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# Increasing the realism of in silico cortex substrates for diffusion MRI simulation

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## Introduction

Numerical simulations have provided an interesting approach to study and validate brain microstructure models<sup>1</sup>. For this purpose, many methods to generate virtual brain cells have been proposed<sup>2,3,4</sup>. However, these methods focus only on the generation of substrates with specific brain cells of a given type. For example, generating a virtual scene populated only by axons<sup>2,3</sup> or generating single neurons of multiple types<sup>4</sup>. To the best of our knowledge, no method was proposed to synthesize virtual microstructure scenes combining neurons with axons. This work aims to close the modeling gap of virtual brain microstructure by extending the MEDUSA framework<sup>5</sup> to allow the generation of hybrid virtual substrates. The presented method allows the synthesis of volume of interests (VOIs) combining neurons with axons with similar volume fractions to values in the literature on human brain gray matter microstructure<sup>6</sup>.

## Methods

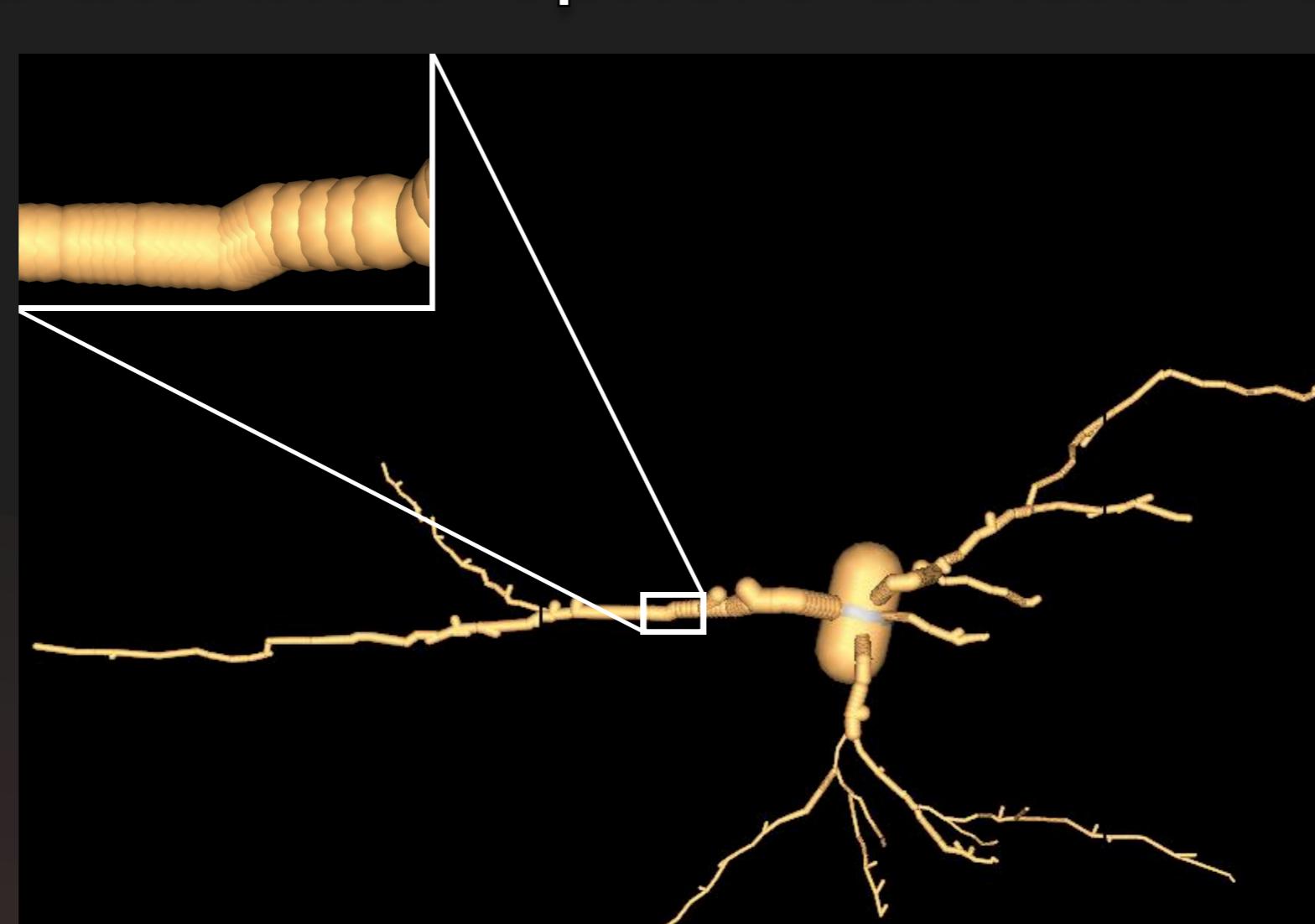
- **Dataset:**

The NEUROMORPHO dataset<sup>7,8</sup> was used to reconstruct virtual neurons of the human brain from the ".SWC" files.

- **Cell reconstruction:**

Spheres are placed on the 3D space using the cell graph and then interpolated using the overlapping ratio metric computed from the radius  $R$  and the inter-sphere distance  $d$ .

$$O_r = \sqrt{1 - \left(\frac{d}{2R}\right)^2}$$



## Results

- **Generation of neuron populations:**

Four substrate types generated in a Volume Of Interest (VOI) of  $(100 \times 100 \times 100) \mu\text{m}^3$  using MEDUSA<sup>5</sup>:

- a) Axons with volume fraction  $V_f=85\%$
- b) Hybrid substrate with axons with  $V_f=44\%$  and pyramidal neurons with  $V_f=6\%$
- c) Same as substrate b) with a higher neuronal VF of  $V_f=12\%$
- d) Pyramidal neurons with a  $V_f=12\%$

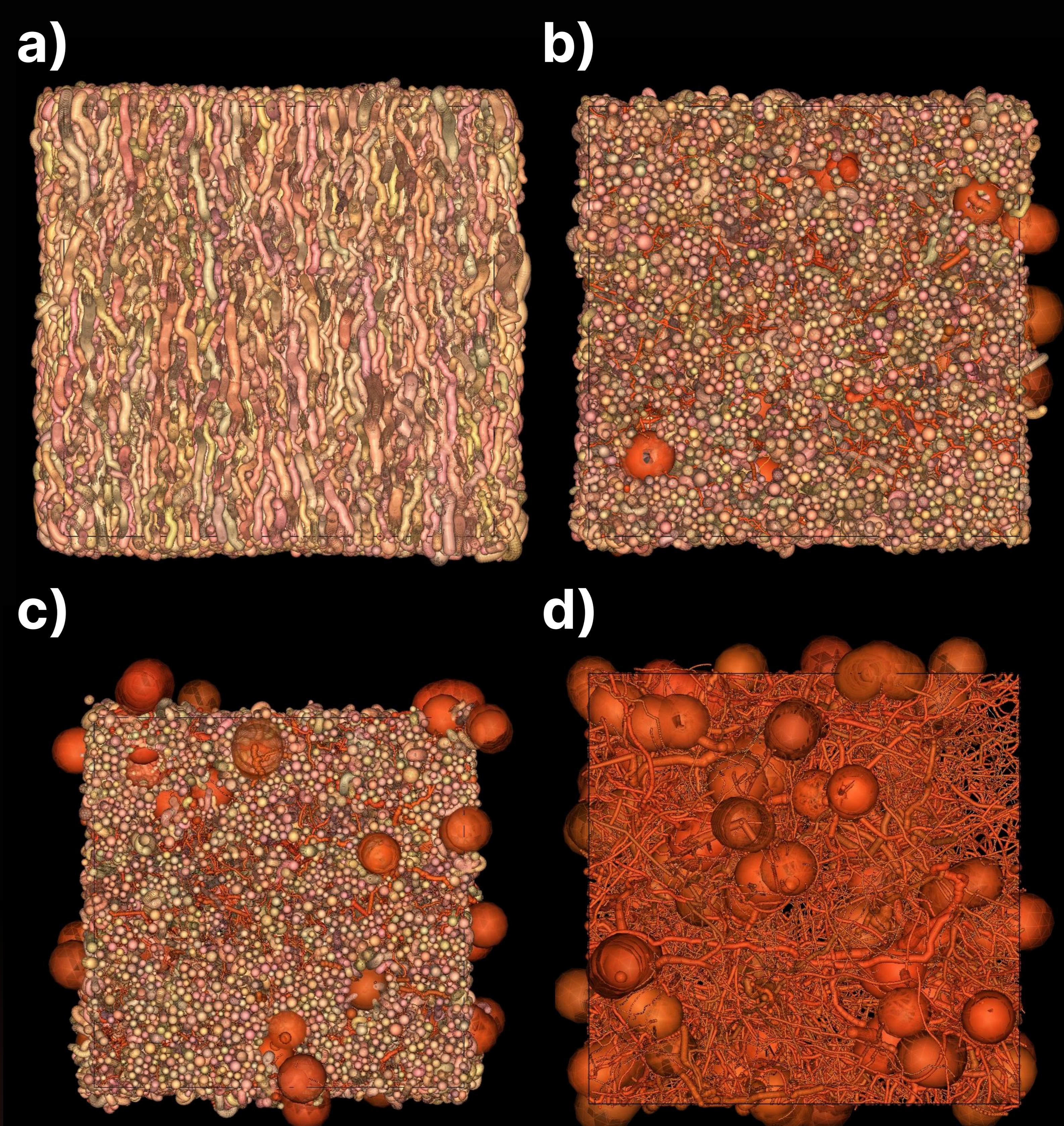
- **Diffusion MRI simulations:**

$D_0=3 \times 10^{-9} \text{ m}^2/\text{s}$ ,  $N_s=500k$  initialized in both intra and extracellular spaces.

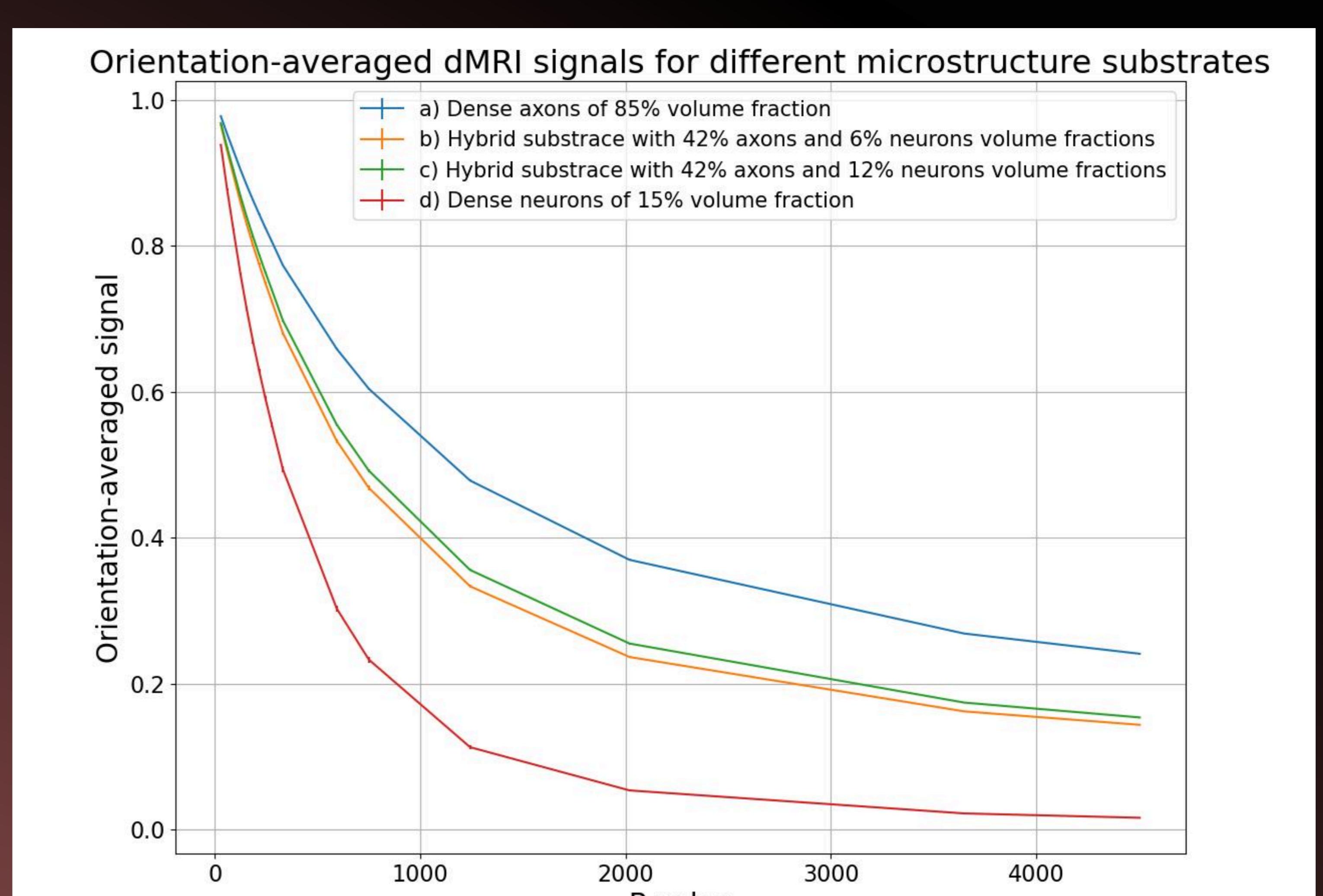
B-values  $\text{s/mm}^2$ : [30, 60, 80, 120, 150, 180, 210, 240, 270, 300, 550, 700, 1000, 1700, 3200, 4000]

Orientations: [6,6,6,6,6,6,6,30,30,30,30,60,60,60]

- **Generated substrates**



- **Simulated signals**



## Conclusion

This work demonstrates a proof of concept for synthesizing virtual substrates with hybrid cells mixing neurons and axons, thus increasing the modeling realism of synthetic gray matter microstructure. Future work directions include large-scale simulation of microstructure and exploring the ability to add more components in the synthetic substrates such as blood vessels and glial cells, which were not included in this study.

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