

# Not 3D Re-ID: Simple Single Stream 2D Convolution for Robust Video Re-identification

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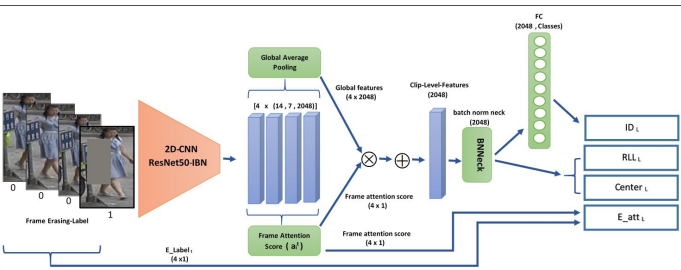


**Issue:** Building robust video-based person Re-ID under varying conditions.

## Method :

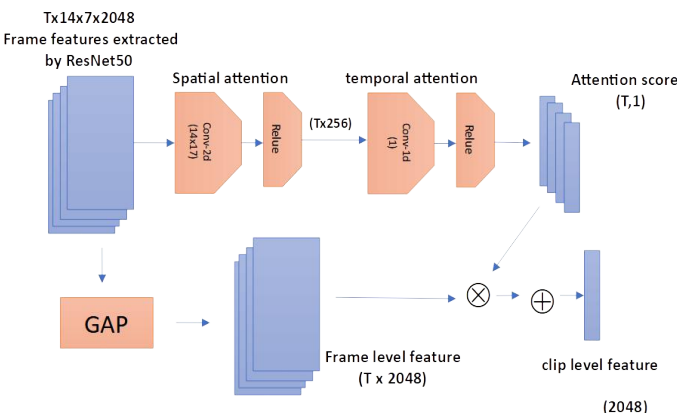
Simple video Re-ID using *{Resnet50+Two-layer spatial-temporal attention}* produce an efficient video features:

- **ResNet50-IBN-a** as a frame features extractor.
- **spatial-temporal attention** following feature extraction to produce video level features (2D convolution + 1D convolution).



## Temporal features aggregation:

The use of **2D-Resnet50** as frame feature extractor is followed by a **temporal aggregation** method to produce video level features from  $T$  frames.



Spatial-temporal attention

## Conclusion:

- **Single stream robust video Re-ID** approach using **only 2D convolution** for video-based Re-ID.
- Using **robust training strategies** without additional complexity **exceeds state of the art accuracy**.
- Our simple 2D method **exceeds performance of prior 3D convolution and complex multi-stream based approaches**.

## Training:

The use of **multiple loss functions** with differing roles succeeds in guiding the **learning process** of the model without additional complexity.

$$RLL_L(\mathbf{x}_i^c; f) = L_P(\mathbf{x}_i^c; f) + \lambda L_N(\mathbf{x}_i^c; f)$$

Pulls similar samples closer in the embedding space and pushes dissimilar samples apart using a predefined distance measurement.

$$ID_L = \sum_{i=1}^N -q_i \log(pre_i).$$

Supports the model in learning more discriminative features.

$$center_L = \frac{1}{2} \sum_{i=1}^B \|f_i - c_{y_i}\|_2^2$$

Supports RLL loss to learn sample centric features.

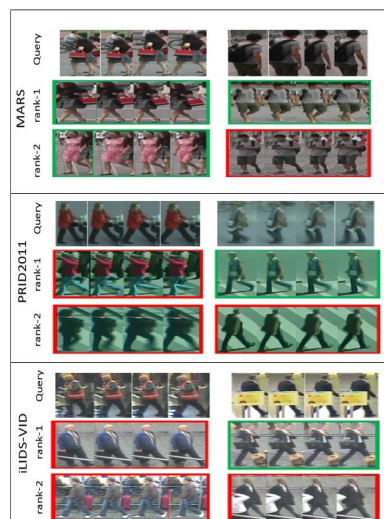
$$E_{att_L} = \frac{1}{T} \sum_{t=1}^T E_{Label_t} a_t^i$$

Guides the model to overcome partial occlusions.

## Experimental Results:

Methods	Publication	MARS [38]		PRID2011 [11]		iLIDS-VID [32]		Memory Usage (MB)		Params	Total Size
		rank-1 (mAP)	rank-1	rank-1	rank-1	rank-1	rank-1	Input	Fore/Backward Pass		
SAN [17]	CVPR 2018	82.3 (65.8)	93.2	80.2							
Att-Driven [37]	CVPR 2019	87.0 (78.2)	93.9	86.3							
VRSTC [12]	CVPR 2019	88.5 (82.3)	–	86.3							
Co-Segment [27]	ECCV 2019	84.9 (79.9)	–	–							
GLTR [16]	ICCV 2019	87.02 (78.47)	95.50	86.00	9.00	214.11	94.47	317.59			
M3D [15]	IEEE-T IP 2020	88.63 (79.46)	96.60	86.67	9.00	1213.83	104.58	1327.41			
VPRT [22]	AAAI 2020	88.6(82.9)	93.3	–	9.19	153.92	290.58	453.69			
Ours	–	<b>89.62 (84.61)</b>	<b>96.6</b>	<b>89.33</b>	9.19	171.92	290.58	471.69			
VPRT [22]	–	–	–	–							
(pre-trained on MARS)	AAAI 2020	–	96.6	–							
Ours	–	–	96.63	<b>97.33</b>							
(pre-trained MARS)	–	–	–	–							
(pre-trained MARS and iLIDS-VID) –	–	88.21(83.10)	<b>97.75</b>	95.33							

Statistical comparison against state-of-the-art methods.



**rank-1 and rank-2 Re-ID results** to given a query samples over 3 leading benchmark datasets

Green: true match  
Red = false match

Full paper:

