2D and 3D Segmentation of uncertain local collagen fiber orientations in SHG microscopy - Supplementary material

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1 Hyperparameters

We used a wide variety of hyperparameters during our experiments and present in Table 1 all relevant selections for our methods. Our methods all used Inception-ResNet-v2 or its 3D version Inception-ResNet-3D as a backbone. These networks were initialized with pretrained ImageNet weights in 2D or transferred weights in 3D. As transfer strategy we used the transfer based on Equation 1. In general the batch size was chosen as large as possible.

	input size	output size	γ	w	bs	optimizer	lr	d
2D classification	64 x 64 x 1	16 x 16 x 1	0	(1,1,1)	32	Adam	0.001	0.8
3D combination of 2D classifications	64 x 64 x 16	16 x 16 x 16	0	(1,1,1)	32	Adam	0.001	0.8
2D semantic segmentation	1024 x 1024x 1	26 x 26 x 1	0	$(\frac{16}{41}, \frac{24}{41}, \frac{1}{41})$	2	Adam	0.001	0.8
3D classification	128 x 128 x 32	8 x 8 x 8	2	(1,1,1)	16	SGD	0.01	0.6
3D two stage segmentation (first stage)	64 x 64 x 16	1536	N/A	N/A	16	N/A	N/A	N/A
3D two stage segmentation (second stage)	16 x 16 x 16 x 1536	16 x 16 x 16	0	$(44.5, 54.5, 1)$	2	SGD	0.01	0.6

Table 1: Overview of selected hyperparameters - The input and output describe the sizes given to and received from the methods. γ and w are the parameters for weighted focal loss. The batchsize is defined by bs while lr gives the learning rate. If dropout was used the dropout probability for a neuron is reported in d.

2 Example Images and Videos

We present example results for all proposed methods in 2D and 3D in the following sections.

2.1 Examples in 2D

Figure 1 and Figure 2 show the results of all described methods for the image shown in Figure 1 in the paper. While some 3D methods like two stage segmentation look like they perform not well, one has to keep in mind that they need to be compared to a 3D ground-truth instead of the ground-truth shown in Figure 1 in the paper. For better visualization of 3D results see subsection 2.2.

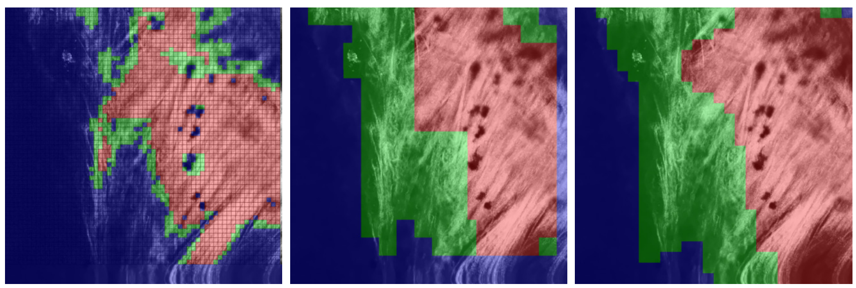

Fig. 1: Example results for the 2D methods: Fourier analysis, Classification and Semantic segmentation - Color code: Similar orientation - red, Dissimilar orientation - green, Not of interest - blue

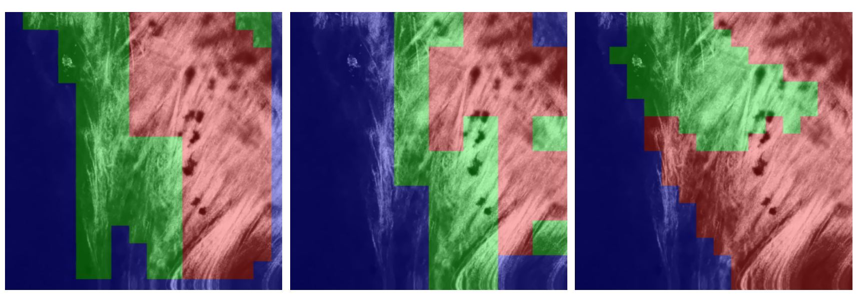

Fig. 2: Example results for the 3D methods: Combination of 2D classifications, Classification, Two stage segmentation - Color code: Similar orientation - red, Dissimilar orientation - green, Not of interest - blue

2.2 Examples in 3D

In this section we provide a sparse sweep through some example 3D data in Figure 3 and Figure 4. On the left side of each double image the expected 3D ground-truth is given. On the right side the prediction of the two stage segmentation is shown. Please see the associated videos inside the supplementary materials for a more detailed 3D sweep through the complete scan.

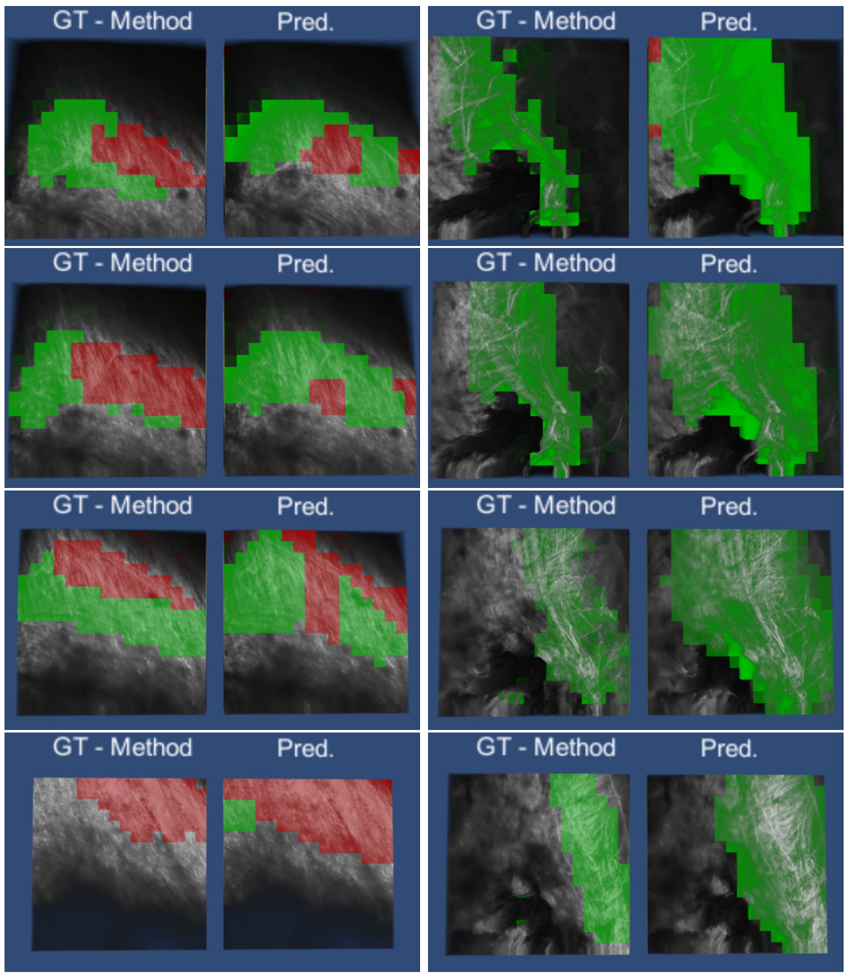

Fig. 3: Additional results for the method two stage segmentation - Double images are on the left side from the video '3D-Visual1.mp4' and on the right side from '3D-Visual2.mp4'. Color code: Similar orientation - red, Dissimilar orientation - green, Not of interest - transparent / not shown

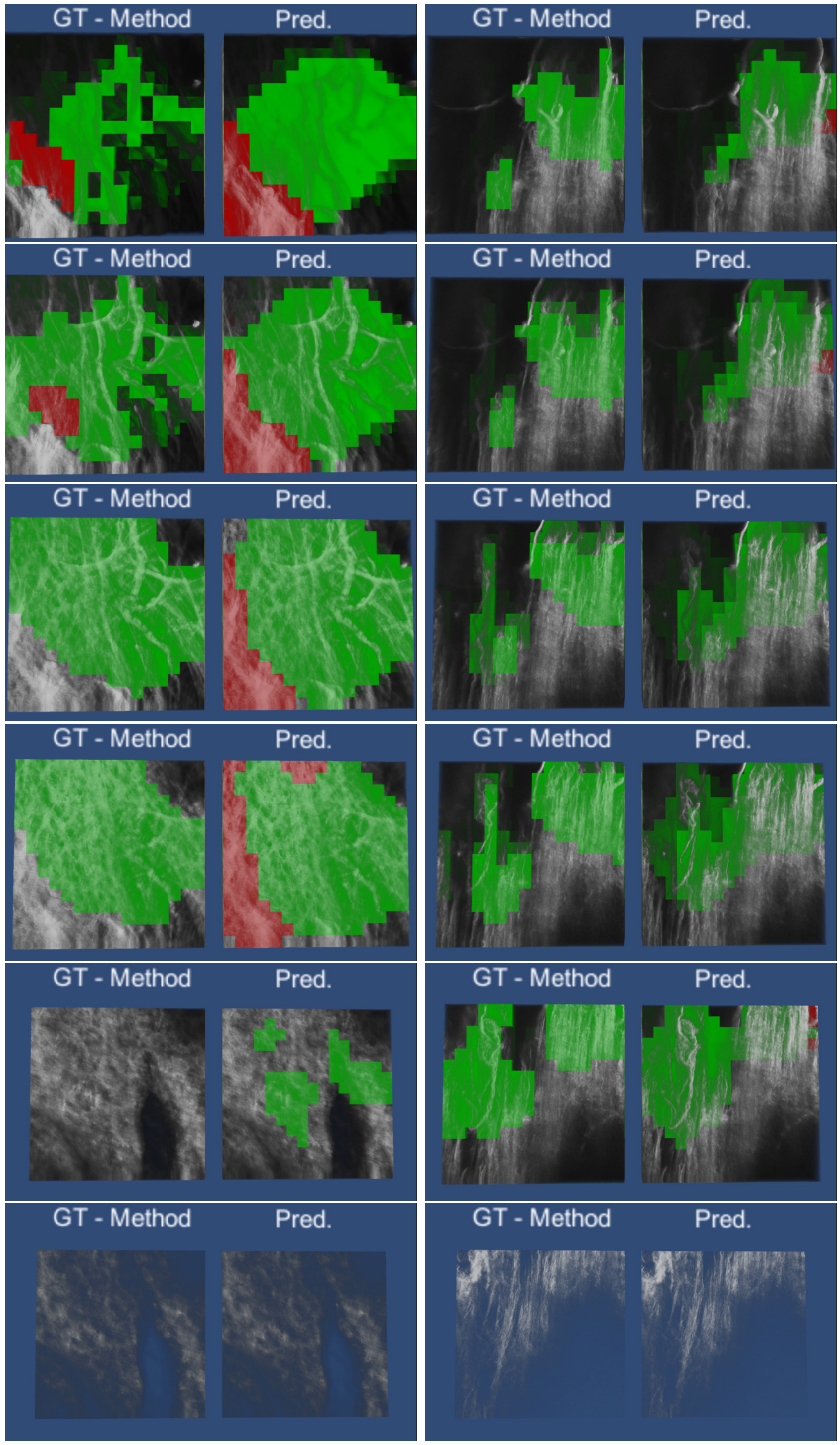

Fig. 4: Additional results for the method two stage segmentation - Double images are on the left side from the video '3D-Visual3.mp4' and on the right side from '3D-Visual4.mp4'. Color code: Similar orientation - red, Dissimilar orientation - green, Not of interest - transparent / not shown

3 Further Results

Beyond the proposed methods in the paper we investigated further approaches which did not lead to promising results. We want to sum up these results here for future researchers. In the 2D case we used other feature spaces like edge detections or histogram of gradients. These features spaces were due to the high noise ratio not useful for any further analysis. Moreover, we analyzed the feature space of the 2D classification with t-Distributed Stochastic Neighbor Embedding. We detected a correspondence between accuracy and visual data point separation while no further knowledge could be gained for other methods.

We investigated also one stage semantic segmentation for 3D data. This semantic segmentation showed inferior performance to other methods. We identified two main reasons for this failure. Firstly, the 3D one stage segmentation suffers from the skewed class balance and it seems this effect is intensified in 3D. Secondly, due to hardware constraints we could not process the whole scan in one pass with the native Inception-ResNet-3D backbone. We believe that the adaptions needed to fit at least parts of the data on one GPU led to the performance drop because pretrained weights were mixed up.