Embedding Human Knowledge into Spatio-Temproal Attention Branch Network in Video Recognition via Temporal Attention

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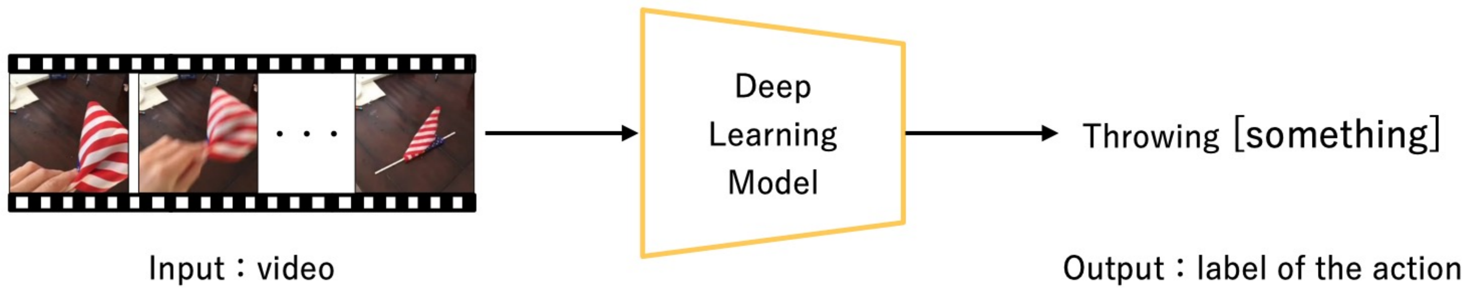
ST-ABN
Attention Editor

Background and Motivation

- Video recognition by deep learning
  - A task for identifying actions performed in a video using multiple frame images
  - Recognize action using both spatial and temporal information



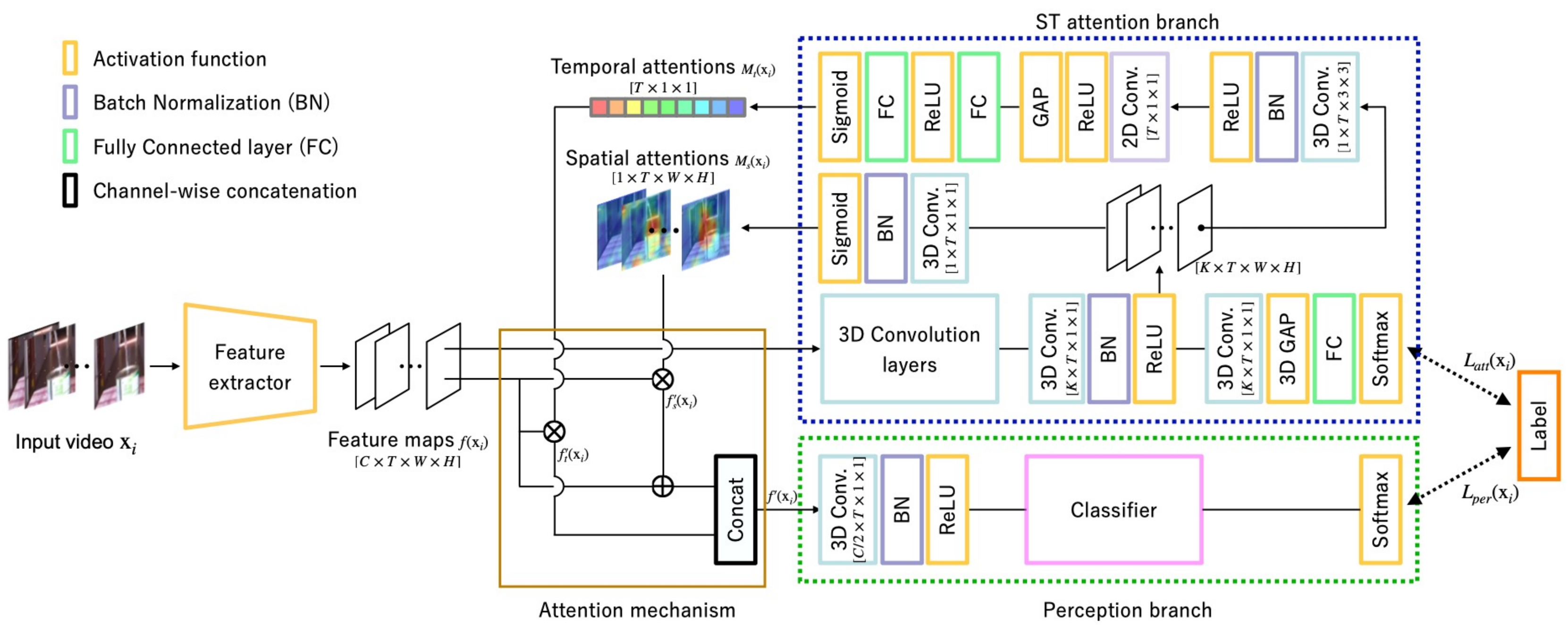
Problem : The basis of the model's decisions is unclear

Approach

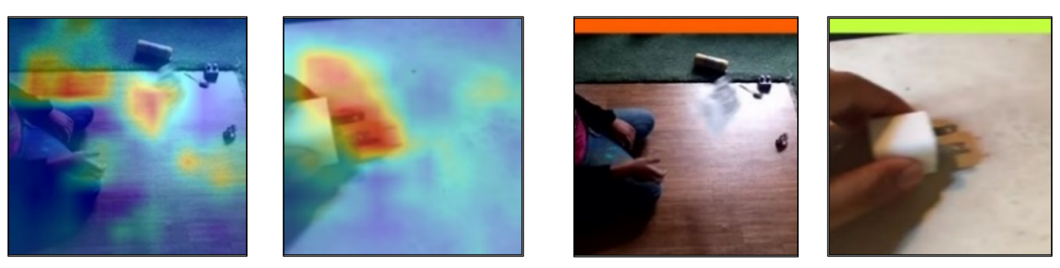
- ST-ABN
  - Visual explanation considering spatial and temporal information
- Embedding human knowledge into the ST-ABN
  - Improvement of recognition accuracy and visual explainability

Spatio-Temporal Attention Branch Network (ST-ABN)

- A network that takes into account important spatio-temporal information
  - ST attention branch : provide visual explanation for spatial and temporal attentions
    - Spatial attentions : Visualize the gazing area for each frame
    - Temporal attentions : Visualize the importance of each frame
  - Attention mechanism : Weight two attentions on the feature maps
- We can embed human knowledge via both spatial and temporal attentions



$$L(\mathrm{x}_i) = L_{att}(\mathrm{x}_i) + L_{per}(\mathrm{x}_i)$$

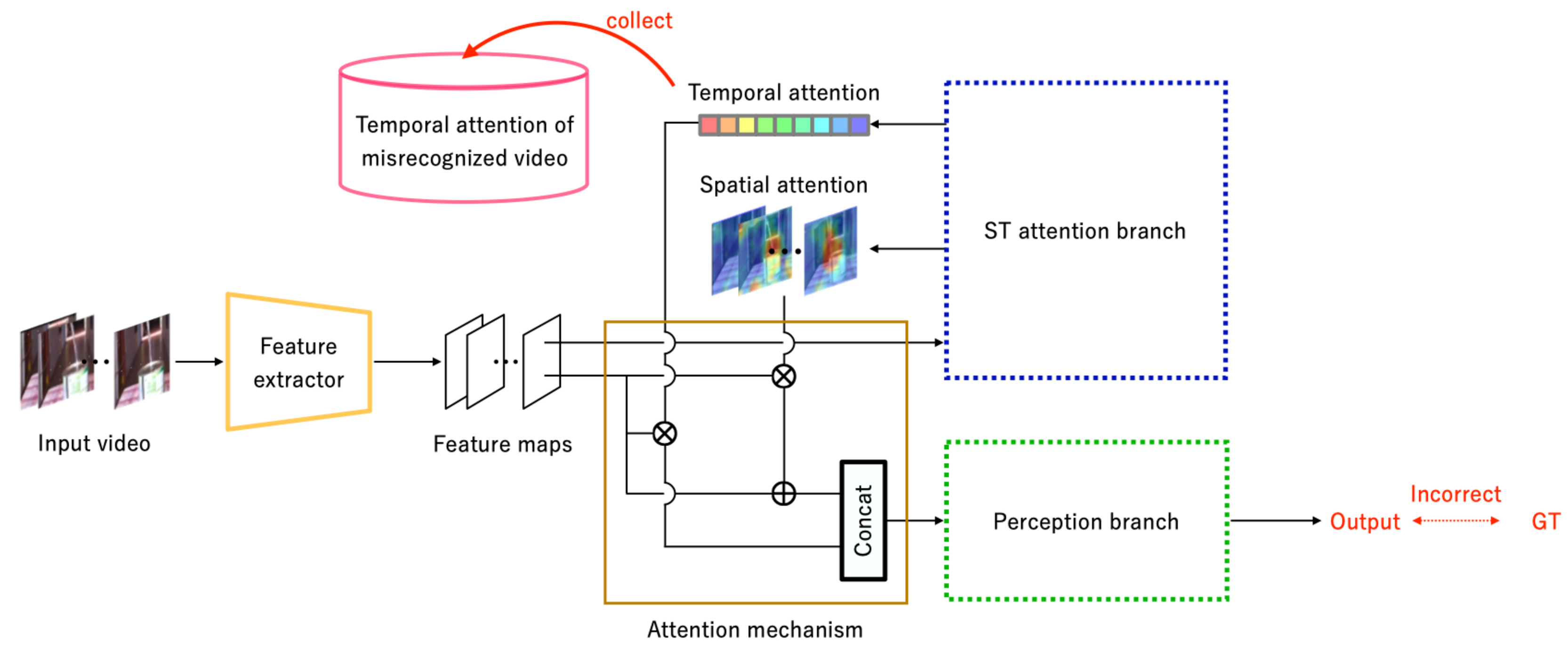


Spatial attentions Temporal attentions

Embedding human knowledge into the ST-ABN

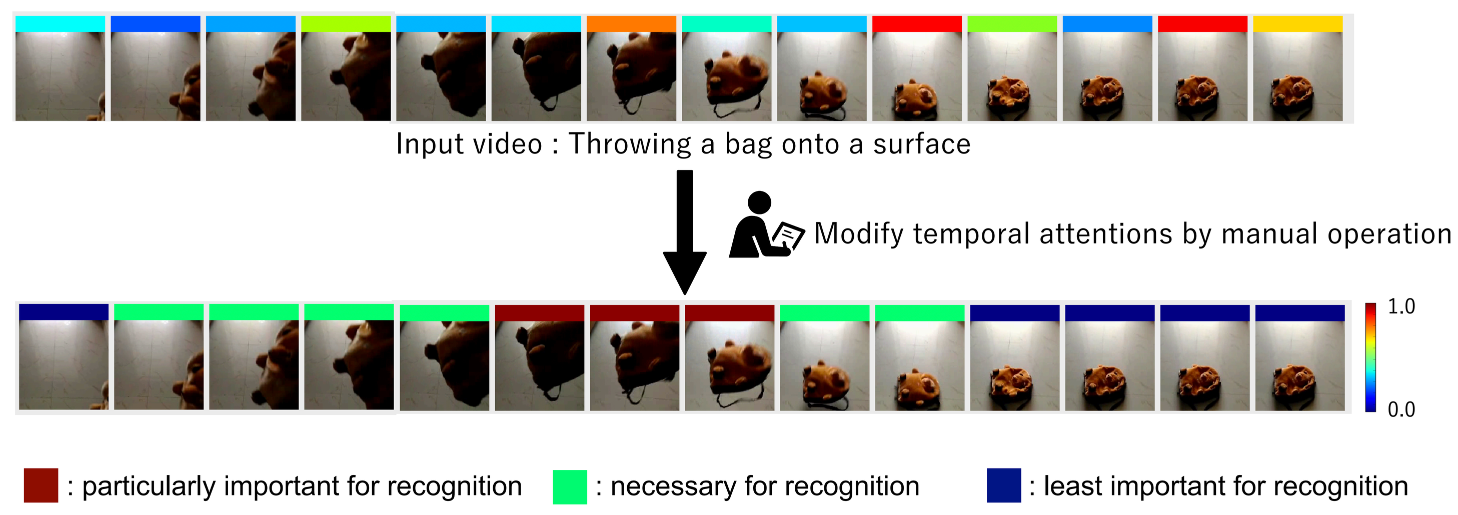
Step 1. Collecting temporal attentions

- Train the ST-ABN and collect temporal attentions
  - Evaluate with training samples and select misclassified videos



Step 2. Temporal attentions modification

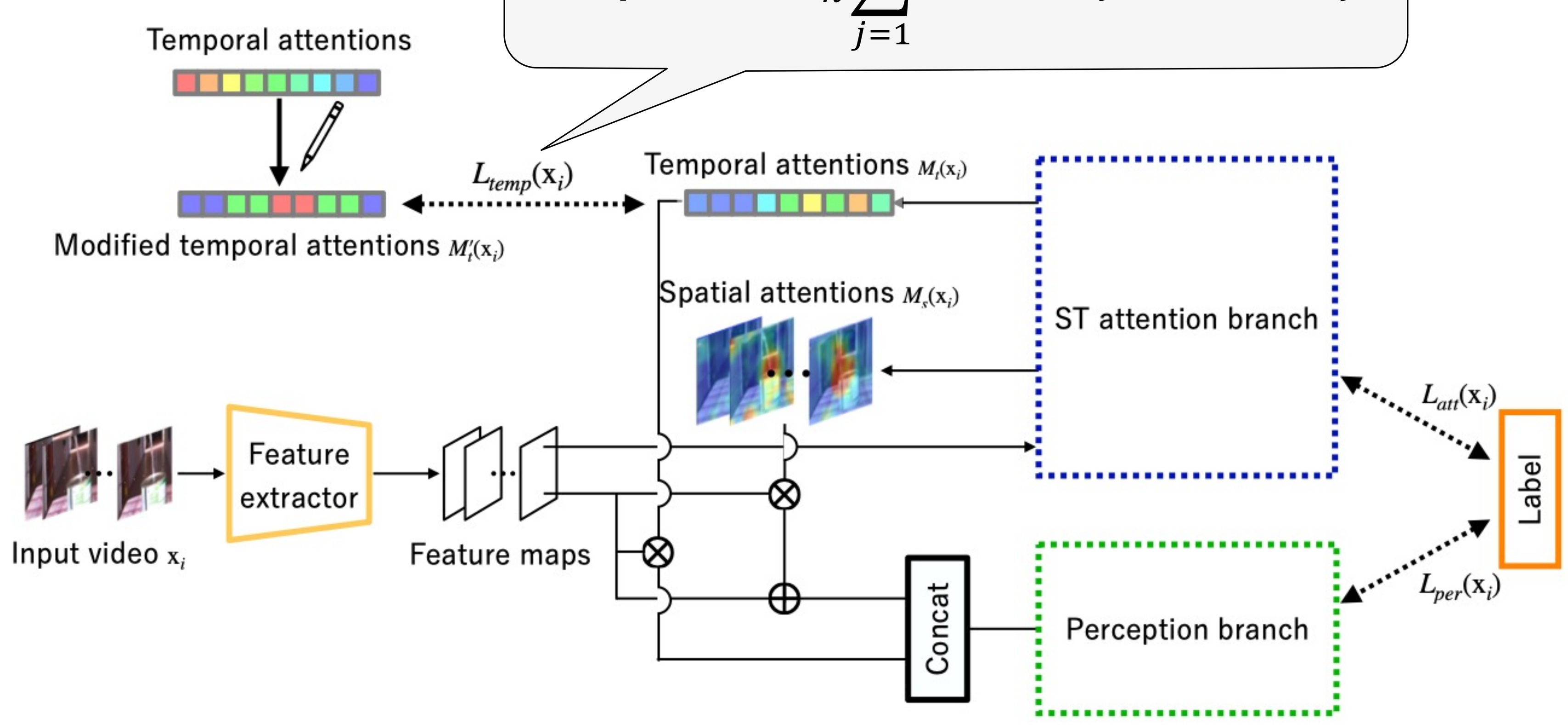
- Manually modify the temporal attentions collected in step 1
- Classify frames into three levels and edit temporal attentions



Step 3. Fine-tune the ST-ABN

- Fine-tune the branches of ST-ABN with modified temporal attentions
- We add a loss function L_{temp} to that of the ST-ABN
  - L_{temp} : Mean squared error with modified temporal attentions
- The ST-ABN optimizes its ST attention and perception branches.

$$L_{temp}(\mathrm{x}_i) = \gamma_t \frac{1}{n} \sum_{j=1}^{n} (\{M_t'(\mathrm{x}_i)\}_j - \{M_t(\mathrm{x}_i)\}_j)^2$$



$$L(\mathrm{x}_i) = L_{att}(\mathrm{x}_i) + L_{per}(\mathrm{x}_i) + L_{temp}(\mathrm{x}_i)$$

Experiments

- Experiment Details
  - Dataset : Something-Something v.2
  - Modified temporal attentions : 2,396 training samples in 8 action classes (1.5% of the total)

- Comparison with Conventional Models

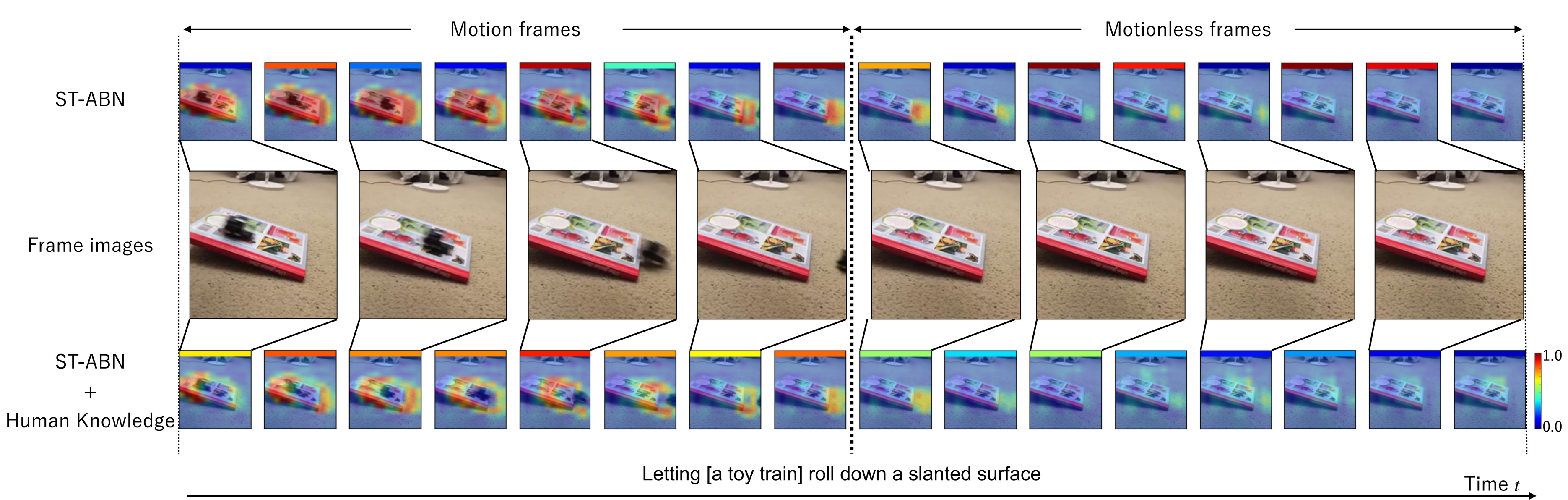
Method	Frames	Top-1 Acc.	Top-5 Acc.
3D ResNet-50	32	51.4	80.1
3D ResNet-50 + ST-ABN	32	**58.6**	**85.5**
3D ResNet-50	32 × 2	63.8	89.2
3D ResNet-50 + ST-ABN	32 × 2	**64.1**	**89.6**
3D ResNet-101	32	57.7	82.8
3D ResNet-101 + ST-ABN	32	**58.0**	**83.2**
3D ResNet-101	32 × 2	65.3	90.1
3D ResNet-101 + ST-ABN	32 × 2	**65.8**	**90.4**

Improved accuracy by introducing the ST-ABN into the backbone network

- Comparison with Embedding Human Knowledge (Backbone network : 3D ResNet-50)

Method	Modified classes	Other classes	All
ST-ABN	20.5	59.8	58.6
ST-ABN + Human Knowledge	**26.3**	**61.7**	**60.7**

Improved accuracy not only modified classes but also other classes



Embedding human knowledge into the ST-ABN obtain better attentions