Person Re-identification by Unsupervised L_1 Graph Learning

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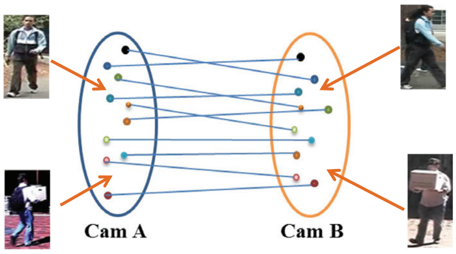
• Existing Supervised Re-ID Approaches

Most are based on supervised learning [1,2]

- ❖ They require large number of labelled images across camera views
  - ▪ Label intensive and unsalable
  - ▪ May not even be possible under an open-world setting



• Our Unsupervised Re-ID Approach

- ❖ Learning cross-view discriminative features from unlabeled data
- ❖ No human annotation required, thus much more scalable

• Contributions

- ❖ We formulate a novel **graph regularised dictionary learning model** for Re-ID with a new robust L_1- norm graph regularisation term and joint graph and dictionary learning.
- ❖ We develop an efficient iterative optimisation algorithm for non-smooth and non-convex objective function of our model.

• Method

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- ❖ Robust L_1- norm graph regularisation term:

$$\Omega(\mathbf{Y}) = \sum_{ij}^{N} \|\mathbf{y}_i - \mathbf{y}_j\|_2^2 \mathbf{W}_{ij} \Rightarrow \|\mathbf{Y}\mathbf{A}_{\mathbf{W}}\|_1$$

- ❖ Full model: Learn dictionary ($\mathbf{D}$) & graph ($\mathbf{W}$):

$$\min_{\mathbf{D},\mathbf{W},\mathbf{Y}} \frac{1}{2}\|\mathbf{X} - \mathbf{D}\mathbf{Y}\|_F^2 + \lambda_1 \|\mathbf{Y}\mathbf{A}_{\mathbf{W}}\|_1 + \lambda_2 \|\mathbf{W}\|_F^2$$

$$\text{s.t.} \quad \|\mathbf{d}_i\|_2^2 \leq 1, \underbrace{\mathbf{W}_i^T 1 = 1, \mathbf{W}_i \geq 0.}_{\text{Validity of graph}}$$

- ❖ Optimisation – we develop a solver based on the ADMM algorithm [3].

2

- ❖ Cross-view matching:
  - ❖ After learning $\mathbf{D}$, given a pair of samples $\mathbf{x}_i^a$ and $\mathbf{x}_i^b$, we first compute their collaborative representations $\mathbf{y}_i^a$ and $\mathbf{y}_i^b$

$$\mathbf{y}_i^{a*} = \arg\min \|\mathbf{x}_i^a - \mathbf{D}\mathbf{y}_i^a\|_2^2 + \lambda \|\mathbf{y}_i^a\|_2^2$$

$$\mathbf{y}_i^{b*} = \arg\min \|\mathbf{x}_i^b - \mathbf{D}\mathbf{y}_i^b\|_2^2 + \lambda \|\mathbf{y}_i^b\|_2^2$$

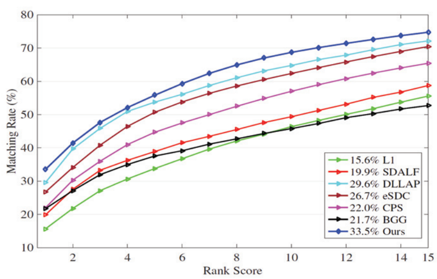
  - ❖ Cosine distance is then used to measure visual similarity.
- ❖ Extension to supervised re-id:
  - ❖ If cross-view pair (i, j) is labelled , $\mathbf{W}_{ij}$ is set to **1** or **0**

• Results

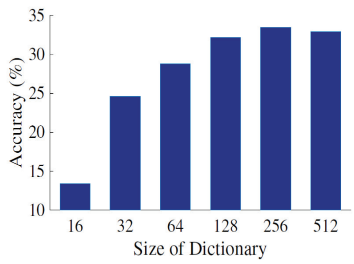
Unsupervised Re-ID results measured at Rank-1

Datasets	VIPeR	PRID	CUHK01	CUHK03
L1	15.6	13.9	10.9	12.5
SDALF	19.9	16.3	9.9	4.9
DLLAP	29.6	21.1	28.4	22.3
eSDC	26.7	-	26.6	7.7
CPS	22.0	-	-	-
GTS	25.2	-	-	-
BGG	21.7	-	-	18.9
Ours	**33.5**	**25.0**	**41.0**	**30.4**

VIPeR: CMC curve



Effect of dictionary size

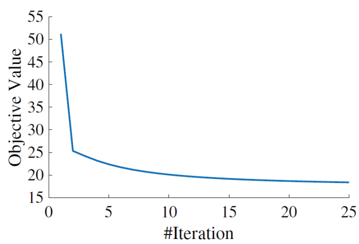


Supervised Re-ID results measured at Rank-1

Datasets	VIPeR		PRID		CUHK01		CUHK03	
	Method	R@1	Method	R@1	Method	R@1	Method	R@1
Single-feature Methods	XQDA	40.0	KCCA	14.5	LMF	34.3	XQDA	46.4
	DEEP	34.8	kLFDA	19.7	DEEP	47.5	DEEP	44.9
	MLAPG	40.7	DLLAP	25.2	Deepreid	29.4	MLAPG	51.2
	EPKF	36.1	MDML	16.0	Deepreid	27.8	Deepreid	19.9
	CDEEP	40.9	MTLR	18.0	XQDA	63.5	CDEEP	52.1
	QLF	30.2	MLAPG	12.3	MLAPG	64.2	MBCNN	59.2
Ours_un	33.5		25.0		41.0		30.4	
Ours_sup	41.5		30.1		50.1		39.0	

VIPeR: Before/after learning graph

Objective function



• References

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Acknowledgments
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