

Abstract

Existing person re-identification algorithms either extract robust visual features or learn discriminative metrics for person images. However, the underlying manifold which those images reside on is rarely investigated. That raises a problem that the learned metric is not smooth with respect to the local geometry structure of the data manifold.

In this paper, we study person re-identification with manifold-based affinity learning, which did not receive enough attention from this area. An unconventional manifold-preserving algorithm is proposed, which can 1) make the best use of supervision from training data, whose label information is given as pairwise constraints; 2) scale up to large repositories with low on-line time complexity; and 3) be plunged into most existing algorithms, serving as a generic post-processing procedure to further boost the performance. Extensive experimental results on five popular person re-identification benchmarks consistently demonstrate the effectiveness of our method. Especially, on the largest CUHK03 and Market-1501, our method outperforms the state-of-theart alternatives by a large margin with high efficiency, which is more appropriate for practical applications.

Introduction

Task

Person re-identification (ReID): an active task driven by the applications of visual surveillance, which aims to identify person images from the gallery that share the same identity as the given probe.

Motivation

Current research interests can be coarsely divided into two mainstreams: those focus on designing robust visual descriptors and those seek for a discriminative metric. Unlike those methods performed in the metric space, we assume that person images reside on an underlying data manifold. The learned relationships between instances should be smooth with respect to the local geometry of the manifold.

Potential Solution

	Semi-supervised learning	Unsupervised manifold learning			
Representatives	Label Propagation [1], Local and Global Consistency [2], etc.	Manifold Ranking [3], Diffusion Process [4], etc.			
1 st Limitation	can only predict the labels of unlabeled data	ignore the beneficial influence from the labeled training data			
2 nd Limitation	high algorithmic complexity (grap	h-based)			

Our Contribution

Supervised Smoothed Manifold (SSM): the similarity value between two instances is estimated in the context of other pairs of instances, thus the learned similarity well reflects the geometry structure of the underlying manifold.

SSM further has three merits specifically customized for ReID, as

- 1) Supervision: take advantage of the supervision in pairwise constraints, which is easily accessible in this task.
- 2) Efficiency: affinity learning is performed only with database instances offline.
- Generalization: a post-processing procedure (or a generic tool) to further boost the identification accuracies of most existing algorithms.

Scalable Person Re-identification on Supervised Smoothed Manifold Song Bai¹, Xiang Bai¹, Qi Tian² ¹Huazhong University of Science and Technology, ²University of Texas at San Antonio

Methods



Figure 1. The pipeline of a person re-identification system. The blue, green and red color indicate training data, gallery and probe, respectively. Previous works focus on feature extracting and metric learning, marked with dashed boxes. Our work can be the post-processing procedure about affinity learning, marked with a solid box.

Basic Methodology

🗖 Goal

Given the probe **p**, the testing gallery **X={x₁,x₂,...,x_N}**, we aim at learning a similarity $\mathbf{Q} \in \mathbb{R}^{N \times N}$, with the help of the labeled training set $\mathbf{Y} = \{\mathbf{y}_1, \mathbf{y}_2, \dots, \mathbf{y}_N\}$.

Construct the affinity graph **G={V,W}**, where **V=p\mathbb{X}\mathbb{Y}**, and **W** $\in \mathbb{R}^{N \times N}$ is the adjacency matrix. **N=1+N_a+N_I**

Observation

For the label set **L** used in ReID, if **v**_i and **v**_i belong to the same identity, then L_{ii}=1, otherwise **0**. For the similarity **Q**, **Q**_{ii} should be larger if **v**_i and **v**_i are similar, and should be zero if dissimilar. Hence, affinity learning can be done by propagating the pairwise constraint label \mathbf{L} with tuples as primitive data.

Supervised Similarity Propagation

Let (v_k, v_i) and (v_l, v_i) be two tuples, the propagation is defined as

$$P^{(1)} = \alpha \sum_{k=1}^{N} \mathcal{P}(ki \to lj) Q_{lj}^{(t)} + (1-\alpha)L_k$$

We hold the *product rule* to calculate $\mathcal{P}(ki \rightarrow lj) = P(k \rightarrow l)P(i \rightarrow j) = P_{kl}P_{ij}$. The iteration converges to $Q = vec^{-1} \left((1 - \alpha)(I - \alpha P)^{-1} \vec{L} \right)$.

Similarity Crop

Since Q can be divided into $Q =$	$egin{array}{c} Q_{pp} \ Q_{Xp} \end{array}$	$\begin{array}{c} Q_{pX} \\ Q_{XX} \end{array}$	$\begin{array}{c} Q_{pY} \\ Q_{XY} \end{array}$, we can obtain the
	Q_{Yp}	Q_{YX}	Q_{YY}	
matching probabilities between t	the pr	obe p a	and th	e gallery X , <i>i.e.</i> , Q ,,, by

cropping **Q**.

Computationally expensive, since the iteration has to be done

- 1) on all the enumerated tuples \rightarrow O(TN⁴).
- 2) once a new probe is observed $\rightarrow O(TN_pN^4)$.

1] X. Zhu and Z. Ghahramani. Learning from labeled and unlabeled data with label propagation. Technical report, 2002. [2] D. Zhou, O. Bousquet, T. N. Lal, J. Weston, and B. Scholkopf. Learning with local and global consistency. In *NIPS*, 2003. [3] D. Zhou, J. Weston, A. Gretton, O. Bousquet, and B. Scholkopf. Ranking on data manifolds. In NIPS, 2004. [4] M. Donoser and H. Bischof. Diffusion processes for retrieval revisited. In CVPR, 2013.



References

[5] S. Liao, Y. Hu, X. Zhu, and S. Z. Li. Person re-identification by local maximal occurrence representation and metric learning. In CVPR, 2015.

[6] T. Matsukawa, T. Okabe, E. Suzuki, and Y. Sato. Hierarchical gaussian descriptor for person re-identification. In CVPR, 2016. [7] C. Liu, S. Gong, C. C. Loy, and X. Lin. Person re-identification: What features are important? In ECCV, 2012.



				EX	pe		me	ent	ts				
 Datasets: GRID, VIPeR, PRID450S, CUHK03 and Market-1501. Features: LOMO [4], GOG [5], EFL6 [6]. Metric: Euclidean and XQDA [4]. 													
	[Feature	Metric Aff	inity r	=1	r=10	r=20		2 ⁸⁰]
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		ELF6	XQDA		l .04	40.72	51.76	5				nifold Ranking	
\frown	Ì	LOMO	Euclidean	< 1.	5.20	30.80	36.40	5) 40	60	80 1	00
		LOMO	Euclidean		5.00	33.68	41.60		fethods		r=1	r=10	r=20
		LOMO	XODA X	< 10 / 1 8	5.56 3.96	41.84 44.16	52.40 55.92	2 E	LF6+RankSVM LF6+PRDC [64	[39]]	10.24 9.68	33.28 32.96	43.68 44.32
	l I	GOG	Euclidean	< 13	3.28	33.76	44.40		LF6+RankSVM	+MR [30]	12.24	36.32	46.56
U		GOG	Euclidean v	/ 14	4.40	36.80	44.48	8 E	LF6 + XQDA [2	25]	10.88	33.84 38.64	40.40 52.56
С С		GOG	XQDA >	$\begin{pmatrix} \\ \\ \\ \end{pmatrix}$	4.80	58.40	68.88		OMO + XQDA	[25]	16.56 16.64	41.84 41.20	52.40 52.96
	l	Eusion	Fuclidean		1.72	35.44	/0.40		LML [18]		24.54	43.53	55.25
n		Fusion	Euclidean		1.76	37.60	44.48	* Pe 8 S	olyMap [9] SDAL [46]		16.30 22.40	46.00 48.00	57.60 58.40
S S		Fusion	XQDA	< 27	7.04	59.36	70.00) M	ItMCML [33]		14.08	45.84	59.84
Ř	ļ	Fusion	XQDA 1	/ 27	7.20	61.12	70.56		EPLER [35]		22.40 18.40	51.28 50.24	61.20
		Fusion'	Euclidean	< 14 / 14	1.80 5.92	35.60	46.24	4 D	R-KISS [47]		20.60 24 24	51.40 54.08	62.60 65.20
		Fusion*	XQDA	< 27	7.20	61.12	71.20) G	OG+XQDA [36]	24.80	58.40	68.88
		Fusion*	XQDA V	/ 27	7.60	62.56	71.60	\mathbf{D} \mathbf{S}	SM (Ours)	arison with s	27.20	61.12	70.56 ID dataset
	1	Table 2. T cates SSN	The comparison with I is used and \times in	th baselin dicates no	es on GI t used.	RID data	aset. $\sqrt{11}$	ndi- The	best and second	best perform	ances ar	e marked in re	ed and blue,
		cutes bon		circutes inc	t usea.			resp	pectively.				
\sim			Methods	Ref	r=1	r=10	r=20	Mathada		Def	4	10	20
			Logal Fisher [29]	CVDP201	2 24 19	67.12		Methods		Kei	r=1	r=10	r=20
Ő	pu		Local Fisher [38] eSDC [60]	CVPR201 CVPR201	3 24.18 3 26.74	67.12 62.37	76.36	SCNCD Semantic	[7] EC	CV2014 PP 2015	r=1 41.60	r=10 79.40 77.50	r=20 87.80 86.70
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CUHKO	n of LOMO and		Local Fisher [38] eSDC [60] SalMatch [59] Mid-Filter [61] SCNCD [54] ImprovedDeep [1] PolyMap [9] XQDA [25] Semantic [44]	CVPR201 CVPR201 ICCV2012 CVPR201 ECCV201 CVPR201 CVPR201 CVPR201 CVPR201	3 24.18 3 26.74 3 30.16 4 29.11 4 37.80 5 34.81 5 36.80 5 40.00 5 41.60	67.12 62.37 65.95 81.20 	- 76.36 - 79.87 90.40 - 91.70 91.08 95.10	SCNCD Semantic CSL [5] XQDA [1 TMA [2] LSSCDL GOG [3]	[7] ECC 2 [6] CV ICC 1] CV 4 ECC 2 [8] CV CV	Ref CV2014 PR2015 CV2015 PR2015 CV2016 PR2016 PR2016	r=1 41.60 44.90 61.38 52.89 60.49 68.40	r=10 79.40 77.50 82.20 91.02 85.78 88.58 94.50	r=20 87.80 86.70 89.80 95.33 93.33 93.60 97.80
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D450S and CUHK0	: the concatenation of LOMO and metric.		Local Fisher [38] eSDC [60] SalMatch [59] Mid-Filter [61] SCNCD [54] ImprovedDeep [1] PolyMap [9] XQDA [25] Semantic [44] MetricEmsemb. [37] QALF [63] CSL [42] MLAPG [26] MTL-LORAE [45] DCIA [13] DGD [51] LSSCDL [58] TPC [10] GOG [36]	CVPR201 CVPR201 ICCV2012 CVPR201 ECCV201 CVPR201 CVPR201 CVPR201 CVPR201 ICCV2012 ICCV20 ICCV	3 24.18 3 26.74 3 30.16 4 29.11 4 37.80 5 34.81 5 34.81 5 36.80 5 40.00 5 41.60 5 45.90 5 30.17 5 34.80 5 40.73 5 42.30 5 42.30 5 42.66 6 47.80 6 49.72	67.12 62.37 - 65.95 81.20 - 83.70 80.51 86.20 88.90 62.44 82.30 82.34 81.60 87.50 - 84.27 84.80 88.67	- 76.36 - 79.87 90.40 - 91.70 91.08 95.10 95.80 73.81 91.80 92.37 89.60 - 91.93 91.10 94.53	SCNCD Semantic CSL [5] XQDA [1 TMA [2] LSSCDL GOG [3] SSM (Ou Table 1. Th Method DeepR XQDA Improv LSSCE	[7] ECO [6] CV ICO ICO ICO ICO ECO [8] CV CV Irs) ne comparison ds eID [23] [25] redDeep [1] DL [58] [5]	Ref CV2014 PR2015 CV2015 PR2016 PR2016 with state-or Labele r=1 20.7 51.7 52.2 54.7 88.3 57.0	r=1 41.60 44.90 44.40 61.38 52.89 60.49 68.40 72.98 of-the-a d r=10 68.3 - 93.3 -	r=10 79.40 77.50 82.20 91.02 85.78 88.58 94.50 96.76 rt on PRID4 Detecte r=1 r=5 19.9 49.0 46.3 - 45.0 75.7 51.2 - 51.2 -	r=20 87.80 86.70 89.80 95.33 93.60 97.80 99.11 50S. 99.11 50S. 4 r=10 64.3 - 83.0 -
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PRID450S and CUHK03	setup: the concatenation of LOMO and XQDA metric.		Local Fisher [38] eSDC [60] SalMatch [59] Mid-Filter [61] SCNCD [54] ImprovedDeep [1] PolyMap [9] XQDA [25] Semantic [44] MetricEmsemb. [37] QALF [63] CSL [42] MLAPG [26] MTL-LORAE [45] DCIA [13] DGD [51] LSSCDL [58] TPC [10] GOG [36] Null [56] SCSP [8] S-CNN [48]	CVPR201 CVPR201 ICCV201 CVPR201 ECCV201 CVPR201 CVPR201 CVPR201 CVPR201 ICCV201 ICCV201 ICCV201 ICCV201 ICCV201 CVPR20 CVPR20 CVPR20 CVPR201 CVPR201 CVPR201 CVPR201 CVPR201 CVPR20	3 24.18 3 26.74 3 30.16 4 29.11 4 37.80 5 34.81 5 36.80 5 40.00 5 41.60 5 45.90 5 30.17 5 34.81 5 45.90 5 30.17 5 34.80 5 40.73 5 42.30 5 42.30 5 63.92 6 38.60 6 47.80 6 49.72 6 51.17 6 53.54 6 37.80	67.12 62.37 - 65.95 81.20 - 83.70 80.51 86.20 88.90 62.44 82.30 82.34 81.60 87.50 - 84.27 84.80 88.67 90.51 91.49 66.90	- 76.36 - 79.87 90.40 91.70 91.08 95.10 95.80 73.81 91.80 92.37 89.60 - 91.93 91.10 94.53 95.92 96.65	SCNCD Semantic CSL [5] XQDA [1 TMA [2] LSSCDL GOG [3] SSM (Ou Table 1. Th Method DeepR XQDA Improv LSSCI MLAP Shi et a Metricl	[7] ECC [6] CV ICC I] CV ECC [8] CV CV Irs) ne comparison ds eID [23] [25] vedDeep [1] DL [58] G [26] al. [43] Emsemb. [37] [51]	Ref $CV2014$ PR2015 $CV2015$ PR2016 PR2016 PR2016 with state-co Labele r=1 r=5 20.7 51.7 52.2 - 54.7 88.3 57.0 - 58.0 - 61.3 - 62.1 89.1	r=1 41.60 44.90 44.40 61.38 52.89 60.49 68.40 72.98 of-the-at d r=10 68.3 - 93.3 - - 93.3 - - 94.3 94.8	r=10 79.40 77.50 82.20 91.02 85.78 88.58 94.50 96.76 rt on PRID4 Detecte r=1 r=5 19.9 49.0 46.3 - 45.0 75.7 51.2 - 51.2 - 51.2 - 52.0 54.7 84.7	r=20 87.80 86.70 89.80 95.33 93.60 97.80 99.11 50S. d r=10 64.3 - 83.0 - - - - - - - - - - - - -
R, PRID450S and CUHK03	ult setup: the concatenation of LOMO and der XQDA metric.		Local Fisher [38] eSDC [60] SalMatch [59] Mid-Filter [61] SCNCD [54] ImprovedDeep [1] PolyMap [9] XQDA [25] Semantic [44] MetricEmsemb. [37] QALF [63] CSL [42] MLAPG [26] MTL-LORAE [45] DCIA [13] DGD [51] LSSCDL [58] TPC [10] GOG [36] Null [56] SCSP [8] S-CNN [48] Shi <i>et al.</i> [43] (1. graph [20]	CVPR201 CVPR201 ICCV201 CVPR201 ECCV201 CVPR201 CVPR201 CVPR201 CVPR201 ICCV201 ICCV201 ICCV201 ICCV201 ICCV201 CVPR20 CVPR20 CVPR201 CVPR201 CVPR201 CVPR201 CVPR201 CVPR2	3 24.18 3 26.74 3 30.16 4 29.11 4 37.80 5 34.81 5 34.81 5 34.81 5 34.81 5 34.81 5 36.80 5 40.00 5 41.60 5 45.90 5 30.17 5 34.80 5 40.73 5 34.80 5 40.73 5 42.30 5 63.92 6 38.60 6 42.66 6 47.80 6 51.17 6 53.54 6 37.80 6 40.91 6 40.91 6 40.91	67.12 62.37 - 65.95 81.20 - 83.70 80.51 86.20 88.90 62.44 82.30 82.34 81.60 87.50 - 84.27 84.80 88.67 90.51 91.49 66.90	- 76.36 - 79.87 90.40 91.70 91.08 95.10 95.80 73.81 91.80 92.37 89.60 - 91.93 91.93 91.10 94.53 95.92 96.65 -	SCNCD Semantic CSL [5] XQDA [1 TMA [2] LSSCDL GOG [3] SSM (Ou Table 1. Th Method DeepR XQDA Improv LSSCI MLAP Shi et d Metricl Null [5 S-LSTI	[7] EC [6] CV ICC ICC I] CV EC [8] CV CV ITS) ne comparison ds eID [23] [25] redDeep [1] DL [58] redDeep [1] DL [58] redDeep [37] [6] M [49]	Ref $CV2014$ PR2015 $CV2015$ PR2016 PR2016 PR2016 PR2016 Vith state-control Labele r=1 r=5 20.7 54.7 88.3 57.0 58.0 61.3 62.1 89.1 62.5 90.0	r=1 41.60 44.90 44.40 61.38 52.89 60.49 68.40 72.98 of-the-ar d r=10 68.3 - 93.3 - - 93.3 - - 93.3 - - 93.3 - - - 94.3 94.8 -	r=10 79.40 77.50 82.20 91.02 85.78 88.58 94.50 96.76 rt on PRID4 Detecte r=1 r=5 19.9 49.0 46.3 - 45.0 75.7 51.2 - 51.2 - 51.2 - 51.2 - 52.0 54.7 84.7 57.3 80.1	r=20 87.80 86.70 89.80 95.33 93.60 97.80 99.11 450S. ed r=10 64.3 - 83.0 - - 94.8 88.3
eR, PRID450S and CUHK0	lefault setup: the concatenation of LOMO and under XQDA metric.		Local Fisher [38] eSDC [60] SalMatch [59] Mid-Filter [61] SCNCD [54] ImprovedDeep [1] PolyMap [9] XQDA [25] Semantic [44] MetricEmsemb. [37] QALF [63] CSL [42] MLAPG [26] MTL-LORAE [45] DCIA [13] DGD [51] LSSCDL [58] TPC [10] GOG [36] Null [56] SCSP [8] S-CNN [48] Shi <i>et al.</i> [43] ℓ 1-graph [20] S-LSTM [49]	CVPR201 CVPR201 ICCV201 CVPR201 ECCV201 CVPR201 CVPR201 CVPR201 CVPR201 ICCV201 ICCV201 ICCV201 ICCV201 ICCV201 CVPR201 CVPR201 CVPR201 CVPR201 CVPR201 CVPR201 CVPR201 CVPR201 CVPR201 ECCV201	3 24.18 3 26.74 3 30.16 4 29.11 4 37.80 5 34.81 5 34.81 5 34.81 5 34.81 5 34.80 5 40.00 5 41.60 5 45.90 5 30.17 5 34.80 5 42.30 5 63.92 6 38.60 6 42.66 6 47.80 6 47.80 6 47.80 6 53.54 6 37.80 6 40.91 6 41.50 6 42.40	67.12 62.37 - 65.95 81.20 - 83.70 80.51 86.20 88.90 62.44 82.30 82.34 81.60 87.50 - 84.27 84.80 88.67 90.51 91.49 66.90 - - 79.40	- 76.36 - 79.87 90.40 91.70 91.08 95.10 95.80 73.81 91.80 92.37 89.60 - 91.93 91.10 94.53 95.92 96.65 - - - -	SCNCD Semantic CSL [5] XQDA [7 TMA [2] LSSCDL GOG [3] SSM (Ou Table 1. Th Method DeepR XQDA Improv LSSCI MLAP Shi et a Metricl Null [5 S-LST] S-CNN GOG [[7] EC [6] CV ICC ICC I] CV ECC [8] CV CV Irs) ne comparison ds eID [23] [25] vedDeep [1] DL [58] G [26] al. [43] Emsemb. [37] [6] M [49] V [48] 36]	Ref CV2014 PR2015 CV2015 PR2016 PR2016 PR2016 with state-c Labele r=1 r=5 20.7 54.7 58.0 61.3 62.1 89.1 62.5 90.0 - - 67.3	r=1 41.60 44.90 44.40 61.38 52.89 60.49 68.40 72.98 of-the-ar d r=10 68.3 - 93.3 - - 94.3 94.8 - 94.3 94.8 - 94.0	r=10 79.40 77.50 82.20 91.02 85.78 88.58 94.50 96.76 rt on PRID4 Detecte r=1 r=5 19.9 49.0 46.3 - 45.0 75.7 51.2 - 51.2 - 51.2 - 52.0 - 54.7 84.7 57.3 80.1 61.8 80.9 65.5 88.4	r=20 87.80 86.70 89.80 95.33 93.60 97.80 99.11 50S. 4 r=10 64.3 - 83.0 - - 94.8 88.3 88.3 88.3 93.7
IPeR, PRID450S and CUHK03	ie default setup: the concatenation of LOMO and DG under XQDA metric.		Local Fisher [38] eSDC [60] SalMatch [59] Mid-Filter [61] SCNCD [54] ImprovedDeep [1] PolyMap [9] XQDA [25] Semantic [44] MetricEmsemb. [37] QALF [63] CSL [42] MLAPG [26] MTL-LORAE [45] DCIA [13] DGD [51] LSSCDL [58] TPC [10] GOG [36] Null [56] SCSP [8] S-CNN [48] Shi <i>et al.</i> [43] ℓ 1-graph [20] S-LSTM [49] SSDAL [46] TMA [34]	CVPR201 CVPR201 ICCV201 CVPR201 ECCV201 CVPR201 CVPR201 CVPR201 CVPR201 CVPR201 ICCV201 ICCV201 ICCV201 ICCV201 CVPR201 CVPR201 CVPR201 CVPR201 CVPR201 CVPR201 CVPR201 CVPR201 ECCV201	3 24.18 3 26.74 3 30.16 4 29.11 4 37.80 5 34.81 5 34.81 5 34.81 5 34.81 5 34.81 5 40.00 5 41.60 5 45.90 5 30.17 5 34.80 5 42.30 5 42.30 5 42.30 5 42.30 6 38.60 6 42.66 6 47.80 6 53.54 6 37.80 6 40.91 6 41.50 6 42.40 6 43.50 6 43.50 6 48.19	67.12 62.37 - 65.95 81.20 - 83.70 80.51 86.20 88.90 62.44 82.30 82.34 81.60 87.50 - 84.27 84.80 88.67 90.51 91.49 66.90 - - 79.40 81.50 87.65	- 76.36 - 79.87 90.40 - 91.70 91.08 95.10 95.80 73.81 91.80 92.37 89.60 - - 91.93 91.10 94.53 95.92 96.65 - - - - - - - - - - - - - - - - - - -	SCNCD Semantic CSL [5] XQDA [7 TMA [2] LSSCDL GOG [3] SSM (Ou Table 1. Th Method DeepR XQDA Improv LSSCI MLAP Shi et a Metricl Null [5 S-LSTI S-CNN GOG [DGD [[7] EC [6] CV ICC ICC I] CV ECC [8] CV CV Irs) ne comparison ds eID [23] [25] vedDeep [1] DL [58] 'G [26] al. [43] Emsemb. [37] i6] M [49] V [48] 36] 51]	Ref CV2014 PR2015 CV2015 PR2016 PR2016 PR2016 PR2016 Image: state of the state	r=1 41.60 44.90 44.40 61.38 52.89 60.49 68.40 72.98 of-the-a d r=10 68.3 - 93.3 - 93.3 - - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - -	r=10 79.40 77.50 82.20 91.02 85.78 88.58 94.50 96.76 rt on PRID4 Detecte r=1 r=5 19.9 49.0 46.3 - 45.0 75.7 51.2 - 51.2 - 51.2 - 52.0 - 54.7 84.7 57.3 80.1 61.8 80.9 65.5 88.4	r=20 87.80 86.70 89.80 95.33 93.60 97.80 99.11 50S. rd r=10 64.3 - 83.0 - - 94.8 88.3 88.3 88.3 93.7 -
VIPeR, PRID450S and CUHK03	The default setup: the concatenation of LOMO and GOG under XQDA metric.		Local Fisher [38] eSDC [60] SalMatch [59] Mid-Filter [61] SCNCD [54] ImprovedDeep [1] PolyMap [9] XQDA [25] Semantic [44] MetricEmsemb. [37] QALF [63] CSL [42] MLAPG [26] MTL-LORAE [45] DCIA [13] DGD [51] LSSCDL [58] TPC [10] GOG [36] Null [56] SCSP [8] S-CNN [48] Shi <i>et al.</i> [43] <i>ℓ</i> 1-graph [20] S-LSTM [49] SSDAL [46] TMA [34] SSM (Ours) bla 5. The communicant	CVPR201 CVPR201 ICCV201 CVPR201 ECCV201 CVPR201 CVPR201 CVPR201 CVPR201 ICCV201 ICCV201 ICCV201 ICCV201 ICCV201 CVPR201 CVPR201 CVPR201 CVPR201 CVPR201 CVPR201 CVPR201 ECCV20 ECCV20 ECCV20 ECCV20 ECCV20 ECCV20 ECCV20 ECCV20 ECCV20 ECC	3 24.18 3 26.74 3 30.16 4 29.11 4 37.80 5 34.81 5 36.80 5 40.00 5 41.60 5 45.90 5 30.17 5 34.80 5 40.73 5 42.30 5 42.30 5 42.66 6 38.60 6 42.66 6 47.80 6 51.17 6 53.54 6 37.80 6 40.91 6 42.40 6 43.50 6 43.50 6 43.50 6 48.19	67.12 62.37 - 65.95 81.20 - 83.70 80.51 86.20 88.90 62.44 82.30 82.34 81.60 87.50 - 84.27 84.80 88.67 90.51 91.49 66.90 - 79.40 81.50 87.65 91.49	- 76.36 - 79.87 90.40 91.70 91.70 91.08 95.10 95.80 73.81 91.80 92.37 89.60 - - 91.93 91.10 94.53 95.92 96.65 - - - - - 89.00 93.54	SCNCD Semantic CSL [5] XQDA [1 TMA [2] LSSCDL GOG [3] SSM (Ou Table 1. Th Method DeepR XQDA Improv LSSCI MLAP Shi et d Metricl Null [5 S-LSTI S-CNN GOG [DGD [SSM (0 Table 6. 7	[7] EC0 2 [6] CV IC0 1] CV 4 EC0 2 [8] CV CV 113 13 CV 4 EC0 CV 14 15 15 15 15 15 15 15 15 15 15	Ref $CV2014$ $PR2015$ $CV2015$ $PR2016$ $PR2017$ $S1.7$ $S2.2$ 54.7 88.3 57.0 62.1 89.1 62.5 90.0 $ 67.3$ 91.0	r=1 41.60 44.90 44.40 61.38 52.89 60.49 68.40 72.98 of-the-ar d r=10 68.3 - 93.3 - 93.3 - 94.3 94.8 - - 94.3 94.8 - - 94.3 94.8 - - 94.3 94.8 - - 94.3 94.8 - - 98.0 - - 98.0 - - 98.0 - - 98.0 - - - - - - - - - - - - -	r=10 79.40 77.50 82.20 91.02 85.78 88.58 94.50 96.76 rt on PRID4 Detecte $r=1$ $r=5$ 19.9 49.0 46.3 - 45.0 75.7 51.2 - 52.0 - 54.7 84.7 57.3 80.1 61.8 80.9 65.5 88.4 - - 72.7 92.4 on CUHK03 -	r=20 87.80 86.70 89.80 95.33 93.60 97.80 99.11 50S. d r=10 64.3 - 83.0 - - 94.8 88.3 88.3 93.7 - 96.1 dataset.
VIPeR, PRID450S and CUHK03	The default setup: the concatenation of LOMO and GOG under XQDA metric.	Ta	Local Fisher [38] eSDC [60] SalMatch [59] Mid-Filter [61] SCNCD [54] ImprovedDeep [1] PolyMap [9] XQDA [25] Semantic [44] MetricEmsemb. [37] QALF [63] CSL [42] MLAPG [26] MTL-LORAE [45] DCIA [13] DGD [51] LSSCDL [58] TPC [10] GOG [36] Null [56] SCSP [8] S-CNN [48] Shi <i>et al.</i> [43] ℓ 1-graph [20] S-LSTM [49] SSDAL [46] TMA [34] SSM (Ours) ble 5. The comparison	CVPR201 CVPR201 ICCV201 CVPR201 ECCV201 CVPR201 CVPR201 CVPR201 CVPR201 ICCV201 ICCV201 ICCV201 ICCV201 ICCV201 CVPR201 CVPR201 CVPR201 CVPR201 CVPR201 CVPR201 CVPR201 ECCV20 ECCV20 ECCV20 ECCV20 ECCV20 ECCV20 ECCV20 ECCV20 ECCV20 ECCV20 ECCV20 ECCV20 ECCV20 ECCV20	3 24.18 3 26.74 3 30.16 4 29.11 4 37.80 5 34.81 5 36.80 5 40.00 5 41.60 5 45.90 5 30.17 5 34.81 5 45.90 5 40.03 5 42.30 5 42.30 5 42.30 5 42.66 6 38.60 6 49.72 6 51.17 6 53.54 6 37.80 6 40.91 6 41.50 6 43.50 6 43.50 6 43.50 6 43.50 6 43.50 6 43.50 6 43.50 6 43.50	67.12 62.37 - 65.95 81.20 - 83.70 80.51 86.20 88.90 62.44 82.30 82.34 81.60 87.50 - 84.27 84.80 88.67 90.51 91.49 66.90 - 79.40 81.50 87.65 91.49 n VIPeR of	- 76.36 - 79.87 90.40 91.70 91.70 91.08 95.10 95.80 73.81 91.80 92.37 89.60 - - 91.93 91.10 94.53 95.92 96.65 - - - - - 89.00 93.54 96.08 Iataset.	SCNCD Semantic CSL [5] XQDA [1 TMA [2] LSSCDL GOG [3] SSM (Ou Table 1. Th Method DeepR XQDA Improv LSSCI MLAP Shi et a Metricl Null [5 S-LSTI S-CNN GOG [DGD [SSM (0 Table 6. 1	[7] EC0 2 [6] CV IC0 1] CV 4 EC0 2 [8] CV CV 113 13 CV 4 EC0 CV 143 143 153 154 155 155 155 155 155 155 155	Ref $CV2014$ PR2015 $CV2015$ PR2016 PR2016 PR2016 with state-or $r=1$ $r=5$ 20.7 51.7 52.2 - 54.7 88.3 57.0 - 58.0 - 61.3 - 62.1 89.1 62.5 90.0 - - 67.3 91.0 75.3 - 76.6 94.6 with state-of	r=1 41.60 44.90 44.40 61.38 52.89 60.49 68.40 72.98 of-the-art d r=10 68.3 - 93.3 - 93.3 - 93.3 - 94.3 94.8 - 94.3 94.8 - 96.0 - 98.0 - the-art of	r=10 79.40 77.50 82.20 91.02 85.78 88.58 94.50 96.76 rt on PRID4 Detecte $r=1$ $r=5$ 19.9 49.0 46.3 - 45.0 75.7 51.2 - 52.0 - 54.7 84.7 57.3 80.1 61.8 80.9 65.5 88.4 - - 72.7 92.4 on CUHK03 -	r=20 87.80 86.70 89.80 95.33 93.60 97.80 97.80 99.11 50S. d r=10 64.3 - 83.0 94.8 88.3 93.7 - 96.1 dataset.
VIPeR, PRID450S and CUHK0	The default setup: the concatenation of LOMO and GOG under XQDA metric.	-1501	Local Fisher [38] eSDC [60] SalMatch [59] Mid-Filter [61] SCNCD [54] ImprovedDeep [1] PolyMap [9] XQDA [25] Semantic [44] MetricEmsemb. [37] QALF [63] CSL [42] MLAPG [26] MTL-LORAE [45] DCIA [13] DGD [51] LSSCDL [58] TPC [10] GOG [36] Null [56] SCSP [8] S-CNN [48] Shi <i>et al.</i> [43] <i>l</i> 1-graph [20] S-LSTM [49] SSDAL [46] TMA [34] SSM (Ours) ble 5. The comparison	CVPR201 CVPR201 ICCV201 CVPR201 CVPR201 CVPR201 CVPR201 CVPR201 CVPR201 ICCV201 ICCV201 ICCV201 ICCV201 ICCV201 CVPR20 CVPR201 CVPR201 CVPR201 CVPR20 CVPR201 CVPR201 CVPR2	3 24.18 3 26.74 3 30.16 4 29.11 4 37.80 5 34.81 5 34.81 5 34.81 5 34.81 5 34.81 5 34.81 5 34.80 5 40.00 5 41.60 5 40.73 5 30.17 5 30.17 5 30.17 5 30.17 5 30.17 5 30.17 5 30.17 5 30.17 5 30.17 5 30.17 5 30.17 5 30.17 5 30.17 5 30.17 5 35.40 6 47.80 6 47.80 6 40.91 6 41.50 6 42.40 6 43.	67.12 62.37 - 65.95 81.20 - 83.70 80.51 86.20 88.90 62.44 82.30 82.34 81.60 87.50 - 84.27 84.80 88.67 90.51 91.49 66.90 - - 79.40 81.50 87.65 91.49 n VIPeR of	- 76.36 - 90.40 - 91.70 91.70 91.08 95.10 95.80 73.81 91.80 92.37 89.60 - - 91.93 91.93 91.10 94.53 95.92 96.65 - - - - - - - - - - 89.00 93.54 - - - - - - - - - - - - - - - - - - -	SCNCD Semantic CSL [5] XQDA [1 TMA [2] LSSCDL GOG [3] SSM (Ou Table 1. Th Method DeepR XQDA Improv LSSCI MLAP Shi et a Metricl Null [5 S-LSTI S-CNN GOG [DGD [SSM (0 Table 6. T	[7] EC [6] CV ICC ICC I] CV ECC [8] CV CV ITS) The comparison ds eID [23] [25] vedDeep [1] DL [58] G [26] al. [43] Emsemb. [37] i6] M [49] V [48] 36] 51] Ours) The comparison QUETV A	Ref $CV2014$ $PR2015$ $CV2015$ $PR2015$ $CV2016$ $PR2016$ $r=1$ $r=5$ 20.7 51.7 52.2 58.0 61.3 62.1 89.1 62.5 90.0 $ 67.3$ 91.0 76.6	r=1 41.60 44.90 44.40 61.38 52.89 60.49 68.40 72.98 of-the-ar d r=10 68.3 - 93.3 - - 94.3 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.8 - 94.3 94.8 - - 94.3 94.8 - - 94.3 94.8 - - 94.9 - - 94.9 - - - - - - - - - - - - -	r=10 79.40 77.50 82.20 91.02 85.78 88.58 94.50 96.76 rt on PRID4 Detecte r=1 r=5 19.9 49.0 46.3 - 45.0 75.7 51.2 - 51.2 - 51.2 - 51.2 - 52.0 - 54.7 84.7 57.3 80.1 61.8 80.9 65.5 88.4 - 72.7 92.4 on CUHK03 With	r=20 87.80 86.70 89.80 95.33 93.60 97.80 99.11 450S. 4 r=10 64.3 - 83.0 - - 94.8 88.3 88.3 93.7 - 96.1 dataset.
VIPeR, PRID450S and CUHKO	The default setup: the concatenation of LOMO and GOG under XQDA metric.	-1501	Local Fisher [38] eSDC [60] SalMatch [59] Mid-Filter [61] SCNCD [54] ImprovedDeep [1] PolyMap [9] XQDA [25] Semantic [44] MetricEmsemb. [37] QALF [63] CSL [42] MLAPG [26] MTL-LORAE [45] DCIA [13] DGD [51] LSSCDL [58] TPC [10] GOG [36] Null [56] SCSP [8] S-CNN [48] Shi <i>et al.</i> [43] <i>l</i> 1-graph [20] S-LSTM [49] SSDAL [46] TMA [34] SSM (Ours) ble 5. The comparison	CVPR201 CVPR201 ICCV201 CVPR201 CVPR201 CVPR201 CVPR201 CVPR201 CVPR201 CVPR201 ICCV201 ICCV201 ICCV201 ICCV201 ICCV201 CVPR20 CVPR201 CVPR20 CVPR201 CVPR201 CVPR201 CVPR201 CVPR2	3 24.18 3 26.74 3 30.16 4 29.11 4 37.80 5 34.81 5 34.81 5 34.81 5 34.81 5 34.80 5 40.00 5 41.60 5 45.90 5 30.17 5 30.17 5 30.17 5 30.17 5 30.17 5 30.17 5 30.17 5 30.17 5 30.17 5 30.17 5 30.17 5 30.17 5 30.17 5 34.80 6 40.73 6 42.30 6 47.80 6 47.80 6 47.80 6 41.50 6 42.40 6 43.50 6 48.	67.12 62.37 - 65.95 81.20 - 83.70 80.51 86.20 88.90 62.44 82.30 82.34 81.60 87.50 - 84.27 84.80 88.67 90.51 91.49 66.90 - 79.40 81.50 87.65 91.49 66.90 - 79.40 81.50 87.65	76.36 - 79.87 90.40 91.70 91.70 91.08 95.10 95.80 73.81 91.80 92.37 89.60 - 91.93 91.93 92.37 89.60 - - - - - - - - - - - - - - - - - - -	SCNCD Semantic CSL [5] XQDA [7 TMA [2] LSSCDL GOG [3] SSM (Ou Table 1. Th Method DeepR XQDA Improv LSSCI MLAP Shi et a Metricl Null [5 S-LST] S-CNN GOG [DGD [SSM (O Table 6. T	[7] EC [6] CV ICC ICC I] CV ECC [8] CV CV Irs) ne comparison ds eID [23] [25] vedDeep [1] DL [58] G [26] al. [43] Emsemb. [37] i6] M [49] V [48] 36] 51] Ours) The comparison QUERY A to iLc	Ref $CV2014$ PR2015 $CV2015$ PR2016 PR2016 PR2016 with state-or Labele r=1 r=5 20.7 54.7 88.3 57.0 58.0 61.3 62.1 89.1 62.5 90.0 - - 67.3 91.0 75.3 76.6 94.6 with state-of	r=1 41.60 44.90 44.40 61.38 52.89 60.49 68.40 72.98 of-the-ar d r=10 68.3 - 93.3 - - 94.3 94.3 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - - 94.3 94.8 - - 94.3 94.8 - - 94.3 94.8 - - 94.9 (r=10 79.40 77.50 82.20 91.02 85.78 88.58 94.50 96.76 rt on PRID4 Detecte r=1 r=5 19.9 49.0 46.3 - 45.0 75.7 51.2 - 51.2 - 51.2 - 51.2 - 52.0 - 54.7 84.7 57.3 80.1 61.8 80.9 65.5 88.4 - 72.7 92.4 on CUHK03 With	r=20 87.80 86.70 89.80 95.33 93.60 97.80 99.11 50S. 4 r=10 64.3 - 83.0 - - 94.8 88.3 88.3 93.7 - 96.1 dataset.
NIPeR, PRID450S and CUHKO	ald end by The default setup: the concatenation of LOMO and GOG under XQDA metric.	-1501 ery. F	Local Fisher [38] eSDC [60] SalMatch [59] Mid-Filter [61] SCNCD [54] ImprovedDeep [1] PolyMap [9] XQDA [25] Semantic [44] MetricEmsemb. [37] QALF [63] CSL [42] MLAPG [26] MTL-LORAE [45] DCIA [13] DGD [51] LSSCDL [58] TPC [10] GOG [36] Null [56] SCSP [8] S-CNN [48] Shi <i>et al.</i> [43] <i>l</i> 1-graph [20] S-LSTM [49] SSDAL [46] TMA [34] SSM (Ours) ble 5. The comparison	CVPR201 CVPR201 ICCV2013 CVPR201 CVPR201 CVPR201 CVPR201 CVPR201 CVPR201 CVPR201 ICCV2013 ICCV2013 ICCV2013 ICCV2013 ICCV2014 CVPR2	3 24.18 3 26.74 3 30.16 4 29.11 4 37.80 5 34.81 5 34.81 5 34.81 5 34.81 5 36.80 5 40.00 5 41.60 5 45.90 5 30.17 5 34.80 5 42.30 5 42.30 5 42.30 6 38.60 6 47.80 6 47.80 6 47.80 6 53.54 6 37.80 6 42.40 6 43.50 6 42.40 6 43.50 6 48.19 start of the-art of the start of the s	67.12 62.37 - 65.95 81.20 - 83.70 80.51 86.20 88.90 62.44 82.30 82.34 81.60 87.50 - 84.27 84.80 88.67 90.51 91.49 66.90 - 79.40 81.50 87.65 91.49 n VIPeR of 80 M	- 76.36 - 79.87 90.40 - 91.70 91.08 95.10 95.80 73.81 91.80 92.37 89.60 - - 91.93 91.10 94.53 95.92 96.65 - - - - - 89.00 93.54 96.08 lataset.	SCNCD Semantic CSL [5] XQDA [1 TMA [2] LSSCDL GOG [3] SSM (Ou Table 1. Th Method DeepR XQDA Improv LSSCI MLAP Shi et a Metricl Null [5 S-LSTI S-CNN GOG [DGD [SSM (0 Table 6. T	[7] EC [6] CV ICC ICC I] CV ECC [8] CV CV Irs) ne comparison ds eID [23] [25] vedDeep [1] DL [58] 'G [26] al. [43] Emsemb. [37] i6] M [49] V [48] 36] 51] Ours) The comparison QUEYY A etails.	Ref CV2014 PR2015 CV2015 PR2016 PR2016 PR2016 PR2016 with state-of $r=1$ $r=5$ 20.7 51.7 52.2 54.7 88.3 57.0 58.0 61.3 62.1 89.1 62.5 67.3 76.6 94.6	r=1 41.60 44.90 44.40 61.38 52.89 60.49 68.40 72.98 of-the-a d r=10 68.3 - 93.3 - - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - - 94.3 94.8 - - 94.3 94.8 - - 94.3 94.8 - - 94.3 94.8 - - 94.3 94.8 - - - 94.3 94.8 - - - - - - - - - - - - - - - - - - -	r=10 79.40 77.50 82.20 91.02 85.78 88.58 94.50 96.76 rt on PRID4 Detecte r=1 r=5 19.9 49.0 46.3 - 45.0 75.7 51.2 - 51.2 - 51.2 - 52.0 - 54.7 84.7 57.3 80.1 61.8 80.9 65.5 88.4 - 72.7 92.4 on CUHK03	r=20 87.80 86.70 89.80 95.33 93.60 97.80 99.11 50S. d r=10 64.3 - 83.0 - 94.8 88.3 88.3 93.7 - 96.1 dataset.
NIPeR, PRID450S and CUHKO	ald end b and The default setup: the concatenation of LOMO and GOG under XQDA metric.	-1501 Iery. F	Local Fisher [38] eSDC [60] SalMatch [59] Mid-Filter [61] SCNCD [54] ImprovedDeep [1] PolyMap [9] XQDA [25] Semantic [44] MetricEmsemb. [37] QALF [63] CSL [42] MLAPG [26] MTL-LORAE [45] DCIA [13] DGD [51] LSSCDL [58] TPC [10] GOG [36] Null [56] SCSP [8] S-CNN [48] Shi <i>et al.</i> [43] <i>ℓ</i> 1-graph [20] S-LSTM [49] SSDAL [46] TMA [34] SSM (Ours) ble 5. The comparison	CVPR201 CVPR201 ICCV2013 CVPR201 CVPR201 CVPR201 CVPR201 CVPR201 CVPR201 ICCV2013 ICCV2013 ICCV2013 ICCV2013 ICCV2014 CVPR	3 24.18 3 26.74 3 30.16 4 29.11 4 37.80 5 34.81 5 36.80 5 40.00 5 41.60 5 45.90 5 40.73 5 34.80 5 40.73 5 42.30 5 42.30 5 42.66 6 38.60 6 42.66 6 47.80 6 51.17 6 53.54 6 37.80 6 42.40 6 43.50 6 42.40 6 43.50 6 48.19 Starrage Ges.	67.12 62.37 - 65.95 81.20 - 83.70 80.51 86.20 88.90 62.44 82.30 82.34 81.60 87.50 - 84.27 84.80 88.67 90.51 91.49 66.90 - 79.40 81.50 87.65 91.49 n VIPeR of 80 W	- 76.36 - 79.87 90.40 - 91.70 91.70 91.08 95.10 95.80 73.81 91.80 92.37 89.60 - - 91.93 91.10 94.53 95.92 96.65 - - - - 89.00 93.54 96.08 Iataset.	SCNCD Semantic CSL [5] XQDA [1 TMA [2] LSSCDL GOG [3] SSM (Ou Table 1. Th Method DeepRi XQDA Improv LSSCI MLAP Shi et d Metricl Null [5 S-LSTI S-CNN GOG [DGD [SSM (0 Table 6. T	[7] EC [6] CV ICC ICC ICC ICC ICC ICC ICC I	Ref CV2014 PR2015 CV2015 PR2016 PR2016 PR2016 with state-or Labele r=1 r=5 20.7 51.7 52.2 54.7 88.3 57.0 58.0 61.3 62.1 89.1 62.5 90.0 - 67.3 91.0 75.3 76.6 94.6 with state-of	r=1 41.60 44.90 44.40 61.38 52.89 60.49 68.40 72.98 of-the-at d r=10 68.3 - 93.3 - - 93.3 - - 93.3 - - 94.3 - 94.8 - 94.3 - 94.8 - - 94.3 - 94.8 - - - 94.3 - 94.8 - - - - - 94.3 - 94.8 - - - - - - - - - - - - - - - - - - -	r=10 79.40 77.50 82.20 91.02 85.78 88.58 94.50 96.76 rt on PRID4 Detecte r=1 r=5 19.9 49.0 46.3 - 45.0 75.7 51.2 - 51.2 - 51.2 - 51.2 - 52.0 54.7 84.7 57.3 80.1 61.8 80.9 65.5 88.4 72.7 92.4 on CUHK03 With	r=20 87.80 86.70 89.80 95.33 93.60 97.80 99.11 50S. - - - 94.8 88.3 88.3 93.7 - 96.1 dataset.
NIPER, PRID450S and CUHKO	The default setup: the concatenation of LOMO and GOG under XQDA metric.	-1501 lery. f	Local Fisher [38] eSDC [60] SalMatch [59] Mid-Filter [61] SCNCD [54] ImprovedDeep [1] PolyMap [9] XQDA [25] Semantic [44] MetricEmsemb. [37] QALF [63] CSL [42] MLAPG [26] MTL-LORAE [45] DCIA [13] DGD [51] LSSCDL [58] TPC [10] GOG [36] Null [56] SCSP [8] S-CNN [48] Shi <i>et al.</i> [43] <i>ℓ</i> 1-graph [20] S-LSTM [49] SSDAL [46] TMA [34] SSM (Ours) ble 5. The comparison	CVPR201 CVPR201 ICCV2013 CVPR201 CVPR201 CVPR201 CVPR201 CVPR201 CVPR201 CVPR201 ICCV2013 ICCV2013 ICCV2013 ICCV2013 ICCV2014 CVPR2	3 24.18 3 26.74 3 30.16 4 29.11 4 37.80 5 34.81 5 36.80 5 40.00 5 41.60 5 45.90 5 40.73 5 34.80 5 40.73 5 42.30 5 42.30 5 42.30 6 38.60 6 47.80 6 47.80 6 47.80 6 51.17 6 53.54 6 37.80 6 40.91 6 42.40 6 43.50 6 43.50 6 48.19 7 53.73 6 53.73 6 53.73 6 43.50 6 43.50 6 43.50 6 53.73 6 53.	67.12 62.37 - 65.95 81.20 - 83.70 80.51 86.20 88.90 62.44 82.30 82.34 81.60 87.50 - 84.27 84.80 88.67 90.51 91.49 66.90 - 79.40 81.50 87.65 91.49 n VIPeR of 80 M aper	- 76.36 - 79.87 90.40 - 91.70 91.70 91.08 95.10 95.80 73.81 91.80 92.37 89.60 - - 91.93 91.10 94.53 95.92 96.65 - - - - 89.00 93.54 - - - 89.00 93.54 - - - - - - 89.00 93.54 -	SCNCD Semantic CSL [5] XQDA [1 TMA [2] LSSCDL GOG [3] SSM (Ou Table 1. Th Method DeepRi XQDA Improv LSSCI MLAP Shi et d Metricl Null [5 S-LSTI S-CNN GOG [DGD [SSM (0 Table 6. T	[7] EC [6] CV ICC ICC ICC ICC ICC ICC ICC I	Ref CV2014 PR2015 CV2015 PR2016 PR2016 PR2016 with state-or Labele r=1 r=5 20.7 51.7 52.2 54.7 88.3 57.0 61.3 62.1 89.1 62.5 90.0 - 67.3 91.0 75.3 76.6 94.6 with state-of md 76.6 94.6 with state-of	r=1 41.60 44.90 44.40 61.38 52.89 60.49 68.40 72.98 of-the-ar d r=10 68.3 - 93.3 - 93.3 - 94.3 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - 94.3 94.8 - - 94.3 94.8 - - 94.3 94.8 - - 94.3 94.8 - - 94.3 94.8 - - 94.3 94.8 - - 94.3 94.8 - - 94.3 94.8 - - 94.9 94	r=10 79.40 77.50 82.20 91.02 85.78 88.58 94.50 96.76 rt on PRID4 Detecte r=1 r=5 19.9 49.0 46.3 - 45.0 75.7 51.2 - 51.2 - 51.2 - 52.0 - 54.7 84.7 57.3 80.1 61.8 80.9 65.5 88.4 - 72.7 92.4 on CUHK03 With On-lin #M	r=20 87.80 86.70 89.80 95.33 93.60 97.80 99.11 50S. 99.11 50S. 99.11 64.3 - 83.0 - 94.8 88.3 93.7 - 96.1 dataset. e

increased especially on larger datasets. In on-line stage, the extra indexing time brought by SSM only occupies a small percentage on all the datasets.

Dotocets	Off-	line	On-line				
Datasets	#M	#M #A		#A			
GRID	0.90s	+2.38s	0.17s	+10.3 <i>ms</i>			
VIPeR	2.19 <i>s</i>	+2.22s	0.19 <i>s</i>	+10.2ms			
PRID450S	1.21s	+0.78s	0.12s	+3.80 <i>ms</i>			
CUHK03	789.6s	+1952s	0.09s	+0.516s			
Market1501	-	+2769s	146.11 <i>s</i>	+21.68s			
Table 8. #M denotes the initial time cost of metric learning using							

XQDA. #A denotes the extra cost brought by the proposed SSM.

Conclusions

In this paper, we do not design robust features or metrics that are superior to others in person re-identification. Instead, we contribute a generic tool called Supervised Smoothed Manifold (SSM), upon which most existing algorithms can easily boost their performances further. SSM is very easy to implement. It can also handle the special kind of labeled data and has potential capacity in large scale ReID. Comprehensive experiments on five benchmarks demonstrate that SSM not only achieves the best performances, but more importantly, incurs acceptable extra on-line cost. In the furture, we will investigate how to effectively fuse multiple features and apply the proposed SSM to other datasets.

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