Coupled Analysis-Synthesis Dictionary Learning For Person Re-Identification

Lingchuan Sun, Yun Zhou, Zhuqing Jiang, Aidong Men

Email： sunlingchuan@bupt.edu.cn

School of Information and Communications Beijing University of Posts and Telecommunications
Beijing, P.R. China

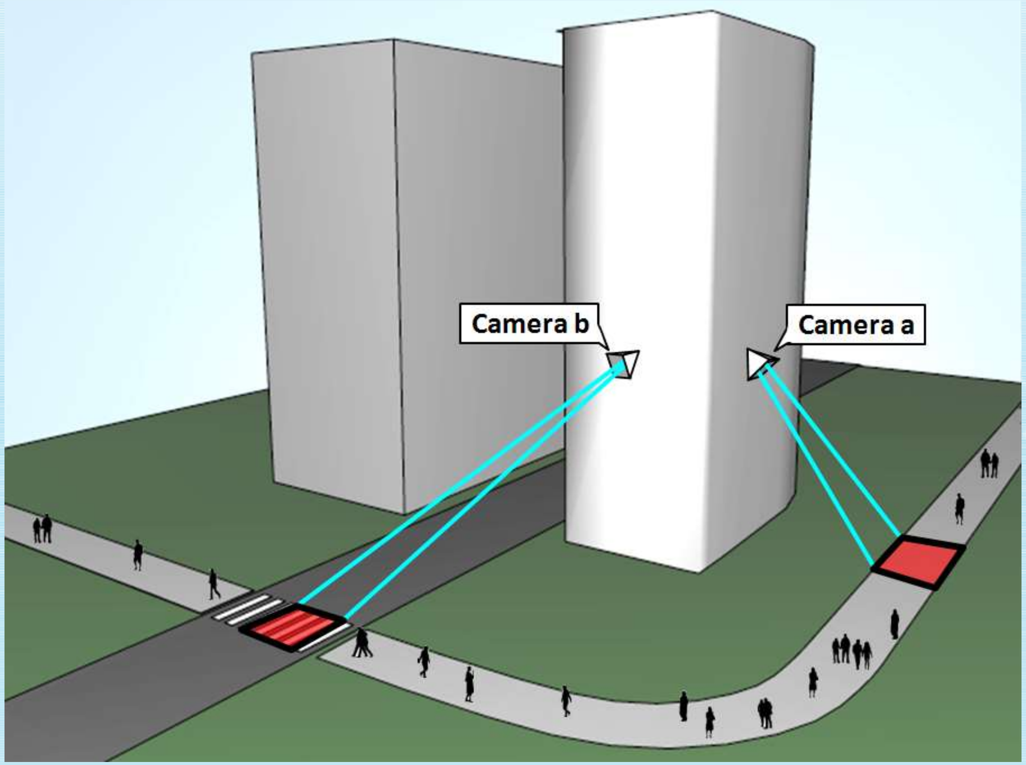
1 **Person Re-Identification Overview**

2 Proposed Method

3 Experiments & Results

1 Person re-identification(re-id) Overview

- Person re-id is the task of matching specific person across non-overlapping camera views.



1 Person re-id Overview

- **Person re-id remains a challenging problem due to a variety of factors:**
- ◆1.Viewpoint Variation
- ◆ 2.Illumination Change
- ◆ 3.Occlusion
- ◆ 4.Pose Variation
- ◆ 5.Similar Dressing Style
- ◆ 6.Low Resolution

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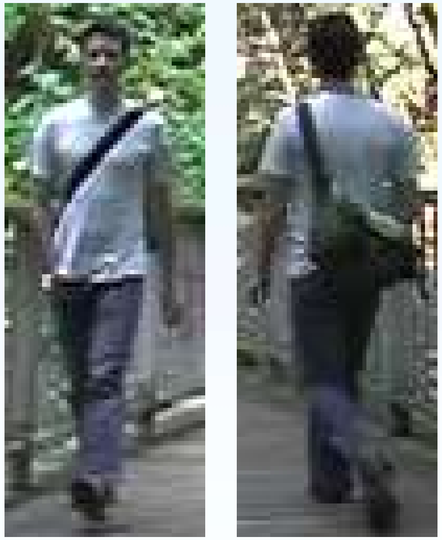

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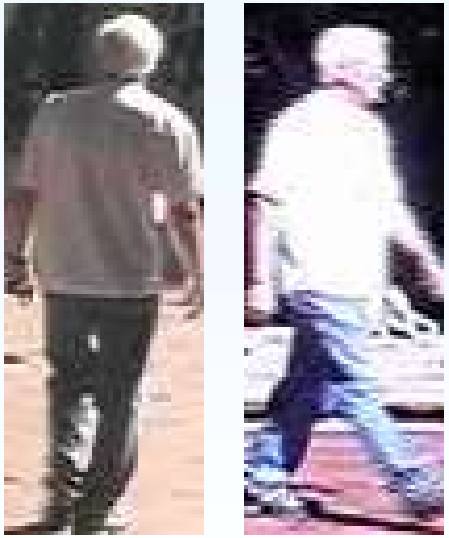

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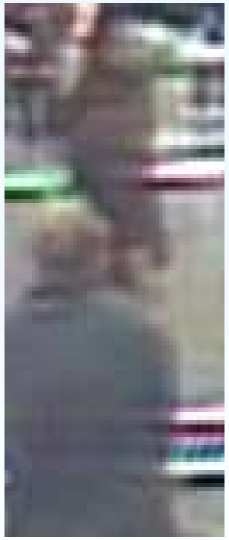

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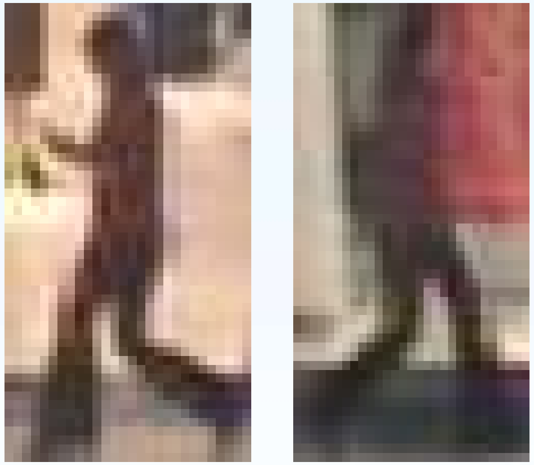


1 Person re-id Overview

- Most of researchers for addressing this challenge mainly focus on following aspects:
  - Feature representation
  - Distance metric learning
  - Deep learning
  - Dictionary learning

1 Person re-id Overview

This paper focus on learning discriminative and robust coupled dictionary , aiming to address the cross-view problem of person re-id.

Contributions:

Step1

- We propose a coupled analysis-synthesis dictionary learning model.

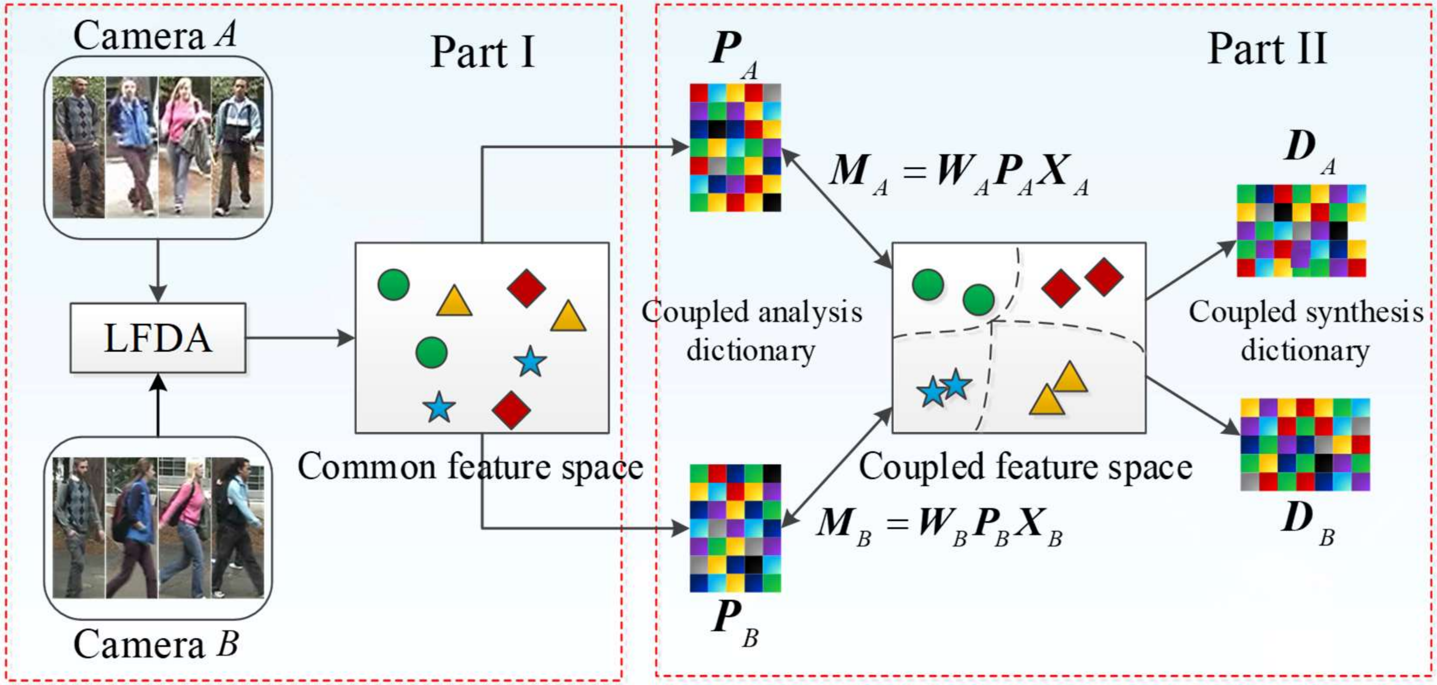
step2

- To improve the representation ability of the coupled synthesis dictionary, we construct an associate function with coupled analysis dictionary.

1. Person Re-Identification Overview
2. **Proposed Method**
3. Experiments & Results

2 Proposed Method

- **System Overview**



LFDA : local Fisher discriminant analysis
P_A, P_B : analysis dictionary
D_A, D_B : synthesis dictionary
X_A, X_B : training data

2 Proposed Method

- **Coupled Analysis-Synthesis Dictionary Learning**

The coupled analysis-synthesis dictionary learning on the common feature space can be formulated under the following framework:

$$\min_{D_A, D_B, P_A, P_B} \|X_A - D_A P_A X_A\|_F^2 + \|X_B - D_B P_B X_B\|_F^2 + \Psi(P_A, P_B) \quad \text{Eq.1}$$
$$s.t. \quad \|d_{A,i}\|_2 \le 1, \|d_{B,i}\| \le 1, \forall i$$

Where $d_{A,i}$ and $d_{B,i}$: *i-th* atoms of D_A and D_B .

$\Psi(P_A, P_B)$: associate function.

The coding coefficient matrix can be analytically obtained as:

$$\boxed{\begin{aligned} Z_A &= P_A X_A \\ X_A &= D_A Z_A \end{aligned}} \qquad \boxed{\begin{aligned} Z_B &= P_B X_B \\ X_B &= D_B Z_B \end{aligned}}$$

2 Proposed Method

Original coupled dictionary learning assumption:

There exists a latent coupled feature space where the coding coefficients of the same object should be strictly equal.

However, this assumption is too strong to handle various changes of image structures from different views.

2 Proposed Method

In this paper, we relax this assumption. We introduced a mapping transform W_A and W_B, and consider the following minimization problem:

$$\begin{aligned} \min \left\| M_A - M_B \right\|_F^2 &= \min \left\| W_A Z_A - W_B Z_B \right\|_F^2 \\ &= \min \left\| W_A P_A X_A - W_B P_B X_B \right\|_F^2 \end{aligned} \qquad \text{Eq.2}$$

To avoid the trivial solution and be more precise, we can derive as: for a same person m:

Camera A

$$m_A = W_A P_A x_A^i \rightarrow P_A x_A^i = W_A^{-1} m_A \rightarrow P_A x_A^i = W_A^{-1} m_B$$

$$\boxed{m_A = m_B} \qquad \text{Eq.3}$$

Camera B

$$m_B = W_B P_B x_B^i \rightarrow P_B x_B^i = W_B^{-1} m_B \rightarrow P_B x_B^i = W_B^{-1} m_A$$

Finally, the **associate function**:

$$\Psi(P_A, P_B) = \left\| P_A X_A - W_A^{-1} M_B \right\|_F^2 + \left\| P_B X_B - W_B^{-1} M_A \right\|_F^2 \qquad \text{Eq.4}$$

2 Proposed Method

The objective function of coupled analysis-synthesis dictionary learning is formulated below:

$$\min_{\substack{D_A, D_B, P_A, P_B, \\ W_A, W_B}} \|X_A - D_A P_A X_A\|_F^2 + \|X_B - D_B P_B X_B\|_F^2 + \lambda_1 \left(\|P_A X_A - W_A^{-1} M_B\|_F^2 + \|P_B X_B - W_B^{-1} M_A\|_F^2 \right)$$

$$+\lambda_2 \left(\|W_A^{-1}\|_F^2 + \|W_B^{-1}\|_F^2 \right) \qquad s.t. \quad \|d_{A,i}\|_2 \le 1, \|d_{B,i}\| \le 1, \forall i$$

Eq.5

2 Proposed Method

- **Matching**

Given the gallery set from camera A and the probe set from camera B , the representation coefficients of the j-th gallery image $p_{A,j}$ and the k-th probe image $p_{B,k}$ are computed with the learned coupled synthesis dictionary as follows:

$$\begin{aligned} \alpha_{A,j} &= \arg\min_{\alpha_{A,j}} \left\| p_{A,j} - D_A \alpha_{A,j} \right\|_F^2 + \mu \left\| \alpha_{A,j} \right\|_1^2 \\ \alpha_{B,k} &= \arg\min_{\alpha_{B,k}} \left\| p_{B,k} - D_B \alpha_{B,k} \right\|_F^2 + \mu \left\| \alpha_{B,k} \right\|_1^2 \end{aligned} \qquad \text{Eq.6}$$

The cosine similarity is employed to compute similarity score between the representation coefficients.

1 Person Re-Identification Overview

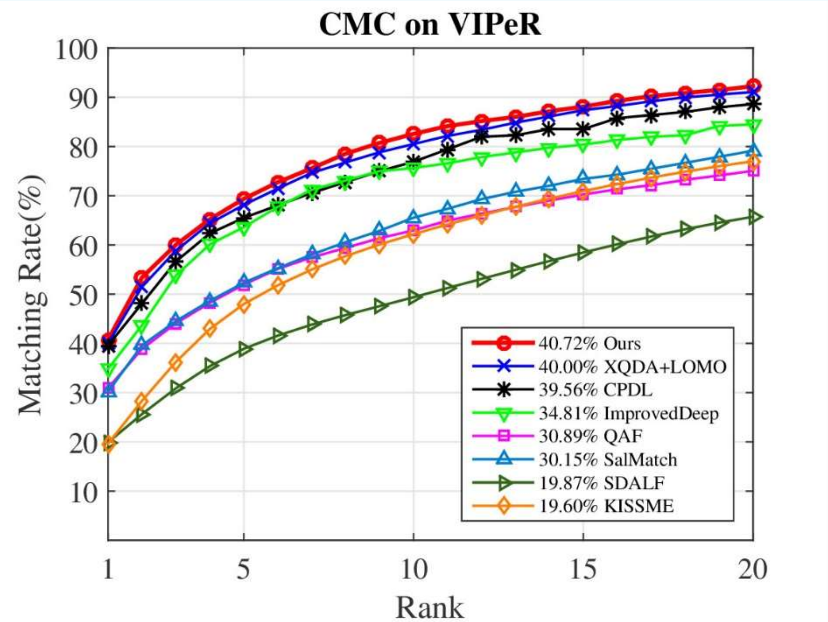
2 Proposed Method

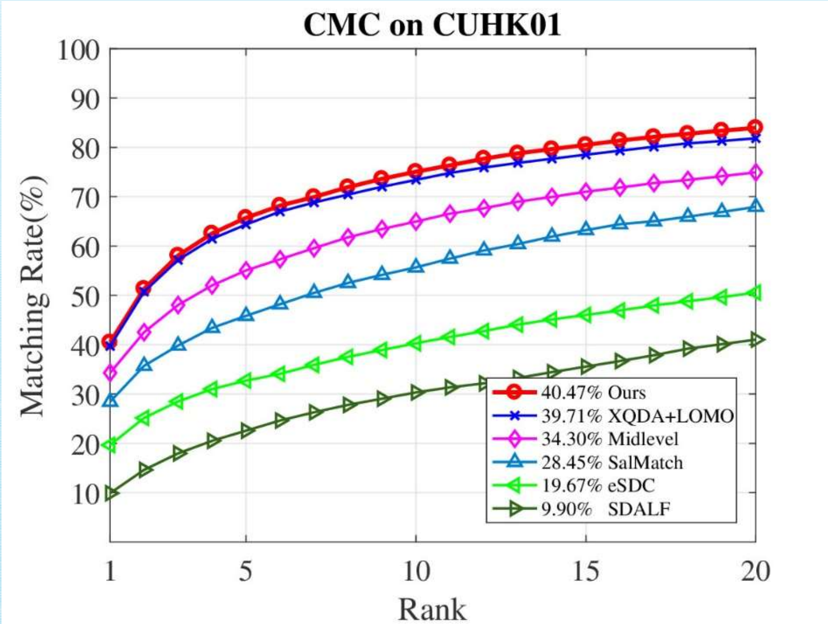
3 **Experiments & Results**

3 Experiments & Results

- Evaluating the proposed method on **VIPeR** and **CUHK01**datasets.
- Cumulative Matching Characteristic(CMC) curves are used to evaluate the performance of the proposed method.
- Local Maximal Occurrence (LOMO) feature is used to our paper.

3 Experiments & Results





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Experiments & Results

Table 1: Top ranked matching rate in (%) on VIPeR

Method	VIPeR(p=316)			
	r=1	r=5	r=10	r=20
KISSME	19.60	48.00	62.20	77.00
SDALF	19.87	38.89	49.37	65.73
SalMatch	30.16	52.31	65.54	79.15
QAF	30.89	51.95	62.96	75.05
ImprovedDeep	34.81	63.61	75.63	84.49
CPDL	39.56	65.51	76.90	88.61
XQDA+LOMO	40.00	68.13	80.51	91.08
Ours	**40.73**	**69.37**	**82.56**	**92.25**

Table 2: Top ranked matching rate in (%) on CUHK01

Method	CUHK01(p=486)			
	r=1	r=5	r=10	r=20
SDALF	9.90	22.57	30.33	41.03
eSDC	19.67	32.72	40.29	50.58
SalMatch	28.45	45.85	55.68	67.95
Midlevel	34.30	55.06	64.96	74.94
XQDA+LOMO	39.71	64.36	73.42	81.83
Ours	**40.47**	**65.72**	**75.06**	**83.95**

- **Conclusion**
  - We propose a coupled analysis-synthesis dictionary learning method.
  - An efficient iterative algorithm is developed for solving the optimization.
  - Experimental results on two public person re-identification datasets demonstrate the effectiveness of the proposed method.

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Thank You !