



Paper Reading

李星泽 2018-12-22



Outline

- Introduction to Person Re-identification
- Part-Aligned Bilinear Representations for Person Re-id(ECCV18)
- **D** End-to-End Deep Kronecker-Product Matching (CVPR 18)
- □ Spatial-Temporal Person Re-id (AAAI 19)

Person Re-identification

Identification

• Trainset and testset have same labels.

Re-identification

- Trainset and testset have different labels.
- It can be viewed as a retrieval task.
- Give a probe, calculate the similarities between probe and gallery, and arrange the gallery in descending order.



Market-1501 Dataset



Person Re-identification

CMC(Cumulative Matching Characteristics)

CMC-K is the percentage that there exists matched person in the top-K similar person.

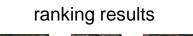
MAP(Mean Average Precision)

K matched person, their ranking positions are P_i

$$AP = \frac{1}{K} \sum_{i=1}^{K} \frac{i}{P_i}$$

probe





	R				
precision	1/1	2/2	2/3	2/4	3/5

AP = (1/1+2/2+3/5) / 3 = 13/15

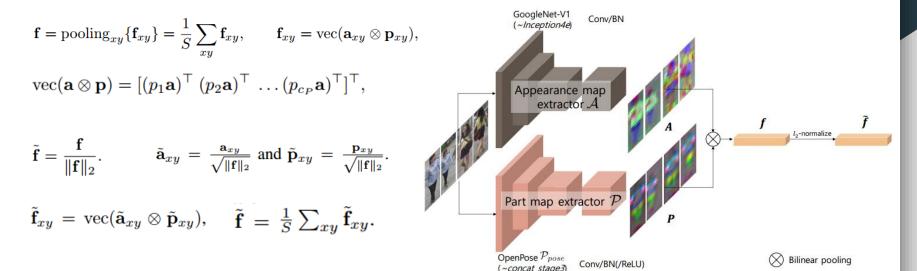
Part-Aligned Bilinear Representations for Person Re-identification

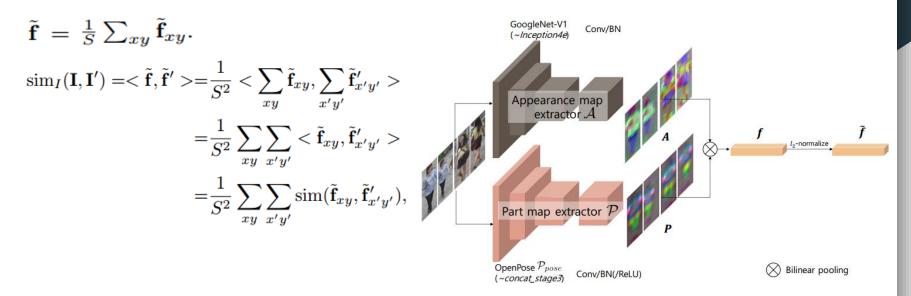
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Motivation:

Body part misalignment is one of the key challenges in person re-id. State-ofthe-art pose estimation solutions are still not perfect. Also, bounding box-based schemes lack fine-grained part localization within the boxes. Our approach learns to represent the human poses as part maps and combine them directly with the appearance maps to compute part-aligned representations.





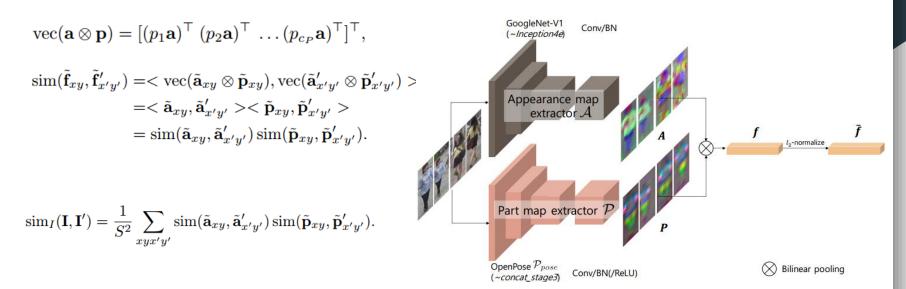


Table 1. Accuracy comparison on Market-1501

	Sinlge Query				Multi Query					
Rank	1	5	10	20	mAP	1	5	10	20	mAP
Varior et al. 2016 58	61.6	-	-	-	35.3	-	-	-	-	-
Zhong et al. 2017 86	77.1	-	-	-	63.6	-	-	-	-	-
Zhao et al. 2017 76	80.9	91.7	94.7	96.6	63.4	-	-	-	-	-
Sun et al. 2017 53	82.3	92.3	95.2	-	62.1	-	-	-	-	-
Geng et al. 2016 16	83.7	-	-	-	65.5	89.6	-	-	-	73.8
Lin et al. 2017 [31]	84.3	93.2	95.2	97.0	64.7	-	-	-	-	-
Bai et al. 2017 2	82.2	-	-	-	68.8	88.2	-	-	-	76.2
Chen et al. 2017 9	72.3	88.2	91.9	95.0	-	-	-	-	-	
Hermans et al. 2017 [19]	84.9	94.2	-	-	69.1	90.5	96.3	-	-	76.4
+ re-ranking	86.7	93.4	-	-	81.1	91.8	95.8	-	-	87.2
Zhang et al. 2017 74	87.7	-	-	-	68.8	91.7	-	-	-	77.1
Zhong et al. 2017 [87]	87.1	-	-	-	71.3	-	-	-	-	-
+ re-ranking	89.1	-	-	-	83.9	-	-	-	-	-
Chen et al. 2017 [8] (MobileNet)	90.0	-	-	-	70.6	-	-	-	-	-
Chen et al. 2017 8 (Inception-V3)	88.6	-	-	-	72.6	-	-	-	-	-
Ustinova et al. 2017 57 (Bilinear)	66.4	85.0	90.2	-	41.2	-	-	-	-	-
Zheng et al. 2017 79 (Pose)	79.3	90.8	94.4	96.5	56.0	-	-	-	-	-
Zhao et al. 2017 75 (Pose)	76.9	91.5	94.6	96.7	-	-	-	-	-	-
Su et al. 2017 50 (Pose)	84.1	92.7	94.9	96.8	65.4	-	-	-	-	-
Proposed (Inception-V1, R-CPM)	88.8	95.6	97.3	98.6	74.5	92.9	97.3	98.4	99.1	81.7
Proposed (Inception-V1, OpenPose)	90.2	96.1	97.4	98.4	76.0	93.2	97.5	98.4	99.1	82.7
+ dilation	91.7	96.9	98.1	98.9	79.6	94.0	98.0	98.8	99.3	85.2
+ re-ranking	93.4	96.4	97.4	98.2	89.9	95.4	97.5	98.2	98.9	93.1

Table 4. Accuracy comparison on DukeMTMC

Rank	1	5	10	20	mAP
Zheng et al. 85	67.7	-	-	-	47.1
Tong et al. 67	68.1	-	-	-	-
Lin et al. 31	70.7	-	-	-	51.9
Schumann et al. 47	72.6	-	-	-	52.0
Sun et al. 53	76.7	86.4	89.9	-	56.8
Chen et al. 8 (MobileNet)	77.6	-	-	-	58.6
Chen et al. 8 (Inception-V3)	79.2	-	-	-	60.6
Zhun et al. 87	79.3	-	-	-	62.4
+ re-ranking	84.0	-	-	-	78.3
Proposed (Inception V1, OpenPose)	82.1	90.2	92.7	95.0	64.2
+ dilation	84.4	92.2	93.8	95.7	69.3
+ re-ranking	88.3	93 .1	95.0	96.1	83.9

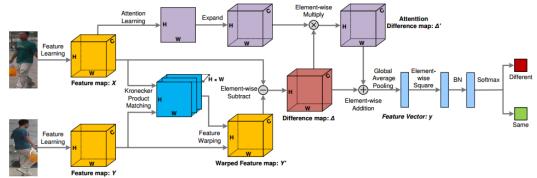
End-to-End Deep Kronecker-Product Matching for Person Re-identification

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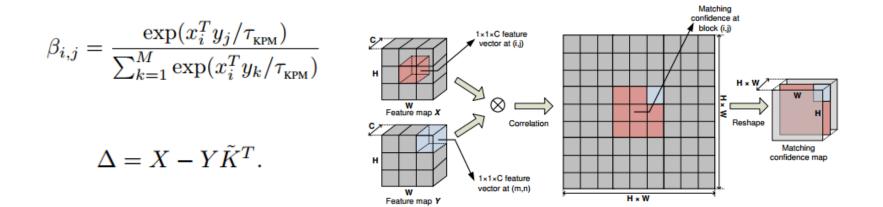
> 1{ytshen, xiaotong, hsli, xgwang}@ee.cuhk.edu.hk 2yishuai@sensetime.com

Motivation:

The global average pooling abandons valuable spatial information. Direct vectorization faces misalignment problems. Use Kronecker Product Matching to recover probabilistic correspondences between spatial regions across two images.



Kronecker Product Matching



Yantao Shen, Tong Xiao, Hongsheng Li, Shuai Yi, Xiaogang Wang, "End-to-End Deep Kronecker-Product Matching for Person Re-identification." CVPR, 2018.

Kronecker Product Matching

Methods	Ref		Market-								
DGD [36]	CVPR'16	mAP 31.9	59.5		top-10						
CADL [18]	CVPR'17	47.1	73.8	-	-	Mathada	Ref	Ι	DukeM	TMC [27]
P2S [48] MSCAN [14]	CVPR'17 CVPR'17	44.3 53.1	70.7 76.3	-	-	Methods	Kei	mAP	top-1	top-5	top-10
SSM [2]	CVPR'17 CVPR'17	68.8	82.2	-	-	BoW+KISSME [42]		12.2	25.1	-	-
SpinNet [39]	CVPR'17	-	76.9	91.5	94.6	LOMO+XQDA [17] ACRN [28]	CVPR'15 CVPR'17	17.0 52.0	30.8 72.6	- 84.8	- 88.9
JLML [16] VI+LSRO [45]	IJCAI'17 ICCV'17	65.5 66.1	85.1 84.0	-	-	Basel+LSRO [45]	ICCV'17	47.1	67.7	-	-
OL-MANS [47]	ICCV ¹⁷ ICCV ¹⁷	-	60.7	-	-	SVDNet [31] Ours	ICCV'17	56.8 63.2	76.7 80.3	86.4 89.5	89.9 91.9
PDC [30]	ICCV'17	63.4	84.1	92.7	94.9				00.0	0,10	10
PA [40]	ICCV'17	63.4	81.0	92.0	94.7						
SVDNet [31] Ours	ICCV'17	62.1 75.3	82.3 90.1	92.3 96.7	95.2 97.9						

Yantao Shen, Tong Xiao, Hongsheng Li, Shuai Yi, Xiaogang Wang, "End-to-End Deep Kronecker-Product Matching for Person Re-identification." CVPR, 2018.

Spatial-Temporal Person Re-identification

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Motivation:

Most methods neglect spatial-temporal constraint. Spatial-temporal constraint eliminates lots of irrelevant target images in gallery, and thus significantly alleviates the appearance ambiguity problem.

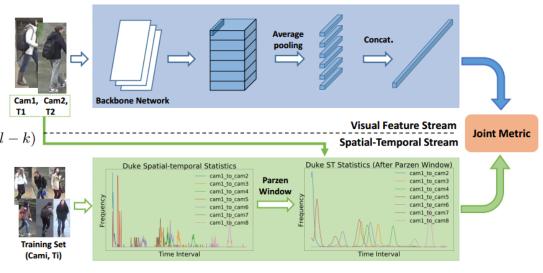
Spatial-Temporal Person Re-id

Histogram

$$\hat{p}(y=1|k,c_i,c_j) = \frac{n_{c_i c_j}^k}{\sum\limits_{l} n_{c_i c_j}^l}$$

- Parzen Window Smoothing $p(y = 1|k, c_i, c_j) = \frac{1}{Z} \sum_{l} \hat{p}(y = 1|l, c_i, c_j) K(l-k)$
- Laplace Smoothing

$$p_{\lambda}(Y = d_k) = \frac{m_k + \lambda}{M + D\lambda}$$



Guangcong Wang, Jianhuang Lai, Peigen Huang, Xiaohua Xie, "Spatial-Temporal Person Re-identification." AAAI, 2019.

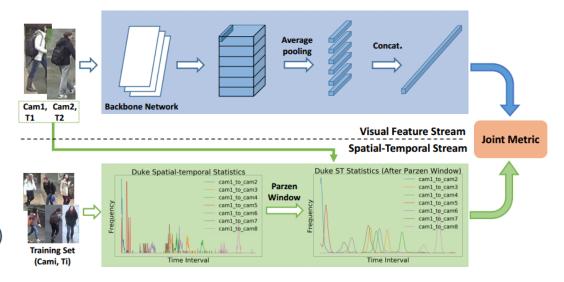
Spatial-Temporal Person Re-id

Visual Feature Distance

 $s(\mathbf{x_i}, \mathbf{x_j}) = \frac{\mathbf{x_i} \cdot \mathbf{x_j}}{||\mathbf{x_i}||||\mathbf{x_j}||}$

- Spatial-Temporal probability $p(y = 1 | k, c_i, c_j)$
- Joint Metric

 $p_{joint} = f(s; \lambda_0, \gamma_0) f(p_{st}; \lambda_1, \gamma_1)$



Guangcong Wang, Jianhuang Lai, Peigen Huang, Xiaohua Xie, "Spatial-Temporal Person Re-identification." AAAI, 2019.

Spatial-Temporal Person Re-id

INALKEL I JU I								
SSDAL	39.4	-	-	19.6				
APR	84.3	93.2	95.2	64.7				
Human Parsing	93.9	98.8	99.5	-				
Mask-guided	83.79	-	-	74.3				
Background	81.2	94.6	97.0	-				
PDC	84.1	92.7	94.9	63.4				
PSE+ECN	90.3	-	-	84.0				
MultiScale	88.9	-	-	73.1				
Spindle Net	76.9	91.5	94.6	-				
Latent Parts	80.3	-	-	57.5				
Part-Aligned	81.0	92.0	94.7	63.4				
PCB(*)	91.2	97.0	98.2	75.8				
TFusion-sup	73.1	86.4	90.5	-				
st-ReID	97.2	99.3	99.5	86.7				
st-ReID+RE	98.1	99.3	99.6	87.6				
st-ReID+RE+re-rank	98.0	98.9	99.1	95.5				

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DukeMTMC

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PAN	71.6	-	-	51.5
SVDNet	76.7	-	-	56.8
HA-CNN	80.5	-	-	63.8
APR	70.7	-	-	51.9
Human Parsing	84.4	91.9	93.7	71.0
PSE+ECN	85.2	-	-	79.8
MultiScale	79.2	-	-	60.6
PCB(*)	83.8	91.7	94.4	69.4
st-ReID	94.0	97.0	97.8	82.8
st-ReID+RE	94.4	97.4	98.2	83.9
st-ReID+RE+re-rank	94.5	96.8	97.1	92.7

Guangcong Wang, Jianhuang Lai, Peigen Huang, Xiaohua Xie, "Spatial-Temporal Person Re-identification." AAAI, 2019.

Thank you