

#### MSR-GCN: Multi-Scale Residual Graph Convolution Networks for Human Motion Prediction



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#### MSR-GCN: Multi-Scale Residual Graph Convolution Networks for Human Motion Prediction

### **Applications**

Samsung Bot<sup>™</sup> Handy 在安防领域应用开来 technology are applied in the fields of security PRO ROBOTS

autonomous driving

human-computer interaction

intelligent security



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## Introduction & Problem





Observed Seq

Future Seq



spatiotemporal dependencies

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# **Related Works**



- Prior efforts neglect the inner-frame kinematic dependencies
- Frame-by-frame prediction manner causes error accumulation
- Graph Convolution Networks (GCNs) exhibit promising results, but not sufficient for more high-quality human motion prediction.

# Key Insights

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- Stabilize the motion pattern by gradually abstracting body parts
- Predict the poses in the coarsest level firstly, and then go up to finer levels gradually



multi-scale joints groping manner from finer levels (left) to coarser levels (right)

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# Key Insights

- GCNs based on learnable fully connected graph
- Start GCN, Residual GCNs, End GCN
- Residual connection helps to simplify the prediction process



the basic GCN model



# **MSR-GCN** Architecture



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- Descending Path
- Ascending Path
- End GCNs and Intermediate Loss
- Residual Connections

loss function:

Mean Per Joint Position Error (MPJPE)

$$egin{aligned} \mathcal{L}_{ ext{MPJPE}} \ &= rac{1}{J imes T} \sum_{t=1}^T \sum_{j=1}^J \left\| \hat{p}_{j,t} - p_{j,t} 
ight\|^2 \end{aligned}$$

#### MSR-GCN: Multi-Scale Residual Graph Convolution Networks for Human Motion Prediction

# **Quantitative Results**



	1															
scenarios	walking				eating				smoking				discussion			
millisecond (ms)	80	160	320	400	80	160	320	400	80	160	320	400	80	160	320	400
Residual sup. [34]	29.36	50.82	76.03	81.51	16.84	30.60	56.92	68.65	22.96	42.64	70.14	82.68	32.94	61.18	90.92	96.19
DMGNN [27]	17.32	30.67	54.56	65.20	10.96	21.39	36.18	43.88	8.97	17.62	32.05	40.30	17.33	34.78	61.03	69.80
Traj-GCN [33]	12.29	23.03	39.77	46.12	8.36	16.90	33.19	40.70	7.94	16.24	31.90	38.90	12.50	27.40	58.51	71.68
MSR-GCN	12.16	22.65	38.64	45.24	8.39	17.05	33.03	40.43	8.02	16.27	31.32	38.15	11.98	26.76	57.08	<b>69.74</b>
scenarios	directions			greeting					pho	oning		posing				
millisecond (ms)	80	160	320	400	80	160	320	400	80	160	320	400	80	160	320	400
Residual sup. [34]	35.36	57.27	76.30	87.67	34.46	63.36	124.60	142.50	37.96	69.32	115.00	126.73	36.10	69.12	130.46	157.08
DMGNN <sup>[27]</sup>	13.14	24.62	64.68	81.86	23.30	50.32	107.30	132.10	12.47	25.77	48.08	58.29	15.27	29.27	71.54	96.65
Traj-GCN [33]	8.97	19.87	43.35	53.74	18.65	38.68	77.74	93.39	10.24	21.02	42.54	52.30	13.66	29.89	66.62	84.05
MSR-GCN	8.61	19.65	43.28	53.82	16.48	36.95	77.32	93.38	10.10	20.74	41.51	51.26	12.79	29.38	66.95	85.01

#### Short-term errors on Human3.6M (H3.6M)

Residual sup. Martinez J, et al., CVPR 2017

DMGNN Li M, et al., CVPR 2020

Traj-GCN Mao W, et al., ICCV 2019

## **Quantitative Results**



scenarios	basketball				basketball signal					directi	ng traffic		jumping			
millisecond (ms)	80	160	320	400	80	160	320	400	80	160	320	400	80	160	320	400
Residual sup. [34]	15.45	26.88	43.51	49.23	20.17	32.98	42.75	44.65	20.52	40.58	75.38	90.36	26.85	48.07	93.50	108.90
DMGNN [27]	15.57	28.72	59.01	73.05	5.03	9.28	20.21	26.23	10.21	20.90	41.55	52.28	31.97	54.32	96.66	119.92
Traj-GCN [33]	11.68	21.26	40.99	50.78	3.33	6.25	13.58	17.98	6.92	13.69	30.30	39.97	17.18	32.37	60.12	72.55
MSR-GCN	10.28	18.94	37.68	47.03	3.03	5.68	12.35	16.26	5.92	12.09	28.36	38.04	14.99	28.66	55.86	69.05
scenarios	running				soccer					wa	lking		washwindow			
millisecond (ms)	80	160	320	400	80	160	320	400	80	160	320	400	80	160	320	400
Residual sup. [34]	25.76	48.91	88.19	100.80	17.75	31.30	52.55	61.40	44.35	76.66	126.83	151.43	22.84	44.71	86.78	104.68
DMGNN [27]	17.42	26.82	38.27	40.08	14.86	25.29	52.21	65.42	9.57	15.53	26.03	30.37	7.93	14.68	33.34	44.24
Traj-GCN [33]	14.53	24.20	37.44	41.10	13.33	24.00	43.77	53.20	6.62	10.74	17.40	20.35	5.96	11.62	24.77	31.63
MSR-GCN	12.84	20.42	30.58	34.42	10.92	19.50	37.05	46.38	6.31	10.30	17.64	21.12	5.49	11.07	25.05	32.51

Short-term errors on CMU Mocap

Residual sup. Martinez J, et al., CVPR 2017

**DMGNN** Li M, et al., CVPR 2020

Traj-GCN Mao W, et al., ICCV 2019

# **Quantitative Results**





MSR-GCN can better handle high-frequency motions

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# **Quantitative Results**



Traj-GCN Mao W, et al., ICCV 2019 DMGNN Li M, et al., CVPR 2020 Res. Sup. Martinez J, et al., CVPR 2017



QR Code for our project:

https://github.com/Droliven/MSRGCN



#### Acknowledgement

This research is sponsored in part by the National Natural Science Foundation of China (62072191, 61802453, 61972160), in part by the Natural Science Foundation of Guangdong Province (2019A1515010860, 2021A1515012301), and in part by the Fundamental Research Funds for the Central Universities (D2190670).