Anisotropic ssTEM Image Segmentation Using Dense Correspondence across Sections

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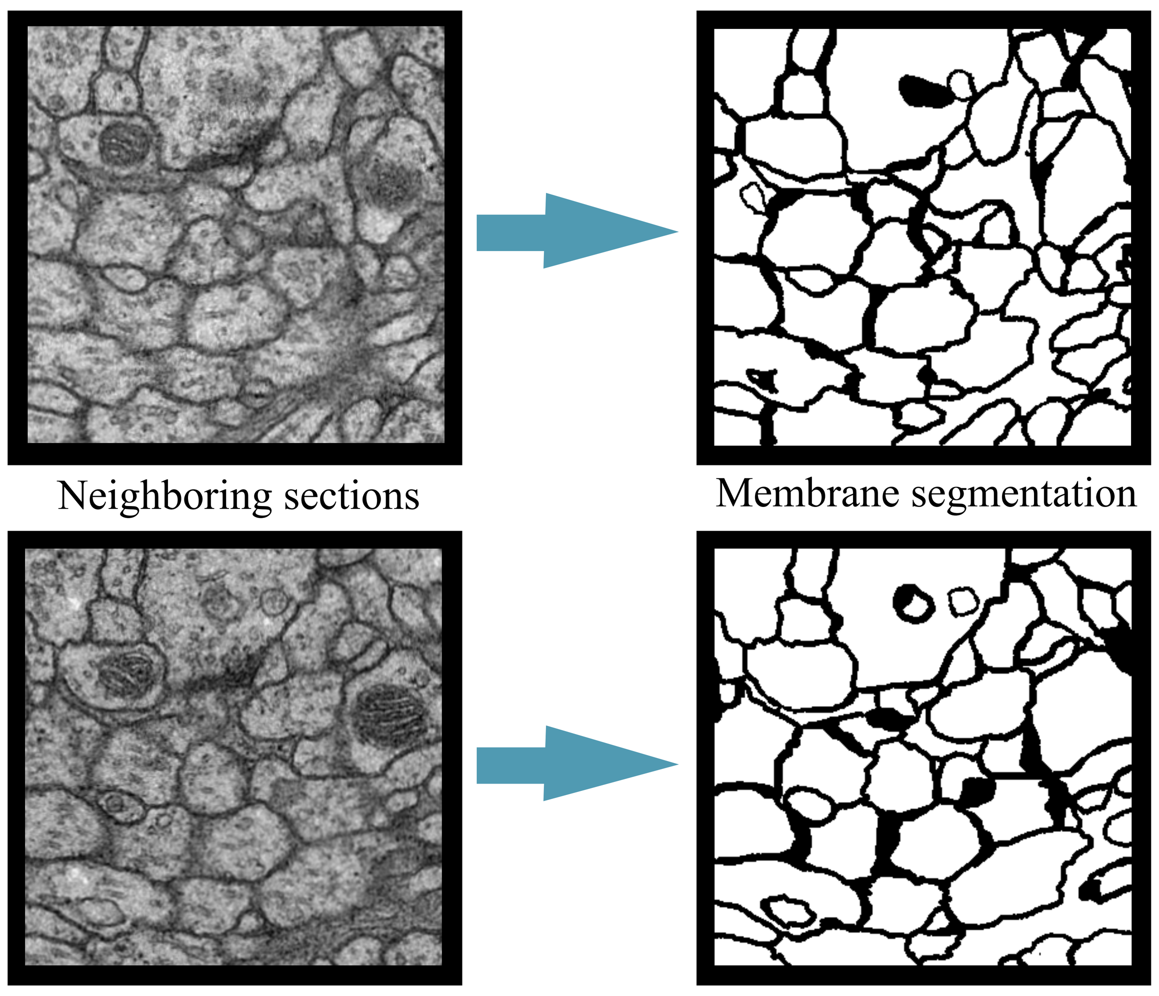
1. Membrane segmentation

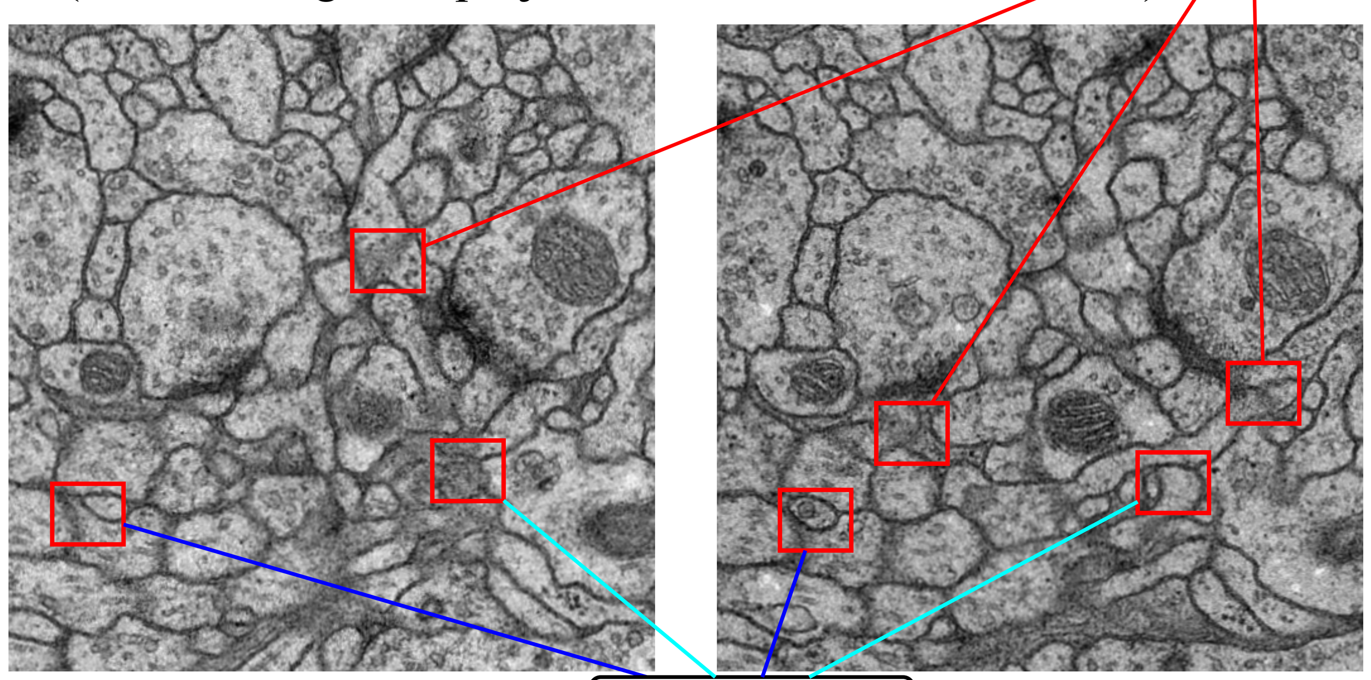
Task: automatic membrane segmentation for *anisotropic stacks* of ssTEM brain tissue



Sections from a ssTEM of the Drosophila first instar larva ventral nerve cord (VNC), imaged at a resolution of 4x4x50 nm/pixel (Cardona, A. et al. in PLoS Biol. 10, 2010)

2. Problems

- Membranes that are not orthogonal to cutting plane are blured (as each image is a projection of the whole thick slice)

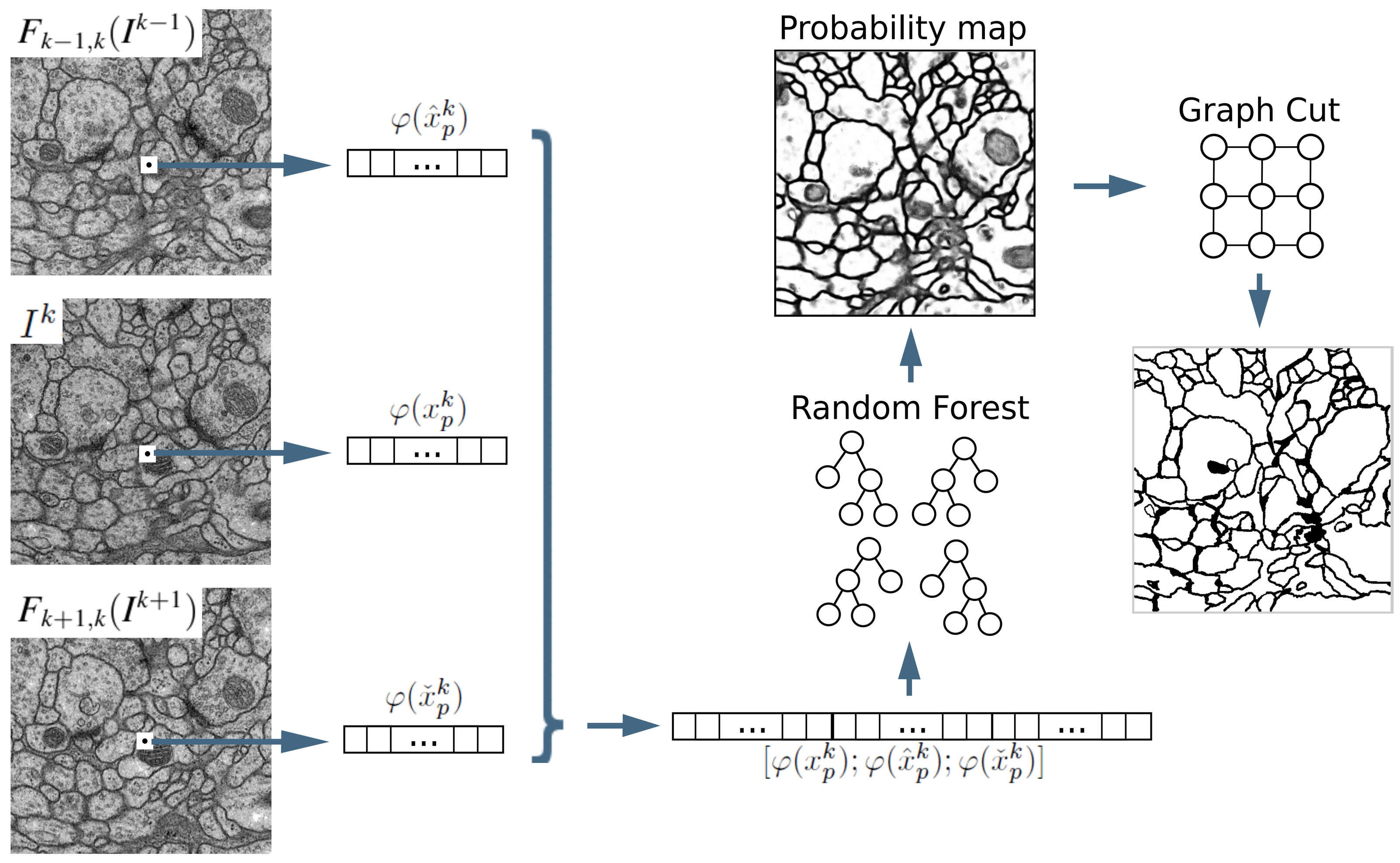


- Neighboring slices are highly different one from another (data is highly anisotropic), so we cannot use methods developed for isotropic data

Key idea

- Approximately find corresponding regions in neighboring sections
- Incorporate the context from neighboring sections

3. Proposed method



(warping images; feature extraction) (concatenation; training RF) (segmentation)

Notation

- I^{k-1}, I^k and I^{k+1} – neighboring sections,
- x_p^k – pixel in section k,
- $\phi(x_p^k)$ – feature vector in pixel x_p^k.
- Non-linear warpings operators:
  - $F_{k-1,k}$: $F_{k-1,k}(x_p^{k-1}) = \hat{x}_p^k$
  - $F_{k+1,k}$: $F_{k+1,k}(x_p^{k+1}) = \check{x}_p^k$.
- Extended feature vector: $[\phi(x_p^k); \phi(\hat{x}_p^k); \phi(\check{x}_p^k)]$.

- In order to incorporate the context from neighboring sections, we need to find warping operator F between sections
- We do it by finding Global Dense Correspondence with SIFT Flow (Ce Liu et al. in ECCV 2008)

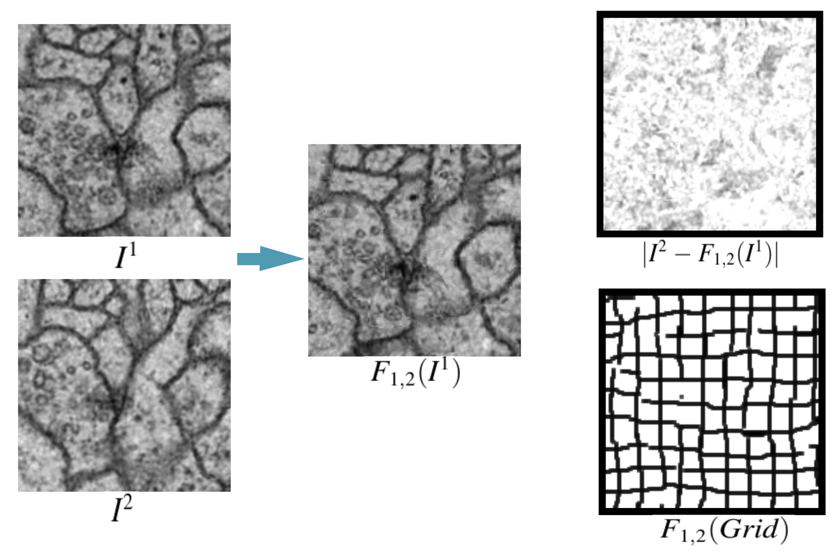
Non-linear warping F is found by searching for a minimum of SIFT flow energy:

$$E(F_{k-1,k}) = \sum_{p=1}^{N} \min\left(\|s(x_p^k) - s(F_{k-1,k}(x_p^{k-1}))\|, t\right) + \sum_{p=1}^{N} \gamma D(x_p^{k-1}, F_{k-1,k}(x_p^{k-1})) + \sum_{(p,q)\in\epsilon} \min\left(\alpha D(F_{k-1,k}(x_p^{k-1}), F_{k-1,k}(x_q^{k-1})), d\right),$$

$s(x_p)$ – sift descriptor in pixel x_p;

$D(x_p, x_q)$ – distance between pixels x_p and x_q;

t, γ, α, d – model parameters.



(input images) (warped image) (difference) (non-linear warping)

- We evaluate feature vectors in corresponding pixels
- Then concatenate them to get **extended feature vector**
- Train Random Forest classifier with these extended vectors

Pixel Features

- Mean, Minimum, Maximum, Median, Variance,
- Gaussian blur, Sobel filter, Hessian, Gradient,
- Bilateral, Lipschitz, Kuwahara, Gabor, Laplacian,
- SIFT descriptors, Radon-like features, Ray features,
- Line Filter Transform.

4. Graph Cut & Postprocessing

- We use graph cut segmentation to take into account the fact that the labels of the neighboring pixels are more likely to have the same value.
- Labelling Y is then estimated as argminimum of the following energy:

$$E(Y) = \sum_{p=1}^{N} E_{rf}(y_p) + \lambda_s \sum_{(p,q)\in\epsilon} E_s(y_p, y_q) + \lambda_{gf} \sum_{p=1}^{N} E_{gf}(y_p) + \lambda_{gc} \sum_{(p,q)\in\epsilon} E_{gc}(y_p, y_q)$$

$E_{rf}(y_p)$ negative log likelihood of a RF;
$E_s(y_p, y_q)$ smoothness term;
$E_{gf}(y_p)$ gradient flux term;
$E_{gc}(y_p, y_q)$ good continuation term.

Posprocessing

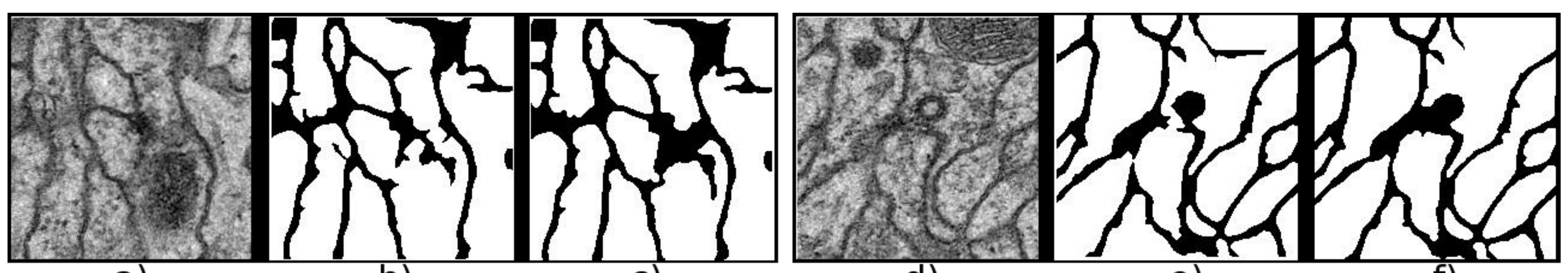
- Filtering connected regions based on their morphological properties: Area, Solidity, Euler Number and Eccentricity.
- Line Filter Transform:

$$LFT(x_p) = \max_{l \in L_r(x_p)} \int_{z \in l} y_z dz$$

Where $L_r(x_p)$ is a set of all the possible lines of the length r.

5. Results

Two examples of the resulted labelling. Original image: (a), (d), no context: (b), (e), our method (c), (f)



Results are based on ISBI 2012 challenge results "Segmentation of neuronal structures in EM stacks" (http://bit.ly/riGDUm).

Method	Pixel error	Warping error	Method	Pixel error	Warping error
Human	$6.7 * 10^{-2}$	$3.4 * 10^{-4}$	*IDSIA*	$6.0 * 10^{-2}$	$4.3 * 10^{-4}$
Dense *ETH*	$7.9 * 10^{-2}$	$6.2 * 10^{-4}$	*CSIRO*	$8.7 * 10^{-2}$	$6.8 * 10^{-4}$
Direct *ETH*	$8.0 * 10^{-2}$	$6.5 * 10^{-4}$	*Utah*	$1.3 * 10^{-1}$	$1.6 * 10^{-2}$
One slice *ETH*	$8.5 * 10^{-2}$	$6.4 * 10^{-4}$	*NIST*	$1.5 * 10^{-1}$	$1.6 * 10^{-2}$

Our method is **3.6** and **6.4%** more accurate in two different accuracy metrics than the algorithm with no context from other sections.