Person Re-Identification Overview

Proposed Method

Experiments & Results
Person re-identification (re-id) Overview

- Person re-id is the task of matching specific person across non-overlapping camera views.
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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Most of researchers for addressing this challenge mainly focus on following aspects:
- Feature representation
- Distance metric learning
- Deep learning
- Dictionary learning
This paper focuses on learning discriminative and robust coupled dictionary, aiming to address the cross-view problem of person re-id.

Contributions:

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

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

\[
\min_{D_A, D_B, P_A, P_B} \|X_A - D_A P_A X_A\|_F^2 + \|X_B - D_B P_B X_B\|_F^2 + \Psi(P_A, P_B) \tag{Eq. 1}
\]

s.t. \(d_{A,i}, d_{B,i} \leq 1, \forall i\)

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:

\[
Z_A = P_A X_A \\
X_A = D_A Z_A \\
Z_B = P_B X_B \\
X_B = D_B Z_B
\]
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.
In this paper, we relax this assumption. We introduced a mapping transform $W_A$ and $W_B$, and consider the following minimization problem:

$$\min \|M_A - M_B\|_F^2 = \min \|W_A Z_A - W_B Z_B\|_F^2$$

$$= \min \|W_A P_A X_A - W_B P_B X_B\|_F^2$$

Eq. 2

To avoid the trivial solution and be more precise, we can derive as:

for a same person $m$:

Camera A

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

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:

$$\Psi(P_A, P_B) = \|P_A X_A - W_A^{-1} M_B\|_F^2 + \|P_B X_B - W_B^{-1} M_A\|_F^2$$

Eq. 4
Proposed Method

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

\[
\min_{D_A, D_B, P_A, P_B, W_A, W_B} \left\| X_A - D_A P_A X_A \right\|_F^2 + \left\| X_B - D_B P_B X_B \right\|_F^2 + \lambda_1 \left( \left\| P_A X_A - W_A^{-1} M_B \right\|_F^2 + \left\| P_B X_B - W_B^{-1} M_A \right\|_F^2 \right) \\
+ \lambda_2 \left( \left\| W_A^{-1} \right\|_F^2 + \left\| W_B^{-1} \right\|_F^2 \right) \quad \text{s.t.} \quad \left\| d_{A,i} \right\|_2 \leq 1, \left\| d_{B,i} \right\| \leq 1, \forall i
\]

Eq.5
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:

$$
\alpha_{A,j} = \arg \min_{\alpha_{A,j}} \left\| p_{A,j} - D_A \alpha_{A,j} \right\|_F^2 + \mu \left\| \alpha_{A,j} \right\|_1
$$

$$
\alpha_{B,k} = \arg \min_{\alpha_{B,k}} \left\| p_{B,k} - D_B \alpha_{B,k} \right\|_F^2 + \mu \left\| \alpha_{B,k} \right\|_1
$$

Eq.6

The cosine similarity is employed to compute similarity score between the representation coefficients.
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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 in our paper.
Experiments & Results

CMC on VIPeR

CMC on CUHK01
# Experiments & Results

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

<table>
<thead>
<tr>
<th>Method</th>
<th>VIPeR(p=316)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>r=1</td>
<td>r=5</td>
</tr>
<tr>
<td>KISSME</td>
<td>19.60</td>
<td>48.00</td>
</tr>
<tr>
<td>SDALF</td>
<td>19.87</td>
<td>38.89</td>
</tr>
<tr>
<td>SalMatch</td>
<td>30.16</td>
<td>52.31</td>
</tr>
<tr>
<td>QAF</td>
<td>30.89</td>
<td>51.95</td>
</tr>
<tr>
<td>ImprovedDeep</td>
<td>34.81</td>
<td>63.61</td>
</tr>
<tr>
<td>CPDL</td>
<td>39.56</td>
<td>65.51</td>
</tr>
<tr>
<td>XQDA+LOMO</td>
<td>40.00</td>
<td>68.13</td>
</tr>
<tr>
<td>Ours</td>
<td>40.73</td>
<td>69.37</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Method</th>
<th>CUHK01(p=486)</th>
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</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>r=1</td>
<td>r=5</td>
</tr>
<tr>
<td>SDALF</td>
<td>9.90</td>
<td>22.57</td>
</tr>
<tr>
<td>eSDC</td>
<td>19.67</td>
<td>32.72</td>
</tr>
<tr>
<td>SalMatch</td>
<td>28.45</td>
<td>45.85</td>
</tr>
<tr>
<td>Midlevel</td>
<td>34.30</td>
<td>55.06</td>
</tr>
<tr>
<td>XQDA+LOMO</td>
<td>39.71</td>
<td>64.36</td>
</tr>
<tr>
<td>Ours</td>
<td>40.47</td>
<td>65.72</td>
</tr>
</tbody>
</table>
Conclusions

- 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.
Thank You!