eSports Broadcasts with Event Cameras

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Abstract. Event cameras, characterized by their ability to capture brightness changes through asynchronous events, hold promise for revolutionizing eSports broadcasting. Unlike traditional cameras, they offer high temporal resolution, immense dynamic range, and no motion blur-features crucial for recording the rapid, fine motor skills of eSports athletes. This paper introduces a novel application of event cameras in an eSports environment to enhance the viewer experience by capturing detailed hand movements. We have developed an algorithm to efficiently extract regions of interest from the event data, pinpointing rapid hand movements. This enables directors to effectively highlight the subtle maneuvers of game players, optimizing directorial decisions and enhancing viewer engagement. Additionally, we have collected a dataset of eSports competition scenes for a detailed comparative analysis against standard RGB cameras. Our findings highlight the superior ability of event cameras to capture nuanced motions that are often missed in traditional broadcasts. By utilizing advanced imaging technology, we pave the way for eSports broadcasting that is both high speed and high dynamic range.

Keywords: Neuromorphic Imaging · Event Camera · Computational Imaging · Video processing · Dynamic Range · Motion Blur · Sports

1 Introduction

The rapid growth of eSports has catalyzed a demand for more dynamic and engaging broadcasting techniques [28]. Traditional broadcasts, reliant on standard RGB cameras, often fall short in capturing the intricate details of eSports competitions, particularly the fast, precise hand movements of professional gamers [18]. These subtle actions, crucial for a comprehensive understanding and enjoyment of the game, typically occur at speeds that surpass the capturing capabilities of conventional video technology, leading to a gap in what viewers can experience and appreciate during live streams or replays. The rapid and coordinated hand movements in eSports highlight the need for advanced capturing technologies to fully convey the players' behavioral decisions and control mechanisms [15,20].

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Enhancing the viewer experience in eSports broadcasting is not merely a matter of entertainment value but is pivotal for the sports growth, audience retention, and educational outreach. The challenge lies in the inherent limitations of traditional broadcast technology, which struggles with low temporal resolution and high motion blur [29]. These technological shortcomings prevent a detailed, clear depiction of quick, minute actions, crucial in fast-paced eSports environments [10]. Additionally, the dynamic range of standard cameras often inadequately handles the varied lighting conditions typical in eSports arenas, leading to over or underexposed footage, further diminishing the broadcast quality [24].

Historically, advancements in sports broadcasting have attempted to address these issues through high-frame-rate cameras and enhanced post-production techniques [12]. While these developments have incrementally improved clarity and detail capture, they often involve significant delays in broadcast feeds and require intensive computational resources. Moreover, even with high-frame-rate technology, the problem of inadequate dynamic range remains unresolved, as these cameras still operate under the constraints of conventional frame-based capture mechanisms. This limitation is particularly pronounced in eSports, where player actions can be both rapid and subtle, requiring an innovative approach beyond traditional methodologies [21].

In response to these challenges, our research introduces a novel application of event cameras for eSports broadcasts. Unlike traditional cameras, event cameras capture changes in brightness through asynchronous events, thereby providing high temporal resolution and an immense dynamic range without the associated motion blur [8,9,14,22,23,31,32,37,42]. This paper proposes the use of event cameras specifically tailored to enhance eSports broadcasts by focusing on the precise, rapid hand movements of players. We design an efficient algorithm to efficiently extract regions of interest (ROI) from the event data, which accurately identifies and highlights critical in-game actions that are typically overlooked. This advanced method allows for automated, real-time directing of broadcasts by dynamically selecting and showcasing the most relevant in-game actions. This capability addresses the previously manual and labor-intensive process of selecting ROI or adjusting camera positions to capture critical gameplay moments.

Our main contributions are as follows:

1. **Innovative Application of Event Cameras:** We propose the use of event cameras in an eSports environment to enhance the visual quality of broadcasts by capturing detailed hand movements.
2. **Efficient ROI Extraction Algorithm:** We design an efficient algorithm for extracting ROI that effectively pinpoints rapid hand movements, which optimizes the broadcasting process by reducing the need for manual direction, thus enhancing both operational efficiency and viewer engagement.
3. **Dataset Collection:** We establish a dataset of eSports competitions, capturing gameplay using both traditional cameras and event cameras simultaneously, which provides a valuable resource for further research.
4. **Experimental Validation:** Our experimental results demonstrate that our approach captures nuanced motions with greater clarity and detail than tra-

Table 1. Comparison of different cameras. Event cameras offer advantages in cost, latency, and dynamic range over low-speed and high-speed traditional cameras.

Type	Low-speed camera	High-speed camera	Event camera
Low cost	✔	✘	✔
Low latency	✘	✔	✔
HDR	✘	✘	✔

ditional broadcasts, achieving a superior video output characterized by both high speed and high dynamic range (HDR), which sets new benchmarks for broadcast quality in eSports.

2 Related Work

2.1 Imaging Systems in Sports Broadcasting

Traditional sports broadcasts use standard cameras limited by motion blur and inadequate dynamic range, affecting human motion capture [16,35,36]. Hilton et al. [13] discuss enhancing broadcasts via 3D-TV production from multi-camera setups, emphasizing dynamic sports challenges. Routhier et al. [26] highlight limitations in capturing fast-paced actions due to temporal resolution constraints.

Chen et al. [4] studied camera selection algorithms for soccer but focused on traditional systems, not the rapid, fine-grained motions in eSports. Rosney et al. [25] explored automating broadcasts with ultra-HD cameras and neural networks, but high computational demands hinder real-time eSports applications. Han et al. [11] improved dynamic camera adaptation in court-net sports videos but may not capture subtle eSports hand movements. Demiris et al. [5] enhanced broadcasts with MPEG-4 augmented reality, improving viewer engagement. Foote et al. [7] developed a touch screen interface for live multi-camera broadcasts, enhancing production with minimal intervention. Shang et al. [27] assessed HDR video quality in sports for superior viewing in varied lighting.

Our algorithm leverages event cameras to focus on eSports athletes' fine motor skills, efficiently extracting ROIs from event data with reduced computational complexity, suitable for real-time applications and capturing rapid, subtle movements in eSports broadcasting.

2.2 Event Cameras

As shown in Table 1, event cameras offer advantages where high temporal resolution and HDR are needed without high cost or computational demands. Pioneering work [22,23] and studies [8,9,14,31,32,37,42] demonstrate their effectiveness in capturing detailed motion.

In autonomous driving, event cameras improve object detection under challenging conditions [3,17,30,41]; Tomy et al. [30] fused event data with RGB images for enhanced detection. In robotic perception, they enable high-speed motion tracking [19], allowing faster reactions due to high temporal resolution. Event cameras are used in IoT applications for efficient sensor data exchange [6], ideal for surveillance with low power consumption and varying lighting. In sports broadcasting, event cameras address limitations of conventional cameras. Their asynchronous data capture allows detailed motion without blur. Angelopoulos et al. [2] demonstrated event-based gaze tracking beyond 10,000 Hz, showcasing potential in capturing fine-grained, high-speed motions.

Our work builds on these foundations, introducing event cameras to eSports, which demands high detail and responsiveness. By leveraging their high temporal resolution and dynamic range, we aim to capture rapid, subtle hand movements of eSports athletes, often missed by traditional methods.

3 Method

3.1 System Overview

We present an overview of our system for eSports broadcasting using traditional and event cameras. It captures detailed hand movements of eSports athletes, crucial for analyzing their fine motor skills. The process involves four primary steps, depicted in Fig. 1.

1. **Scene Capture.** As shown in Fig. 2, we use traditional and event cameras simultaneously to record the same eSports scene. This setup captures both video frames and event data. Traditional cameras provide frame-by-frame video, while event cameras offer a high-temporal-resolution stream of pixel intensity changes.
2. **ROI Extraction.** From the event data, we extract ROIs highlighting motion, especially rapid hand movements. An efficient algorithm identifies these ROIs without manual intervention.
3. **Frame Reconstruction**. Using the extracted ROIs, we reconstruct intensity images (Fig. 3) via existing methods [22,23] without hand-crafted priors, ensuring frames with optimized clarity and detail.
4. **Cropping for Detail.** We crop the reconstructed and traditional frames based on the identified ROIs, focusing on detailed hand movements for closer examination of athletes' fine motor skills.

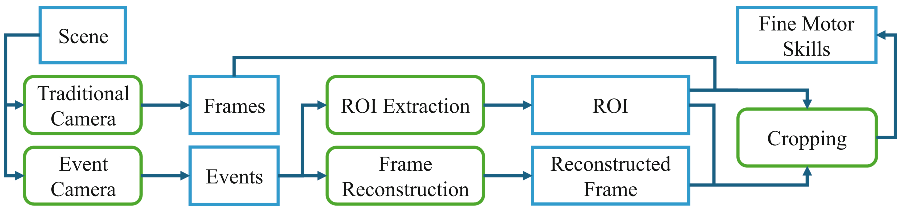

Fig. 1. System workflow for eSports broadcasts using traditional and event cameras. The process includes simultaneous scene capture, ROI extraction from event data, frame reconstruction, and focused cropping to emphasize fine motor skills.

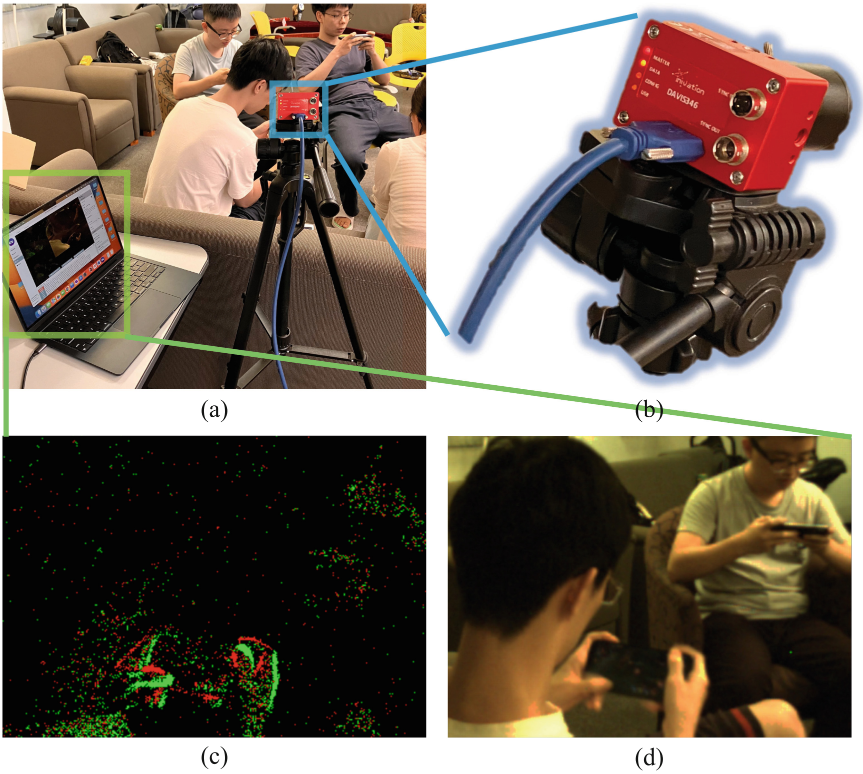

Fig. 2. Our camera setup used in capturing an eSports competition scene in (a). The setup in (b) includes both an event sensor and a traditional frame sensor, allowing for simultaneous recording of event data in (c) and conventional video frames in (d).

3.2 ROI Extraction

In this section, we discuss ROI extraction from event data captured during eSports competitions. Event cameras capture pixel intensity changes as events, providing dynamic and detailed movement crucial for analyzing fast actions.

Following [37], we denote the event stream as $\varepsilon = \{e_i\}_{i=1}^{n}$, where each event $e_i = (x_i, y_i, t_i, p_i)$ includes spatial coordinates (x_i, y_i), timestamp t_i, and polarity $p_i \in \{\pm 1\}$. To extract the ROI, we construct an event map $\mathbf{E} \in 0, 1^{H \times W}$ from the event stream, where H and W denote the height and width, by:

$$\mathbf{E}(a,b) = \sum_{i=1}^{n} \mathbb{1}\{x_i = a\}\mathbb{1}\{y_i = b\}|p_i|, \quad \forall a = 1, \cdots, H, \ \forall b = 1, \cdots, W, \tag{1}$$

where $\mathbf{E}(a,b)$ is the element on the a_{th} row and b_{th} column of the event map.

After obtaining the event map $\mathbf{E}$, we use it to facilitate directing eSports broadcasts. The key insight is that fine motor actions of eSports athletes occur

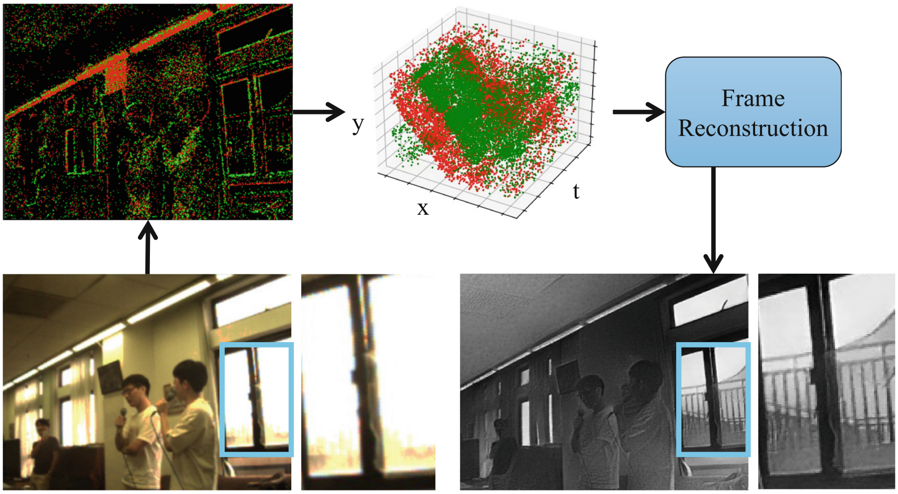

Fig. 3. Frame reconstruction from event data. The areas within the blue boxes illustrate the enhanced clarity and detail achieved with event cameras compared to traditional imaging systems. (Color figure online)

in areas with high event frequency (see Fig. 4); thus, we aim to identify sub-regions where events occur frequently.

Assuming the ROI is a sub-region of height M and width N, the straightforward method is to traverse the entire event map and compute sums within each sub-rectangle, which has a computational complexity of $O(H * W * M * N)$. To improve efficiency, we design an algorithm reducing the complexity to $O(H * W * (M + N))$, as shown in Algorithm 1.

Specifically, our algorithm first performs a horizontal scan across each row of the event map, summing events within predefined window widths to identify regions with the highest event density and storing these indices. Then, it evaluates vertical slices using the stored indices to find the most event-dense vertical sections. By segregating the analysis into horizontal and vertical components and focusing on high-event areas, we streamline the process, reducing complexity from $O(H * W * M * N)$ to $O(H * W * (M + N))$, effectively optimizing ROI detection even in complex eSports environments.

While our algorithm may not guarantee optimal solutions in complex or extreme cases due to efficiency trade-offs, experiments show that in eSports competitions, most areas remain static, with only small regions—the athletes' hands—exhibiting rapid movements that generate many events. Therefore, our algorithm is sufficiently effective and efficient in extracting the ROI for dynamic activities.

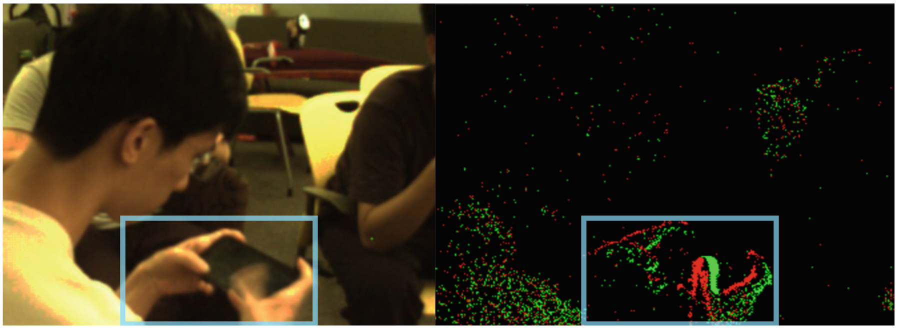

Fig. 4. ROI in an eSports competition scene, highlighted within the blue boxes. The traditional camera image, depicted on the left, suffers from motion blur, making it challenging to discern fine details. In contrast, the event data, shown on the right, presents clear and distinct outlines of hand movements. (Color figure online)

Table 2. Specifications of the event camera DAVIS 346, which is a 346×260 pixels event camera with included active pixel frame sensor [1].

DVS Resolution	346×260 pixels
Frame Resolution	346×260 pixels
DVS Dynamic range	120 dB
APS Dynamic range	56.7 dB
Min. latency	20 us
Lens mount	CS-mount
Connectors / Power	USB 3.0 micro
Bandwidth	12 MEvents / second
Software	DV-Platform
Power consumption	<180 mA @ 5 V DC

Compared to previous algorithms used in sports broadcasting [4,11,25], our method offers significant advantages:

- **Efficiency:** By reducing the computational complexity from $O(H*W*M*N)$ to $O(H*W*(M+N))$, our algorithm is more efficient and suitable for real-time processing, which is crucial in live eSports broadcasts.
- **Accuracy in Fine Movements:** Our algorithm is specifically designed to detect small, rapid hand movements, which are common in eSports but often missed by traditional algorithms that focus on larger-scale motions.
- **Tailored for Event Data:** Unlike previous methods that rely on frame-based data, our approach is optimized for event data, leveraging the high temporal resolution and low latency of event cameras.

Algorithm 1. Efficient Extraction of Regions of Interest (ROI)

```
Require: E, H, W, M, N ▷ E is the event map, H and W are the height and width of
    the event map, respectively; M and N are the desired height and width of the ROI.
Ensure: H, W, M, N > 0
  d ← [0]        ▷ Initialize an array to store the starting indices of the maximum sum
  subarrays for each row.
  for i ← 1 to H do
      m ← 0                          ▷ Initialize maximum sum for the current row.
      for j ← 1 to (W − N) do
          s ← sum(E[i, j : (j + N)])    ▷ Compute sum of elements from within the i_th
  row and the j_th to (j + N)_th columns of the event map E.
          if s > m then
              m ← s, d[i] ← j
          end if
      end for
  end for              ▷ Array d now holds indices of max sum subarrays for each row.
  m ← 0                              ▷ Reset maximum sum for column consideration.
  for i ← 1 to W do
      s ← 0                               ▷ Initialize sum for current column set.
      for j ← 1 to (H − M) do
          for k ← i to i + N do ▷ Check vertical slice from j_th to (j + M − 1)_th rows.
              if (d[j] ≤ k ≤ d[j] + M) then
                  s ← s + 1     ▷ Increment count if column i within the max sum range
  for row k.
              end if
          end for
          if s > m then
              m ← s, x ← j, y ← i ▷ Update maximum and store top-left corner of ROI.
          end if
      end for
  end for
  return x, y         ▷ Return indices x, y as the top-left corner of the extracted ROI.
```

These advantages enable our system to provide a more detailed and responsive broadcasting experience, capturing nuances that are critical for both players and viewers in the eSports domain.

4 Experiment

4.1 Dataset

We captured an entire eSports competition and established a dataset from the recordings; equipment details are outlined in Table 2. While we utilize a single dataset, it is comprehensive and specifically designed to reflect a wide range of real-world eSports scenarios. The dataset includes 40 different scenes with varying degrees of motion intensity, player actions, and lighting conditions, as

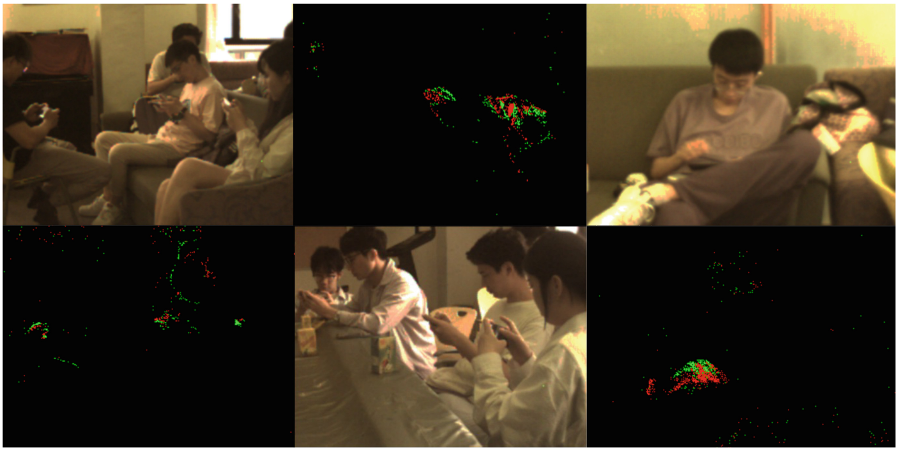

Fig. 5. The diverse scenes and data from an eSports competition form our dataset.

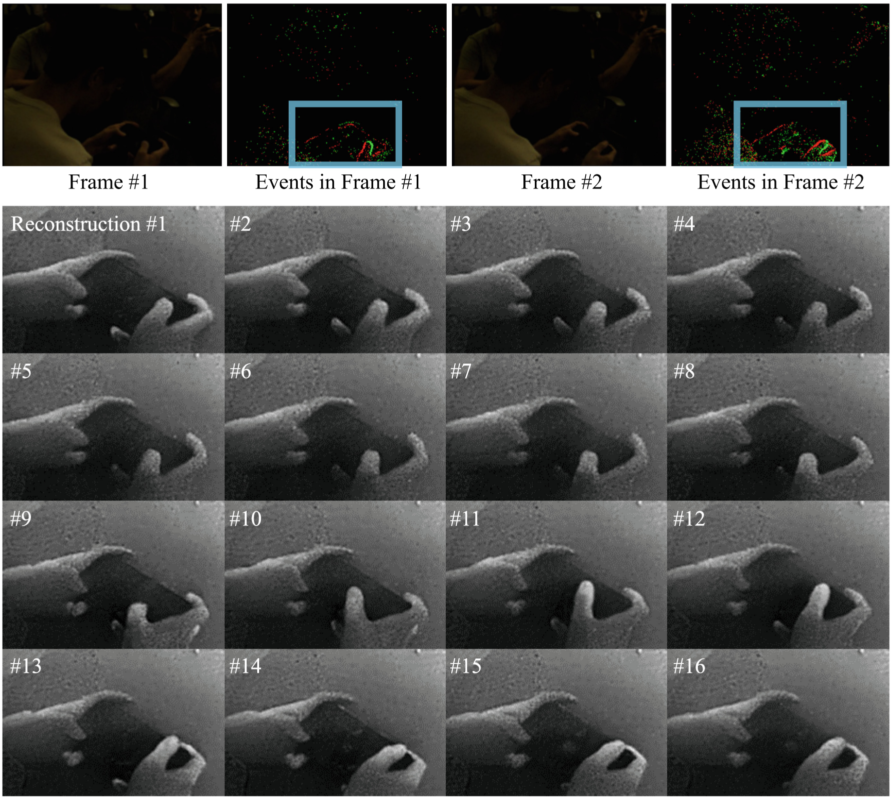

Fig. 6. Illustration of the enhancements in temporal resolution and dynamic range achieved through the reconstruction of frames from event streams in an eSports scene. ROI is highlighted within the blue boxes. (Color figure online)

Table 3. Dataset statistics illustrating the comprehensive nature of our data collection.

Number of scenes	40
Total number of frames	46,491
Average frame number per scene	1,162
Minimum frame number of a scene	33
Medium frame number of a scene	947
Maximum frame number of a scene	5474
Total number of events	779,002,043
Average event number per scene	19,475,051
Minimum event number of a scene	46,509
Medium event number of a scene	11,173,012
Maximum event number of a scene	100,966,145

described in Table 3. This diversity ensures our analysis covers multiple aspects of eSports broadcasting challenges.

We acknowledge that using a single dataset may limit the generalizability of our findings. However, its extensive coverage of different gaming scenes provides a robust foundation for initial analysis. In future work, we plan to incorporate additional datasets, including publicly available ones and data from other eSports competitions, to further validate and strengthen our results.

With 40 different scenes, the dataset includes over 46,000 frames and more than 779 million events. For instance, three different eSports scenes from the dataset are shown in Fig. 5. This extensive collection allows for detailed investigations into the temporal dynamics of scenes, featuring varying degrees of motion intensity and lighting conditions.

4.2 Fine Motor Skills

We analyzed the broadcasting quality improvements achievable with reconstructed frames from event streams in various eSports scenes. Figures 6, 7, and 8 showcase these enhancements across different scenes, highlighting the effectiveness of our method. In Fig. 6, the reconstructions enable viewers to perceive subtle hand gestures and rapid movements more clearly and stably. Similarly, Figs. 7 and 8 illustrate how fast motions are more accurately represented through event-based frame reconstructions.

Improving eSports broadcasts through such reconstructions is evident from the comparison between original frames and reconstructed sequences. Original frames, while serving as a base reference, often lack detail in fast-moving objects or areas with complex lighting. Reconstructed frames, processed from event data, show marked improvements in clarity and exposure, making them superior for broadcast purposes.

4.3 User Study

To validate our framework's efficacy and the advantages of event-based imaging in eSports broadcasting, we conducted a comprehensive user study. We recruited regular eSports viewers via online advertisements, screening them for familiarity with eSports and video quality attributes. Conducted online, participants were shown randomized video clips from our dataset, featuring scenes captured by traditional and event cameras. They watched each clip in a controlled environment to ensure consistent playback quality.

After viewing each clip pair (traditional vs. event camera), participants evaluated them based on: (1) temporal resolution, (2) dynamic range, and (3) motion clarity. Additionally, we asked which feed they would prefer when watching a live eSports match: (A) Only traditional camera output; (B) Only event camera output; (C) A combined view of both traditional and event camera outputs. We

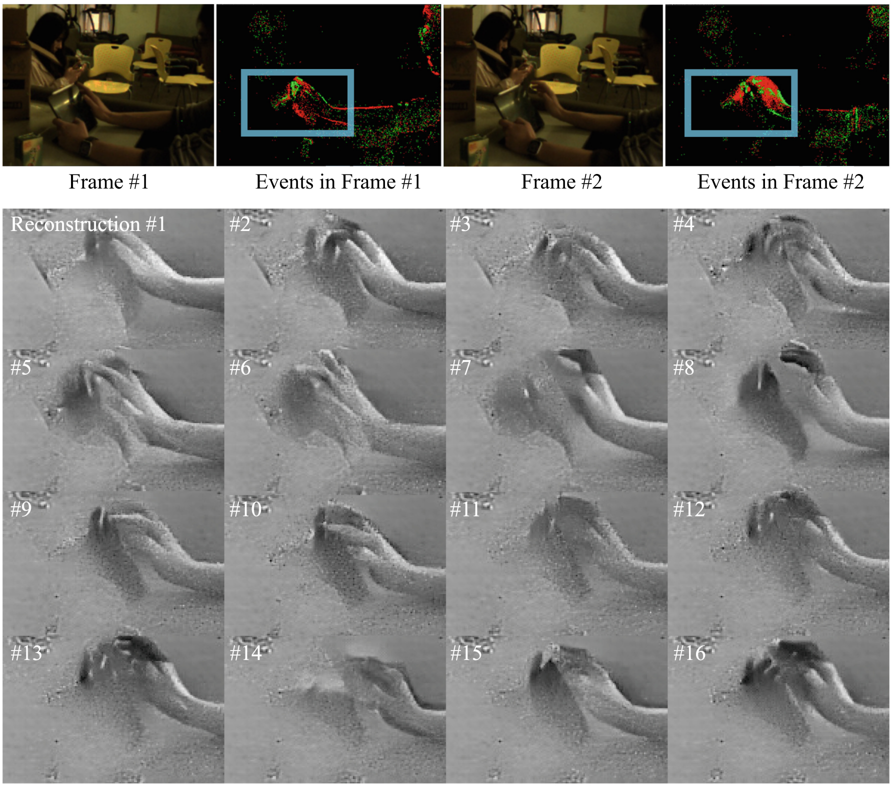

Fig. 7. Illustration of the enhancements in temporal resolution and dynamic range achieved through the reconstruction of frames from event streams in an eSports scene. ROI is highlighted within the blue boxes. (Color figure online)

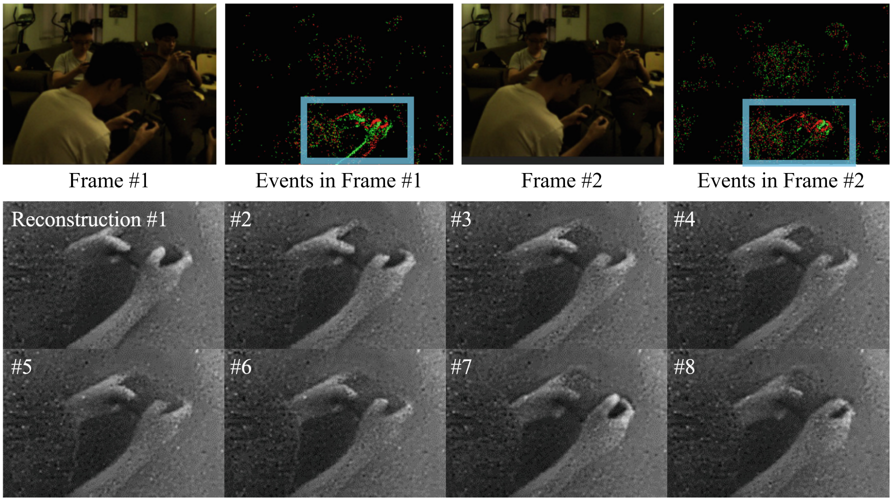

Fig. 8. Illustration of the enhancements in temporal resolution and dynamic range achieved through the reconstruction of frames from event streams in an eSports scene. ROI is highlighted within the blue boxes. (Color figure online)

Table 4. User preferences between traditional and event cameras across three criteria: (1) temporal resolution, (2) dynamic range, and (3) motion clarity, illustrating a strong inclination towards the capabilities of event cameras.

Fine Motor Skills	with a traditional camera	with an event camera
Temporal resolution	9.4%	90.6%
Dynamic range	3.4%	96.6%
Motion Clarity	6.9%	93.1%

ensured validity using standardized instructions and questionnaires. Randomized clip presentation mitigated order effects, and a pilot test refined the survey.

We received 32 responses, as shown in Tables 4 and 5. From the responses, a significant preference for event camera outputs was noted in all three assessed categories, as shown in Table 4. For temporal resolution, 90.6% favored the event camera, indicating a strong viewer preference for higher frame rates and reduced motion blur. Similarly, 96.6% preferred the event camera for its superior dynamic range, crucial for handling the varied lighting conditions of eSports venues. Motion clarity also saw a high preference at 93.1%, highlighting the ability to capture finer details typically missed by traditional cameras.

In terms of viewing setup preferences, as shown in Table 5, 41.4% of participants chose to view content solely from event cameras, while a notable 51.7% preferred a combined setup of both traditional and event cameras. This suggests that while the enhanced capabilities of event cameras are recognized, viewers still value the perspective offered by traditional cameras, indicating a complementary

Table 5. User preferences for different viewing setups during an eSports broadcast.

Setup	Preference
Only a traditional camera	6.9%
Only an event camera	41.4%
Traditional camera + event camera	51.7%

relationship between them in broadcasting. Today, hybrid camera systems have become increasingly common [33,34,38–40].

5 Future Work

Event cameras enhance eSports broadcasts, and they could transform eSports training and performance analysis by capturing minute movements, providing insights into player behavior for tailored training and AI coaching tools. Future studies might integrate event cameras with analytical software to enhance training strategies. Our dataset's diversity suggests potential for adaptive broadcasting systems handling varied gaming scenarios. Expanding the dataset and integrating AI could create dynamic broadcasting tools that adjust settings and predict key moments in live games, improving broadcast quality and scalability.

6 Conclusion

This paper shows the advantages of using event cameras for eSports broadcasts, particularly in enhancing temporal resolution, dynamic range, and motion clarity against traditional ones. By capturing the subtle and rapid movements of eSports athletes more accurately, event cameras not only improve the viewing experience but also offer potential for advanced analytics and training tools in eSports.

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