Brownian Motion Noise Modeling and Simulation for Event Cameras

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Abstract. Event cameras are promising sensors that can capture the rapid brightness changes as a stream of asynchronous events with microsecond resolution. As these sensors are scarce and expensive to obtain, event camera simulators are critical to advance event-driven researches. However, existing simulators use a coarse approximation of noise models, which makes it difficult to transfer prototyping on simulated data to real data. To tackle this problem, we present a practical noise model considering the temperature and parasitic photocurrent effects. It models the photon sensing and disturbances through a Brownian motion with drift. Based on it, we propose an event simulator which samples the events randomly and converts frame-based videos to synthetic event data. ...

Keywords: Event Camera; Simulator

1 Introduction

Event cameras are novel biologically-inspired sensors that capture the brightness changes rapidly as a stream of asynchronous events instead of intensity images at a fixed rate. Because of this paradigm shift, event cameras are endowed with low power consumption, high temporal resolution and high dynamic range, which attracts much attention to exploiting them in challenging scenarios for standard cameras, such as low latency, high-speed motion and broad illumination range.[2] Significant efforts are devoted to taking the advantage of high capacity of deep learning models and designing trainable networks for event-based vision. Despite initial success, these data-driven algorithms are limited by insufficient event data for training due to the novelty of event cameras, which slows down the progress of the community.

Fortunately, some attention has been paid to generative modeling and simulation for events as a viable alternative to the lack of datasets. Prior works[3,7,5] physically model the relationship between events and continuous intensity signals in time. Therefore, they can obtain simulated event datasets approximately from a high frame-rate videos. However, this generative model relies on the working principle of an ideal event camera and does not take noise effect into consideration, which makes prototyping on simulated data transfer more difficultly to real data.

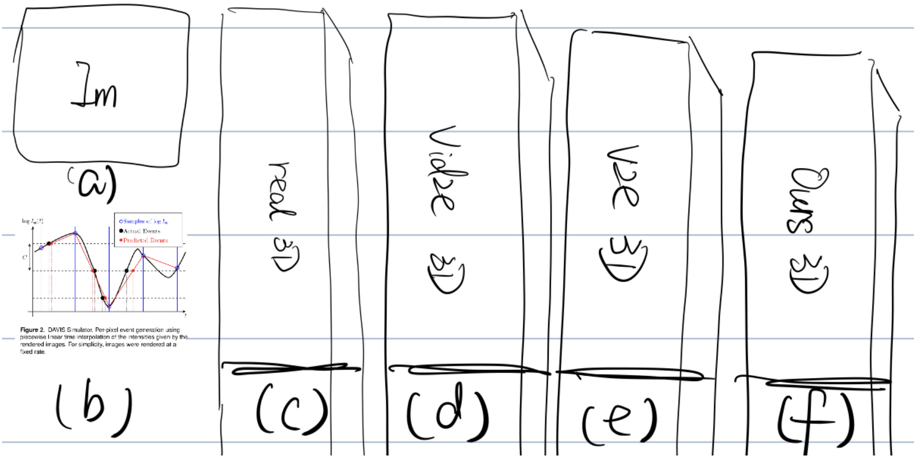

Fig. 1.

Therefore, it would be desirable to reduce the sim-to-real gap for event cameras. [9,4], based on the observation that event cameras trigger events with a variant triggering threshold[6], propose to simplify the noise model with a Gaussian random threshold (see Fig. 1(d)). Delbruck *et al.*[1] further analyze additional noise effect and the statistics of noises by photographing a still scene. They incorporate leak events and temporal noises in the generative model. However, they add temporal noises after clean event generation and inject them when clean events occur, which makes the simulated noise events not realistic and misleads learning-based methods (see Fig. 1(e)). Moreover, the algorithms above adopt linear interpolation to determine the timestamp of events after calculating event amount between two consecutive frames, resulting in equal spacing distribution, as shown in Fig. 1(b).

In this paper, we provide a new perspective on event generative model from stochastic process and develop a realistic simulator based on the principle operation of event cameras. Considering the randomness caused by photon reception, we model the electrical signal transduced in an ideal event cameras as a Brown motion with drift. As for event noises, motivated by [8] which discusses the effects of temperature and parasitic photocurrent, we further introduce a Brown motion term related to temperature and light brightness to simulate noises. As ideal events and noises share the same type of distributions, they can be sampled simultaneously instead of sequentially in [1]. Furthermore, based on the proposed event model, we develop an event simulator to produce events practically and efficiently. We also provide a method to preliminarily calibrate the model parameters of a specific event camera. Different from existing simulator generating events in uniform intervals, the proposed method increases more randomness, reduces the sim-to-real gap and benefits for event-driven application (see Fig. 1(f)).

The main contributions of this paper are summarized as follows:

– We propose a novel insight into event generative model based on stochastic process. Our model hinges on the working principle and the noise sources of event cameras.
– We propose a practical and efficient event simulator to generate realistic event datasets from existing high frame-rate videos, thus encouraging exploration for event cameras.
– We quantitatively evaluate our simulator and show that our simulated events resemble real ones. We further validate our events by training a neural network for object segmentation and intensity-image reconstruction, which generalizes well to real scenes.

2 Conclusions

The paper ends with a conclusion.

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