triCAM: A Real Monocular Multi-Modal Event-based Pedestrian Dataset

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Abstract

Event-based visions offer key advantages, such as low latency, high dynamic range, and microsecond temporal resolution. These strengths have motivated extensive research into their complementarity with other modalities, which led to the creation of several multi-modal event-based datasets. However, most of these datasets are designed for automotive or robotic domains, with limited attention to human-centered perception in everyday settings. In this paper, we introduce triCAM, a real-world monocular multi-modal event-based pedestrian dataset. triCAM integrates event streams, RGB images, depth images, IMU data, and pedestrian bounding box annotations. This dataset contains 20 sequences, each recorded in two different restaurants in both static and dynamic camera motions. By providing a rich dataset on pedestrian activities in socially interactive environments, triCAM contributes to the advancement of research in robust perception and human interaction understanding.

1 Introduction

Event cameras introduce a revolutionary way of capturing motion in the field of computer vision. Unlike traditional cameras, which record entire scenes at fixed intervals, event cameras operate asynchronously by detecting per-pixel brightness changes. This bio-inspired sensing mechanism allows them to achieve high temporal resolution, high dynamic range, and low power consumption. These advantages have led to their adoption in domains requiring high-speed and robust perception, including robotics, autonomous vehicles, and surveillance systems. While event cameras excel at capturing fast motion and high dynamic range scenes, they inherently provide sparse information focused on intensity changes rather than full-textural scene appearance. To alleviate this limitation and facilitate support for a wider range of computer vision tasks, it is beneficial to combine event data with supplementary modalities. Accordingly, several event-based multi-modal datasets have been proposed, often combining events with auxiliary modalities such as RGB images, depth, LIDAR, calibration information, and inertial measurement units (IMU). For instance, MVSEC Zhu et al. (2018), DSEC Gehrig et al. (2021b), M3ED Chaney et al. (2023), CoSEC Peng et al. (2024),SLEDBrebion et al. (2023), and ECMD Chen et al. (2023) are popular benchmarks in automotive and robotics environments with stereo event streams and RGB images. Although these stereo multi-modal datasets contribute greatly to the vision community, their reliance on stereo multi-modal configurations introduces extra hardware cost, multi-sensor calibration complexity, and power consumption. Some researchers try to simplify these stereo datasets by using only one camera from the pair to simulate a monocular setup. But this does not adequately capture the design requirements of a true monocular multi-modal dataset.

As a result, they impose a significant computational cost which makes them unsuitable for resource-constrained applications and provides limited insight into socially interactive environments. In contrast, common places like restaurants remain unexplored, even though understanding pedestrian interactions and motion patterns in such cluttered, dynamic settings is essential. To address this gap, we propose triCAM, a real, monocular, multi-modal dataset targeting pedestrians in restaurant environments. triCAM integrates data from multiple modalities, event streams, RGB images, and depth images (see Figure 2) in addition to the IMU data, pedestrian bounding box annotations, and the sensors' calibration parameters. This dataset was recorded by three sensors, an event camera, a RGB-D camera and an IMU sensor, as displayed in Figure 1.

In summary, triCAM offers several key contributions to the field of event-based multi-modal vision:

1. It represents the first publicly available monocular multi-modal pedestrian dataset, enabling researchers to explore event-based perception alongside complementary modalities RGB, depth, IMU data, calibration parameters, and pedestrian bounding boxes.
2. It is the first multi-modal dataset designed for pedestrian-centered scenarios in both outdoor and indoor restaurant environments.
3. It provides spatially and temporally aligned sequences recorded under both static and dynamic camera motions.

By focusing on social environments, triCAM uniquely complements existing datasets. It opens new directions in event-based vision research, particularly for applications involving human-centered perception and socially interactive contexts such as human behavior analysis, service robot navigation, occupancy detection, and human-robot interaction (HRI) for delivery robots. Furthermore, triCAM can be utilized to perform a variety of tasks, including monocular depth estimation, pedestrian detection, ego-motion estimation, and multi-modal model training.

Figure 1: triCAM Camera Setup.

2 Related Work

Table 1 summarizes the characteristics of both stereo and monocular multi-modal event-based datasets. In this section, we review and compare these existing datasets in detail.

2.1 Stereo Datasets

A popular dataset in event-based vision is MVSEC Zhu et al. (2018). MVSEC was the first large-scale stereo dataset for event-based vision. Its sensor rig is composed of a pair of DAVIS m346B event cameras (346×260) with a baseline of 10 cm, a VI-Sensor with a stereo RGB camera, capturing both indoor and outdoor driving and drone scenarios. It records data from a variety of vehicles, including cars, motorbikes, hexacopters, and handheld devices. It fuses this data with LiDAR, a nine-axis IMU, motion capture, and GPS to provide ground-truth pose and depth images. MVSEC is a key dataset for depth and odometry benchmarking. Another one is DSEC Gehrig et al. (2021b), which expanded scale in the automotive sector by providing high-resolution stereo events with a pair of Prophesee Gen3.1 cameras (640×480) with a baseline of 60 cm with two RGB cameras in outdoor driving scenarios in the city of Zurich.

Table 1: Comparison of existing multi-modal event-based datasets.

Datasets	Type	Events	RGB	Depth	IMU	Env	Scenarios
Stereo							
MVSEC Zhu et al. (2018)	Real	✓	✓	✓	✓	Both	Automotive
DSEC Gehrig et al. (2021b)	Real	✓	✓	✓	✓	Outdoor	Automotive
VECTOR Gao et al. (2022)	Real	✓	✓	✓	✓	Indoor	Diverse
M3ED Chaney et al. (2023)	Real	✓	✓	✓	✓	Both	Robotics
CEAR Zhu et al. (2024)	Real	✓	✓	✓	✓	Both	Robotics
Monocular							
D-eDVS Weikersdorfer et al. (2014)	Real	✓	✓	✓		Indoor	Robotics
DDD17 Binas et al. (2017)	Real	✓	✓			Outdoor	Automotive
VINS-Mono Qin et al. (2018)	Real	✓	✓		✓	Both	Robotics
CED Scheerlinck et al. (2019)	Real	✓	✓			Both	Automotive
EventCap Xu et al. (2020)	Real	✓	✓	✓		Indoor	Robotics
DENSE Hidalgo-Carrio et al. (2020)	Synthetic	✓	✓	✓		Outdoor	Automotive
EventScape Gehrig et al. (2021a)	Synthetic	✓	✓	✓		Outdoor	Automotive
Agri-EBV Zujevs et al. (2021)	Real	✓	✓	✓	✓	Outdoor	Agriculture
TUM-VIE Klenk et al. (2021)	Real	✓	✓		✓	Indoor	Robotics
MonoANC Shi et al. (2023)	Synthetic	✓	✓	✓		Indoor	Automotive
RGB-Event ISP Yunfan et al. (2024)	Real	✓	✓			Outdoor	ISP
HUE Ercan et al. (2024)	Real	✓	✓			Both	Automotive
triCAM (ours)	Real	✓	✓	✓	✓	Both	Restaurant

With additional 16-channel LiDAR and IMU data, DSEC is a widely used benchmark for event-based stereo depth estimation due to its precise calibration and large-scale sequences. VECTOR Gao et al. (2022) shifts attention from driving to indoor robotics, integrating Prophesee Gen3 stereo cameras (640×480), stereo RGB cameras (1224×1024), a LiDAR, and a nine-axis IMU. Collected in structured indoor environments, it supports SLAM and localization under controlled but dynamic human-centric conditions, broadening event-based applications beyond automotive use cases. M3ED Chaney et al. (2023) targets robotics applications by recording data from both forest and urban environments using ground, aerial, and legged robots. Alongside stereo event cameras (1280×720) and RGB cameras (1280×800), the dataset includes LiDAR and IMU, supporting perception tasks in unstructured and dynamic scenarios. ME3D is suited for robotic navigation and mapping tasks. Finally, CEAR Zhu et al. (2024) pushed stereo event datasets further with a strong focus on agile quadruped robots. With stereo event cameras combining DAVIS 346 and DVXplorer Lite, RGB-D, LiDAR, and a 12-axis IMU sensor, CEAR captures indoor and outdoor sequences under rapid motion where conventional cameras fail due to blur, making it the first dataset focused explicitly on agile event-based robotics.

2.2 Monocular Datasets

Monocular multi-modal event-based datasets can be categorized into two different groups based on their type. First, we will discuss the synthetic datasets, followed by the real datasets.

2.2.1 Synthetic Datasets

EventScape Gehrig et al. (2021a) is a simulated multi-modal dataset. This dataset provides large-scale asynchronous event streams generated from the CARLA simulator Dosovitskiy et al. (2017), rendered at 500 Hz, and converted into events via an event simulator tool, ESIM Rebecq et al. (2018). Each event arises from pixel-wise brightness changes simulated from the rendered RGB images, and it also includes depth images, semantic segmentation and vehicle navigation parameters, making it an ideal benchmark for automotive scenarios. Its focus on tightly synchronized RGB and event data establishes a foundation for multi-modal perception research. Building upon this idea of simulated multi-modal data, the DENSE dataset Hidalgo-Carrió et al. (2020) further explores event-RGB integration. Like EventScape, it uses CARLA Dosovitskiy et al. (2017) for data generation, but the virtual event camera is modeled after the DAVIS346B sensor with a resolution of 346×260 pixels. Recorded at 30 frames per second, DENSE provides depth images, RGB images, and simulated event streams under diverse lighting and weather conditions.

This allows researchers to study event-driven perception in controlled yet varied environments. Lastly, MonoANC Shi et al. (2023) extends these efforts into more challenging driving conditions. Specifically designed to tackle night-time scenarios and adverse weather, MonoANC offers 11,191 samples of synchronized RGB, event, and depth data. Its multi-modal nature also supports research into robust event-RGB integration. By emphasizing asynchronous events combined with frame-based data, MonoANC demonstrates the value of multi-modal approaches for perception in low-light and dynamic conditions.

2.2.2 REAL DATASETS

The first event-based multi-modal dataset is D-eDVS Weikersdorfer et al. (2014). This dataset's sensor rig is composed of a PrimeSense RGB-D camera and an e-DVS. The eDVS operated at a resolution of approximately 128×128 eDVS event camera to capture asynchronous events, while the PrimeSense sensor provided synchronized RGB and depth data. This dataset targeted indoor robotics applications. The DDD17 Binas et al. (2017) dataset captured automotive data with a DAVIS346B sensor, which outputs both events and active pixel sensor (APS) frames at 346×260 pixels. No depth sensor or IMU data were provided, but the dataset included vehicle telemetry such as steering angle, throttle, brake, and GPS. It was designed for outdoor automotive perception in challenging driving conditions. Another widely used dataset is VINS-Mono Qin et al. (2018), for monocular visual-inertial odometry (VIO). It employed a rolling-shutter monocular camera with a resolution of 752×480 pixels, complemented by a 9-axis IMU providing accelerometer, gyroscope, and magnetometer data. The dataset spans both indoor and outdoor robotics environments. Scheerlinck et al. (2019) presented a colored event cameras dataset (CED). This dataset was collected using a color-DAVIS346 sensor (resolution 346×260), which provides both real events coupled with synthetic colored events generated by ESIM Rebecq et al. (2018) and ground-truth RGB images. CED primarily focused on automotive and robotics navigation in indoor settings. EventCap Xu et al. (2020) introduced a revolutionary way of capturing 3D human motion using a DAVIS240C event camera (240×180) along with their generated intensity frame from the same camera. This dataset provides object-wise depth images for human pose estimation. The human actions were recorded with a Sony RX0 camera, which produces high frame rate (between 250 and 1000 fps) RGB videos at 1920 × 1080 resolution. This dataset consists of 12 sequences of 6 actors performing different activities, including karate, dancing, javelin throwing, and boxing. The dataset covers indoor robotics scenarios, with an emphasis on human motion and interaction. HUE Ercan et al. (2024) is a high-resolution multi-modal dataset collected with a Prophesee Gen4M with a resolution of 1280×720 and Allied Vision Alvium compact CMOS cameras with a resolution of 1456×1088. This dataset contains only RGB images and event streams and was primarily designed for indoor automotive and robotics applications under low-light and high-dynamic-range conditions. The RGB-Event ISP dataset Zujevs et al. (2021) provided pixel-aligned RAW images and event streams captured with a hybrid vision sensor from a monocular viewpoint. It contains over three thousand samples across diverse scenes, lighting conditions, exposures, and lenses, with color calibration generated by a ColorChecker. Unlike previous event datasets that mainly target high-level vision tasks, this dataset is designed to support research on event-guided image signal processing (ISP). Zujevs et al. (2021) presented their work titled *"An Event-based Vision Dataset for Visual Navigation Tasks in Agricultural Environments"*. Agri-EBV is a dataset designed for agricultural robotics featuring different agricultural environments. It used a DAVIS240 camera (240×180), a RealSense RGB-D depth camera, LIDAR-16, and an IMU for inertial measurements. This dataset uniquely emphasizes outdoor crop monitoring and agricultural tasks under challenging movement in a rural area.

While multi-modal event-based datasets reviewed above provide an important contribution, they largely overlook pedestrian-centered scenarios in social and crowded environments. Although Pedro Boretti et al. (2023) is a monocular event-based pedestrian dataset, it lacks other modalities to expand research in this area.

3 HARDWARE SETUP

The triCAM sensor rig consists of a dual camera setup and an IMU sensor, as displayed in Figure 1. The depth, RGB images, and IMU data were captured by a RGB-D RealSense D435i depth camera, the event streams from a Prophesee Gen3 camera, and the additional IMU data from a WitMotion sensor. For detailed information about the characteristic of each sensor (see Table 2).

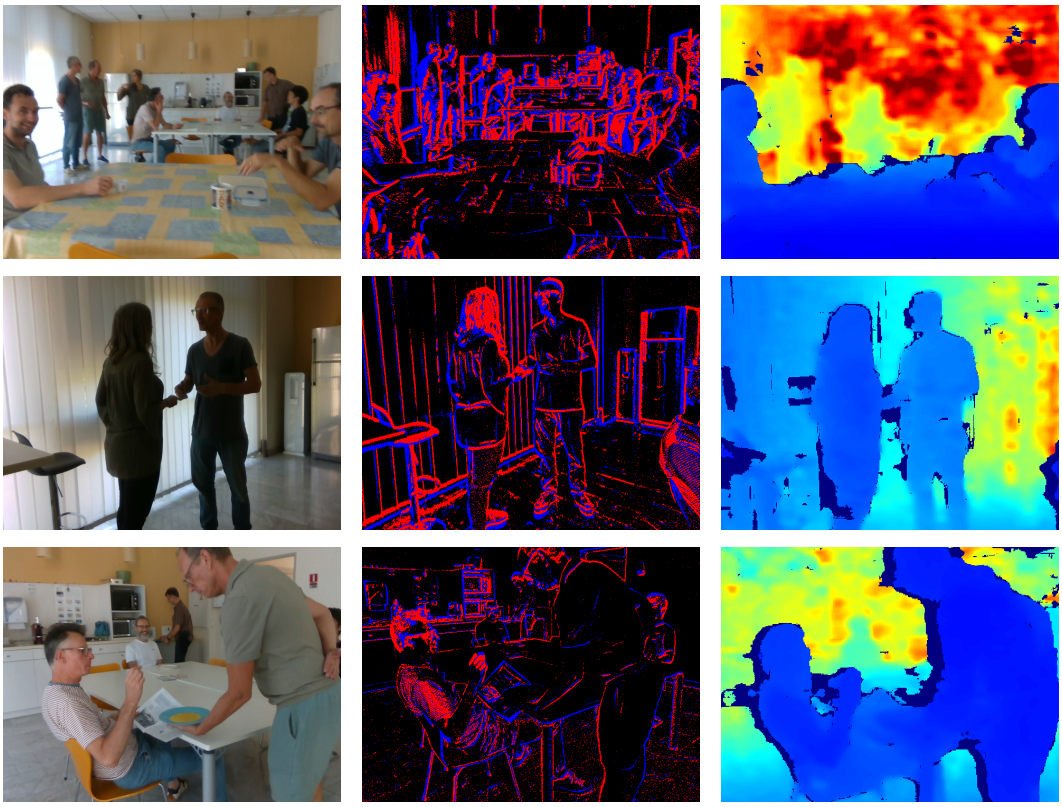

Figure 2: Overview of triCAM sequences with RGB , event and depth modalities. From top to bottom, each image row illustrates pedestrians siting, chatting and carrying items.

These sensors are mounted on a standard tripod for both static and handheld dynamic motion scenarios. In the following section, we describe the data post-processing pipeline, synchronization across cameras, and calibration parameters extraction.

3.1 Hardware and Software

The triCAM data acquisition pipeline was managed through a custom graphical user interface (GUI) application developed using Tkinter Lundh (1999). Therefore, the cameras were connected to a laptop during the recording period. The GUI application facilitated user interaction and controlled a backend program responsible for coordinating the sensors. Specifically, the backend handled scene metadata storage and triggered simultaneous recording of the two cameras and the IMU via a multi-threaded process. Once the recordings were captured, several post-processing steps were performed entirely in Python. First, all the images were resized into the same resolution of 640x480 pixels. The RealSense SDK 2.0 Schmidt et al. (2019) was employed to temporally and spatially align the depth and RGB images and to extract timestamps for each modality, accounting for their distinct fields of view. Camera calibration was carried out using the OpenCV Calib library, while pedestrian detection and annotation of each modality were semi-automatically generated using YOLOv8x Hussain (2023).

3.2 Time Synchronization

The synchronization of the RGB and depth images from the RealSense camera was straightforward, as these images were temporally aligned and spatially preprocessed using the RealSense SDK 2.0 Schmidt et al. (2019). However, temporally aligning the event streams with the RGB and depth frames required more processing due to the event camera's continuous and asynchronous output.

Table 2: triCAM Hardware Specifications.

Sensors	Descriptions
1X Prophesee Gen3	Resolution : 640 × 480 3/4" CMOS Monochrome $\geq$ 120 dB dynamic range
1X RealSense D435i	**Depth:** Stereoscopic FOV: 87°H/ 58°V Resolution : 1280 × 720 frame rate: Up to 90 fps Accuracy: $< 2\%$ at 2 m **RGB:** monoscopic Resolution : 1920 × 1080 FOV: 69°H /42°V frame rate: 30 fps **IMU:** 63 Hz & 200 Hz 3-axis Accelerometer 3-axis Gyroscope
1X WitMotion IMU	200 Hz 3-axis Accellerometer 3-axis Gyroscope 3-axis Magnetometer 4-axis Quaternion Roll,Pitch,Yaw

Then, the start time of the event camera recording and the timestamps of each depth frame were recorded.Each event timestamp was converted to a global reference by adding the event camera's start time. Since the RGB-D camera operated at approximately 30 FPS (one frame every 33 ms), the event streams were segmented into 33 ms intervals corresponding to consecutive depth timestamps on a global timeline in order to align the two modalities temporally. For each depth frame, all events that occurred between its timestamp and the next were aggregated. In this way, each depth frame was synchronized with its corresponding events in time.

To achieve temporal synchronization between the two IMUs, RGB-D, and event cameras, the depth frame timestamps from the RealSense RGB-D camera were used again as the reference timeline. This is because the IMU measurements from the Realsense D435i camera are timestamped using the depth sensor's hardware clock, ensuring that accelerometer and gyroscope readings are already aligned with the depth frames. Since the IMU of this dataset had different sampling rates with 200 Hz for the event camera IMU, 63 Hz for the RGB-D accelerometer, and 200 Hz for the RGB-D gyroscope as showcased in Table 2. All signals were resampled using linear interpolation to a high frequency of 1 kHz timeline covering the duration of the recording. Any systematic temporal offsets between the two IMU and depth frames were then estimated using cross-correlation of motion signals, and the IMU timestamps were adjusted accordingly. Finally, to keep everything in sync, we grouped the IMU samples that fell within each frame interval for every modality, aligning the IMU, RGB-D, and event streams on a shared timeline.

3.3 Spatial Synchronization

The multi-modal content of this dataset was spatially synchronized using the OpenCV Calib library to extract both intrinsic and extrinsic calibration parameters of each camera. These calibration parameters were generated from a 12x8 checkerboard grid with a square size of 30 mm. This calibration pattern was captured in various rotations and positions to ensure robust calibration results. For the RGB camera, calibration was performed directly on grayscale images of the checkerboard grid. While for the event camera, we followed the calibration pipeline proposed by Muglikar et al. (2021).

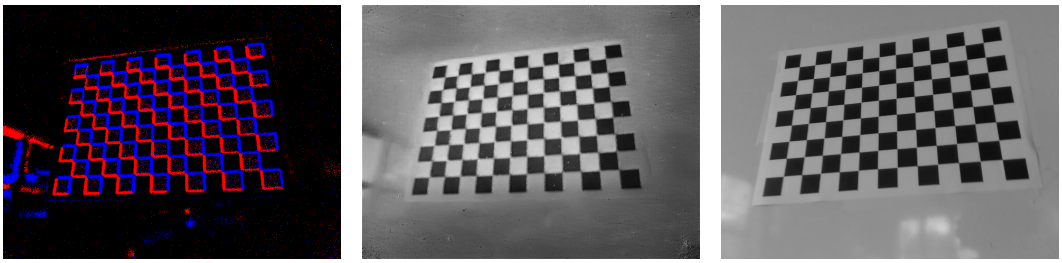

Figure 3: Checkerboard calibration images. From left to right, the raw event frame, the reconstructed grayscale event frame, and the grayscale RGB image of the checkerboard.

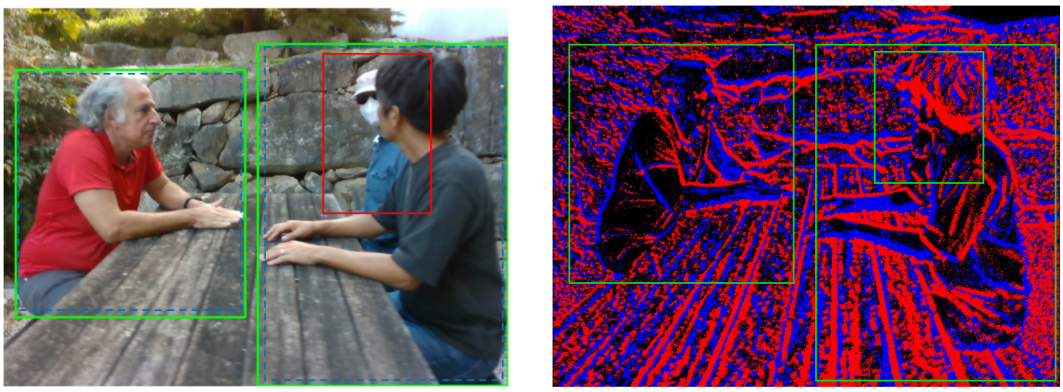

Figure 4: triCAM data labeling results. The blue dashed bounding boxes represent the YOLOv8x model predictions, the green ones are the manually annotated ground truth, and the red ones highlight the pedestrian missed by YOLOv8x.

Following this approach, the event streams were first transformed into image-like representations by aggregating events over brief temporal windows of 33.33 ms to ensure temporal synchronization with the RGB-D camera and then reconstructing them into grayscale event frames using a pretrained event-to-video E2VID model (Rebecq et al., 2019a;b), as illustrated in Figure 3. The resulting grayscale event frames were then used together with the RGB frames to estimate both intrinsic camera parameters (focal length, principal point, and distortion coefficients) and extrinsic parameters (rotation and translation between the RGB and event sensors) with the projection of the event camera to the RGB-D camera.

4 Dataset

4.1 Dataset Labeling

The triCAM dataset was collected using two camera the Realsense RGB-D camera and a Prophesee Gen3 event camera. To encourage multi-modal learning as well as mono-modal learning, this dataset contains two bounding box annotations for each modality namely the RGB and event data. Given that the RGB and depth data are spatially and temporally aligned, the RGB bounding boxes correspond perfectly to the depth ones. The RGB image labeling process was done semi-automatically, the RGB images were annotated automatically using the pretrained object detection model YOLOv8x Hussain (2023). However, the results were unreliable due to the low resolution of the images and the clustered nature of the pedestrians in the scene, as showcased in Figure 4. Therefore, these images were double-checked manually to ensure high-quality annotations using one of the most popular image annotation tools, LabelImg Tzutalin (2015).On the other hand, the event streams from the Prophesee Gen3 camera were converted into an image-like representation to generate their corresponding pedestrian bounding boxes.

This process was done entirely manually because the labeling tool fails to detect pedestrians in the scene due to the non-textural nature of this rendering.

4.2 Dataset Format

The dataset is distributed in the ROS bag format to ensure compatibility with widely used robotics and computer vision frameworks. Each sequence contains synchronized recordings from multiple sensing modalities, including raw RGB images, depth images, event streams, each camera's IMU data and the calibration parameters. For these raw modalities, pedestrian bounding boxes are provided for both image and event frames in YOLO format and global bounding box annotation format. The RGB-D data namely RGB, depth images and IMU information are stored under the topic name starting with `/rgb-d_camera/` namespace, with the RGB and depth images saved in PNG format. While the event camera's data are stored under `/even_camera/`, with the event streams stored in NumPy format. Both intrinsic and extrinsic camera calibration of each sensor and their projection is stored under the `/cameras/calibration` namespace. Both cameras' IMU data are saved as CSV files, and calibration parameters in YAML format.

4.3 Dataset sequences

The triCAM dataset was captured in two distinct restaurants and captured people going about their usual activities, such as eating, drinking, chatting, walking between tables, interacting with waiters, calling or waving to the waiters, and carrying trays, cups, plates, or other items, as illustrated in Figure 2. The special motion and interaction patterns displayed by each activity capture the organic dynamics of a busy restaurant setting. The dataset features a group of participants aged 20 to 70 of diverse ethnicities to provide a rich variety of manners and behaviors. Table 3 summarizes how each activity was documented as a distinct sequence for clarity because each sequence name is composed of the restaurant location, the pedestrians' activities, the environment (indoor or outdoor), and the number of identical scenes. Each sequence was recorded in both dynamic and static camera motion, and all dynamic scenarios were handheld. Figure 5 illustrates the distance of each pedestrian from the camera across all dataset sequences by comparing the static and dynamic scenes. This image highlights the diversity of each setup.

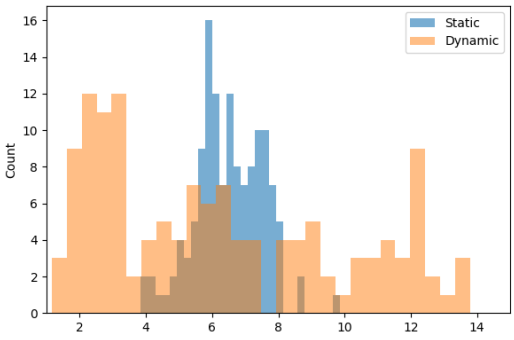

Figure 5: Pedestrian Distance to the camera across all sequences.

This dataset will be publicly available. However, we refrain from sharing the dataset website due to the double-blinding review procedure of this conference.

5 Experiment results

We conducted a pedestrian detection evaluation on the triCAM dataset sequences, using the object detection YOLOv8x Hussain (2023) model. We trained the YOLOv8x Hussain (2023) model separately on Event-only and RGB-only data. The event numpy streams were converted into voxel-grids. Each dataset was split into training and testing sets, with images size of 640×480, a batch size of 16, and 50 training epochs. Ground-truth bounding boxes were used for supervision. The training, validation and testing sets consisted of 15, 2 and 3 sequences respectively. To ensure the robustness of this model in such difficult scenarios, 80% dynamic sequences were allocated in the testing and validation sets. The model performance was evaluated on three metrics, the Mean Average Precision 50 (mAP50), Precision, and Recall.

As shown in Table 4, the RGB-only model outperformed the Event-only model, reflecting the richer spatial information in RGB frames. Event data alone achieved moderate detection performance.

Table 3: The triCAM sequences details of one of the restaurants. Each sequence was recorded in two camera motions.***Static*** with the camera fixed on a table and ***Dynamic*** with the camera handheld in constant motion. **Occlusion** is the occlusion level of the persons in the scene,**Time** represents the duration, **Persons** indicates the number of people, and **Events** shows the total number of events generated in each sequence.

Sequences	Camera Motion	Occlusion Level	Time (s)	Persons	Events (M)
R1_walk_in_01	Static	high	172	8	54
	Dynamic	high	180	8	140
R1_walk_in_02	Static	low	182	4	234
	Dynamic	low	130	4	400
R1_sit_eat_out_01	Static	high	185	10	302
	Dynamic	high	190	10	385
R1_sit_eat_out_02	Static	high	185	8	72
	Dynamic	high	190	8	105
R1_sit_eat_in_01	Static	medium	205	6	340
	Dynamic	medium	160	6	245
R1_interact_in_01	Static	high	195	7	100
	Dynamic	high	200	7	195
R1_interact_out_01	Static	low	195	4	198
	Dynamic	low	200	4	790
R1_carry_out_01	Static	low	178	5	230
	Dynamic	low	185	5	418
R1_carry_out_02	Static	low	178	3	120
	Dynamic	low	185	3	232
R1_chat_in_01	Static	medium	178	6	53
	Dynamic	medium	185	6	187

Table 4: Baseline Results for Pedestrian Detection using YOLOv8x.

Modality	mAP50 (%)	Precision (%)	Recall (%)
Event-only	50.2	66.1	61.5
RGB-only	82.7	84.2	79.0
Event + RGB	88.5	90.6	83.3

For the multi-modal baseline, we combined predictions from both Event-only and RGB-only models using a late fusion approach. Each model produced its own set of bounding boxes, which were then merged using Non-Maximum Suppression (NMS) Bodla et al. (2017) with an IoU threshold of 0.5. NMS removes overlapping boxes with lower confidence, keeping only the most reliable detections. This process produced a single set of bounding boxes per frame, improving overall detection performance by leveraging complementary motion and appearance information. From this result, we conclude that the triCAM dataset provides sufficient information to advance and improve pedestrian detection algorithms.

6 Conclusion

In this paper, we introduce triCAM, the first monocular, multi-modal, event-based pedestrian dataset. Designed for real-world applications, triCAM provides high-quality, synchronized data from indoor and outdoor restaurant environments under both static and dynamic camera motions. Unlike existing datasets, it captures natural human interactions in crowded scenes, offering a unique benchmark for studying pedestrian detection and human behavior. By combining complementary sensing modalities, triCAM enables robust representation learning and paves the way for advances in event-based perception.

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