SEPARABLE-SPARSE GRAPH CONVOLUTIONAL NETWORK

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Abstract

A new Separable-Sparse Graph Convolutional Network (SeS-GCN) for pose forecasting is proposed. SeS-GCN bottlenecks the interaction of the spatial, temporal and channel-wise dimensions in GCNs. It learns sparse adjacency matrices by a teacher-student framework. SeS-GCN improves the SoA in human pose forecasting by 3.6% on Human3.6M and it achieves the best performance in CHICO. It reaches an average error of 53.0mm with a run time of 2.3msec, enabling cobots to be aware of human operators.

Applications

- *Human-Robot Collaboration*: the study of collaborative processes where human and robot agents work together to achieve shared goals and avoid collisions;
- *Game Forecasting*: predicting the trajectory of players on playing fields such as football and basketball;
- *Human Pose Forecasting*, *Anomaly Detection* and *Action Recognition*.

Datasets & Results

- We obtain SoA results on an established dataset such as *Human3.6M*, improving performance by 3.6%;
- Our model outperforms recent SoA techniques on CHICO (Cobots and Humans in Industrial COllaboration), with an average error of 53.0mm.

	$H36M$	$CHICO$	$RunTime$
$W.Mao, ECCV20$	112.1	76.4	9.1×10^{-3}
$L.Dang, ICCV21$	114.1	136.5	25×10^{-3}
$STSGCN[1]$	75.6	59.0	2.3×10^{-3}
$SeS-GCN$	72.9	53.0	2.3×10^{-3}

Separable & Sparse Graph Convolutional Network

SeS-GCN is an accurate, memory efficient and fast GCN by bridging three diverse research directions: **I.** Space-time separable adjacency matrices; **II.** Depth-wise separable graph convolutions; **III.** Sparse adjacency matrices. This results in an all-Separable and Sparse GCN encoder for the human body kinematics, from which the future frames are forecast by a Temporal Convolutional Network.

I. Space-Time Separability

A Space-Time separable GCN [1] factorizes the adjacency matrix A of a GCN into two terms A_s and A_t.

$$\mathcal{X}^{(l+1)} = \sigma\left(A_s^{(l)} A_t^{(l)} \mathcal{X}^{(l)} W^{(l)}\right)$$

It reduces the memory-footprint of a GCN by approx. *4x*.

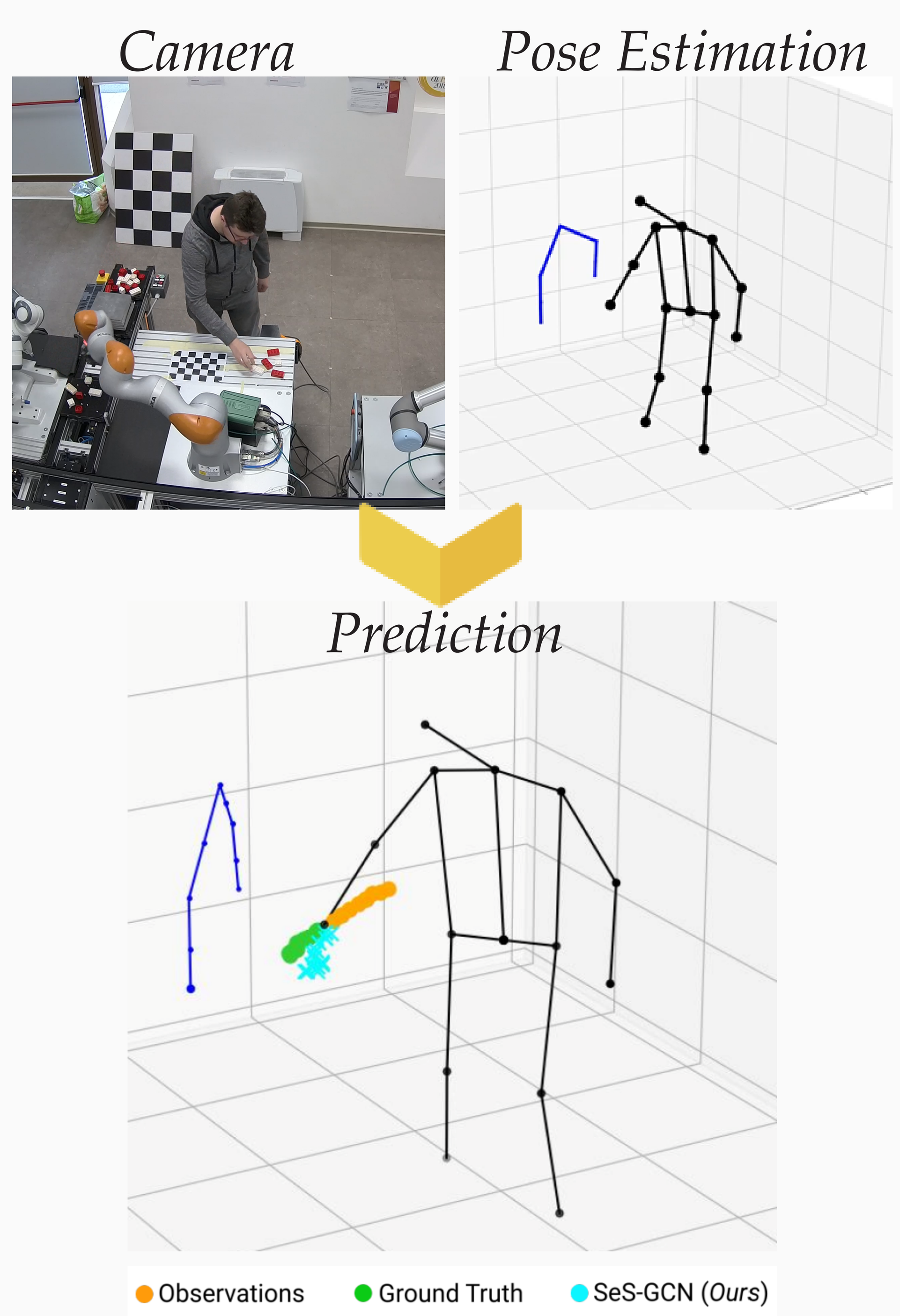
II. Depth-wise Convolution

Depth-wise (DW) graph convolution for pose forecasting is considered. Its formulation bottlenecks the interplay of space and time with the channels of the graph convolution.
The resulting all-separable model is formulated as such:

$$\mathcal{H}^{(l)} = \gamma\left(A_s^{(l)} A_t^{(l)} \mathcal{X}^{(l)} W_{DW}^{(l)}\right)$$
$$\mathcal{X}^{(l+1)} = \sigma\left(\mathcal{H}^{(l)} W_{\text{MLP}}^{(l)}\right)$$

Pose Forecasting

The following is the process involved, from the acquisition of the sequences to the human pose forecasting.



The sequences were acquired by the *ICE Lab* at the University of Verona

III. Sparse GCN

Sparsification is used to improve the efficiency (memory and runtime) of neural networks. The learned masks $\mathcal{M}$ perform a pruning of the adjacency matrices.
Then SeS-GCN:

$$\mathcal{H}^{(l)} = \gamma\left((\mathcal{M}_s^{(l)} \odot A_s^{(l)})(\mathcal{M}_t^{(l)} \odot A_t^{(l)})\mathcal{X}^{(l)} W_{DW}^{(l)}\right)$$
$$\mathcal{X}^{(l+1)} = \sigma\left(\mathcal{H}^{(l)} W_{\text{MLP}}^{(l)}\right)$$

Take Home Message

- SeS-GCN is an all-separable framework and achieves SoA on human pose forecasting;
- It is an efficient network and requires only 2.3msec at inference time.

References & Acknowledge

[1] Sofianos T.*, Sampieri A.*, Franco L, Galasso F., Space-Time-Separable Graph Convolutional Network for Pose Forecasting, in *ICCV*, 2021
[2] Chollet F., Xception: Deep learning with depthwise separable convolutions, in *CVPR*, 2017
[3] LeCun V., Denker J., Solla S.: Optimal brain damage, in *NIPS*, 1989

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PINLAB

Feel free to contact us!
Code, Video and other...