THE ANNUAL TRECVID WORKSHOP

Analysis of tracked objects for detecting activities in extended videos using 3D-CNN architectures

part of “CERTH-ITI participation in TRECVID 2020”

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Objective of the submission

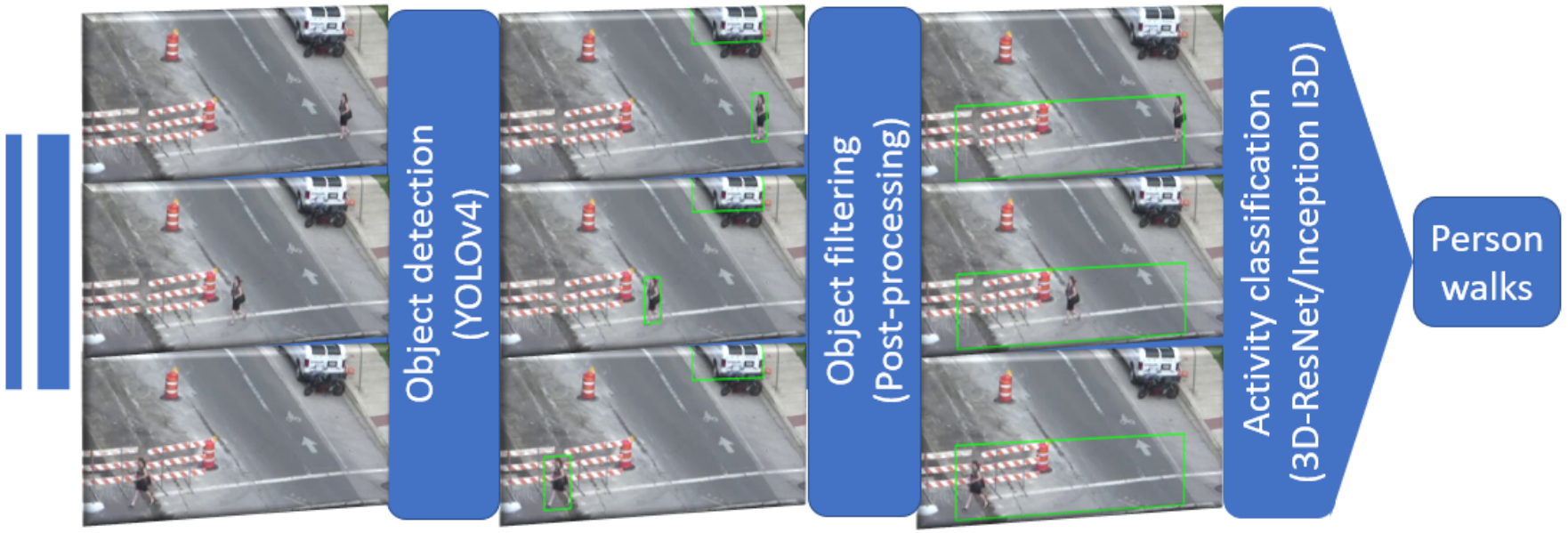
- Detecting Activities in Extended Video (ActEV) task aims to:
  - **Detect** activities of interest over time
  - **Recognize** the detected activities
- Challenges:
  - Camera's **field of view** is extremely large and includes multiple activities in very small areas
  - Detect **multiple activities at the same time**
  - **Untrimmed** videos are difficult to be watched, analyzed, and observed by humans

Activities recognition methods: Traditional approaches

- Try to classify short (in terms of duration) clips (trimmed) to predefined categories
  - **One or more** activities that occur in parallel
  - Classification of a **frame sequence**
  - Different **modalities** such as depth and optical flow contribute to enhance the performance
  - You only have to do with the **type** of activity and dismiss the temporal boundaries

Proposed approach

- Two-step approach:
  - Detection of objects in order to extract the **Extended Activity Bounding Boxes** (**EABBox**) using YOLOv4
  - Activity recognition for the objects identified in each **EABBox** using **3D-CNNs, 3D-ResNet** and **Inception I3D**

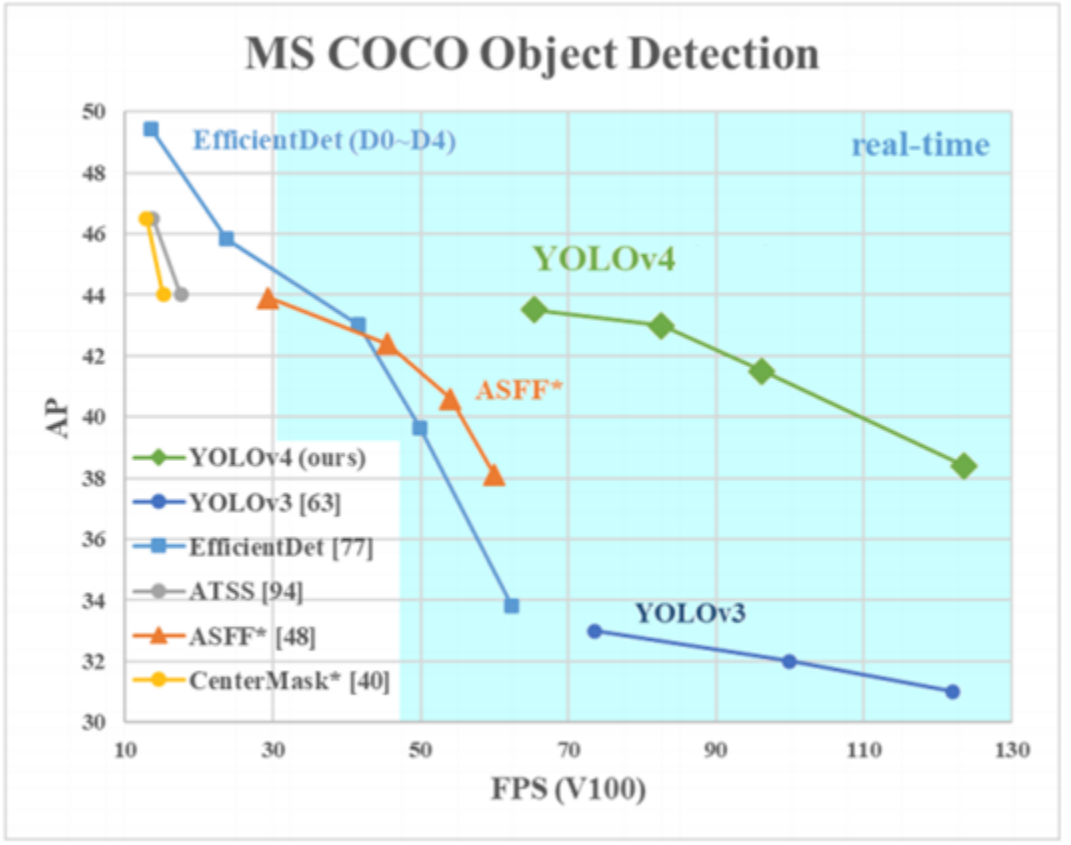


Challenge dataset

- Dataset:
  - The dataset consists of **35 person and vehicle related activities**
  - **Outdoor** environment
  - **Natural** light condition

Object detection
YOLOv4

- State-of-the-art **real-time object detector**
- **Pre-trained** using Microsoft COCO dataset
  - Include objects such as "person", "car", "truck
- Applied on **validation** and **evaluation** sets
- Detected objects are described by a **bounding** box and a **confidence score**
- **Object tracker** based on **Euclidean distance**



Bochkovskiy, A., Wang, C. Y., & Liao, H. Y. M. (2020). YOLOv4: Optimal Speed and Accuracy of Object Detection. *arXiv preprint arXiv:2004.10934*.

Post-processing 1
Examine the effect of merging overlapped EABBoxes

1. **Process** only the **selected frames** according to the **annotations** of the dataset
2. **Select the objects** with class name belong to one of the following **categories**:
   - "person", "car", "bus", "truck" and "bicycle"
3. **Select** the predictions that have **confidence score** above a certain **threshold**
   - The value of the threshold was set at **25% empirically** to deal with the wrong detections of YOLOv4
4. **Select one class for every object**
   - In the case that an object is described by **two or more similar to target labels** (i.e. "car" and "truck")
     - We keep the class with a higher confidence score
   - Considering the **Intersection over the Union** (IoU)
     - With a certain threshold as a metric for overlapping, experimentally was set at **70%**

Post-processing 1
Examine the effect of merging overlapped EABBoxes

5. **Select** only the **moving objects**
   - The **detection of moving objects** calculated by checking the **global** start and the end position
     - Short positions are excluded as **considered static**
   - The class "**person**" is excluded as the data consists of both **static** and **movable** person-related activities
6. **Merge objects**
   - In cases that **two detected** objects are involved in one activity
     - A pair has to **include the class "person"** and one of the vehicle classes i.e. "car"
     - **Temporal overlapping** with less than 30 frames difference
     - **Spatial overlapping** with IoU bigger than 70%
7. **Calculate the EABBox** for each object(s)

Post-processing 2
Examine the immobility of objects at short intervals

1. **Process** only the **selected frames** according to the **annotations** of the dataset
2. **Select the objects** with class name belong to one of the following **categories**:
   - "person", "car", "bus", "truck" and "bicycle"
3. **Select** only the **moving objects**
   - The **detection of moving objects** calculated by checking the start and the end position
     - Short positions are excluded as **considered static**
   - The class "**person**" is excluded as there are person-related activities both **static** and **dynamically moving**

Post-processing 2
Examine the immobility of objects at short intervals

4. **Examine the immobility** of an object in short time intervals
   - Experimentally set at 10 seconds
   - We keep only the slots of time that an object moves
     - i.e. vehicle turn right -> stop for a long time -> vehicle turn left
5. **Calculate the EABBox** for each object
6. **Sequences** with less than **20** frames are rejected

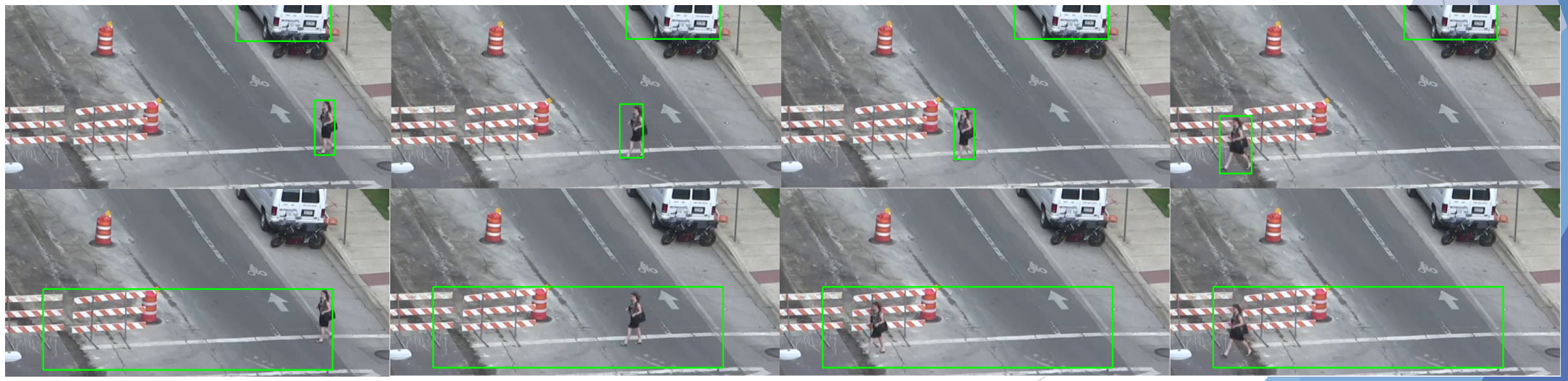
Post-processing 1 vs Post-processing 2

Commons

- **Process** only the **selected frames**
- **Select the objects categories**:
  - "person", "car", "bus", "truck" and "bicycle“
- **Select** only the **moving objects (global)**
- **Calculate the EABBox** for each object(s)

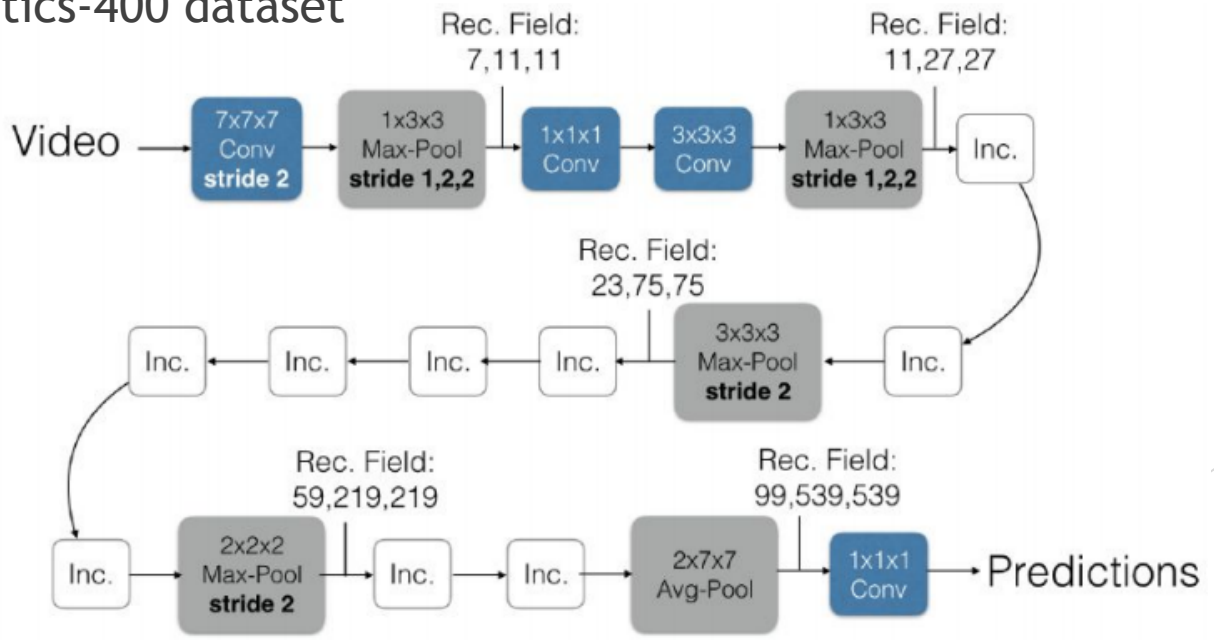
Differences

- **Ps1: Select** above a certain **threshold**
- **Ps1: Select one class for every object**
- **Ps1: Merge objects**
- **Ps2: Examine the immobility (local)**
- **Ps2: Sequences <20** frames are rejected



Activity classification Inception I3D

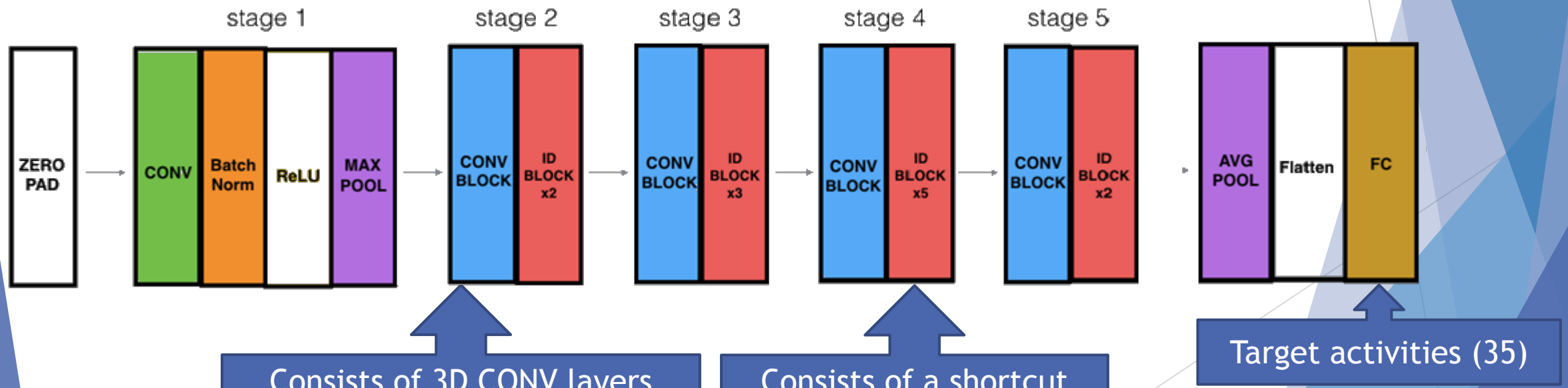
- Two-Stream Inflated 3D ConvNet (I3D)
  - 2D ConvNet inflation
- Inception model
- Loaded weights: Kinetics-400 dataset
- Total epochs: 1000
- Sample size: (32x224x224)(frames X width X height)
- Batch size: 8



https://www.cs.princeton.edu/courses/archive/spring18/cos598B/public/outline/Computer%20Vision%20Seminar%20Pres.pdf

Activity classification 3D-ResNet Training parameters

- Number of layers: 50
- Loaded weights: Kinetics-400 dataset
- Total epochs: 750
- Sample size: (16x112x112)(frames X width X height)
- Loss: categorical weighted cross-entropy
- Batch size: 64



https://engmrk.com/residual-networks-resnets/

Submitted systems

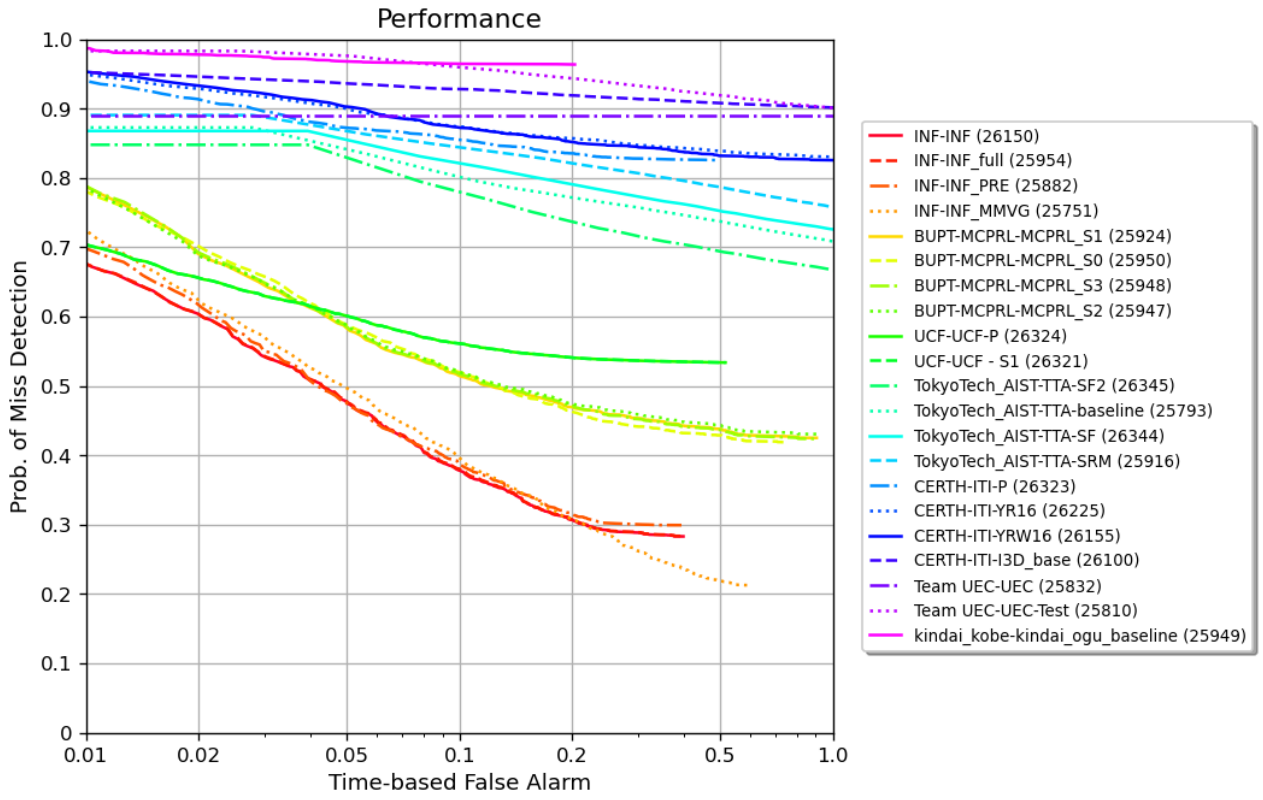
- **CERTH-ITI-I3D_base**: Ps1, I3D
- **CERTH-ITI-YRW16**: Ps1, 3D-ResNet-50, weighted cross-entropy loss
- **CERTH-ITI-YR16**: Ps1, **CERTH-ITI-YRW16**, considering activities more than 20 frames
- **CERTH-ITI-P**: Ps2, **CERTH-ITI-YR16**

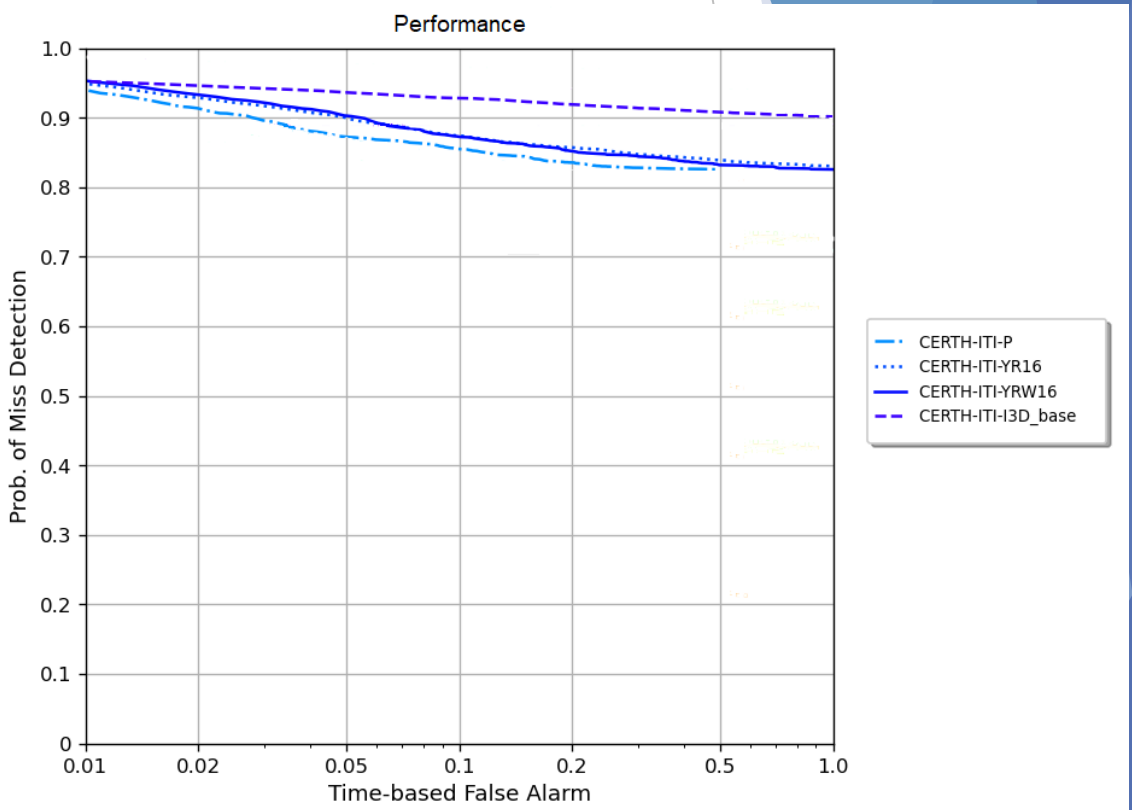
Evaluation results

System Name	PARTIAL AUDC	MEAN-P MISS@0.15TFA	MEAN-W_P MISS@ 0.15RFA
CERTH-ITI-I3D_base	0.93125	0.92318	0.92850
CERTH-ITI-YRW16	0.88530	0.86136	0.91187
CERTH-ITI-YR16	0.88511	0.86165	0.89439
CERTH-ITI-P	**0.86576**	**0.84454**	**0.88237**

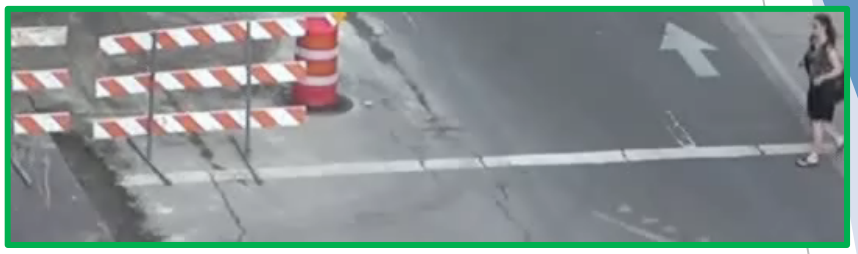
PARTIAL AUDC is the primary metric

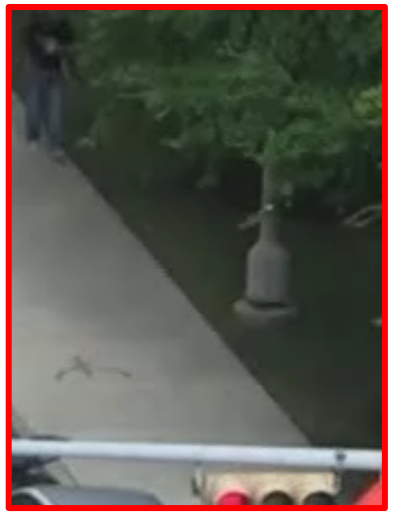
Experimental evaluation

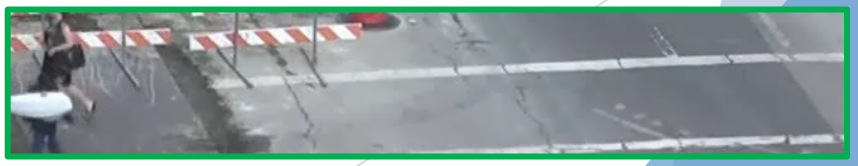




Indicative results
“Person walks”







Thank You

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MultiMoDal Data Fusion and Analytics Group

MKLab Multimedia Knowledge and Social Media Analytics Laboratory

Information Technologies Institute

CERTH CENTRE FOR RESEARCH & TECHNOLOGY HELLAS

aqua3S

ReTV

CONNEXIONs

PREVISION

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