OCSplats: Observation Completeness Quantification and Label Noise Separation in 3DGS

Supplementary Material

6. Calculation Details of Dynamic Anchor Points T_b and T_o

Input. We normalized the input $\mathcal{A}_h^{oc}$ and converted it into a histogram $\mathcal{H}$.

Details of Calculating T_o. Firstly, we calculate the probability P of each gray level in the histogram $\mathcal{H}$, the cumulative distribution function w, and the cumulative mean M:

$$P(i) = \frac{\mathcal{H}(i)}{N} \tag{25}$$

$$\omega(t) = \sum_{i=0}^{t} P(i) \tag{26}$$

$$M(t) = \sum_{i=0}^{t} i \cdot P(i) \tag{27}$$

where N is the total number of pixels in $\mathcal{A}_h^{oc}$. P, ω and M are vectors of length L (in our experiment, L=1000).

Next, we calculate the inter-class variance for each grayscale level:

$$\sigma^2(t) = \frac{[\omega(t) \cdot (M_{\text{global}} - M(t))]^2}{\omega(t) \cdot (1 - \omega(t)) + \epsilon} \tag{28}$$

where $M_{\text{global}} = M(L-1)$, $\epsilon = 10^{-8}$.

Finally, we calculate the maximum inter-class variance threshold T_o:

$$t^* = \arg\max_t \sigma^2(t) \tag{29}$$

$$T_o = \frac{t^*}{L} \tag{30}$$

Details of Calculating T_b. T_b is the intra-class centroid of the background pixels, which can be calculated by the following formula:

$$C_0 = \frac{\sum_{i=0}^{t^*} i \cdot P(i)}{\sum_{i=0}^{t^*} P(i)} \tag{31}$$

$$T_b = \frac{C_0}{L} \tag{32}$$

7. Scope of Application

The OCSplasts in this paper can work well when the noise content of scene labels is above 5%. When there is less noise, it may cause dynamic threshold failure. We have set up an automatic judgment mechanism in the code; that is, when the max inter-class variance $\sigma^2(t^*)$ in Eq. 28 is greater than $K(K = 2000)$, the dynamic threshold is used, and vice versa, a fixed threshold is used.

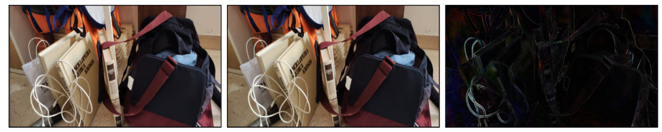

Figure 11. **Pose Error.** Even in completely stationary scenes, camera pose errors can cause edge position reconstruction to fail.

8. Stochastic Uncertainty and Threshold Classification

One notable advantage of using a stochastic uncertainty loss [22, 30] is that it automatically suppresses complex regions to learn by adjusting loss weights, eliminating the need to set thresholds manually. However, because it **cannot distinguish between truly noisy areas and those that are merely hard to reconstruct, it often yields suboptimal reconstruction quality**. In contrast, threshold classification methods—though lacking generalizability—can produce better reconstruction results when the noise classification is correct. Our proposed dynamic anchor threshold approach circumvents threshold-based methods' poor generalizability while maintaining high reconstruction quality.

9. More Visualization Results

In Fig. 12, we present more visualized results of OCSplasts on existing datasets. Even if the scene has different proportions of noise and scene characteristics, OCSplasts can still accurately segment foreground noise and reconstruct clear static backgrounds.

10. Limitations

Currently, most reconstruction methods rely on the pose provided by COLMAP [32, 33], but we have found that the COLMAP pose may have some errors. This kind of pose error is often reflected in the texture edges of the object, as shown in Fig.11. Even in entirely stationary scenes, the reconstruction interference caused by slight pose misalignment is inevitable. Similarly, errors at these edges are objectively present in reconstructing scenes containing dynamic objects, so these inherent edge noises have been interfering with the noise measurement. In our future work,

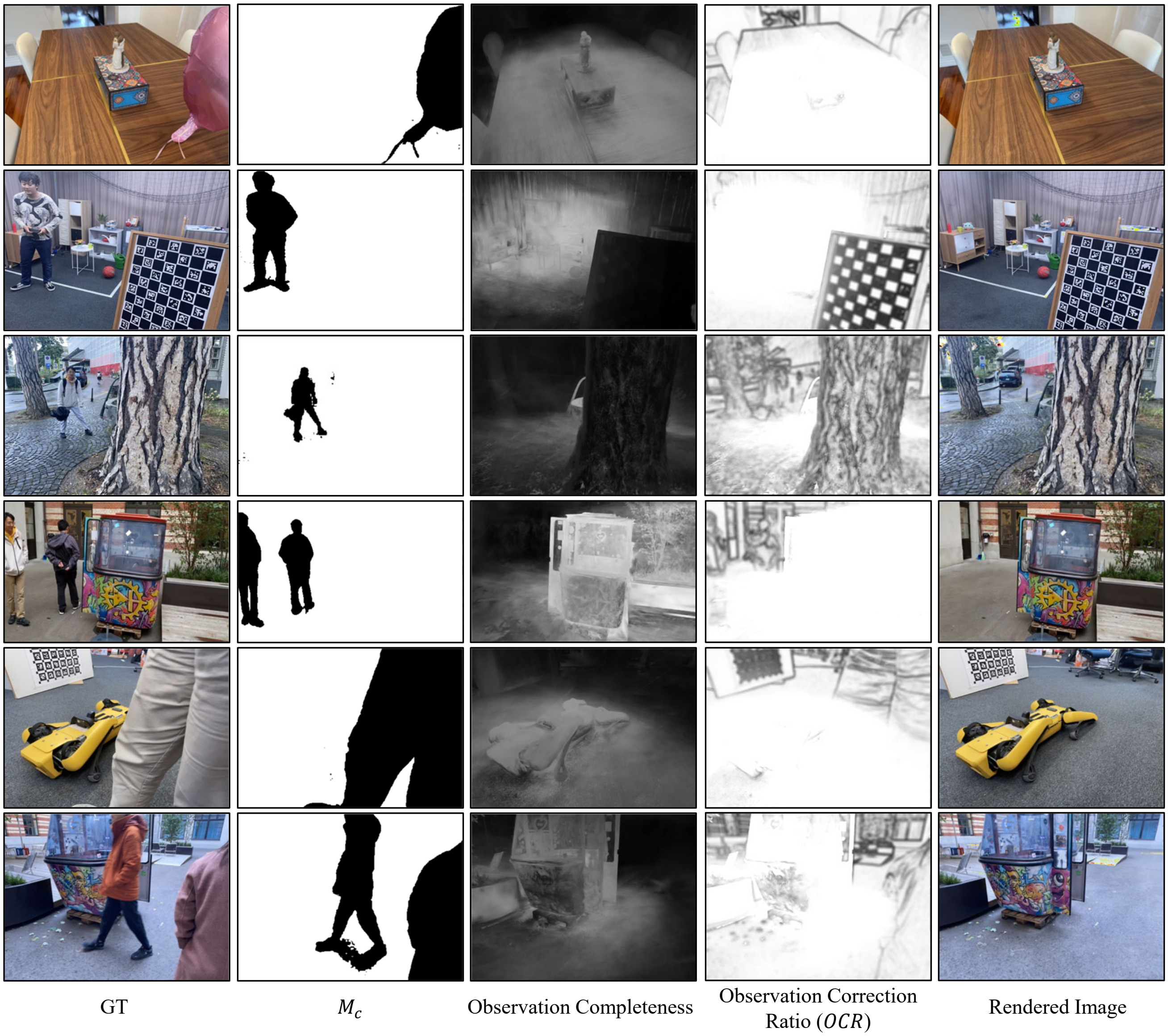

Figure 12. **Qualitative Results in Indoor and Outdoor Scenes.** OCSplats detect areas with learning difficulties based on observation completeness and use OCR to correct noise assessments, achieving accurate noise segmentation in scenes of different complexities.

we will attempt to evaluate camera pose errors and quantify these inherent edge interferences to eliminate their impact on noise label separation.