

STMT: A SPATIAL-TEMPORAL MESH TRANSFORMER FOR MoCAP-BASED ACTION RECOGNITION

Anonymous authors

Paper under double-blind review

1 MODEL ARCHITECTURE

The input to surface field convolution is a set of vertices in shape $N \times C$ and the coordinates of a set of centroids of size $N' \times 3$, where N is the number of vertices, C is the feature dimension, and N' is the number of centroids. The outputs are groups of vertex sets of size $N' \times K \times C$, where each group corresponds to a local region and K is the number of vertices in the nearest neighborhood of centroid vertices. To learn both intrinsic and extrinsic features, we sample the K nearest neighbors in Geodesic and Euclidean space, respectively. Then each local region is abstracted by its centroid and local feature that encodes the centroid’s neighborhood. Output data size is $N' \times C'$. We use two surface field convolution blocks. In the first block, we sample 64 centroids with 8 nearest neighbors. In the second block, we sample 32 centroids with 8 nearest neighbors. The feature dimension C and C' equal 256. For the hierarchical spatial-temporal transformer, we use 2 offset-attention layers for the intra-frame attention module. The inter-frame attention module contains a self-attention block with 8 heads.

2 DATASETS

2.1 DATA PRE-PROCESSING

As most of the existing skeleton-based and point-cloud-based baselines are for single-class classification, we only use the MoCap sequences with single-class annotations. There are 6,570 and 21,653 sequences for KIT and BABEL after data cleaning. For 3D skeleton-based baselines, we use the pre-processed 3D skeletons provided by the official BABEL dataset Punnakal et al. (2021). It predicted the 25-joint skeleton used in NTU RGB+D Shahroudy et al. (2016) from the vertices of the SMPL-H mesh. The process involves human efforts to identify the vertices in the SMPL+H mesh that correspond to these joints in the NTU RGB+D skeleton. The vertices’ cartesian coordinates are used as input to point cloud models. The vertices’ cartesian coordinates along with their adjacent matrices are used as input to our *STMT* model. As MoCap sequences have variant lengths, we sample 24 frames from each MoCap sequence. We use farthest point sampling to sample 128 vertices from each frame.

2.2 DATASET LICENSES

AMASS Mahmood et al. (2019): <https://amass.is.tue.mpg.de/license.html>

BABEL Punnakal et al. (2021): <https://babel.is.tue.mpg.de/license.html>

3 EXPERIMENTS

3.1 TRAINING DETAILS

For skeleton-based baselines, we use the official implementations of 2s-ACGN, CTR-GCN, and MS-G3D from Shi et al. (2019), Chen et al. (2021), and Liu et al. (2020), respectively. We train models for 250 epochs with a batch size of 64. The other hyper-parameters are the same as the hyper-parameters used in NTU-RGB+D dataset. For point-cloud-based baselines, we use the official implementations of PSTNet, SequentialPointNet, P4Transformer from Fan et al. (2021c), Li et al. (2021), and Fan et al. (2021b). All models use Adam optimizer Kingma & Ba (2014) with a learning

rate of 0.0001. We train models for 200 epochs with a batch size of 32. Our *STMT* model is pre-trained using Adam optimizer with a learning rate of 0.0001 for 120 epochs. The batch size is 128. We use equal weights ($\lambda_1 = \lambda_2 = 0.5$) for masked vertex reconstruction loss and future frame prediction loss. The hyper-parameters and data augmentation for fine-tuning are the same as the point-cloud baselines for a fair comparison. Our model converges after 30 epochs. The pre-training stage takes 18 hours on 8 Tesla V100 (32GB) GPUs, and the fine-tuning stage takes 1.5 hours on 4 Tesla V100 (16GB) GPUs.

3.2 COMPUTATIONAL EFFICIENCY AND MEMORY USAGE

We evaluate the computational efficiency and memory usage, *i.e.*, the number of parameters and GFLOPs, of our method. As mesh’s local connectivity cannot be directly aggregated in the temporal domain, we cannot use temporal stride as in P4TransformerFan et al. (2021a). Therefore, we compare our ablated model which only takes 6 frames as input with P4Transformer, which is the best point-cloud-based baseline. We can see that our light-weighted model with much fewer parameters and smaller GFLOPs, can outperform P4Transformer by 1.35%.

Method	# Frames	# Parameters (M)	GFLOPs	Top-1 Accuracy (%)
P4TransformerFan et al. (2021a)	24	44.21	65.94	62.15
STMT (Lightweight)	6	10.55	59.59	63.50

Table 1: Comparison of Parameters and GFLOPs.

4 LIMITATIONS

Similar to most self-supervised learning models, our self-supervised pre-training stage needs a large number of action sequences. Although we alleviate the problem with the proposed Joint Shuffle, the pre-training stage still takes a long time to converge. Therefore, more work can be done to select the most discriminative sequences from a large number of unlabeled sequences to enable efficient training. Besides, although we validated our method on BABEL, which combines more than 10 datasets, it still suffers from the long-tailed problem. Some action classes have very few sequences and may not represent the intra-class variances. (2) Most of the action sequences in BABEL are around 30.0 seconds. In the real world, it is likely that we encounter action lengths of varying durations, and training on fixed-length action sequences could lead to a negative impact on the generalization ability.

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