Learning a Discriminative Null Space for Person Re-identification

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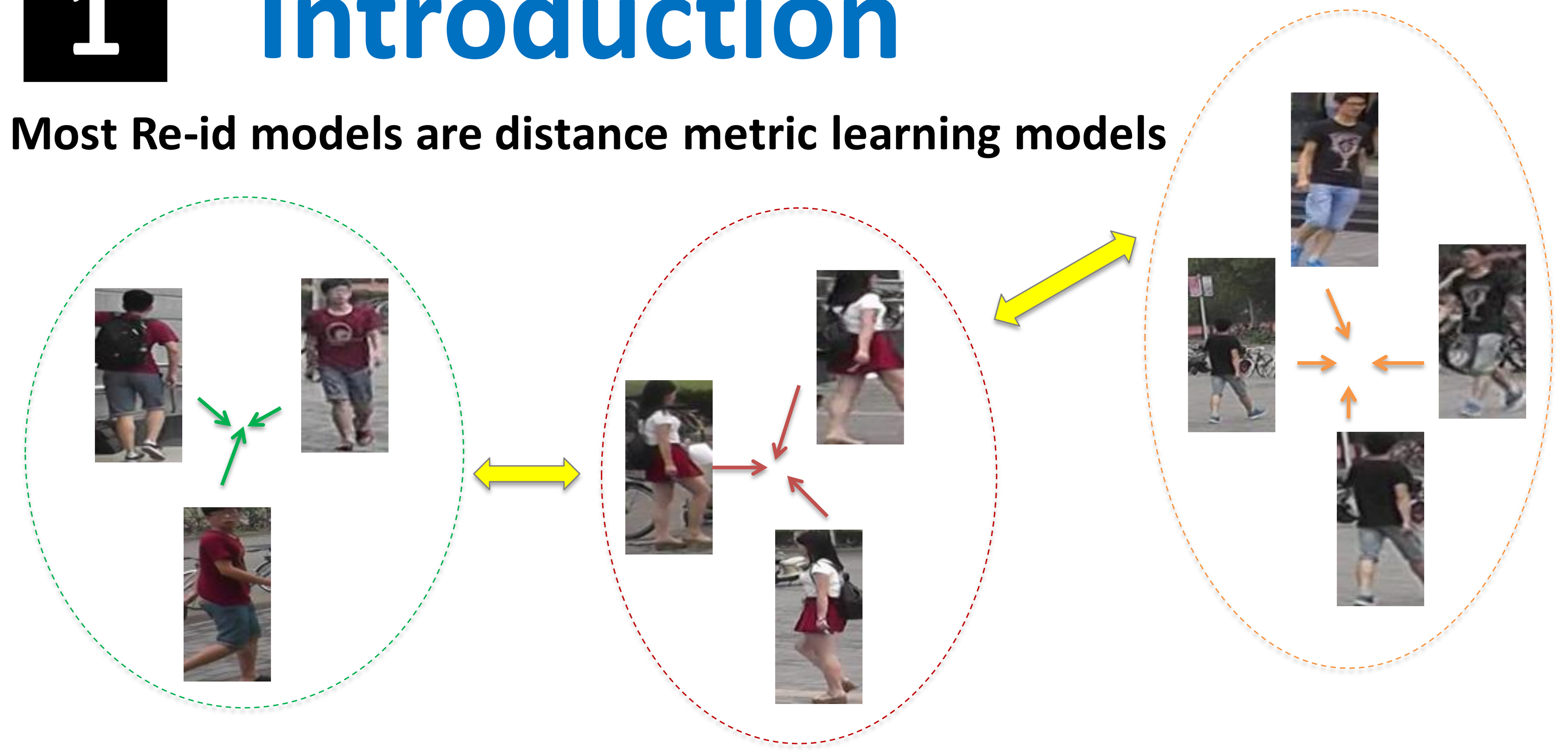
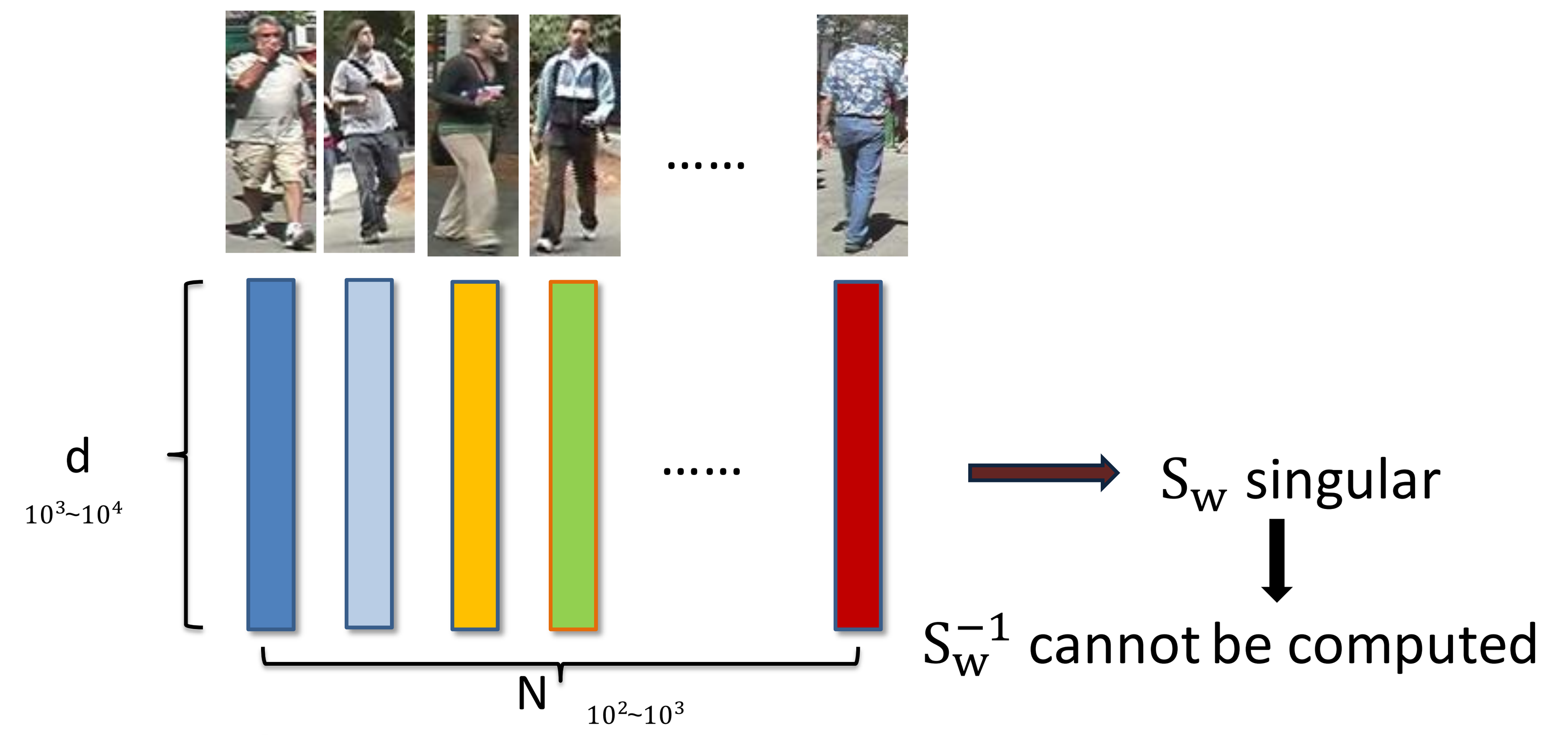
1 Introduction

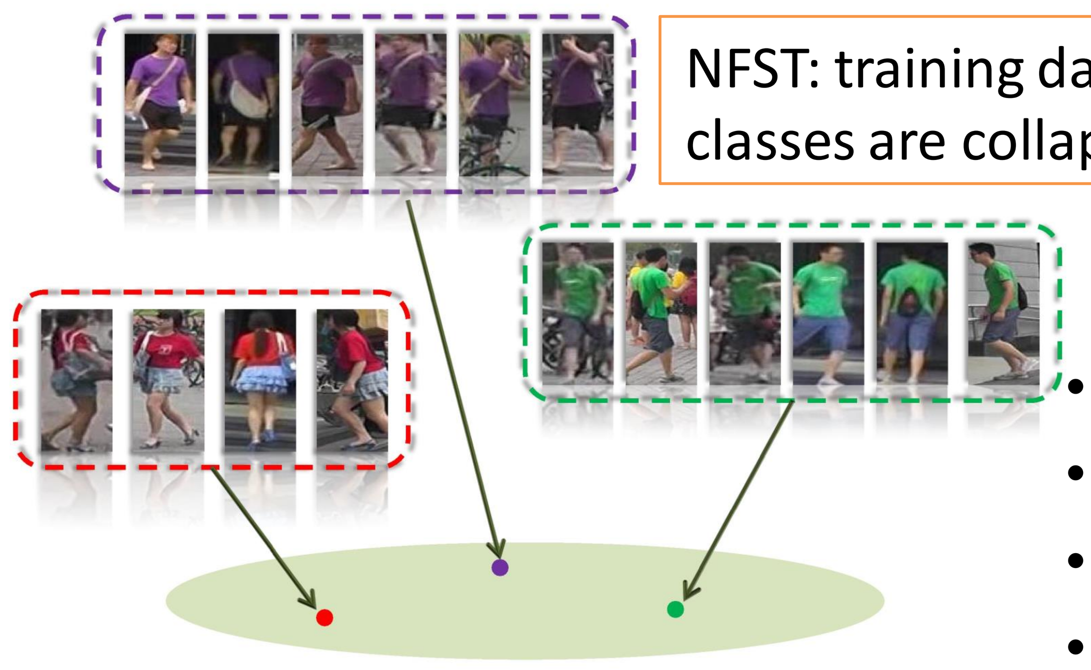
Most Re-id models are distance metric learning models



They suffer from the Small Sample Size (SSS) problem: High feature dimension and sparse training samples



Our approach:



NFST: training data points of each classes are collapsed to a single point

- Fixed dimension
- No parameter
- No pre-processing
- Closed-form solution

2 Methodology

Foley-Sammon Transform

- Objective function of FST

$$J(w) = \frac{w^T S_b w}{w^T S_w w}$$

- Solving the generalised eigen-problem

$$S_b w = \lambda S_w w$$

Null Foley-Sammon Transform

$$w^T S_w w = 0$$

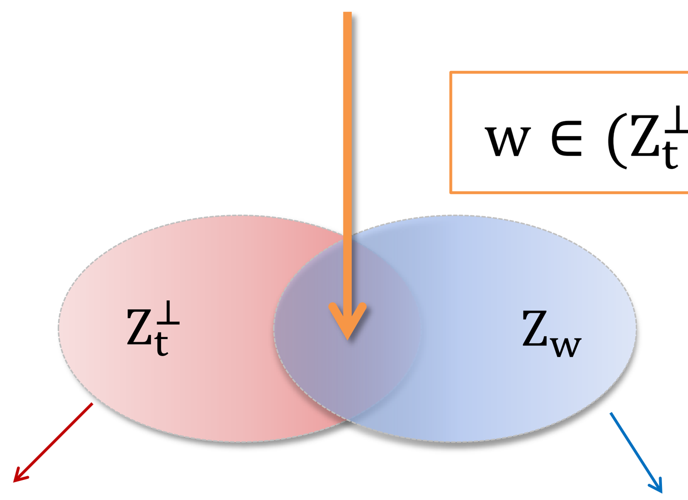
$$w^T S_b w > 0$$

•$w^T S_t w > 0$, where $S_t = S_b + S_w$;
•w called Null Projection Direction (NPD).

We denote the null space of the S_t and S_w as:

$$Z_t = \{z \in R^d \mid S_t z = 0\}$$
$$Z_w = \{z \in R^d \mid S_w z = 0\}$$

$$w \in (Z_t^\perp \cap Z_w)$$



$Z_t^\perp$ is the subspace by zero-mean data. We can obtain the orthonormal basis U of the zero-mean data:

$$w = \beta_1 u^{(1)} + \cdots + \beta_{N-1} u^{(N-1)} = U\beta$$

$$w^T S_w w = 0$$

$$(U^T S_w U)\beta = 0 \rightarrow \beta^{(1)} \ldots \beta^{(C-1)}$$

Kernelisation

$$S_w \rightarrow K_w = K(I-L)(I-L)^T K$$
$$U \rightarrow K_t = K(I-M)(I-M)^T K$$

Eigen-decomposition: $K_t = VEV^T, \hat{V} = VE^{-1/2}$

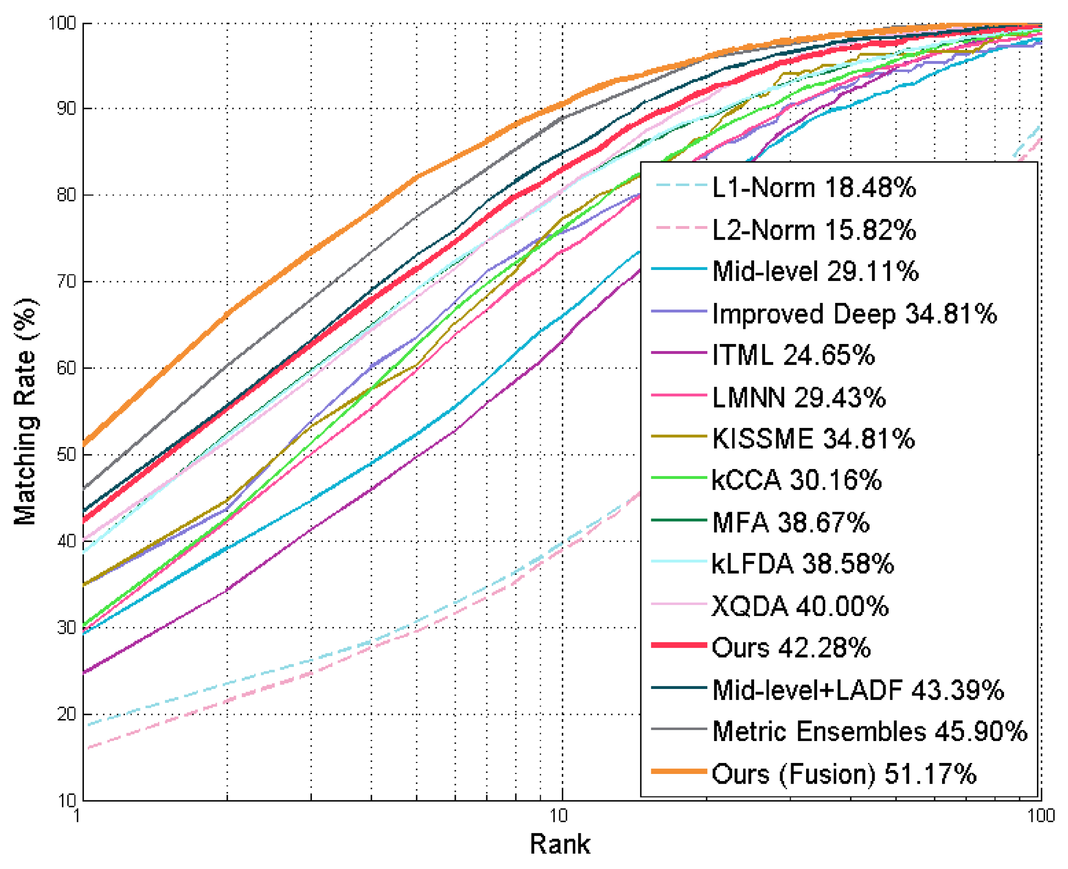
Let $H = \left((I-M)\hat{V}\right)^T K(I-L)$

Final eigen-problem: $HH^T\beta = 0$

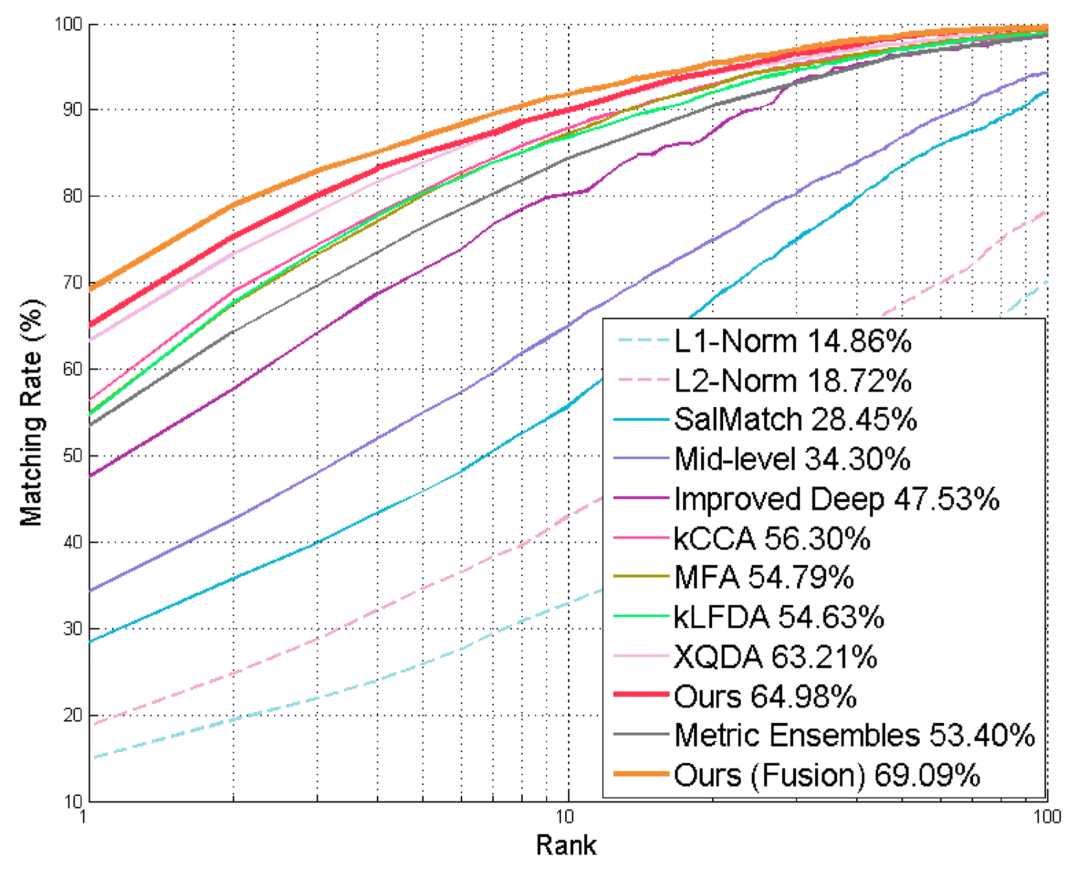
Null projection direction: $w^{(i)} = \left((I-M)\hat{V}\right)^T \beta^{(i)} \quad \forall i = 1, \ldots, C-1$

3 Experiments

Results on VIPeR



Results on CUHK01



Results on PRID2011

Rank	1	5	10	20
RPLM	15.00	32.00	42.00	54.00
kCCA (LOMO)	14.30	37.40	47.60	62.50
MFA (LOMO)	22.30	45.60	57.20	68.20
kLFDA (LOMO)	22.40	46.50	58.10	68.60
XQDA (LOMO)	26.70	49.90	61.90	73.80
Ours (LOMO)	**29.80**	**52.90**	**66.00**	**76.50**
Metric Ensembles	17.90	39.00	50.00	62.00
Ours (Fusion)	**40.90**	**64.70**	**73.20**	**81.00**

Results on CUHK03

Dataset	CUHK03 (Manual)				CUHK03 (Detected)			
Rank	1	5	10	20	1	5	10	20
DeepReID	20.65	51.50	66.50	80.00	19.89	50.00	64.00	78.50
Improved Deep	54.74	**86.50**	**93.88**	**98.10**	44.96	76.01	83.47	93.15
XQDA (LOMO)	52.20	82.23	92.14	96.25	46.25	78.90	88.55	94.25
Ours (LOMO)	**58.90**	85.60	92.45	96.30	**53.70**	**83.05**	**93.00**	**94.80**
Metric Ensembles	62.10	89.10	94.30	97.80	-	-	-	-
Ours (Fusion)	**62.55**	**90.05**	**94.80**	**98.10**	**54.70**	**84.75**	**94.80**	**95.20**

Results on Market1501

Query	singleQ		multiQ	
Evaluation metrics	Rank-1	mAP	Rank-1	mAP
Baseline	34.38	14.10	42.64	19.47
Baseline (+HS)	-	-	47.25	21.88
KISSME (LOMO)	40.50	19.02	-	-
MFA (LOMO)	45.67	18.24	-	-
kLFDA (LOMO)	51.37	24.43	52.67	27.36
XQDA (LOMO)	43.79	22.22	54.13	28.41
Ours (LOMO)	**55.43**	**29.87**	**67.96**	**41.89**
Ours (Fusion)	**61.02**	**35.68**	**71.56**	**46.03**

Runtime on Market (in seconds)

Method	Ours	XQDA	kLFDA	MFA
Training	393.1	3233.8	995.2	437.8
Testing	31.3	1.6	43.4	43.2

Code available!

Acknowledgments

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