PROGRESSIVE MULTI-STAGE FEATURE MIX FOR PERSON RE-IDENTIFICATION

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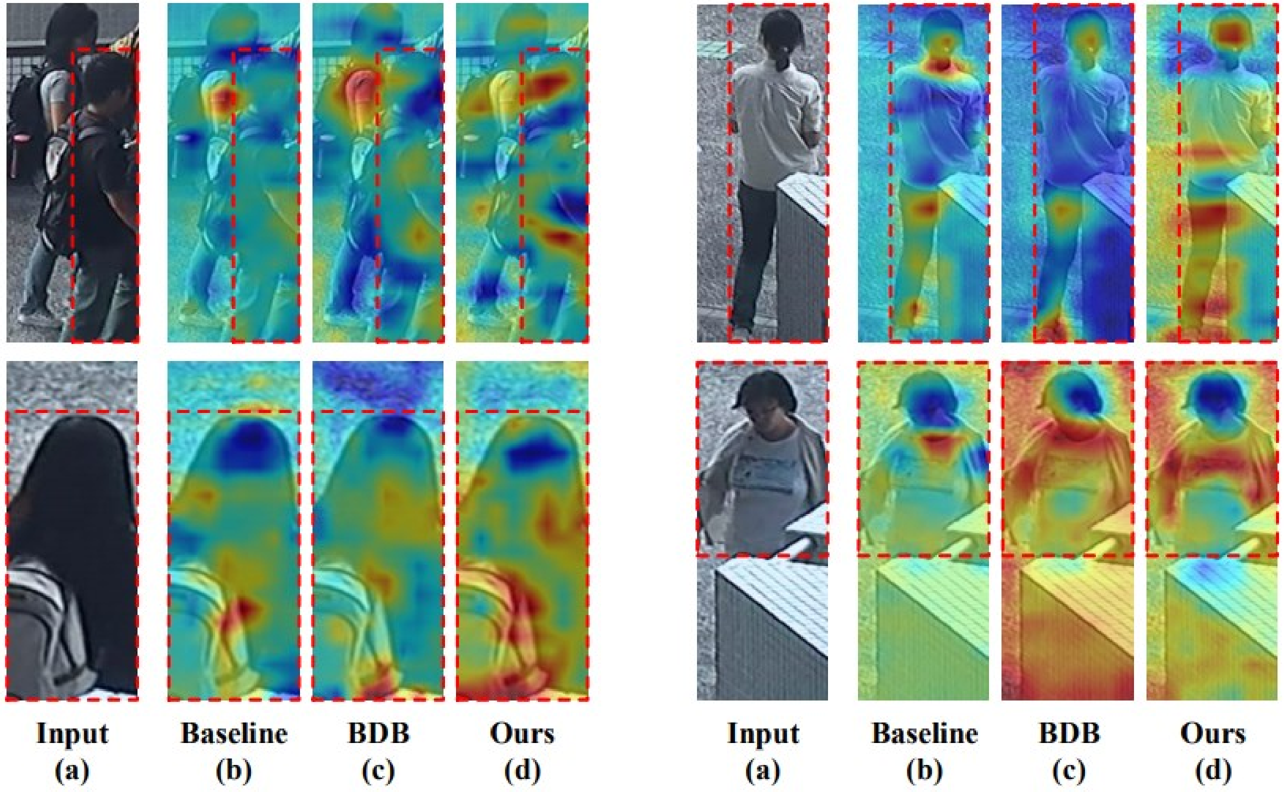
Motivation

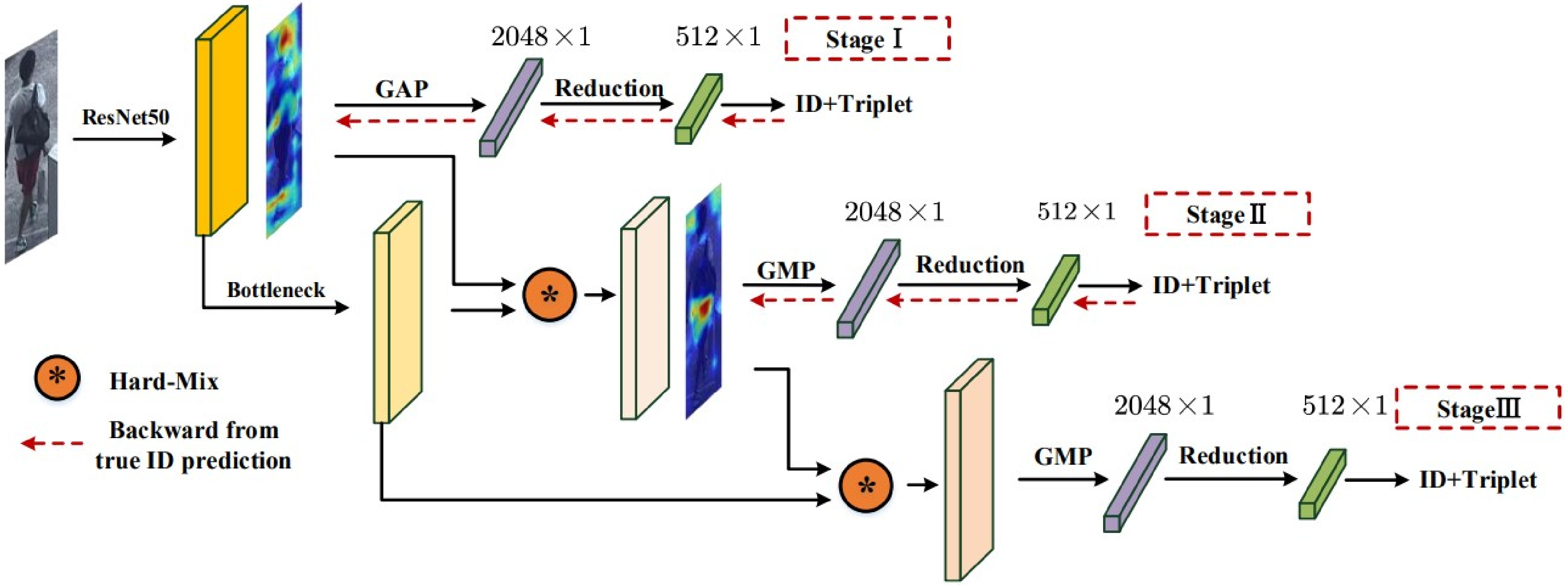


CNN suffers from :

- Only focusing on small local regions
- Expanding highly-responded areas without rules

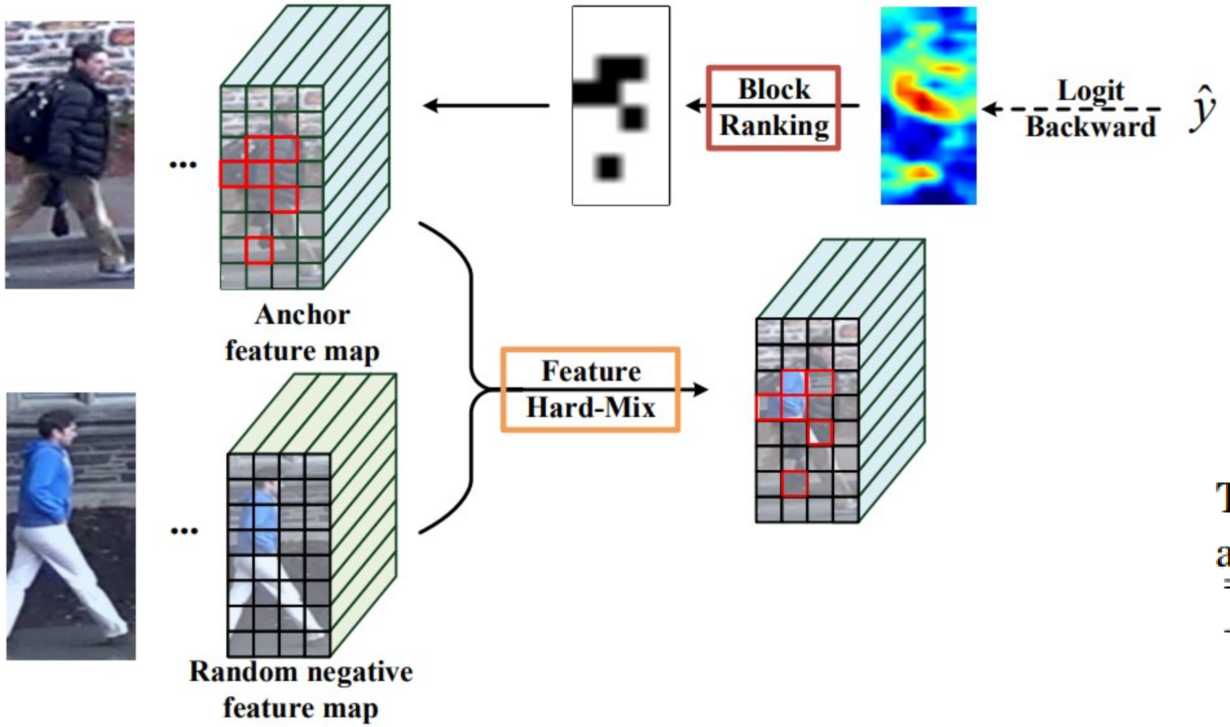
[1] Dai, Z., Chen, M., Gu, X., Zhu, S., & Tan, P. (2019). Batch dropblock network for person re-identification and beyond. In *Proceedings of the IEEE/CVF International Conference on Computer Vision* (pp. 3691-3701).

PMM Framework



Key points : 1. With the same constrains 2. Suppressing the already highly responded regions
3. Concatenate the features from three stages together for inference

Attentive Hard-Mix



$$\boldsymbol{m}_j = \begin{cases} 0 & j \in \{b_i\} \ \&\ e_i \in \{top_k(e)\} \\ 1 & others \end{cases} \qquad (1)$$

$$\tilde{\boldsymbol{f}} = \boldsymbol{m} \odot \boldsymbol{f}_a + (1 - \boldsymbol{m}) \odot \boldsymbol{f}_n \qquad (2)$$

Table 1. Specific differences between the attentive Hard-Mix and other augmentation methods.

	BDB	CutMix	A-CutMix	A-Hard-Mix
aug on feature / image	feature	image	image	feature
attentive	×	×	✓	✓
mix feature / image	×	✓	✓	✓
mix label	×	✓	✓	×

[1] Yun, S., Han, D., Oh, S. J., Chun, S., Choe, J., & Yoo, Y. (2019). Cutmix: Regularization strategy to train strong classifiers with localizable features. In *Proceedings of the IEEE/CVF International Conference on Computer Vision* (pp. 6023-6032).
[2] Walawalkar, D., Shen, Z., Liu, Z., & Savvides, M. (2020, May). Attentive cutmix: An enhanced data augmentation approach for deep learning based image classification. In *ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)* (pp. 3642-3646). IEEE.

Experiments

Comparison with SOTA

Table 2. Comparison results with the state-of-the-art methods on the classic reID datasets.

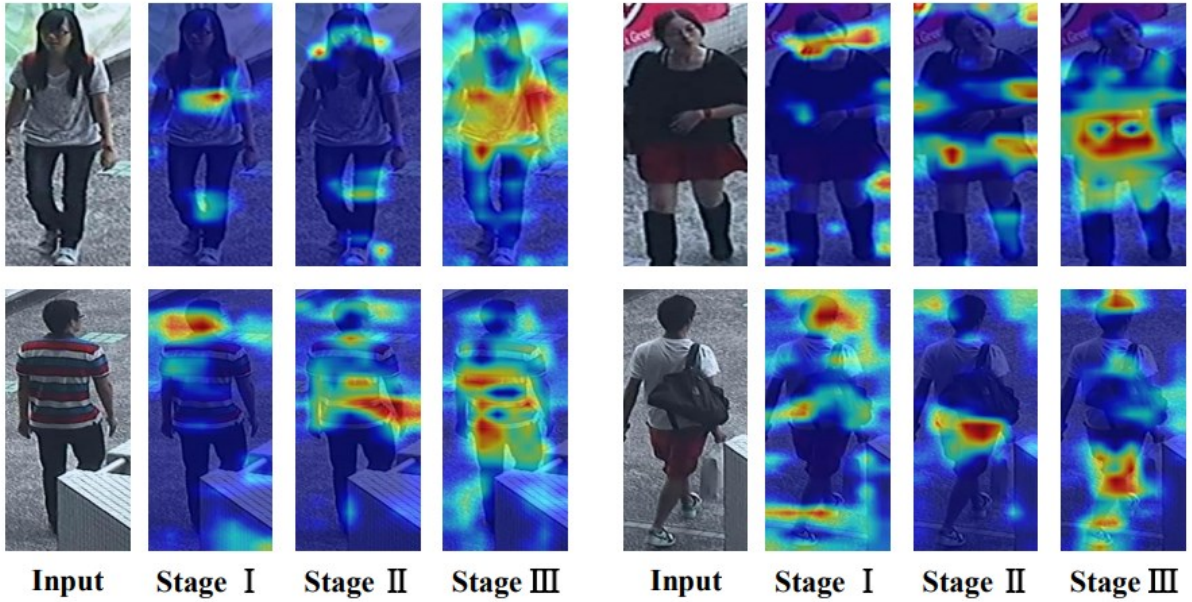
Methods	CUHK03		DukeMTMC		Market	
	Rank-1	mAP	Rank-1	mAP	Rank-1	mAP
AOS [21]	54.6	56.1	79.2	62.1	91.3	78.3
PCB+RPP [17]	62.8	56.7	83.3	69.2	93.8	81.6
CAMA [18]	66.6	64.2	85.8	72.9	**94.7**	84.5
BDB*[1]	73.5	69.8	87.1	74.5	94.0	84.9
Ours	**76.3**	**73.0**	**88.0**	**74.6**	94.1	**85.2**

Ablation on A-Hard-Mix

Table 3. Comparison results between different feature augmentation methods.

Methods	Market-1501		DukeMTMC		CUHK03	
	Rank-1	mAP	Rank-1	mAP	Rank-1	mAP
CutOut	94.1	84.7	87.1	74.5	73.5	69.8
CutMix	92.8	82.4	85.8	72.0	74.3	69.9
A-CutMix	91.6	78.1	83.8	68.7	65.6	62.8
A-Hard-Mix	**94.1**	**85.2**	**88.0**	**74.6**	**76.3**	**73.0**

Ablation on Different Stages



Conclusion

- We design a **Progressive Multi-stage feature Mix (PMM)** to **suppress the most salient features** for the current classifier, and force the head in the later stage to **find out other clues**.

- We propose an **attentive Hard-Mix** feature augmentation method, which **synthesizes the harder samples** with mixing the negative pairs.

- We do intensive experiments on three different reID benchmarks, showing the effectiveness of our method.

Contact

- **Github:** https://github.com/crazydemo/Progressive-Multi-stage-Feature-Mix-for-Person-Re-Identification

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Thank You