Neuromorphic Dynamic Speckle Pattern Synthesis for Imaging through Scattering Media

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ABSTRACT

Dynamic speckles result from moving scatterers such as fog and living tissue, or objects with time-varying behaviors. These speckles encode critical spatiotemporal information about scattering dynamics. Nevertheless, traditional frame-based imaging systems often face challenges in resolving them due to fixed frame rates, limiting applications like real-time cellular motion tracking in biomedical imaging or navigation in foggy environments. Event cameras stand out with their microsecond temporal resolution and asynchronous sensing, offering unprecedented capabilities to analyze complex speckle dynamics. However, controlled experimental validation remains difficult owing to demanding optical collimation and calibration requirements. To address this, we introduce an open-source framework that synthesizes event streams for dynamic speckles by simulating object kinematics, medium turbulence, and sensor noise. The proposed framework accelerates algorithm development for imaging through scattering media, reducing reliance on costly physical trials while fostering innovation in biomedicine, robotics, and remote sensing.

Keywords: Event camera, Dynamic speckle, Scattering medium, Speckle simulation

1. INTRODUCTION

Dynamic speckle analysis is of considerable significance across diverse scientific and engineering disciplines, as speckle fluctuations encode valuable information regarding motion and scattering phenomena within complex media.[1,2] In biomedical imaging, these fluctuations facilitate minimally invasive monitoring of cellular dynamics and tissue perfusion. In remote sensing and navigation, dynamic speckles provide critical information that enhances vision in adverse conditions such as fog, smoke, or atmospheric turbulence. More broadly, the study of dynamic speckles contributes to a deeper understanding of light–matter interactions in scattering environments.[3,4]

Despite their importance, conventional frame-based imaging systems face fundamental limitations in capturing dynamic speckles. Due to fixed frame rates, they often undersample rapid temporal variations, resulting in motion blur and loss of critical dynamic information.[5] These temporal constraints hinder real-time applications requiring high temporal fidelity, such as biomedical monitoring and autonomous navigation.

In recent years, event cameras, also known as neuromorphic cameras, have emerged as a promising alternative for dynamic speckle analysis. Operating asynchronously with microsecond temporal resolution, they capture speckle fluctuations at their native timescales with high fidelity.[6,7] This has driven growing interest in computational neuromorphic imaging (CNI) and tracking through scattering media.[8–10] While some prior work has focused on synthesizing frame-based dynamic speckles,[11–13] there remains a notable lack of computational tools for generating neuromorphic speckle data. Experimental studies are challenging due to the complexity of maintaining stable scattering conditions and calibrating event-based systems, limiting access to large, reproducible datasets essential for algorithm development and validation.

Therefore, there is a critical need for computational tools capable of synthesizing realistic event streams of dynamic speckle patterns under controllable and reproducible conditions. In this work, we introduce an open-source computational framework that integrates statistical speckle theory with neuromorphic vision principles. Our platform simulates event streams generated by dynamic speckle patterns arising from both moving scatterers

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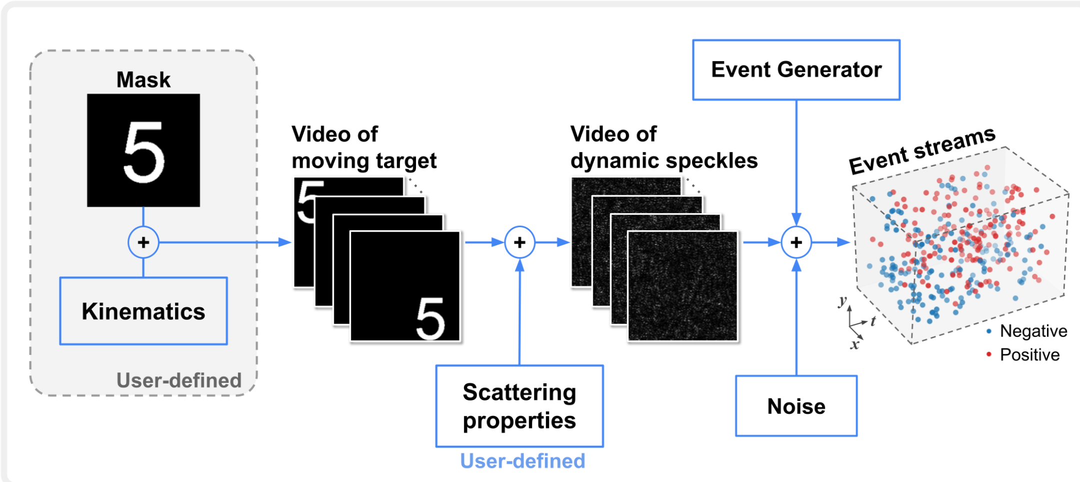

Figure 1. Schematic of neuromorphic dynamic speckle synthesis model.

and macroscopic objects. By enabling reproducible and controllable speckle synthesis, the proposed framework facilitates the development and evaluation of CNI algorithms, supports benchmarking of computational pipelines, and promotes exploration of applications spanning biomedical imaging, navigation, and remote sensing.

2. METHODS

The model for our neuromorphic dynamic speckle synthesis is illustrated in Fig. 1. The key aspects of dynamic speckle synthesis and neuromorphic event generation are detailed in the following.

2.1 Dynamic speckle synthesis

When a coherent laser beam is scattered from a rough or inhomogeneous surface, the reflected wavefront acquires spatially varying phase delays due to microscopic variations in surface profile or refractive index. The superposition of many independent scattered wavelets produces a random interference pattern known as speckle, whose statistical behavior can be modeled probabilistically.[1,2]

The scattered complex field at an observation point is modeled as a sum of random phasors $S = \sum_{n=1}^{N} A_n e^{i\phi_n}$, where the phases $\{\phi_n\}$ are independent and uniformly distributed on $[-\pi, \pi)$, and the amplitudes $\{A_n\}$ are independent and identically distributed. For large N, by the central limit theorem, the real and imaginary components: $X = \sum_{n=1}^{N} A_n \cos\phi_n$ and $Y = \sum_{n=1}^{N} A_n \sin\phi_n$. They approach zero-mean Gaussian variables with equal variance $\sigma^2 = \mathbb{E}[A_n^2]/2$. The speckle amplitude $R = |S| = \sqrt{X^2 + Y^2}$ follows a Rayleigh distribution

$$f_R(r) = \frac{r}{\sigma^2} \exp\left(-\frac{r^2}{2\sigma^2}\right), \quad r \geq 0. \tag{1}$$

This probabilistic model underpins our speckle synthesis. Numerically, speckle patterns are generated by drawing two independent Gaussian random fields for the real and imaginary parts,[11] followed by Fourier-based propagation.[14] The squared magnitude of the resulting complex field produces intensity patterns with Rayleigh-distributed statistics.[15]

To model dynamic speckle, we incorporate time-dependent object motion into the phase evolution of the scattered field. At time t, the complex field is

$$S(t) = \sum_{n=1}^{N} A_n \exp\big(i[\phi_n^{(0)} + \Delta\phi_n(t)]\big), \tag{2}$$

where $\phi_n^{(0)}$ is the static phase and $\Delta\phi_n(t)$ encodes phase modulation from user-defined kinematics. Combining Eq. 1 and Eq. 2, time-varying dynamic speckle frames can be simulated.

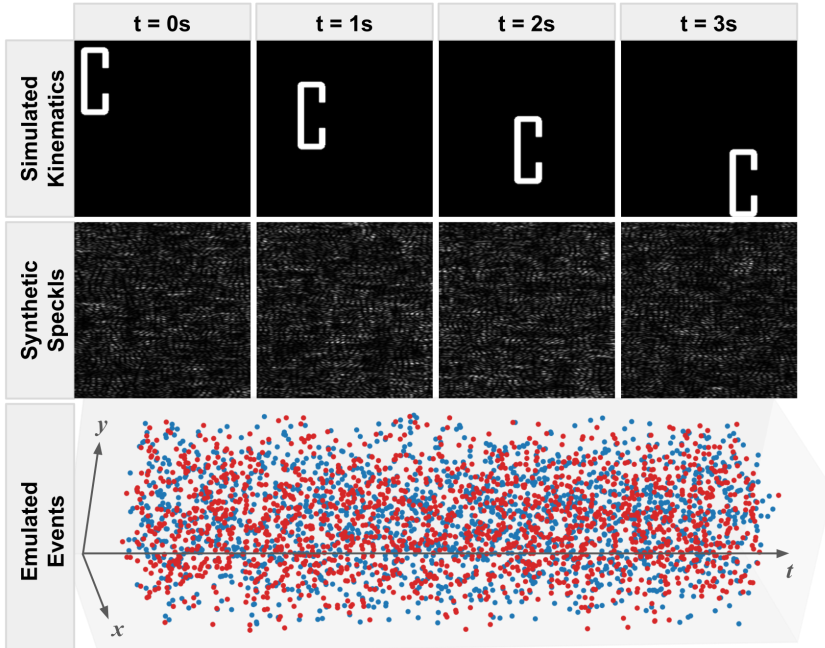

Figure 2. Example of synthetic results for neuromorphic dynamic speckles.

2.2 Neuromorphic event generation

Neuromorphic event cameras, unlike conventional frame-based sensors, asynchronously record pixel-level brightness changes with microsecond temporal resolution by outputting discrete events. Each event encodes a change in log-intensity exceeding a predefined threshold, capturing only temporal variations rather than absolute intensity values. Formally, an event is triggered at pixel $\mathbf{x}$ and time t when the change in log-brightness crosses a positive or negative threshold C as

$$\Delta L(\mathbf{x}, t) = \log I(\mathbf{x}, t) - \log I(\mathbf{x}, t_{\text{last}}). \tag{3}$$

To emulate such events from traditional video frames, we employ the V2E framework[16] using a temporally dense interpolation of intensity images to approximate continuous-time brightness signals. Then this thresholding rule is applied to generate event streams. To emulate realistic sensor behavior, per-pixel thresholds are sampled from Gaussian distributions to model transistor mismatch and threshold variability. Additionally, temporal noise and spontaneous leak events are incorporated as Poisson processes, further enhancing fidelity to real sensor output. Event timestamps within successive time stamps are distributed uniformly to preserve the asynchronous nature of event generation.

3. RESULTS AND DISCUSSIONS

Figure 2 presents representative snapshots and temporal event data from our neuromorphic dynamic speckle simulation over a 3-second interval. The first row shows the moving mask with simulated kinematics at discrete time points $t = 0, 1, 2, 3$ seconds, illustrating the controlled spatial translations applied to the object. The second row depicts the corresponding synthetic speckle intensity patterns generated by coherent scattering influenced by the mask motion. These speckle frames display the expected granular texture and subtle temporal variations associated with the dynamic mask. The third row visualizes the emulated event streams over the entire 3-second duration, represented as a 3D spatiotemporal plot with axes x, y, and time t. Events are color-coded by polarity to capture pixel-level intensity changes occurring asynchronously over time. The event distribution aligns with the underlying mask motion and speckle fluctuations.

These results demonstrate the simulator's ability to reproduce realistic dynamic speckle patterns and their corresponding neuromorphic event representations. The temporal correspondence between the moving mask and speckle intensity changes confirms the physical consistency of the model. Moreover, the event streams preserve the asynchronous and sparse nature of neuromorphic sensing. This validates the potential of our approach as a powerful tool for studying dynamic speckle phenomena and developing CNI applications.

4. CONCLUSIONS

By providing versatile datasets independent of complex experimental setups, simulation platforms like ours can substantially accelerate research in neuromorphic speckle analysis. This approach lowers the barriers to entry by eliminating the need for time-consuming and costly optical system construction, enabling researchers to rapidly test and validate new ideas. Consequently, it fosters collaborative advancement and facilitates rigorous benchmarking of imaging techniques through complex scattering media across various disciplines.

Acknowledgements

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