Joint 3D Shape and Motion Estimation from Rolling Shutter Light-Field Images

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Abstract

In this paper, we propose an approach to address the problem of 3D reconstruction of scenes from a single image captured by a light-field camera equipped with a rolling shutter sensor. Our method leverages the 3D information cues present in the light-field and the motion information provided by the rolling shutter effect. We present a generic model for the imaging process of this sensor and a two-stage algorithm that minimizes the re-projection error while considering the position and motion of the camera in a motion-shape bundle adjustment estimation strategy. Thereby, we provide an instantaneous 3D shape-and-pose-and-velocity sensing paradigm. To the best of our knowledge, this is the first study to leverage this type of sensor for this purpose. We also present a new benchmark dataset composed of different light-fields showing rolling shutter effects, which can be used as a common base to improve the evaluation and tracking the progress in the field. We demonstrate the effectiveness and advantages of our approach through several experiments conducted for different scenes and types of motions. The source code and dataset are publicly available at: https://github.com/ICB-Vision-AI/RSLF.

1. Introduction

Light-field (LF) cameras (also known as plenoptic), introduced by Adelson and Wang [1] and prototyped by Ng [25], consist of a conventional camera with a micro-lens array in front of the photosensitive sensor. This type of imaging sensor has the particularity of being able to capture a light field of a scene in a single capture. LF cameras are now an established solution used in computer vision, photogrammetry and robotics [7, 15, 37]. The miniaturization of these cameras, e.g. in the context of applications such as intra-corporeal micro-robotics, requires the choice of a rolling shutter (RS) photosensitive sensor. Conversely to global shutter (GS) cameras, where all pixels of the image are acquired at the same time, the image acquisition by rolling shutter is sequential [24]. Notably, a RS sensor creates image deformations in the case of dynamic scenes or when the camera is moving, as depicted in Fig. 1. The rolling shutter then often degrades the performance and challenge existing reconstruction and pose estimation approaches. Ait-Aider et al. [3] have shown that, in the case of a conventional perspective monocular camera, these deformations can be leveraged in order to compute the motion of the scene with respect to the camera. However, their proposed model and subsequent improved
strategies [4, 18] have the strong limitation of requiring the shape of the object/scenes to be known. Conversely, this paper proposes to jointly estimate the motion and the structure of a scene from a single view shot and in less constrained conditions. Although the possibilities given by RS, when properly modelled, has been shown for several computer vision and graphics problems, the combination with LF has not been yet exploited in a unified approach. One important motivation of this paper is to show the possibilities that this sensor modality presents, such as of being able to allow the estimation of the camera motion (or from the scene/object) from a single view without priors on the scene shape. We are particularly motivated by showing the interest of a unified approach (and its properties) that is capable of leveraging RS with existing light-field consumer devices. Indeed, such sensors are available, like the entry level cameras of Raytrix (R8, R42, R10μ, R20) or any camera array with RS sensors (like Pelican Imaging), but unfortunately no public dataset is available to be the best of the authors’ knowledge. In this context, another core motivation of this paper is to present a suitable and challenging LF dataset collected with a RS camera with different motion levels and scene geometries. For that, we have generated new models and leveraged existing scene models (from Matterport3D) into an adapted rendering engine (based on Blender) to create LF data affected by RS distortions in different conditions (e.g., from mild to strong motions). The main contributions of this paper are as follows:

- We propose a generic projection model of a rolling shutter light-field (RSLF) camera. This model is capable to represent a light-field with both global shutter and rolling shutter settings.
- A non-linear bundle adjustment strategy is designed to estimate jointly the 3D shape and motion for this sensor modality. We also design a linear initialization strategy in order to recover a first coarse estimate of the 3D shape. This initialization is essential for the convergence of our approach as shown in the ablation studies.
- We also present a new dataset composed of Rolling Shutter Light Fields (RSLF) paired with ground truth depth maps, on several synthetic scenes and with different types and levels of motion. We aim this dataset to be used as a common base to improve the evaluation and help tracking the progress in the field.

2. Related Work

Depth estimation from light-fields. Light-field contains rich information cues about the geometry of the scene. The seminal work of Adelson and Wang [1] for the plenoptic camera exploit this ability for “single lens stereo”. They used sub-aperture images (SAI) to perform a standard two frame displacement analysis with multiple pairs horizontally and vertically. In the same direction, multi-view stereo matching-based methods try to reproduce the results of classical stereo with plenoptic images [12, 16, 27, 38]. In this context, Georgiev and Lumsdaine [12] introduced the focused plenoptic camera and proposed a complete setup in order to recover depth with this new design. The method simultaneously render the image and estimate a per micro-lens depth map by computing the cross correlation between patches in micro images. Similarly, Perwass and Wietzke [27] introduced a multi-focused plenoptic camera model alongside a depth estimation algorithm based on point correspondences between micro images. Jeon and Park [16] explored the phase-shift theorem of the Fourier transform to estimate an accurate sub-pixel disparity map by computing a matching cost volume between SAI. Zeller et al. [38] proposed a filtering method for the estimation of semi-dense probabilistic depth maps for focused plenoptic cameras, with a Kalman filter like approach preserving discontinuities in the depth map. Ferreira and Goncalves [11] proposed a similar but faster depth map estimation method, with SIFT correspondences and through epipolar lines on the micro images. Bok et al. [5] proposed a calibration of the light-field camera based on a bundle adjustment method and Zhang et al. [39] proposed a generic multi-projection model (along with its calibration algorithm) for LF cameras. Most of these techniques rely on generating SAI and then applying classic stereo matching algorithms to estimate the depth of the scene. However, they assume GS cameras (or with slow moving objects and camera motions). Our approach, on the other hand, can handle scenes with a camera in movement and is far less affected by RS distortions due to camera motions.

Epipolar plane images and learning-based LF analysis. The scene structure can also be extracted from Epipolar Plane Images (EPI) [6, 8, 32, 36]. These approaches estimate depth information from the slopes of the lines observed in the Epipolar planes. Tao et al. [34] improved the accuracy of the depth estimation with a weighted sum between the defocus and correspondence cues present in EPIs. Zhang et al. [40] proposed a spinning parallelogram operator to determine the line slopes. Lin et al. [21] leveraged the refocus capability of light-fields and the possibility to use Shape-From-Focus. Closely related to our work, Srinivasan et al. [33] proposed a motion estimation from a single view with a light-field camera based on motion blur. Heber and Pock [13] first used a Convolutional Neural Network to compute depth from light-field images. Shin et al. [31] proposed a fast and accurate light field depth estimation method based on a fully-convolutional neural network and a light-field image-specific data augmentation. These techniques suffer by the lack of generalization to new/unseen scenes and often dependence on significant amount of data.
Rolling shutter structure-from-motion estimation. The potential of RS images received increased attention for scene analysis. Meingast et al. [24] developed a general projection equation for a rolling shutter camera and also proposed a calibration to estimate the rate of the rolling shutter. Ait-Aider et al. [3] first showed that the rolling shutter effect could be leveraged to estimate the motion of an object, but of known shape, when the majority of previous studies on the rolling shutter were about compensating effects for stereo vision. Recently Lao et al. [19] proposed a calibration to estimate the rate of the rolling shutter. Ait-Aider et al. [4] investigated RS effects in scene analysis. Meingast et al. [24] developed a general projection equation for a rolling shutter camera and also obtained the virtual projection of the 3D point inside the camera as:

\[
\lambda_c \bar{p} = DK_c \bar{M}_w u \bar{p},
\]

with \(\lambda_c\) a scaling factor. For a given viewpoint \(c = (s, t, 0)^T\), i.e. a projection center, the projection of the point \(\bar{p}\) onto the image plane is given by:

\[
\lambda_s^{s,t} \bar{m}^{s,t} = K_s^{s,t} \bar{p} = \begin{bmatrix} f & 0 & -fs \\ 0 & f & -ft \\ 0 & 1 & 0 \end{bmatrix} \bar{p},
\]

with \(\bar{m}^{s,t} = (x^{s,t}, y^{s,t}, 1)^T\) the final LF image points, \(f\) the focal length of the micro-lenses and \(\lambda_s\) a scaling factor.

Rolling shutter modeling. We follow a similar formalism to Ait-Aider et al. [3] to represent an RS imaging process. The main insight is to define a projection model dependent of the camera pose and as a function of the micro-image line \(t\) being observed. We adopt the hypothesis that the speeds \((v, \Omega)\) are constant during the LF acquisition. Adapting the initial projection defined in Eq. (1) for the RS we have:

\[
\lambda_c \bar{p} = DK_c \bar{M}_w u \bar{p},
\]

with \(\delta R^t = a_0^T(1 - \cos(\Omega \tau t)) + I \cos(\Omega \tau t) + [\hat{a}] \sin(\Omega \tau t)\), and \(\delta T^t = v \tau t\), where \(\Omega\) (angular velocity) and \(v\) (linear velocity) describe the uniform movement of the camera coordinate frame with respect to the world coordinates frame and \(\tau\) the time between the acquisition of two lines of the micro-images. The full Rolling Shutter LF projection from Eq. (3) that projects the 3D point \(u \bar{p}\) to an image point \(\bar{m}^{s,t} \in \mathbb{P}_2\), given a center of projection \(c = (s, t, 0)^T\) is then

\[
\lambda m^{s,t}_i = K_s^{s,t} DK_c [\delta R^t e \bar{R}_w | e \bar{T}_w + \delta \bar{T}_w^t | e \bar{w}_i],
\]

where \(K_s^{s,t} DK_c\) can be represented as a single compact intrinsic Rolling Shutter LF tensor:

\[
K_s^{s,t} DK_c = \begin{bmatrix} f & 0 & -f/(O_x - s) & f(O_x - s) \\ 0 & f & -f/(O_y - t) & f(O_y - t) \\ 0 & 0 & 1 - d^T/F & d \end{bmatrix},
\]

with \(F\) the focal length of the main lens. This formulation has the strong advantage of being generic and represent both GS and RS configurations. Another advantage is that all parameters of this unified model can be calibrated with existing techniques such as Bok et al. [5] for the intrinsic parameters and Meingast et al. [24] for the rolling shutter rate.
Generalization and particular cases. When \( \tau = 0 \) (i.e., no temporal delay between two consecutive lines), this model can be simplified to a GS light-field camera as the position of the sensor with respect to the scene will be identical for any \( t \). The situation where the camera has no velocity with respect to the scene can also be seen as GS for similar reasons. The proposed projection model in Eq. (4) generalizes to a conventional pinhole camera projection in the case where the MLA is composed of a unique lens. More details are given in the Supplementary material.

3.1. Scene Structure and Motion Estimation

For a given set of matching points inside a calibrated LF and assuming that all points belong to the same rigid scene in a uniform movement with respect to the camera, we can recover the position of the points in the 3D world as well as their motion at a given time. We will use a re-projection error minimization in order to find jointly these 3D coordinates and the dynamic parameters describing the movement of the camera.

Linear initialization. A classical multi-view stereo strategy is applied to provide a first estimate of the 3D points in the scene. In order to reduce the influence of the RS effect, we apply the multi-view stereo only horizontally, thereby ensuring that each measured point \( w\mathbf{p}_i \in \mathbb{R}^3 \) is captured at the same instant. From the experiments, this first estimate is essential to allow convergence of the following non-linear optimization.

Non-linear bundle adjustment. Using this 3D initialization of the observed points in the light field and our projection model, we design a re-projection error in order to recover simultaneously a refined structure of the scene and the camera motion. From our projection in Eq. (4) we compute the point:

\[
(u_i, v_i, w_i)^T = K_s \mathbf{D} K_c \delta \mathbf{R}^t \delta \mathbf{T}^t w\mathbf{p}_i
\]

and deduce the Euclidean pixel coordinates, the scalars \( x_i^{s,t} \) and \( y_i^{s,t} \), computed as:

\[
\begin{align*}
x_i^{s,t} &= \frac{u_i^{s,t}}{w_i^{s,t}} := \xi_s^{x,t}(w\mathbf{p}_i, \Omega, \mathbf{a}, \mathbf{v}), \\
y_i^{s,t} &= \frac{v_i^{s,t}}{w_i^{s,t}} := \xi_s^{y,t}(w\mathbf{p}_i, \Omega, \mathbf{a}, \mathbf{v}),
\end{align*}
\]

with \( \xi^{s,t} \) the projection function that, given a center of projection \( \mathbf{c} = (s, t, 0)^T \), return the coordinates of the image point with respect to its static position and its movement. The re-projection error function is obtained by computing the distance between the measured points \( \mathbf{m}_i = (x_i^{s,t}, y_i^{s,t}, 0) \) and the coordinates estimated with \( \xi_{(x)}^{s,t} \) and \( \xi_{(y)}^{s,t} \) from Eq. (7) as follows:

\[
\epsilon = \sum_s \sum_t \sum_i \left( \hat{x}_i^{s,t} - \xi_{(x)}^{s,t}(w\mathbf{p}_i, \Omega, \mathbf{a}, \mathbf{v}) \right)^2 + \left( \hat{y}_i^{s,t} - \xi_{(y)}^{s,t}(w\mathbf{p}_i, \Omega, \mathbf{a}, \mathbf{v}) \right)^2.
\]

This problem has three unknowns for \( \Omega \mathbf{a} \), three unknowns for \( \mathbf{v} \), and three unknowns for every \( w\mathbf{p}_i \). It can be solved if at least four non-coplanar 3D points can be observed, meaning that they need to be located at least an LF image in two different lines and at two different columns of micro-images.

Regularization. For the moment, the rotation axis \( \mathbf{a} \) in Eq. (8) is defined to pass through the world origin, which

\[\text{Figure 2. left} - A \text{ raw plenoptic image from a near viewpoint in the scene shown in Fig. 1 and a detail of the micro-images. right} - The adopted LF coordinate frames: The 3D point is projected in a 3D virtual scene by thin lens projection, then on the 2D image plane by pinhole projection which coordinate frame depends on the considered viewpoint.\]
corresponds to the optical center of the main lens. However, this is generally not the instantaneous center of rotation of the movement between the camera and the scene. To ease the description of the movement, we regularize the optimization by providing a “center of rotation” \( g \) to the point cloud. This allows to express all points \( p_i \) in a new coordinate frame centered on this center of rotation. It also allows to compute normalized points \( n p_i \) from which the coordinates are lying in the range \([-1, 1]\). The final non-linear adapted re-projection error from Eq. (8) using the normalized points and the center of rotation regularization is then:

\[
\varepsilon = \sum_s \sum_t \sum_i \left( \tilde{x}_{i,s,t} - n \xi_{(x)}(np_i, g, \Omega, \mathbf{v}) \right)^2 + \left( \tilde{y}_{i,s,t} - n \xi_{(y)}(np_i, g, \Omega, \mathbf{v}) \right)^2,
\]

where \( n \xi_{(x)} \) and \( n \xi_{(y)} \) are designed to handle the normalization, and \( g \) is also optimized in the loop so that the model is able to find the optimal center of rotation on-the-fly. Further details on the optimization are provided in the supplementary material.

4. Rolling Shutter Light-Field Dataset

Despite the potential of rolling shutter plenoptic cameras, to the best of the authors’ knowledge, all existing LF datasets are done assuming a global shutter hypothesis [2, 9, 26, 29]. Unfortunately, there is no public data available showing the rolling shutter effect on light-field images. Therefore, we have carefully designed and collected a new dataset with seven different synthetic scenes build on Blender, containing notably pseudo-real scenes created from Habitat-Matterport benchmark [28]. This new dataset (inspired by the HCI 4D LF benchmark [14]) is composed of four photo-realistic scenes from Matterport and three synthetic scenes (as the examples depicted in Fig. 1 and Fig. 4). We provide, per scene, the following data:

(i) Config files with camera settings and disparity ranges.
(ii) Different motion scenarios:
   - **GS**: This is the static configuration. It allows to have a good measure of the performance difference with or without RS distortion by having the same scene in both scenarios. It is equivalent to a GS light field.
   - **slow**: The motions affect the image enough to affect largely the perception of the scene geometry.
   - **fast**: The linear and angular camera velocities are about three times more important than for the slow motions.

We collect 11 light field sequences per scene (1 GS, 5 slow, 5 fast). Please see the table in the supplementary with the velocity intervals for each motion scenario.

(iii) Each light field is of dimension \( 9 \times 9 \times 512 \times 512 \times 3 \), which is equivalent to a light field captured from a plenoptic camera with a \( 512 \times 512 \) micro-lense array and \( 9 \times 9 \) micro-images.

(iv) A depth map corresponding to the geometry of the scene at middle time of exposition (i.e., the pose of the camera during the acquisition of the center line).

We believe this dataset has the potential to help the evaluation and to promote further investigation of RS applications for scene analysis with light fields. Visualizations and additional details of the dataset are provided in the supplementary material.

5. Experiments

**Metrics and competitors.** We have selected two representative algorithms for comparison: the model-based approach of Jeon et al. [16], and a recent learning-based 3D estimation from LF of Wang et al. [35]. The comparison is done in both GS and RS scenarios for all methods with the aim of fair conditions for the competitors. Six commonly used metrics are selected for the evaluation abs rel, abs diff, RMS, \( \delta < 1.25 \), \( \delta < 1.25^2 \) and \( \delta < 1.25^3 \). abs rel is the absolute difference between the estimation and the ground truth (gt), normalized by the gt. abs diff is the absolute difference between the estimation and the gt. RMS is the Root Mean Square Error between the estimation and the gt. \( \delta < 1.25 \), \( \delta < 1.25^2 \) and \( \delta < 1.25^3 \) are respectively the proportion of the points in a range of 1.25 times the gt, 1.25^2 times the gt and 1.25^3 times the gt.

5.1. Results

The evaluation and averaged metrics for all scenes (and different motion conditions) are shown in Tab. 1. We can observe the proposed method achieves the best scores overall in several of the considered metrics (e.g., “abs rel” and “abs diff”), and notably for all metrics of the “fast” sequences’ split. We can also notice that it has even a competitive performance to the recent competitors in the GS scenario. This aspect will be further investigated in the ablation and sensitivity analysis. As we can observe, the two competitors perform far worse when motion is present. The detailed metrics for three representative scenes considering the eleven light fields sequences per scene (1 GS, 5 slow, 5 fast) are shown in Tab. 2, where we can see that our method performs better in most cases. Please check some qualitative examples of the obtained shape reconstructions for these three scenes shown in Fig. 4. We alternate, for these three scenes, the GS case and a RS case with high velocity (motion scenario number 9). We can clearly see the capacity of our algorithm to model the RS deformations. In the scene “bedroom”, motion scenario 9, (the last line of Fig. 4), one can clearly notice from visual inspection the compensation
Table 1. Average reconstruction error metrics in different scenarios for all dataset sequences: GS (global shutter, equivalent to a static camera scenario), slow (RS with small camera linear and angular velocities), and fast (RS with camera motion three times higher velocities than in the slow case). The upward arrow means that a higher score is better. Our approach is significantly better than the considered methods, and with competitive results even for the GS case. Please see the text for details.

<table>
<thead>
<tr>
<th>Method</th>
<th>Method GS</th>
<th>Method slow fast</th>
<th>Method GS</th>
<th>Method slow fast</th>
<th>Method GS</th>
<th>Method slow fast</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jeon-CVPR [16]</td>
<td>0.040 0.053 0.110</td>
<td>0.027 0.036 0.071</td>
<td>0.035 0.048 0.092</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>OACC-Net [35]</td>
<td>0.143 0.171 0.196</td>
<td>0.091 0.109 0.125</td>
<td>0.109 0.128 0.144</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ours</td>
<td>0.040 0.041 0.059</td>
<td>0.031 0.032 0.044</td>
<td>0.046 0.051 0.064</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 2. Detailed reconstruction error metrics for three representative scenes “rabbit”, “table” and “bedroom” considering the eleven different motion scenarios (from 0 to 10) of the dataset. The upward arrow means that a higher score is better.

<table>
<thead>
<tr>
<th>Method</th>
<th>abs rel ↓</th>
<th>abs diff ↓</th>
<th>RMS ↓</th>
</tr>
</thead>
<tbody>
<tr>
<td>Method GS</td>
<td>Method slow fast</td>
<td>Method GS</td>
<td>Method slow fast</td>
</tr>
<tr>
<td>Jeon-CVPR [16]</td>
<td>0.993 0.976 0.894</td>
<td>1.000 0.999 0.973</td>
<td>1.000 1.000 0.998</td>
</tr>
<tr>
<td>OACC-Net [35]</td>
<td>0.767 0.720 0.676</td>
<td>0.959 0.945 0.933</td>
<td>1.000 0.997 0.997</td>
</tr>
<tr>
<td>Ours</td>
<td>0.958 0.961 0.949</td>
<td>0.989 0.988 0.982</td>
<td>0.999 0.999 0.999</td>
</tr>
</tbody>
</table>

Finally, we analyse the performance of the approaches in the easy to understand “chart” scene as shown in the quantitative results from Tab. 3 and visualizations in Fig. 3. Similarly to all other scenes, it is composed of eleven light fields (1 GS, 5 slow, 5 fast), where a double checkerboard pattern is joint in a 90° angle configuration. Our method achieves the best scores for every metric in both the slow and fast scenarios. However, we can also obtain competitive results to both strong competitors in the case of GS. We can also notice that sometimes our obtained estimation is more accurate when the camera is moving slowly than when the camera is static. This will be discussed in the ablation study Sec. 5.2. Tab. 3 also indicates that our method slightly degrades with the augmentation of the camera speed, but it still considerably outperforms all the competitors in the fast scenarios for the four first metrics. Fig. 3 shows some qualitative examples of the three methods in the different scenarios and the associated point clouds. We can observe how our method is still capable of fitting the object shape even with the presence of RS and fast camera motions. Looking at the object 3D reconstruction results obtained by the other methods, we can clearly observe deformation effects caused by the misinterpretation of the RS checkerboard images. These degradation of performance can be explained if we observe that the computed disparity maps of the competitors map the distortions of the scene due to RS from the center view. They also interpret the movement of the camera between vertically distant views only as spatial disparity. Thus, if a point moves vertically downwards during acquisition, it will have a bigger disparity than it should (between two viewpoints, where the point is moving because of changes in point of view but also because of its own movement). Inversely, if a point moves vertically upwards during acquisition, it will have a smaller disparity than it should. These two effects contribute to degrade the performance of GS-designed algorithms in the estimation of the 3D geometry of the scene.
Table 3. Detailed reconstruction error metrics in different scenarios for the “chart” sequence: GS (global shutter, equivalent to a static camera scenario), slow (RS with small camera linear and angular velocities), and fast (RS with camera motion three times higher velocities than in the slow case). The upward arrow means that a higher score is better. Our approach performed significantly better than the two recent considered methods.

<table>
<thead>
<tr>
<th>Method</th>
<th>abs rel ↓</th>
<th>abs diff ↓</th>
<th>RMS ↓</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>GS slow fast</td>
<td>GS slow fast</td>
<td>GS slow fast</td>
</tr>
<tr>
<td>Jeon-CVPR [16]</td>
<td>0.003 0.013 0.049</td>
<td>8.464 30.293 76.824</td>
<td>17.489 47.647 129.720</td>
</tr>
<tr>
<td>OACC-Net [35]</td>
<td>0.003 0.013 0.051</td>
<td>12.214 30.882 79.938</td>
<td>26.197 54.799 140.215</td>
</tr>
<tr>
<td>Ours</td>
<td>0.004 0.003 0.003</td>
<td>13.692 15.395 23.754</td>
<td>22.146 25.327 44.791</td>
</tr>
</tbody>
</table>

Figure 3. Qualitative examples of reconstruction for different motion scenarios for the “chart” sequence. The "GS" scenario on the left. A "slow" scenario in the middle. A "fast" scenario on the right. - first column: The central view of the LF, the disparity map of Jeon-CVPR [16], the disparity map of OACC-Net [35]. - Second column: The 3D point clouds (red dots) obtained for our method, Jeon-CVPR [16], OACC-Net [35]. Despite the fact that the images look different, due to the rolling shutter effect, the reconstruction is supposed to give the same result (in green crosses in the point clouds).

5.2. Ablation study

We performed different ablation studies in order to evaluate the relevance of the different parts of the method. In the first ablation, we retained two major components for evaluation, the contribution of i) linear initialization strategy (No Init.), and ii) the regularization (No Reg.) as shown in Tab. 4. For the ablation of the initialization, we initialized the optimization Eq. (9) with all the points clustered in a position near the center of mass of the point cloud we should have found with the linear initialization. We show in Tab. 4 that, even after convergence, the solution is still far from correct. For the ablation of the regularization, we see that the method without the regularization gives worst results in the RS scenarios. These evaluations confirm the importance of these components in the designed method.

A second ablation study was designed to evaluate the performance of our method without the RS modelling (Ours No RS) depicted in Tab. 5. By modeling the RS effect we also have additional degrees of freedom that lead to a slight degradation of the results when compared to a GS scheme for the GS scenes. We performed an evaluation to verify the effect of constraining the dynamic degrees of freedom ($\Omega = 0$ and $v = 0$) in case of GS would result in the estimation. The results in Tab. 5 show an improvement on all the metrics of up to about 6%. This concurs with the aforementioned hypothesis. The obtained performance is on par with the competitors which are specifically designed for GS settings.

5.3. Discussion

From the experiments, we can observe that our method is capable of handling different camera motions and provides...
improved scene structure estimates. The proposed model is designed to handle rigid scenes, yet it can estimate the structure and motion parameters for 3D scene points independently if at least four image points are available, i.e., to compute a “3D scene flow” from a single LF image. We assumed rigidity in order to compute a common set of dynamic parameters to each point (corresponding to a camera motion in a rigid scene). We believe our strategy could be also extended to handle scenes with dynamic objects independently (or non-rigid) with multiple camera motion hypotheses. The adopted RS projection also assumes that both linear and angular velocities to be uniform during the LF image acquisition (i.e., zero acceleration). However, RS devices, while having a sequential acquisition, usually have a small time of total exposure per frame (about 0.1 s for a 4K image). Therefore the assumption of constant camera speeds during the frame acquisition holds in typical motion-scene scale scenarios. Nevertheless, the proposed approach could still be applied for accelerated motions with a piece-wise decomposition of the plenoptic image in horizontal bands. Such a strategy of piece-wise decomposition in horizontal bands for classic images has been investigated in [22] for a classic monocular RS sensor. The motion and shape estimation could then be done at different time instants and allow to recover more complex scenes (e.g., non-rigid) and motion scenarios.

6. Conclusion

In this paper, we proposed a projection model for a light-field camera equipped with a rolling shutter sensor. This model allows us to jointly estimate the shape and motion on unknown scenes from a single light field image. The approach has been evaluated on different motions and 3D scenes. Furthermore, it does not suffer from shape/motion ambiguity thanks to the relatively reasonable assumption of a row-wise GS. To fill the lack of publicly available rolling-shutter LF data, we created a dataset that includes simulated photo-realistic light fields with different motion scenarios, and we will make it publicly available. We plan to build upon this model to generate denser depth maps and extend the motion estimations to non-rigid scenes. Our proposed model shows improved 3D scene geometry estimates, and we believe that it will inspire further research in this area, notably for applications in the context of robot vision, manipulation and micro-robotics.

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<table>
<thead>
<tr>
<th>Abl.</th>
<th>RMS ↓</th>
<th>No Init.</th>
<th>No Reg.</th>
<th>Full</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>GS</td>
<td>slow</td>
<td>fast</td>
<td></td>
</tr>
<tr>
<td>No Init.</td>
<td>0.243</td>
<td>0.242</td>
<td>0.240</td>
<td></td>
</tr>
<tr>
<td>No Reg.</td>
<td>0.045</td>
<td>0.060</td>
<td>0.086</td>
<td></td>
</tr>
<tr>
<td>Full</td>
<td>0.046</td>
<td>0.051</td>
<td>0.064</td>
<td></td>
</tr>
</tbody>
</table>

Table 4. Reconstruction errors for the ablation study of our method for the initialization and regularization steps.

<table>
<thead>
<tr>
<th>Abl.</th>
<th>abs rel ↓</th>
<th>abs diff ↓</th>
<th>RMS ↓</th>
<th>δ &lt; 1.25 ↑</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jeon-CVPR [16]</td>
<td>0.040</td>
<td>0.027</td>
<td>0.035</td>
<td>0.993</td>
</tr>
<tr>
<td>Ours Full</td>
<td>0.040</td>
<td>0.031</td>
<td>0.046</td>
<td>0.958</td>
</tr>
<tr>
<td>Ours No RS</td>
<td>0.040</td>
<td>0.029</td>
<td>0.041</td>
<td>0.976</td>
</tr>
</tbody>
</table>

Table 5. Ablation study of the dynamic motion parameters with a static GS scene.
References


