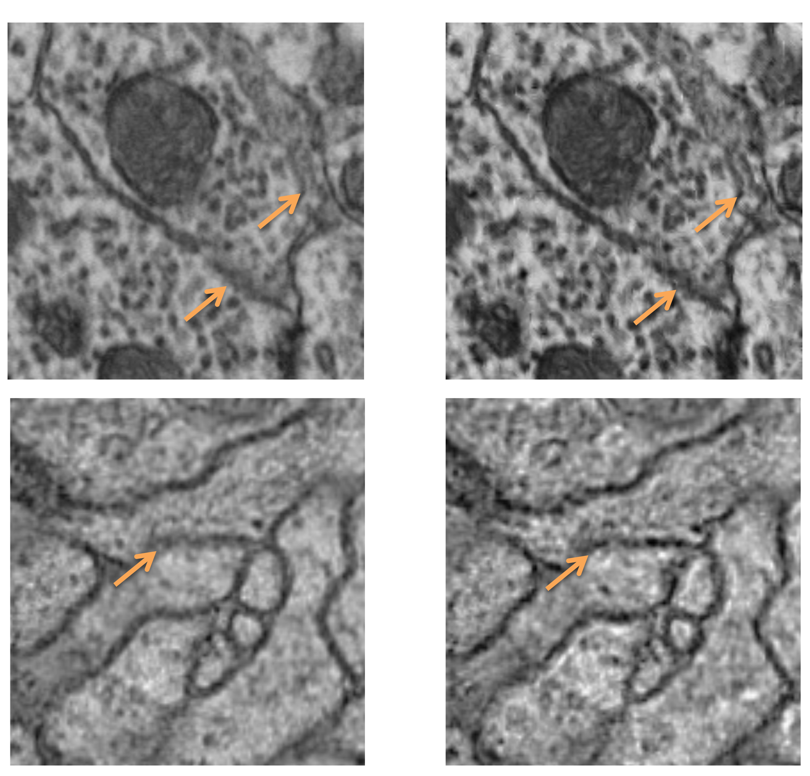
Smoothness within the frame

$$+ \gamma \sum_{\substack{x_p^{n,l}; x_q^{n,l} \in \epsilon(x_p^{n,l}) \\ l=1,\ldots,L}} \Big(i(x_p^{n,l}) - i(x_q^{n,l}) \Big)^2$$

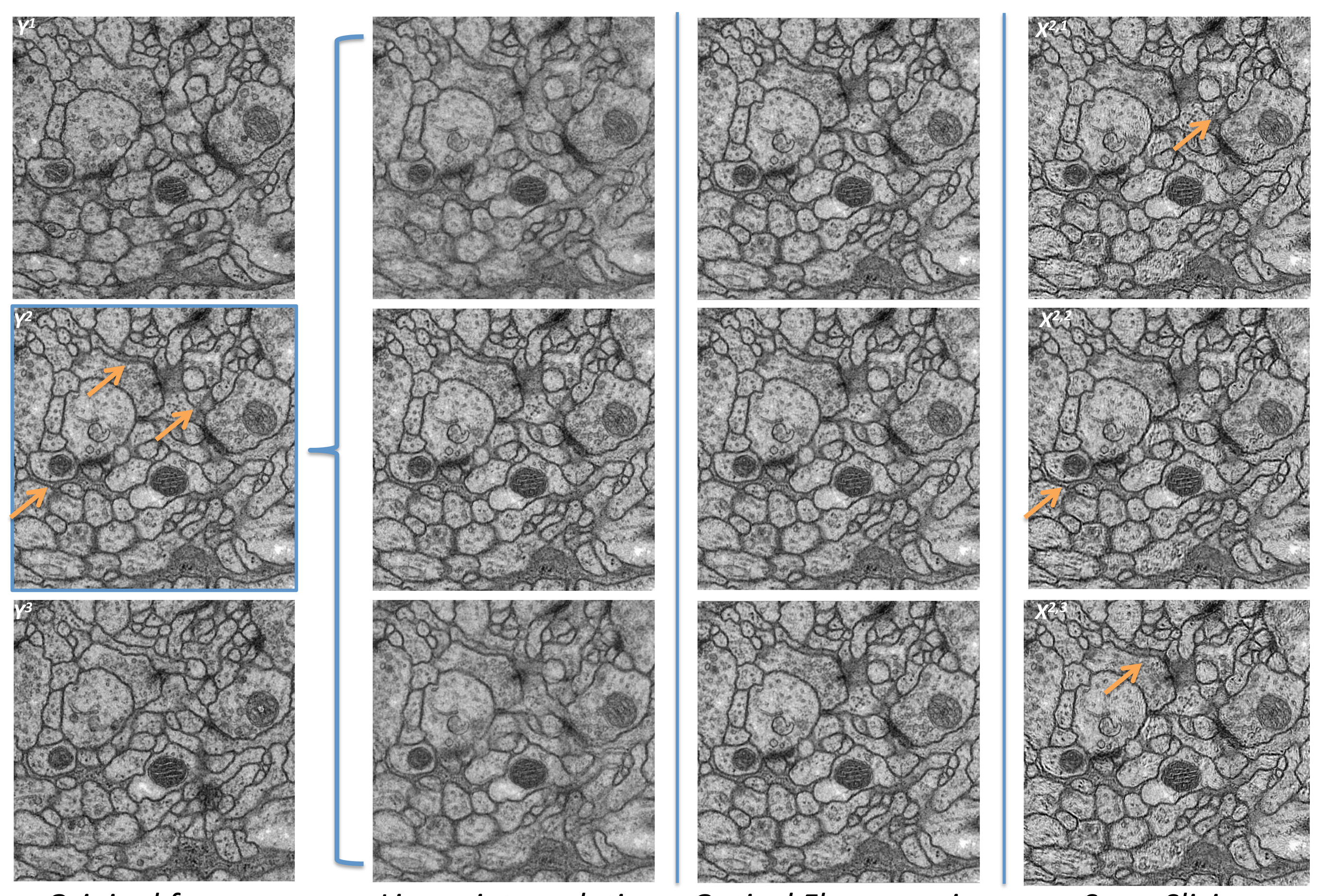
Quadratic programming
=> global optimum

5. Results

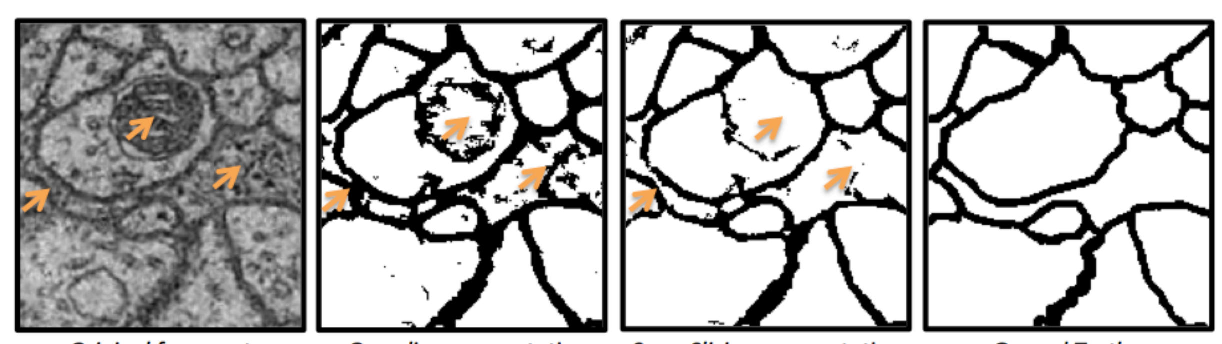
Produces more isotropic slices with better visible structures, smoother interpolation, and results in better segmentation



Original frame   Reconstructed sub-frame



Original frames   *Linear interpolation*   *Optical Flow warping*   *SuperSlicing*



Original fragment   *One-slice segmentation*   *SuperSlicing segmentation*   *Ground Truth*

Method	Warping error	
One section segmentation	$2.87*10^{-3}$	(17%)
Three section segmentation	$2.69*10^{-3}$	(11%)
SuperSlicing segmentation	$2.38*10^{-3}$	