





Visual Computing and AI Department



# **EventHands: Real-Time Neural 3D Hand Pose Estimation from an Event Stream** V. Rudnev<sup>1</sup> V. Golyanik<sup>1</sup> J. Wang<sup>1</sup> H.-P. Seidel<sup>1</sup> F. Mueller<sup>2</sup> M. Elgharib<sup>1</sup> C. Theobalt<sup>1</sup> <sup>1</sup>MPI Informatics, Saarland Informatics Campus <sup>2</sup>Google Inc.

#### Motivation

- Hand pose estimation is important for Interations in Virtual Environments, Gesture Recognition, Gaming and more.
- Current RGB(D) methods have their limitations:
- Fail on fast moving hands due to motion blur,
- Fail in low-light conditions due to sensor sensitivity,
- Consume large data bandwidth

## **Related Work**









Zhou et al.



Boukhayma et al



Contributions



Live Demo

Hand Pose Prediction

- Live 3D Hand Pose Estimation at 1 KHz from a Single Event Stream
- New High-Throughput Event Stream Simulator for Hands
- Large-Scale Annotated Dataset of Synthetic Hand Event Streams

#### **Event Cameras**

 React to brightness changes (events) asynchronously per-pixel, instead of shooting full frames,

 Use abstract data representation useful for generalization,

 Have low data bandwidth, essentially infinite temporal resolution and high dynamic range

### MANO and HTML models









Event camera





Depth and Output Pose Moon et al. Depth-based



Large-Scale Dataset



Input Event Stream





**Event Representation LNES** 



Datasets



		synthetic		real	1.00
		2D-AUCp	<b>3D-AUC</b>	2D-AUCp	
	no filtering no aug.	0.89 0.88	0.85 0.86	<b>0.75</b> 0.70	0.75
EOI	33ms 100ms	0.86 0.78	<b>0.85</b> 0.80	0.70 0.56	A A A 0.50
ECI-S	33ms 100ms	0.83 0.69	0.81 0.76	0.66 0.56	5D-
ECI	33ms 100ms	0.86 0.76	0.83 0.79	0.69 0.52	0.25
LNES	33ms 300ms <b>proposed</b>	<b>0.88</b> 0.87 <b>0.88</b>	0.85 0.84 0.85	0.72 0.72 <b>0.77</b>	0.00



Reference (500 fps)

RGB Input (30 fps)

#### **Various Results**



Input

Our Result





#### Low-Light Performance (0.77 2D-PCKp AUC)



Original RGB (ISO 320)

#### References

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Mueller *et al.* [36] Boukhayma *et al.* [10] Zhou *et al.* [71]

*EventHands* (Ours)



Input

Our Result

Input

Our Result







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