EVIMO2: An Event Camera Dataset for Motion Segmentation, Optical Flow, Structure from Motion, and Visual Inertial Odometry in Indoor Scenes with Monocular or Stereo Algorithms

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Abstract

A new event camera dataset, EVIMO2, is introduced that improves on the popular EVIMO dataset by providing more data, from better cameras, in more complex scenarios. As with its predecessor, EVIMO2 provides labels in the form of per-pixel ground truth depth and segmentation as well as camera and object poses. All sequences use data from physical cameras and many sequences feature multiple independently moving objects. Typically, such labeled data is unavailable in physical event camera datasets. Thus, EVIMO2 will serve as a challenging benchmark for existing algorithms and rich training set for the development of new algorithms. In particular, EVIMO2 is suited for supporting research in motion and object segmentation, optical flow, structure from motion, and visual (inertial) odometry in both monocular or stereo configurations.

EVIMO2 consists of 41 minutes of data from three 640×480 event cameras, one 2080×1552 classical color camera, inertial measurements from two six axis inertial measurement units, and millimeter accurate object poses from a Vicon motion capture system. The dataset’s 173 sequences are arranged into three categories. 3.75 minutes of independently moving household objects, 22.55 minutes of static scenes, and 14.85 minutes of basic motions in shallow scenes. Some sequences were recorded in low-light conditions where conventional cameras fail. Depth and segmentation are provided at 60 Hz for the event cameras and 30 Hz for the classical camera. The masks can be regenerated using open-source code up to rates as high as 200 Hz.

This technical report briefly describes EVIMO2. The full documentation is available online1. Videos of individual sequences can be sampled on the download page2.

1. Introduction

EVIMO2 is an event camera dataset featuring per-pixel ground truth depth, segmentation, and object pose for the footage from three event cameras and one classical color camera. It generally improves on its predecessor EVIMO [24] by using better cameras, featuring longer recordings, providing different categories of recordings, and using an improved data format. The recordings feature indoor, dynamic scenes with multiple independently moving objects. In contrast to existing simulated [10, 11, 15–17, 21, 26–28, 30, 33, 34] and physical [1–5, 7–9, 12–14, 18–20, 22, 25, 26, 29, 31, 32, 35–38, 38, 38] event camera datasets, EVIMO2 focuses on close range indoor situations with fast moving objects and provides per-pixel ground truth depth and segmentation as well as poses for the physical cameras and all

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1https://better-flow.github.io/evimo
2https://better-flow.github.io/evimo/download_evimo_2.html
objects.

While pixel accurate semantic segmentation is sometimes available in simulated event camera datasets [11, 21, 28, 33, 34] it is not usually available for physical event camera datasets with the exception being EVIMO2’s direct predecessor [24]. On the other hand, while depth and semantic bounding boxes are sometimes present in physical event camera datasets from LIDAR, structured light sensors, and hand labeling [2, 12, 19, 20, 23, 29, 38], EVIMO2’s depth and segmentation comes from 3D scans of household objects combined with Vicon pose measurements. This results in more detailed ground truth depth maps and optical flow fields than could previously be achieved, even in datasets designed for optical flow estimation [1, 3, 26, 32].

Due to the availability of ground truth pose of the camera, EVIMO2 is suitable for indoor Visual Inertial Odometry (VIO) and Simultaneous Localization and Mapping (SLAM) research. It differs from existing VIO and SLAM event camera datasets by focusing on close-up indoor scenes containing moving household objects. In contrast, existing datasets focus on indoor scenes without moving objects [3, 5, 9, 18, 26, 35], outdoor or driving/flying scenes [4, 8, 13, 18, 31, 38], or extreme environments [19, 20, 23]. Further, EVIMO2 provides poses for the camera and all objects which opens up exciting opportunities for object pose estimation.

EVIMO2’s ground truth depth and segmentation masks are obtained using the same methods as its predecessor EVIMO [24]. The 3D scans of the objects are projected into the camera’s field-of-view using poses measured by a Vicon motion capture system. 60 Hz ground truth is available for event cameras and 30 Hz ground truth for the classical camera. Higher framerate ground truth can be generated using the released open-source tools. Due to the detailed 3D object scans and the high quality tracking of the Vicon system, exceptional ground-truth optical flow can be generated for scenes with fast moving objects undergoing complex motions as shown in Figure 1 and 3.

2. Methods

EVIMO2 features sensor data from three event cameras, one classical camera, two six-axis inertial measurement units, and poses from a Vicon motion capture system. Two of the event cameras are Prophesee Gen3 VGA 640×480 sensors with a 71 degree diagonal field-of-view. They are arranged in a binocular stereo configuration with a baseline of approximately 22 cm. The third event camera is a Samsung DVS Gen3 with 640×480 resolution and 75 degree diagonal FOV. The classical camera is a Flea 3 camera featuring the Sony IMX036 sensor which recorded at 2080×1552 and 30 Hz while fitted with a lens

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https://docs.prophesee.ai/stable/hw/evk/gen3.html

https://rpg.ifi.uzh.ch/docs/CVPR19workshop/CVPRW19_Eric_Ryu_Samsung.pdf
that achieved a 64 degree diagonal FOV\(^5\). The inertial measurements are supplied by the Prophesee camera’s internal MPU9250 IMUs which are sampled at 1 kHz\(^6\).

2.1. Objects

The dataset features over 20 real world objects including a large table that forms the main backdrop of many sequences as illustrated by Figure 2. The other objects are small household items such as toy blocks, remote control cars, and small drones. Silver motion capture markers are attached to each object to enable tracking by the Vicon motion capture system.

The 3D Models for the objects were obtained using an Artec Space Spider scanner\(^7\). This results in high quality meshes, which were then edited using the open-source Meshlab software to remove the Vicon markers [6].

2.2. Ground Truth

Ground truth depth and segmentation masks are calculated using Vicon pose estimates and 3D scans of small objects and a large table. This makes accurate ground truth depth available for the objects and the table, which typically cover most of the field of view as exemplified by Figure 2.

Due to the small size of the objects used, and the sensitivity of the Vicon motion capture system to occlusion of object’s markers, there are occasional temporal gaps in ground truth availability. As a result, users must take care to respect that the ground truth data is not evenly spaced in time.

2.3. Sensor Availability

Not all sensors are available in all sequences. A complete camera availability matrix is available on the EVIMO2 downloads page. The left Prophesee camera is available in 155 sequences. The right Prophesee camera is available in 124 sequences. The Samsung camera is available in 154 sequences. The Flea3 camera is available in 139 sequences (the Flea3 data is excluded from several of the low-light sequences because it did not produce usable data).

2.4. Sequence Categories

The sequences are organized in three distinct categories. “Independently Moving Objects” (IMO), “Structure from Motion” (SfM), and “Simple Motion in Planar Scenes” (Sanity). All categories have a smaller set of sequences designated “low light”. In low light sequences the ambient light levels in the recording room were greatly reduced which makes the events much “noisier”. Video previews of a prototypical member of each category are available on EVIMO2’s download page.

3. Conclusion

EVIMO2 is an event camera dataset featuring three event cameras, one classical camera, two IMUs, per-pixel ground truth depth, segmentation, and object poses. Typically, ground segmentation and object poses are only available in simulated datasets. Further, EVIMO2 contains numerous sequences with small, independent, fast moving objects, which present a challenge for optical flow, visual odometry, and SLAM methods. Thus, EVIMO2 provides a chal-
lenging benchmark for existing methods and rich set of sequences for training new ones.

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References

[1] Mohammed Almatrafi, Raymond Baldwin, Kiyoharu Aizawa, and Keigo Hirakawa. Distance surface for event-based optical flow. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 42(7):1547–1556, 2020.
[2] Alexander Andreopoulos, Hirak J. Kashyap, Tapan K. Nayak, Arnon Amir, and Myron D. Flickner. A low power, high throughput, fully event-based stereo system. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 7532–7542, June 2018.
[3] Francisco Barranco, Cornelia Fermüller, Yiannis Aloimonos, and Tobi Delbruck. A dataset for visual navigation with neuromorphic methods. *Frontiers in Neuroscience*, 10, 2016.
[4] Jonathan Binas, Daniel Neil, Shih-Chii Liu, and Tobi Delbruck. DDD17: End-to-end DAVIS driving dataset. *arXiv preprint arXiv:1711.01458*, 2017.
[5] Samuel Bryner, Guillermo Gallego, Henri Rebecq, and Davide Scaramuzza. Event-based, direct camera tracking from photometric depth maps. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 40(10):2402–2412, 2018.
[6] Yuhuang Hu, Jonathan Binas, Daniel Neil, Shih-Chii Liu, and Tobi Delbruck. DDD20 End-to-end event camera driving dataset: Fusing frames and events with deep learning for improved steering prediction. In *Proceedings of the IEEE 23rd International Conference on Intelligent Transportation Systems (ITSC)*, pages 1–6. IEEE, 2020.
[7] Tobi Delbruck. Frame-free dynamic digital vision. In *Proceedings of International Symposium on Secure-Life Electronics, Advanced Electronics for Quality Life and Society*, volume 1, pages 21–26, 2008.
[8] Jeffrey Delmerico, Titus Cieslewski, Henri Rebecq, Matthias Faessler, and Davide Scaramuzza. Are we ready for autonomous drone racing? the UZH-FPV drone racing dataset. In *Proceedings of the International Conference on Robotics and Automation (ICRA)*, pages 6713–6719, 2019.
[9] Guillermo Gallego, Jon E.A. 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, 2018.
[10] Daniel Gehrig, Mathias Gehrig, Javier Hidalgo-Carrió, and Davide Scaramuzza. Video to events: Recycling video datasets for event cameras. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 3586–3595, June 2020.
[11] Daniel Gehrig, Michelle Ruegg, Mathias Gehrig, Javier Hidalgo-Carrió, and Davide Scaramuzza. Combining events and frames using recurrent asynchronous multimodal networks for monocular depth prediction. *IEEE Robotics and Automation Letters*, 6(2):2822–2829, 2021.
[12] Mathias Gehrig, Willem Aarents, Daniel Gehrig, and Davide Scaramuzza. DSEC: A stereo event camera dataset for driving scenarios. *IEEE Robotics and Automation Letters*, 6(3):4947–4954, 2021.
[13] Yuhuang Hu, Jonathan Binas, Daniel Neil, Shih-Chii Liu, and Tobi Delbruck. DDD20 End-to-end event camera driving dataset: Fusing frames and events with deep learning for improved steering prediction. In *Proceedings of the IEEE 23rd International Conference on Intelligent Transportation Systems (ITSC)*, pages 1–6. IEEE, 2020.
[14] Yuhuang Hu, Hongjie Liu, Michael Pfeiffer, and Tobi Delbruck. DVS Benchmark datasets for object tracking, action recognition, and object recognition. *Frontiers in Neuroscience*, 10, 2016.
[15] Yuhuang Hu, Shih-Chii Liu, and Tobi Delbruck. v2e: From video frames to realistic DVS events. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)* Workshops, pages 1312–1321, June 2021.
[16] Damien Joubert, Alexandre Marcireau, Nic Ralph, Andrew Jolley, André van Schaik, and Gregory Cohen. Event camera simulator improvements via characterized parameters. *Frontiers in Neuroscience*, 15, 2021.
[17] Jacques Kaiser, J. Camilo Vasquez Tieck, Christian Hubschner, Peter Wolf, Michael Weber, Michael Hoff, Alexander Friedrich, Konrad Wojtasik, Arne Roennau, Ralf Kohlhass, Rüdiger Dillmann, and J. Marius Zöllner. Towards a framework for end-to-end control of a simulated vehicle with spiking neural networks. In *Proceedings of the IEEE International Conference on Simulation, Modeling, and Programming for Autonomous Robots (SIMPAR)*, pages 127–134, 2016.
[18] Simon Klenk, Jason Chui, Nikolaus Demmel, and Daniel Cremers. TUM-VIE: The TUM stereo visual-inertial event

| Category       | Sequences Train | Sequences Test | Minutes Train | Minutes Test |
|----------------|-----------------|----------------|--------------|--------------|
| IMO            | 21              | 8              | 2.74         | 0.51         |
| IMO LL         | 3               | 2              | 0.36         | 0.14         |
| SfM            | 52              | 10             | 16.17        | 2.45         |
| SfM LL         | 5               | 6              | 2.56         | 1.37         |
| Sanity         | N/A             | 31             | N/A          | 6.96         |
| Sanity LL      | N/A             | 35             | N/A          | 7.89         |
| Totals         | 81              | 92             | 21.83        | 19.32        |

Table 1. Number of sequences and duration of sequences for each sequence category in EVIMO2. Abbreviations: Independent Moving Objects (IMO), Structure from Motion (SfM), Simple Motion in Planar Scenes (Sanity), Low Light (LL).
dataset. In Proceedings of the International Conference on Intelligent Robots and Systems (IROS), pages 8601–8608, 2021. 1, 2

[19] Alex Junho Lee, Younggun Cho, Young-sik Shin, Ayoung Kim, and Hyun Myung. ViViD++: Vision for visibility dataset. IEEE Robotics and Automation Letters, 7(3):6282–6289, 2022. 1, 2

[20] Alex Junho Lee, Younggun Cho, Sungho Yoon, Youngsik Shin, and Ayoung Kim. ViViD: Vision for visibility dataset. In IEEE Int. Conf. Robotics and Automation (ICRA) Workshop: Dataset Generation and Benchmarking of SLAM Algorithms for Robotics and VR/AR, 2019. 1, 2

[21] Wenbin Li, Sajad Saeedi, John McCormac, Ronald Clark, Jiangyi Li, and Juan Pablo Rodriguez-Gomez. EVENT: Monocular event camera. In Proceedings of the IEEE International Conference on Robotics and Automation (ICRA), pages 6105–6112, Nov 2019. 1, 2

[22] Min Liu and Tobi Delbruck. EDFLOW: Event driven optical flow camera with keypoint detection and adaptive block matching. IEEE Transactions on Circuits and Systems for Video Technology, pages 1–1, 2022. 1, 4

[23] Anton Mitrokhin, Cornelia Fermüller, Chethan Parameshwara, and Yiannis Aloimonos. Event-based moving object detection and tracking. In Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pages 1–9, 2018. 2

[24] A. Mitrokhin, C. Ye, C. Fermüller, Y. Aloimonos, and T. Delbruck. Ev-imo: Motion segmentation dataset and learning pipeline for event cameras. In Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pages 6105–6112, Nov 2019. 1, 2

[25] Diederik Paul Moey, Federico Corradi, Emmett Kerr, Philip Vance, Gautham Das, Daniel Neil, Dermot Kerr, and Tobi Delbruck. Steering a predator robot using a mixed frame/event-driven convolutional neural network. In Proceedings of the Second International Conference on Event-based Control, Communication, and Signal Processing (EBCCSP), pages 1–8, 2016. 1

[26] Elias Mueggl, Henri Rebecq, Guillermo Gallego, Tobi Delbruck, and Davide Scaramuzza. The event-camera dataset and simulator: Event-based data for pose estimation, visual odometry, and slam. The International Journal of Robotics Research, 36(2):142–149, 2017. 1, 2

[27] Jalees Nehvi, Vladislav Golyanik, Franziska Mueller, Hans-Peter Seidel, Mohamed Elgharib, and Christian Theobalt. Differentiable event stream simulator for non-rigid 3d tracking. In Proceedings of the IEEE/CFV Conference on Computer Vision and Pattern Recognition (CVPR) Workshops, pages 1302–1311, June 2021. 1

[28] Chethan M Parameshwara, Nitin J Sanket, Chahat Deep Singh, Cornelia Fermüller, and Yiannis Aloimonos. 0-MMS: Zero-shot multi-motion segmentation with a monocular event camera. In Proceedings of the IEEE International Conference on Robotics and Automation (ICRA), pages 9594–9600. IEEE, 2021. 1, 2

[29] Etienne Perot, Pierre de Tourmire, Davide Nitti, Jonathan Masci, and Amos Sironi. Learning to detect objects with a 1 megapixel event camera. In H. Larochelle, M. Ranzato, R. Hadsell, M.F. Balcan, and H. Lin, editors, Advances in Neural Information Processing Systems, volume 33, pages 16639–16652. Curran Associates, Inc., 2020. 1, 2

[30] Henri Rebecq, Daniel Gehrig, and Davide Scaramuzza. ESIM: an open event camera simulator. In Aude Billard, Anca Dragan, Jan Peters, and Jun Morimoto, editors, Proceedings of The 2nd Conference on Robot Learning, volume 87 of Proceedings of Machine Learning Research, pages 969–982. PMLR, 29–31 Oct 2018. 1

[31] Juan Pablo Rodriguez-Gomez, Raul Tapia, Julio L. Paneque, Pedro Grau, Augusto Gomez Eguiu, Jose Ramiro Martinez-de Dios, and Anibal Ollero. The GRIFFIN perception dataset: Bridging the gap between flapping-wing flight and robotic perception. IEEE Robotics and Automation Letters, 6(2):1066–1073, 2021. 1, 2

[32] Bodo Rueckauer and Tobi Delbruck. Evaluation of event-based algorithms for optical flow with ground-truth from inertial measurement sensor. Frontiers in Neuroscience, 10, 2016. 1, 2

[33] Nitin J Sanket, Chethan M Parameshwara, Chahat Deep Singh, Ashwin V Kuruttukulam, Cornelia Fermüller, Davide Scaramuzza, and Yiannis Aloimonos. EVDodgeNet: Deep dynamic obstacle dodging with event cameras. In Proceedings of the IEEE International Conference on Robotics and Automation (ICRA), pages 10651–10657. IEEE, 2020. 1, 2

[34] Shital Shah, Debadeepa Dey, Chris Lovett, and Ashish Kapoor. AirSim: High-fidelity visual and physical simulation for autonomous vehicles. In Field and Service Robotics, 2017. 1, 2

[35] David Weikersdorfer, David B. Adrian, Daniel Cremers, and Jörg Conradt. Event-based 3D SLAM with a depth-augmented dynamic vision sensor. In Proceedings of the IEEE International Conference on Robotics and Automation (ICRA), pages 359–364, 2014. 1, 2

[36] Yi Zhou, Guillermo Gallego, Henri Rebecq, Laurent Kneip, Hongdong Li, and Davide Scaramuzza. Semi-dense 3D reconstruction with a stereo event camera. In European Conference on Computer Vision (ECCV), pages 235–251, 2018. 1

[37] Yi Zhou, Guillermo Gallego, and Shaojie Shen. Event-based stereo visual odometry. IEEE Transactions on Robotics, 37(5):1433–1450, 2021. 1

[38] Alex Zihao Zhu, Dinesh Thakur, Tolga Özaslan, Bernd Pfommer, Vijay Kumar, and Kostas Daniilidis. The multi-vehicle stereo event camera dataset: An event camera dataset for 3D perception. IEEE Robotics and Automation Letters, 3(3):2032–2039, 2018. 1, 2