Probabilistic Object Reconstruction with Online Loop Closure - Supplementary Material

BMVC 2017 Submission # 611

1 Segmentation Model Details

The segmentation model from which the probability maps are derived is an on-line Random Forest trained on patch features. The patch features are derived from the RGB and depth frames, incorporating information such as colour, depth, colour gradients and depth gradients. In some of our experiments however, slightly better segmentation quality(qualitatively) has been achieved using features from a Deep Residual Neural Network [1]. Such is the case for the *DinoHead* and *Rock* sequences.

Every n frames the on-line Random Forest is trained with the mask for the current frame used to determine the positive/negative class training instances. In our experiments $n = 10$.

2 Comparison with Ren et al

In the main paper a comparison is drawn on the reconstruction efficacy of our method versus that of Ren et al [2] using a large shape prior. In figure 1 we demonstrate the systems lack of ability to converge to a reasonable shape given a smaller shape prior.

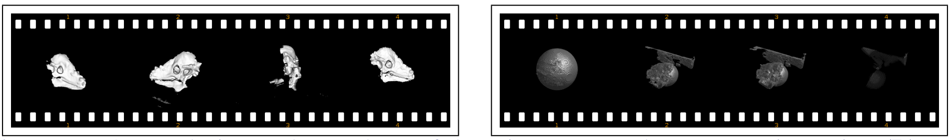

Figure 1: Quarterly interval snapshots of the Dinosaur Head reconstruction using **(L)** our method, and **(R)** the one proposed by Ren et al. [2] with a small shape prior.

In addition to the comparisons between our method and that of [2] on the *DinoHead* sequence we also provide quarterly reconstruction snapshots on the *Rock* sequence. Similar performance may be seen in figure 2 for a large shape prior and in figure 3 for a small shape prior. It should be noted that although results from the system of Ren et al [2] have been presented for two of the sequences our system was tested on, the results for the remaining sequences were very similar. We were unable to reconstruct any of our test objects with the system of Ren et al [2].

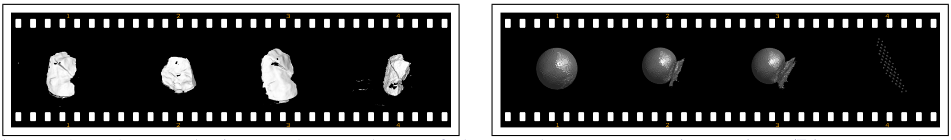

Figure 2: Quarterly interval snapshots of the Rock reconstruction using **(L)** our method, and **(R)** the one proposed by Ren et al. [2] with a large shape prior.

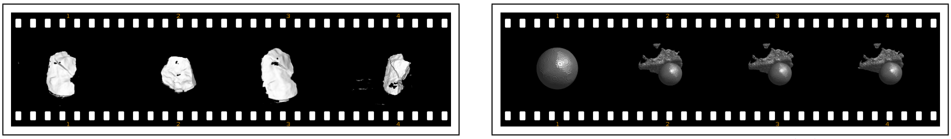

Figure 3: Quarterly interval snapshots of the Rock reconstruction using **(L)** our method, and **(R)** the one proposed by Ren et al. [2] with a small shape prior.

3 Robustness to Noisy Probability Maps

In this section we demonstrate robustness to instantaneously noisy and erroneous probability maps by showing clean reconstructions when the corresponding probability map for the current given frame has noise. Two sequences where this is particularly noteworthy are the *DinoHead* and *Rock* sequences. The examples of this for the *DinoHead* sequence can be seen in figure 4. For the *Rock* sequence, refer to figure 5.

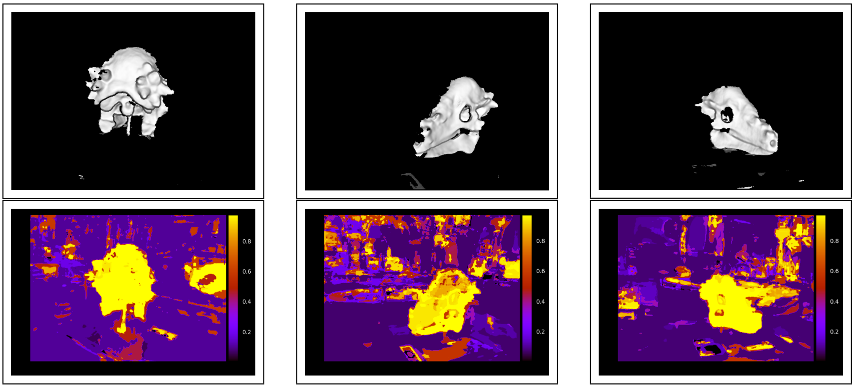

Figure 4: Three reconstruction snapshots of the *DinoHead* sequence and their associated probability maps.

4 Tracking Object Motion

In addition to the reconstruction of the objects presented in the main paper and these supplementary materials, an experiment was performed in which the motion of a head is successfully tracked using only the geometry of the face. Quarterly snapshots are shown in figure 6.

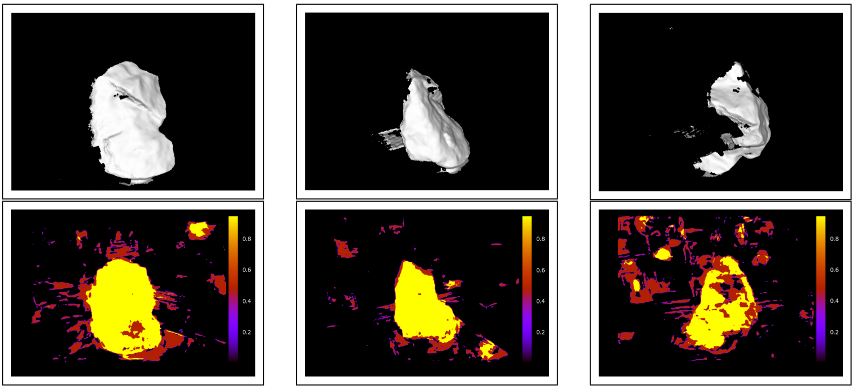

Figure 5: Three reconstruction snapshots of the *Rock* sequence and their associated probability maps.

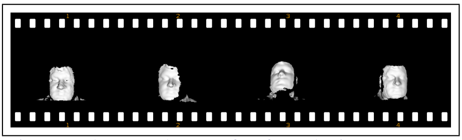

Figure 6: Quarterly interval snapshots of a face being reconstructed and tracked.

References

[1] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *2016 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2016, Las Vegas, NV, USA, June 27-30, 2016*, pages 770–778, 2016. doi: 10.1109/CVPR.2016.90. URL http://dx.doi.org/10.1109/CVPR.2016.90.

[2] Carl Yuheng Ren, Victor Prisacariu, David Murray, and Ian Reid. Star3d: Simultaneous tracking and reconstruction of 3d objects using rgb-d data. In *The IEEE International Conference on Computer Vision (ICCV)*, December 2013.