Supplementary Materials

Fengyuan Sun Sezer Karaoglu Theo Gevers University of Amsterdam & 3DUniversum Amsterdam, The Netherlands

fengyuansun2000@gmail.com s.karaoglu@3duniversum.com Th.Gevers@uva.nl

1. Additional qualitative examples

To further evaluate the proposed method, visualizations of multi-view inconsistent predictions and their resulting segmentation are provided in Figures 1 and 2. Our method predicts segmentation that is consistent with respect to each view by leveraging spatial and multi-view information. Figure 3 displays examples of temporal inconsistency, and Figure 4 further shows examples of the predictions in 3D.



Figure 1. Visualization of cross-view inconsistency. From left to right: rgb image, ViT-Adapter, ViT-weighted averaging, ours, ground-truth. The initial segmentation is inconsistent between views. Consequently, weighted averaging fails to create a unified prediction. In contrast, the proposed method predicts a correct and consistent segmentation.



Figure 2. Visualization of an ambiguous class in 2D. From left to right: rgb image, ViT-Adapter, ViT-weighted averaging, ours, ground-truth. Some views in the initial segmentation confuse curtain with shower curtain.



Figure 3. Visualization of temporal inconsistency. From left to right: rgb image, ViT-Adapter segmentation, ViT-weighted averaging segmentation, our segmentation, ground-truth segmentation. Minimal changes in viewpoint can result in significant changes in appearance, global context information and occlusions. This causes flickering in the video segmentation. By leveraging multiview information, the proposed method is able to create predictions that are consistent in time.



Figure 4. Visualization of the resulting semantic mesh. From left to right: colored mesh, weighted averaging segmentation, our segmentation, ground-truth segmentation. In contrast to weighted averaging, the proposed method is able to increase segmentation coherency and recover ambiguous predictions.