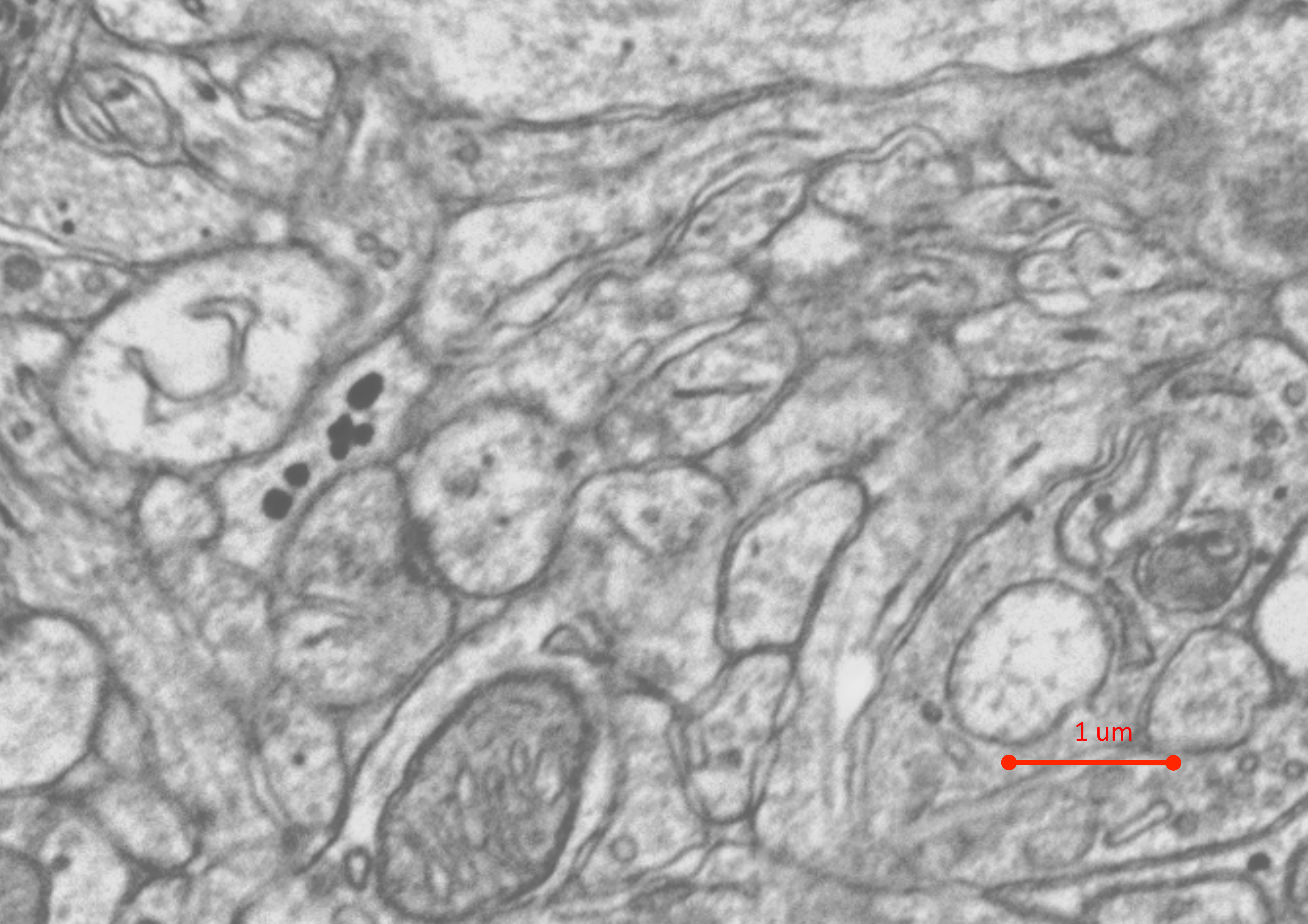
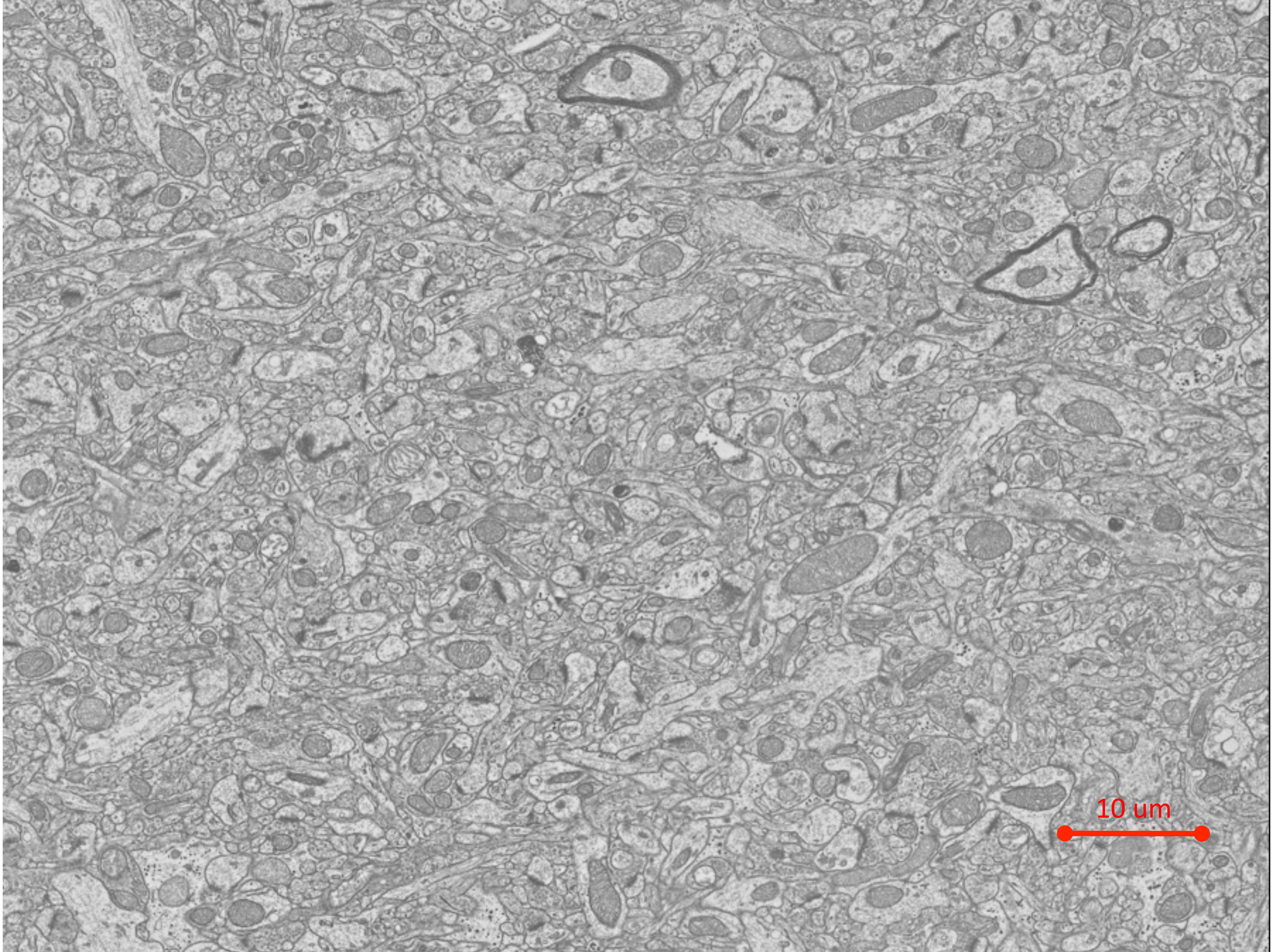
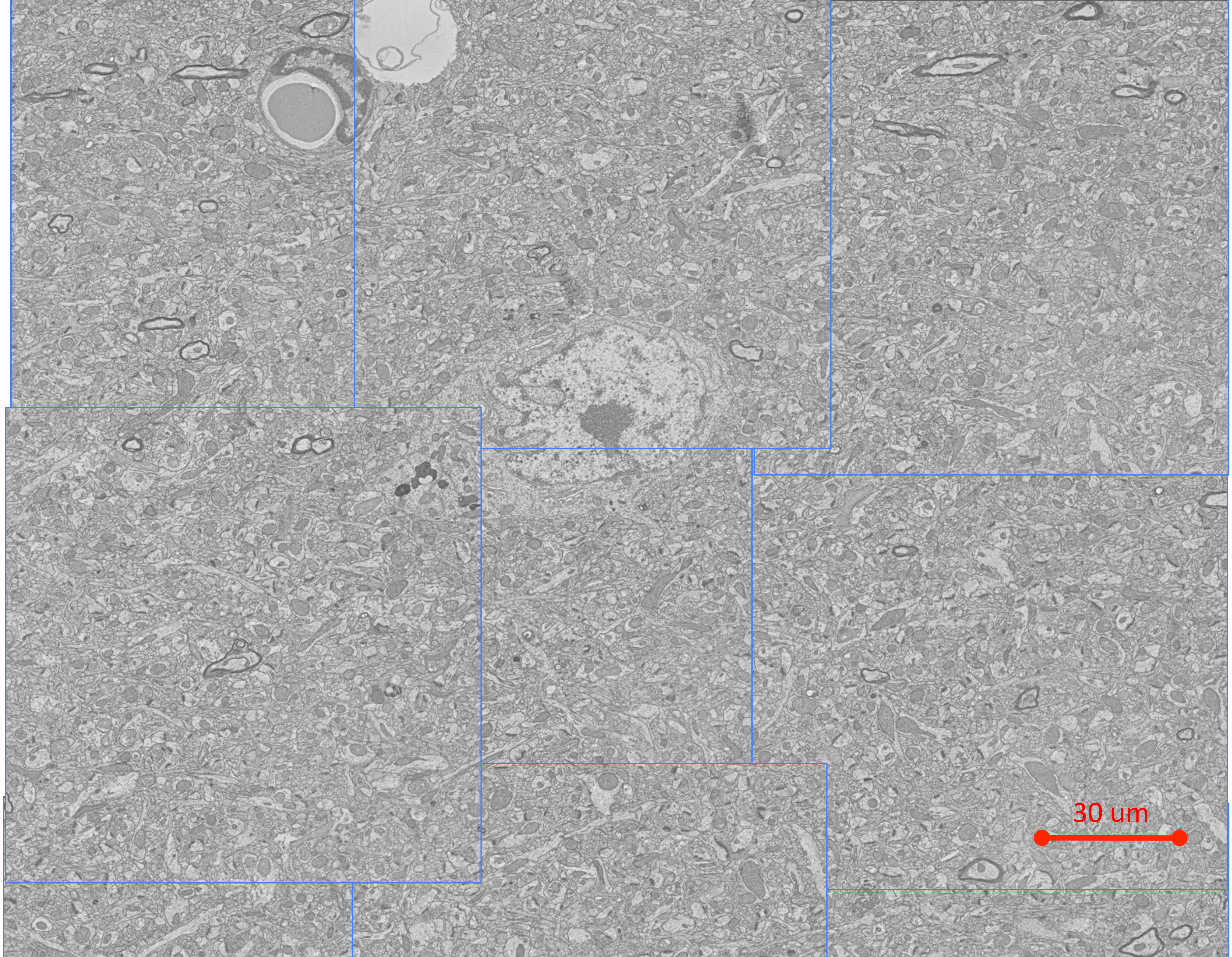
Compact Rotation Invariant Image Descriptors by Spectral Trimming

Maxime Taquet, Laurent Jacques, Benoît Macq, Sylvain Jaume


1 um


10 um


30 um

Compact Rotation Invariant Descriptors

3 take-home messages

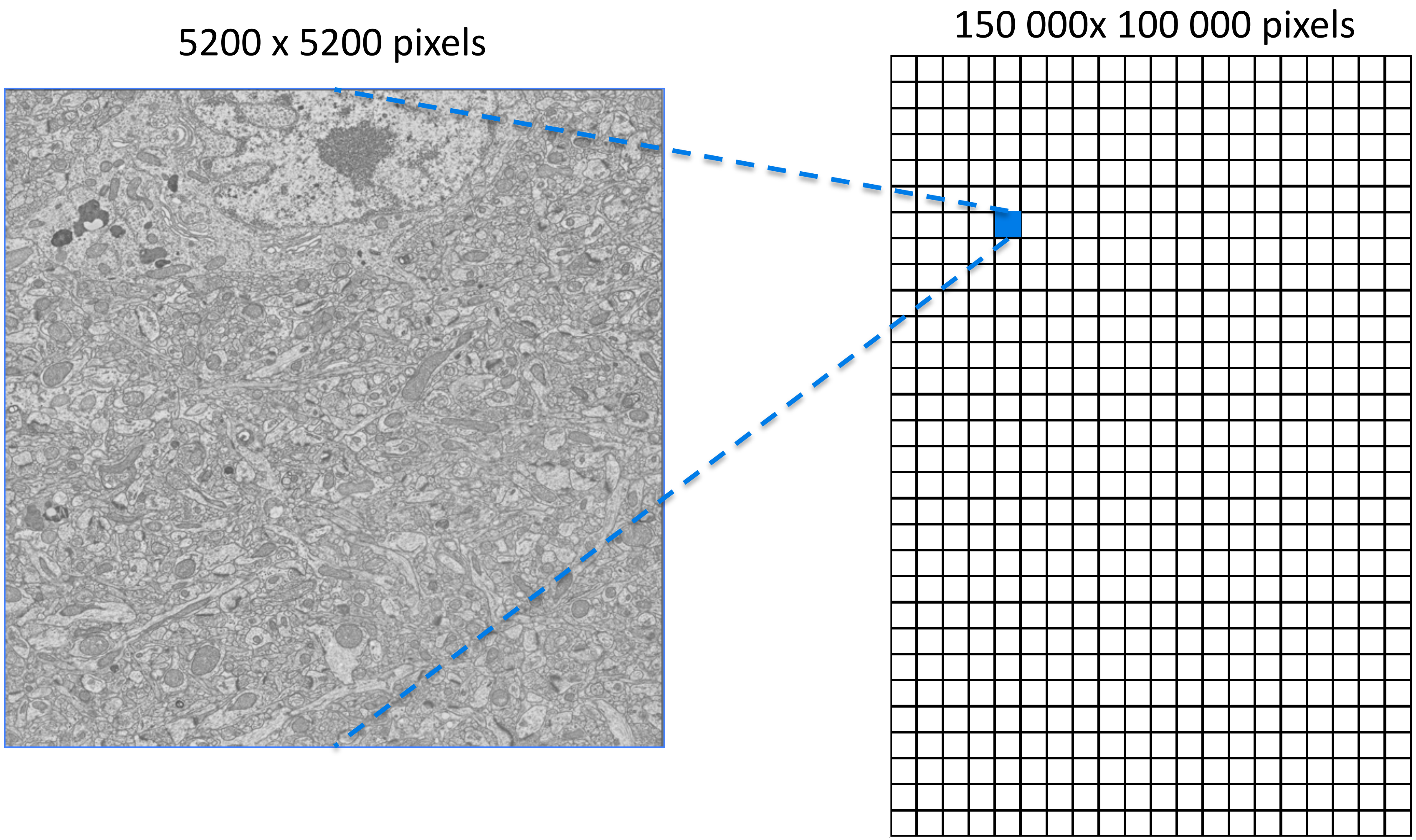
Compact rotation invariant descriptors are required.

Common rotation invariance strategies are not suitable.

Spectral graph theory can achieve rotation invariance.

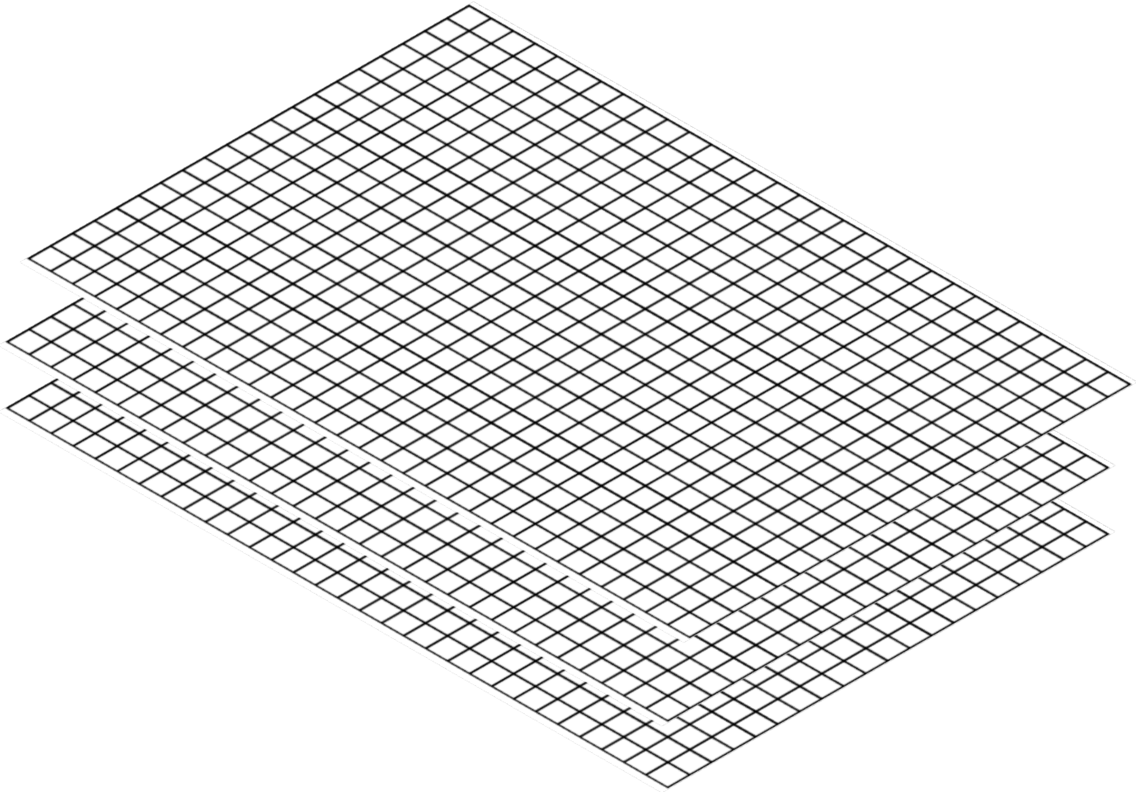
Large-scale TEM are very large images.

Compact rotation invariant descriptors are required.



The goal is to reconstruct a volume.

Compact rotation invariant descriptors are required.



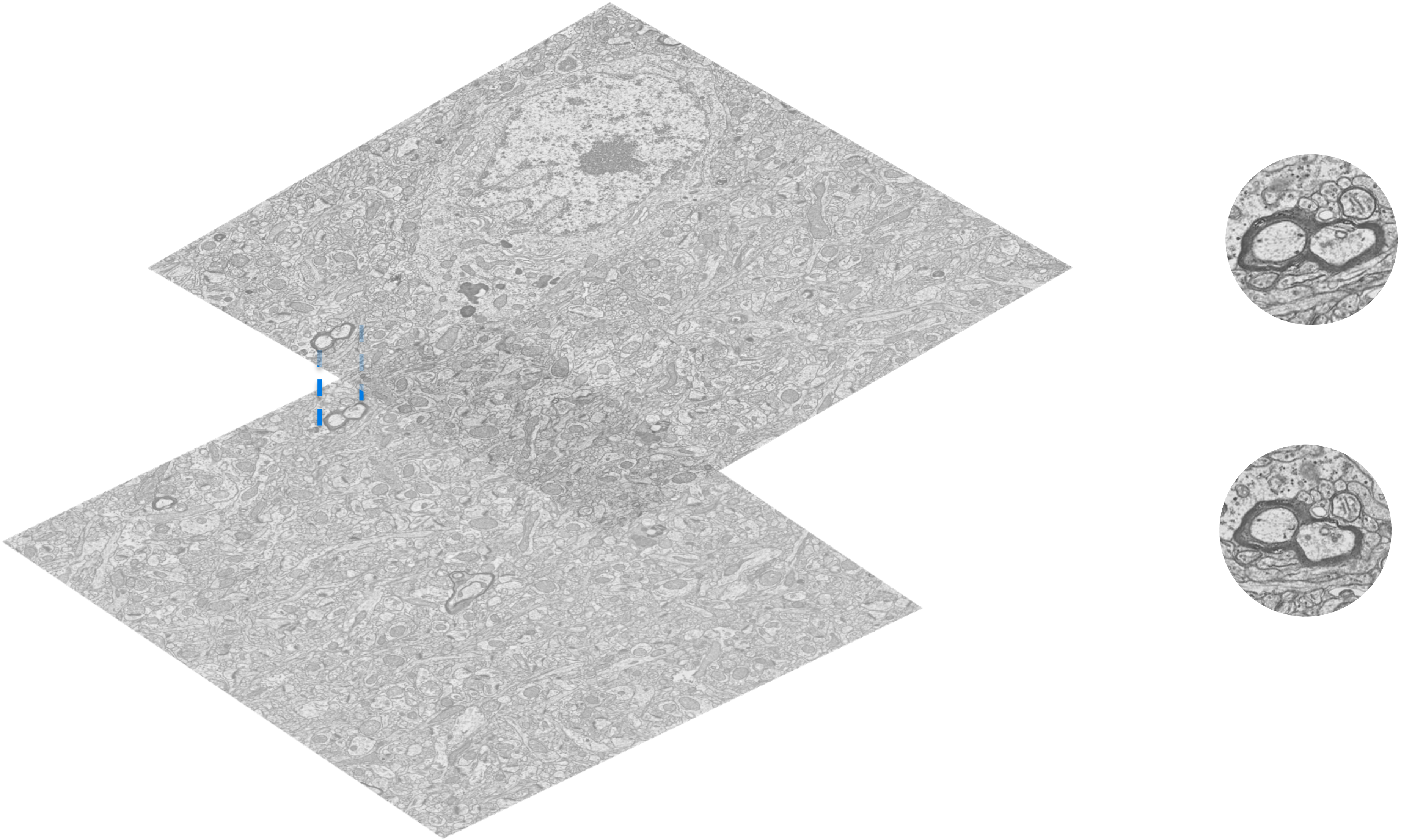
1000 slices to reconstruct a volume

A pixel based alignment would be too cumbersome.

→ We want sparse correspondences

Rotation invariant descriptors are required.

Compact rotation invariant descriptors are required.



Rotation invariant descriptors are required.

Compact rotation invariant descriptors are required.

N descriptors of dimension **D**

→Computation of the descriptors: $O(NDt_0)$

→Comparison of the descriptors: $O(N^2Dt_1)$

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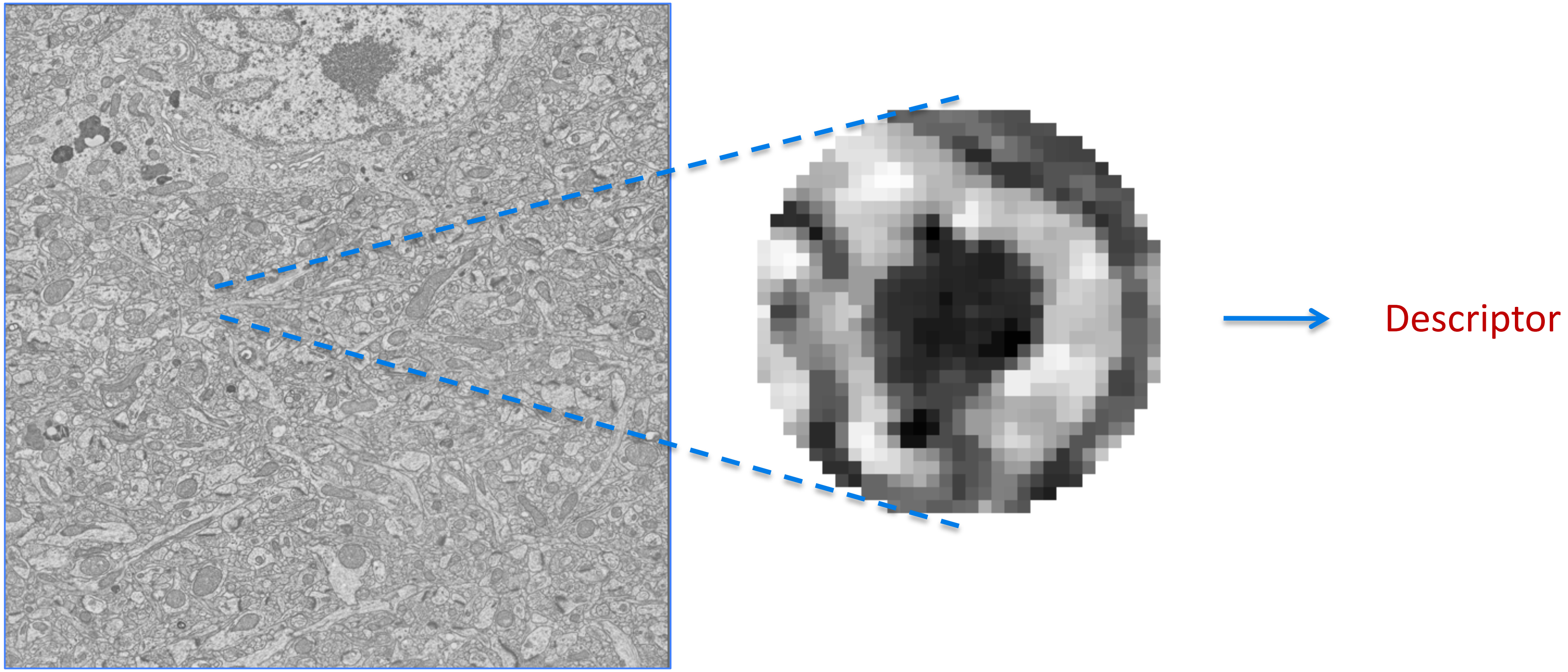

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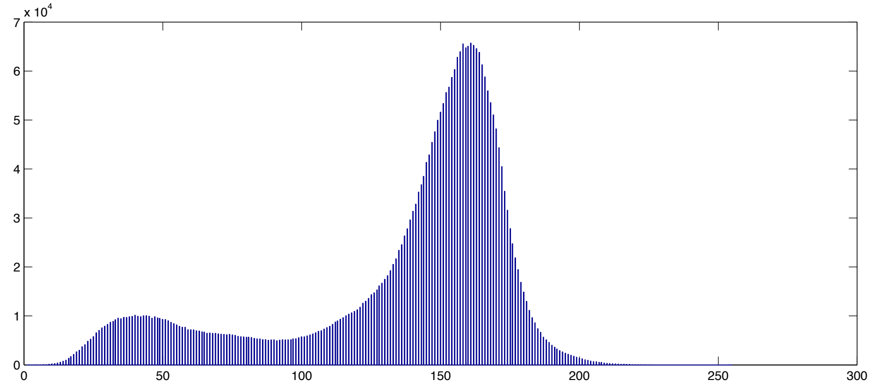
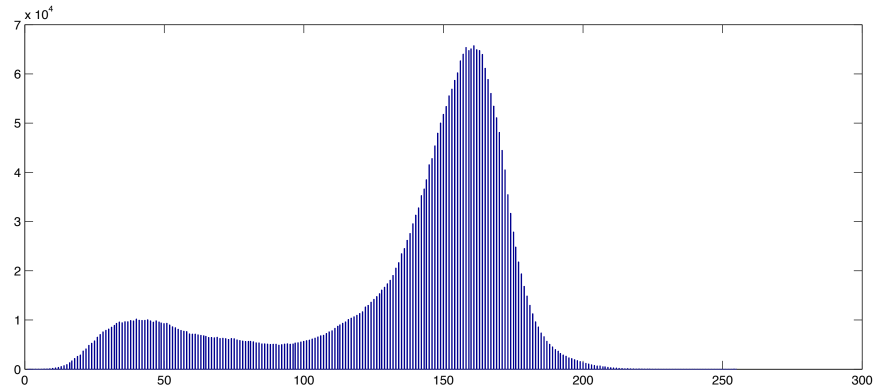
Spectral graph theory can achieve rotation invariance.

Three classical ways to achieve rotation invariance

1. Histogram of an invariant characteristics of the pixels





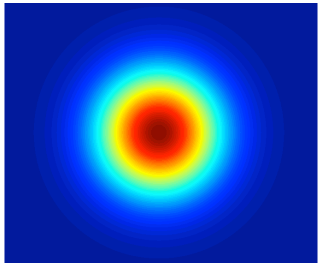
Three classical ways to achieve rotation invariance

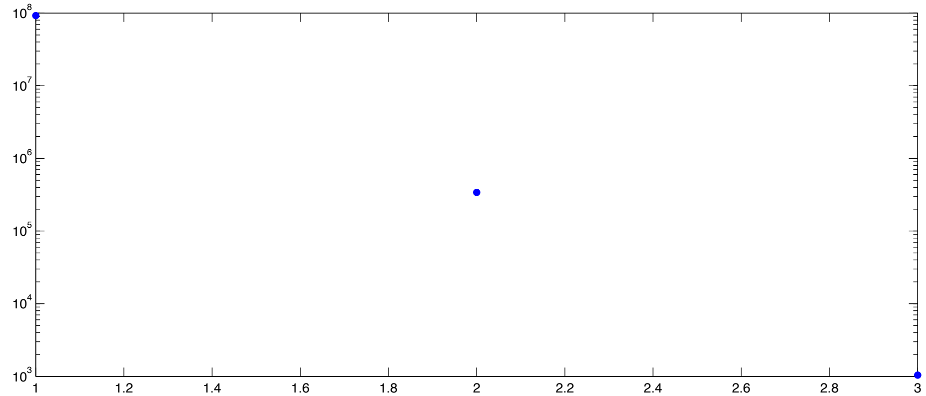
1. Histogram of an invariant characteristics of the pixels

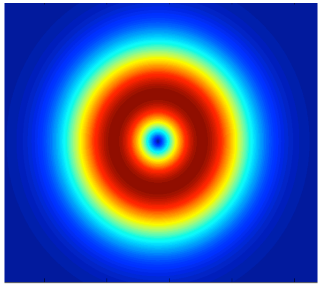
… but the specificity tends to be too low.

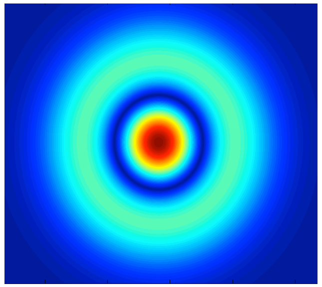
Three classical ways to achieve rotation invariance

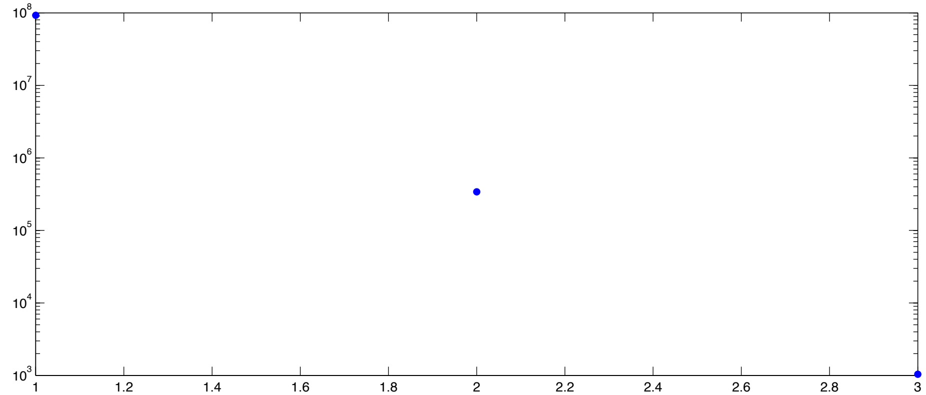
2. Inner product with rotation invariant functions











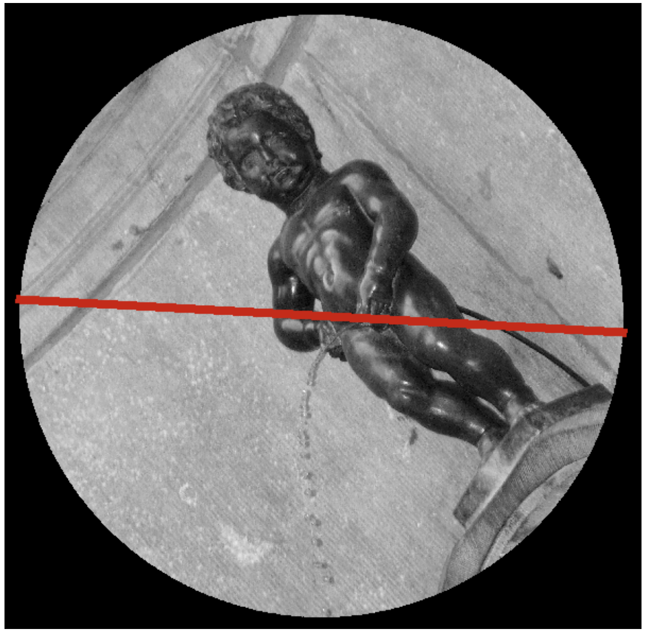
Three classical ways to achieve rotation invariance

2. Inner product with rotation invariant functions

… but, again, the specificity tends to be too low.

Three classical ways to achieve rotation invariance

3. Detection of a principal direction



Three classical ways to achieve rotation invariance

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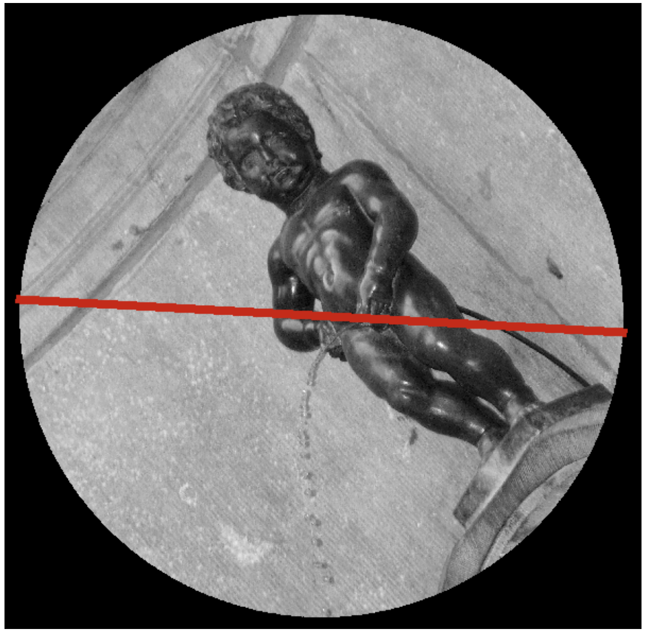
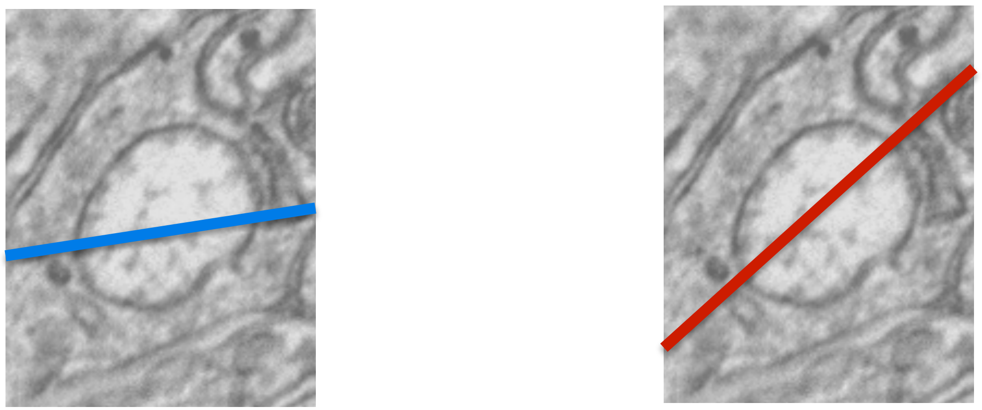


… but what if a principal direction cannot be properly defined?

Three classical ways to achieve rotation invariance

3. Detection of a principal direction



… but what if a principal direction cannot be robustly defined?

Compact Rotation Invariant Descriptors

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Compact rotation invariant descriptors are required.

Common rotation invariance strategies are not suitable.

Spectral graph theory can achieve rotation invariance.

The Graph Fourier Transform is invariant under relabeling of the vertices.

Let $\mathcal{G}$ be a graph with:
vertices V
adjacency matrix A
degree matrix D

The graph Laplacian is:
$$L = \mathbb{I} - D^{-1/2} A D^{-1/2}$$
and let $\mathcal{B}$ its eigenbasis

If f is a function defined on V,
then its Graph Fourier Transform is:
$$\hat{f} = \mathcal{B}^T f$$
and is invariant under relabeling of V

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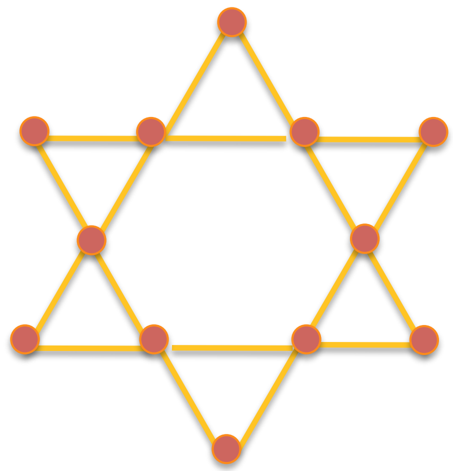

The Graph Fourier Transform is invariant under relabeling of the vertices.

If f is a function defined on V,
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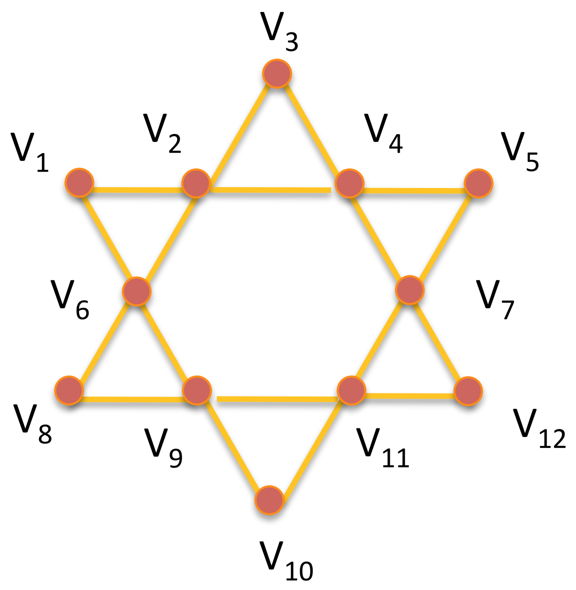
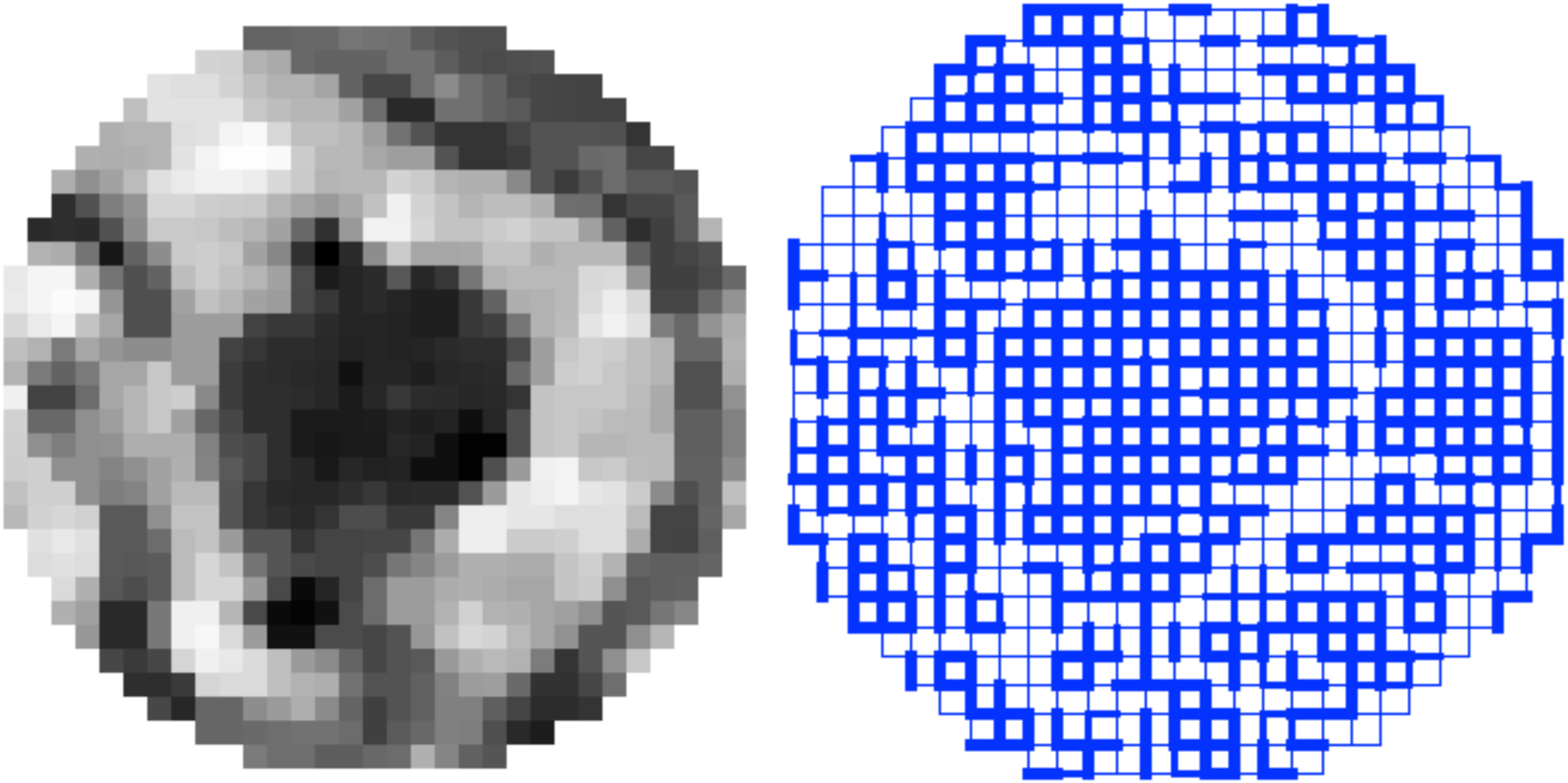
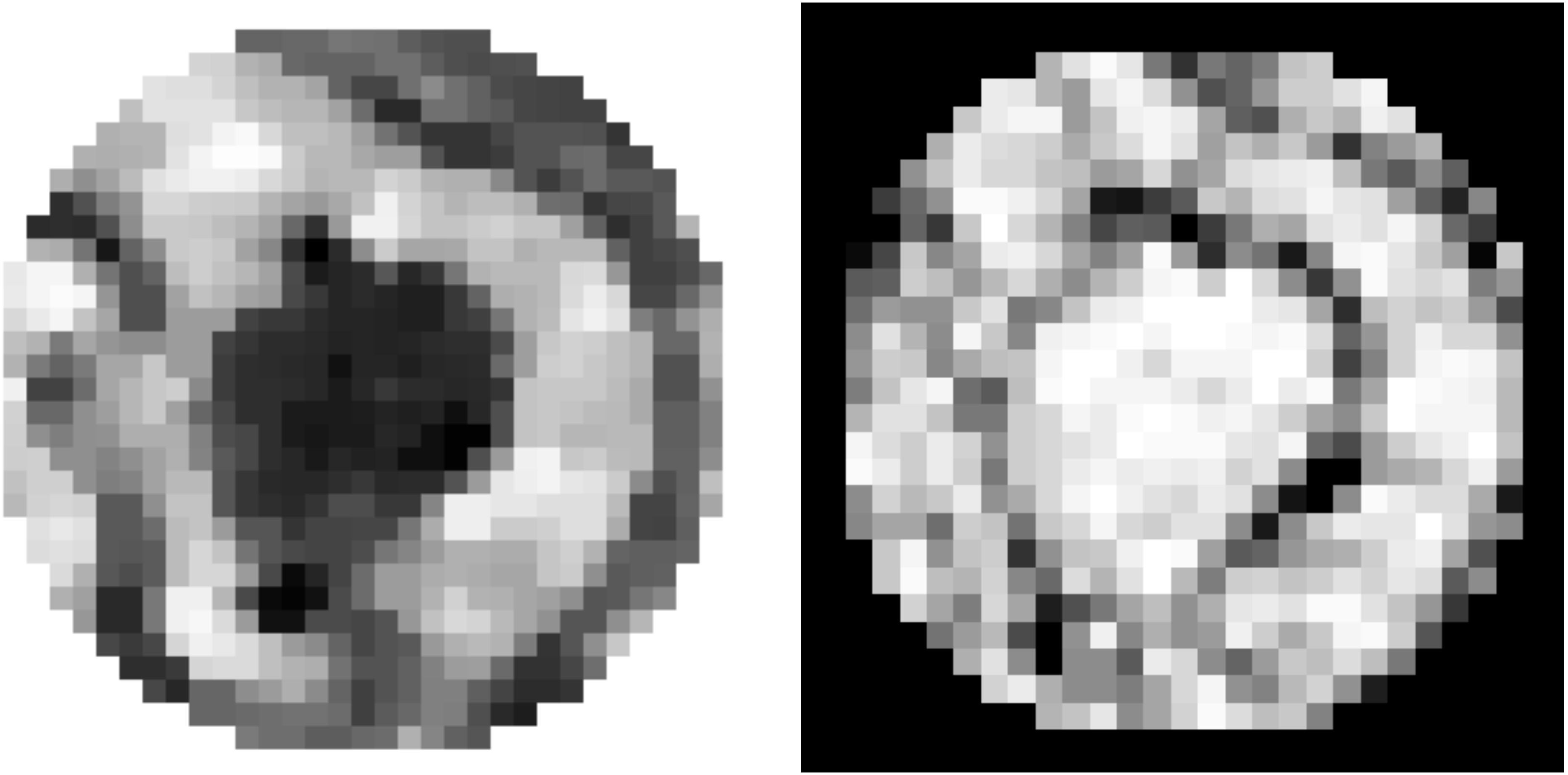


A graph can be defined for an image neighborhood.



Edges are weighted by a gaussian of the difference of intensities between neighboring pixels.

A function can be defined on the vertices (pixels)



We choose the pixel’s degree as a function but any function that is rotation invariant would work.

The descriptor is the Graph Fourier Transform of the function.

If f is a function defined on V,
then its Graph Fourier Transform is:

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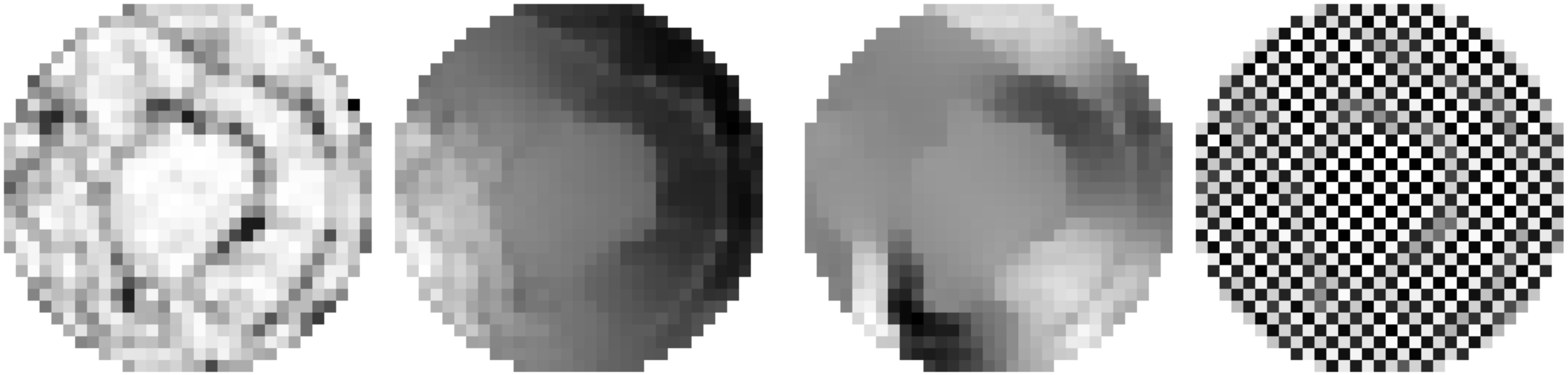
and is invariant under relabeling of V



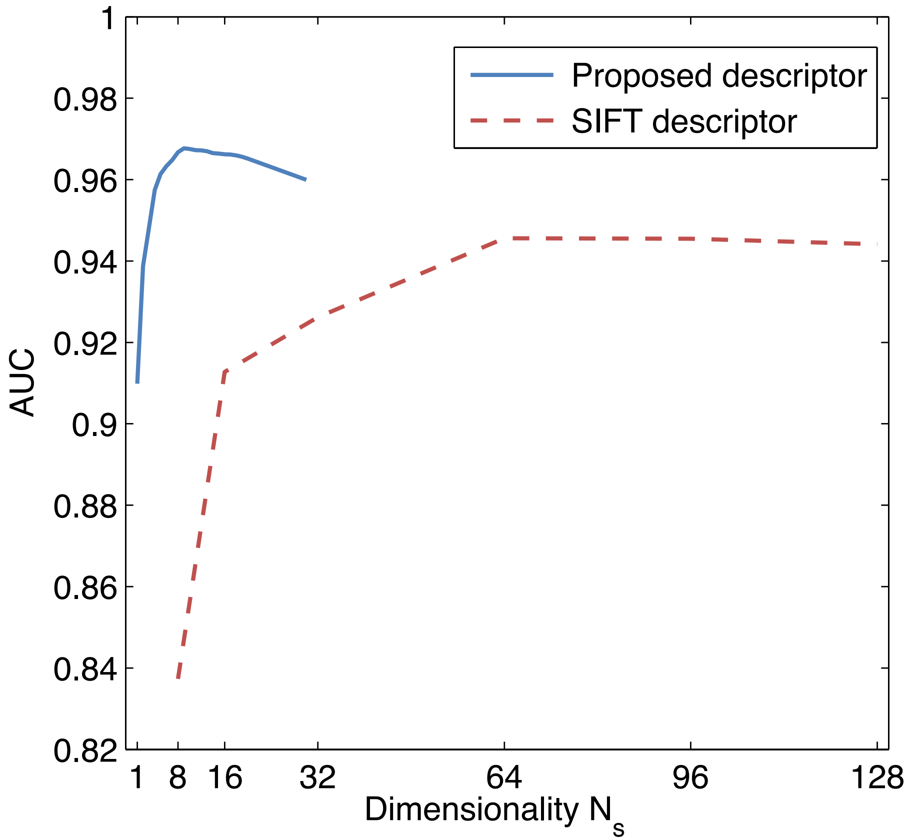
1st eigenvector 2nd eigenvector 9th eigenvector 750th eigenvector

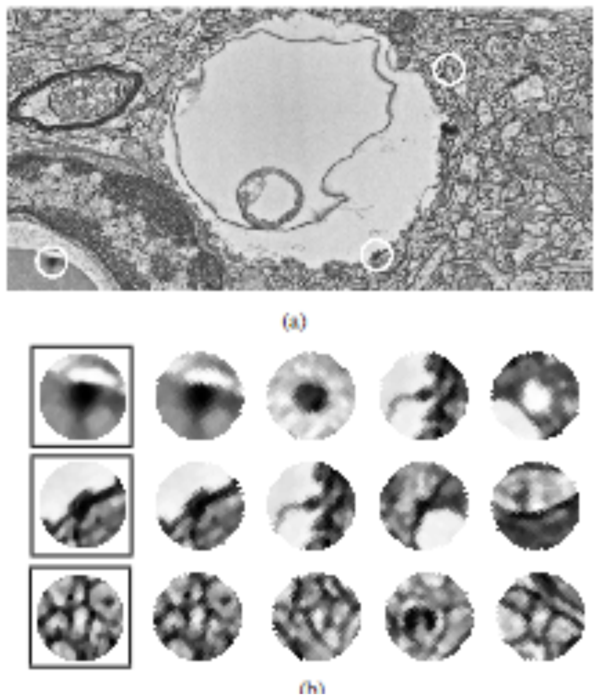
This descriptor is rotation invariant (up to discretization)

When the image is rotated, what changes is the labeling of the pixels

but the graph remains unchanged (up to discretization)

Compared to SIFT, our descriptor is more specific and more compact.





520 keypoints in a scene of 5200x5200 pixels

18 rotation from 10° to 180°

→ Database with 9360 descriptors organized as 520 equivalence classes

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Thank you!