

Figure 2. Framework overview. First, features are matched between consecutive segmented images, to obtain a coarse pose estimate (Sec. 3.1). Some of these posed frames are stored in a memory pool, to be used and refined later (Sec. 3.2). A pose graph is dynamically created from a subset of the memory pool (Sec. 3.3); online optimization refines all the poses in the graph jointly with the current pose. These updated poses are then stored back in the memory pool. Finally, all the posed frames in the memory pool are used to learn a Neural Object Field (in a separate thread) that models both geometry and visual texture (Sec. 3.4) of the object, while adjusting their previously estimated poses.

- Code runs!
- Milk film: CUDA out of memory
 - 7.79 GB total capacity; 2.63 GB already allocated; 219 MB free; 3.31 GB reserved in total by PyTorch
- HO3D dataset: Unable to find a valid cuDNN algorithm to run convolution

- Code runs!
- Milk film:
 - 7.79 GB reserve
- HO3D dat convolution

No more out of memory issues!

- Batch size from 64 to 1
- Training iteration steps from 500 to 300
- Reduce number of keyframes
 - Coinflip to take or discard keyframe
 - Change the minimal required rotation from precedent keyframes from 5° to 10°

GB



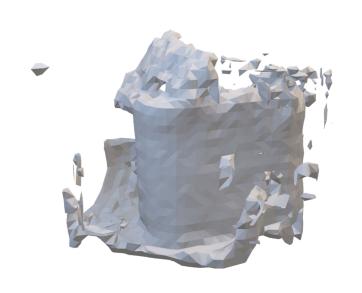
Default 190 keyframes



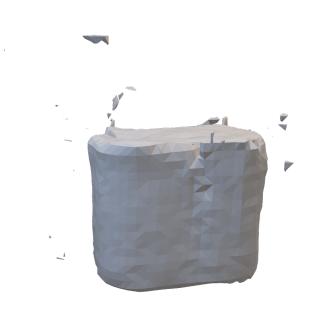
10°deg 90 keyframes



10°deg + cutoff 76 keyframes







default

10°deg

10°deg + cutoff











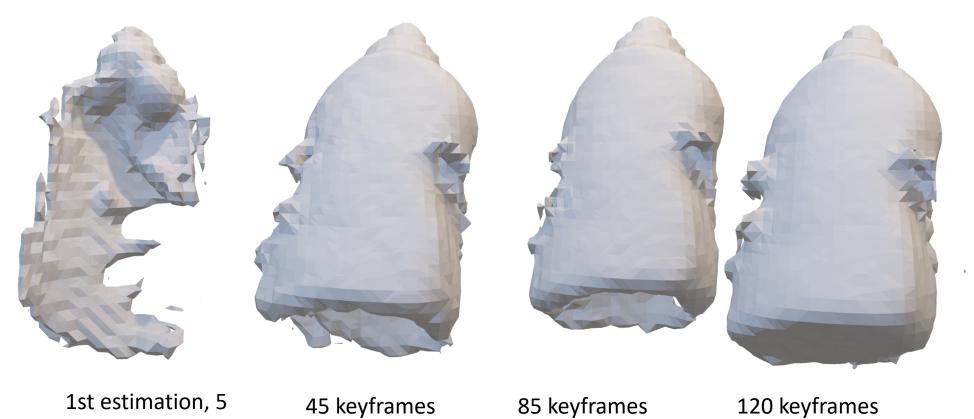
30 keyframes

55 keyframes

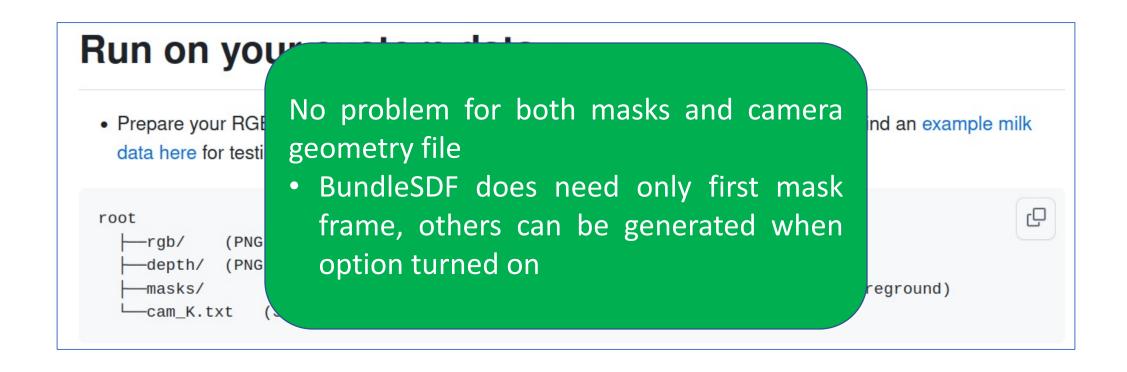
85 keyframes

keyframes

10°deg version



DATASETS



DATASETS

