Event-based Non-Rigid Reconstruction from Contours

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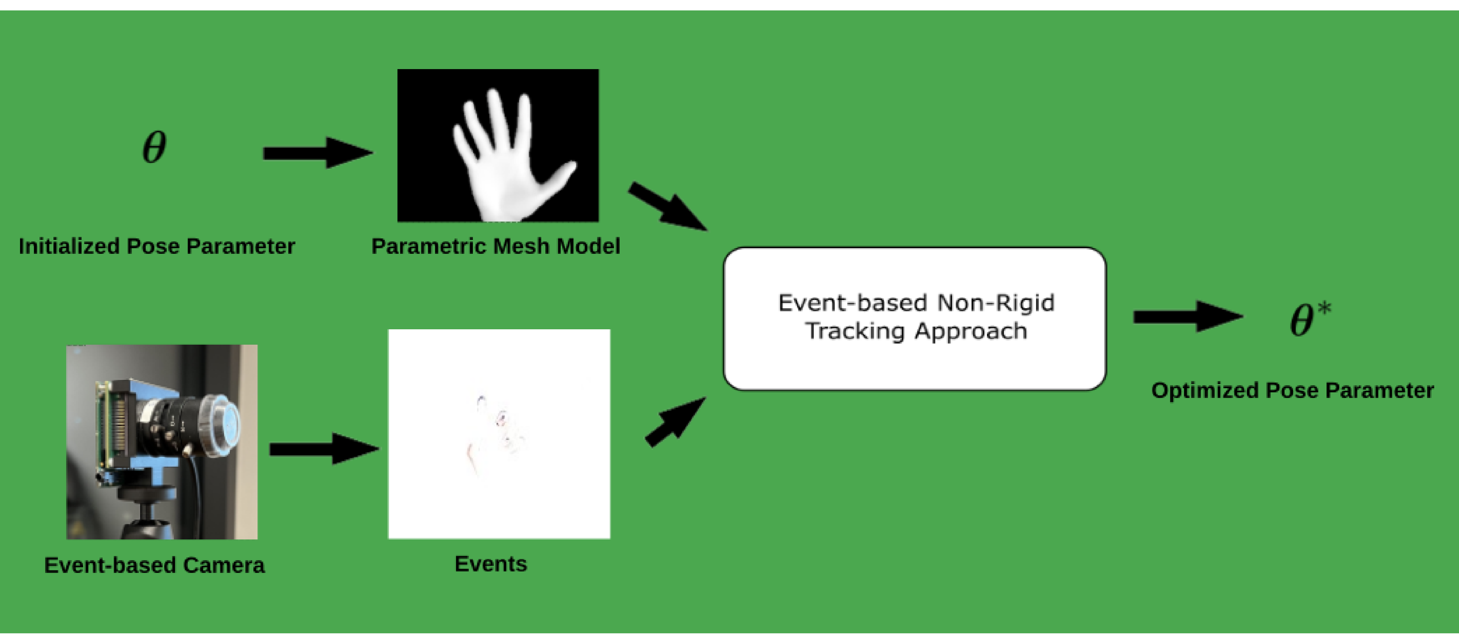
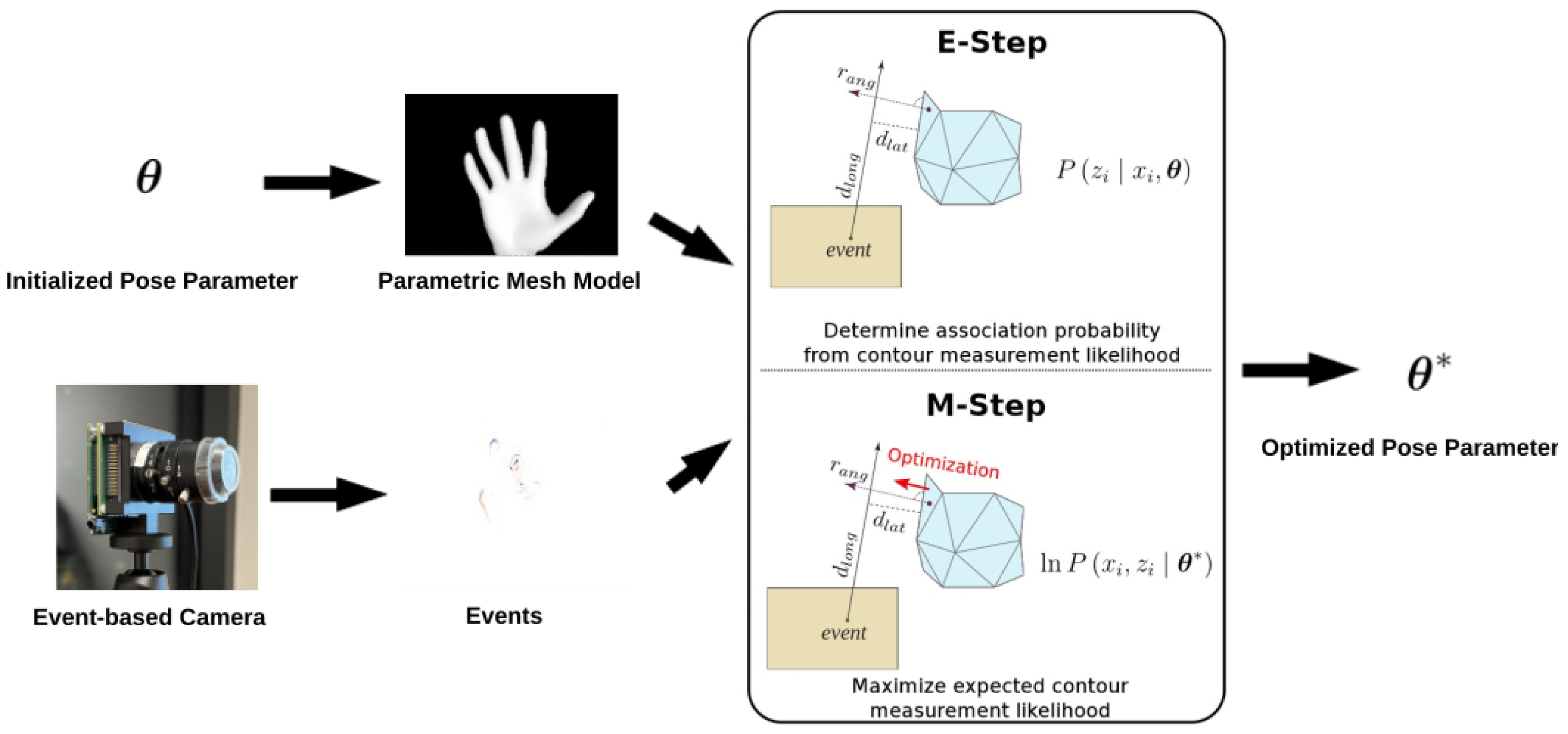


We propose a novel approach for **reconstructing fast non-rigid object deformations** using measurements from **event-based cameras**.

We observe that the majority of events of texture-less object motions are generated at the object **contour**. Our approach estimates the deformation of objects from **events generated at the object contour** in a **probabilistic optimization framework**.

Compared to baseline approaches, our method outperforms them in non-rigid reconstruction quantitatively and qualitatively.

Event-based Non-Rigid Reconstruction



E-step: Determine association probability based on latest MANO[6] pose parameter.

$$p(z_i = j \mid x_i, \boldsymbol{\theta}) = \frac{p(x_i \mid z_i = j, \boldsymbol{\theta})p(z_i = j \mid \boldsymbol{\theta})}{\sum_{j'} p(x_i \mid z_i = j', \boldsymbol{\theta})p(z_i = j' \mid \boldsymbol{\theta})} = \frac{p(x_i \mid z_i = j, \boldsymbol{\theta})}{\sum_{j'} p(x_i \mid z_i = j', \boldsymbol{\theta})}$$

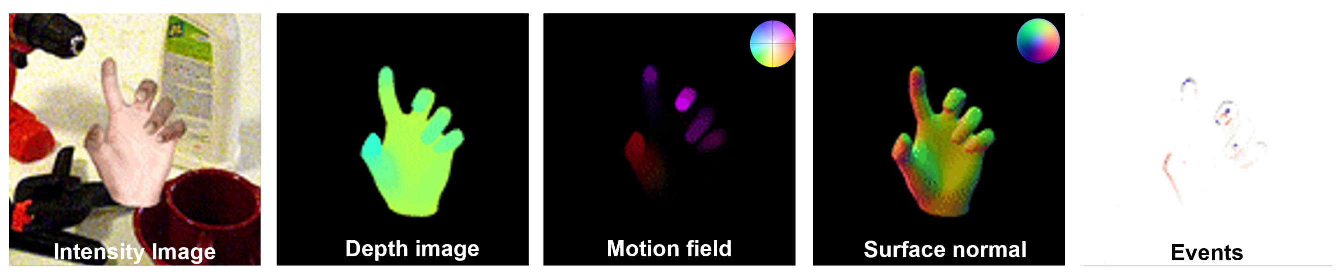
M-step: Maximize the expected contour measurement likelihood to update pose parameter.

$$p(x_i, z_i = j \mid \boldsymbol{\theta}) = p(x_i \mid z_i = j, \boldsymbol{\theta})p(z_i = j \mid \boldsymbol{\theta}) \propto p(x_i \mid z_i = j, \boldsymbol{\theta})$$

Iteration: optimize pose parameter by alternating E- and M-step.

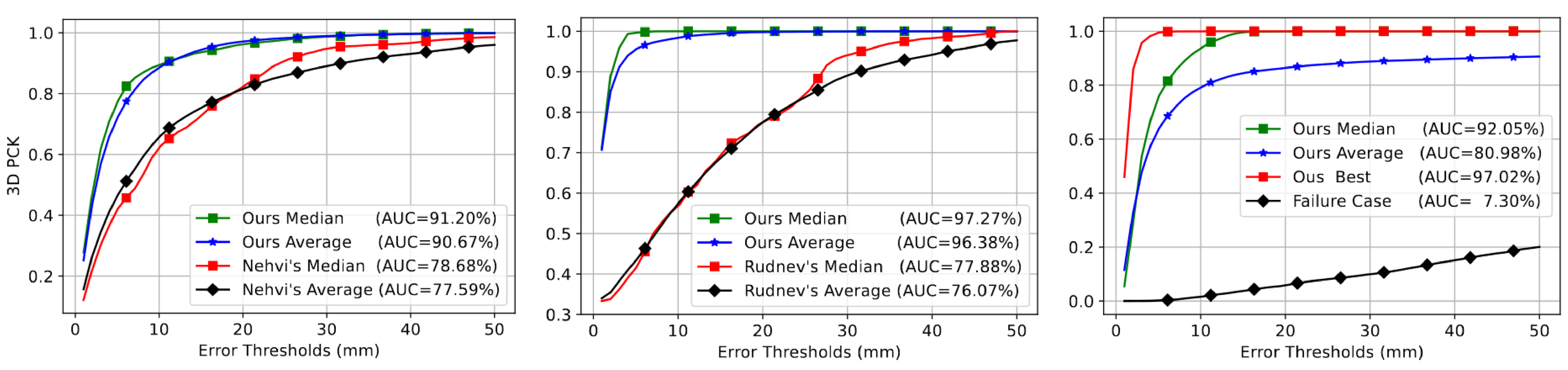
Event Stream Simulator

Inspired by state-of-the-art works, we propose our event stream simulator which supports **more data modalities** and **parametric body models**.



Quantitative Results on Synthetic Data

Scenario	Method	Mean MPJPE (mm)	Median MPJPE (mm)
MANO hand	Nehvi et al. [3]	11.61	10.85
	Ours	**4.52**	**4.27**
SMPL-X hand	Rudnev et al. [4]	11.88	10.73
	Ours	**1.11**	**0.76**
SMPL-X arm & hand	**Ours**	**15.39**	**3.93**



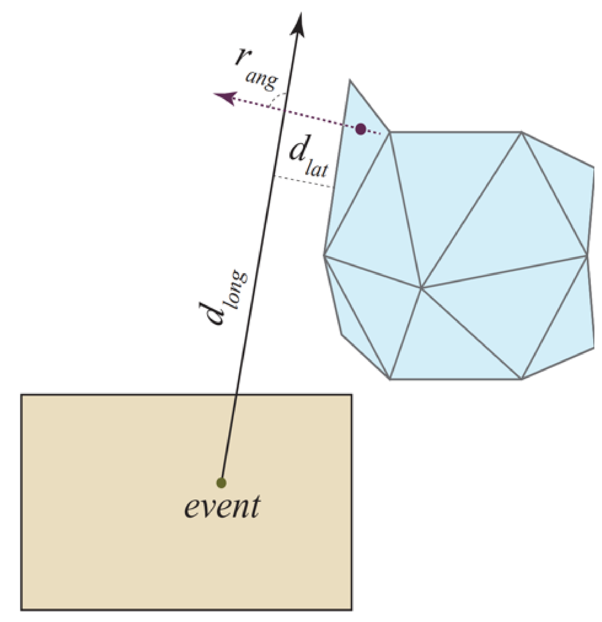
Results on MANO [6] (left), SMPL-X [2] hand (middle), and SMPL-X [2] arm & hand (right) scenario.

Conclusion & Outlook

Contribution: propose the definition of **contour events**; an **EM**-based **non-rigid reconstruction** approach from contour events; an efficient multi-modal **event stream simulator**
Limitation: ill-constrained settings, e.g. not enough contour events; not real-time capable yet.
Future Works: combine events and intensity frames to recover global rigid transformation; assign event to smaller range of mesh face and use parallel programming to increase efficiency

Measurement Likelihood

We use the measurement likelihood in E-step (to calculate the association likelihood) and M-step.



We formulate the measurement likelihood that an event x_i is caused by a mesh face f_j using

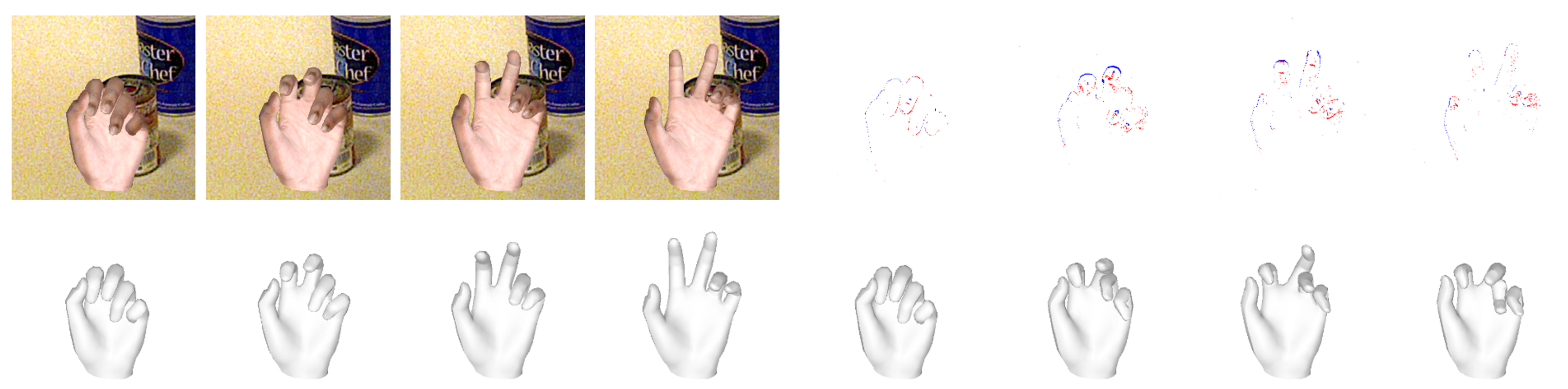
- lateral distance d_{lat}
- longitudinal distance d_{long} (not used in M-step)
- angular error r_{ang}

between the line of sight through event x_i and the mesh face f_j.

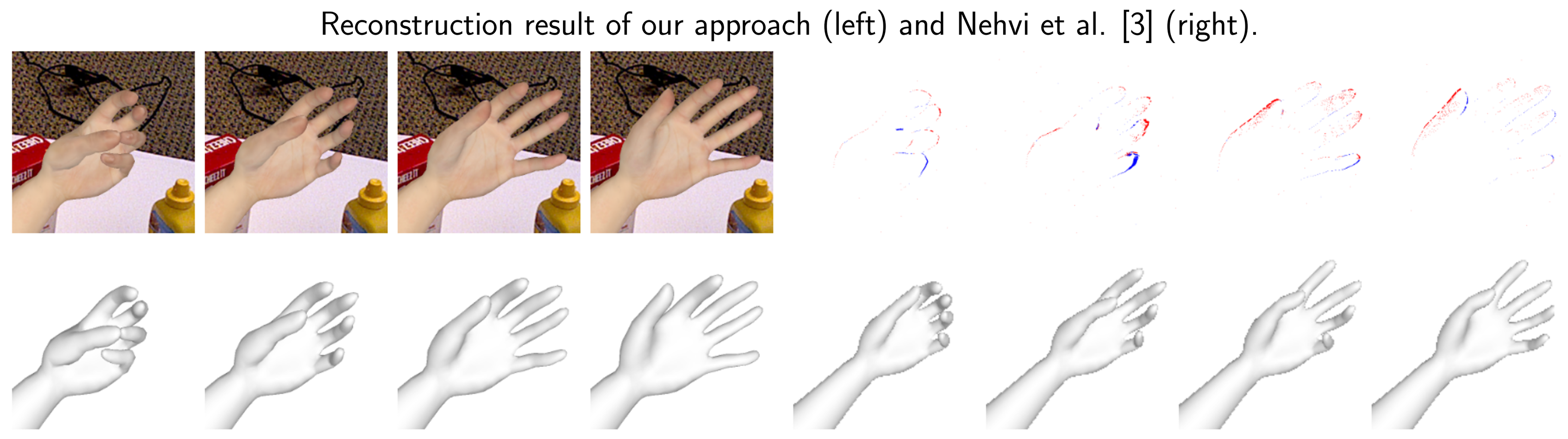
We formulate the measurement likelihood on the observed contour as

$$p(x_i \mid z_i = j, \boldsymbol{\theta}) \propto \underbrace{\sigma\left(\delta_j^i \frac{d_{\text{lat}}^2(i,j)}{\alpha}\right)}_{lateral} \underbrace{\exp\left(-\frac{d_{\text{long}}(i,j)}{\beta}\right)}_{longitudinal} \underbrace{\exp\left(-\frac{r_{\text{ang}}(i,j)}{\gamma}\right)}_{contour}$$

Results on Synthetic Data

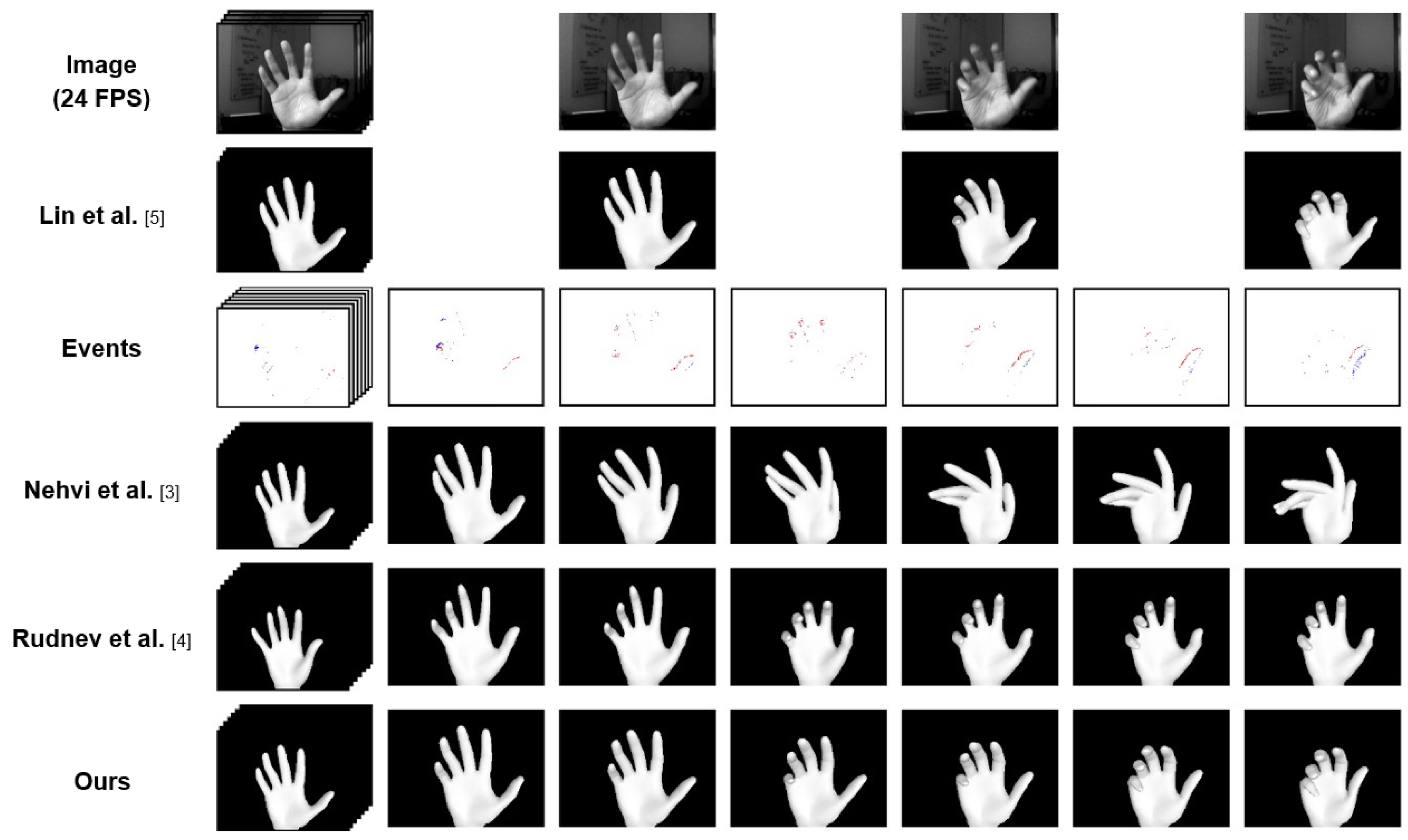


Reconstruction result of our approach (left) and Nehvi et al. [3] (right).



Reconstruction result of our approach (left) and Rudnev et al. [4] (right).

Results on Real Data



Reconstruction result on DAVIS 240C captured events.

Acknowledgements:

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References:

[1] Xue, Y., Li, H., Leutenegger, S., and Stueckler, J. (2022). Event-based Non-Rigid Reconstruction from Contours. In *BMVC 2022*.

[2] G. Pavlakos et al. (2019). Expressive Body Capture: 3D Hands, Face, and Body from a Single Image. In *CVPR 2019*.

[3] J. Nehvi et al. (2021). Differentiable Event Stream Simulator for Non-Rigid 3D Tracking. In *CVPRW 2021*.

[4] V. Rudnev et al. (2021). EventHands: Real-Time Neural 3D Hand Pose Estimation from an Event Stream. In *ICCV 2021*.

[5] K. Lin et al. (2021). Mesh Graphormer. In *ICCV 2021*.

[6] J. Romero et al. (2017). Embodied Hands: Modeling and Capturing Hands and Bodies Together. In *SIGGRAPH Asia 2017*.