Context-Aware Video Reconstruction for Rolling Shutter Cameras

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Abstract

With the ubiquity of rolling shutter (RS) cameras, it is becoming increasingly attractive to recover the latent global shutter (GS) video from two consecutive RS frames, which also places a higher demand on realism. Existing solutions, using deep neural networks or optimization, achieve promising performance. However, these methods generate intermediate GS frames through image warping based on the RS model, which inevitably result in black holes and noticeable motion artifacts. In this paper, we alleviate these issues by proposing a context-aware GS video reconstruction architecture. It facilitates the advantages such as occlusion reasoning, motion compensation, and temporal abstraction. Specifically, we first estimate the bilateral motion field so that the pixels of the two RS frames are warped to a common GS frame accordingly. Then, a refinement scheme is proposed to guide the GS frame synthesis along with bilateral occlusion masks to produce high-fidelity GS video frames at arbitrary times. Furthermore, we derive an approximated bilateral motion field model, which can serve as an alternative to provide a simple but effective GS frame initialization for related tasks. Experiments on synthetic and real data show that our approach achieves superior performance over state-of-the-art methods in terms of objective metrics and subjective visual quality. Code is available at https://github.com/GitCVfb/CVR.

1. Introduction

Many modern CMOS cameras equipped with rolling shutter (RS) dominate the consumer photography market due to their low cost and simplicity in design, and are also prevalent in the automotive sector and motion picture industry [16, 48, 52, 62]. Within this acquisition mode, pixels on the rolling shutter CMOS sensor plane are exposed from top to bottom in a row-by-row fashion with a constant inter-row delay. This leads to undesirable visual distortions called the RS effect (e.g. wobble, skew) in the presence of fast motion, which is a hindrance to scene understanding and a nuisance in photography. With the increased demand for high quality and high framerate video of consumer-grade devices (e.g. tablets, smartphones), video frame interpolation (VFI) has attracted increasing attention in the computer vision community. Unfortunately, despite the remarkable success, the currently existing VFI methods [2, 18, 38, 39, 56] implicitly assume that the camera employs a global shutter (GS) mechanism, i.e. all pixels are exposed simultaneously. They are therefore unable to produce satisfying in-between frames with rolling shutter video acquired by e.g. these devices in dynamic scenes or fast camera movements, resulting in RS artifacts remaining [9].

To address this problem, many RS correction methods [13, 17, 24, 43, 55, 63] have been actively studied to eliminate the RS effect. In analogy to VFI generating non-existent intermediate GS frames from two consecutive GS frames, recovering the latent intermediate GS frames from two consecutive RS frames, e.g. [10, 24, 61, 62], serves as a tractable

Figure 1. GS video reconstruction example. The left column shows two input consecutive RS images, and three ground-truth GS images at time 0, 0.5, and 1, respectively. Rows to the right show five GS frames (at times 0, 0.25, 0.5, 0.75, 1) extracted by [9] (top) and our method (below), followed by two corresponding zoom-in regions. The orange box represents occluded black holes and the red box indicates motion artifacts specific to moving objects. Our method recovers higher fidelity GS images due to contextual aggregation and motion enhancement. Note that the black image edges by our method are because they are not available in both RS frames (cf. blue circle). Best viewed on Screen.
goal that overcomes the limited acquisition framerate and RS artifacts of commercial RS cameras. This is significantly challenging because the output GS frames must follow coherence both temporally and spatially. To this end, traditional methods [61, 62] are often based on the assumption of constant velocity or constant acceleration camera motion, which struggle to accurately reflect the real camera motion and scene geometry, resulting in the persistence of ghosting and unsmooth artifacts [9, 24]. Recent deep learning-based solutions have achieved impressive performance, but they typically can only recover one GS image corresponding to a particular scanline, such as the first [10] or central [24, 60] scanline, limiting their potentials for view transitions from RS to multiple-GS.

In this paper, we tackle the task of reviving and reliving all latent views of a scene as beheld by a virtual GS camera in the imaging interval of two consecutive RS frames. Therefore, we must jointly deal with VFI and RS correction tasks, i.e., interpolating smooth and trustworthy distortion-free video sequences. It is worth mentioning that the most relevant work to our task is [9], which is dedicated to the geometry-aware RS inversion by warping each RS frame to its corresponding virtual GS counterpart. Nevertheless, as illustrated in Fig. 1, the GS images recovered by [9] still suffer from two limitations:

- **Masses of black holes** (cf. orange box). This is a common issue for warping-based methods (e.g. [9, 44, 61–63]) due to the occlusion between the RS and GS images, leading to the possibility of permanent loss of some valuable image contents. To maintain visual consistency, a cropping operation is used to discard the resulting holes, but may degrade the visual experience.
- **Noticeable object-specific motion artifacts** (cf. red box). When recording dynamic scenes, the moving object violates the constant velocity motion assumption of RS cameras used in [9], resulting in its inability to accurately capture motion boundaries specific to moving objects. Thus severe motion artifacts are generated.

In contrast, we investigate contextual aggregation and motion enhancement based on the bilateral motion field (BMF) to alleviate these issues, which aims to synthesize crisp and pleasing GS video frames by occlusion reasoning and temporal abstraction. Specifically, we propose CVR (Context-aware Video Reconstruction architecture), which consists of two stages to recover a faithful and coherent GS video sequence from two input consecutive RS images. In the first initialization stage, we adopt a motion interpretation module to estimate the initial bilateral motion field, which warps the two RS frames to a common GS version. We design two schemes to achieve this goal. One is based on [9] which requires a pre-trained encoder-decoder network; the other is our proposed approximation of [9], without resorting to a deep network. Also, we show that this simple approximation is able to provide a feasible solution for the initial prediction. Afterward, a second refinement stage is introduced to handle black holes and ambiguous misalignments caused by occlusions and object-specific motion patterns. As a result of exploiting bilateral motion residuals and occlusion masks, it can guide the subsequent GS frame synthesis to reason about complex motion profiles and occlusions. Furthermore, inspired by [10], we propose a contextual consistency constraint to effectively aggregate the contextual information, such that the unsmooth areas can be enhanced in an adaptive manner. Extensive experimental results demonstrate that our method surpasses the state-of-the-art (SOTA) methods by a large margin in removing RS artifacts. Meanwhile, our method is capable of generating high-fidelity GS videos.

The main contributions of this paper are three-fold:

1) We propose a simple yet effective bilateral motion field approximation model, which serves as a reliable initialization for GS frame refinement.

2) We develop a stable and efficient context-aware GS video reconstruction framework, which can reason about complex occlusions, motion patterns specific to objects, and temporal abstractions.

3) Experiments show that our method achieves SOTA results while maintaining an efficient network design.

2. Related Work

**Video frame interpolation** has been widely studied in recent years, which can be categorized into phase-based [31, 32], kernel-based [5, 28, 36], and flow-based [2, 18, 38, 49] methods. With the latest advances in optical flow estimation [7, 50, 51], the flow-based VFI methods have been actively studied to explicitly exploit motion information. After the seminal work [18], subsequent improvements are dedicated to better intermediate flow estimation on one hand, such as quadratic [56], rectified quadratic [26], and cubic [4] flow interpolations. Moreover, Bao et al. [2] strengthened the initial flow field using the predicted depth map via a depth-aware flow projection layer. Park et al. estimated a symmetric bilateral motion [38] to produce the intermediate flows directly, and they have recently developed an asymmetric bilateral motion model [39] to refine the intermediate frame. On the other hand, better refinement and fusion of details were focused on, including contextual warping [2, 33, 34], occlusion inference [3, 57], cycle constraints [27, 42] for more accurate frame synthesis, and softmax splatting [35] for more efficient forward warping, etc.

All of these VFI approaches work with a common assumption that the camera employs a GS mechanism. Hence, they are incapable of correctly synthesizing the in-between frames in the case of RS images. In this paper, we integrate...
an effective motion interpretation module to boost the reliable estimation of the initial flow field, yielding high-quality results without aliasing.

**Rolling shutter correction** advocates the mitigation or elimination of RS distortion, i.e., recovering the latent GS image, from a single frame [22, 43, 44, 63] or multiple frames [1, 15, 24, 47, 53, 61]. Dai et al. [6] derived the discrete two-view RS epipolar geometry. Zhuang et al. [61] proposed a differential RS epipolar constraint to undistort two consecutive RS images, whose stereo version was further explored in [12]. Likewise, Lao et al. [23] developed a discrete RS homography model to perform the plane-based RS correction. Zhuang and Tran [62] presented a differential RS homography to account for the scanline-varying RS correction.

Very recently, Fan and Dai [9] developed the first rolling shutter temporal super-resolution network to extract a high framerate GS video from two consecutive RS images. It warps each RS frame to a latent GS frame corresponding to any of its scanlines through geometry-aware propagation. As a result, undesirable holes (e.g., black edges) appear due to the occlusion between the RS and GS images. Furthermore, it leverages a constant velocity motion assumption, which does not accurately capture the motion boundaries and produces artifacts around the moving objects. Two examples are shown in Figs. 1 and 6. In contrast, we propose a GS frame synthesis module, which is composed of contextual aggregation and motion enhancement layers, to reason about complex occlusions and motion patterns specific to moving objects, resulting in a significantly improved performance of GS video reconstruction.

### 3. RS-aware Frame Warping

**RS image formation model.** When an RS camera is in motion during the image acquisition, all its scanlines are exposed sequentially at different timestamps. Hence each scanline possesses a different local frame, as illustrated in Fig. 2. Without loss of generality, we assume that all pixels in the same row are exposed instantaneously at the same time. The number of rows in the image is $h$, and the constant inter-row delay time is $\tau_d$. Therefore, the RS image formation model can be obtained as follows:

$$\left[ \mathbf{I}(x) \right]_s = \left[ \mathbf{I}_s^g(x) \right]_s,$$

where $\mathbf{I}^g_s$ is virtual GS images captured at time $\tau_d(s - h/2)$, and $[\cdot]_s$ denotes the extraction of pixel $x$ in scanline $s$.

**RS effect removal by forward warping.** Since an RS image can be viewed as the result of successive row-by-row combinations of virtual GS image sequences within the imaging duration, one can invert the above RS imaging mechanism to remove RS distortions by

$$\mathbf{I}^r(x) = \mathbf{I}_s^g(x + \mathbf{u}_{r \rightarrow s}),$$

where $\mathbf{u}_{r \rightarrow s}$ is the displacement vector of pixel $x$ from the RS image $\mathbf{I}^r$ to the virtual GS image $\mathbf{I}_s^g$. Stacking $\mathbf{u}_{r \rightarrow s}$ of all pixels yields a pixel-wise motion field, a.k.a. undistortion flow $\mathbf{U}_{r \rightarrow s}$, which can be used to RS-aware forward warping analogous to [9, 10, 24, 60]. However, when multiple pixels are mapped to the same location, forward warping is prone to suffer from conflicts, inevitably leading to overlapping pixels and holes. Softmax splatting [35] alleviates these problems by adaptively combining overlapping pixel information. Thus, the target GS frame corresponding to scanline $s$ can be generated by

$$\hat{\mathbf{I}}_s^g = \mathcal{W}_F(\mathbf{I}^r, \mathbf{U}_{r \rightarrow s}),$$

where $\mathcal{W}_F$ represents the forward warping operator. We use softmax splatting in our implementation.

**Problem setup.** As depicted in Fig. 2, time $t$ and scanline $s$ correspond to each other. For compactness, in the following we will discard the symbol $s$ and use the subscript $t$ to denote the GS image $\mathbf{I}_t^g$ corresponding to time $t$. Following [12, 24, 62], we further assume that the readout time ratio [61], i.e., the ratio between the total scanline readout time (i.e., $h\tau_d$) and the inter-frame delay time, is equal to one. That is to say, the idle time between two adjacent RS frames is ignored in a short period of imaging time (e.g., $<50$ ms). This is proved to be effective to account for the scanline-varying camera poses, avoiding non-trivial readout calibration [30]. Moreover, this also ensures temporally tractable frame interpolation for RS images. See the supplementary material for further instructions. Consequently, the central scanlines of the two consecutive RS images are recorded at time instances 0 and 1, respectively.
Given two RS frames $I^0_t$ and $I^1_t$ at adjacent times 0 and 1, we aim to synthesize an intermediate GS frame $I^0_1$, $t \in [0, 1]$. This time interval is chosen because, as observed in [10], many details of the recovered GS images corresponding to time $t \in [-0.5, 0] \cup (1, 1.5]$ are more likely to be missing due to too much deviation from the temporal consistency.

### 3.1. Bilateral Motion Field Initialization

**Network-based bilateral motion field (NBMF).** To deliver each RS pixel $x$ exposed at time $t$ (i.e., $\tau_0 \in [-0.5, 0.5]$ or $\tau_1 \in [0.5, 1.5]$), with subscripts indicating the image index) to the GS canvas corresponding to the camera pose at time $t \in [0, 1]$, we need to estimate the motion field $U_{0\rightarrow t}$ or $U_{1\rightarrow t}$ (c.f. Eq. (3)) to constrain each pixel’s displacement. Note that the subscripts 0 \to t and 1 \to t indicate the RS-aware forward warping from RS images $I^0_t$ and $I^1_t$ to $I^0_1$, respectively. According to [9], we extend to the time dimension to model the BMF $U_{0\rightarrow t}$ and $U_{1\rightarrow t}$ by a scaling operation on the corresponding optical flow fields $F_{0\rightarrow 1}$ and $F_{1\rightarrow 0}$ between two consecutive RS frames, i.e.,

$$
U_{0\rightarrow t}(x) = C_{0\rightarrow t}(x) \cdot F_{0\rightarrow 1}(x),
$$

$$
U_{1\rightarrow t}(x) = C_{1\rightarrow t}(x) \cdot F_{1\rightarrow 0}(x),
$$

where

$$
C_{0\rightarrow t}(x) = \frac{(t - \tau_0)(h - \pi_v)}{h},
$$

$$
C_{1\rightarrow t}(x) = \frac{(\tau_1 - t)(h + \pi'_v)}{h},
$$

represent the bilateral correction maps. $\pi_v$ and $\pi'_v$ encapsulate the underlying RS geometry [9] to reveal the inter-RS-frame vertical optical flow, depending on the camera parameters, the camera motion, and the depth and position of pixel $x$. Furthermore, the BMF corresponding to different time steps $t_1$ and $t_2$ can be directly interconverted by

$$
U_{t_1\rightarrow t_2}(x) = \frac{t_2 - \tau}{t_1 - \tau} \cdot U_{t_1\rightarrow t_2}(x), \quad i = 0, 1.
$$

Note that the motion field for RS removal has a significant time dependence (a.k.a. scanline dependence [9]). To capture the correction map in Eq. (5), a geometric optimization problem was posed in [61, 62] based on the differential formulation [11, 29]. Recently, as shown in Fig. 3 (a), an encoder-decoder network was proposed in [9] to essentially learn the underlying RS geometry, such that the BMF can be computed by Eq. (4) coupled with the estimated bidirectional optical flows, termed as NBMF. The arbitrary-time GS images are then generated by image warping based on explicit intra-frame propagation in Eq. (6). However, since the occlusion view is not available during warping, the resulting holes are visually unsatisfactory. Also, [9] is not adaptive to dynamic objects due to the reliance on a constant velocity motion assumption of the RS camera.

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**Approximated bilateral motion field (ABMF).** We observe that $\pi_v$ and $\pi'_v$ in Eq. (5) characterize the latent inter-GS-frame vertical optical flow, which are usually much smaller than the number of image rows $h$ (c.f., supplementary materials for in-depth analysis). Hence, we propose an approximated constraint $h - \pi_v \approx h + \pi'_v$ to rewrite Eq. (5) as:

$$
C_{0\rightarrow t}(x) = t - \tau_0, \quad C_{1\rightarrow t}(x) = \tau_1 - t,
$$

where the time dependence is retained while the parallax effects (i.e. depth variation and camera motion) are neglected. That is, it is independent of the image content and can be pre-defined for a given image resolution. As depicted in Fig. 3 (b), such approximation is able to reach the correction map and then the ABMF via Eq. (4) in a simple and straightforward manner instead of relying on specialized deep neural networks. Note that the interconversion between varying ABMF satisfies Eq. (6) as well. The experimental results in Sec. 6.1 show that our ABMF, coupled with the contextual aggregation and motion enhancement, can serve as a strong and tractable baseline for GS frame synthesis.

### 4. Context-aware Video Reconstruction

We advocate recovering the intermediate global shutter image $I^0_t$, $t \in [0, 1]$ from two input consecutive rolling shutter images $I^0_0$ and $I^1_1$. In this section, we will explain how to design a deep network to reason about time-aware motion profiles and occlusions, such that the photorealistic time-arbitrary GS image can be recovered faithfully.

**4.1. Architecture Overview**

As shown in Fig. 4, the proposed network consists of two modules, i.e. an NBMF-based or ABMF-based motion interpretation module, and a context (i.e. occlusions and partial dynamics) aware GS frame synthesis module. Firstly, we estimate the bidirectional optical flow fields $F_{0\rightarrow 1}$ and $F_{1\rightarrow 0}$ between $I^0_t$ and $I^1_t$, followed by the BMF estimation $U_{0\rightarrow t}$ and $U_{1\rightarrow t}$ via Eq. (4), which is based on NBMF (i.e. Eq. (5)) or ABMF (i.e. Eq. (7)), as illustrated in Fig. 3. Then, the input RS frames are forward warped using the initial bilateral motions, resulting in two initial intermediate GS frame candidates at time $t$. Finally, the GS frame
The NBMF-based CVR approach (called CVR*) performs well despite its simplicity, while our NB MF-based CVR approach (called CVR) can further improve the quality of the final GS images.

**Motion interpretation module** $\mathcal{M}$ is composed of two submodules: an optical flow estimator and a bilateral motion field estimator. We first utilize the widely used PWC-Net [50] as the optical flow estimator to predict the bidirectional optical flows. To obtain an effective initial BMF, we follow [9] and use a dedicated encoder-decoder U-Net architecture [37, 46] as the optical flow estimator to predict the bidirectional optical flows. To obtain an effective initial BMF, we need to pre-train the network with the ground-truth (GT) GS images.

Alternatively, we propose to exploit its approximate version as shown in Fig. 3 (b), i.e., an ABMF-based motion interpretation module $\mathcal{M}_A$, to yield a simpler and faster prediction of the initial BMF. Finally, two initial intermediate GS frame candidates $I^0_{0 \rightarrow t}$ and $I^1_{0 \rightarrow t}$ can be generated by Eq. (3) based on the initial BMF estimations $U_{0 \rightarrow t}$ and $U_{1 \rightarrow t}$, respectively.

**GS frame synthesis module** $\mathcal{G}$ can be boiled down to two main layers: a motion enhancement layer (MEL) and a contextual aggregation layer (CAL). Note that some black holes and ambiguous misalignments may exist in the initial intermediate GS frame candidates due to heavy occlusions and partial moving objects, degrading the visual experience. Therefore, we aim at alleviating artifacts at the boundaries of dynamic objects and filling the occluded holes. Towards this goal, $I^0_t$, $I^1_t$, $F_{0 \rightarrow 1}$, $F_{1 \rightarrow 0}$, $U_{0 \rightarrow t}$, $U_{1 \rightarrow t}$, $I^0_{0 \rightarrow t}$, and $I^1_{0 \rightarrow t}$ are concatenated and fed into $\mathcal{G}$ to estimate the BMF residuals $\Delta U_{0 \rightarrow t}$ and $\Delta U_{1 \rightarrow t}$ and the bilateral occlusion masks $O_{0 \rightarrow t}$ and $O_{1 \rightarrow t}$. This time-aware occlusion mask is essential to guide GS frame synthesis to handle occlusions. We employ an encoder-decoder U-Net network [37, 46] as the backbone of $\mathcal{G}$, which has the same structure but different channels as the network in $\mathcal{M}_N$. The network is fully convolutional with skip connections and leaky ReLu activation functions. Besides, we leverage a sigmoid activation function on the output channels corresponding to the bilateral occlusion mask to limit its value between 0 and 1. Because $\mathcal{G}$ accepts cascades at different time instances, it can implicitly model the temporal abstraction to recover GS frames corresponding to arbitrary time step $t \in [0, 1]$.

Specifically, the final enhanced BMF can be obtained as:

$$
\hat{U}_{0 \rightarrow t} = U_{0 \rightarrow t} + \Delta U_{0 \rightarrow t},
$$

$$
\hat{U}_{1 \rightarrow t} = U_{1 \rightarrow t} + \Delta U_{1 \rightarrow t},
$$

which can improve the quality of BMF by combining it with the proposed contextual consistency constraint, especially in motion boundaries and unsmooth regions. Subsequently, we can produce two refined intermediate GS frame candidates $I^0_{0 \rightarrow t}$ and $I^1_{1 \rightarrow t}$ by RS-aware forward warping in Eq. (3). Further, we assume that the content of the target GS image corresponding to $t \in [0, 1]$ can be recovered by at least one of the input RS images, which is promising as discussed in [10]. We therefore impose the constraint that $O_{1 \rightarrow t} = 1 - O_{0 \rightarrow t}$. Intuitively, $O_{0 \rightarrow t}(x) = 0$ implies $O_{1 \rightarrow t}(x) = 1$, i.e. target pixels can be faithfully rendered by fully trusting $I^1_t$, and vice versa. Similar to [18, 37, 56], we also take advantage of the temporal distances $1-t$ and $t$ for the input RS frames $I^0_t$ and $I^1_t$, such that the temporally-closer pixels can be assigned a higher confidence. At last, the final intermediate GS frame $I^0_t$ can be synthesized by

$$
\hat{I}^0_t = \frac{(1-t)O_{0 \rightarrow t}I^0_{0 \rightarrow t} + tO_{1 \rightarrow t}I^1_{1 \rightarrow t}}{(1-t)O_{0 \rightarrow t} + tO_{1 \rightarrow t}}.
$$
represent the best and
where \( \lambda \) are hyper-parameters. More details can be found in the supplementary material.

5. Experimental Setup

**Datasets.** We use the standard RS correction benchmark datasets \[24\] including Carla-RS and Fastec-RS, and divide the training and test sets as in \[24\]. The Carla-RS dataset is synthesized based on the Carla simulator \[8\], involving general 6-DOF camera motions. The Fastec-RS dataset records real-world RS images synthesized by a high-FPS GS camera mounted on a ground vehicle. Since they provide the first- and central-scanline GT supervisory signals, \( i.e. \ t = 0, 0.5, \) and 1, we utilize this triplet as GT to train our network. Note that we add a small perturbation to make Eq. (9) work properly, for example, transforming them to \( t = 0.01, 0.5, \) and 0.99, respectively. At the test phase, our method is capable of recovering GS video frames at any time \( t \in [0, 1] \).

**Training details.** Our method is trained end-to-end using the Adam optimizer \[21\] with \( \beta_1 = 0.9 \) and \( \beta_2 = 0.999 \). We empirically set \( \lambda_r = 10, \lambda_c = 5, \) and \( \lambda_{te} = 0.1 \). The experiments are performed on an NVIDIA GeForce RTX 2080Ti GPU with a batch size of 4. We propose to train our network in two stages. Firstly, we solely train \( \mathcal{M} \) by \( L \) for fine-tuning. We keep the vertical resolution constant and adopt a uniform random crop with a horizontal resolution of 256 pixels to augment the training data, similar to \[9,10\] for better contextual exploration.

**Evaluation strategies.** As the Carla-RS dataset has the GT occlusion mask, we perform quantitative evaluations as follows: Carla-RS dataset with occlusion mask (CRM), Carla-RS dataset without occlusion mask (CR), and Fastec-RS dataset (FR). Standard metrics PSNR and SSIM, and learned perceptual metric LPIPS \[58\] are applied. Higher PSNR/SSIM or lower LPIPS score indicates better quality. Note that unless otherwise stated, we refer to the GS images at time \( t = 0.5 \) for consistent comparisons.
Baselines. We perform comparisons with the following baselines. (i) DiffSSIM [61] and DiffHomo [62] are traditional two-image based RS correction methods that require sophisticated optimization using RS models. (ii) SUNet [10] and DeepUnrollNet [24] recover only one GS frame from two consecutive RS frames by designing specialized CNNs. While RSCD [60] achieves this goal from three adjacent RS images. (iii) RSSR [9] generates a GS video from two consecutive RS images using deep learning, but suffers from black holes and motion artifacts. Moreover, we integrate the proposed ABMF model into RSSR to yield RSSR*. (iv) DAIN [2] and BMBC [38] are SOTA VFI methods that are tailored for GS cameras. (v) Cascaded method generates two GS images sequentially from three consecutive RS inputs using DeepUnrollNet, and then interpolates in-between GS ones using DAIN. (vi) CVR and CVR* are our proposed methods based on NBMF and ABMF, respectively. Note that our RSSR*, RSSR, our CVR*, and our CVR form a clear hierarchy of RS-based video reconstruction methods.

6. Results and Analysis

In this section, we compare with the baseline approaches and provide analysis and insight into our method.

6.1. Comparison with SOTA Methods

We report the quantitative and qualitative results in Table 1 and Fig. 5, respectively. Our proposed method achieves overwhelming dominance in RS effect removal, which is mainly attributed to context aggregation and motion pattern inference. Furthermore, although our proposed ABMF model is inferior to RSSR [9] when used to remove the RS effect (i.e. RSSR*), it can serve as a strong baseline for GS video frame reconstruction when combined with GS frame refinement. We believe that our hierarchical pipeline can provide a fresh perspective for the video reconstruction task with RS cameras. More results and analysis are shown in the supplementary material.

Note that our method is able to produce a continuous GS sequence, which is far beyond [10, 24, 60], although [10] can decode the plausible details of the GS image at a specific time. Traditional methods [61, 62] cannot estimate the underlying RS geometry robustly and accurately, resulting in ghosting artifacts. They are also computationally inefficient due to the complicated handling. Due to inherent flaws in the network architectures, the VFI methods [2, 38] fail to remove the RS effect. An intuitive cascade of RS correction and VFI methods tends to accumulate errors and is prone to blurring artifacts and local inaccuracies. Such cascades also have large models and thus be relatively time-consuming. In contrast, our end-to-end pipeline performs favorably against the SOTA methods in terms of both RS correction and inference efficiency. Note also that obnoxious black holes and object-specific motion artifacts appear in [9], degrading the visual experience, as outlined in Sec. 1. In general, our CVR improves RSSR and therefore recovers higher realism results, and our CVR* also develops a new concise and efficient framework for related tasks.

6.2. GS Video Reconstruction Results

We apply our method to generate multiple in-between GS frames at arbitrary time $t \in [0, 1]$. The visual results for $5 \times$ temporal upsampling are shown in Fig. 6. More results are provided in our supplementary materials. Our method can not only successfully remove the RS effect, but also can robustly reconstruct smooth and continuous GS videos.

6.3. Ablation Studies

Ablation on motion interpretation module $\mathcal{M}$. We first replace NBMF and ABMF with linear BMF (i.e. LBMF), which is a widely used BMF initialization scheme in popular VFI methods, e.g. [18, 34, 35, 38, 49]. Then, we replace PWC-Net with the SOTA optical flow estimation pipeline RAFT [51]. Finally, we freeze $\mathcal{M}$ and solely train $\mathcal{G}$ in the
Combined with Fig. 7, one can observe that they adaptively infer occlusions and enhance motion boundaries. In summary, our method can remove MEL will reduce the adaptability of our method. 

CAL, which causes aliasing effects during context aggregation, significantly outperforming the SOTA methods. We remove the loss terms one by one to analyze their respective roles. From Table 2, our loss function is effective because it performs best when all loss terms are used.

### 6.4. Limitation and Discussion

Our method relies on optical flow estimation, so there may be aliasing artifacts in areas such as low/weak textures. Besides, although we have assumed that the pixels of the target GS image at time \( t \in [0, 1] \) are visible in one of the RS images, some of them at the edges of the GS image may not be available, e.g. the lower right corner of GS images at \( t = 0 \) in Figs. 1 and 6, due to severe occlusions from fast camera motion or object motion. Future use of more frames may be able to fill in these possible invisible regions.

### 7. Conclusion

In this paper, we have presented a context-aware architecture CVR for end-to-end video reconstruction of RS cameras, which incorporates temporal smoothness to recover high-fidelity GS video frames with fewer artifacts and better details. Moreover, we have developed a simple yet efficient pipeline CVR* based on the proposed ABMF model which works robustly with RS cameras. Our proposed framework exploits the spatio-temporal coherence embedded in the latent GS video via motion interpretation and occlusion reasoning, significantly outperforming the SOTA methods. We hope this study can shed light for future research on video frame reconstruction of RS cameras.

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