EventHands: Real-Time Neural 3D Hand Reconstruction from an Event Stream

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Abstract

3D hand pose estimation from monocular videos is a long-standing and challenging problem, which is now seeing a strong upturn. In this work, we address it for the first time using a single event camera, i.e., an asynchronous vision sensor reacting on brightness changes. Our EventHands approach has characteristics previously not demonstrated with a single RGB or depth camera such as high temporal resolution at low data throughputs and real-time performance at 1000 Hz. Due to the different data modality of event cameras compared to classical cameras, existing methods cannot be directly applied to and re-trained for event streams. We thus design a new neural approach which accepts a new event stream representation suitable for learning, which is trained on newly-generated synthetic event streams and can generalise to real data. Experiments show that EventHands outperforms recent monocular methods using a colour (or depth) camera in terms of accuracy and its ability to capture hand motions of unprecedented speed. Our method, the event stream simulator and the dataset will be made publicly available.

1. Introduction

Event cameras are vision sensors which respond to events, i.e., local changes in the incoming brightness signals. In contrast to conventional RGB cameras which record images at a pre-defined frequency (e.g., 30–60 fps), event cameras operate asynchronously, which enables high clock speeds and temporal resolution of up to 1µs [26]. Due to their unique properties and high-dynamic range, event cameras have already found applications in low-level vision [6, 37, 40, 66], low-latency robotics [51, 14], visual simultaneous localisation and mapping (SLAM) [62, 22], feature and object tracking [1, 32], gesture recognition [2, 59], experimental physics (particle tracking and velocimetry) [8, 60] and astronomy [12, 71], among other fields.

In this work, we are interested in 3D hand pose regression using a single event camera. Due to the drastically different and less regular data from event cameras, existing RGB- or depth-based methods [9, 67, 29, 34] cannot be directly applied to event streams. A naïve way would be to reconstruct greyscale images from an event stream at arbitrary temporal resolutions first, and then run the same monocular methods [5, 9, 67, 68, 38] on those. This policy would, unfortunately, nullify most advantages of the event cameras such as low data bandwidth, abstraction from a large variety in textures and illumination conditions and supposedly better generalisation ability of events. It is also not clear how existing methods would perform on low-resolution greyscale images reconstructed from event streams, as the latter often contain artefacts, and cannot reproduce the exact occurred brightness, due to the non-deterministic event thresholds and noise [6, 13, 43]. The primary research ques-
tion is thus how hands can be reconstructed and tracked in 3D directly from event streams.

We pursue in this paper a learning-based approach and propose the first—to the best of our knowledge—method for 3D reconstruction of a human hand from a single event stream (see Fig. 1). Our neural EventHands approach learns to regress 3D hand poses, represented as global rotation and translation as well as pose parameters of a parametric hand model [41], from locally-normalised event surfaces (LNES), which is a new way of accumulating events over temporal windows for learning. We generate training data for our neural network using a new high-throughput event stream simulator relying on a parametric hand model [41, 38]. The training data includes variations in hand shape and texture, lighting, and scene background, and accurately mimics the characteristics of a real event camera. Hence, EventHands generalises well to real data despite being trained with synthetic data only. Next, EventHands runs at 1 KHz, which is significantly faster than any image-based prior works. In summary, our contributions are:

- **EventHands**, *i.e.*, the first approach for 3D hand pose estimation, including rotation and translation in 3D, from a single event stream, running at 1 KHz.
- A new high-throughput event stream simulator supporting a parametric 3D hand model for diverse poses, shapes, and textures, multiple light sources, adjustable event stream properties (*e.g.*, event threshold distributions, noise patterns) and further scene augmentation.
- A live real-time demonstrator of our method running orders of magnitude faster than previous image-based work on a workstation with a single GPU. See our supplementary video for recordings thereof.

We evaluate the proposed approach on a wide variety of motions with real and synthetic data, and provide numerical evidence for our design choices as well as comparisons to prior work. We show that EventHands yields accurate estimates even when existing RGB- and depth-based techniques fail due to fast motion. Our method, the event stream simulator and the dataset will be made publicly available.

2. Related Work

We next review related works on 3D hand reconstruction and event-based vision. Our EventHands is the first approach for 3D hand pose estimation operating on event streams and has multiple advantages compared to existing RGB- or depth-based methods highlighted in the following.

### 3D Hand Reconstruction Methods

The vast majority of existing works for 3D hand reconstruction from depth [55, 35, 57, 16, 33, 25, 15] and monocular RGB [70, 10, 50, 34, 64, 49] regresses sparse hand joints. Several recent works also address dense 3D reconstructions of hands [5, 9, 67, 68, 30, 29, 58, 45, 38], some of which rely on a parametric 3D hand model such as MANO [41] for pose and shape or HTML [38] for textures. Hampali et al. [18] introduces a new benchmark for hand-object interaction methods. The dataset is then leveraged for 3D hand pose estimation from RGB images by fitting the MANO model to the predicted 2D hand joints. Taylor et al. [54] proposed an approach for hand tracking from a new custom-built depth sensor. Their custom depth camera supports 180 fps which is significantly faster than commodity depth cameras (30–60fps) but still far from the temporal resolution of an event camera.

All the aforementioned methods cannot be directly applied to event streams. Even though intensity images and videos can be reconstructed from event streams [13, 43], the obtained greyscale images considerably differ from the data used by existing hand reconstruction techniques and they may exhibit domain-specific artefacts. Bridging this domain gap is not straightforward. On the other hand, direct operation on event streams has the advantage of low data bandwidth and abstraction from appearance variation occurring in RGB images.

### Event-Based Vision Techniques

Since dynamic vision sensors or event cameras became available for computer vision and robotics researchers, they have been predominantly used for low-level and mid-level problems such as greyscale image restoration from events [37, 66], optical flow [6, 36] as well as feature detection and tracking [56, 1, 32]. In the context of our work, noteworthy are SLAM methods [62, 61, 65, 22] which rely on sparse rigid 3D reconstruction as an auxiliary task to localise moving robots, event-driven stereo matching [44, 39], and 2D gesture recognition [2, 59]. To apply learning-based method on event streams, a suitable representation of the input must be found. Examples of those are event frames [20], event count images [31, 69], surfaces of active events (SAE) [7], time-surfaces [24], averaged time surfaces [48], and differentiable event spike tensors [17], among others. Our LNES representation relates to SAE and differs from it by representing time stamps in window-normalised time units.

A related method to ours which tracks a humans in 3D from a hybrid input of events and greyscale images is EventCap [63]. It relies on event correspondences between greyscale anchor frames and assumes a known rigged and skinned human body template. Compared to human bodies, hands exhibit much more self-occlusions, which makes it difficult to obtain event trajectories or perform image-based model fitting. Instead, we train a neural network to regress 3D hand poses directly from an event representation suitable for learning (LNES), enabling live applications running five orders of magnitude faster. Our EventHands approach thus further advances the underexplored area of 3D reconstruction and tracking of non-rigid objects from events.
3. Event Camera Model

While event cameras obey the pinhole camera model of geometric projections from the 3D space to the 2D image plane, each pixel of an event camera independently and asynchronously reacts to differences in the observed logarithmic brightness $L(u, t)$. An event $e_i = (u_i, t_i, p_i)$ is a 3-tuple with the pixel identifier $u_i$, triggering time $t_i$ and the binary polarity flag $p_i \in \{-1, 1\}$ signalling whether the logarithmic brightness has increased or decreased by an absolute threshold $|C|$, i.e., an event is triggered at time $t_i$ as soon as one of the following two conditions is satisfied:

$$
\begin{align*}
L(u_i, t_i) - L(u_i, t_p) &= C \quad (p = 1) \\
L(u_i, t_i) - L(u_i, t_p) &= -C \quad (p = -1),
\end{align*}
$$

where $t_p$ is the previous triggering time of an event at $u_i$. The event camera we use in our experiments (DAVIS240C) provides the microsecond precision for $t_i$. Due to the hardware reasons, $C$ is not a fixed threshold but rather follows an unknown distribution of the thresholds $\chi$. In event camera modelling, it is, however, convenient and sufficient to assume $C$ to be equal to the expected value of $\chi$. Moreover, a capacitor attached to each sensor pixel can suddenly overfill, which leads to a spurious noise event registration.

4. Event Stream Simulator and the Dataset

Due to the lack of event stream dataset for hand pose estimation, and the difficulty of obtaining accurate 3D ground-truth annotations on real data, we build a highly efficient event stream simulator to generate a large-scale synthetic event stream dataset with annotations. In total, we generated 100 hours of simulated event data, which provides $3.6 \cdot 10^8$ discrete time steps with ground-truth annotations for training. This places our data among the most extensive event stream datasets available for research purposes so far. We plan to release both the dataset and the simulator.

4.1. Scene Modelling

Hand and Arm Model. Our simulator models both arm and hand geometry, as modelling the hand alone would generate spurious events generated from the seam at the wrist. Hence we use SMPL+H [41], i.e., a model that combines the hand model MANO [41] and the body model SMPL [27]. To capture events generated by the hand appearance, we use the texture model of Qian et al. [38] for the hand. The arm texture is obtained by extending the average hand boundary colour to the rest of the SMPL+H mesh.

Model Animation. To simulate hand articulation, we sample individual model poses using the provided MANO PCA-based parameter spaces to obtain a natural distribution of hand poses. Additional random offsets to the translation and pose parameters of SMPL+H are added to account for rigid body transformations of the hand and to increase variations in arm events. To generate plausible motion, we select a new random pose every single simulated second and smoothly interpolate between those poses using a quadratic Bezier curve. The curve’s middle control point is also randomly selected every single simulated second. This ensures that every second, there would be a sharp change in the motion direction (e.g., as in hand waving motions).

Lighting Model. We use a Lambertian lighting model with two lights. Suppose that $n \in \mathbb{R}^3$ is the normal vector to the object surface, $l_1, l_2 \in \mathbb{R}^3$ are light directions and $c_1, c_2, c_{\text{ambient}} \in \mathbb{R}^3$ are light colours. Then,

$$
\text{light} = \langle n, l_1 \rangle c_1 + \langle n, l_2 \rangle c_2 + c_{\text{ambient}},
$$

where “$\circ$” denotes element-wise product.

Image Formation. The scene model and the light model are used to form an RGB image $F_i \in [0, 255]^{W \times H \times 3}$ at time $t_i$. We convert $F_i$ to a log-brightness image $L(t_i) \in \mathbb{R}^{W \times H}$ using the estimate

$$
L(t_i) = \log(0.2F_i^r + 0.7F_i^g + 0.1F_i^b + \epsilon),
$$

where $\epsilon = 1.0$ is added for numerical stability, and $F_i^r, F_i^g$ and $F_i^b$ are red, green and blue image channels, respectively.

4.2. Event Camera Simulation

Event Stream Generation. To simulate events at a time $t_i$, at each pixel location $u_i$, we extract log-brightness $L(u_i, t_p)$. We additionally maintain a memory frame $M \in \mathbb{R}^{W \times H}$, where $M(u_i) \approx L(u_i, t_p)$ is the absolute log-brightness of the last generated event at $u_i$ at time $t_p$. An event tuple $(u_i, t_i, p_i)$ is simulated using the following steps:

1. Noise events: Emit an event tuple with positive or negative polarity with probability $p_{\text{positive}}$ and $p_{\text{negative}}$, respectively.

2. Calculate the logarithmic brightness difference $\Delta = L(u_i, t_i) - M(u_i)$, and

2.1. If $\Delta \geq C$, emit $[\Delta/C]$ positive events. Update memory frame $M(u_i) = M(u_i) + [\Delta/C]C$.

2.2. If $\Delta \leq -C$, emit $[-\Delta/C]$ negative events. Update $M(u_i) = M(u_i) - [-\Delta/C]C$.

The threshold $C$ and the noise event rates $p_{\text{positive}}, p_{\text{negative}}$ are calibrated to match our DAVIS240C event camera. See supplementary material for the details.

Data Augmentation. Augmentation is critical for successful synthetic-to-real domain transfers [4]. Thus, we re-randomise most of the aspects of the simulation every 50 simulated seconds. Those are the hand and body shapes,
body position, hand texture, light directions and intensities, background image and its cropped region, as well as \( C \). Please refer to the supplementary document for the randomisation ranges for each variable.

**Simulation Runtime.** The simulation is capable of rendering and extract events from around 2000 log-brightness images per second. Using temporal resolution of 1000 fps, this allows us to generate \( \approx 100 \) hours of simulated event data in two days on a single NVIDIA GTX 1070 GPU. Fig. 1 (right) shows sample data synthesised using our simulator.

## 5. Proposed Approach

In the previous section, we introduced the **EventHands** dataset generated by our new event stream simulator. We now describe our neural approach for 3D hand pose prediction from event streams for which an overview is shown in Fig. 2. We first describe our event stream representation for learning (Sec. 5.1). Next, we elaborate on our method which consists of two stages, *i.e.*, hand pose prediction (Sec. 5.2) and temporal filtering (Sec. 5.3).

### 5.1. Our Representation of Events for Learning

The original event stream output of an event camera is an asynchronous 1D stream. At the same time, most recent advances in visual machine learning have explored models that work on spatial 2D images, 3D voxel grids, or graphs. The straightforward way to convert the 1D event stream to a 2D representation is to accumulate and collapse all events in a time interval, which leads to the loss of temporal resolution within the interval [31]. Therefore, we propose a 2D event stream representation called **Locally-Normalised Event Surfaces (LNES)**, which encodes all events within a fixed time window as an image \( \mathcal{I} \in \mathbb{R}^{W \times H \times 2} \) (see Fig. 2, left). Using separate channels for positive and negative events preserves polarity information and reduces the number of overwritten events. As mentioned in Sec. 2, LNES relates to SAE [7] in that it saves the time stamps of latest events per pixel in a window and preserves the event polarities. In contrast to SAE, LNES operates with window-normalised time stamps.

Consider the \( k \)-th time window in an event stream with size \( L \). We can create the LNES representation of this window, \( \mathcal{I}_k \), by first initializing it with zeros. We then collect events \( \mathcal{E} = \{ \{ t_i, x_i, y_i, p_i \} \}_{i=1}^{E_k} \) which have timestamps \( t_i \) within this window. \( \mathcal{I}_k \) is updated by iterating through \( \mathcal{E} \) and doing the following assignment

\[
\mathcal{I}(x_i, y_i, p_i) = \frac{t_i - t_0}{L},
\]

Thus, \( \mathcal{I}(x_i, y_i, p_i) \neq 0 \) is a window-normalised timestamp of the event which preserves the relative temporal correlation of the events within the window. For our experiments, we used a fixed time length window of 100ms with a 99ms overlap between consecutive windows. Hence, our representation has an effective temporal resolution of 1 ms.

The proposed event stream representation allows for several augmentations. For example, different contrasts between skin tone and background colour can be simulated by switching the polarity of some events. This can be easily performed in LNES by swapping the content of the two channels at a subset of pixels. We also augment the speed of the motion during training by changing the window length without having to re-generate a dataset with new settings.

Note that in contrast to naive event accumulation in a time window [20, 31], where the temporal ordering of the events within the window is lost, LNES preserves temporal information of the events which leads to a more expressive input for learning. In addition, this enables our method to run with large window sizes without losing temporal resolution and hence prediction quality. In Sec. 6.2, we provide experimental evidence for the merits of our representation.

### 5.2. Hand Pose Prediction

We represent the hand pose with \( \theta = [t, R, \alpha] \in \mathbb{R}^{12} \), where \( \alpha \in \mathbb{R}^6 \) are the coefficients of the MANO PCA pose space, and \( t, R \in \mathbb{R}^3 \) encode the rigid translation in
During training, we minimise the following loss function:

\[ \mathcal{L} = \mathcal{L}_\alpha + \lambda_1 \mathcal{L}_t + \lambda_2 \mathcal{L}_R, \]

(5)

with the MANO loss \( \mathcal{L}_\alpha \), translation loss \( \mathcal{L}_t \), rotation loss \( \mathcal{L}_R \) (all \( \ell_2 \) losses) along with the weights \( \lambda_1 = 500.0 \) and \( \lambda_2 = \frac{1}{750} \). These weights are chosen empirically for normalisation to account for parameters of different magnitudes. We use the most significant MANO components corresponding to the six largest eigenvalues during training and inference. We use 45 hours of synthetically-generated event streams to train our neural network.

5.3. Temporal Filtering

Although our novel input representation explicitly models relative temporal information of the events within the event window, and we use overlapping event windows for pose prediction, sequences of raw network predictions still exhibit temporal jitter due to missing longer-term correlation across event windows. This is especially relevant on real test data where jitter is more severe due to the domain gap (see Sec. 6.2). Hence, we apply additional temporal filtering by using a constant-velocity Kalman filter [21] on the raw network outputs. We set the process noise \( W = \omega(0.1) \) and the observation noise \( v = 5.0 \) for low-speed movements and \( W = \omega(3.0) \) and \( v = 1.0 \) for high-speed movements, with \( \omega(\cdot) \) being discrete white noise covariance matrix operator [23]. See our supplement for the exact form of \( \omega(\cdot) \).

6. Results

We perform experiments on multiple sequences and demonstrate the ability of our approach in capturing a wide variety of motions, including translation, rotation and articulations. EventHands is able to accurately reconstruct hands that are moving at speeds previously unseen in the literature. We first introduce our evaluation metrics and test data (Sec. 6.1). Then we present evaluations of our design choices (Sec. 6.2), compare against related techniques [68, 34, 9, 33] (Sec. 6.3) and provide additional results of our method (Sec. 6.4). For more visual results and comparisons, please refer to the supplemental video.

We visualise results on a mean hand shape [41] with a mean texture [38]. Note that our work focuses on predicting the motion of only the hand, and not the arm. For visualisation purposes, we render the arm using the predicted parameters to ensure it attaches to the predicted hand. Nevertheless, this can produce arm movement different from the ground truth. We kindly ask readers to ignore the predicted motion of the arm as it is outside the scope of our work.

6.1. Metrics and Test Data

Evaluation Metrics. For synthetic data, we have access to 3D ground-truth positions for all joints. Here, we evaluate the root-aligned percentage of correct 3D keypoints (3D-PCK) [34] and the area under the PCK curve (3D-AUC) with thresholds ranging from 0 to 100mm.

For real data, we cannot calculate the 3D-PCK since we do not have access to ground-truth 3D annotations and obtaining them manually is challenging. Instead, we manually annotate 2D joint positions of five finger tips, the middle finger MCP joint and the wrist on our event representation \( \mathcal{T} \). We report the 2D-PCK and the corresponding area under the curve (2D-AUC). To make the 2D-PCK comparable across different data modalities when comparing to existing RGB methods, we use the wrist and middle finger MCP annotations to calculate the average palm length in pixels for each sequence and normalise the 2D errors by it. Analogously to the 2D body pose estimation literature [3], we refer to the palm-normalised 2D-PCK as 2D-PCKp and the corresponding AUC as 2D-AUCp. Here, we use a threshold ranging from 0 to 150% of the relative palm length.

Test Data. For the synthetic test set, we simulate a total of 1240 seconds of hand motions with \( 2.64 \cdot 10^8 \) events. Ground-truth annotations are available at 1ms intervals.

We recorded four real event sequences totalling 16328 milliseconds and \( 7.72 \cdot 10^6 \) events using the DAVIS240C event camera for evaluation. Considering each LNES event window sampled at 1ms temporal resolution as a frame, these sequences are annotated evenly at 30 frames per second for a total of 470 frames and 3318 keypoints. To provide comparison with existing RGB approaches, we use a high-speed RGB camera Sony RX0 and simultaneously capture RGB videos of the test sequences at 500 fps. We manually sync the RGB footage with our event representation \( \mathcal{T} \) by aligning an easily identifiable unique point in the motion across the two data modalities. We obtain the input to the RGB techniques at 30 fps by applying a moving average filter with a window size of 16 frames on the 500 fps data. We used the two pointers technique to ensure an effective sampling rate of 16.67 frames. We also apply a gamma correction of 2.2 before averaging as the original high-speed footage was sRGB. To perform quantitative comparisons, we use OpenPose [11, 46] on the 500 fps high-speed RGB footage to obtain automatic reference annotations for the RGB techniques. We manually inspect the generated reference annotations for errors.

5
6.2. Ablation Study

We quantitatively evaluate the different design choices of our technique on synthetic (Tab. 3a) and real data (Fig. 3b). Note that the synthetic test data is an easier setting for our method since it was trained on synthetic event streams. Hence, different versions achieve similar results. The tests on real sequences show the benefits of our design choices for the more important setting of generalising to real data. In this section, we discuss how existing methods perform on real data.

**Influence of Data Augmentation.** As discussed in Sec. 4.2, we use several data augmentation schemes to diversify our event stream data used for training. Augmentation does not help on synthetic data because there is no domain gap to be bridged. On real data, using data augmentation significantly improves the quality of the predictions.

**Influence of Temporal Filtering.** We use a Kalman filter to improve the longer-term temporal smoothness of our predictions (see Sec. 5.3). On synthetic data, both versions perform similar (Fig. 3a). On real data, however, where temporal jitter is larger due to the domain gap, the proposed filtering improves the results (Fig. 3b). Since temporal smoothness is best examined in videos, we refer to our supplemental video for visual results of this ablation study.

**Influence of Input Event Representation.** Naive event windows accumulate all events within the same time span, which leads to loss of their temporal ordering. In contrast, our event representation LNES is designed to preserve temporal information of events within the window. EventHands uses an LNES window of 100ms. Using a naive event window of the same length performs significantly worse. We also observe that using a shorter temporal window of 33ms leads to the similar performance of the naive and the LNES window. This is expected since less temporal information is lost in a shorter naive window. However, our LNES representation supports very long windows (300 ms) without sacrificing the accuracy much. In contrast, the performance of the naive window decays rapidly with increasing window size due to more events being accumulated without any temporal ordering information.

6.3. Comparisons to the State of the Art

We compare our approach against a variety of RGB techniques [68, 34, 9]. In addition, we show how existing depth-based methods [33] fail on fast moving hands.

**Depth-based Methods.** Most commodity depth cameras rely on structured-light or time-of-flight techniques to estimate the depth. However, for fast motion scenarios targeted by our method, these techniques produce depth estimates that are severely corrupted with many missing depth values. As shown in Fig. 4, depth-based state-of-the-art methods such as Moon et al. [33] cannot handle such artefacts and hence produce erroneous pose estimates.

**RGB-based Methods.** Fig. 5 shows qualitative comparisons against different monocular RGB-based hand pose estimation methods. The bounding box estimation of Mueller
et al. [34] is severely impacted by fast motion since they use simple temporal propagation. Even if the bounding box step succeeds, the blurred input image often leads to erroneous network predictions which are propagated to the inverse kinematics skeleton fit. The method of Boukhayma et al. [9] also struggles on our test sequences. In the presence of motion blur, the estimated rigid rotation is inaccurate, and the articulation often defaults to the MANO mean pose (first and last row). Zhou et al. [68] do not predict any hand translation and hence fails in capturing translational movements (first two rows). It also fails to capture fast articulations due to motion blur. Our approach, however, clearly outperforms the RGB-based methods for fast motions. Furthermore, EventHands also captures fists (third row) where the other methods fail although there is no blur in the input.

For the quantitative comparison, we use the palm-length-normalised 2D-PCKp to ensure a fair comparison across different data modalities. For Zhou et al. [68], we could not calculate any 2D error since they do not provide translation estimates. In Fig. 3c, we show that our proposed method performs significantly better than the existing RGB-based methods by Mueller et al. [34] and Boukhayma et al. [9].

6.4. Additional Results

We evaluate our method EventHands on several real videos and show results in Fig. 6. For each time segment, we show the input event stream and our predictions composited on a green background. We overlay the input events
over the rendering of the predicted hand to show that our predictions follow the input motion. Our approach handles different subjects performing a wide variety of poses and articulations, under fast motion.

In contrast to image-based sensors, event cameras monitor relative brightness changes and are able to record reasonable data in dark environments. We show one such example in Fig. 7 and our supplemental video.

7. Discussion

Our EventHands assumes that the scene background is approximately static, i.e., although being robust to a certain degree of noise events, there should not be events in the input that are generated from other moving objects in the scene or due to camera movement. Future work could investigate how to filter out background events or how to best train a predictor with event data from fully-dynamic scenes.

We also used a fixed time window of 100 ms for building our LNES input representation. For very slow motion or a still hand, there might not be enough events within 100 ms for our network to produce a meaningful prediction. In follow-up work, this could be addressed by automatically adapting the window size to the event count.

Our method would additionally benefit from a learned motion prior. Such statistical temporal model could replace the white-noise assumption of Kalman filter.

8. Conclusions

We presented EventHands, the first method for 3D hand pose estimation from event streams. Our method runs at 1000 Hz and can reconstruct significantly faster hand motions than any previous work, which is shown in our thorough experiments. We believe that the proposed method is also a step forward in general non-rigid 3D reconstruction from event streams, and the presented ideas can be applied in related scenarios and for other types of non-rigid objects.

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References


[22] Hannie Kim, Stefan Leutenegger, and Andrew Davison. Real-time 3d reconstruction and 6-dof tracking with an event camera. In European Conference on Computer Vision (ECCV), 2016. 1, 2


[34] Franziska Mueller, Florian Bernard, Oleksandr Sohychenko, Dushyant Mehta, Srinath Sridhar, Dan Casas, and Christian Theobalt. Generated hands for real-time 3d hand tracking from monocular rgb. In Computer Vision and Pattern Recognition (CVPR), 2018. 1, 2, 5, 6, 7
[37] Liyuan Pan, Cedric Scheerlinck, Xin Yu, Richard Hartley, Miaomiao Liu, and Yuchao Dai. Bringing a blurry frame alive at high frame-rate with an event camera. In Computer Vision and Pattern Recognition (CVPR), 2019. 1, 2
[40] Henri Rebecq, René Ranftl, Vladlen Koltun, and Davide Scaramuzza. High speed and high dynamic range video with an event camera. IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI), 2020. 1


[66] Song Zhang, Yu Zhang, Zhe Jiang, Dongqing Zou, Jimmy Ren, and Bin Zhou. Learning to see in the dark with events. In *European Conference on Computer Vision (ECCV)*, 2020. 1, 2

[67] Xiong Zhang, Qiang Li, Hong Mo, Wenbo Zhang, and Wen Zheng. End-to-end hand mesh recovery from a monocular rgb image. In *International Conference on Computer Vision (ICCV)*, 2019. 1, 2


**EventHands :: Appendix**

In this appendix, we provide more insights on our EventHands method and additional experimental results. First, Sec. A discusses our ablation study and further qualitative results. Subsequently, we explain the parameters of the Kalman filter in detail (Sec. B) and the architecture choice for our neural network (Sec. C). Sec. D contains further details about our simulator and the dataset, including the value ranges used for augmentation.

**A. Experimental Details**

**A.1. Naïve Representation**

Here we describe the naïve event windows used for the ablation study. We define $N_k \in \mathbb{R}^{W \times H \times 2}$ to be the naïve representation of the $k$-th window of events which is initialised with zeros at the beginning. Then, for each event in $E = \{(t_i, x_i, y_i, p_i)\}_{i=1}^{N_k}$, we update the naïve representation by the following assignment:

$$N_k(x_i, y_i, p_i) = 1. \quad (6)$$

Thus, $N_k(x_i, y_i, p_i)$ indicates whether an event has occurred in the window, but it does not consider the event history.

**A.2. Additional Results**

Fig. 8 shows more qualitative results for different subjects that we captured with the DAVIS240C event camera (EventHands uses event stream only). Furthermore, we provide results of a network trained with the arm entering the field of view from the bottom in Fig. 9. In this experiment, we use additional 55 hours of generated event stream data for training.

**B. Temporal Filtering**

We use a Kalman filter [23] with constant velocity assumption to post-process our raw predictions $\theta \in \mathbb{R}^{12}$. The corresponding state vector $S \in \mathbb{R}^{24}$ is given by

$$S = [\theta_1 \ \dot{\theta}_1 \ \ldots \ \theta_{12} \ \dot{\theta}_{12}]^T, \quad (7)$$

where $\dot{\theta}_i$ is the velocity of $i$-th parameter $\theta_i$. We model changes in velocities $\dot{\theta}_i$ as independent Gaussian white noise (i.e., temporally uncorrelated). For a given process noise variance $\sigma_p^2$, the *discrete white noise covariance matrix operator* produces a block-diagonal covariance matrix

$$\omega(\sigma_p^2) = \sigma_p^2 \begin{pmatrix} W_1 & & \\ & \ddots & \\ & & W_{12} \end{pmatrix}. \quad (8)$$

This matrix models uncertainty in updating both the position $\theta$ and velocity $\dot{\theta}$ in the state vector $S$. In Eq. (8), $W_i$ is the process noise covariance matrix of $[\theta_i, \dot{\theta}_i]$:

$$W_i = \begin{pmatrix} \frac{1}{2} \Delta t^4 & \frac{1}{2} \Delta t^3 \\ \frac{1}{2} \Delta t^3 & \Delta t^2 \end{pmatrix}, \quad (9)$$

where $\Delta t$ is the temporal step size.

**C. Choosing Network Architecture**

Besides ResNet-18, we examined other base models including VGG-[11,13,16,19] (with batch normalisation) [47], MobileNet v2 [42], ShuffleNet v2 [28], Inception v3 [52], MnasNet [53] and ResNet-34. Out of these models, only MobileNet v2, ResNet-34 and VGG networks produced validation losses comparable to ResNet-18. However, the smallest examined VGG network and ResNet-34 were unable to handle real-time processing at 1000 Hz, which was one of our main goals. Furthermore, while the inference time of MobileNet v2 was faster than that of ResNet-18, we select ResNet-18 as the base model as it has higher prediction accuracy and enables 1000 frames per second.

**D. Simulator and Dataset Details**

This section provides more details on the implementation of our GPU-based event simulator and the format used for storing our dataset.

**D.1. Implementation Details**

The simulator is developed in C++ using

- CUDA, cuBLAS, cuRAND – for computing MANO pose-corrective mesh offsets (that reduce skinning artefacts) on GPU and event camera simulation,
- OpenGL – for posing the skinned and corrected MANO mesh as well as rendering the scene,
- xtensor – for computing MANO shape template mesh and textures on CPU and for loading MANO data, and
- SDL2 – for image loading and OpenGL context management.

All mesh operations that happen every frame are performed entirely on GPU using GPU memory only. Only two CPU-GPU memory transfers are needed per frame to obtain the current pose vector and the event stream output.

This and other optimisations allow fast simulation of the full SMPL+H body model at $240 \times 180$ resolution, which is the resolution of the DAVIS240C event camera that we use for the experiments. On a single NVIDIA GeForce GTX1070, two instances of the simulator can be launched.
simultaneously to obtain events at rates of around 2000 simulated time steps per second. Considering that we use a time step equal to 1/1000 of a second, that means we can simulate data at twice the real-time speed with 1 ms temporal resolution.

D.2. Event Camera Calibration

To reduce the domain gap between the simulated and real event data, we used the event threshold value and the noise event rate of our DAVIS240C event camera.

To calibrate the event threshold $C$, we shot several sequences by moving an object (a checkerboard) monotonously from one side to the other with different speeds. We captured both the events $\{(t_i, u_i, p_i)\}_{i=1}^{N_{\text{events}}}$ and instant intensity images $\{\Omega_j\}_{j=1}^{N_{\text{images}}}$ simultaneously. By moving monotonously from one side to the other side, we eliminate cases when the event stream contains events that cancel themselves between two consecutive intensity images. To estimate the event threshold from the captured data, we use the following observation. According to our camera model, if the camera emits $N$ events in total, then the intensity images would have the total log-intensity change of $\approx NC$. Thus, $C$ can be estimated by dividing the total log-intensity change by the total number of events $N$.

Hence, we counted the total intensity change of the instant intensity images $\Delta_{\text{total}}$ as

$$\Delta_{\text{total}} = \sum_{i=1}^{N_{\text{images}}-1} |\log(\max(\Omega_{i+1}, \varepsilon)) - \log(\max(\Omega_i, \varepsilon))|,$$

(10)

where $\varepsilon = 10$ is a constant added for numerical stability. Then, we estimate $C$ as

$$C \approx \Delta_{\text{total}}/N_{\text{events}}.$$

(11)

For our event camera, we obtain $C = 0.5–0.55$. 

**Figure 8.** Additional results of EventHands on real event sequences captured with different subjects.

**Figure 9.** Results of EventHands on real data where the hand is entering the frame from the bottom.
To estimate the noise event rate, we shot the static background and count the number of positive and negative recorded events. For our DAVIS240C, we estimate the noise to be ≈2500 positive and ≈100 negative events per second.

D.3. Dataset Format

The generated dataset consists of two files, i.e., the event stream and the metadata stream. The event stream file format is tailored for the frame-by-frame event stream simulation. It consists of blocks of four bytes: two bytes for $x$ coordinate, one byte for $y$ coordinate and one byte for polarity $p$. At the start, the timestamp is considered to be zero. A new frame is indicated by the polarity value $p = 255$, which signals that the timestamp should be incremented by one time step. We use the time step of 1/1000 of a second. The file starts with a four-byte integer that specifies the number $N$ of metadata fields per each frame. Then, the stream starts and it consists of $8N + 2$ byte blocks. The block contains $N$ eight-byte double-precision reals and two-byte magic. We use $N = 12$ for six MANO articulation coefficients, three components of the hand root translation vector, and three components of the hand root rotation vector.

We also implement a high-speed C++/Python loader for the proposed dataset format. It allows loading $\sim 8.6 \cdot 10^5$ simulated frames per second or $\sim 1.75 \cdot 10^8$ events per second when using storage capable of 1000 MB/s read speeds. With the fixed rate of 1000 simulated frames per second, this amounts to loading 860 simulated seconds per second. Thus, we are able to load a 45-hours-long dataset in just three minutes.

D.4. Simulation Parameters

We next describe how we augment the simulation for generating the event data. SMPL+H body shape $\beta$ is drawn from $\mathcal{U}[-2, 2]$. Body position $\theta$ is drawn as follows. First, we sample $\xi \sim \mathcal{U}[-0.2, 0.2]$. Then $\theta = \xi \otimes g + o$, where $g$ is the gain vector, $o$ is the offset vector and $\otimes$ is the component-wise multiplication operator.

For the dataset in which the arm comes from the top and right edges, the gain is

$$ g_i^{(1)} = \begin{cases} 100, & \text{if } i = 16 \cdot 3 + 9, \\ 40, & \text{if } i = 16 \cdot 3 + 10, \\ 10, & \text{if } i = 16 \cdot 3 + 11, \\ 40, & \text{if } i = 16 \cdot 3 + 15, \\ 40, & \text{if } i = 16 \cdot 3 + 16, \\ 40, & \text{if } i = 16 \cdot 3 + 17, \\ 1, & \text{otherwise}, \end{cases} $$

and the offset is

$$ o_j^{(1)} = \begin{cases} 0.2, & \text{if } j = 13 \cdot 3 + 5, \\ 0.1, & \text{if } j = 16 \cdot 3 + 5, \\ 1.4\epsilon, & \text{if } j = 16 \cdot 3 + 9, \\ 0.5, & \text{if } j = 16 \cdot 3 + 11, \\ 0, & \text{otherwise}, \end{cases} $$

where $\epsilon$ is sampled randomly and is either $-1$ or $1$ with equal probability. Global translation vector has $(x, y)$ components sampled from $\mathcal{U}[-0.3, 0.3]$. The depth component $z$ is taken from $\mathcal{U}[-0.09, 0.09]$.

For the dataset in which the arm comes from the bottom edge, the gain is

$$ g_i^{(2)} = \begin{cases} 100, & \text{if } i = 16 \cdot 3 + 9, \\ 10, & \text{if } i = 16 \cdot 3 + 11, \\ 40, & \text{if } i = 16 \cdot 3 + 15, \\ 40, & \text{if } i = 16 \cdot 3 + 16, \\ 40, & \text{if } i = 16 \cdot 3 + 17, \\ 1, & \text{otherwise}, \end{cases} $$

and the offset is

$$ o_j^{(2)} = \begin{cases} -2.3, & \text{if } j = 2, \\ 0.2, & \text{if } j = 13 \cdot 3 + 5, \\ 0.1, & \text{if } j = 16 \cdot 3 + 5, \\ 1.4\epsilon - 3.8, & \text{if } j = 16 \cdot 3 + 9, \\ 0.5, & \text{if } j = 16 \cdot 3 + 11, \\ 0, & \text{otherwise}, \end{cases} $$

where $\epsilon$ is also chosen randomly and is either $-1$ or $1$ with equal probability. Global translation vector has $x$ component drawn from $\mathcal{U}[-1.5, -0.9]$, $y$ component taken from $\mathcal{U}[-0.52, 0.08]$ and depth component $z$ taken from $\mathcal{U}[-0.09, 0.09]$.

The hand MANO articulation parameters are sampled from $\mathcal{U}[-2, 2]$, whereas hand texture PCA coefficients are chosen from $\mathcal{N}(0, 0.4I)$. Light directions are sampled uniformly from all possible directions and light intensities are drawn from $\mathcal{U}[0.9, 1.1]$. Finally, the background image is drawn randomly from the collected set of nine background images. The event generation threshold is drawn from $\mathcal{N}(0.5, 0.0004)$.  

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