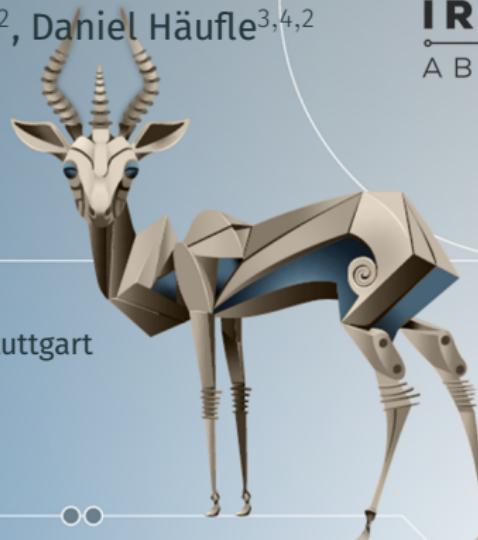


GazeMotion: Gaze-guided Human Motion Forecasting

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Table of Contents

Research Background

Related Work

Method

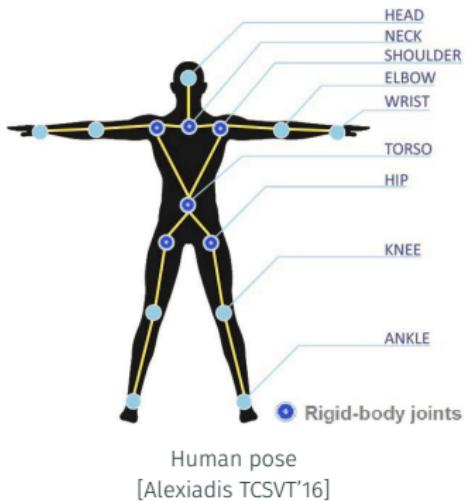
Results

Discussion

Conclusion

Research Background

- **Human pose:** 3D positions of human joints (e.g. wrist, elbow, shoulder, knee, ankle)
- **Motion forecasting:** predict future human poses from historical poses

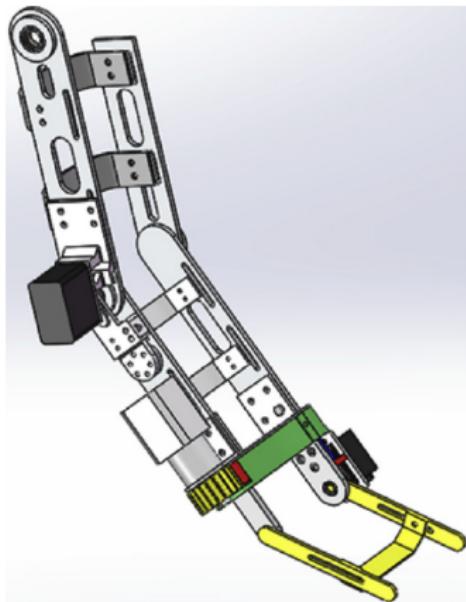


Research Background

Applications of human motion forecasting



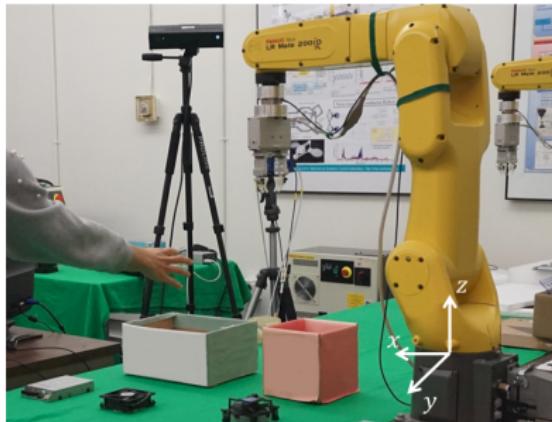
Wearable arm exosuit
[Lotti RAM'20]



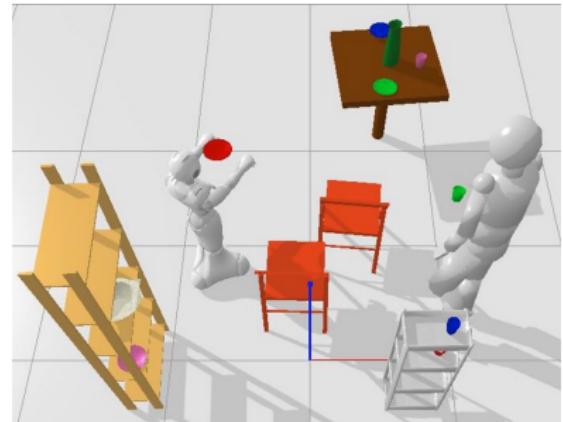
Upper limb exoskeleton
[Zhang BSPC'19]

Research Background

Applications of human motion forecasting



Human-robot collaboration
[Landi IRS'19]



Human-robot collaboration
[Le RHIC'21]

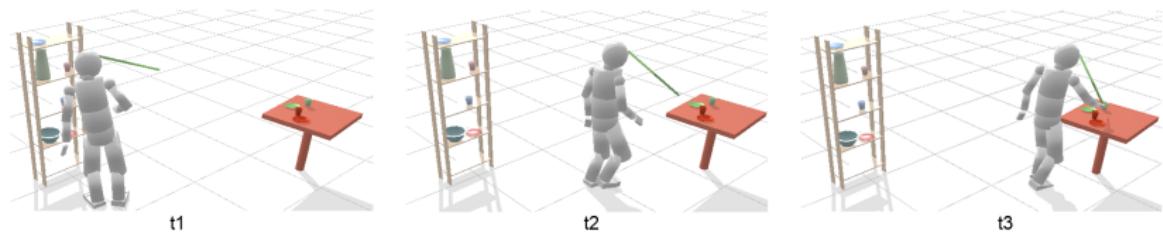
Applications of human motion forecasting



Human-human and human-robot interaction
[Duarte RAL'18]

Eye-body coordination

- Eye-head coordination [Hu TVCG'19; Hu TVCG'20; Hu TVCG'21]
- Eye-hand-head coordination [Emery ETRA'21]
- Eye-head-torso coordination [Sidenmark ToCHI'19]



Eye and body movements in daily pick and place activities

Use eye gaze information to guide human motion forecasting

Contributions

- A novel method that first **predicts future eye gaze from past gaze** and then **forecasts future poses** using the predicted gaze and past poses through a **spatio-temporal GCN**
- Experiments on **three public datasets** that demonstrate **significant performance improvements** over prior methods
- A **user study** that validates our method **outperforms** prior methods in both **precision** and **realism**

Table of Contents

Research Background

Related Work

Method

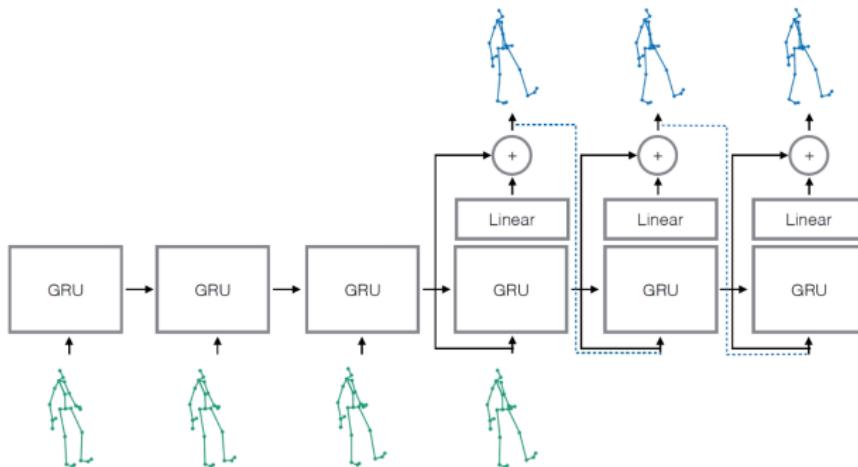
Results

Discussion

Conclusion

Res-RNN: residual recurrent neural network

- Sequence-to-sequence architecture
- Residual architecture

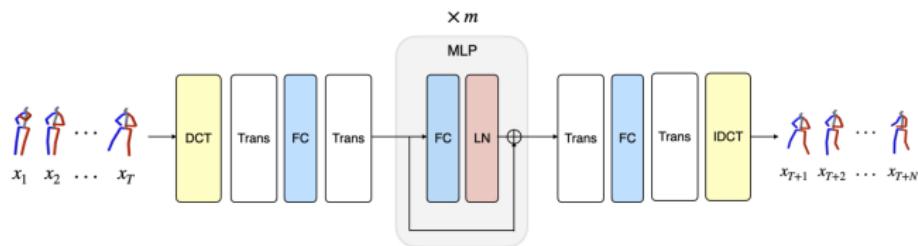


[Martinez CVPR'17]

Related Work

siMLPe: simple multi-layer perceptrons

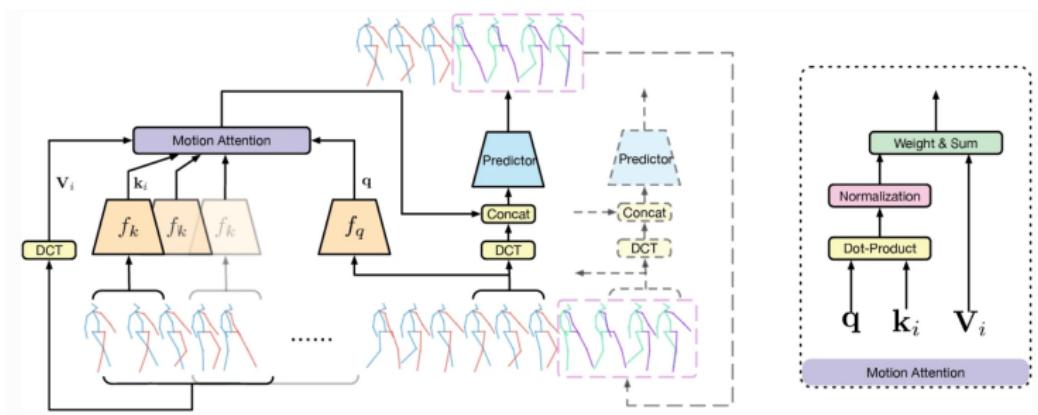
- Fully connected layers, layer normalisation, and transpose operations
- Residual architecture



[Guo WACV'23]

HisRep: human motion forecasting via motion attention

- Sequence-to-sequence architecture
- Attention-based architecture

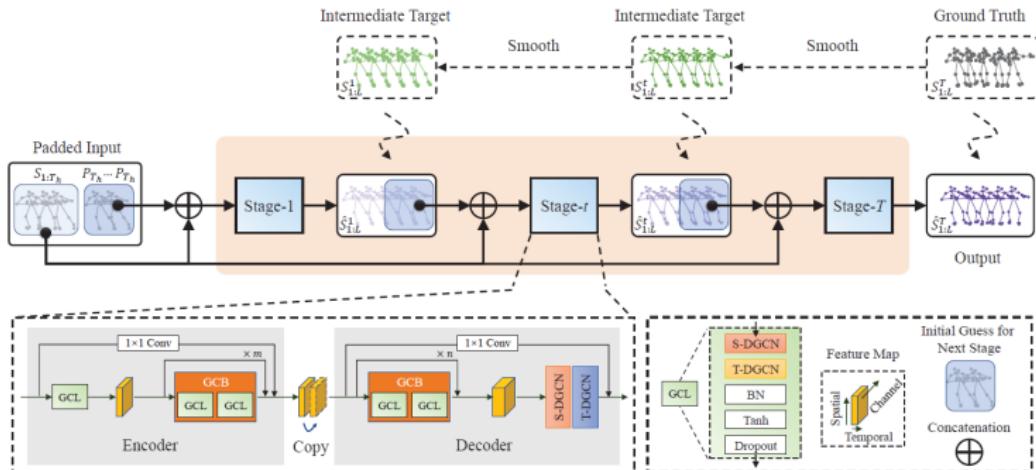


[Mao ECCV'20]

Related Work

PGBIG: progressively generating better initial guesses

- Multi-stage human motion forecasting framework
- Spatial and temporal dense graph convolutional networks



[Ma CVPR'22]

Traditional methods

- Predict future poses from historical poses

Our method

- Predict future eye gaze from historical gaze
- Predict future poses from past poses and the predicted gaze

Table of Contents

Research Background

Related Work

Method

Results

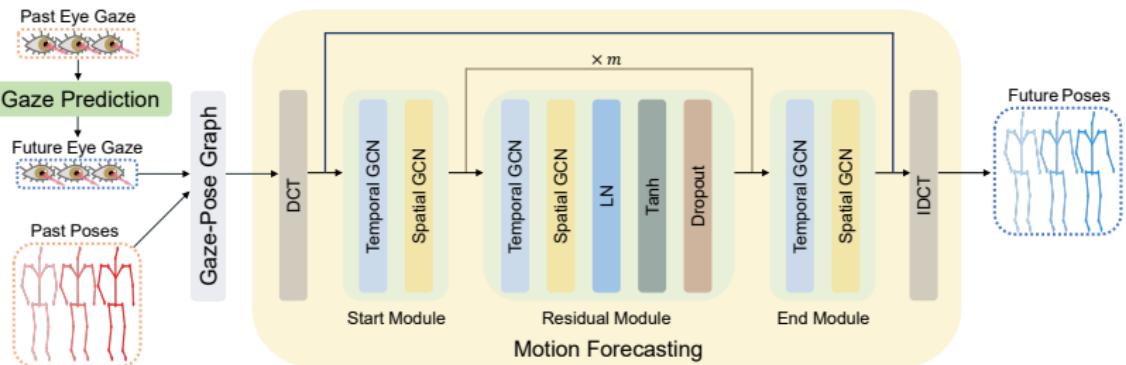
Discussion

Conclusion

Method

GazeMotion method

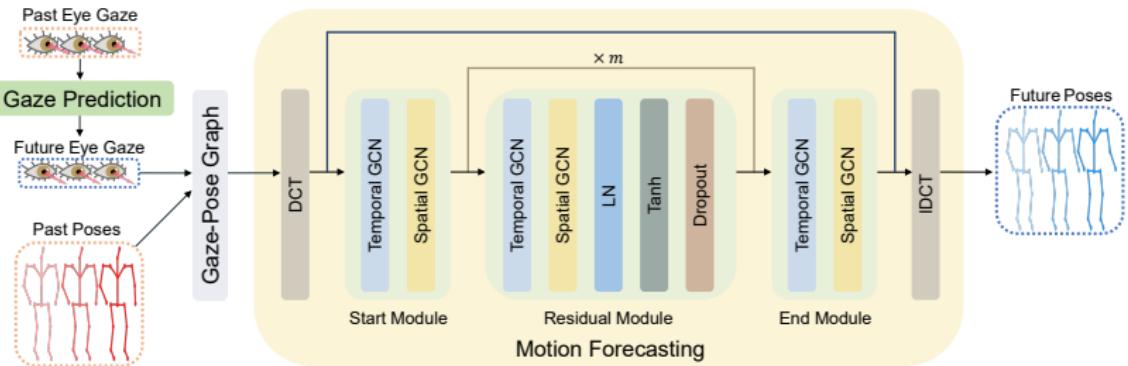
- Eye gaze prediction
- Gaze-pose fusion
- Motion forecasting



Method

GazeMotion method: Eye gaze prediction

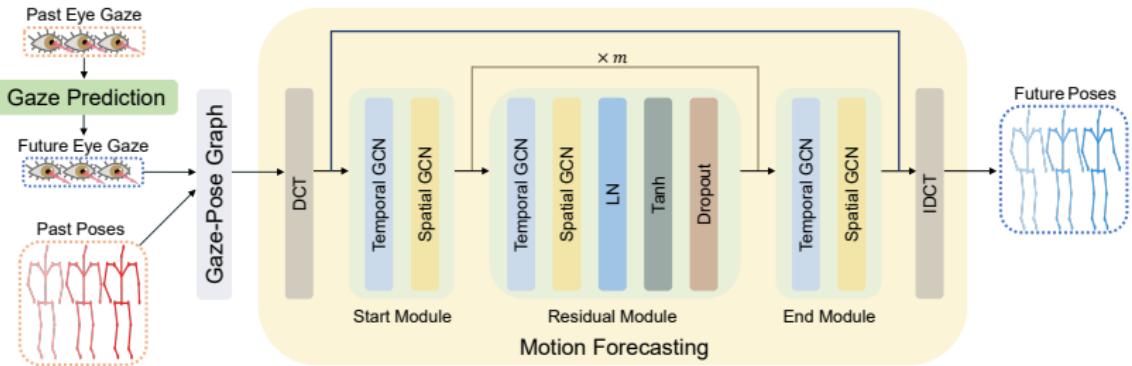
- 1D convolutional neural network



Method

GazeMotion method: Gaze-pose fusion

- Treat eye gaze and body joints as **nodes** in a graph
- Fully-connected spatio-temporal graph



GazeMotion method: Motion forecasting

- Spatio-temporal graph convolutional network
- Start module, residual module, end module

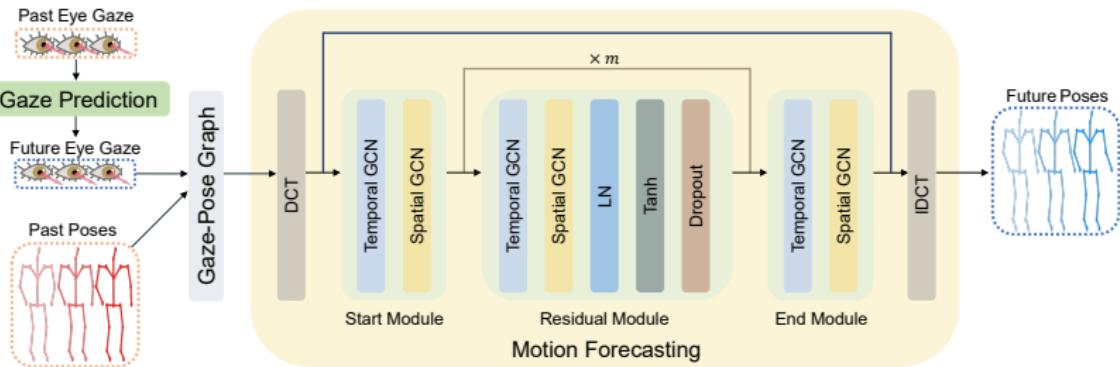


Table of Contents

Research Background

Related Work

Method

Results

Discussion

Conclusion

Evaluation settings

- Datasets: **MoGaze** [Kratzer RAL'20], **ADT** [Pan ICCV'23], **GIMO** [Zheng ECCV'22]
- Metric: mean per joint position error (MPJPE)
- Input: 10 frames in the past
- Output: 30 frames in the future

Results

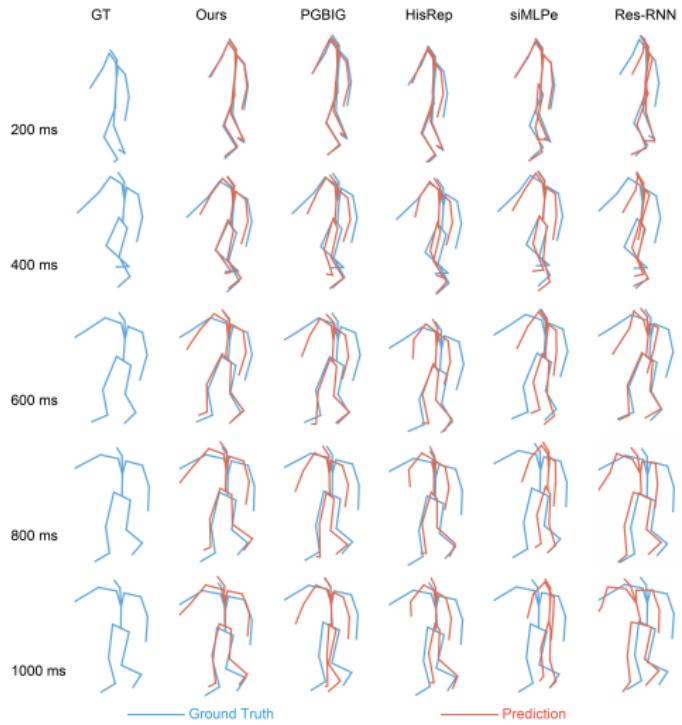
Motion forecasting performance

Dataset	Method	200 ms	400 ms	600 ms	800 ms	1000 ms	Average
MoGaze	Res-RNN [Martinez CVPR'17]	53.1	91.3	136.8	187.5	240.8	124.3
	siMLPe [Guo WACV'23]	40.6	72.0	108.8	152.6	201.0	99.5
	HisRep [Mao ECCV'20]	31.4	60.5	95.4	135.3	177.9	85.3
	PGBIG [Ma CVPR'22]	29.4	57.7	92.0	130.7	171.5	82.0
	Ours w/o gaze	<u>27.2</u>	<u>55.3</u>	<u>88.9</u>	<u>126.9</u>	<u>167.1</u>	<u>79.0</u>
	Ours	25.8	53.3	85.8	122.0	160.0	75.9
ADT	Res-RNN [Martinez CVPR'17]	35.6	55.7	77.8	100.0	122.5	70.1
	siMLPe [Guo WACV'23]	29.9	48.3	69.1	93.8	120.7	63.8
	HisRep [Mao ECCV'20]	15.5	30.5	47.6	66.8	88.2	42.3
	PGBIG [Ma CVPR'22]	14.5	28.7	45.4	64.4	85.8	40.6
	Ours w/o gaze	<u>12.0</u>	<u>26.6</u>	<u>44.0</u>	<u>63.8</u>	<u>85.3</u>	<u>39.1</u>
	Ours	11.7	25.8	42.8	62.1	82.8	38.0
GIMO	Res-RNN [Martinez CVPR'17]	82.6	126.4	170.2	212.9	255.4	152.8
	siMLPe [Guo WACV'23]	42.8	78.3	114.6	150.7	188.5	100.3
	HisRep [Mao ECCV'20]	41.8	78.1	115.0	152.7	192.4	100.2
	PGBIG [Ma CVPR'22]	38.0	68.6	101.9	136.1	172.2	89.2
	Ours w/o gaze	<u>33.7</u>	<u>66.1</u>	<u>99.7</u>	<u>134.4</u>	<u>170.4</u>	<u>86.8</u>
	Ours	32.6	64.1	97.0	130.0	162.4	83.8

Our method (Ours and Ours w/o gaze) **consistently outperforms** prior methods at different time intervals

Results

Motion forecasting performance



Results

Ablation study

Method	200 ms	400 ms	600 ms	800 ms	1000 ms	Average
w/o spatial GCN	30.9	62.1	96.3	133.8	173.1	84.7
w/o temporal GCN	46.6	74.0	107.9	147.0	188.0	99.3
w/o gaze	27.2	55.3	88.9	126.9	167.1	79.0
past gaze	26.3	54.3	87.2	123.8	162.0	77.1
Ours	25.8	53.3	85.8	122.0	160.0	75.9

Our method **consistently outperforms** the ablated versions

User study

- Stimuli: 24 randomly selected motion forecasting samples
- Participants: 20 users (12 males and 8 females)
- Procedure: rank different methods according to *precision* (*align with the ground truth*) and *realism* (*physically plausible*)

Results

User study

		Ours	PGBIG	HisRep	siMLPe	Res-RNN
<i>Precision</i>	Mean	1.6	<u>3.2</u>	<u>3.2</u>	3.3	3.7
	SD	0.9	1.2	1.2	1.3	1.3
<i>Realism</i>	Mean	1.9	3.3	<u>3.1</u>	3.3	3.5
	SD	1.3	1.2	1.3	1.3	1.4

Our method outperforms prior methods in terms of both *precision* and *realism*

Table of Contents

Research Background

Related Work

Method

Results

Discussion

Conclusion

Limitations

- Long-term motion forecasting performances are not as good as short-term performances
- Ignore the stochastic nature of human motions

Future work

- Integrate more **context** information such as user's **goal** or **task** into human motion forecasting
- Explore other important body signals such as **hand gestures** for motion forecasting
- Integrate our method into motion-related applications such as **assistive devices**

Table of Contents

Research Background

Related Work

Method

Results

Discussion

Conclusion

Main contributions

- A novel method consisting of three components: **eye gaze prediction, gaze-pose fusion, and motion forecasting**
- Experiments on **three public datasets** that demonstrate the **superiority** of our method over prior methods
- A **user study** that validates the **precision** and **realism** of our predictions

Code available at zhiminghu.net/hu24_gazemotion ↗

Acknowledgement

Thank you!



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