Rolling-Shutter-Aware Differential SfM and Image Rectification Supplementary Material

Bingbing Zhuang, Loong-Fah Cheong, Gim Hee Lee
National University of Singapore
zhuang.bingbing@u.nus.edu, {eleclf,gimhee.lee}@nus.edu.sg

1. Implementation Detail

We utilize the Deepflow [2] algorithm to compute the optical flow due to its robust performance in practice. While the optical flow algorithm always returns a dense motion field, the reliability and accuracy are not the same for every pixel. To prevent unreliable flow from degrading the performance of our algorithm, we check the forward-backward consistency error and preserve the top 20% most reliable measurements as the input for motion estimation.

We note here that for the GS model and RS model under constant velocity motion, we are able to build a large homogeneous linear system by making use of all those points deemed as inliers to the best minimal solution of RANSAC. As per common practice, we use the solution to this large linear system as a more robust means to bootstrap the nonlinear refinement.

2. Additional results on synthetic data

The quantitative evaluation results on the *Castle* data under constant acceleration motion are shown in Fig. 1 respectively. As can be seen, the RS model in general produces better accuracies compared to the GS model, which corroborates the analysis presented in the main paper.

3. Additional remarks on synthetic experiment

Source of noise. Although the synthesized motions are tested as they are and no noise is introduced, there are two other extant noise sources that explain the non-zero errors. First, the estimation of optical flow introduces noises. Note that the optical flow used for motion estimation is not synthesized but computed using [2] on the rendered image. This makes our synthetic experiments more realistic. Second, as mentioned in Sec. 3 of the main paper, the differential epipolar constrain is true only in the limiting case of infinitesimal motion and is always an approximation in practice. This will introduce errors in the motion estimation.

More analysis on the error curves:

1. we remark here that although the accuracy gap between the results from the GS and RS model are caused by RS distortion, the overall trend of the errors might also be largely influenced by the motion type tested. For example, one can observe that the translation errors decrease noticeably while increasing the amount of translation, even for the GS model. This can be explained by the reduced dominance asserted by the rotation when the translation is increased. Specifically, when the translation is close to zero, the rotation is more dominant (which is known to have a detrimental effect on the translation estimate), leading to larger translation errors. Conversely, reduced rotation dominance with increasing translation leads to a drop in the errors.

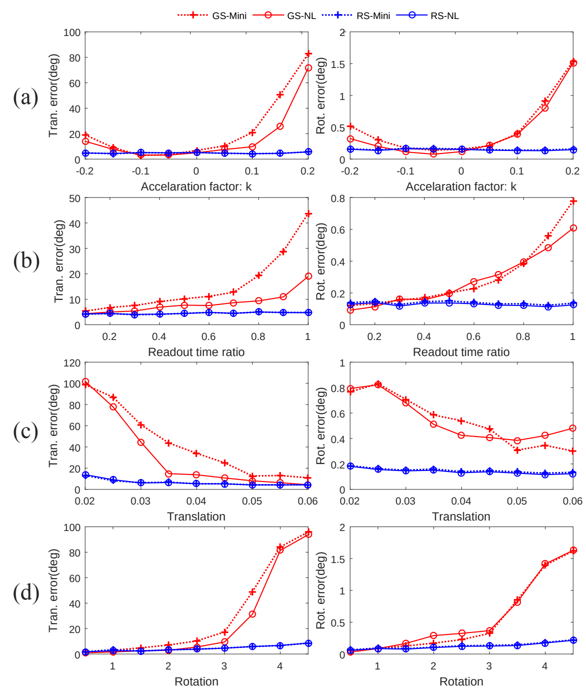

Figure 1: Quantitative evaluation for constant acceleration model on *Castle*. GS-Mini/RS-Mini and GS-NL/RS-NL stand for the results from the minimal solver and non-linear refinement respectively using GS/RS model.

2. From the quantitative result, one can see that the GS

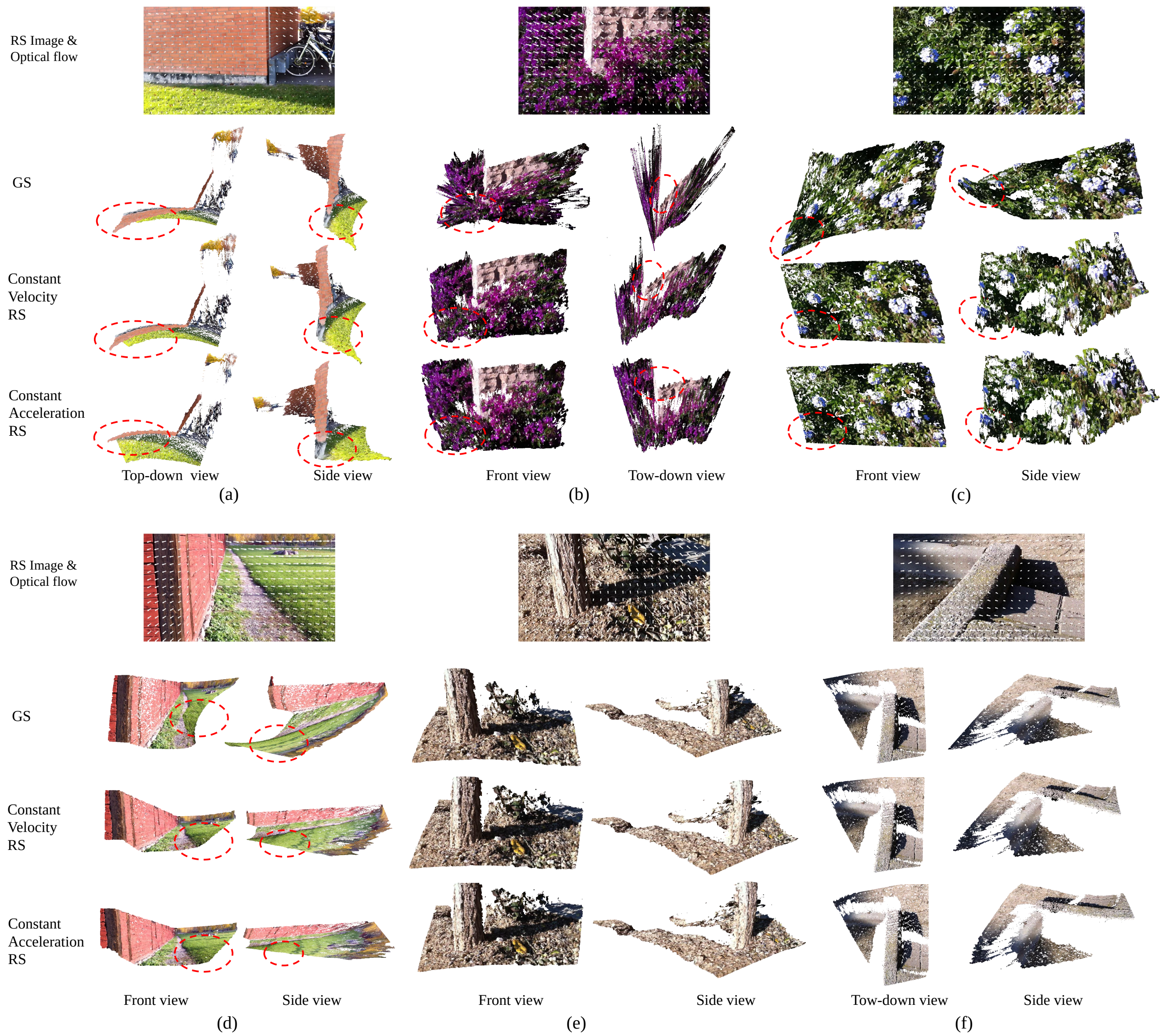

Figure 2: Additional SfM results on real image data. Top row: original RS images. Bottom 3 rows: reconstructed 3D point clouds by the GS and our RS models with constant velocity and acceleration from different viewpoints.

model can achieve equally well or even better accuracy when the magnitude of rotation is small, e.g. in Fig. 1(d). We posit that under small rotation the RS effect is not strong enough to introduce bias to the GS model, under which case the fidelity of the simpler GS model is higher, hence sometimes giving more accurate results. This also happens when the translation is large relative to the rotation. In such case, the first term (consisting of only translation) of Eq.13 in the main paper becomes more dominant than the second term (involving RS effect), reducing the impact of RS effect. In the extreme case of pure translation, the translation direction estimation using GS model is not affected by the RS effect at all, though GS model will lead to bias in the reconstruction of the scene due to wrong scanline pose estimation as a result of wrong camera model.

4. Additional results on real data

Additional Structure from Motion (SfM) results by our algorithm on the public dataset [1] are shown in Fig. 2. For each scene, we show the input RS image with optical flow in the top row, and the reconstructed point clouds by the GS and our RS models with constant velocity and acceleration in the bottom three rows. We plot the point clouds from two different viewpoints for better visualization. In the examples shown in Fig. 2(a) - (d), we can see that the point clouds returned by the GS model are significantly distorted, while the point clouds returned by our RS models are of higher quality—as highlighted by the red ellipses. This means that our RS models have successfully compensated for the RS effect and mitigated the RS induced bias in SfM. We observe that our RS model with constant acceleration performs better than (Fig. 2(a) - (b)) or equally well as (Fig. 2(c) - (d)) our RS model with constant velocity. This is to be expected given the more realistic motion assumption. In Fig. 2(e) & (f), the quality of the point clouds returned by all the models are similar. This is to be expected since careful inspection in the original consecutive images will reveal that the RS effect in these two cases is not strong.

References

[1] J. Hedborg, P.-E. Forssen, M. Felsberg, and E. Ringaby. Rolling shutter bundle adjustment. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 1434–1441, 2012.

[2] P. Weinzaepfel, J. Revaud, Z. Harchaoui, and C. Schmid. Deepflow: Large displacement optical flow with deep matching. In *International Conference on Computer Vision (ICCV)*, pages 1385–1392, 2013.