Concept Study for Dynamic Vision Sensor Based Insect Monitoring

Regina Pohle-Fröhlich and Tobias Bolten
Institute for Pattern Recognition, Niederrhein University of Applied Sciences, Krefeld, Germany

Keywords: Insect Monitoring, Dynamic Vision Sensor, Event Camera.

Abstract: A decline in insect populations has been observed for many years. Therefore, it is necessary to measure the number and species of insects to evaluate the effectiveness of the interventions taken against this decline. We describe a sensor-based approach to realize an insect monitoring system utilizing a Dynamic Vision Sensor (DVS). In this concept study, the processing steps required for this are discussed and suggestions for suitable processing methods are given. On the basis of a small dataset, a clustering and filtering-based labeling approach is proposed, which is a promising option for the preparation of larger DVS insect monitoring datasets. An U-Net based segmentation was tested for the extraction of insect flight trajectories, achieving an F1-score of ≈ 0.91. For the discrimination between different species, the classification of polarity images or simulated grayscale images is favored.

1 INTRODUCTION

Climate and landscape changes caused by human influence have a major impact on biodiversity. An observed and scientifically proven process in recent years is the population decline of many insect species (Hallmann et al., 2017). In order to better understand the processes of species reduction and habitat shifts, a prototype for long-term monitoring of insects is being developed, which works non-invasively and enables a determination of the number of insect flight movements and discrimination of species in the observation area. For data generation, a Dynamic Vision Sensor (DVS) is used.

The Dynamic Vision Sensor technology is a result of the continuing research in the field of neuromorphic engineering. The operating and output paradigm of this sensor differs fundamentally from well-known and widely used conventional cameras. A DVS does not record frames at a fixed sampling rate (frames per second), but rather each pixel responds independently and asynchronously to changes in brightness over time. For each detected brightness change above a defined threshold, its spatial position in the sensor array (x, y), a very precise timestamp t of triggering, and an indicator p for the direction of change is transmitted immediately. Thus, the native output of a DVS is a data-driven stream of so-called events (see Figure 1 for an example).

As a result, Dynamic Vision Sensors offer technical advantages over classical imagers for insect monitoring. In comparison, significantly less redundant information has to be transmitted, stored and finally processed, since the output of the sensor is already driven by changes only. The very high time resolution in the continuous sensor output, which reaches the microsecond range, supports the detection of very fast moving objects such as insects. In addition a DVS has a significantly higher dynamic range so they provide meaningful data in areas with changing illumination or even in very dark environments.

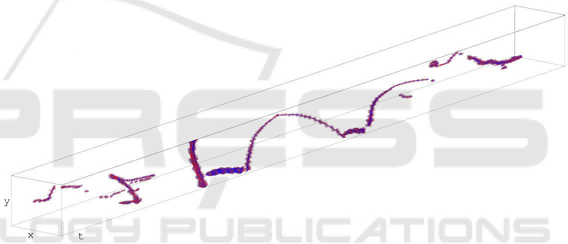


Figure 1: Example of DVS output stream for flying insects in front of the DVS.

In this paper, we address the task of insect monitoring in DVS sensor data within such a challenging outdoor scenario. We discuss possibilities

- for semi-automatic labeling of the event data
- for extracting the flight trajectories
- for differentiation between different insect species

The rest of this paper is structured as follows. Section 2 gives an overview of related work. In Section 3 the processing pipeline currently planned is described with approaches that can be applied for data labeling,

Pohle-Fröhlich, R. and Bolten, T.
Concept Study for Dynamic Vision Sensor Based Insect Monitoring.
DOI: 10.5220/0011775500003417
In *Proceedings of the 18th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications (VISIGRAPP 2023) - Volume 4: VISAPP*, pages 411-418
ISBN: 978-989-758-634-7; ISSN: 2184-4321

detecting of the flight paths and to distinguish the different insect species. Finally, a brief summary and an outlook on future work is given.

2 RELATED WORK

2.1 Insect Monitoring

Currently, there are different ways for monitoring insects in a habitat. These vary depending on the specific monitoring task (Wägele et al., 2022). Malaise traps are used to capture passing insects. For nocturnal moths, light trapping and, less frequently, bait trapping are used. It should be noted that all these trapping methods are extremely labour-intensive. Usually, the insects are killed in the traps and then DNA analyses are performed. Furthermore, a disadvantage of these monitoring methods is, that they only collect data over a short time interval.

For scientific studies of butterflies or diurnal moths, random manual observations or manual capture-mark-recapture methods are utilized.

For non-invasive detection of insects, bio-acoustic identification methods and camera traps can be applied. Acoustic evaluations are very dependent on ambient noise. Moreover, they only provide very rough information about the number of insects in a given area (Wägele et al., 2022).

Camera traps usually work with motion detectors. Since insects are very small, these detectors must be adequately sensitive, but they also react to plant movements due to wind. As a result, a lot of image data is recorded that does not contain any information about insects. Another disadvantage of using conventional cameras is that the insects are blurred as a result of the rapid movement, so that the detection of the insects in the images is difficult and prone to error (Wägele et al., 2022).

Finally, there is the possibility of using radar data. However, radar detection only shows the movement of dense insect swarms. Species identification is difficult (Wang et al., 2017). To our knowledge, using a DVS for insect monitoring has not been investigated until now.

2.2 DVS-Based Datasets

The event-based computer vision is a comparatively young domain. The foundation of the field was laid in the early 1990s (Gallego et al., 2022). As a result, the availability of DVS-based datasets is, compared to the frame-based domain, more limited. Furthermore, many of the available datasets were recorded indoor or even under laboratory conditions and are therefore not suitable for developing an insect monitoring system.

In the context of monitoring real-world outdoor scenarios, datasets from the automotive sector are available. These datasets often do not provide object annotations at all (Binas et al., 2017; Hu et al., 2020) or include only classes that are unusable for insect monitoring (Alonso and Murillo, 2019; de Tournemire et al., 2020). To the best of the authors' knowledge, currently there is only one DVS-based dataset called *DVS-OUTLAB* providing annotations on a semantic level and including the superclass INSECT (Bolten et al., 2021). This dataset was recorded in the context of an urban person monitoring and contains insects only as aspects of environmental influence and noise. In addition, these annotations are only available on limited spatial and short temporal regions of interest and do not include details about the insect species. Thus, there is currently no public and labeled dataset that allows a quantitative evaluation of insect monitoring and approaches to extracting their trajectories.

2.3 DVS-Based Processing

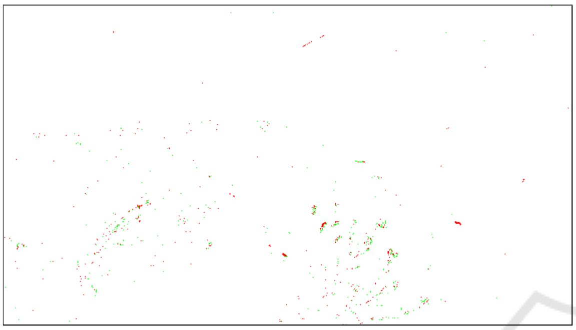
There are a variety of methods to encode and process the novel output stream of a DVS (see (Gallego et al., 2022) for an comprehensive overview). This includes methods that cluster the sensor event output and thus form and assign objects (Bolten et al., 2019; Rodríguez-Gomez et al., 2020). Frequently, the events are also converted into classic 2D frames and then processed further using established computer vision methods.

In the work (Bolten et al., 2022), semantic segmentation using point clouds as well as frame-based representations was evaluated on basis of the *DVS-OUTLAB* dataset. Utilizing PointNet++ and MaskR-CNN, resulted in high F1 scores of over 0.9 for the included class INSECT within their ten class segmentation scenario. Although this study does not allow a general statement on insect monitoring due to the mentioned dataset limitations, this still shows the potential of the sensor type within this use case scenario and motivates further research.

3 PLANNED PROCESSING STEPS

Due to the fact that no suitable DVS data were available as open data for the question of insect monitoring, seven own datasets were captured for our concept study. These datasets with a length between 30 sec-

(a) RGB frame.



(b) DVS polarity frame (red ≙ negative, green ≙ positive) (sparse input data; best viewed in color and digital zoomed).

Figure 2: Comparison between a RGB camera frame and the output of the DVS sensor accumulated over a time window of 60 milliseconds.

onds and almost 6 minutes were used to develop the processing pipeline and to assess the quality of the individual steps. All datasets were recorded with a model of the Prophesee GEN4.1-HD DVS. Figure 2 shows a comparison between a RGB camera image and the output of the DVS sensor accumulated over a time window of 60 milliseconds. This DVS provides an image resolution of 1280x720 pixels with a time resolution in microseconds. To estimate the applicability of the proposed methods, a dataset of 30 seconds in length was manually labeled and used in the following experiments. Since the species of insects was currently not available for the sample DVS data, the events were only subdivided into the classes INSECT and ENVIRONMENTAL influences including noise. To evaluate the methods for differentiating between different insects, additional event data was simulated from slow-motion videos by using methods from the Metavision SDK[1].

A pre-requirement for our processing pipeline is to prepare the datasets for using AI methods. For labeling, pre-filtering of the data is necessary to reduce the manual effort in order to separate events caused by insect movements from events caused by noise and environmental influences. Using the labeled data, the detection of flight paths is then carried out in any recordings. In order to visualize the insects' movements, an approximation of the detected trajectories by spline functions is then planned. Finally, the individual trajectories can be assigned to a specific species using derived features or images.

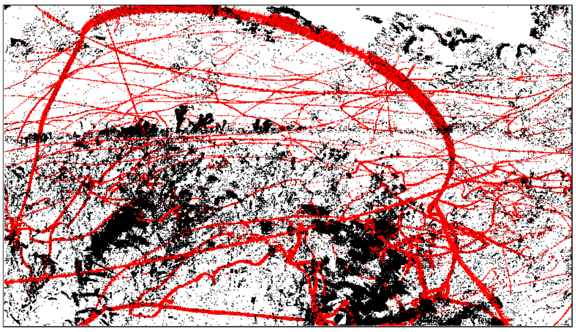
3.1 Labeling

There are only a few tools for labelling 3D data that either require additional image material, allow the manual placement of bounding boxes[2] or work on voxel data (Berger et al., 2018). Because these procedures were not applicable to our data, a combination of pre-filtering followed by clustering was tested for labeling. For pre-filtering, the fact can be used that most insects are moving very fast on a spatial compact flight path. In comparison, environmental influences such as shadow casts by cloud movement or the movement of grasses and leaves in the wind lead to more spatially distributed events. To reduce noise events, a statistical outlier removal is initially applied. It calculates the average distance of each point to its 15 nearest neighbors. The value of the neighbors is chosen so large because insects mostly have dense flight paths. Then the events that are more distant than the average distance plus a multiple of the standard deviation are discarded. For the standard deviation we chose a small value of 0.5 in order to remove less compact areas from the event stream. Since in our test dataset only flying insects occur at a distance of 0.5 to approx. 5 meter, we calculate the linearity feature for all events according to (Hackel et al., 2016). In our calculation only events within a radius of three are used for the calculation of the Eigen values, in order to separate the narrow elongated structures of the flight paths from the more compact structures of the plant movements. Then we removed all events with a linearity value of less than 0.1 in order to filter out as few insect events as possible. This threshold was determined experimentally from the data. For the insects, the mean linearity value was 0.44 ± 0.24 and for the background, the mean value was 0.23 ± 0.3. Figure 3 shows an example of the result of these filtering steps. In this Figure it can be seen that many events resulting from noise and environmental influences (black points) have been removed. The events of the insect tracks (red points) remain largely unaffected by the filtering. This strategy still needs to be tested for a larger dataset and for a wider range of insect species.

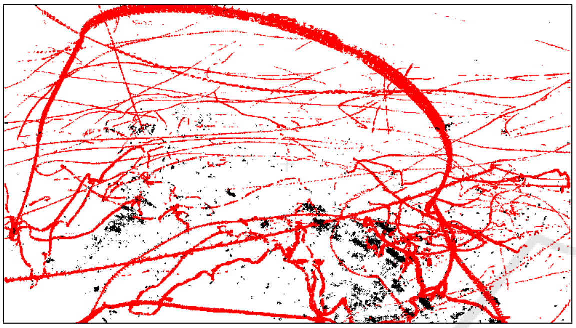
After filtering, we used the DBSCAN algorithm (Ester et al., 1996) to cluster the data. This algorithm

[1]https://docs.prophesee.ai/stable/index.html

[2]https://mathworks.com/help/lidar/labeling.html



(a) Original input.



(b) Filter result.

Figure 3: Projected 3D event space-time point cloud of a wildflower meadow with insects (30 second time period) colored using manual class mapping for events from insects (red) and events from the environment and noise (black).

works density-based and is able to recognize multiple clusters. It was chosen because this algorithm does not require the number of clusters to be known in advance. In addition, the insects' flight paths form very dense structures compared to the events of moving grasses. In our tests, the threshold for the neighborhood search radius was set to 30 and the minimum number of neighbors required to identify a core point was set to 10. With these parameters, the algorithm delivers 1131 clusters for our manually labeled example (see Figure 4). It can be seen that a large number of the flight paths were found correctly, so that the manual labeling effort was significantly reduced. In addition, entire clusters can be relabeled with this method. Another advantage of this approach is that the data can also be easily prepared for instance segmentation.

3.2 Detection of Flight Trajectories

In the literature, various neural networks are used for semantic segmentation of event data. In many applications, graph-based or point-cloud-based neural networks are used (Bolten et al., 2022). In both approaches, however, the number of events must be

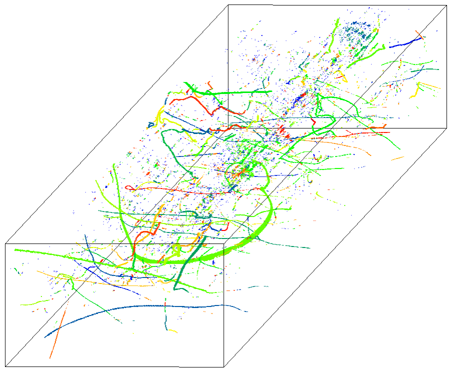


Figure 4: 3D event space-time point cloud after clustering. Clusters are highlighted by random colors.

reduced considerably. Typical neural networks for point clouds, such as PointNet++ (Qi et al., 2017), only process point clouds with a fixed size. Often less than 4096 points are used due to computational requirements. To achieve a reduction in the number of events, the event point clouds are often divided into patches-of-interest, with additional random subsampling used for data reduction for each patch. However, the point cloud used for our tests contained 1943504 events in total. As the flight paths sometimes contain only a few points, such patching and subsampling would lead to the data no longer containing interesting structures cause by insects.

Another approach for segmenting the event streams is to convert them into 2D images. Typical techniques for generating frames from DVS event streams are based on considering a fixed number of events or selecting a time window of fixed length. Depending on the focus of the application, different encoding rules are used that aim to preserve different aspects of the underlying event stream (Bolten et al., 2022). Classic encoder-decoder networks are then used to segment these frames (Alonso and Murillo, 2019). One of such encoder-decoder structures is the U-Net, which was originally developed by Ronneberger (Ronneberger et al., 2015) for segmenting medical images. One advantage of its architecture is that it works with few training images and achieves precise segmentations. For this reason, it was chosen for the first tests to segment the flight paths.

For our investigation, all events were encoded into a frame within a time window of 60 milliseconds. We examined two different encoding types. In binary encoding, a pixel is set as soon as an event occurs in the time window. With time encoding, the time stamps are set as grey values so that the temporal dynamics in a scene are preserved. For each coding type, 507 images were generated from the manually labeled point cloud. From each of these, 100 images were

Table 1: Resulting confusion matrices for UNet experiment.

class	BACKGROUND	ENVIRONMENT	INSECT
BACKGROUND	91795957	115889	15024
ENVIRONMENT	2245	192232	3108
INSECT	154	2610	32781
F1	0.999	0.756	0.758

(a) Plain inference after 300 epoch training.

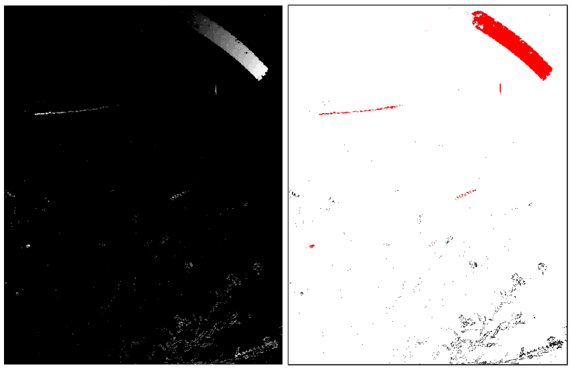
class	BACKGROUND	ENVIRONMENT	INSECT
BACKGROUND	91926870	0	0
ENVIRONMENT	2891	191596	3098
INSECT	510	2598	32437
F1	0.999	0.978	0.912

(b) Corresponding results after pre-processing.

randomly selected as the evaluation set, the rest were used for training. Furthermore, different layer depths within the network were used.

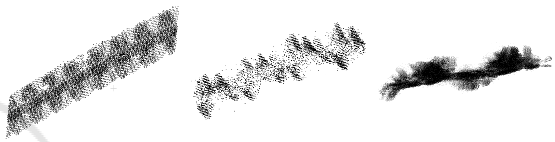
The best results according to F1 score were achieved using a network layer depth of six in combination with the time-encoded input images after 300 training epochs. The resulting confusion matrix is given in Table 1. The F1 values for the BACKGROUND class were 0.99, for the ENVIRONMENT class 0.76 and for the INSECT class 0.76. When looking at the result images, it became obvious that the classes ENVIRONMENT and INSECT were mostly detected somewhat too large and filled, which led to the low F1 values. Within a post-processing, only those class predictions were considered where events actually occurred. This makes sense because only these are important for the backpropagation of the results to the original 3D event stream for further processing. The confusion matrix after this post-processing is shown in Table 1b. The F1 values then improved to 0.98 for the ENVIRONMENTAL class and 0.91 for the INSECT class. An example of this segmentation can be found in Figure 5.

The obtained F1 scores in our tests correspond approximately to the values achieved in Bolten (Bolten et al., 2022). Thus, it could be demonstrated that the detection of flight paths by means of a neural network is applicable for our scenario. For practical use, however, further investigations are required with respect to the network structure and network configuration as well as for the selection of the optimal time window.



(a) Time encoded input frame. (b) UNet result.

Figure 5: Cropped example frames for UNet based segmentation. Segmentation shown in colors: white ≙ BACKGROUND, black ≙ ENVIRONMENT, red ≙ INSECT.



(a) Bee. (b) Dragonfly. (c) Butterfly.

Figure 6: Example for flight patterns.

3.3 Approaches for Differentiation Between Insect Species

After detecting the trajectories successfully, there are several possibilities for classifying them to a specific species.

Classification Based on Derived Features Directly from DVS Events

A first way for differentiating between insect species is to analyze flight patterns. A rough differentiation is provided by the analysis of trajectories. Some butterflies, for example, tend to flutter uncontrollably and in zigzags, while bumblebees, for example, tend to fly purposefully towards a flower.

The distance travelled is also different. While butterflies and beetles satisfy their hunger and fly to fewer flowers, honey bees land more frequently on flowers of one species successively until they return to their hive with the collected material.

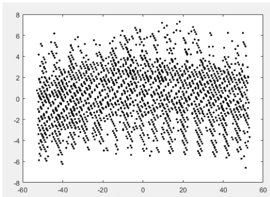
Looking at the recorded events along the flight paths of different insects, these resulting flight patterns also provide a possibility for a rough differentiation. For comparison, preferably linear flight segments should be selected, which can then be classified e.g. with neural networks for point clouds, such as PointNet++ (Qi et al., 2017). Figure 6 shows example data for such flight segments of a bee, a dragonfly and a butterfly.

In addition, the individual insect species also differ in the number of wing beats when flying. Most butterflies, for example, achieve between 10 and 20 wing beats, the pigeon tail between 60 and 70, the ladybird between 75 and 90, the honey bee between 180 and 250, bumblebees 90, flies between 200 and 240 and mosquitoes almost 300 (Greenewalt, 1962). The wing beat frequency of insects is considered potentially valuable for species identification and is used e.g. in radar entomology (Wang et al., 2017). In order to assess the usefulness of this distinguishing criterion, we first examined only the wing beat frequency for bees. In our study, the number of wing beats for different bees was calculated from different parts of the recorded point clouds. To perform the frequency analysis, the extracted point clouds were transferred into a new coordinate system using a PCA and the coordinate with the lowest eigenvalue was omitted for the projection (Figure 7a).

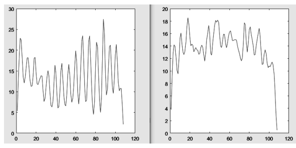
To convert the projection images into curves, the number of points for the discretized x-values was counted separately for the positive and negative y-values in each case in order to exclude a shift in the wing movement due to the projection (Figure 7b). The frequency spectrum was then calculated using FFT and the amplitude values of both curves were summed up (Figure 7c). To calculate the number of wing beats, the frequency corresponding to the second local maximum was selected, because the first local maximum contained the curvature of the entire flight path. From these detected frequencies and the corresponding time intervals, the number of wing beats per second was calculated for 14 selected trajectories of bees. These varied between 89 and 175 wing beats, with a mean value of 147.9 ± 6.5. This variation in values is probably related to the respective position of the section in the overall flight path (take-off, in flight, landing). The different loading with pollen could also play a role. It can therefore be assumed that the number of wing beats is not a good method for classifying the insect species in the selected scenario.

Classification Based on Polarity Frames

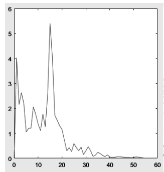
A second approach is to generate frames by accumulating the previous segmented events and then classifying them. It is only necessary to consider one frame per trajectory. Therefore it is searched for the largest bounding box in the images with the projected events over each 60 milliseconds corresponding to the just considered trajectory. This ensures that the closest possible position to the camera is always selected. For



(a) Projection.

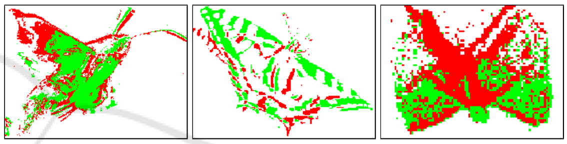


(b) Curves.



(c) FFT coefficients.

Figure 7: Projection of the point cloud containing only the events from the selected bee trajectory, derived curves for $y > 0$ and $y < 0$ and sum of the FFT coefficients.



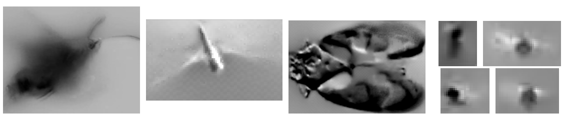
(a) Pigeon Tail. (b) Dovetail. (c) Dragonfly.

Figure 8: Example for generated frames from the polarity information.

classification of the insect species the polarity values of the events are used for frame generation. This encoding method has shown the best results in previous studies for classification (Bolten et al., 2022). This approach is especially useful for insects with a typical shape or pattern, such as butterflies. Some image examples can be found in Figure 8.

Classification Based on Simulated Grayscale Images

Another approach is to simulate a grayscale image based on the event stream and select the part within the largest bounding box. Then it can also be classified with a neural network. Such event-based image reconstruction methods are based on artificial neural networks (e.g. (Han et al., 2021), (Wang et al., 2021)). In our case the reconstruction methods implemented



(a) Pigeon Tail. (b) Dragon Fly. (c) Blood Cicada. (d) Bees .

Figure 9: Example for simulated gray value frames from event information.

in the Metavision SDK is used. Figure 9 shows some example images reconstructed with this method.

Evaluation of suitable classification approaches is part of future work.

4 CONCLUSION & OUTLOOK

In this article, individual steps of a processing pipeline for long-term monitoring of insects using a DVS are presented. These steps within the pipeline are examined using a small dataset. The results of the tests have shown that a combination of filtering and density-based clustering is a possibility to label larger datasets that are needed for a more detailed investigation. In addition, it was found that neural networks can be used to segment trajectories. Finally, neural networks based on polarity images or simulated gray scale images were favored for insect species classification. In order to evaluate the individual steps more precisely, a larger dataset will be recorded and annotated in the next step.

REFERENCES

Alonso, I. and Murillo, A. C. (2019). EV-SegNet: Semantic Segmentation for Event-Based Cameras. In *2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, pages 1624–1633.

Berger, D. R., Seung, H. S., and Lichtman, J. W. (2018). VAST (Volume Annotation and Segmentation Tool): Efficient Manual and Semi-Automatic Labeling of Large 3D Image Stacks. *Frontiers in neural circuits*, 12:88.

Binas, J., Neil, D., Liu, S.-C., and Delbruck, T. (2017). DDD17: End-To-End DAVIS Driving Dataset. In *ICML'17 Workshop on Machine Learning for Autonomous Vehicles (MLAV 2017)*.

Bolten, T., Lentzen, F., Pohle-Fröhlich, R., and Tönnies, K. (2022). Evaluation of Deep Learning based 3D-Point-Cloud Processing Techniques for Semantic Segmentation of Neuromorphic Vision Sensor Event-streams. In *Proceedings of the 17th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications - Volume 4: VISAPP*, pages 168–179. INSTICC, SciTePress.

Bolten, T., Pohle-Fröhlich, R., and Tönnies, K. D. (2019). Application of Hierarchical Clustering for Object Tracking with a Dynamic Vision Sensor. In Rodrigues, J. e. a., editor, *Computational Science – ICCS 2019*, volume 11540 of *Lecture Notes in Computer Science*, pages 164–176, Cham. Springer.

Bolten, T., Pohle-Fröhlich, R., and Tönnies, K. D. (2021). DVS-OUTLAB: A Neuromorphic Event-Based Long Time Monitoring Dataset for Real-World Outdoor Scenarios. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) Workshops*, pages 1348–1357.

de Tournemire, P., Nitti, D., Perot, E., Migliore, D., and Sironi, A. (2020). A Large Scale Event-based Detection Dataset for Automotive. *arXiv*, abs/2001.08499.

Ester, M., Kriegel, H.-P., Sander, J., Xu, X., et al. (1996). A Density-Based Algorithm for Discovering Clusters in Large Spatial Databases with Noise. In *Proceedings of the Second International Conference on Knowledge Discovery and Data Mining*, pages 226–231.

Gallego, G., Delbrück, T., Orchard, G., Bartolozzi, C., Taba, B., Censi, A., Leutenegger, S., Davison, A. J., Conradt, J., Daniilidis, K., and Scaramuzza, D. (2022). Event-Based Vision: A Survey. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 44(1):154–180.

Greenewalt, C. H. (1962). Dimensional relationships for flying animals. *Smithsonian miscellaneous collections*.

Hackel, T., Wegner, J. D., and Schindler, K. (2016). Contour Detection in Unstructured 3D Point Clouds. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 1610–1618.

Hallmann, C. A., Sorg, M., Jongejans, E., Siepel, H., Hofland, N., Schwan, H., Stenmans, W., Müller, A., Sumser, H., Hörren, T., et al. (2017). More than 75 percent decline over 27 years in total flying insect biomass in protected areas. *PloS one*, 12(10):e0185809.

Han, J., Yang, Y., Zhou, C., Xu, C., and Shi, B. (2021). EvIntSR-Net: Event Guided Multiple Latent Frames Reconstruction and Super-resolution. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 4882–4891.

Hu, Y., Binas, J., Neil, D., Liu, S.-C., and Delbruck, T. (2020). DDD20 End-to-End Event Camera Driving Dataset: Fusing Frames and Events with Deep Learning for Improved Steering Prediction. In *2020 IEEE 23rd International Conference on Intelligent Transportation Systems (ITSC)*, pages 1–6.

Qi, C. R., Yi, L., Su, H., and Guibas, L. J. (2017). PointNet++: Deep Hierarchical Feature Learning on Point Sets in a Metric Space. *Advances in neural information processing systems*, 30.

Rodríguez-Gomez, J., Eguíluz, A. G., Martínez-de Dios, J., and Ollero, A. (2020). Asynchronous event-based clustering and tracking for intrusion monitoring in UAS. In *2020 IEEE International Conference on Robotics and Automation (ICRA)*, pages 8518–8524.

Ronneberger, O., Fischer, P., and Brox, T. (2015). U-Net: Convolutional Networks for Biomedical Image Segmentation. In *International Conference on Medical image computing and computer-assisted intervention*, pages 234–241. Springer.

Wägele, J. W., Bodesheim, P., Bourlat, S. J., Denzler, J., Diepenbroek, M., Fonseca, V., Frommolt, K.-H., Geiger, M. F., Gemeinholzer, B., Glöckner, F. O., et al. (2022). Towards a multisensor station for automated biodiversity monitoring. *Basic and Applied Ecology*, 59:105–138.

Wang, L., Kim, T.-K., and Yoon, K.-J. (2021). Joint Framework for Single Image Reconstruction and Super-Resolution With an Event Camera. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 44(11):7657–7673.

Wang, R., Hu, C., Fu, X., Long, T., and Zeng, T. (2017). Micro-Doppler measurement of insect wing-beat frequencies with W-band coherent radar. *Scientific reports*, 7(1):1–8.