NTT_CQUPT@TRECVID2019 ActEV

Yongqing Sun¹, Xu Chen², Chaoyu Li², Kiyohito Sawada³, Takashi Hosono¹, Jun Zhu², Chengjuan Xie², Sixiang Huang², Lan Wang², Kai Hu², Qingsong Zhou², Chengiang Gao², Jun Shimamura¹, Atsushi Sagata¹

1: NTT, 2: Chongging Univ. of Posts and Telecommunications, 3: National Police Academy **Unique points**

- 1. Classification by Conv-LSTM, which can preserve spatial-temporal information
- 2. Various post-processing to suppress false alarm
- 3. Proposal alignment to learn efficiently with few training data

System overview



• **Object detection:** detect objects by Mask R-CNN fine-tuned • **Classification:**



- with our extra annotation
- **Proposal generation:** track each object by tracking method and merge them if person and vehicle are nearby
- Feature extraction: divide proposal into snippets and extract features using I3D network

Feature extraction and classification

- X and y axis of I3D feature have spatial information, and z axis has temporal information
- Problem: simple flattening algorithm loses spatialtemporal information
- Solution: reshape I3D features and use Conv-LSTM

Flow of action likelihood prediction for each clip



- ✓ Reshape I3D feature and predict likelihood for each action by Conv-LSTM
- ✓ Fine-tune by hard negative mining
- **Post-processing:** merge estimation results for each proposal and delete those that seem to be false alarm

Post-processing

- Problem: simply merging results of each clip produces extra estimation results
- Solution: remove extra results by likelihood consistency check, threshold, merge, label consistency check and NMS



Assumption: clips that have large likelihood difference of boundary snippet and mean of all snippets are extra results



Proposal alignment* * it's not included in submitted system

- **Observation:** Each action has diversity of appearance due to various movement/object direction
- Assumption: this diversity makes learning and predicting action recognition difficult
- Solution: rotate proposals to align movement/object direction

Vehicle proposal alignment





Whole system results on test data

Evaluation

• Difference among our systems is post-processing threshold • 5th accuracy at time of submission

System	Partial AUCD	Mean-Pmiss @0.15TFA	Mean W Pmiss @0.15RFA
p-NTT-CQUPT	0.60058	0.51122	0.87254
p2_NTT_CUPT	0.60396	0.51677	0.87168
system2	0.60524	0.51755	0.87381
NIST-TEST (baseline)	0.85649	n/a	n/a

Each module results on validation data Object detection results Proposal generation result Method Number of mAP Method Recall proposals **Original Mask R-CNN** 19.6% Ours 4,151 85.6% Fine-tuned Mask R-CNN 44.1% **Proposal alignment results Classification results** ✓ We used GT proposals ✓ We used our proposals Method mAP mAP Method Input Before fine-tuning 13.2% Without alignment 46.1% RGB With alignment 49.7% After fine-tuning 16.7%

Before fine-tuning 12.8% Optical flow After fine-tuning 13.1%