REVIEW ARTICLE

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Reconstructing Reality Unified Correction of Rolling Shutter and Motion Blur from a Single Image

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Abstract

The widespread use of CMOS sensors in modern digital imaging devices has introduced a significant challenge in the form of rolling shutter (RS) distortions and motion blur (MB), especially under camera or object motion. Unlike CCD sensors with global shutters, CMOS sensors capture images row-by-row, leading to geometric distortions when motion occurs during exposure. These distortions are often further complicated by motion blur, resulting in visually degraded images. This paper addresses the challenging task of restoring a single image affected by rolling shutter motion blur (RSMB) a combination of both artifacts without requiring multiple frames or auxiliary sensors. We adopt a model-based approach that represents RSMB as a weighted integration of the sharp latent image transformed under varying camera poses. By discretizing the pose space and applying the Efficient Filter Flow (EFF) approximation, we enable fast and spatially accurate deblurring using only a single input image. The proposed framework not only recovers visually faithful reconstructions but also provides practical benefits for real-world applications where re-capturing the scene is infeasible.

Keywords: Rolling shutter motion blur, CMOS, CCD, Efficient Filter Flow

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Introduction

With the rapid advancement and widespread adoption of digital photography, most modern imaging devices including smartphones, drones, and consumer cameras, are now equipped with CMOS sensors. These sensors offer low power consumption and high-speed performance, making them ideal for mobile applications[1]. However, CMOS sensors typically use a rolling shutter (RS) mechanism, which exposes the image sensor row by row rather than all at once. This results in characteristic distortions, especially when capturing scenes with motion [2].

When we revisit our photos, there is often a mismatch between what we remember and what was recorded. While our brain filters out distractions and transient details, digital sensors capture everything indiscriminately, including motion artifacts such as motion blur (MB) and rolling shutter distortion[3]. These effects become especially problematic in scenarios involving hand-held shooting, fast-moving subjects, or cameras mounted on moving platforms[4]. Correcting rolling shutter artifacts from a single image remains a challenging problem, as motion blur is a spatially variant process and RS distortions are temporally correlated[5]. Successful restoration often requires understanding the natural structure of specific scene types rather than relying solely on geometric assumptions [6]. Deep learning-based solutions, especially those employing convolutional neural networks (CNNs), have shown promising results by learning blur patterns from data instead of hand-crafted priors [7]. Furthermore, recent studies demonstrate that end-to-end neural networks can jointly estimate blur kernels and compensate for RS artifacts, often outperforming traditional optimization-based methods[8].

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This paper aims to address image restoration from a single degraded image affected by rolling shutter and motion blur. It focuses on recovering sharp images by estimating blur parameters and underlying camera motion[9].

Background

The rolling shutter mechanism may be implemented either mechanically or electronically. One advantage of this method is that the sensor can continue accumulating photons during the readout process, thereby enhancing image sensitivity [10]. This technique is commonly employed in digital still and video cameras equipped with CMOS sensors [11]. However,

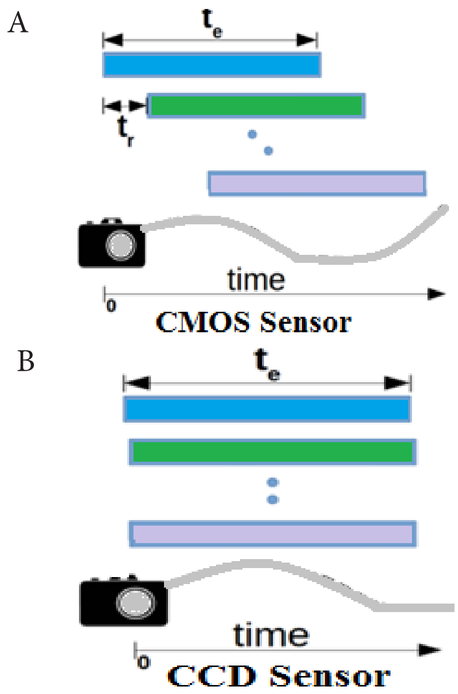

Figure 1: (A&B) Temporal resolution of rolling-shutter (left) and global shutter (right), where t_e is exposer time and t_r is read-out time

rolling shutter artifacts become particularly noticeable under high-speed motion or rapid light fluctuations [12]. Although some CMOS sensors incorporate global shutter functionality, the vast majority in consumer devices utilize rolling shutters due to cost and power efficiency [13]. In contrast, CCD (Charge-Coupled Device) sensors are generally more sensitive and expensive [14]. They typically employ global shutters, which capture the entire image simultaneously [15]. As a result, CCD-based systems are largely immune to the motion-induced distortions characteristic of rolling shutter systems [16], as illustrated in Figure 1.

Theoretical Modelling

This paper focuses on restoring images affected by rolling shutter motion blur (RSMB) using different models. Unlike traditional methods that rely on multiple frames or external motion sensors, this approach uses only a single blurred image, reducing computational and hardware dependencies. The method models the image formation process by considering 3D camera motion, primarily rotation, which leads to spatially variant blur. The blur is represented as a weighted combination of camera poses, each inducing a unique homography on the image plane. To manage computational cost, the model adopts the Efficient Filter Flow (EFF) approximation, assuming locally uniform blur within small patches [17]. This significantly accelerates the deblurring process while maintaining accuracy. Beyond motion correction, the framework can also remove occluding objects from images taken in crowded scenes.

This paper is motivated by both practical and emotional factors: many blurred or occluded images capture moments that cannot be recreated. Rather than proposing new hardware, the aim is to enhance post-processing capabilities, effectively turning computational models into the "brain" behind the digital "eyes" of modern cameras.

RSMB Model

Although motion blur and rolling shutter (RS) distortions are inherently interrelated—both arising from relative motion between the camera and scene—most prior approaches have addressed them independently. Traditional deblurring algorithms typically fail to account for RS-induced wobble, while existing RS correction methods generally do not handle motion blur. In this section, we present a unified generative model for rolling shutter motion blur (RSMB).

As previously discussed, in cameras employing CCD sensors, the entire image is captured at a single time instance, and therefore undergoes a uniform camera motion during exposure. In such a scenario, the motion-blurred image $B \in R_{M\times N}$ can be modeled by integrating the sharp latent image L along the continuous trajectory of the camera over the exposure time interval [0, t_e] [4]. It is given by following equation:

$$B = \frac{1}{t_e}\int_0^{t_e} L^{P(t)}\,dt \qquad (1)$$

Here, P(t) denotes the 6-degree-of-freedom (6-DoF) camera pose at time instant t0, and LP(t) is the latent sharp image transformed according to the camera pose P(t). The parameter te represents the total shutter duration.

In contrast, CMOS sensors with a rolling shutter capture the image row-by-row over time, resulting in each sensor row being exposed under a different camera pose due to the staggered exposure window. Thus, a global warp for the entire latent image cannot be applied; instead, each image row must be modeled independently. The ith row of a rolling shutter motion-blurred image is expressed as:

$$B_i = \frac{1}{t_e}\int_0^{t_e} L_i^{P(1+i\cdot t_r)}\,dt \qquad (2)$$

where represents the transformed i^{th} row of the latent image L. t_e is the exposure time for a single row, and t_r denotes the inter-row readout delay, i.e., the time difference between the start of exposure for consecutive rows.

Recent RS deblurring models discretize this continuous formulation (Eq. 2) into a temporal sampling model by integrating the transformed image row over a set of discrete camera poses. This leads to:

$$B = \int_P \omega'(p) L_i^P\,dp \quad i \in \{1, 2, \ldots, \mathrm{M}\} \quad (3)$$

where P denotes the pose-space, L_i^P is the transformed i^{th} row of the latent image under pose P and $\omega'(p)$ is weight representing the time spent at each pose—effectively modeling the motion density function (MDF).

To enhance accuracy, the pose space P is discretized finely such that the displacement between adjacent poses is less than one pixel. This yields the following discrete approximation:

$$B = \sum_{P_j \in \mathrm{P}} \omega_P^{'}(p) L_i^P \quad i \in \{1, 2, \ldots, \mathrm{M}\} \qquad (4)$$

Here is the discretized pose-space, and the discrete weight $\omega_i^{'}(p_T)$ represents the aggregated weights over a small neighborhood of pose P_j. This discretized motion model enables computationally efficient and spatially accurate deblurring under rolling shutter and motion blur conditions.

Conclusion

This work presents a unified framework for restoring images degraded by rolling shutter distortion and motion blur using a single input image. By modeling the image formation process through 6-DoF camera motion and temporally staggered row-wise exposure, we provide a physically grounded and computationally tractable method for deblurring RS images. The discretized pose-space representation, combined with the Efficient Filter Flow approximation, enables efficient inference while preserving spatial accuracy. Unlike traditional methods that handle RS and motion blur separately, our approach integrates both phenomena into a single generative model. Beyond aesthetic enhancement, the method supports high-level tasks such as occlusion removal and face recognition, offering significant practical value. Ultimately, this research advances post-capture image restoration techniques, aiming to bridge the gap between what the camera records and what the human eye perceives.

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