# Supplemental Material for
# Reconstruction of Articulated Objects from a Moving Camera

Kaan Yücer[1,2] Oliver Wang[2] Alexander Sorkine-Hornung[2] Olga Sorkine-Hornung[1]

[1]ETH Zurich [2]Disney Research

## 1. Evaluation

We present results from two experiments conducted with the ground truth. In the first experiment (see Figure 1), we plot how the reconstruction error changes with respect to the smoothness parameter for piecewise rigid reconstruction (Sec 3.2)

In the second experiment (see Figure 2), we apply Gaussian noise to the point tracks and compute the shape and motion of the object given the noisy point tracks. Again we plot how reconstruction error changes when varying the amount of the temporal smoothness in the piecewise rigid reconstruction (see Sec 3.2). Note that the algorithm with kinematic constraints behaves in the same way when temporal smoothness is applied.

In Figure 3, we show how the reconstruction error changes over time for the Robot dataset as a result of all three steps of the algorithm. Since for the other datasets, we do not have ground truth, we choose the final result of our algorithm as the ground truth and show how the results of the other two steps behave with respect to the final results over time (see Figure 4 to Figure 6).

As the reconstruction error, we used the normalized reconstruction error as defined in Eq. 13 from the paper.

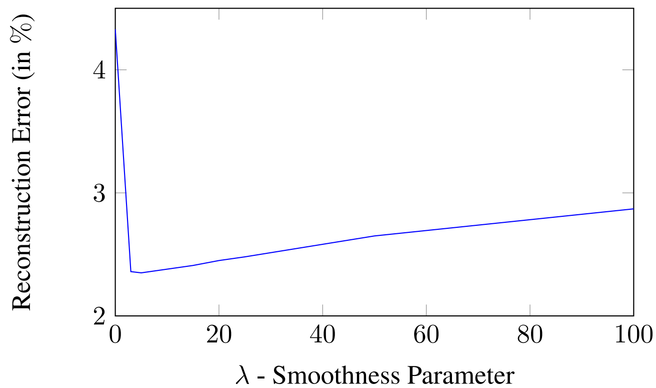


Figure 1. Effect of changing the smoothness parameter in the piecewise rigid reconstruction. Note that the curve is v-shaped. Applying some smoothness helps the algorithm to get better results by enforcing the points not to move around freely. However, overly increasing the smoothness parameter makes the points overly static, resulting in loss of motion information.

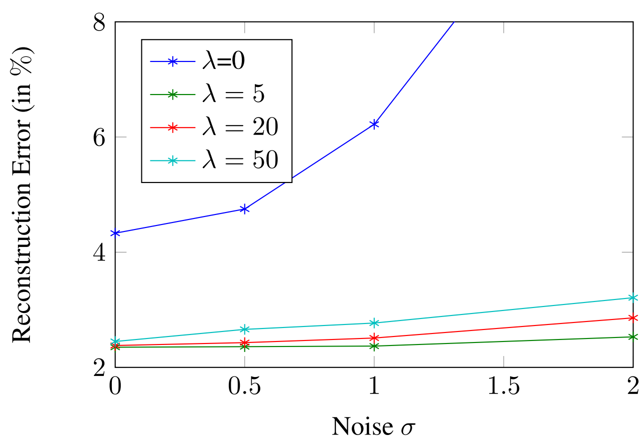


Figure 2. Effect of adding Gaussian noise to the point tracks. Applying smoothness makes the algorithm more robust in case of noisy point tracks, whish is usually the case in real capture scenarios. Again, applying too much temporal smoothness can make the results slightly worse, since it enforces the object to become static.

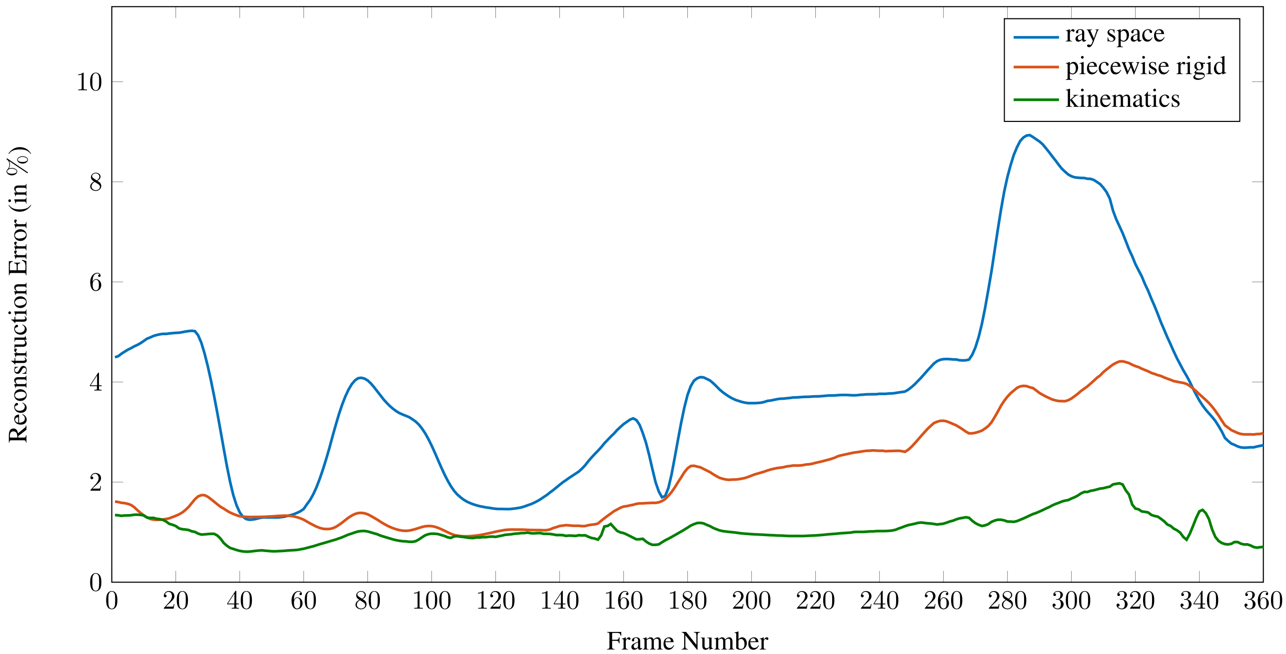


Figure 3. Effect of the different steps of our pipeline on the reconstruction error. When the object motion is fast, the ray space optimization fails to find a good solution. However, each step of the pipeline descreases the reconstruction error steadily.

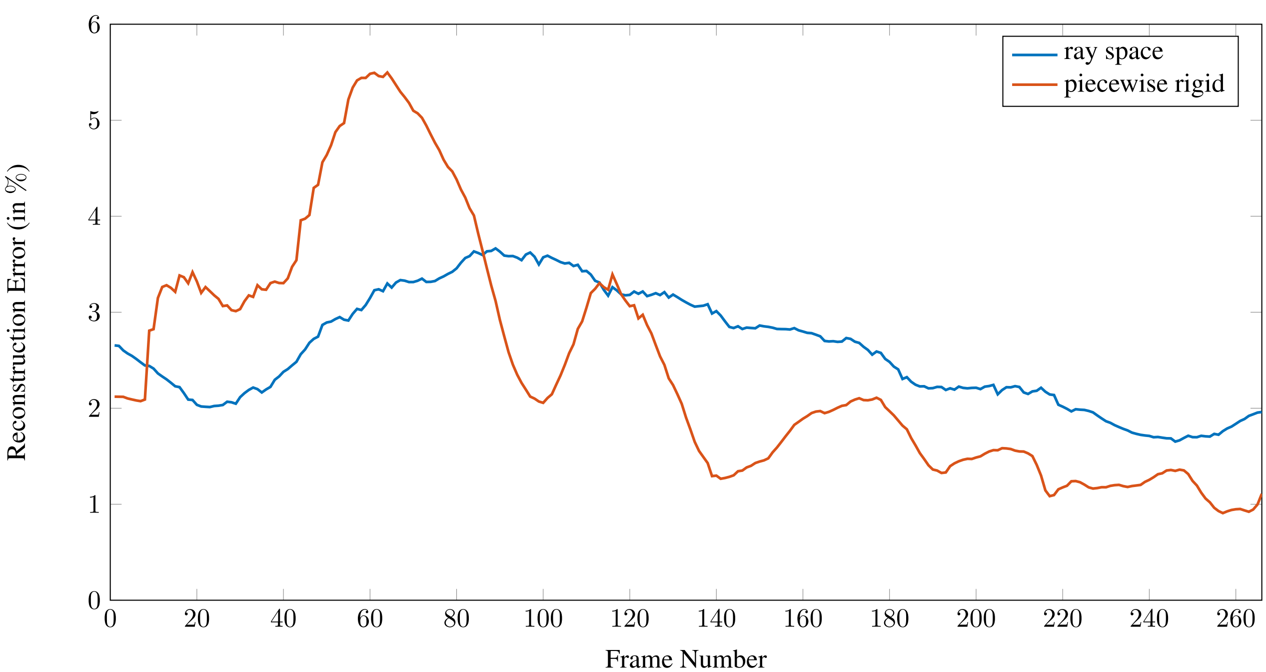


Figure 4. The error in the Person dataset is high for the piecewise rigid reconstruction during the first frames due to the misalignment in one of the piecewise-rigid segments. The reconstructed point cloud gets closer to the kinematic reconstruction after some frames

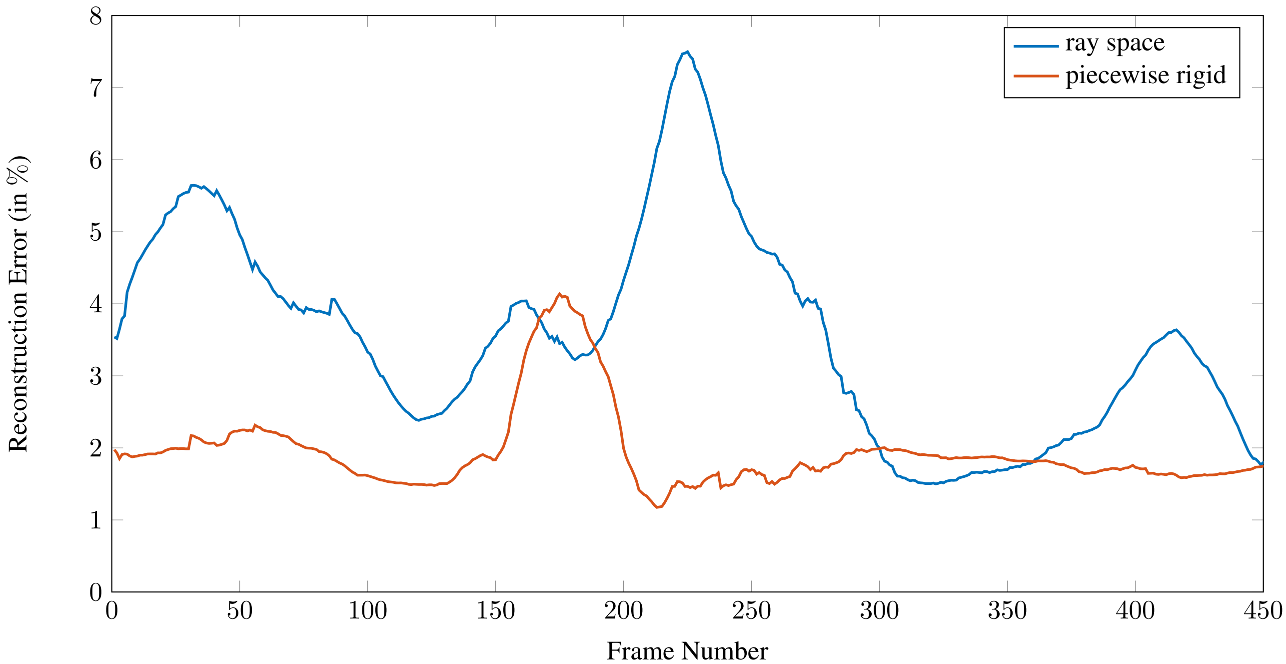


Figure 5. The error in the Body dataset gets steadily lower after each step of the pipeline, *i.e*. the reconstruction steadily converges to the final result

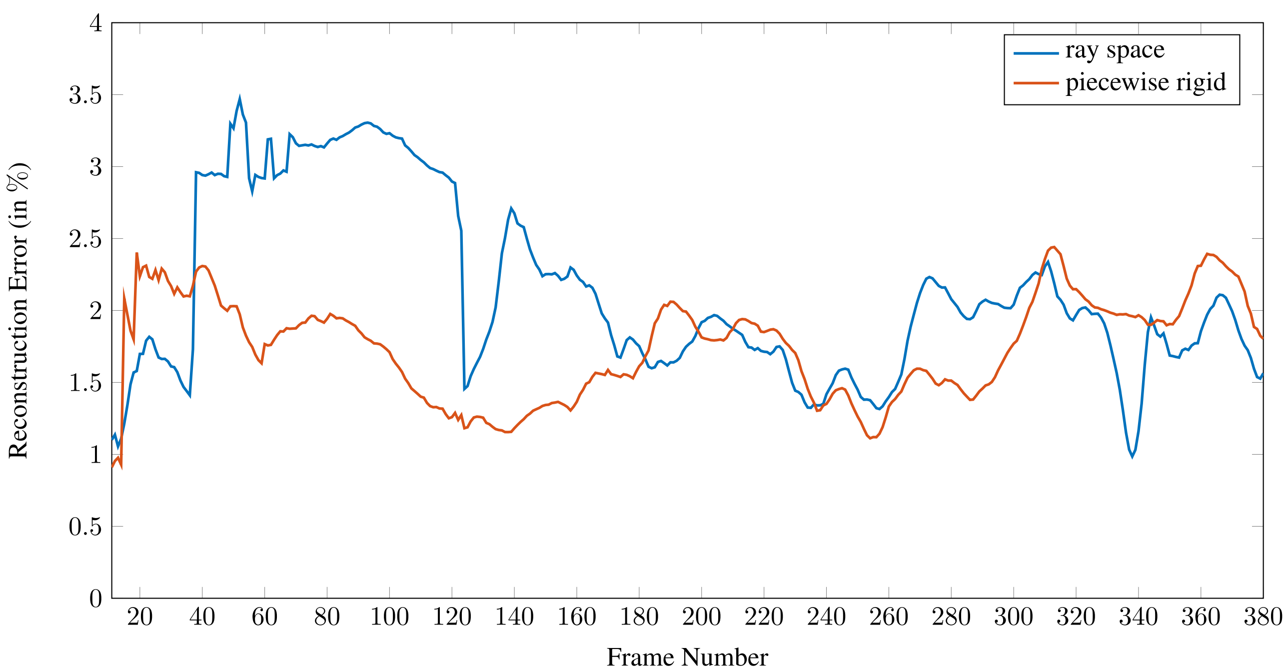


Figure 6. In the Lamp dataset, the results of the first two steps are pretty similar to each other and away from the final result. This shows the importance of the kinematic constraints to get a physically plausible reconstruction.