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An Asynchronous LLM Architecture for Event Stream Analysis with Cameras

Zeyu Wang[1*], Zong Cheng Chu[2], Minghao Chen[3], Yiqian Zhang[4] and Rui Yang[5]
[1]*University of California, Los Angeles, USA*
[2]*ByteDance, USA*
[3]*foshan top2top Technology Co. Ltd., China*
[4]*State Key Laboratory of Biotherapy, West China Hospital, China*
[5]*University of California, Riverside, USA*

[*]***Corresponding Author:*** *Zeyu Wang*

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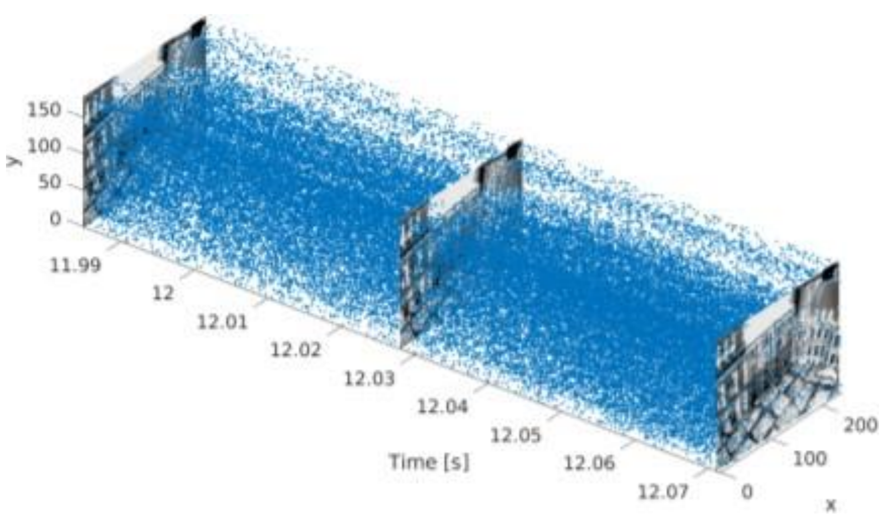
ABSTRACT
Event-based cameras, as bio-inspired vision sensors, record intensity changes asynchronously. The Dynamic and Active-pixel Vision Sensor (DAVIS) enhances information diversity by combining a standard camera with an event-based camera. However, current methods analyze event streams synchronously, contradicting their nature and introducing noise. To address this, most approaches accumulate events within a time interval to create synchronous frames, wasting sensitive intensity changes. This paper introduces a novel neural asynchronous approach for event stream analysis. Our method asynchronously extracts dynamic information by leveraging historical motion information and critical features of grayscale frames. Extensive experiments demonstrate our model's significant improvements over state-of-the-art baselines.

Keywords: *llm architecture, stream analysis, pixel, cameras*

I. INTRODUCTION

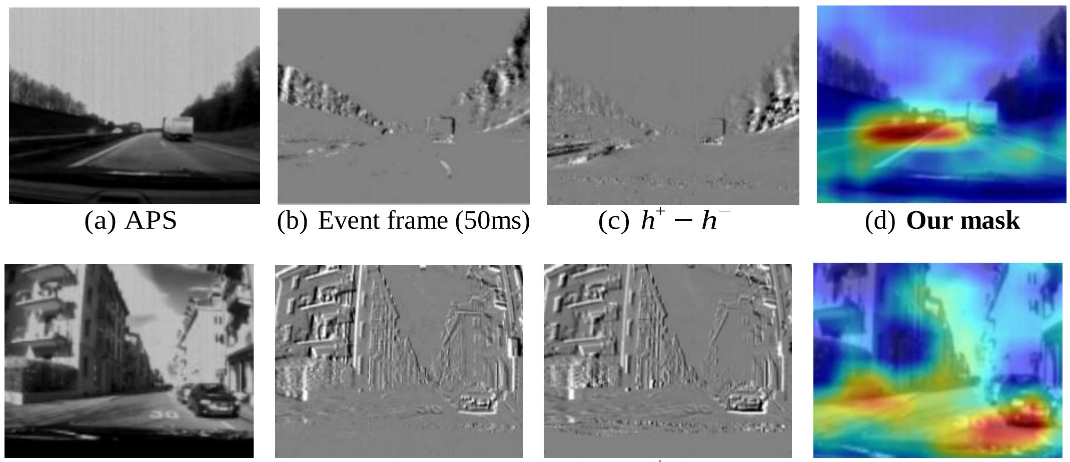
Event-based cameras, such as the Dynamic and Active-pixel Vision Sensor (DAVIS)[1,2,3,4,5], are novel bio-inspired vision sensors that record asynchronous events when pixel intensity changes. Unlike traditional cameras capturing grayscale frames at fixed intervals, event-based cameras produce a sequential event stream. The event stream is represented as a sequence of quads (*x, y, t, p*), where *x* and *y* indicate pixel position, *t* is the timestamp, and indicates brightness changes.

Event-based cameras offer advantages such as low-latency , high dynamic range, low band- width (¿120dB), high temporal resolution, low storage capacity, and low processing time and power consumption. DAVIS combines these benefits with those of traditional cameras.



Visualization of the event stream generated from DAVIS

Figure 1: DAVIS camera combines a standard camera and an event-based camera. It provides grayscale frames (images) and the event stream occurring between these frames. Image slices indicate grayscale images recorded at fixed rates, while blue dots indicate events recorded by the event-based camera, showing brightness changes for corresponding pixels between images. This provides advantages such as low latency, high dynamic range, and high temporal resolution, effectively promoting computer vision tasks.



(a) APS (b) Event frame (50ms) (c) $h^+ - h^-$ (d) **Our mask**

(e) APS (f) Event frame (50ms) (g) $h^+ - h^-$ (h) **Our mask**

Figure 2: Visualization of Different Frames. There are two independent cases: the top and bottom lines. **APS** (i.e., (a), (e)) are the original grayscale images provided [10,11,12,13,14,15,16]by the standard camera of DAVIS. **Event frame (50ms)** (i.e., (b), (f)) are the accumulated events within 50ms. h^+ h^- (i.e., (c), (g)) collects more information from the accumulated events. **Our mask** (i.e., (d), (h)) is the attention mask of our model inthe form of a heat map.

DAVIS includes both an event-based and a standard camera, producing asynchronous event streamsand synchronous grayscale frames. Asynchronous events occur randomly, unlike synchronous objects with fixed intervals. Event-based cameras outperform standard ones in tasks like motion estimation, feature extraction, and object tracking. Existing models accumulate events over time to create synchronous frames [Gehrig et al., 2018], losing potential dynamic information. Recent studies attempt to split these frames into parts for brightness and darkness events. Our novel neural architecture addresses these issues by analyzing event streams [20,22,23,24,25,26,27] asynchronously.

II. RELATED WORK

Event-based cameras have shown significant improvements over standard cameras in computer vision tasks [Vasco et al., 2016]. However, analyzing the event stream remains challenging. Traditional models accumulate events over time to create synchronous frames, losing dynamic information. Researchers have attempted to split these frames into parts for positive and negative events, improving optical flow estimation. Despite their efficiency, these methods introduce noise and increase latency, wasting the low-latency property of [Kueng et al., 2016]event-based cameras. Recent asynchronous approaches combine events and grayscale images for feature tracking, outperforming synchronous models. Our work builds on these advances by presenting the first deep learning-driven framework for asynchronous event stream analysis [Mueggler et al., 2015], leveraging channel-wise and spatial-wise attention mechanisms.

III. METHOD

3.1 Representation of Event Cameras and Event Stream

Event-based cameras track intensity changes in each pixel, recording events when log intensity changes exceed a predefined [Kim and Canny, 2017] threshold C:

where I_t is the intensity at timestamp t. Each event includes four elements: x, y pixel location, timestamp t, and polarity p:

Due to the asynchronous nature of events, extracting dynamic events for APS feature extraction is challenging.

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3.2 Neural Architecture

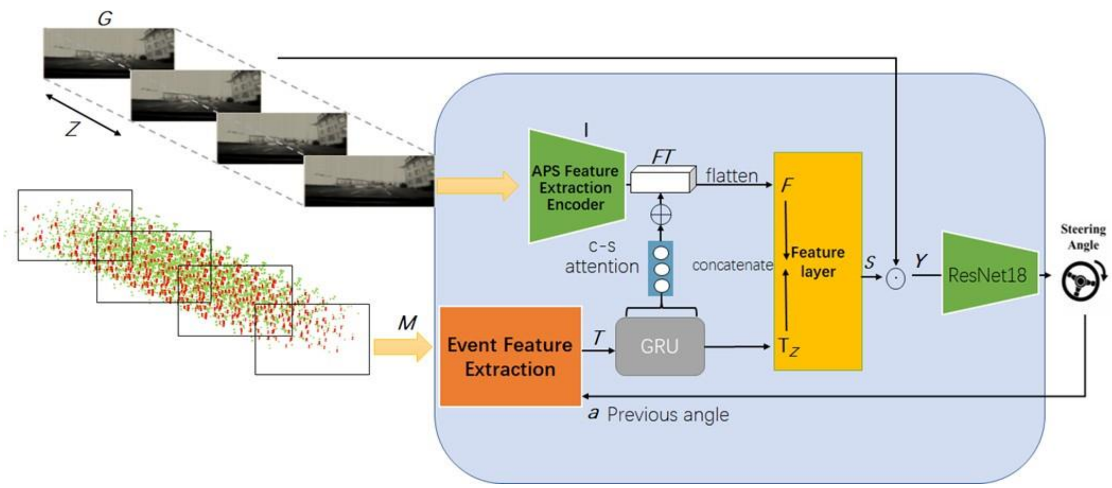

Figure 3: Proposed Neural Architecture. First, grayscale images G are encoded into image-specific feature tensor I. The event matrix M is constructed under the same timestamp and compressed into timestamp-specific vector T by the event feature extraction module. Second, GRU processes timestamp-specific vectors T in sequence to achieve hidden representation h for each timestamp [Lagorce et al., 2017]. Third, channel-wise and spatial-wise attention mechanism transforms image- specific tensor I into image-specific feature tensor FT. Fourth, the flattened image-specific feature tensor$F$ and timestamp-specific vector T_Z are concatenated as the input of the feature layer. The feature layer produces a mask S to cover the original grayscale image G as masked image Y. Finally, ResNet maps the masked image Y into the steering angle D.

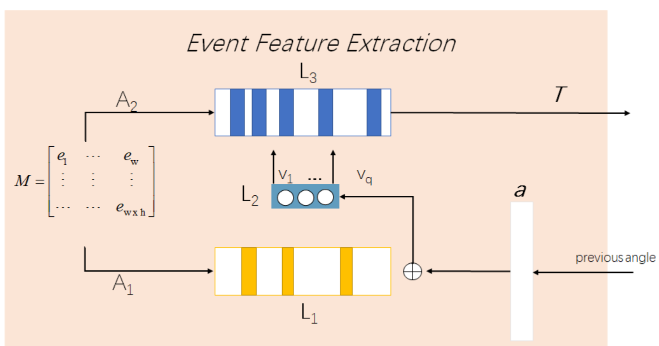

Figure 4: The inputs of this module are the event matrix M and the latest q angles $a = (a_1, \quad a_q)$. The output is timestamp-specific vector T . The event matrix M is projected with a linear layer, processed with the latest angle vector a, and projected again with another linear layer. An attention vector is generated and column-wisely multiplied with the output to achieve timestamp-specific vector T .

The neural architecture comprises five stages:

1. Grayscale images G are encoded into image-specific feature tensor I by the APS feature extractionencoder. The event matrix M is constructed and compressed into timestamp-specific vector T.

2. GRU processes timestamp-specific vectors T in sequence to achieve hidden representation h.

3. Channel-wise and spatial-wise attention mechanism transforms image-specific tensor I into image- specific feature tensor FT, which is then flattened into vector F.

4. The flattened image-specific feature tensor F and timestamp-specific vector T_Z are concatenated as the input of the feature layer. The feature layer produces a mask S to cover the original grayscaleimage G.

5. ResNet maps the masked image Y into the steering angle D.

3.2.1 APS Feature Extraction Encoder

The APS feature extraction encoder extracts hidden features from grayscale images. The input is a grayscale image I, and the output is an image-specific feature tensor I.

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3.2.2 Event Matrix Construction

The event matrix construction module constructs the event matrix M from the event set under the same timestamp. The event matrix M has the same size as the original grayscale image I. Events are recorded in the matrix, with unrecorded entries filled with 0.

3.2.3 Event Feature Extraction Module

The event feature extraction module processes the event matrix M and the latest q angles composed vector a. The output is timestamp-specific vector T. The module encodes the event stream asynchronously, using a series of linear layers and attention mechanisms.

IV. EXPERIMENTS

4.1 Performance Metrics

We use the root-mean-squared error (RMSE) to measure performance:

$$\text{RMSE} \doteq \sqrt{\frac{1}{N}\sum_{j=1}^{N}\left(\hat{\alpha}_j - \alpha_j\right)^2}$$

where α̂ are predicted values and α are observed values. Explained variance (EVA) evaluates model stability:
where β is the RMSE of the baseline and β̂ is the RMSE of our methods.

4.2 Datasets

We use the public benchmark dataset [Binas et al., 2017], which contains over 12 hours of driving records collected by vehicles under real and challenging scenarios. The dataset includes asynchronous events, grayscale images (APS), and other sensor data such as vehicle speed, GPS position [Nguyen et al., 2017], driver steering, and throttle. The dataset is segmented into four subsets: day, day sun, evening, and night, according to weather and scenarios. Most steering angles are slight deviations of ±10 degrees, and speedsare uniformly distributed over 0-160 km/h. [70,71,72]

RMSE (EVA) / Methods — Scenarios	Maqueda (APS)	Maqueda (ResNet18)	Maqueda (ResNet50)	Asynchronous (Ours)
day	4.57 (0.047)	2.99 (0.551)	2.33 (0.728)	**2.17 (0.812)**
day sun	20.07 (0.125)	10.87 (0.742)	9.47 (0.805)	**8.05 (0.875)**
evening	7.23 (0.172)	5.45 (0.518)	5.01 (0.602)	**4.67 (0.734)**
night	6.96 (0.181)	4.51 (0.654)	**3.82 (0.753)**	3.94 (0.711)

Table 2: Comparison with synchronous learning approaches using grayscale (APS) frames and event frames for each scenario. The APS baseline is based on the ResNet18 network.

4.3 Implementation

We split the data into four parts [40,51,53,54,55,56]according to scenarios: day, day sun, evening, and night. We use the same dataset segmentation, pre-processing, and tricks as state-of-the-art baselines for fair comparison. Grayscale images are processed and encoded into tensors. The event matrix M is constructed identically to grayscale images. The event feature extraction module uses parameter matri- ces and attention vectors to produce a timestamp-specific vector. We flatten the feature tensor FT and concatenate it with the timestamp-specific vector T_Z, producing an image mask.

Our optimal settings include $w = 260$, $h = 346$, $q = 256$, $Z = 10$ in 10fps dataset or $Z = 50$ in 50fps. The model is trained using ADAM with hyper-parameters $\beta_1 = 0.9$, $\beta_2 = 0.999$, $\epsilon = 10^{-8}$, andan initial learning rate of 0.0001.

4.4 Results & Analysis
Experimental results in Table 2 address two critical questions:

1. How does our asynchronous approach outperform traditional synchronous approaches for event streams? 2. Why can our asynchronous approach extract dynamic information better?

For fair comparison, we use the same ResNet18 [23,51,60,62,63,64,65,66,67,68]or ResNet50 networks as feature encoders. Our model outperforms those using only grayscale images, with approximately 33.34
In the night dataset, ResNet50-based models slightly outperform ours, but our ResNet18-based model still shows significant improvements over corresponding baselines. Future work will explore using more effective CNN networks like ResNet101 or inception for further performance gains.

Results Methods Metric	**Maqueda (ResNet18)**	**Ours (Full)**	**w/o C-S attention**	**w/o APS Branch**	**LSTM**
RMSE	5.65	**5.07**	5.23	5.41	5.15
EVA	0.512	**0.673**	0.642	0.614	0.652

Table 3: Ablation study on the effects of key components of our methods. RMSE & EVA are shown with a held out test set on each component with fixed random seed.
(c)
Evening

(d) Dark Night
Figure 4: Gray-scale images extracted from the dataset [Binas et al., 2017] for the four scenarios.

In conclusion, our asynchronous approach better extracts dynamic information by filtering out distracting objects. Visualization of different frames shows that event-based cameras capture dynamic pointsmore effectively than grayscale images, especially under high velocities [Amir et al., 2017]. Our attention masks focus on critical features like cars, houses, and route lines, ignoring background noise like trees and clouds [Fu et al., 2017].

4.5 Ablation Study
We conducted an ablation study to analyze the contributions of each module using a segmented dataset of DDD17. Table 3 shows RMSE & EVA results for a model without C-S attention, without the APS branch, and using LSTM instead of GRU. Results demonstrate that C-S attention, the APS branch, and GRU are necessary components, and naive event asynchronous models also outperform traditional methods.

V. CONCLUSION

This paper proposes an attention-based asynchronous approach for self-driving tasks. Our method ana- lyzes the event stream asynchronously, extracting dynamic points to filter out distractions. We leverage attention mechanisms to jointly analyze asynchronous event streams and grayscale images, achieving substantial improvements over state-of-the-art baselines. Experiments demonstrate the effectiveness ofour approach.

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