Comparison of Spatio-Temporal Hand Pose Denoising Models

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Hand Pose Estimation

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https://github.com/NVIDIA-AI-IOT/trt_pose_hand



Estimation Algorithms

FrankMocap



Rong, Yu, et al.. Frankmocap: A monocular 3d whole-body pose estimation system via regression and integration. In IEEE ICCV Workshops, 2021.

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Estimation Algorithms

- FrankMocap
- Mesh Graphormer



Rong, Yu, et al.. Frankmocap: A monocular 3d whole-body pose estimation system via regression and integration. In IEEE ICCV Workshops, 2021. Lin, Kevin and Wang, Lijuan and Liu, Zicheng.. Mesh Graphormer



Jitter Small displacement.

Typical Errors



Inversion Error on the same instance.









Swap

Error on different instances.

(a) Jitter

(b) Inversion

n (c) Swap

(d) Miss



Miss Not exists keypoint.

Gyeongsik Moon, Ju Yong Chang, Kyoung Mu Lee.. PoseFix: Model-Agnostic General Human Pose Refinement Network. CVPR, 2019







Durham Research , Kanglei Zhou , Zhiyuan Cheng , Hubert P H Shum , Frederick W B Li , Liang , Xiaohui Liang. STGAE: Spatial-Temporal Graph Auto-Encoder for Hand Motion Denoising. ISMAR, 2021.





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UDIVA

Understanding Dyadic Interactions from Video and Audio signals

Palmero, Cristina, et al. "Context-Aware Personality Inference in Dyadic Scenarios: Introducing the UDIVA Dataset." WACV (Workshops). 2021.

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UDIVA v0.5

• 4 tasks from 145 sessions: 116 for training (raw annotations), 18 for validation and 11 for testing (cleaned annotations).



Talk

Animals

Lego

Ghost

UDIVA v0.5





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Hand Pose estimation Algorithm: FrankMocap

Landmarks extraction



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Visual inspection

Validation (18 sessions) and test (11 sessions) sets underwent a visual inspection process. •



Hands interpolation



Hand Representation



- 1x20 right hand landmarks
- 1x20 left hand landmarks (flip horizontally)
- Absolute coordinates were transformed to root-relative coordinates.

Left Hand

Left Hand Transformed









Perturbation Algorithm

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1.3) There are 14.4%/8.0% of left/right hands missing inside the segments (joints equal to 0).



- Architectures:
 - \circ MLP $\leftarrow \rightarrow$ MLP Frequential
 - \circ Seq2Seq $\leftarrow \rightarrow$ Seq2Seq-Bidirectional
 - Spatio-Temporal Transformer

- Data:
 - Participant 1
 - Two hands consecutively
 - Ground Truth: Cleaned Frames



MSE_root_AVG: 277.70

Dist Euclidean AVG: 0.46

MSE root: 102.50

Dist Euclidean: 22.82

Visual Results



18

MSE root: 103.56

Dist Euclidean: 16.89



Visual Results



RNN				\rightarrow
		Sample 2 - [H] Frame 0		
Context	Raw	Groundtruth	Difference	algorithm_0
<i>b</i> r	≉	#	\$	<u>s</u>
MSE_AVG: 356.57 MSE_ind_AVG: 671.89 MSE_root_AVG: 90.99 Dist_Euclidean_AVG: 0.16	MSE: 189.70 MSE_ind: 195.30 MSE_root: 32.00 Dist_Euclidean: 15.62			MSE: 421.59 MSE_ind: 1395.90 MSE_root: 795.49 Dist_Euclidean: 27.90
• Transformer				
		Sample 36 - [H] Frame 0		
Context	Raw	Groundtruth	Difference	algorithm_0
1)]+	1)//-	<i>#</i>	**	117
MSE_AVG: 1127.01 MSE_ind_AVG: 728.35 MSE_root_AVG: 79.86 Dist_Euclidean_AVG: 0.40	MSE: 1116.70 MSE_ind: 791.17 MSE_root: 74.50 Dist_Euclidean: 41.17			MSE: 393.35 MSE_ind: 424.97 MSE_root: 218.67 Dist_Euclidean: 27.41



- Pose Architectures:
 - MLP
 - MLP Frequential
 - Transformer

- Trajectory Architectures:
 - Seq2Seq
 LSTM



Ranking

Model	Prediction
TransformerMixed_BI_100	8.649507
TransformerMixed_100	10.361105
Mixed_BI_100	10.661939
Mixed_100	11.080834
Mixed_Freq_100	11.377095
Mixed_Freq_BI_100	11.522652
Transformer_100	12.230602
RNN_BI_100	18.057422
RNN_100	21.049572
MLP_Freq_100	23.856506
MLP_100	29.756484



Mean Error of Euclidean Distance: Two hands

• Baseline: 9.138526



More Evaluation





Performance of the 100 observation length models respect to noise application.



More Evaluation



Counting frames with MSE less than the threshold. Normalized values.





Best Algorithm Visual Result

Mixed Transformed Bidirectional



	Raw	Groundtruth	Difference	algorithm_0
First Case	MSE: 0.00 MSE_ind: 0.00 MSE_root: 0.00 Dist_Euclidean: 0.00	X	(MSE: 15.61 MSE_ind: 6.29 MSE_root: 3.40 Dist_Euclidean: 5.04
	Raw	Groundtruth	Difference	algorithm_0
Second Case	MSE: 503450.00 MSE_ind: 463797.50 MSE_root: 495378.00 Dist_Euclidean: 1003.06	(m	L (m)	MSE: 24067.67 MSE_ind: 7004.61 MSE_root: 10887.46 Dist_Euclidean: 217.08
	Raw	Groundtruth	Difference	algorithm_0
Third Case	MSE: 167.95 MSE_ind: 363.33 MSE_root: 32.50 Dist_Euclidean: 16.35		A.	MSE: 36.89 MSE_ind: 64.71 MSE_root: 5.68 Dist Euclidean: 7.78



- We carefully reviewed all related state-of-the-art literature on pose denoising.
- The innovative Data Perturbation algorithm allows to worsen the hand poses.
- The frequency space **improves** results in simple models over the original space, but not is representative.
- Mixed model **are more robust** applying more noise.

• **Pose and Trajectory disentanglement** is a good solution approach to find a robust denoising architecture algorithms.

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Future Work

- How the observation window affects model performance.
- Not add noisy into cleaned frames.
- New recent Deep Learning Models.
- Use frequency domain only in trajectory.
- Instead of denoising a unique pose, denoising a sequence of poses.



Thanks!

Do you have any questions?





