Data-driven Feature Tracking for Event Cameras

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Abstract

Because of their high temporal resolution, increased resilience to motion blur, and very sparse output, event cameras have been shown to be ideal for low-latency and low-bandwidth feature tracking, even in challenging scenarios. Existing feature tracking methods for event cameras are either handcrafted or derived from first principles but require extensive parameter tuning, are sensitive to noise, and do not generalize to different scenarios due to unmodeled effects. To tackle these deficiencies, we introduce the first data-driven feature tracker for event cameras, which leverages low-latency events to track features detected in a grayscale frame. We achieve robust performance via a novel frame attention module, which shares information across feature tracks. By directly transferring zero-shot from synthetic to real data, our data-driven tracker outperforms existing approaches in relative feature age by up to 120% while also achieving the lowest latency. This performance gap is further increased to 130% by adapting our tracker to real data with a novel self-supervision strategy.

Multimedia Material A video is available at https://youtu.be/dtkXvNXcWRY and code at https://github.com/uzh-rpg/deep_ev_tracker

1. Introduction

Despite many successful implementations in the real world, existing feature trackers are still primarily constrained by the hardware performance of standard cameras. To begin with, standard cameras suffer from a bandwidth-latency trade-off, which noticeably limits their performance under rapid movements: at low frame rates, they have minimal bandwidth but at the expense of an increased latency; furthermore, low frame rates lead to large appearance changes between consecutive frames, significantly increasing the difficulty of tracking features. At high frame rates, the latency is reduced at the expense of an increased bandwidth overhead and power consumption for downstream systems. Another problem with standard cameras is motion blur, which is prominent in high-speed low-lit scenarios, see Fig. 1. These issues are becoming more prominent with the current commodification of AR/VR devices.

Event cameras have been shown to be an ideal complement to standard cameras to address the bandwidth-latency trade-off [16, 17]. Event cameras are bio-inspired vision sensors that asynchronously trigger information whenever the brightness change at an individual pixel exceeds a predefined threshold. Due to this unique working principle, event cameras output sparse event streams with a temporal resolution in the order of microseconds and feature a high-dynamic range and low power consumption. Since events are primarily triggered in correspondence of edges, event cameras present minimal bandwidth. This makes them ideal for overcoming the shortcomings of standard cameras.

Existing feature trackers for event cameras have shown...
Event-Based Feature Tracking

In recent years, multiple works have explored event-based feature tracking to increase robustness in challenging conditions, such as fast motion scenarios with large pixel displacement between timesteps and HDR scenes with very bright and dark areas [17]. Early works [26,33,48] tracked features as point-sets of events and used ICP [5] to estimate the motion between timesteps, which can also be combined with frame-based trackers to improve performance [12]. Instead of point sets, EKLT [17] estimates the parametric transform between a template and a target patch of brightness increment images alongside the feature’s velocity. Other event-based trackers align events along Bézier curves [36] or B-splines [10] in space and time to obtain feature trajectories.

To exploit the inherent asynchronicity of event streams, event-by-event trackers have also been proposed [2,11]. One of them is HASTE [4], which reduces the space of possible transformations to a fixed number of rotations and translations. In HASTE, every new event leads to confidence updates for the hypotheses and a state transition if the confidence threshold is exceeded. Another work called eCDT [23] first represents features as event clusters and then incorporates incoming events into existing ones, resulting in updated centroids and, consequently, updated feature locations. In a similar direction to feature tracking, sev-
eral event-based feature detectors [8, 31] were proposed, of which some are performing feature tracking based on proximity of detections in the image [3, 9]. Apart from event-based feature tracking and detection, multiple works tackle the problem of object tracking using event cameras [7, 14, 27, 34, 44, 45].

The task of optical flow estimation using event cameras gained popularity as well. Zhu et al. [48] estimates the optical flow of features from events using ICP and an objective function based on expectation maximization to solve for the parameters of an affine transform. More recently, an adaptive block matching algorithm [29] was proposed to estimate optical flow. Finally, recent data-driven methods for event-based optical flow estimation [18, 47] leverage advances in deep optical-flow estimation. Inspired by these advances, our tracking network leverages a correlation layer to update a feature’s location.

3. Method

Feature tracking algorithms aim to track a given point in a reference frame in subsequent timesteps. They usually do this by extracting appearance information around the feature location in the reference frame, which is then matched and localized in subsequent ones. Following this pipeline, we extract an image patch \( P_0 \) in a grayscale frame for the given feature location at timestep \( t_0 \) and track the feature using the asynchronous event stream. The event stream \( E_j = \{ e_{ij} \}_{i=1}^{n_j} \) between timesteps \( t_{j-1} \) and \( t_j \) consists of events \( e_{ij} \), each encoding the pixel coordinate \( x_i \), timestamp with microsecond-level resolution \( \tau_i \) and polarity \( p_i \in \{-1, 1\} \) of the brightness change. We refer to [15] for more information about the working principles of event cameras.

Given the reference patch \( P_0 \), our network predicts the relative feature displacement \( \Delta f \) during \( t_{j-1} \) and \( t_j \) using the corresponding event stream \( E_j \) in the local neighborhood of the feature location at the previous timestep \( t_{j-1} \). The events inside the local window are converted to a dense event representation \( P_j \), specifically a maximal timestamp version of SBT [42] where each pixel is assigned the timestamp of the most recent event. Once our network has localized the reference patch \( P_0 \) inside the current event patch \( P_j \), the feature track is updated, and a new event patch \( P_{j+1} \) is extracted at the newly predicted feature location while keeping the reference patch \( P_0 \). This procedure can then be iteratively repeated while accumulating the relative displacements to construct one continuous feature track. The overview of our method and our novel frame attention module are visualized in Fig. 2.

In Sec. 3.1, we explain how the feature network processes each feature track independently. The resulting network output is given as input to our frame attention module, which combines information from all feature tracks in one image, see Sec. 3.2. Finally, we introduce in in Sec. 3.3 our supervision scheme for data with ground truth and our self-supervision strategy based on camera poses. For the specific architectural details of each network, we refer to the supplementary.

3.1. Feature Network

To localize the template patch \( P_0 \) inside the current event patch \( P_j \), the feature network first encodes both patches using separate encoders based on Feature Pyramid Networks [28]. The resulting outputs are per-pixel feature maps for both patches that contain contextual information while keeping the spatial information. To explicitly compute the similarity measure between each pixel in the event patch and the template patch, we construct a correlation map \( C_j \) based on the bottleneck feature vector \( R_0 \) of the template patch encoder and the feature map of the event patch, as visualized in Fig. 2. Together with the correlation map \( C_j \), both feature maps are then given as input to a second feature encoder in order to refine the correlation map. This feature encoder consists of standard convolutions, and one ConvLSTM block [37] with a temporal cell state \( F_j \). The temporal information is crucial to predicting consistent feature tracks over time. Moreover, it enables the integration of the motion information provided by the events. The output of the feature network is a single feature vector with spatial dimension \( 1 \times 1 \). Up to now, each feature has been processed independently from each other.

3.2. Frame Attention Module

To share information between features in the same image, we introduce a novel frame attention module, which is visualized in Fig. 2. Since points on a rigid body exhibit correlated motion in the image plane, there is a substantial benefit in sharing information between features across the image. To achieve this, our frame attention module takes the feature vectors of all patches at the current timestep \( t_j \) as input and computes the final displacement for each patch based on a self-attention weighted fusion of all feature vectors. Specifically, we maintain a state \( S \) for each feature across time in order to leverage the displacement prediction of the previous timesteps in the attention fusion. The temporal information should facilitate the information-sharing of features with similar motion in the past. This way, it is possible to maintain vulnerable feature tracks in challenging situations by adaptively conditioning them on similar feature tracks. Each input feature vector is individually first fused with the current state \( S_{j-1} \) using two linear layers with Leaky ReLU activations (MLP). All of the resulting fused features in an image are then used as key, query, and value pairs for a multi-head attention layer (MHA) [41], which performs self-attention over each feature in an image. To facilitate the training, we introduce a skip connec-
tion around the multi-head attention for each feature, which is adaptively weighted during the training by a Layerscale layer [40] (LS). The resulting feature vectors are then used in a simple gating layer to compute the updated state \( S_j \) based on the previous state \( S_{j-1} \) (GL), see Eq. (3).

\[
\begin{align*}
Z_j^k &= MLP(F_j, S_{j-1}) \\
\tilde{Z}_j^k &= MHA(Z_j^k) \\
S_j &= GL(S_{j-1}, LS(\tilde{Z}_j^k))
\end{align*}
\]

Finally, the updated state \( S_j \) is then processed by one linear layer to predict the final displacement \( \Delta \hat{f}_j \).

3.3. Supervision

In general, the supervision of trackers, extractors, or even flow networks is still an open research field since datasets containing pixel-wise correspondences as ground truth are rare. To make matters worse, there exist even fewer event-based datasets containing accurate pixel correspondences. To overcome this limitation, we train our network in the first step on synthetic data from the Multiflow dataset [19], which contains frames, synthetically generated events, and ground truth pixel flow. However, since the noise is not modeled, synthetic events differ significantly from events recorded by a real event camera. Thus, in the second step, we fine-tune our network using our novel pose supervision loss to close the gap between synthetic and real events.

**Synthetic Supervision** Synthetic data has the benefit that it provides ground truth feature tracks. Thus, a loss based on the L1 distance can be directly applied for each prediction step \( j \) between the predicted and ground truth relative displacement, see Fig. 3. It is possible that the predicted feature tracks diverge beyond the template patch such that the next feature location is not in the current search. Thus, if the difference between predicted and ground truth displacement \( ||\Delta \hat{f}_j - \Delta f_j||_1 \) exceeds the patch radius \( r \), we do not add the L1 distances to the final loss to avoid introducing noise in supervision. Our truncated loss \( L_{rp} \) is formulated as follows.

\[
err_j = \begin{cases} 
||\Delta \hat{f}_j - \Delta f_j||_1 & ||\Delta \hat{f}_j - \Delta f_j||_1 < r \\
0 & \text{else}
\end{cases}
\]

\[
L_{rp} = \frac{\sum_j I(err_j \neq 0)err_j}{\sum_j I(err_j \neq 0)}
\]

To reduce the gap between synthetic and real data, we apply on-the-fly augmentation during training, which significantly increases the motion distribution. To teach the network geometrically robust representations, affine transformations \( W \) are applied to the current event patch \( P_j \) to obtain an augmented Patch \( P_{j}^{aug} \) at each prediction step, as formulated in Eq. (6). The augmentation parameters for rotation, translation, and scale \( \theta = (\theta_r, \theta_t, \theta_s) \) are randomly sampled from a uniform distribution at each prediction step during training. Our tracker \( T \) then predicts a relative displacement \( \Delta \hat{f}_j^{aug} \) given the augmented patch \( P_{j}^{aug} \) and original template patch \( P_0 \). The loss is then computed between the predicted displacement \( \Delta \hat{f}_j^{aug} \) and the augmented ground truth \( \Delta f_j^{aug} \), which is obtained by applying the same affine transformation \( W \).

\[
P_{j}^{aug} = W(P_j, \theta)
\]

\[
\Delta f_j^{aug} = T(P_0, P_{j}^{aug})
\]

\[
\Delta \hat{f}_j^{aug} = W^{-1}(\Delta \hat{f}_j^{aug}, \theta)
\]

The corrected displacement \( \Delta \hat{f}_{j-1} \) is then accumulated in
order to extract the next event patch \( P_{j+1} \). Our augmentation strategy introduces dynamic trajectories and changes in patch appearance during training that improve performance on real data.

**Pose Supervision** To adapt the network to real events, we introduce a novel pose supervision loss solely based on ground truth poses of a calibrated camera. The ground truth poses can easily be obtained for sparse timesteps \( t_j \) using structure-from-motion algorithms, e.g., COLMAP [35], or by an external motion capture system. Since our supervision strategy relies on the triangulation of 3D points based on poses, it can only be applied in static scenes.

In the first step of the fine-tuning, our network predicts multiple feature tracks for one sequence. For each predicted track \( i \), we compute the corresponding 3D point \( X_i \), using the direct linear transform [1]. Specifically, for each feature location \( x_j \), we can write the projection equation assuming a pinhole camera model using the camera pose, represented as a rotation matrix \( R_{t_j} \) and a translation vector \( T_{t_j} \), at timestep \( t_j \), and the calibration matrix \( K \), see Eq. (9). The resulting projection matrix can be expressed as matrix \( M_j \) consisting of column vectors \( m_{k}^{T_j} \) with \( k \in \{1, 2, 3\} \).

\[
x_j = K[R_{t_j}|T_{t_j}]X_j = M_jX_j = \begin{bmatrix} m_{1}^{T_j} \\ m_{2}^{T_j} \\ m_{3}^{T_j} \end{bmatrix}X_i \tag{9}
\]

Using the direct linear transform, we can reformulate the projection equations as the homogenous linear system in Eq. (10). By using SVD, we obtain the 3D point \( X_j \), which minimizes the least square error of Eq. (10).

\[
\begin{bmatrix} u_{j}m_{1}^{T_j} - m_{2}^{T_j} \\ m_{1}^{T_j} - v_{j}m_{3}^{T_j} \\ \vdots \end{bmatrix} = AX_i = 0 \tag{10}
\]

Once the 3D position of \( X_i \) is computed, we can find the reprojected pixel point \( \hat{x}_j \) for each timestep \( t_j \) using perspective projection Eq. (9). The final pose supervision loss is then constructed based on the predicted feature \( \hat{x}_j \) and the reprojected feature \( x_j \) for each available camera pose at timestep \( t_j \), as visualized in Fig. 4. As in the supervised setting of Eq. (5), we use a truncated loss which excludes the loss contribution if the reprojected feature is outside of the event patch.

4. Experiments

**Datasets** We compare our proposed data-driven tracker on the commonly used Event Camera dataset [32] (EC), which includes APS frames (24 Hz) and events with a resolution of \( 240 \times 180 \), recorded using a DAVIS240C camera [6]. Additionally, the dataset provides ground truth camera poses at a rate of 200 Hz from an external motion capture system. Moreover, to evaluate the tracking performance with a newer sensor setup, we test our method on the newly published Event-aided Direct Sparse Odometry dataset [22] (EDS). Compared to EC, the EDS dataset contains higher resolution frames and events (640 \( \times \) 480 pixels) captured with a beam splitter setup. Similar to the EC dataset, it includes ground truth poses at a rate of 150 Hz from an external motion capture system. Most scenes in both datasets are static since the primary purpose of EDS and EC is the evaluation of camera pose estimation. For the specific finetuning and testing sequence selection, we refer to the supplementary.

**Evaluation** To evaluate the different feature trackers, we first extract features for each sequence with a Harris Corner detector [21]. Based on the initial feature set, each tested tracker predicts the feature displacements according to its specific update rate. Unfortunately, no ground truth feature tracks are available for EDS and EC. To evaluate the event-based feature trackers without ground truth, previous works used tracks predicted by the frame-based KLT tracker as ground truth. Instead, to increase the accuracy of KLT tracks, we use an evaluation scheme based on our proposed pose supervision method. Specifically, the ground...
truth tracks are obtained by triangulating KLT tracks using ground truth poses and reprojecting them afterward to each of the selected target frames. The triangulation of KLT tracks has the benefit that minor tracking errors of KLT are filtered out, leading to geometrically consistent ground truth tracks. To verify the proposed evaluation, we conducted an experiment in simulation in which ground truth feature tracks are available. In this simulated setup, we computed the Pearson correlation between the KLT reprojected error and the ground truth feature tracks, which was 0.716. This indicates a significant correlation between our proposed evaluation technique and ground truth feature tracks verifying the effectiveness of our evaluation technique.

Since each tested tracker has its update rate, we linearly interpolated all feature tracks to the ground truth pose timesteps in order to compute the evaluation metric. Furthermore, to effectively test the event-based tracking abilities of the methods, we do not update the feature templates during evaluation. In addition, we deactivate any terminal criterion and report the time until the feature exceeds a certain distance to the ground truth, known as the feature age. Instead of choosing one error threshold as done in previous work [4], we evaluate the resulting tracks for multiple error thresholds in a range from 1 to 31 pixels with a step size of 1 pixel. Thus, we do not report the endpoint error since we test each trajectory with different error thresholds, which effectively incorporates the distance error into the feature age. As a first performance metric, we compute the tracked feature age normalized by the ground truth track duration in order to account for different trajectory lengths. However, since some feature tracks are lost immediately in the beginning, we report the feature age of stable tracks, i.e., we discard feature tracks lost during the early phase of the sequence for the feature age computations. The second error metric accounts for the lost tracks by taking the ratio of stable tracks and ground truth tracks. This ratio is then multiplied by the feature age, which gives us the expected feature age as the second performance metric. This metric combines the quality and the number of feature tracks tracked by a method. For more information about the two performance metrics, we refer to the supplementary.

**Training Schedule** As mentioned in Sec. 3, we first train our models supervised on the Multiflow [19] dataset on 30000 feature tracks in a continual learning fashion with a learning rate of $1 \times 10^{-4}$ using the ADAM optimizer [25] to gradually adapt the network recurrence to longer trajectory lengths. Starting initially from 4 unroll steps, we progressively increase the number of unroll steps to 16 and then 24 after 80000 and 120000 training steps, respectively. After training on Multiflow, we finetune our model using our novel supervision method for 700 optimization steps with a reduced learning rate of $1 \times 10^{-6}$ on specific training sequences of both datasets, which are not used for evaluation.

### 4.1. Benchmark Results

**Baselines** We compare our method against the current state-of-the-art method EKLT [17], which extracts a template patch from a grayscale image for each feature and tracks the feature with events, similar to our tracker. As another tracker relying on grayscale template patches, we also run the ICP [26] tracker used for event-based visual odometry. In addition, we evaluate against the pure event-based trackers HASTE [4] and EM-ICP [48]. For EKLT, HASTE, and EM-ICP, we adopted the publicly available code to run the experiments. The implementation of ICP was taken from a related work [12]. The hyper-parameters of all methods were tuned for the specific datasets, which required multiple hours to achieve optimal performance.

**EC Results** On the commonly used event-based tracking benchmark, EC, our proposed data-driven method outperforms the other baselines in terms of non-zero feature age and expected feature age, see Tab. 1. The second best approach is EKLT, which tracked the features for a duration similar to our proposed method as represented by the non-zero feature age metric in Tab. 1. However, our method was able to track more features from the initial feature set as reported by the expected feature age. The higher ratio of successfully tracked features and the longer feature age makes our method better suited for downstream tasks such as pose estimation [35]. The top row of Fig. 5 shows that our method produces a higher number of smooth feature tracks compared to the closest baselines EKLT and HASTE. As expected, a performance gap exists between pure event-based methods (HASTE, EM-ICP) and methods using grayscale images as templates (Ours, EKLT). This confirms the benefit of leveraging grayscale images to extract template patches, which are subsequently tracked by events.

**EDS Results** Similar to the performance on the EC dataset, our proposed method outperforms all of the existing trackers on the EDS dataset with an even larger margin in terms of both non-zero feature age and expected feature age as reported in Tab. 1. The significant performance boost confirms the capability of our data-driven methods to deal with high-resolution data in various 3D scenes with different lighting conditions and noise patterns. Since a beam splitter setup was used to record the data for the EDS dataset, there are misalignment artifacts between events and images, as well as low-light noise in the events due to the reduction of the incoming light. Additionally, the EDS includes faster camera motions leading to an overall lower tracking performance of all methods compared to the EC dataset. Nevertheless, our learned method is able to deal with these different noise sources and still predict smooth feature tracks for a large number of features, as shown in the middle and bottom row of Fig. 5. For more qualitative examples, we refer to the supplementary.
Table 1. The performance of the evaluated trackers on the EDS and EC dataset are reported in terms of "Feature Age (FA)" of the stable tracks and the "Expected FA", which is the multiplication of the feature age by the ratio of the number of stable tracks over the number of initial features.

| Method          | EDS Feature Age (FA) | Expected FA | EC Feature Age (FA) | Expected FA |
|-----------------|----------------------|-------------|---------------------|-------------|
| ICP [26]        | 0.060                | 0.040       | 0.256               | 0.245       |
| EM-ICP [48]     | 0.161                | 0.120       | 0.337               | 0.334       |
| HASTE [4]       | 0.096                | 0.063       | 0.442               | 0.427       |
| EKLT [17]       | 0.325                | 0.205       | 0.811               | 0.775       |
| Ours (zero-shot)| 0.549                | 0.451       | 0.795               | 0.787       |
| Ours (fine-tuned)| 0.576               | 0.472       | 0.825               | 0.818       |

Figure 5. Qualitative tracking predictions (blue) and ground truth tracks (green) for the EC dataset (top) and EDS dataset (middle / bottom). Our method predicts more accurate tracks for a higher number of initial features.

Figure 6. The two plots show the tracking performance in terms of expected feature age in relation to the real-time factor, which is the ratio of compute time over track time. Thus, the top left corner represents the goal. Additionally to the existing implementation of HASTE, we also report the ideal HASTE*, which assumes perfect parallelization for processing all feature tracks.

4.2. Combination of Events and Frames

In a step to combine the contextual information of grayscale images and the high-latency information from events, we extended our event-based tracker using the popular KLT tracker for frames. Specifically, we use our event tracker to track features during the blind time between two frames and use the displacement prediction of our tracker as an initial guess for the KLT tracker once a new frame arrives. This has the benefit of effectively mitigating the negative effects of large baselines between two frames caused by high-speed motion. Additionally, the combination with...
our event tracker provides feature positions for the time in between two frames, significantly increasing the frequency of feature position updates. On the other side, the KLT tracker can correct the feature position once reliable frame information is available. As used for the ground truth creation based on the camera poses, we use a KLT tracker with three hierarchical scales to cope with larger motion. We compare the combination of our method and the KLT tracker (ours+KLT) against the pure KLT tracker for different pixel motions between frames, as reported in Fig. 7. The different pixel motions are achieved by skipping frames in a sequence of the EC dataset, which corresponds to increasing the pixel motion between two frames. As can be seen in Fig. 7, the combination of ours and KLT performs comparably to a pure KLT tracker for small pixel displacement between frames. However, with increasing pixel motion, the initial guess provided by our method helps the KLT tracker to track features over a longer time duration than a KLT tracker alone. In addition, our event-based tracker can provide robust feature tracks during periods of high-speed motion in which the frames suffer from motion blur. This can be qualitatively observed in Fig. 1, which shows smooth features tracks predicted by our event-based tracker on a motion blurred frame due to high-speed motion. This high-rotational motion sequence was recorded by us with a beam splitter setup.

4.3. Ablations

To test the specific contribution of each introduced network block, we perform several ablation experiments based on the reference model, which represents our model without the frame attention module, see Tab. 2. As verified by the performance drop (w/o augmentation), the augmentations during the training on synthetic data significantly boost the zero-shot transfer from synthetic to real-world data. Furthermore, the recurrence in the feature encoder leads to longer feature age (w/recurrence), which is also achieved on a smaller scale by introducing the correlation map (w/o correlation). While there is no improvement on the EC dataset, our proposed frame attention module significantly improves the performance on the challenging sequences of EDS. This performance increase confirms the benefit of sharing information between similar feature tracks for challenging scenarios. By adapting our network based on the frame attention module (Ref+Frame Attention) to real data using our self-supervision scheme, we achieve the highest tracking performance. Finally, the frame attention module relies on state variables (w/o state) to fully exploit the potential of sharing information across features in a frame. For more ablations regarding the input representation and specific augmentation parameters, we refer to the supplementary.

5. Conclusion

We presented the first data-driven feature tracker for event cameras, which leverages low-latency events to track features detected in a grayscale frame. With our novel frame attention module, which fuses information across feature tracks, our tracker outperforms state-of-art methods on two datasets while being faster in terms of inference time. Furthermore, our proposed method does not require intensive manual parameter tuning and can be adapted to new event cameras with our self-supervision strategy. Finally, we can combine our event-based tracker with a KLT tracker to predict stable tracks in challenging scenarios. This combination of standard and event cameras paves the path for the concept of sparingly triggering frames based on the tracking quality, which is a critical tool for future applications where runtime and power consumption are essential.

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