Computational neuromorphic imaging: Principles and applications

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ABSTRACT

The widespread presence and use of visual data highlight the fact that conventional frame-based electronic sensors may not be well-suited for specific situations. For instance, in many biomedical applications, there is a need to image dynamic specimens at high speeds, even though these objects occupy only a small fraction of the pixels within the entire field of view. Consequently, despite capturing them at a high frame rate, many resulting pixel values are uninformative and therefore discarded during subsequent computations. Neuromorphic imaging, which makes use of an event sensor that responds to changes in pixel intensities, is ideally suitable for detecting such fast-moving objects. In this work, we outline the principle of such detectors, demonstrate their use in a computational imaging setting, and discuss the computational algorithms to process such event data for a variety of applications.

Keywords: Computational imaging, event sensors, neuromorphic imaging, optical applications

1. INTRODUCTION

Computational imaging has become ubiquitous in advanced research and contemporary society, encompassing applications from macro to micro scales.[1,2] These applications have been significantly enhanced by computational algorithms, e.g., leveraging deep learning to build intelligent vision systems.[3,4] Nonetheless, conventional cameras do come with certain limitations, and the major drawback is the restricted performance of their sensors. Consequently, the field of computational imaging is undergoing a significant transformation, driven by the emergence of groundbreaking and advanced sensor technologies.[5,6] Notably, the development of a camera that emulates the functionality of the human retina, known as a neuromorphic camera with event sensors, has revolutionized visual information processing. This camera is capable of efficiently handling vast amounts of visual data with exceptional temporal resolution, a high dynamic range (HDR), and minimal data redundancy, among other remarkable features. As a result, the convergence of neuromorphic engineering and computational imaging has propelled the rapid growth and advancement of the field of neuromorphic imaging.

Over the past decade, vast amounts of vision applications have been implemented based on event sensors.[5] Recently, in pursuit of superior imaging performance, many researchers have also used it in the field of optical applications, e.g., super-resolution imaging in localization microscopy[7] and speckle analysis in lensless imaging systems.[8] The motivation for using event sensors over conventional frame-based image sensors lies in their superior capability to process super-fast dynamics and ultra-high dynamic range of scenes. Equipped with event sensors and computational algorithms that directly take in the event data as inputs, we anticipate that computational neuromorphic imaging (CNI) — encompassing high-sensitivity sensing, time-efficient reconstruction, HDR imaging, and dynamic analysis — will be a fast emerging area in optical imaging. With it, we can perform different dimensions of imaging and sensing enhancement based on the hardware response properties and data characteristics of the event sensors.

This paper provides an overview of CNI, with a focus on optical applications to solve as well as challenging computational imaging tasks. The rest of this paper is organized as follows: Section 2 presents the principle and event representation of neuromorphic imaging. Section 3 introduces several optical applications using neuromorphic imaging techniques. The conclusion and future directions are discussed in Section 4.

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2. OVERVIEW OF NEUROMORPHIC IMAGING

2.1 Principle of Event Sensors

The event sensor is also termed silicon retina since its form and function are inspired by the vertebrate retina.[9] The studies on the biological photoreceptors have revealed that their electrical response to the incident light is almost proportional to the log intensity at the center part of the photoreceptors' range.[10] Mathematically, such a response relationship can be represented by

$$u \propto \log(I), \tag{1}$$

where u denotes the electrical response of a biological photoreceptor, and I denotes the light intensity. To simplify the notation and emphasize the subsequent analysis in the logarithmic context, the log intensity can be defined as $L \triangleq \log(I)$.

The logarithmic nature of this response, which can compress a large input range into a smaller output range, enables the photoreceptor to work in a high dynamic range. To mimic this property, the photoreceptors of silicon retinas are generally designed based on two components, i.e., a photodetector that generates an electrical photocurrent proportional to the incident light and a circuit with the logarithmic current-voltage characteristic.[10–12]

Furthermore, inspired by the action-potential used by biological neurons, which occurs when the membrane potential rapidly rises and falls, the event sensor at each pixel independently triggers an output in the form of an event once the log intensity change is larger than a specified threshold.[13,14] Such an event-triggering paradigm has several advantages. First, the log intensity change ΔL is determined by the ratio of the intensity change ΔI to the background intensity I_0, i.e.,

$$\Delta L = \log(I_0 + \Delta I) - \log I_0 = \log\left(1 + \frac{\Delta I}{I_0}\right), \tag{2}$$

which is invariant to the illumination level. As such, this event-triggering strategy can normally work under a wide range of lighting conditions. Second, in contrast to conventional cameras which outputs an image frame at regular time intervals, this event-triggering paradigm is asynchronous and data-driven. The event sensor at each pixel independently and automatically determines its output rate based on the intensity change. On the one hand, when there is no change in the pixel intensity, the event sensor outputs nothing, consuming much less energy and data communication resources than the conventional cameras. On the other hand, when the intensity at one pixel changes over a threshold, the corresponding event sensor immediately outputs an event to report the change information with a high temporal resolution and a low latency.

2.2 Event Representation and Processing

The k^{th} event point, denoted as $\mathbf{e}_k = (\mathbf{r}_k, p_k, t_k)$, is triggered at the pixel located at $\mathbf{r}_k$ when the log intensity change exceeds a predetermined threshold C. Here, $\mathbf{r}_k = (x_k, y_k)$ represents the spatial location of the pixel, and t_k is the corresponding timestamp. The symbol $p_k \in \{-1, 1\}$ indicates whether there is a positive ($p_k = +1$) or negative ($p_k = -1$) polarity of the event increment. An illustration of the event-triggering mechanism at a specific pixel is provided in Fig. 1. To elaborate on the event triggering definition, the pixel-wise logarithmic intensity (brightness) increment $\Delta L(\mathbf{r}_k, t_k)$ at a specific timestamp t_k can be defined as

$$\Delta L(\mathbf{r}_k, t_k) \triangleq L(\mathbf{r}_k, t_{k+1}) - L(\mathbf{r}_k, t_k) = p_k C, \tag{3}$$

where $L(\mathbf{r}_k, t_k) = \log\big(I(\mathbf{r}_k, t_k)\big)$ is the brightness at the specific pixel.

In terms of specific applications involving photometric changes, the practical generation of neuromorphic imaging data can be classified into three general categories: (i) scenarios that involve illumination changes. This category encompasses various factors that influence the ambient illumination, such as the excitation process of fluorescent material or the scintillation of the light source; (ii) scenarios that involve moving targets: The intensity changes in this scenario are directly caused by the translational motion of targets, typically the rigid objects, often referred to as optical flow; and (iii) the mixed scenarios, where the intensity changes are caused by complex factors, including the combination of the first and the second categories and more intricate scenarios

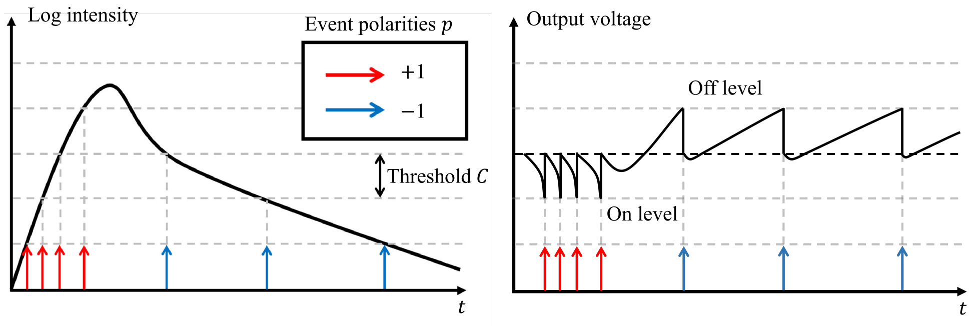

Figure 1. Event triggering mechanism, where the red and blue arrows represent the event points triggered by the changed log intensity L on a single pixel with positive $(+1)$ and negative (-1) polarities, respectively.

such as diffraction. Additionally, it is important to note that dealing with noise effects in this unique imaging paradigm presents a particularly challenging task.

Based on the aforementioned first three categories of scenarios, we discuss and summarize common post-processing mathematical models applicable for general usage.

1. Category (i). There is no motion-blur effect in such a scenario, hence, the informative measurement comes from the direct observation of the temporal increment of brightness within a short time interval Δt. The accumulation method involves counting the polarities of individual points on a pixel-wise basis, resulting in an event image that provides an estimation of the magnitude of brightness increment within Δt. Mathematically, this can be expressed as

$$\Delta \hat{L}(\mathbf{r}; \Delta t) = \sum_{t_k \in \Delta t} p_k C \delta(\mathbf{r} - \mathbf{r}_k). \tag{4}$$

   The chosen time interval Δt serves as a hyper-parameter, representing the equivalent temporal resolution required to determine the estimated brightness increment $\Delta \hat{L}(\mathbf{r}; \Delta t)$ that aligns with the specific objectives of the given applications.

2. Category (ii). Applications such as trajectory tracking are common in such situations, where the ambient illumination remains constant. Hence, the detected log intensity change is dominantly caused by regional translating motion. Considering the known optical flow model under the assumption of photometric consistency, the event generative model[15] can be established. Such a model described the events caused by the edges moving at an application-determined velocity of $\mathbf{v} = (\frac{\partial \mathbf{v}}{\partial x}, \frac{\partial \mathbf{v}}{\partial y})^\intercal$ within Δt can be written as the dot product of the photometric gradient and the regional optical flow

$$\Delta L(\mathbf{r}; \Delta t) = -\nabla L(\mathbf{r}) \cdot \mathbf{v} \Delta t, \tag{5}$$

   where $\nabla L(\mathbf{r}) = (\frac{\partial L}{\partial x}, \frac{\partial L}{\partial y})^\intercal$ represents the brightness gradient which is assumed invariant as the contours/edges of the rigid-moving object during motion.

3. Category (iii): Currently, there is no general model to interpret mixed scenarios. However, the event data modality can be further transformed into a 3D voxel data representation through bilinear interpolation, which can then be used as input for common neural networks for more general post-processing.[5]

3. OPTICAL APPLICATIONS WITH NEUROMORPHIC IMAGING

CNI techniques have been fueling optical applications, enabling high-sensitivity sensing, time-efficient reconstruction, HDR imaging, and dynamic analysis. As shown in Figure 2, event sensors offer better properties compared to conventional sensors, especially temporal resolution and HDR response. In this section, we introduce several optical applications with neuromorphic imaging, harnessing the advantages of event sensors, presenting according to the challenging tasks, and predicting future potential capabilities.

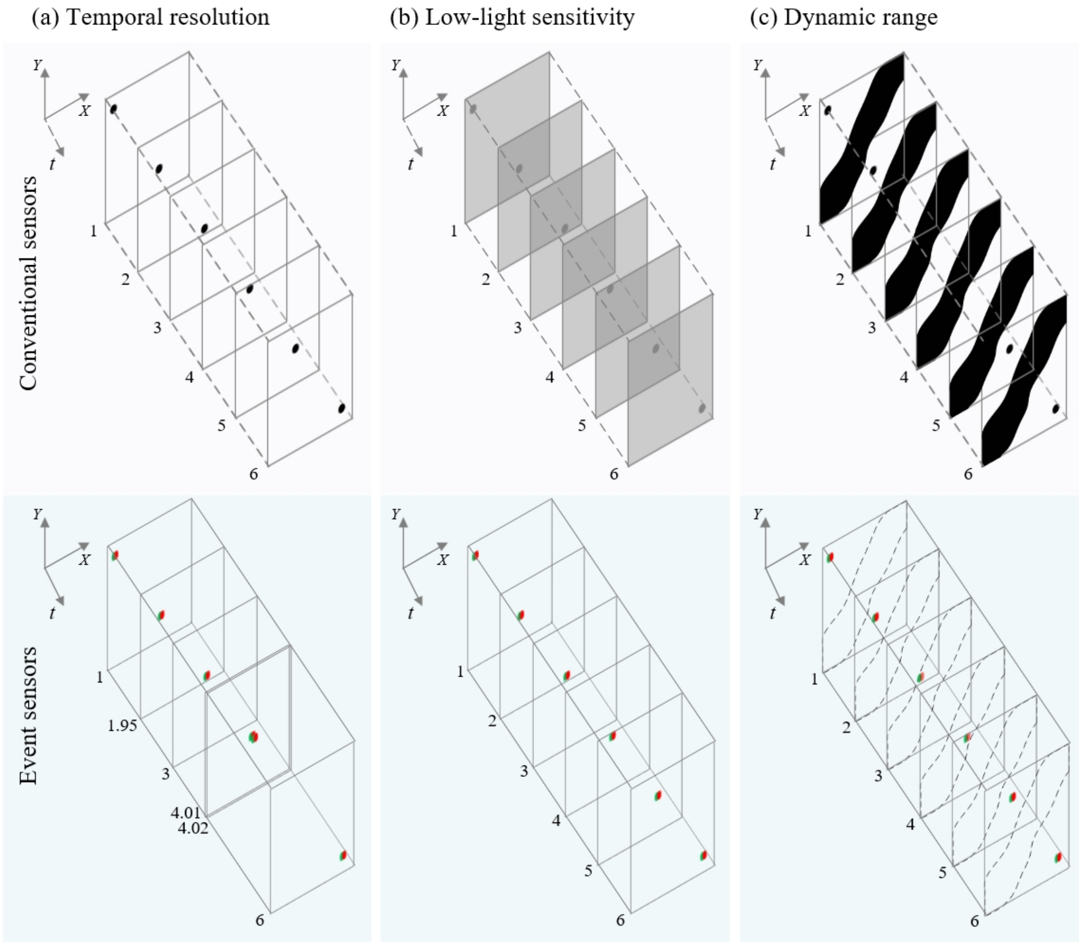

Figure 2. Representation of conventional sensors and event sensors. (a) Event sensors have higher temporal resolution than conventional frame-based sensors. (b) Logarithmic intensity response indicates that event sensors have more sensitive capability in low light conditions. (c) Event sensors also have better performance in HDR environments.

3.1 Super-resolution Imaging

Super-resolution imaging encompasses a range of techniques that aim at enhancing the resolution of imaging systems. This field can greatly benefit the utilization of event sensors and the unique data design offered by neuromorphic imaging, e.g., improving imaging temporal resolution and sensing much faster, as displayed in Figure 2(a). Each event represents a change in log intensity yet not a simple linear response, and thus event sensors are more sensitive to variations in low light conditions. As illustrated in Figure 2(b), the target information can be detected reliably with higher contrast events. Therefore, compared with conventional microscopic methods, event sensors that only respond to local changes in light intensity can enable weak signal detection and super-resolution via the localization microscopy with a higher sensitivity.[7,16] The CNI-enhanced super-resolution approach has widespread applications in precisely tracking and understanding stochastic processes in biomedical engineering. Moreover, many super-resolution imaging techniques are exploiting machine learning to provide rapid analysis of event-stream datasets. The spiking neural network is a potential way to ameliorate low-level reconstruction with neuromorphic imaging,[17] which can be further explored in super-resolution imaging.

3.2 3D Reconstruction

The 3D reconstruction technique is a process of obtaining the depth estimation and creating a 3D image of an object.[18] Leveraging the high temporal resolution of event sensors, depth information can be enhanced and the reconstruction error can also be reduced. For example, the fringe projection profilometry system, high-speed scanning, and accurate reconstruction are usually limited by the camera performance, especially by the response time.[19] Meanwhile, the high temporal resolution can also be utilized to resist multipath interference to meet the epipolar constraint.[20] As shown in Figure 2(c), event sensors have better HDR response to the full scene that can promote the applicability to 3D reconstruction under strong global illumination.[21] So far, most of the 3D reconstruction techniques via neuromorphic imaging are ray-based optical imaging from depth measurements, which simply uses the high-speed characteristic. Therefore, wave-based optical imaging can be designed and implemented, such as holographic imaging in different optical applications.

3.3 Autofocusing

Autofocusing involves determining the focal plane quickly and accurately, typically by acquiring data from different depths through axial scanning. Introducing the principles of neuromorphic imaging to improve scanning speed and data robustness in challenging lighting conditions is both inspiring and reasonable. The formation of events in autofocusing can be understood by analyzing how the point spread function changes with the axial scanning.[22] Additionally, the incorporation of polarity information has been shown to further enhance the speed and precision of autofocusing.[23] This highlights the significance of utilizing polarity in the autofocusing process. On the other hand, considering the image as a whole and analyzing the spatial correspondence using the optical flow constraint, the event rate can be related to the distribution of regional photometric gradient.[24] This approach enables deriving a metric directly from the optical flow prior or the event generative model.

3.4 Wavefront Sensing

Enhancing wavefront sensing keeps challenging current advanced adaptive optics systems, particularly in extreme adaptive optics scenarios. In these cases, the actuators should dynamically compensate for the wavefront change induced by the changing turbulence with a servo-loop of larger than 1000 Hz under photo-starved conditions. The first validation of the combining was demonstrated on a Shack-Hartmann (SH) wavefront sensor, showcasing the benefits of neuromorphic imaging, especially in terms of speed and HDR.[25] A theoretical model linking angle-based wavefront sensing and the optical flow model is then analyzed in the context of neuromorphic imaging. It was suggested to extract the high-dimensional trajectories of SH spots implicitly through a motion compensation strategy to enhance the signal-to-noise ratio.[26]

3.5 Speckle Analysis

Speckle occurs in a signal when it is made up of numerous independently phased additive complex components.[27] Many lensless imaging systems utilize speckle analysis, which offers advantages in size, weight, and form factor. However, speckles in most ill-posed inverse problems are usually highly dynamic and present in low-light conditions.[28] The event sensors have applicable advantages for analyzing speckles in high-dynamic scenes or weak measurement conditions. Therefore, the event sensors with low latency and high contrast sensitivity can be implemented for micro motion estimation.[29] The event sensors only respond to per-pixel brightness change, thus, we can leverage this basic characteristic for non-line-of-sight (NLOS) tracking.[30] The event-based NLOS tracking approach effectively circumvents the disturbance of the relay surface that can be used to directly obtain displacement information of the hidden object. Therefore, the CNI technique has great potential capability for solving such inverse scattering problems.

4. FUTURE OUTLOOK

Neuromorphic imaging offers considerable advances in high speed, HDR, low redundancy, and form paradigms compared to traditional frame-based imaging techniques. That makes CNI an attractive option for numerous challenging optical applications. We have provided an overview of various optical applications, ranging from micro imaging in biomedical analysis to macro imaging in wavefront sensing. Although the event camera will not completely replace the traditional frame-based camera, it will be a good alternative for many optical imaging applications, and it will open up new possibilities for computational imaging. Nevertheless, it should also be noted that due to the spatially sparse, photometric sensing, and stochastic noise of event data, we need to find a suitable way to extract useful information or use its data characteristic for a given task. In conclusion, the computational algorithm is a powerful tool for resolving challenges due to the novel imaging paradigm.

Computational neuromorphic imaging and its applications are emerging topics, there are plenty of opportunities in optical fields and numerous different imaging systems. The neuromorphic paradigm opens up additional strength in imaging technology that can enable novel and valued optical applications.

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