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Blockwise Temporal-Spatial pathway network

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Overview

We propose a 3D-CNN-based action recognition model, called the blockwise temporal-spatial path-way network (**BTSNet**), which can **adjust the temporal and spatial receptive fields by multiple pathways**. We designed a novel model inspired by an adaptive kernel selection-based model, which chooses spatial receptive fields for image recognition. Expanding this approach [1] to the temporal domain, **our model extracts temporal and channel-wise attention and fuses information on various candidate operations.** We confirm that proposed TSP block supports a better representation for 3D convolutional blocks based on our visualization.

Receptive Fields

Both the SlowFast [2] and TSP blocks have a widened view along the temporal axis. However, the TSP block has more generalized RFs and can control the contributions of the RFs at each timestep. Two hyper-parameters to handle the RF in our pathway block: **the number of pathways M** and the **RF option** (O1 and O2).

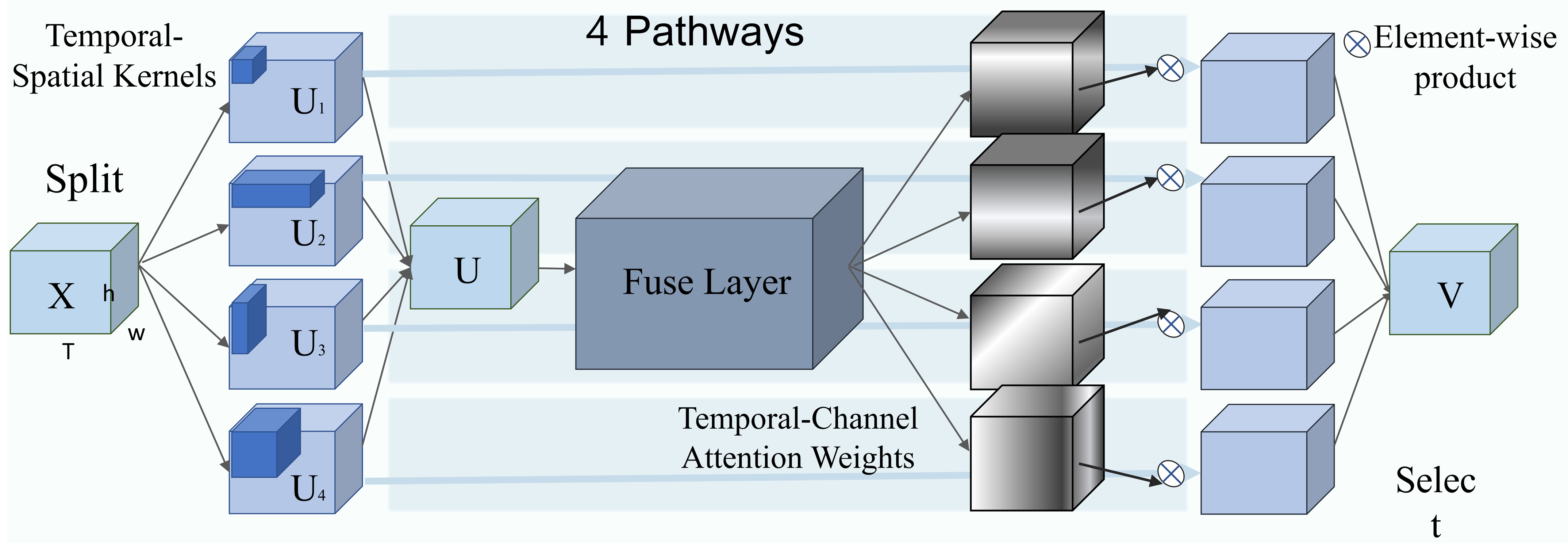
- **O1**: cube-like RFs. For dilation parameters (T, H, W), $D = \{D_1, D_2, \cdots, D_M\}, D_i = (i, i, i)$
- **O2**: customized dilation parameters eg. for M=4, $\{(1,1,1),(4,4,4),(1,4,4),(4,1,1)\}$

Temporal-Spatial Pathway Block

Split. For any given feature $X \in \mathbb{R}^{C' \times T' \times H' \times W'}$, transformation functions $F_{1,2,..,m}$ are applied first.
Our pathway blocks can be considered as slow, fast, or spatially enlarged pathways. $F_m : X \rightarrow U_m \in \mathbb{R}^{C \times T \times H \times W}$

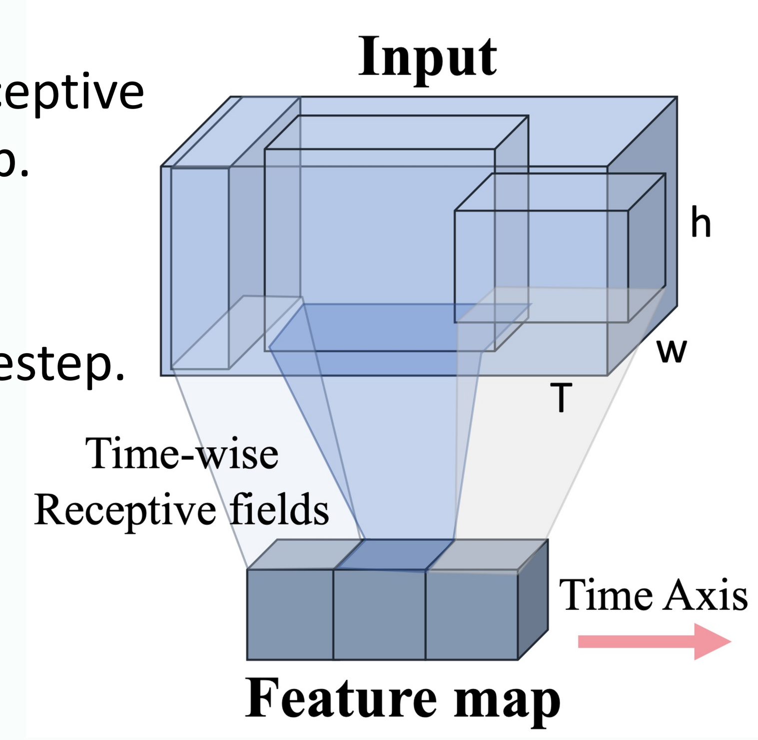
Fuse Layer. To fuse information from multiple receptive fields, we combine the previous features by adding all U_m.
Then, global average pooling (GAP) is applied to compress features U.
There are two options for this layer: **temporal-channel attention (TC)** and **channel-wise attention (C)**.
A compact feature $Z \in \mathbb{R}^{d \times T}$ or $Z \in \mathbb{R}^{d}$ can be attained by a set of operations. The set is composed of a convolution with a (1,1,1) kernel, batch normalization, and ReLU.
Z should be resized to $Z' \in \mathbb{R}^{M \times C}$ or $Z' \in \mathbb{R}^{M \times C \times T}$ to attain the attention vectors, therefore convolution with kernel size 1 is applied.
Select. To highlight the information among multiple pathways, we use temporal-channel or channel-wise attention mechanisms in this procedure. $Attn = softmax(Z')$ These attention weights emphasize each pathway along the temporal-channel axis, which has a different RFs. The final output V of the block is: $V = \sum_{m=1}^{M} Attn_m * U_m.$

Left: Procedure of TSP block of BTSNet.



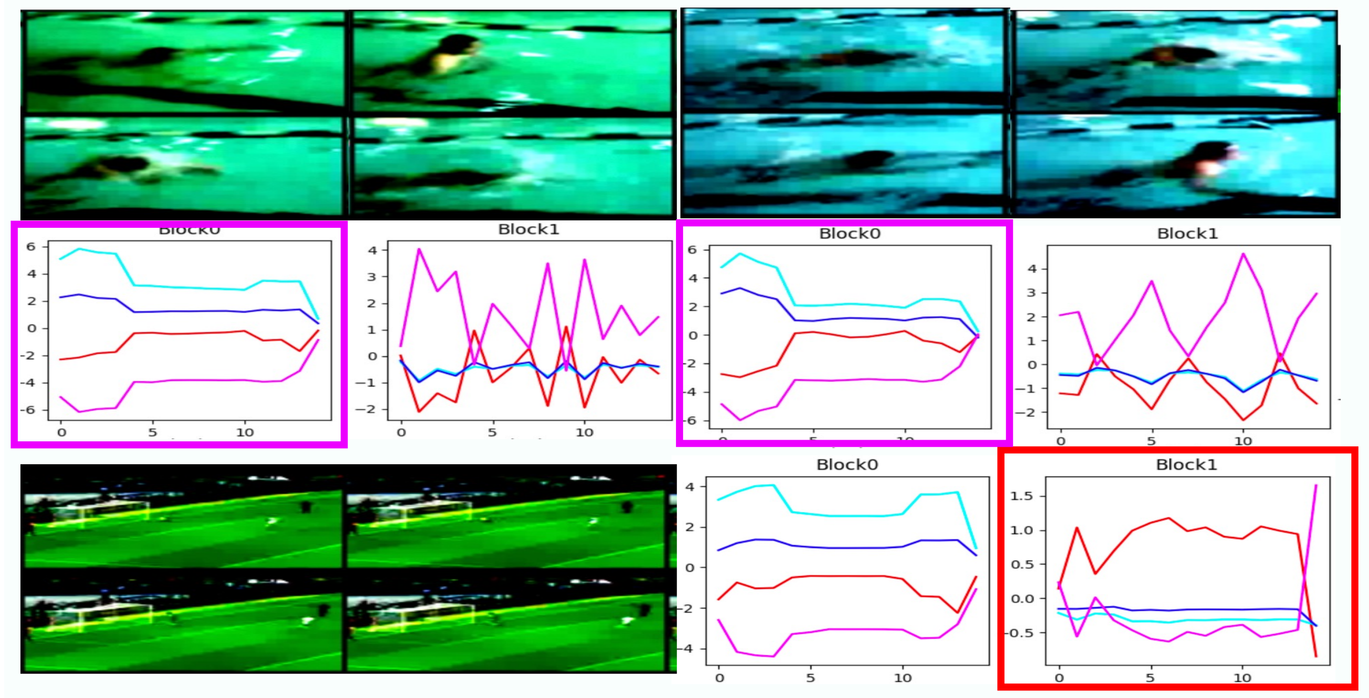
Right. Corresponding receptive fields for the feature map.

Pathways have top-1 contribution at each timestep.



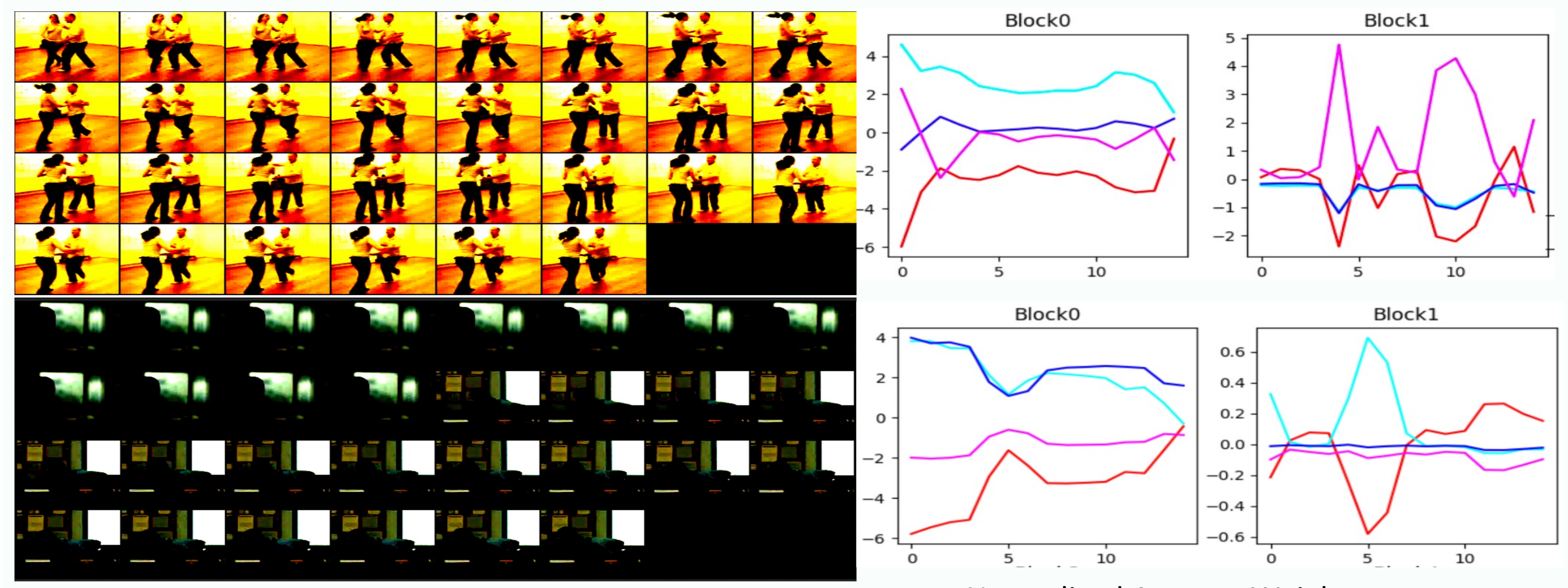
Results

To summarize, **our model attain informative areas** when there are enough pathways with temporal-channel attention. In visualization, receptive fields [T,H,W] are notated as red [1,1,1], cyan[4,4,4], blue [1,4,4], magenta[4,1,1].



(a)
- Same Action
- Dynamic
- Large Variance

(b)
- Different Action
- Stable
- Small variance



[Ablation Study]

Row 1. fuse layer.

Ablation	M3-O2-26	M4-O2-26	M3-O1-26	M3-O1-50	M3-O1-101
C	57.507	59.913	58.974	58.459	58.565
TC	60.283	60.058	61.829	59.120	60.005
TC-C	**2.776**	**0.145**	**2.855**	**0.661**	**1.440**

Row 2. the number of pathways M.

Ablation	TC-O2-50
M=2	55.855
M=3	58.895
M=4	58.274
M=7	58.551
Max Gap	3.04

Ablation	TC-O1-26	TC-O1-50	TC-O1-101
M=2	60.019	58.842	56.133
M=3	**61.829**	**59.120**	**60.005**
Ablation	C-O2-26	C-O2-50	C-O1-26
M=3	57.507	57.454	58.974
M=4	**59.913**	**58.261**	**59.252**

Row 3. RF option

Ablation	C-M4-26	C-M4-50	TC-M3-50	TC-M4-50
O1	59.252	48.678	59.120	58.961
O2	59.913	58.261	58.895	58.274
O2-O1	**0.661**	**9.583**	-0.225	-0.687

References

[1] Xiang Li, Wenhai Wang, Xiaolin Hu, and Jian Yang,"Selective kernel networks," in2019 IEEE/CVF Con-ference on Computer Vision and Pattern Recognition(CVPR), 2019, pp. 510–51
[2] C. Feichtenhofer, H. Fan, J. Malik, and K. He, "Slow-fast networks for video recognition," in2019 IEEE/CVFInternational Conference on Computer Vision (ICCV),2019, pp. 6201–621

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