Harnessing Noise for Materials Differentiation in Computational Neuromorphic Imaging

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***Abstract*—Event cameras are emerging neuromorphic devices with more attractive properties than conventional ones, which asynchronously capture per-pixel luminance changes. However, event cameras are specifically designed for changes and motion measurement, it is generally assumed that nothing can be detected in static scenes. Hence, event generation in static scenes is treated as useless noise and is typically deemed detrimental to computational neuromorphic imaging (CNI) applications. Here, we show that event noise carries useful information that can be extracted and harnessed for material differentiation. We analyze the generation of event noise and evaluate the impact through experiments with real data. The results confirm the applicability of the proposed method for material differentiation in the CNI framework. Owing to the informative nature of events in static scenes, harnessing noise can serve as a flexible tool for specific high-dimensional imaging tasks and extend the imaging scenes with the CNI paradigm.**

Keywords—computational neuromorphic imaging, imaging system, event noise, material differentiation

I. INTRODUCTION

Event cameras respond to super-fast dynamics in the spatiotemporal domain, helping to resolve vast amounts of challenging tasks with event-based reconstruction and neuromorphic computing [1]. Equipped with event cameras, optics, and computational models that take in the event data as inputs, computational neuromorphic imaging (CNI) encompassing high-sensitivity sensing, time-efficient reconstruction, and dynamic analysis—will be an emerging and promising area in computational imaging [2-5]. In principle, there should be no event for a static scene. However, in practical conditions, even when imaging focuses on a steady-state scene, event cameras are susceptible to various forms of variation, such as changes in lighting and environmental disturbances. These factors can result in the generation of events, usually treated as useless noise. In most existing CNI applications, event noise is considered an uninformative part of the background activity [6, 7].

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Noise collected in the sensor can be associated with imaging scenes and gathered with informative aspects, e.g., scattering imaging and speckle metrology [8-11]. Therefore, noise can serve as more than just an obstacle to signal detection and used as an informative reference for micro to macro measurements. By drawing inspiration from the concept that speckle noise can carry valuable information, event noise in static scenes may also have potential utility and provide advantages for the CNI applications. For steady-state visual scenes, conventional frame-based cameras are generally considered to have better capabilities in various vision and imaging tasks. A naive solution to the challenges associated with event cameras is to use existing event-based image reconstruction methods [12-14] to convert events into images, which can then be processed using conventional frame-based computational models. However, this approach may not fully meet the requirements of steady-state vision or imaging applications with the CNI scheme. For existing CNI applications, event noise is also considered a detrimental factor that affects the quality of accumulated luminance and limits the performance of subsequent computational methods.

The identification of materials can offer significant advantages in various imaging tasks, e.g., object recognition and image segmentation [15, 16]. Recently, several new techniques based on time-correlated detectors have been proposed to capture the interaction of light with different materials, resulting in a distinctive temporal point spread function [16, 17]. However, classifying materials based on optical measurements remains an active research problem in computational imaging due to the inherent ambiguity in appearance measurements. Previous methods for material differentiation have employed two distinct techniques. The first method determines material identity by analyzing reflectance as an intrinsic property of the material surface. Meanwhile, the second method identifies material labels based on the surface appearance within a real-world scene. One challenge in utilizing reflectance for material recognition is the difficulty and inconvenience of obtaining accurate measurements.

In this paper, we provide a new perspective on the CNI paradigm by harnessing event noise for material differentiation in static scenes. We explain the generation and analysis of event noise by combining the optical flow model and ambient light perturbation model. Experimental results are provided to support the proposed ideas. The possibility of achieving reliable distinctions between different materials using event noise is demonstrated in static scenes.

II. Ease of Use

There exists a strong correlation mapping relationship between noise and informative regions. It can be referenced that there are situations where speckle noise itself can be instructive [8]. As shown in Fig. 1, turbulence results in image variation even in a static imaging scene. The event noise is assumed to be caused by the pixel-wise local motion on the object surface with disturbance. Unstable elements are commonly found in real-world scenes (e.g., ambient interference light and turbulence). The lighting condition influences the event noise originating from external activity and primarily serves as a source of event noise related to imaging scenarios. Although event noise is inevitable, prior knowledge of visual scenes and external lighting conditions can be leveraged for further analysis and measurement [18]. Noise presents a significant challenge and is a focal point in various research fields. The processing and utilization of noise are of fundamental importance for numerous modern technologies. Each point on the target surface has a luminance value that is detected by neuromorphic sensors, and variations in this value trigger events. The luminance at the image plane corresponds to the target surface.

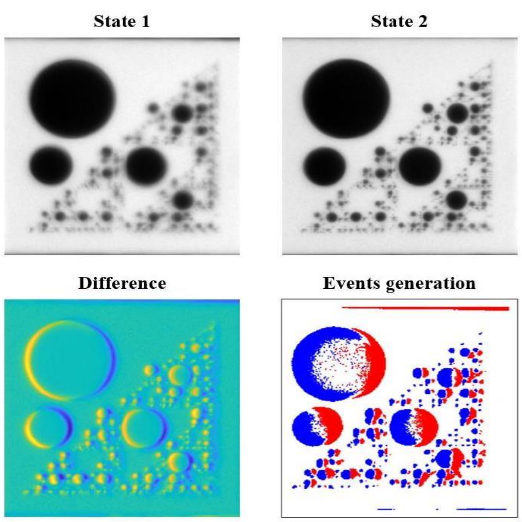

Fig. 1. Disturbance results in event noise under a static scene.

We propose that the generation of noise on the target surface can be modeled as the observed 2D optical flow induced by external ambient light disturbances. The external environmental illumination itself carries lateral perturbations (the projection of scene flow on the two-dimensional plane), which results in light reflected from static objects also carrying perturbations modulated by the object surface. It is important to note that motion is relative; therefore, we perceive the perturbations induced by the external light source as local distortions (motion) of objects under steady-state illumination. In the realm of optics, the fixed surface texture of static objects can be regarded as an optical mask [19].

Since neuromorphic imaging only responds to changes in light intensity contrast, variations in amplitude do not modulate the texture information. Therefore, given the Cartesian coordinates of the image plane $\mathbf{r} = (x, y)^\top$, the illumination perturbations can be approximated as local linear phase increment at timestamp t, i.e., $\Phi(\mathbf{r}, t)$. There exists a relationship between the local linear phase temporal derivative and the resulting local motion of the object, with

$$\frac{d\mathbf{r}}{dt} \triangleq \dot{\mathbf{r}} = z\frac{\partial \Phi(\mathbf{r}, t)}{\partial t}, \tag{1}$$

where $\dot{\mathbf{r}}$ is defined as the temporal derivative of the coordinates, representing the velocity that describes the local motion, and z is the distance from the object to the sensor.

Optical flow estimation refers to the process of determining the apparent motion vector of pixels on the image plane of the target surface over time [20]. Given the image intensity at a specific time denoted as $I(\mathbf{r}, t)$, the event sensor captures the intensity change in logarithmic scale, i.e., the scene luminance, which is defined as $\tilde{I} \triangleq \log I(\mathbf{r}, t)$. The generative model for eventconcerningonstructed by combining the optical flow of the object surface with the external ambient light disturbance. The lighting condition is influenced by the luminance value of the target surface [18, 20]. Additionally, the total derivative $d\tilde{I}/dt$ becomes zero for trajectories that assume constant luminance on the target surface, leading to the optical flow constraint [21]

$$\frac{d\tilde{I}}{dt} = \langle \nabla_{\mathbf{r}} \tilde{I}, \dot{\mathbf{r}} \rangle + \frac{\partial \tilde{I}}{\partial t} = 0, \tag{2}$$

where $\langle \cdot,\cdot \rangle$ denotes the inner product, $\nabla_{\mathbf{r}} \tilde{I} = \left(\frac{\partial \tilde{I}}{\partial x}, \frac{\partial \tilde{I}}{\partial y}\right)^\top$ represents the first partial derivatives to spatial coordinates (object texture), and $\dot{\mathbf{r}} = \left(\frac{\partial x}{\partial t}, \frac{\partial y}{\partial t}\right)^\top$ denotes the motion field.

The event camera detects luminance change, meaning that an event is generated at an image point $\mathbf{r}$ if the amount of luminance change $\Delta\tilde{I}$ surpasses a threshold C during a time interval Δt. Thus, an event $e_k = (x_k, y_k, t_k, p_k)$ can be triggered when the luminance of each pixel reaches the threshold under the external ambient light disturbance. Here, (x_k, y_k) represent the pixel coordinates of the event, t_k is its time-stamp, and $p_k \in \{-1,1\}$ denotes the pixel-wise event polarity, encoding the positive or negative change of luminance.

Therefore, for static scenes with external ambient light, the event noise generated within a certain range can be estimated by integrating the event-induced temporal increment within the full spatiotemporal scene, i.e., $\mathcal{V} = \Omega \times \Delta t$, where Ω represents the spatial area. The averaged noise rate can therefore be obtained by utilizing the finite difference approximation and Equation. 2, i.e.,

$$N_e \propto \frac{1}{\Delta t}\int_{\Delta t}\int_{\Omega} \Delta\tilde{I}(\mathbf{r}, t) d\mathbf{r} dt. \tag{3}$$

When the image scene remains stable, the event noise generation rate N_e is also stable. Therefore, the variable N_e for an event camera can be utilized to indicate the variable states in different materials.

Due to the differentiated microstructures of different target surfaces, their reflective properties are determined by their materials. Hence, the reflection can be used as a coefficient to indicate the material characteristics and as a parameter to multiply N_e. The collected event noise is correlated with the material and can be utilized for recognition and segmentation. The influence of reflection modulation is analogous to the focus-to-defocus process, whereby an image is modulated with a convolution kernel. By modulating the reflection coefficient k_r, the event noise collection rate of another material N_e' can be relatively expressed as

$$N_e' \triangleq k_r N_e. \tag{4}$$

By harnessing the statistical properties of the event noise distribution, we can recognize different material types. Therefore, it is highlighted that the event generation can be correlated with the material reflectance using the optical modulation mechanism.

III. Experiments and Results

We collect a dataset of event noise and validate our methods using a set of steady-state experimental data. Then, we present practical materials in static scenes to showcase the differentiation capability of the proposed method in the CNI framework through the use of event noise.

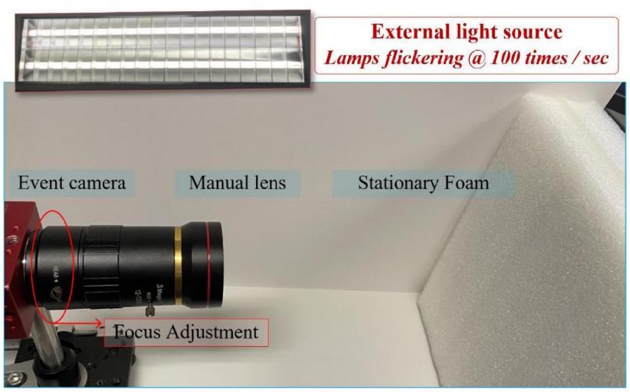

Fig. 2. Neuromorphic imaging setup consists of an event camera and a manual adjustable lens. The imaging scene is illuminated by the incandescent lamp. The entire system is in static scene condition.

The experimental setup is shown in Fig. 2. We used a static event camera (iniVation, DAVIS 346, 346×260 pixels) with a time resolution of approximately 1 μs (output precision, single event) and a manual lens (ZLKC, VM12120MPC, F1.8, 12-120 mm) to capture the event noise. The imaging scene with indoor illumination (i.e., incandescent lamp) has been verified via the proposed CNI-informed method. with As the frequency of the alternating current is 50 Hz, the lamp exhibits a flickering effect occurring 100 times per second. Therefore, illumination with an incandescent lamp is the most obvious phenomenon that demonstrates our scheme. Event cameras are designed for high-time resolution and can be sensitive to external light sources. To facilitate experimental comparison and analysis, both event and frame data can be simultaneously recorded using the DAVIS 346 camera. In our experiment, we set the exposure time for the camera's frame mode to approximately 0.04 s, and the accumulated event noise was integrated over the same time interval for further analysis. The event noise collection rates presented below are also calculated based on the time interval between such events, i.e., Δt=0.04 s.

The reflective properties of various materials can be used to classify and identify target materials [15]. We utilize event noise to classify different materials based on their spatial and reflection response to external ambient light disturbance. Different materials respond and modulate differently to external ambient light, ultimately affecting the event noise ratio captured by the imaging system. We first place targets with different materials in the same state on a fixed position within the depth-of-field range. When the system is stationary and stable, the corresponding event noise is captured and recorded. As shown in Fig. 3, the first column shows the photographs of different white materials. We chose white and visually confusing materials for experimental validation, which can prove the effectiveness and information of event noise. The second column displays the accumulated intensity maps of event noise, which can intuitively reveal that the intensity maps are under the influence of materials with different grey levels and distribution of event noise. The third column presents the cumulative maps of the event noise collection, which can help us more intuitively observe the number of events collected by the system due to the influence of the material.

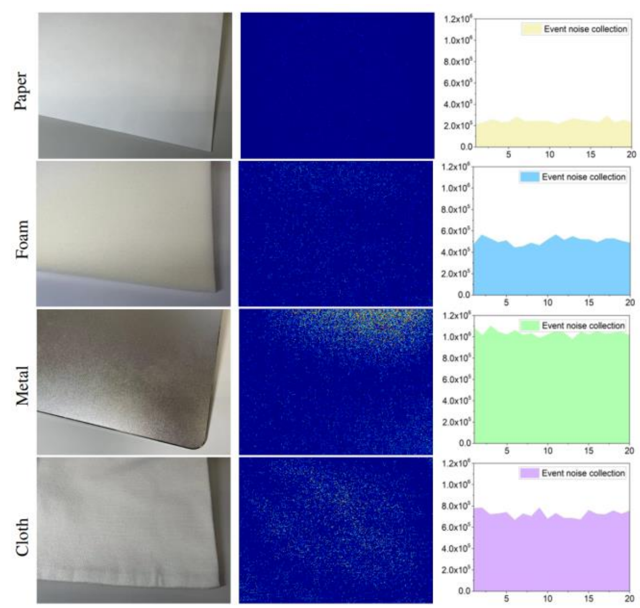

Fig. 3. Analysis of the influence of the material type on the event noise collection rate. Left: photograph of material. Center: accumulated intensity. Right: event noise collection rates at different times.

With the same time duration, the captured event noise rates of different materials are significantly different. We employ a simple k-means algorithm to classify the captured event noise rates, as shown in Fig. 4. The parameters obtained after classification can be referenced and input into another batch of data for further classification. Then, we use the existing recognition parameters to identify 100 sets of unfamiliar event noise occurring at different time points. The results of this identification process are depicted in Fig. 4. The material can be accurately identified by effectively utilizing its noise properties. This approach enables rapid differentiation of different event noise categories. Furthermore, collecting more datasets for model improvement can promote this method to discriminate different materials with high resolved accuracy more accurately.

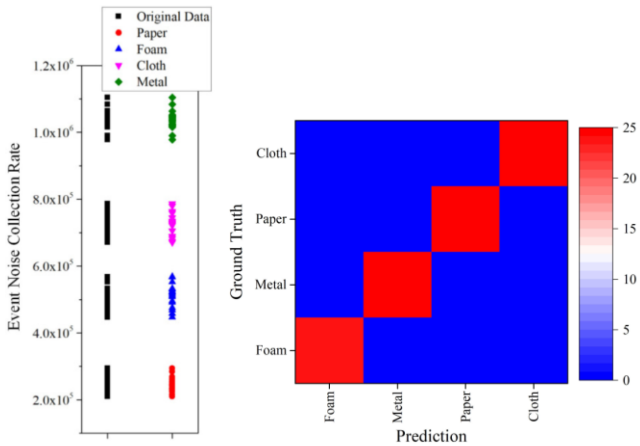

Fig. 4. Analysis of the influence of the camera focus state on the event noise collection rate. Left: Data clustering. Right: Predicted results.

IV. Conclusion and Discussion

To summarize, this paper introduces and validates a novel method for material differentiation with event noise in static scenes in the CNI paradigm. We establish the relationships between event noise and corresponding imaging models, which extend the applicability of event cameras in static conditions. Practical experiment results and corresponding analysis are provided to support the proposed scheme. We investigate the generation of event noise by employing an optical flow model to represent the target surface. Through experiments and analysis of real-world data, we utilize the event noise to tackle the CNI-informed material differentiation in static scenes. The proposed approach demonstrates that a purely event-based camera can efficiently accomplish optical tasks without the need for traditional frame-based imagers. Our findings further lay the groundwork for the CNI framework across a broad range of computational imaging applications, extending the visual scenes in which event cameras can be used, no longer limited by conventional motion-driven conditions.

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