

# Event fields: Capturing light fields at high speed, resolution, and dynamic range

Ziyuan Qu  
Dartmouth College

Zihao Zou  
UNC Chapel Hill

Vivek Boominathan  
Rice University

Praneeth Chakravarthula  
UNC Chapel Hill

Adithya Pediredla  
Dartmouth College

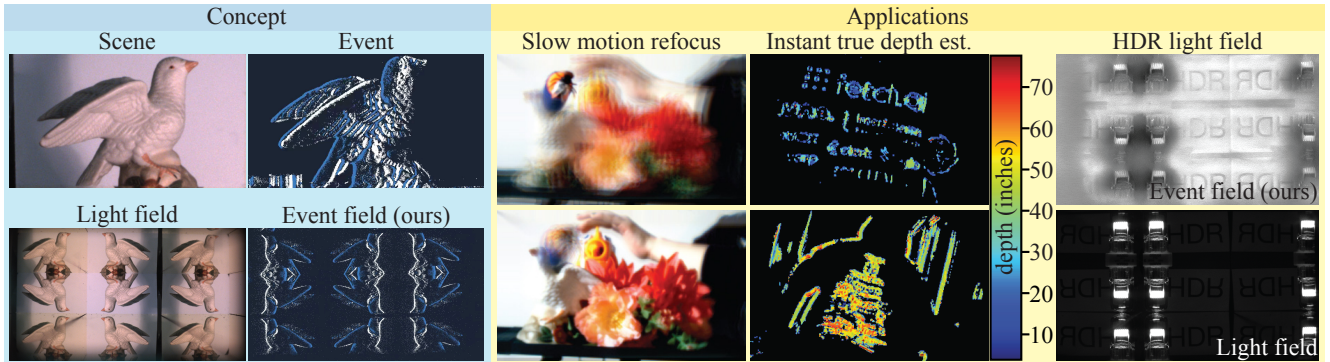


Figure 1. We introduce *Event Fields*, a novel framework that leverages event cameras to capture light fields at high speed, resolution, and dynamic range using innovative optical designs. Event fields integrate the unique advantages of event sensing—such as low latency, data efficiency, and power-saving capabilities—with the detailed angular information provided by light field sensing. We demonstrate the versatility of the event fields through three application scenarios: slow motion refocus (SloMoRF), instant true depth estimation, and high dynamic range (HDR) light field imaging.

## Abstract

Event cameras, which feature pixels that independently respond to changes in brightness, are becoming increasingly popular in high-speed applications due to their lower latency, reduced bandwidth requirements, and enhanced dynamic range compared to traditional frame-based cameras. Numerous imaging and vision techniques have leveraged event cameras for high-speed scene understanding by capturing high-framerate, high-dynamic range videos, primarily utilizing the temporal advantages inherent to event cameras. Additionally, imaging and vision techniques have utilized the light field—a complementary dimension to temporal information—for enhanced scene understanding.

In this work, we propose “Event Fields”, a new approach that utilizes innovative optical designs for event cameras to capture light fields at high speed. We develop the underlying mathematical framework for Event Fields and introduce two foundational frameworks to capture them practically: spatial multiplexing to capture temporal derivatives and temporal multiplexing to capture angular derivatives. To realize these, we design two complementary optical setups—one using a kaleidoscope for spatial multiplexing and another using a galvanometer for temporal multiplexing. We

evaluate the performance of both designs using a custom-built simulator and real hardware prototypes, showcasing their distinct benefits. Our event fields unlock the full advantages of typical light fields—like post-capture refocusing and depth estimation—now supercharged for high-speed and high-dynamic range scenes. This novel light-sensing paradigm opens doors to new applications in photography, robotics, and AR/VR, and presents fresh challenges in rendering and machine learning.

## 1. Introduction

Capturing high-speed visual phenomena in real-time is essential for advancing science and engineering. Traditional high-speed frame cameras like Phantom, Photron, and IDT can achieve impressive frame rates (up to 100,000 fps) but are bulky, have finite capture duration, and are expensive (exceeding \$100,000), restricting accessibility. In contrast, event cameras offer a more affordable and efficient solution with high temporal resolution (down to  $1\mu\text{s}$ ) and continuous data acquisition, suitable for real-time applications. Unlike traditional cameras, which require substantial bandwidth (e.g., 100,000 fps, HD capture requires 100 GBps), event cameras capture only changes in the scene using asyn-

chronous pixel readouts, reducing bandwidth demands and enabling continuous streaming. This approach has recently been harnessed for high-speed applications, including optical flow, object tracking, high-dynamic range imaging, structured light scanning, and photometric stereo [6, 10].

In this work, we extend event camera capabilities by introducing angular capture, allowing for post-capture manipulation of high-speed video—a previously unexplored functionality. Capturing angular radiance information is known as light field imaging [24, 25, 53], enabling features such as post-capture refocusing and depth estimation. We propose “Event Fields” that record radiance *derivatives* across angular and temporal dimensions, extending light field imaging principles to high-speed, high-dynamic-range scenarios (see Fig. 1). To capture these Event Fields, we introduce two complementary hardware systems: a kaleidoscope-based design and a galvanometer-based design, each with unique advantages for this purpose.

The kaleidoscope design (see Fig. 3), inspired by Manakov *et al.* [30], captures angle-resolved time derivatives by placing a rectangular kaleidoscope in the optical path. This approach allows for capturing angular information affordably and simply at  $3 \times 3$  views. The galvanometer design (see Fig. 4) uses a galvanometer positioned in the optical path to capture angular derivatives directly. By controlling the mirrors at 250 Hz, the incoming rays are shifted along a curve, enabling the capture of both angular and temporal derivatives. As angular derivatives are sparse [21, 56], this design does not significantly increase bandwidth requirements. Table 1 compares the relative advantages of these two hardware approaches.

To systematically evaluate the relative merits of the hardware designs, we build a Blender plugin to render event-fields with physics based light simulation. We also build hardware imaging prototypes with kaleidoscope and galvanometer, and algorithms to demonstrate new imaging capabilities in challenging environments. These include post-capture refocusing on dynamic scenes (e.g., a rotating fan at 480 RPM), focus tracking of nerf darts traveling at 20 m/s, high-speed depth reconstruction, and high-resolution, high dynamic range light fields.

**Contributions.** To state explicitly, the manuscript makes the following contributions:

- Introduces *event fields*; spatial and temporal multiplexing techniques to capture them.
- Builds a physics-based simulator and two hardware prototypes to systematically evaluate the merits and limitations of the multiplexing techniques.
- New applications and related algorithms, including slow motion refocus (SLoMoRF), true-depth estimation, and high dynamic range light field imaging.
- Open source simulator, data, and processing codes [43].

	Kaleidoscope	Galvanometer
Derivatives	Temp.	Ang. + Temp.
Recon. Performance	Scene dep.	Scene indep.
Color	Yes	No
Static LF Capture	No	Yes
Dynamic LF capture	Yes	Yes
Refocus Fidelity	Choppy	Smooth
Bandwidth Required	Low	High

Table 1. Relative advantages of kaleidoscope vs. galvanometer design for capturing event fields.

## 2. Related Work

**Light field sensing:** One of the first approaches to light field capture [54] involves using multiple sensors to gather angular information from various perspectives. However, this setup is bulky, costly, and requires high bandwidth communication. An alternative is time-sequential capture, which mounts a sensor on a mechanical gantry to capture the light field of a static scene [12, 25]. Rather than moving the sensor itself, a mirror can be used to redirect the view. Ihrke *et al.* [19] proposed using a movable planar mirror to shift the view temporally. However, this method requires individual calibration for each image, adding complexity. Fujii *et al.* [8] uses a galvanometer and pairs it with a high-speed camera. Inspired by their approach, we developed a similar design, precisely controlling the galvanometer’s movement. A key distinction is that our galvanometer operates continuously, while their system selects discrete positions from a lookup table, making it slower.

In addition to time-sequential capture, angular information can also be measured with spatial multiplexing. One way to achieve this is through a microlens array [39], which has been widely adopted in commercial light field cameras like Raytrix [44] and Lytro [28]. While effective, microlens arrays are challenging to manufacture and install. Taguchi *et al.* [48] suggested using a mirror ball to expand the camera’s field of view, though this setup results in the camera being visible in the mirror ball’s reflection. Alternatively, Manakov *et al.* [30] introduced a kaleidoscope-like mirror array that can be attached to a standard camera without modification. Inspired by this design, we adapted it to convert a conventional event camera into a device capable of capturing the event field.

**Event camera designs:** From the first neuromorphic sensor by Mahowald *et al.* [29] to the recent Sony IMX636, event sensing saw exponential growth. We briefly review designs most relevant to our manuscript and refer the readers to recent surveys [6, 10]. Event cameras are regularly used in robotics and autonomous navigation for optical flow computation [2, 11, 52], feature tracking [49], and motion segmentation [34, 57], but event cameras cannot detect edges in the direction of the camera motion. Inspired by microsac-



cadences in human eye movement, He *et al.* [17] placed a rotating wedge mask before the event camera aperture to capture edges in all directions. Similar to them, our galvanometer design detects edges oriented in all directions, independent of camera and object motion, as shown in Fig. 6. Our galvanometer design also finds inspiration from the designs of Muglikar *et al.* [37], who used a rotating polarizer in the aperture plane to capture high-fidelity polarization information for shape-from-polarization and Yu *et al.* [55], who used a rotating light source and event camera for fast photometric stereo.

Habuchi *et al.* [16] captured light fields for static scenes by placing an LCOS device in the aperture plane of event cameras and using CNN to recover the light field. While the technique is quite novel, it is limited to static scenes due to the LCOS response time (22 ms). Guo *et al.* [14] placed a microlens array (MLA) on the event sensor to capture the light field for dynamic scenes and showed microscopic imaging applications with their prototype. We built our prototypes for macroscopic applications, and our kaleidoscope design is functionally same as MLA design. However, the galvanometer design can capture angular information even for static scenes without trading off the spatial resolution like Guo *et al.* [14].

**Event processing algorithms:** Event cameras capture scene information at higher temporal resolution (in  $\mu\text{s}$ ) and dynamic range (140 dB) compared to standard cameras (60 dB) [10]. These features enable solutions to challenges where standard frame-based sensors struggle, such as high-speed motion estimation [9], high frame rate reconstruction [45], and high dynamic range imaging [45]. Besides, event cameras and standard frame-based cameras are complementary; event cameras provide high-speed, sparse data, while standard cameras capture color and fine details. By fusing these two types of sensors, algorithms like Timelens [50] and Timelens++ [51] effectively interpolate RGB frames using event information. We adapt these event processing algorithms for processing event field data.

**Other event-based fusions:** Apart from RGB cameras, other computational imaging systems can also be made fast by fusing with event sensors [58]. Event-based structured light sensing techniques [18, 23, 31, 32, 35, 47] reconstruct 3D scenes at high speed by replacing standard intensity sensors with event cameras. Event cameras are also used for foveated depth sensing [36] to scan moving objects at a higher spatial resolution. Muglikar *et al.* [38] combined single-photon avalanche diodes (SPADs) with event cameras to achieve high-speed, low-light, low-bandwidth imaging capabilities.

### 3. Technical Background

We will briefly review the image formation models for light field and event cameras that are useful in developing the

mathematical models for event fields.

#### 3.1. Light Field

The plenoptic model of light  $L(\vec{x}, \vec{\omega}, \lambda, t)$  is a comprehensive representation that captures all the dimensions of light emitted by a scene [1, 33]. Here,  $\vec{x} = (x, y, z)$  represents the spatial coordinates of the observer through which the light passes;  $\vec{\omega} = (\omega_x, \omega_y)$  are the angular coordinates;  $\lambda$  is the wavelength, and  $t$  is the time. At a given time, the measurement of a monochromatic light is 5D function. Levoy and Hanrahan [25] and Gortler *et al.* [12] showed that the 5D representation has redundancies and have reduced it to 4D by assuming that the light field is measured in free space. Under this assumption, as the radiance of a ray remains a constant in a straight line, the static monochromatic light field is a 4D function  $L(\vec{u}, \vec{s})$ , where  $\vec{u} = (u, v)$  is a point on the virtual sensor and  $\vec{s} = (s, t)$  is a point on the virtual aperture.

To synthesize an image from a given light field, we integrate the light field over the aperture as:

$$I(x, y) = \int_{\vec{s}} L(\vec{u}, \vec{s}) d\vec{s}. \quad (1)$$

Light field allows us to change the focus plane after imaging by computationally changing the distance between the sensor and aperture planes [3, 25]. If  $d_0$  is the original distance between the planes and  $d$  is the distance required to focus at a given depth, the light field that focuses at  $d$  will be  $L_d(\vec{u}, \vec{s}) = L(\vec{u} + (d_0/d)\vec{s}, \vec{s})$ . The refocused image can be synthesized by integrating angles, as shown in Eq. (1).

#### 3.2. Event Camera

An event camera asynchronously records the brightness ( $B \doteq \log(\int_{\vec{\omega}} L d\vec{\omega})$ ) change event for each pixel independently [4, 26, 29, 42]. Specifically, in an ideal and noise-free scenario, a pixel  $\mathbf{x} = (x_k, y_k)^T$  will be triggered at time  $t_k$  as soon as the brightness change reaches a predefined threshold  $C$  since the last triggered event. The polarity  $p_k \in \{+1, -1\}$ , which is the sign of the brightness change, will be recorded for each trigger. Mathematically,

$$\begin{aligned} \Delta B(\mathbf{x}_k, t_k) &\doteq B(\mathbf{x}_k, t_k) - B(\mathbf{x}_k, t_k - \Delta t_k) = p_k C \\ \frac{\partial B(\mathbf{x}_k, t_k)}{\partial t} &\approx \frac{p_k C}{\Delta t_k} \Rightarrow \frac{\partial L(\mathbf{x}_k, t_k)}{\partial t} \approx L \frac{p_k C}{\Delta t_k}. \end{aligned} \quad (2)$$

Therefore, event cameras capture a high-speed temporal derivative slice  $(\mathbf{x}, t_k)$  of the plenoptic function.

In the related work, we referred to several techniques that excel at extracting high-speed spatial information from sparse event streams. These algorithms can do so as the scene information typically changes slowly [10], making the temporal gradient  $\frac{\partial L(\mathbf{x}_k, t_k)}{\partial t}$  inherently sparse. This redundancy also applies to angular dimension as light field

is mostly smooth [21, 56] and hence,  $\frac{\partial L(\vec{x}, \vec{\omega}, \vec{s}, \lambda, t)}{\partial \vec{\omega}}$  and  $\frac{\partial L(\vec{x}, \vec{\omega}, \vec{s}, \lambda, t)}{\partial t}$  are sparse. We exploit this sparsity to capture event fields with a single event camera in the next section.

## 4. Event Field

As mentioned briefly in Sec. 3.2, an event camera’s photodetector measures brightness by taking the logarithm of radiance integrated over all angles. This integration results in a loss of angular information. Our objective, through event fields is to retain this angular information  $\vec{\omega}$ . To achieve this goal, we need to multiplex angular information into either the spatial or temporal dimensions that the event camera captures. We advocate for and design both spatial and temporal multiplexing techniques, as they offer complementary advantages.

### 4.1. Spatial Multiplexing

We encode discrete angular information ( $\omega_i$ ) into the spatial dimension using a mapping function defined as:

$$(\omega_i, \mathbf{x}_s(\omega_i)) \mapsto \mathbf{x}, \quad (3)$$

where  $\mathbf{x}_s(\omega_i)$  represents the spatial coordinate for each measured view ( $\omega_i$ ). Let the number of discrete angular views be  $\mathbf{n}$ , the spatial resolution of the sensor be  $\mathbf{r}$ , and  $\mathbf{r}$  is an integral multiple of  $\mathbf{n}$ . The specific mapping function  $\mathbf{x}_s$  varies based on the hardware design. The two commonly used mapping functions are:

- **Multi-sensor array [54] or kaleidoscope [30]:** In this design, the mapping function is  $\mathbf{x}_s = \mathbf{x} \bmod (\mathbf{r}/\mathbf{n})$ .
- **Microlens array [39]:** In this design, the mapping function is  $\mathbf{x}_s = \mathbf{x}/\mathbf{n}$ .

By applying this mapping function to Equation (2), the measurements are:

$$\frac{\partial B}{\partial t}(\underbrace{\mathbf{x}_s, \omega}_{\mathbf{x}_k}, t_k) \approx \frac{p_k C}{\Delta t_k}, \quad (4)$$

and the event camera will now measure the temporal brightness changes across both spatial and angular dimensions. Note that the brightness derivatives are still related to time, and we lose spatial resolution (by a factor of  $n$ ) to improve angular resolution.

### 4.2. Temporal Multiplexing

To encode angular information in the temporal dimension, we steer the incoming rays along a closed periodic curve  $\mathcal{C}(t)$  with period  $T$ . This steering could be accomplished by either moving the camera or placing steerable galvanometer in the optical path of the camera. The galvanometer can be steered fast along Lissajous curves [8, 41]; hence, we use it in all our experiments.

The temporal multiplexing does not sacrifice spatial resolution but sacrifices temporal resolution and always detects

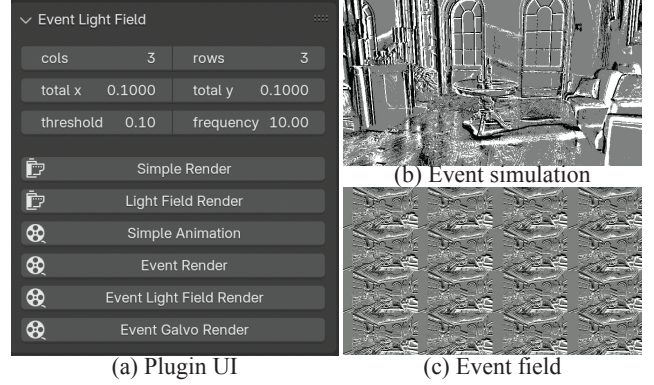


Figure 2. **Blender plugin** for physics-based event field rendering.

more events than spatial multiplexing. At any given time instant, the angular view will be at  $\mathcal{C}(t \bmod T)$  and the temporally varying light field is  $L(\mathbf{x}, \mathcal{C}(t \bmod T), t)$ . For static scenes, the event camera measurement is

$$\frac{\partial B(\mathbf{x}, \mathcal{C}(t))}{\partial t} = \frac{\partial B(\mathbf{x}, \omega)}{\partial \omega} \frac{\partial \mathcal{C}(t)}{\partial t} \bigg|_{t=t_k} \approx \frac{p_k C}{\Delta t_k}, \quad (5)$$

Therefore, temporal multiplexing technique measures the angular derivatives of the light field  $\frac{\partial L(\mathbf{x}, \omega)}{\partial \omega}$  along the scanning curve.

While we restricted the scanning curves to be Lissajous curves, specifically circles in most of the results, in principle, the scanning curve can be any periodic curve, including space-filling curves [15, 46]. Space-filling curves result in dense angular light-field capture at the cost of losing temporal information. However, typically light field is highly redundant and smooth and a circular scan captures most of the light-field diversity as we show in the results.

## 5. Simulator and Hardware Design

To validate our approach, we built a physics-based simulator and two hardware prototypes, kaleidoscope for spatial multiplexing and galvanometer for temporal multiplexing. The simulator allows us to precisely control the scene and design parameters, enabling an accurate and fair comparison between the two multiplexing techniques. Hardware prototypes show the real-world feasibility of our designs as well as new capabilities.

### 5.1. Simulator

We have used a straightforward approach to simulating events, which involves rendering the full plenoptic function, calculating brightness by propagating the plenoptic data through optics, and tracking the brightness difference from the previous event. A new event is triggered for each pixel when this difference exceeds a manually set threshold.

We chose Blender [7] as our backend as it is open-source, physically based, supports GPU acceleration (Cycles), Python APIs, and brandishes a user-friendly GUI. We

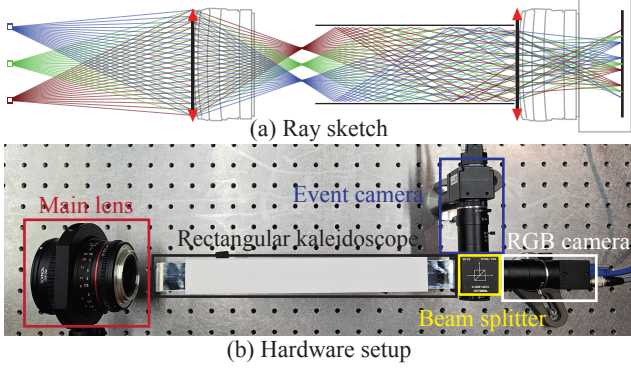


Figure 3. **Kaleidoscope design.** (a) Illustration shows rays from various angles being directed towards the event camera. (b) The main lens focuses the scene onto the kaleidoscope, splitting the view into multiple angles. The beam splitter directs these multiple views to the RGB camera for standard light-field imaging and the event camera for event-field imaging.

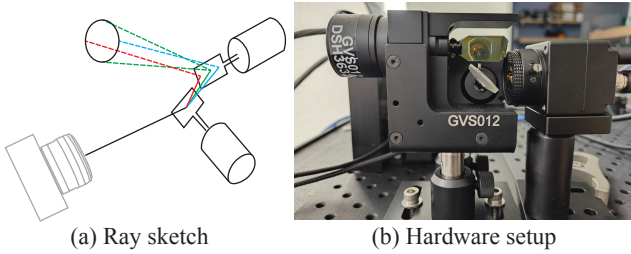


Figure 4. **Galvanometer design.** (a) Ray sketch illustrating the angular separation achieved by controlling mirror angles in the galvanometer setup. (b) Hardware setup showing the galvanometer mirror system integrated with the event camera. This design allows for capturing angular derivative events by dynamically controlling the mirror position.

developed a Blender plugin to render event fields for either spatial or temporal multiplexing design, along with a simple GUI to facilitate community use. The GUI and sample simulation results are presented in Fig. 2.

## 5.2. Kaleidoscope for Spatial Multiplexing

A kaleidoscope is a common optical instrument composed of multiple first-surface mirrors. Manakov *et al.* [30] introduced this optical device as an add-on for sensor fusion. As shown in Fig. 3, this kaleidoscope is a rectangular design made of four mirrors. The lens at the front forms an image at the entrance of the kaleidoscope. After multiple reflections within the kaleidoscope, the rear camera captures the image, resulting in several flipped images, each with a different virtual camera location. Therefore, the light field information is spatially multiplexed onto the camera sensor.

## 5.3. Galvanometer for Temporal Multiplexing

While the kaleidoscope design offers a simple solution without moving parts, it has two key limitations. First, although it provides angularly separated events, the events

still represent the derivative of light intensity over time. Second, the spatial resolution of current event cameras is not very high (1 megapixel), and this resolution would further decrease with spatial multiplexing. Temporal multiplexing offers an alternate approach.

For temporal multiplexing, we place a galvanometer, as shown in Fig. 4, in the optical path of the event camera. A galvanometer consists of two mirrors that can be precisely adjusted at high speed (Eg. GVS012 from Thorlabs can scan a thousand Lissajous curves per second). Moving mirrors allow us to rotate the camera virtually at a high speed and capture the event field. In this design, the captured information represents the derivative of light intensity with respect to angle, rather than time, as we discussed in Sec. 4.2.

## 6. Results

We evaluate the proposed techniques on various scenes. We first summarize the observations and then provide details.

*Simulations* demonstrate that each design is optimal in different contexts. The kaleidoscope (spatial multiplexing) excels in capturing dynamic scenes with high frame rates but suffers from lower spatial resolution and is ineffective for static scenes, as no events are generated without motion. The galvanometer (temporal multiplexing) captures both static and dynamic scenes at full spatial resolution by recording angular derivatives but introduces motion blur if the object motion is significant.

*Real-world applications* demonstrate each design’s post-capture refocusing capabilities. Specifically, with the galvanometer setup, we show high-resolution refocusing of static and dynamic parts of the scene. With the kaleidoscope setup, we perform sensor fusion with an RGB camera, providing vibrant, high-speed refocusing for dynamic scenes. These results underscore the complementary nature of the two designs: the kaleidoscope for high-speed dynamic capture and the galvanometer for detailed, high spatial-angular light field recovery.

In the following sections, we compare our proposed hardware designs (see Section 6.1), followed by applications for each setup. Specifically, we explore HDR light fields (Section 6.2) and slow-motion refocusing (Section 6.3) using the kaleidoscope configuration, as well as high-speed post-capture refocusing (Section 6.4) and instant true depth estimation (Section 6.5) using the galvanometer-based design.

### 6.1. Kaleidoscope vs. Galvanometer Designs

In practical applications, differences in optical properties—such as focal lengths—make it challenging to compare two cameras under identical conditions. The simulator, however, allows us to control these variables, enabling a fair comparison of both designs. We, therefore, used Blender to create a scene containing swirling water and moving objects



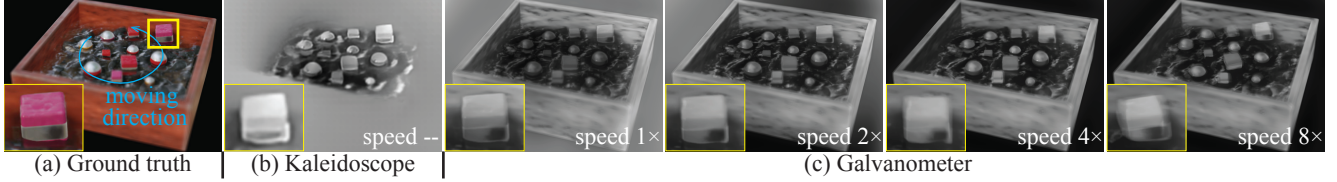


Figure 5. **(Simulation) comparison of spatial (kaleidoscope) and temporal (galvanometer) multiplexing techniques.** (a) A simulated scene with swirling water and objects, with a stationary box. (b) Refocused image using the kaleidoscope design, showing reduced spatial resolution. However, the image quality is independent of scene motion. The static wooden box is not reconstructed. (c) Refocused images using the galvanometer design at different object movement speeds ( $1\times$ ,  $2\times$ ,  $4\times$ , and  $8\times$ ) while maintaining a constant scanning speed.  $1\times$  corresponds to about 2.5 pixels per scan for the highlighted object. As the scene motion increases, the highlighted object, unlike in the kaleidoscopic design, suffers from motion blur. The static wooden boxes are perfectly reconstructed, unlike the kaleidoscopic design.

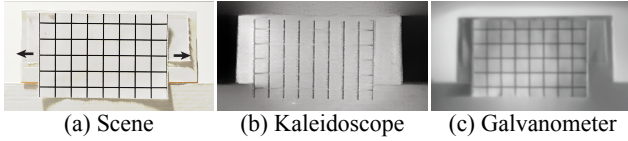


Figure 6. **(Experimental) comparison of multiplexing techniques.** (a) Reference scene with a grid pattern. (b) When the grid moves horizontally, the kaleidoscope design cannot capture horizontal lines as intensity does not change along this axis. (c) Using a galvanometer that scans in a circular motion ensures complete capture, avoiding information loss in the angular domain.

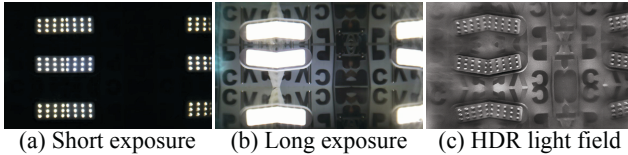


Figure 7. **High dynamic range (HDR) light field.** A high dynamic range scene is captured with a standard RGB camera using (a) short exposure and (b) long exposure, and both fail to capture the full dynamic range. In contrast, (c) the HDR light field reconstructed from the event field effectively captures the complete dynamic range of the scene.

within a stationary box (see Fig. 5) to assess the strengths and limitations of each design.

The first significant difference is that the galvanometer design can fully reconstruct scene information by capturing angular derivatives, whereas the kaleidoscope design can only capture moving objects, as no events are generated in static regions. The stationary wooden box is clearly visible in the galvanometer design but is absent in the kaleidoscope design. We also observe this in a real experiment (Fig. 6), where a rectangular mesh is translated horizontally, and the kaleidoscope fails to reconstruct horizontal lines.

A second key difference is that the galvanometer design multiplexes the event field into the time domain, making it susceptible to motion blur from rapidly moving objects. This is visible in the zoomed insets in Fig. 5. The kaleidoscope design, by contrast, avoids motion blur but instead suffers from lower spatial resolution. However, both designs can capturing and refocusing dynamic objects.

## 6.2. HDR Light Fields

Event fields are not only high-speed but also high-dynamic range light fields. We demonstrate this in Fig. 7, where the scene containing bright LED light in the foreground and diffuse texture in the background is captured using both an RGB camera and the event camera through a kaleidoscope. The event fields have a large dynamic range and capture the spatial structure of both LEDs and the background texture, whereas the RGB camera either captures the light sources (short exposure) or the background (long exposure).

## 6.3. SloMoRF: Slow Motion Refocusing

We augment the kaleidoscope design with a co-located RGB camera to capture and reconstruct slow-motion RGB frames with dynamic refocusing capability, called SloMoRF. The hardware setup, shown in Fig. 3, features a beam splitter for identical kaleidoscope views for RGB and event camera without interfering with the main lens.

We utilize the TimeLens algorithm [50] for sensor fusion<sup>1</sup>. Using the captured event data, we interpolate frames to generate a  $5\times$  higher frame-rate RGB video (from 120 to 720 fps). The interpolated results are presented in Fig. 8.

This approach allows us to generate a high-speed color light field. We treat this light field as unstructured as we found it empirically easier than calibrating the views. To align the images, we estimate the necessary shift at a specified patch using a basic pattern-matching algorithm. Note that this shift computation is *only needed once* for the entire video sequence as long as the target focal plane remains fixed. Figure 8 shows refocusing results across three focal planes. Additionally, the captured event field allows for focus tracking on a high-speed object moving along the depth. We demonstrate this capability in Fig. 9, where we visually compare sequence of images that focus on a fast-moving toy dart vs. focusing solely on the background. These results demonstrate the high frame rate, color, and refocusing capabilities of our kaleidoscope design when combined with the state-of-the-art sensor fusion algorithms.

<sup>1</sup>code for the updated TimeLens++ [51] is not publicly available

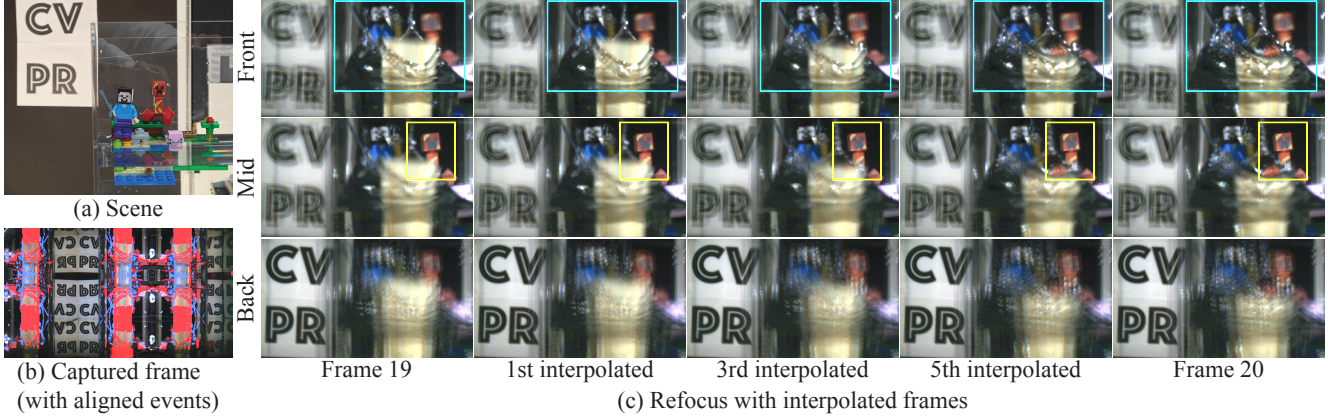


Figure 8. **SlowMoRF: Slow motion refocusing with kaleidoscope and sensor fusion.** (a) Original setup with Lego pieces floating in a water tank as a wooden brick is thrown in, with CVPR in the background, (b) Captured raw frames with aligned events using kaleidoscope design, and (c) Interpolated refocused frames at three focal planes (back, mid, and front). Between the frames, the fall of the wooden block and changes in water splash and caustics can be observed in the front refocus. Mid and back refocus show sharp Lego toys and CVPR. This setup achieves high-speed (720 fps) refocusing with enhanced clarity across focal depths. The supplementary contains the full video.

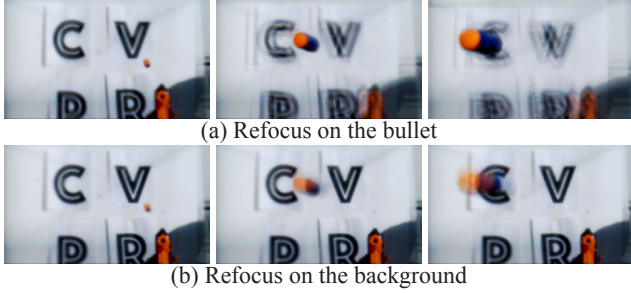


Figure 9. **High-speed refocusing on a toy dart.** The original video was captured at 120 fps, interpolating seven frames between each pair of original frames, resulting in a 960 fps high-speed light field video. The images shown here are all the middle (the fourth) interpolated frames, demonstrating refocusing on two planes: (a) the moving dart and (b) the background. Current high-speed videography cannot adjust focus during capture, so dynamic objects must remain at a fixed focal plane to stay sharp. Our technique eliminates this limitation and can focus on dynamic object.

## 6.4. High-Speed Post-capture Refocusing

In this section, we test the post-capture refocusing ability of the galvanometer setup on dynamic scenes. Compared to unstructured event field captured by kaleidoscope design, our galvanometer design produces a fully structured event field after calibration, as we precisely control the galvanometer with a signal generator to determine the angle relative to time. The supplementary materials provide calibration details.

Using E2VID, we generate a high-speed video at 10,000 fps (0.1 ms per frame) from the captured event field data. The galvanometer is operating at 250 Hz. Therefore, we reconstruct the light field at 250 fps and 40 views, the fastest recorded so far at a megapixel resolution.

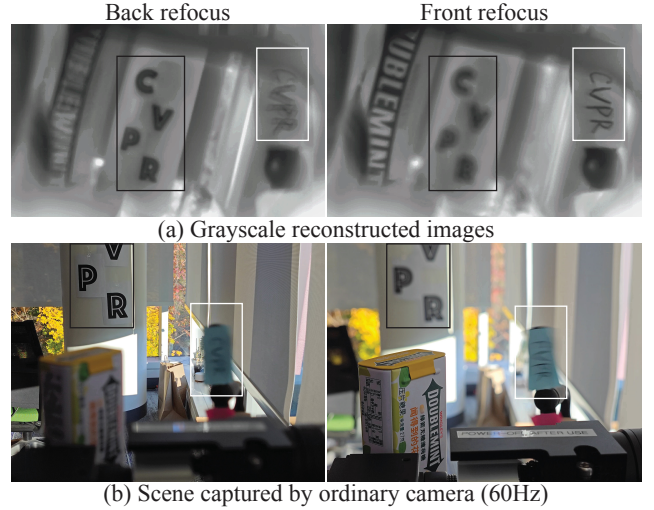


Figure 10. **Dynamic scene refocusing.** Using our galvanometer design at 250 Hz, we capture a scene with a rotating fan marked with “CVPR”, spinning at 300 rpm. (a) Using prior knowledge of the scanned mirror’s location, we refocus on the background or the rotating fan in the foreground. (b) An ordinary camera captures the scene at 60Hz, focusing on the background and foreground from different viewpoints. The camera lacks refocus ability and causes motion blur on the fan due to the slower shutter speed.

Using this light field and equations in Sec. 3.1, we can do post-capture refocusing. Note that even though E2VID generates noisy frames at high speed (due to low light), the noise gets averaged out when we synthesize a refocused image. In Fig. 10, we show refocusing results on the background texture (left figure) or foreground fan (right figure) and can observe that they are noise-free. We further stress-tested our hardware setup in Fig. 11 and noticed that the event camera begins to lose events due to the readout bandwidth limit when the galvanometer operates beyond 250 Hz.



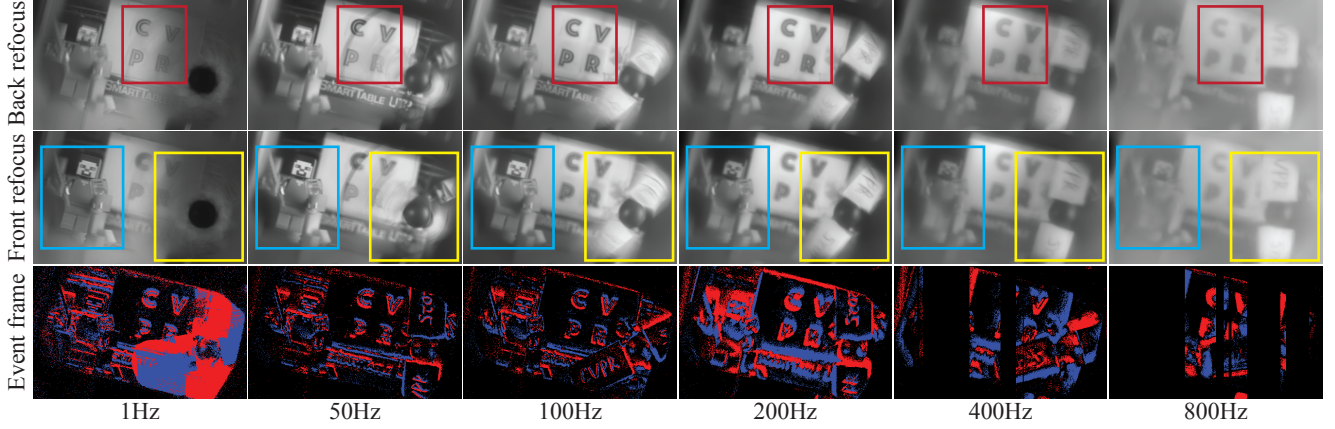


Figure 11. **Effect of galvo scan frequency for refocusing accuracy.** The scene consists of two static objects positioned in the foreground and background, along with a fan (highlighted in yellow boxes) in the foreground rotating at 480 RPM. The static objects (highlighted in red and blue boxes) remain sharp up to a scanning frequency of 200 Hz but become increasingly blurry as the scan speed increases. This counter intuitive phenomenon occurs as event camera reaches its maximum bandwidth capacity, resulting in random event loss, as seen in the *Event frame* row. However, the text on the rotating fan becomes clearer at higher scan speeds due to reduced motion blur.

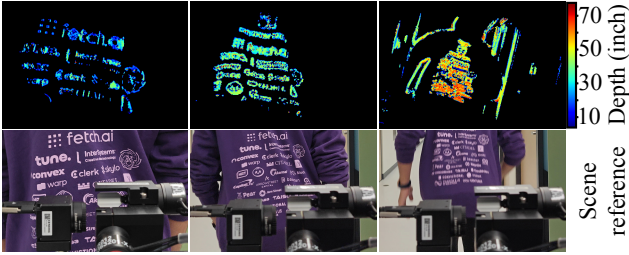


Figure 12. **Instant true depth estimation at 100 Hz.** Depth mapping of a running person, shown in three frames with color-coded depth scale (in inches), highlighting the system’s capability for rapid, accurate depth measurement in dynamic scenes.

### 6.5. Instant True Depth Estimation

In addition to refocusing, our galvanometer design enables real-time true depth estimation. Unlike SLAM-based methods [5], our approach provides instant true depth estimation based on the event field. As outlined in Sec. 6.4, our galvanometer design generates a structured light field, requiring only a single calibration step to determine the depth-to-disparity ratio. We employ the “depth from focus” algorithm [13] to calculate the depth of each pixel. This involves first constructing a focal stack by refocusing the light field at various depths. For each pixel, we determine the focal stack image where the pixel appears sharpest, and the depth associated with that image is the depth of the pixel.

By adopting this approach, we obtain the instant true depth at the same frequency as the galvanometer’s scanning speed. As shown in Fig. 12, a 100 Hz galvo scan successfully captures a person running away from the camera, offering sparse yet real-time depth information of the letters on their shirt at a rate of 100 fps.

## 7. Discussion and Future Work

In this manuscript, we introduce “event field”, a new approach for capturing high-speed, high resolution, HDR light fields using two optical configurations—kaleidoscope and galvanometer—combined with an event camera. Our kaleidoscope design enables capturing temporal derivatives for multiple views, while the galvanometer design captures angular derivatives along curves. We validate both designs through simulations and real-world data, demonstrating their unique advantages.

Our experiments showcase several potential applications. Most notably, our setup enables high-speed refocusing on fast-moving objects, real-time true depth estimation, and high-dynamic-range light field capture. Supplementary PDF and video provides further visualizations of these results across additional scenes.

While our approach shows several new possibilities, it also creates new research problems in the graphics, imaging, and vision fields. Our current brute-force simulation of the event field could benefit from optimal importance sampling techniques that improve the rendering speed by orders of magnitude similar to previous importance techniques for computational cameras [20, 22, 27, 40]. Additionally, as shown in Fig. 11, static parts of the scene do not require high bandwidth. By implementing adaptive scanning (e.g., slower scans for static parts, faster scans for dynamic areas) with a MEMS array, we can enhance bandwidth efficiency. We currently use pre-trained E2VID and Timelens models, which are optimized for time-sequential event streams. Generating sufficient event field data, possibly through an optimal simulator and training models specifically for our event fields, would yield a significant performance boost.



## Acknowledgment

This project is funded by NSF awards 2403122, 2326904, 2107454, and 2107313 and ARPA-H award D24AC00296.

We thank Laurence Rubin at Boston Craft Works, Joseph Poissant at Dartmouth Engineering Machine Shop, and Hannah Machesky at Two Way Mirrors for providing mirrors and polishing expertise for our kaleidoscope design.

We also extend our gratitude to the RISC lab members, Atul Agarwal, Dhawal Sirikonda, Kedari Chowtoori, and Sarah Friday, for their generous assistance in capturing the data and their 3D printing and laser cutting skills.

## References

- [1] Edward H Adelson, James R Bergen, et al. *The plenoptic function and the elements of early vision*. Vision and Modeling Group, Media Laboratory, Massachusetts Institute of . . . , 1991. 3
- [2] Ryad Benosman, Charles Clercq, Xavier Lagorce, Sio-Hoi Ieng, and Chiara Bartolozzi. Event-based visual flow. *IEEE transactions on neural networks and learning systems*, 25 (2):407–417, 2013. 2
- [3] Tom E Bishop and Paolo Favaro. The light field camera: Extended depth of field, aliasing, and superresolution. *IEEE transactions on pattern analysis and machine intelligence*, 34(5):972–986, 2011. 3
- [4] Christian Brandli, Raphael Berner, Minhao Yang, Shih-Chii Liu, and Tobi Delbruck. A  $240 \times 180$  130 db 3  $\mu$ s latency global shutter spatiotemporal vision sensor. *IEEE Journal of Solid-State Circuits*, 49(10):2333–2341, 2014. 3
- [5] Cesar Cadena, Luca Carlone, Henry Carrillo, Yasir Latif, Davide Scaramuzza, José Neira, Ian Reid, and John J Leonard. Past, present, and future of simultaneous localization and mapping: Toward the robust-perception age. *IEEE Transactions on robotics*, 32(6):1309–1332, 2016. 8
- [6] Bharatesh Chakravarthi, Aayush Atul Verma, Kostas Daniilidis, Cornelia Fermuller, and Yezhou Yang. Recent event camera innovations: A survey. *arXiv preprint arXiv:2408.13627*, 2024. 2
- [7] Blender Online Community. Blender - a 3d modelling and rendering package, 2024. 4
- [8] Toshiaki Fujii and Masayuki Tanimoto. A real-time ray-space acquisition system. In *Stereoscopic Displays and Virtual Reality Systems XI*, pages 179–187. SPIE, 2004. 2, 4
- [9] Guillermo Gallego, Jon EA Lund, Elias Mueggler, Henri Rebecq, Tobi Delbruck, and Davide Scaramuzza. Event-based, 6-dof camera tracking from photometric depth maps. *IEEE transactions on pattern analysis and machine intelligence*, 40(10):2402–2412, 2017. 3
- [10] Guillermo Gallego, Tobi Delbrück, Garrick Orchard, Chiara Bartolozzi, Brian Taba, Andrea Censi, Stefan Leutenegger, Andrew J Davison, Jörg Conradt, Kostas Daniilidis, et al. Event-based vision: A survey. *IEEE transactions on pattern analysis and machine intelligence*, 44(1):154–180, 2020. 2, 3
- [11] Mathias Gehrig, Mario Millhäusler, Daniel Gehrig, and Davide Scaramuzza. E-raft: Dense optical flow from event cameras. In *2021 International Conference on 3D Vision (3DV)*, pages 197–206. IEEE, 2021. 2
- [12] Steven J. Gortler, Radek Grzeszczuk, Richard Szeliski, and Michael F. Cohen. The lumigraph. In *Proceedings of the 23rd Annual Conference on Computer Graphics and Interactive Techniques*, page 43–54, New York, NY, USA, 1996. Association for Computing Machinery. 2, 3
- [13] Paul Grossmann. Depth from focus. *Pattern recognition letters*, 5(1):63–69, 1987. 8
- [14] Ruipeng Guo, Qianwan Yang, Andrew S Chang, Guorong Hu, Joseph Greene, Christopher V Gabel, Sixian You, and Lei Tian. Eventlfr: Event camera integrated fourier light field microscopy for ultrafast 3d imaging. *Light: Science & Applications*, 13(1):144, 2024. 3
- [15] Mohit Gupta, Andreas Velten, Shree K Nayar, and Eric Breitenbach. What are optimal coding functions for time-of-flight imaging? *ACM Transactions on Graphics (TOG)*, 37(2):1–18, 2018. 4
- [16] Shuji Habuchi, Keita Takahashi, Chihiro Tsutake, Toshiaki Fujii, and Hajime Nagahara. Time-efficient light-field acquisition using coded aperture and events. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 24923–24933, 2024. 3
- [17] Botao He, Ze Wang, Yuan Zhou, Jingxi Chen, Chahat Deep Singh, Haojia Li, Yuman Gao, Shaojie Shen, Kaiwei Wang, Yanjun Cao, et al. Microsaccade-inspired event camera for robotics. *Science Robotics*, 9(90):eadj8124, 2024. 3
- [18] Xueyan Huang, Yueyi Zhang, and Zhiwei Xiong. High-speed structured light based 3d scanning using an event camera. *Optics Express*, 29(22):35864–35876, 2021. 3
- [19] Ivo Ihrke, Timo Stich, Heiko Gottschlich, Marcus Magnor, and Hans-Peter Seidel. Fast incident light field acquisition and rendering. *Journal of WSCG*, 2008. 2
- [20] Adrian Jarabo, Julio Marco, Adolfo Munoz, Raul Buisan, Wojciech Jarosz, and Diego Gutierrez. A framework for transient rendering. *ACM Transactions on Graphics (ToG)*, 33 (6):1–10, 2014. 8
- [21] Jing Jin, Junhui Hou, Hui Yuan, and Sam Kwong. Learning light field angular super-resolution via a geometry-aware network. In *Proceedings of the AAAI conference on artificial intelligence*, pages 11141–11148, 2020. 2, 4
- [22] Juhyeon Kim, Wojciech Jarosz, Ioannis Gkioulekas, and Adithya Pediredla. Doppler time-of-flight rendering. *ACM Trans. Graph.*, 42(6), 2023. 8
- [23] T Leroux, S-H Ieng, and Ryad Benosman. Event-based structured light for depth reconstruction using frequency tagged light patterns. *arXiv preprint arXiv:1811.10771*, 2018. 3
- [24] M. Levoy. Light fields and computational imaging. *Computer*, 39(8):46–55, 2006. 2
- [25] Marc Levoy and Pat Hanrahan. Light field rendering. In *Proceedings of the 23rd Annual Conference on Computer Graphics and Interactive Techniques*, page 31–42, New York, NY, USA, 1996. Association for Computing Machinery. 2, 3

- [26] Patrick Lichtsteiner, Christoph Posch, and Tobi Delbruck. A  $128 \times 128$  120 db  $15\mu\text{s}$  latency asynchronous temporal contrast vision sensor. *IEEE journal of solid-state circuits*, 43(2):566–576, 2008. 3
- [27] Yang Liu, Shaojie Jiao, and Wojciech Jarosz. Temporally sliced photon primitives for time-of-flight rendering. In *Computer Graphics Forum*, pages 29–40. Wiley Online Library, 2022. 8
- [28] Lytro. Lytro. <https://www.lytro.com/>, 2017. [Online; accessed 6-Oct-2024]. 2
- [29] Misha Mahowald and Misha Mahowald. The silicon retina. *An Analog VLSI System for Stereoscopic Vision*, pages 4–65, 1994. 2, 3
- [30] Alkhazur Manakov, John Restrepo, Oliver Klehm, Ramon Hegedus, Elmar Eisemann, Hans-Peter Seidel, and Ivo Ihrke. A reconfigurable camera add-on for high dynamic range, multispectral, polarization, and light-field imaging. *ACM Transactions on Graphics*, 32(4):47–1, 2013. 2, 4, 5
- [31] Ashish Rao Mangalore, Chandra Sekhar Seelamantula, and Chetan Singh Thakur. Neuromorphic fringe projection profilometry. *IEEE Signal Processing Letters*, 27:1510–1514, 2020. 3
- [32] Nathan Matsuda, Oliver Cossairt, and Mohit Gupta. Mc3d: Motion contrast 3d scanning. In *2015 IEEE International Conference on Computational Photography (ICCP)*, pages 1–10. IEEE, 2015. 3
- [33] Leonard McMillan and Gary Bishop. Plenoptic modeling: An image-based rendering system. In *Seminal Graphics Papers: Pushing the Boundaries, Volume 2*, pages 433–440. Association for Computing Machinery, 2023. 3
- [34] Anton Mitrokhin, Zhiyuan Hua, Cornelia Fermuller, and Yiannis Aloimonos. Learning visual motion segmentation using event surfaces. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 14414–14423, 2020. 2
- [35] Manasi Muglikar, Guillermo Gallego, and Davide Scaramuzza. Esl: Event-based structured light. In *2021 International Conference on 3D Vision (3DV)*, pages 1165–1174. IEEE, 2021. 3
- [36] Manasi Muglikar, Diederik Paul Moeys, and Davide Scaramuzza. Event guided depth sensing. In *2021 International Conference on 3D Vision (3DV)*, pages 385–393. IEEE, 2021. 3
- [37] Manasi Muglikar, Leonard Bauersfeld, Diederik Paul Moeys, and Davide Scaramuzza. Event-based shape from polarization. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 1547–1556, 2023. 3
- [38] Manasi Muglikar, Siddharth Somasundaram, Akshat Dave, Edoardo Charbon, Ramesh Raskar, and Davide Scaramuzza. Event cameras meet spads for high-speed, low-bandwidth imaging. *arXiv preprint arXiv:2404.11511*, 2024. 3
- [39] Ren Ng, Marc Levoy, Mathieu Brédif, Gene Duval, Mark Horowitz, and Pat Hanrahan. *Light field photography with a hand-held plenoptic camera*. PhD thesis, Stanford university, 2005. 2, 4
- [40] Adithya Pediredla, Yasin Karimi Chalmiani, Matteo Giuseppe Scopelliti, Maysamreza Chamanzar, Srinivasa Narasimhan, and Ioannis Gkioulekas. Path tracing estimators for refractive radiative transfer. *ACM Transactions on Graphics (TOG)*, 39(6):1–15, 2020. 8
- [41] Luboš Poláček, Jana Jurmanová, and Zdeněk Navrátil. Laser galvo mirrors: perfect instrument for the demonstration of lissajous figures. *Physics Education*, 54(5):055002, 2019. 4
- [42] Christoph Posch, Daniel Matolin, and Rainer Wohlgenannt. A qvga 143 db dynamic range frame-free pwm image sensor with lossless pixel-level video compression and time-domain cds. *IEEE Journal of Solid-State Circuits*, 46(1):259–275, 2010. 3
- [43] Ziyuan Qu. Event field. <https://dartmouth-risc-lab.github.io/event-field-website/>, 2024. 2
- [44] A Raytrix. 3d light field camera technology, 2017. 2
- [45] Henri Rebecq, René Ranftl, Vladlen Koltun, and Davide Scaramuzza. High speed and high dynamic range video with an event camera. *IEEE transactions on pattern analysis and machine intelligence*, 43(6):1964–1980, 2019. 3
- [46] Hans Sagan. *Space-filling curves*. Springer Science & Business Media, 2012. 4
- [47] Dhawal Sirikonda, Praneeth Chakravarthula, Ioannis Gkioulekas, and Adithya Pediredla. Structured light with a million light planes per second. *arXiv preprint arXiv:2411.18597*, 2024. 3
- [48] Yuichi Taguchi, Amit Agrawal, Srikumar Ramalingam, and Ashok Veeraraghavan. Axial light field for curved mirrors: Reflect your perspective, widen your view. In *2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pages 499–506. IEEE, 2010. 2
- [49] David Tedaldi, Guillermo Gallego, Elias Mueggler, and Davide Scaramuzza. Feature detection and tracking with the dynamic and active-pixel vision sensor (davis). In *2016 Second International Conference on Event-based Control, Communication, and Signal Processing (EBCCSP)*, pages 1–7. IEEE, 2016. 2
- [50] Stepan Tulyakov, Daniel Gehrig, Stamatios Georgoulis, Julius Erbach, Mathias Gehrig, Yuanyou Li, and Davide Scaramuzza. Time lens: Event-based video frame interpolation. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 16155–16164, 2021. 3, 6
- [51] Stepan Tulyakov, Alfredo Bochicchio, Daniel Gehrig, Stamatios Georgoulis, Yuanyou Li, and Davide Scaramuzza. Time lens++: Event-based frame interpolation with parametric non-linear flow and multi-scale fusion. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 17755–17764, 2022. 3, 6
- [52] Zhexiong Wan, Yuchao Dai, and Yuxin Mao. Learning dense and continuous optical flow from an event camera. *IEEE Transactions on Image Processing*, 31:7237–7251, 2022. 2
- [53] Gaochang Wu, Belen Masia, Adrian Jarabo, Yuchen Zhang, Liangyong Wang, Qionghai Dai, Tianyou Chai, and Yebin Liu. Light field image processing: An overview. *IEEE Journal of Selected Topics in Signal Processing*, 11(7):926–954, 2017. 2
- [54] Jason C Yang, Matthew Everett, Chris Buehler, and Leonard McMillan. A real-time distributed light field camera. *Rendering Techniques*, 2002(77-86):2, 2002. 2, 4

- [55] Bohan Yu, Jieji Ren, Jin Han, Feishi Wang, Jinxiu Liang, and Boxin Shi. Eventps: Real-time photometric stereo using an event camera. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 9602–9611, 2024. [3](#)
- [56] Mingyuan Zhao, Hao Sheng, Da Yang, Sizhe Wang, Ruixuan Cong, Zhenglong Cui, Rongshan Chen, Tun Wang, Shuai Wang, Yang Huang, et al. A survey for light field super-resolution. *High-Confidence Computing*, page 100206, 2024. [2](#), [4](#)
- [57] Yi Zhou, Guillermo Gallego, Xiuyuan Lu, Siqu Liu, and Shaojie Shen. Event-based motion segmentation with spatio-temporal graph cuts. *IEEE transactions on neural networks and learning systems*, 34(8):4868–4880, 2021. [2](#)
- [58] Zihao Zou, Ziyuan Qu, Xi Peng, Vivek Boominathan, Adithya Pediredla, and Praneeth Chakravarthula. High-speed dynamic 3d imaging with sensor fusion splatting. *arXiv preprint arXiv:2502.04630*, 2025. [3](#)



# Event fields: Capturing light fields at high speed, resolution, and dynamic range

## Supplementary Material

### 1. Calibration details for galvanometer setup

The galvanometer scans on a Lissajous curve, and we need to register the exact location of the galvanometer corresponding to each event time stamp to know the light field view we are measuring. One way to achieve this is to synchronize the event clock with the signal sent to the Galvanometer. However, this complicates the hardware design and generates additional events for the synchronization clock, decreasing the overall useful bandwidth. Instead, we took an algorithmic approach to achieve this synchronization using the captured event field data itself.

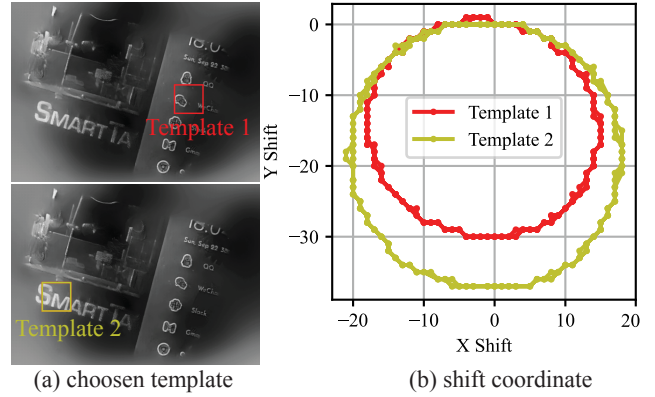
The key idea for the algorithmic approach is the observation that any patch in the reconstructed sequence of images will best correlate with other images in the sequence along the scanned Lissajous curve path. For example, we use circular Lissajous curves for scanning in Supp. Fig. 1. For two patches, we show the shifts for best-correlated patches for all subsequent reconstructed frames and notice that the shifts lie on a circle. The size of the circle (or, in general, the size of the Lissajous curve) depends on the depth of the patch. Therefore, by computing the view of the first frame (i.e., its location on the scanning curve), we calibrate the views for the entire light field sequence. This calibration can be accomplished from just one patch and by correlating with as few as three images for circular Lissajous curves, though we used 40 images for robustness.

In Supp. Fig. 2, we use this procedure to calibrate the light field views and use the equations in Sec. 3.1 to refocus the reconstructed light field at different depths. We show two images corresponding to the back refocus and front refocus of the light field data for two static scenes along the rows. In the main manuscript, we also showed refocusing results for dynamic scenes. (see Fig. 10 and Fig. 11)

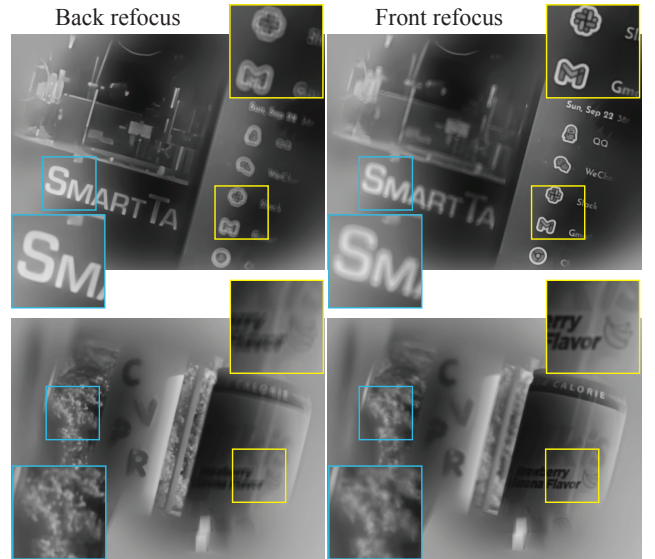
### 2. Depth Calibration Details

Event fields capture multi-view images and hence capture true-depth information about the scene. As mentioned in Sec. 6.5, we use depth from focus to capture the depth of each pixel in the scene. The depth from focus gives us disparity (i.e., the size of the Lissajous curve) for each pixel, and as mentioned in the previous section, the size of the Lissajous curve is proportional to the patch depth. We compute the proportionality constant by calibrating the system.

We placed a single bright point light source (LED) at a known depth from the galvanometer and computed the size of the Lissajous curve. We repeated this experiment for different depth locations of the light source and plotted them as shown in Supp. Fig. 3. The slope of this line gives

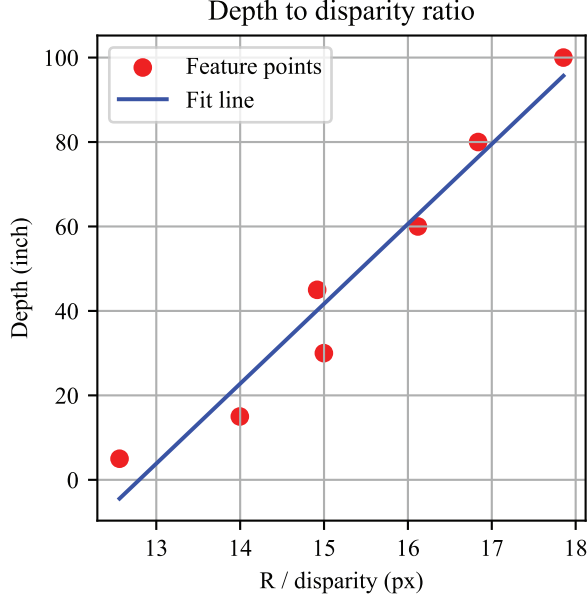


Supp. Figure 1. **Result of template matching.** (a) Two templates are selected from the reconstructed light field image—one in the foreground and one in the background. A template matching algorithm is applied to each template across all light field images to determine the shift amounts in (x,y). (b) The calculated shift amounts are plotted, forming a circular pattern consistent with the scanning curve, validating our concept.

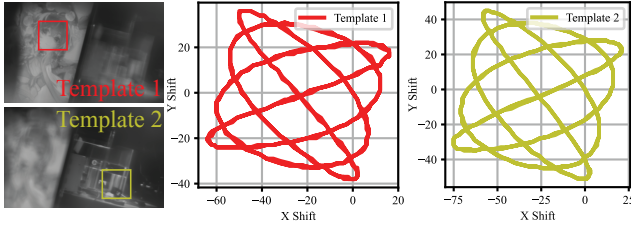


Supp. Figure 2. **Static scene refocusing.** Two distinct static scenes are captured using our galvanometer design at a scan speed of 1 Hz. E2VID is used to reconstruct 100 light field frames. For each scene, we present the reconstructed refocusing result on two selected regions.

us the proportionality constant, and the y-intercept (depth = 0) gives us the bias which is the distance between the camera and the galvo location in pixels.



Supp. Figure 3. **Depth calibration.** We calibrate 7 depth points using an LED light placed at distances ranging from 15 inches to 100 inches. The depth (in inches) is linearly fitted to the disparity (in pixels) within this range, serving as our calibrated ratio. For new scenes, we detect disparity using a depth-from-focus algorithm and convert it into real-world depth using this calibrated relationship.



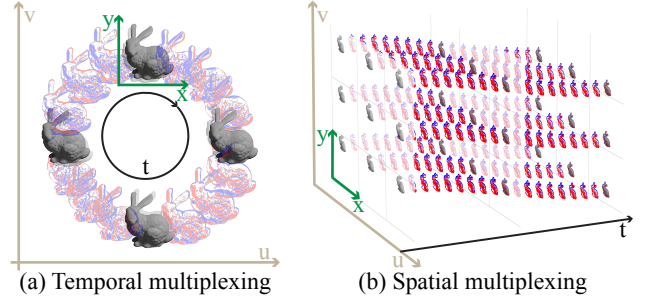
Supp. Figure 4. Scan and refocus with non-circular Lissajous curves.

### 3. Other Lissajous Curves

The galvanometer supports any Lissajous curves (Supp. Fig. 4), not only circular scan. We can also use a look-up table for arbitrary scanning like Fujii *et al.* [8], but it will slow down the scanning similar to theirs. Calibration details are presented in the supplementary material. Galvos are repeatable, accurate ( $\approx 15\mu\text{rad}$ ), and easy to calibrate.

### 4. Illustration

Since everything is 5D and involves derivatives, we illustrated the event field coordinate in the supplementary video. Following the reviewers' advice, we made Supp. Fig. 5 for detailing the event field coordinate frame in both temporal multiplexing and spatial multiplexing.



Supp. Figure 5. Temporal multiplexing captures angular derivatives where as spatial multiplexing embeds angular information in spatial domain. (Bunny is falling down.)

## 5. Codes and Videos

Along with this supplementary PDF, we provide additional materials to support and reproduce the results presented in the paper, including a short video summarizing the paper's contributions, as well as the code and datasets used to generate the results:

- **Images and Videos:** All images and videos from the main paper and supplementary materials are included separately in the “./results/” folder.
- **Refocusing Algorithms and Raw Data:** The code for the refocusing algorithms, based on our kaleidoscope and galvanometer designs, is available on GitHub [43]. Additionally, we provide a short version of the raw data corresponding to the galvanometer design showcased in Fig. 10, as well as the kaleidoscope design highlighted in the slow-motion refocus example in Fig. 1. We will make all these public in the non-anonymous version of the manuscript.