Person Re-identification by Salience Matching

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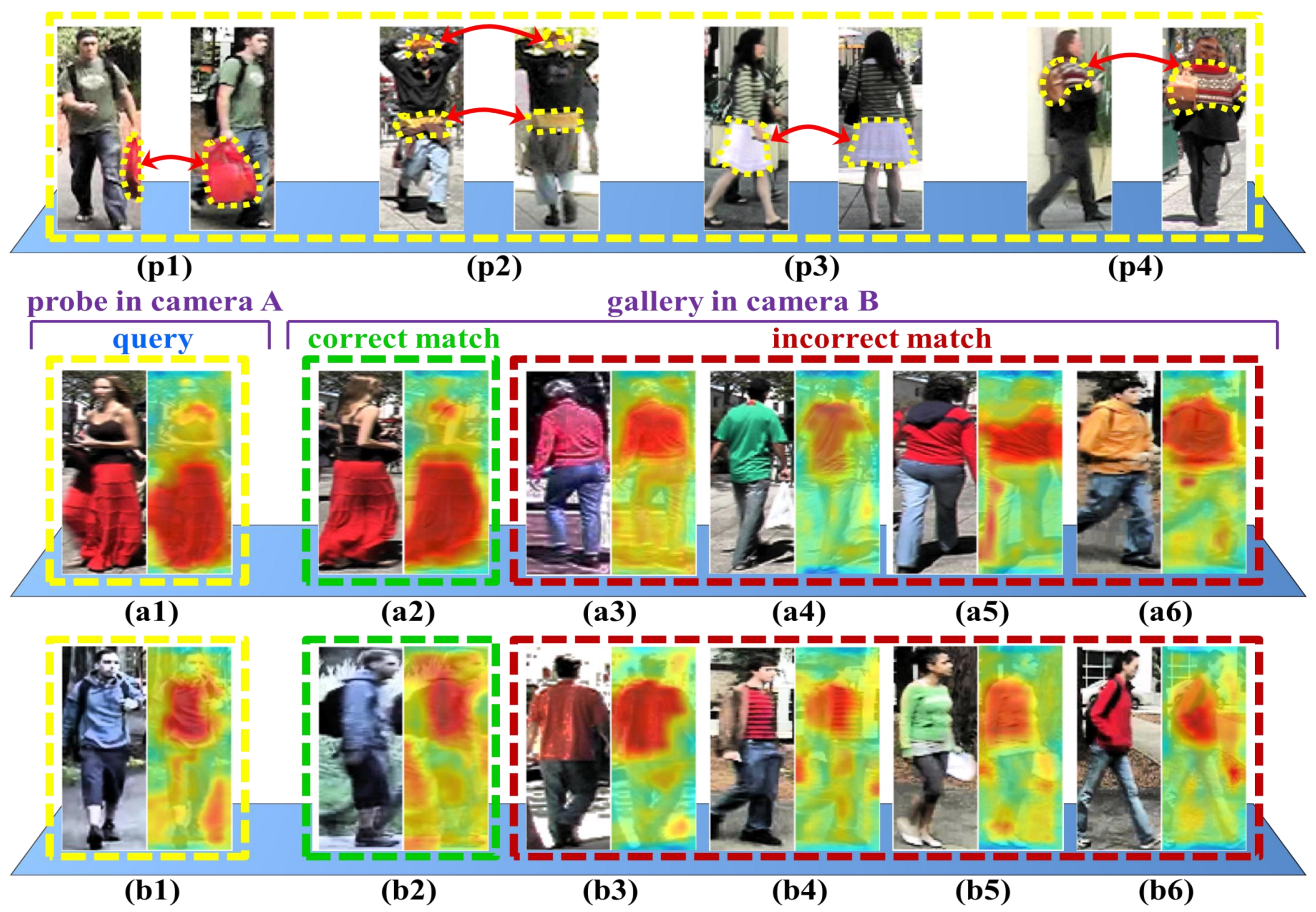


Motivation

- Misalignment is caused by variations of viewpoints and poses, which commonly exist in person re-identification.
- Some local patches are more distinctive and reliable when matching two persons.
- Images of the same person captured from different camera views have some invariance property on their spatial distribution on salience.

Contribution

- A probabilistic distribution of salience is reliably estimated with our approach.
- We formulate person re-identification as a salience matching problem.
- Salience matching and patch matching are tightly integrated into a unified structural RankSVM learning framework.

Unsupervised Human Salience Learning

Algorithm 1 Compute human salience.

Input: image $\mathbf{x}^{A,u}$ and a reference image set $\mathcal{R} = \{\mathbf{x}^{B,v}, v = 1, \dots, N_r\}$

Output: salience probability map $P(l^{A,u}_{m,n} = 1 \mid x^{A,u}_{m,n})$

1: **for** each patch $x^{A,u}_{m,n} \in X$ **do**

2: compute $X_{NN}(x^{A,u}_{m,n})$ with Eq. (1)

3: compute $score(x^{A,u}_{m,n})$ with Eq. (2)

4: compute $P(l^{A,u}_{m,n} = 1 \mid x^{A,u}_{m,n})$ with Eq. (3)

5: **end for**

Step 1: construct nearest-neighbor patch set

$$X_{NN}(x^{A,u}_{m,n}) = \{x \mid \underset{x^{B,v}_{i,j}}{\operatorname{argmin}}\, d(x^{A,u}_{m,n}, x^{B,v}_{i,j}), \quad x^{B,v}_{i,j} \in \mathfrak{S}(x^{A,u}_{m,n}, \mathbf{x}^{B,v}), v = 1, \dots, N_r\}, \tag{1}$$

Step 2: compute k-NN distances as salience score

$$score(x^{A,u}_{m,n}) = d_k(X_{NN}(x^{A,u}_{m,n})), \tag{2}$$

Step 3: convert to salience probability

$$P(l^{A,u}_{m,n} = 1 \mid x^{A,u}_{m,n}) = 1 - exp(-score(x^{A,u}_{m,n})^2/\sigma_0^2), \tag{3}$$

Supervised Salience Matching Framework

Matching based on Salience:

$$f_z(\mathbf{x}^A, \mathbf{x}^B, \mathbf{l}^A, \mathbf{l}^B; \mathbf{p}, \mathbf{z}) = \sum_{p_i} \Big\{ z_{p_i,1} l^A_{p_i} l^B_{p'_i} + z_{p_i,2} l^A_{p_i}(1 - l^B_{p'_i}) + z_{p_i,3}(1 - l^A_{p_i}) l^B_{p'_i} + z_{p_i,4}(1 - l^A_{p_i})(1 - l^B_{p'_i}) \Big\},$$

- Hidden Salience label: $\mathbf{l}^A = \{l^A_{p_i} \mid l^A_{p_i} \in \{0,1\}\} \quad \mathbf{l}^B = \{l^B_{p'_i} \mid l^B_{p'_i} \in \{0,1\}\}$
- Matching score: $\mathbf{z} = \{z_{p_i,k}\}_{k=1,2,3,4}$

$$z_{p_i,k} = \alpha_{p_i,k} \cdot s(x^A_{p_i}, x^B_{p'_i}) + \beta_{p_i,k}, \quad s(x^A_{p_i}, x^B_{p'_i}) = \exp\Big(-\frac{d(x^A_{p_i}, x^B_{p'_i})^2}{2\sigma_0^2}\Big),$$

Marginalization:

$$f^*(\mathbf{x}^A, \mathbf{x}^B; \mathbf{p}, \mathbf{z}) = \sum_{\mathbf{l}^A, \mathbf{l}^B} f_z(\mathbf{x}^A, \mathbf{x}^B, \mathbf{l}^A, \mathbf{l}^B; \mathbf{p}, \mathbf{z}) p(\mathbf{l}^A, \mathbf{l}^B \mid \mathbf{x}^A, \mathbf{x}^B) = \sum_{p_i} \sum_{k=1}^{4} \Big[\alpha_{p_i,k} \cdot s(x^A_{p_i}, x^B_{p'_i}) + \beta_{p_i,k}\Big] c_{p_i,k}(x^A_{p_i}, x^B_{p'_i}),$$

Probabilistic salience matching

$$c_{p_i,k}(x^A_{p_i}, x^B_{p'_i}) = \begin{cases} P(l^A_{p_i} = 1 \mid x^A_{p_i}) P(l^B_{p'_i} = 1 \mid x^B_{p'_i}), & k = 1, \\ P(l^A_{p_i} = 1 \mid x^A_{p_i}) P(l^B_{p'_i} = 0 \mid x^B_{p'_i}), & k = 2, \\ P(l^A_{p_i} = 0 \mid x^A_{p_i}) P(l^B_{p'_i} = 1 \mid x^B_{p'_i}), & k = 3, \\ P(l^A_{p_i} = 0 \mid x^A_{p_i}) P(l^B_{p'_i} = 0 \mid x^B_{p'_i}), & k = 4. \end{cases}$$

Final Formulation:

$$f^*(\mathbf{x}^A, \mathbf{x}^B; \mathbf{p}, \mathbf{z}) = \mathbf{w}^{\mathrm{T}} \Phi(\mathbf{x}^A, \mathbf{x}^B; \mathbf{p}) = \sum_{p_i} w^{\mathrm{T}}_{p_i} \phi(x^A_{p_i}, x^B_{p'_i}),$$

- Weighting parameters: $w_{p_i} = [\{\alpha_{p_i,k}\}_{k=1,2,3,4}, \{\beta_{p_i,k}\}_{k=1,2,3,4}]$.
- Matching feature: $\phi(x^A_{p_i}, x^B_{p'_i})$

$$\phi(x^A_{p_i}, x^B_{p'_i}) = \begin{bmatrix} s(x^A_{p_i}, x^B_{p'_i}) P(l^A_{p_i} = 1 \mid x^A_{p_i}) P(l^B_{p'_i} = 1 \mid x^B_{p'_i}) \\ s(x^A_{p_i}, x^B_{p'_i}) P(l^A_{p_i} = 1 \mid x^A_{p_i}) P(l^B_{p'_i} = 0 \mid x^B_{p'_i}) \\ s(x^A_{p_i}, x^B_{p'_i}) P(l^A_{p_i} = 0 \mid x^A_{p_i}) P(l^B_{p'_i} = 1 \mid x^B_{p'_i}) \\ s(x^A_{p_i}, x^B_{p'_i}) P(l^A_{p_i} = 0 \mid x^A_{p_i}) P(l^B_{p'_i} = 0 \mid x^B_{p'_i}) \\ P(l^A_{p_i} = 1 \mid x^A_{p_i}) P(l^B_{p'_i} = 1 \mid x^B_{p'_i}) \\ P(l^A_{p_i} = 1 \mid x^A_{p_i}) P(l^B_{p'_i} = 0 \mid x^B_{p'_i}) \\ P(l^A_{p_i} = 0 \mid x^A_{p_i}) P(l^B_{p'_i} = 1 \mid x^B_{p'_i}) \\ P(l^A_{p_i} = 0 \mid x^A_{p_i}) P(l^B_{p'_i} = 0 \mid x^B_{p'_i}) \end{bmatrix}.$$

Ranking by Partial Order

- **Task** – finding a good ranking:

$$\mathbf{y}^{A,u}_* = \underset{\mathbf{y}^{A,u} \in \mathcal{Y}^{A,u}}{\operatorname{argmax}}\, \mathbf{w}^{\mathrm{T}} \Psi_{po}(\mathbf{x}^{A,u}, \mathbf{y}^{A,u}; \{\mathbf{x}^{B,v}\}^V_{v=1}, \{\mathbf{p}^{u,v}\}^V_{v=1}),$$

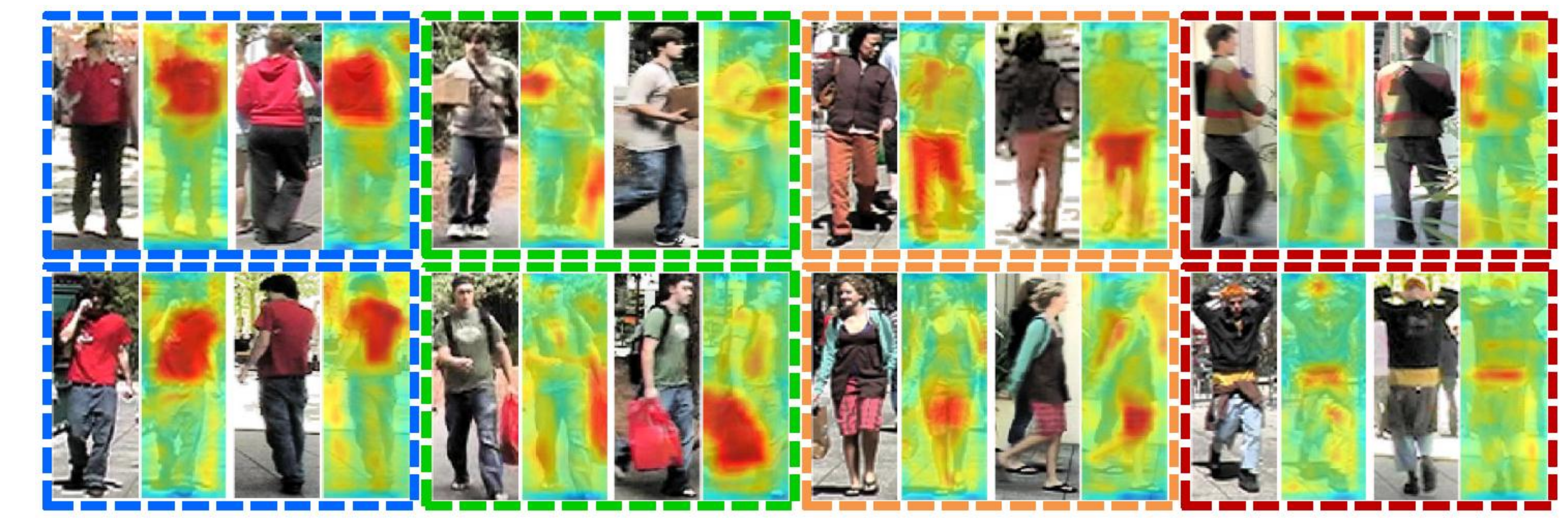
Partial order feature for structural RankSVM training:

$$\Psi_{po}(\mathbf{x}^{A,u}, \mathbf{y}^{A,u}; \{\mathbf{x}^{B,v}\}^V_{v=1}, \{\mathbf{p}^{u,v}\}^V_{v=1}) = \sum_{\mathbf{x}^{B,v} \in S^+_{\mathbf{x}^{A,u}}} \sum_{\mathbf{x}^{B,v'} \in S^-_{\mathbf{x}^{A,u}}} y^{A,u}_{v,v'} \frac{\Phi(\mathbf{x}^{A,u}, \mathbf{x}^{B,v}; \mathbf{p}^{u,v}) - \Phi(\mathbf{x}^{A,u}, \mathbf{x}^{B,v'}; \mathbf{p}^{u,v'})}{|S^+_{\mathbf{x}^{A,u}}| \cdot |S^-_{\mathbf{x}^{A,u}}|},$$

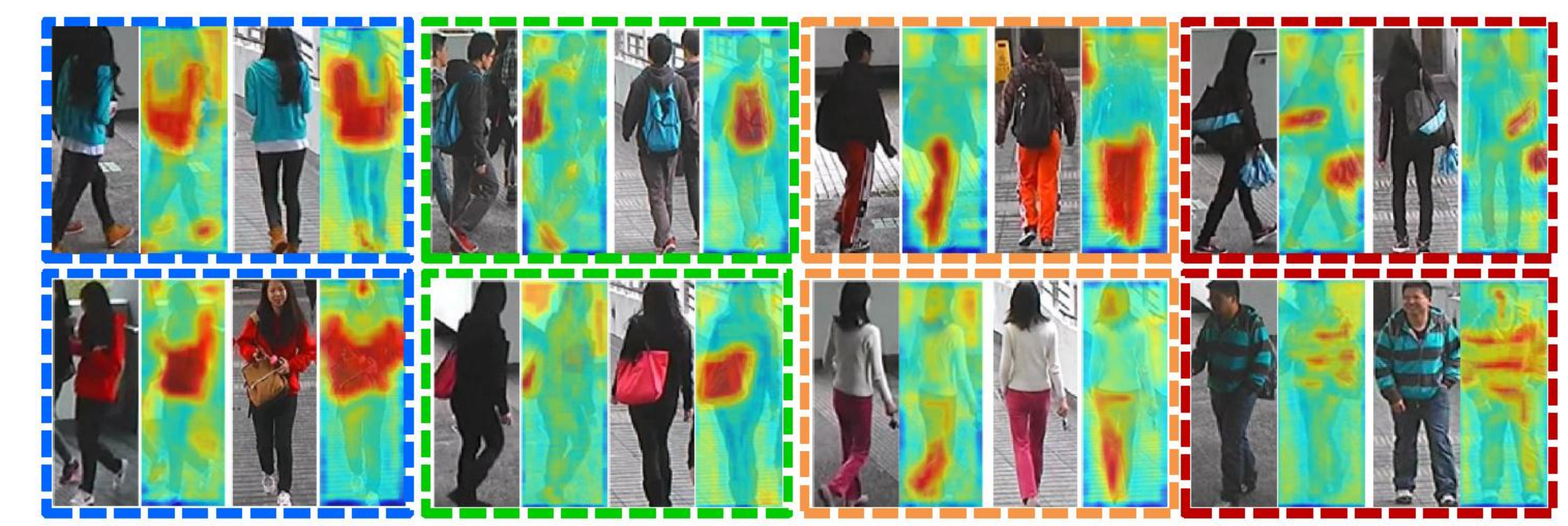
- **Solution** – sorting gallery by $\{\mathbf{w}^{\mathrm{T}}\Phi(\mathbf{x}^{A,u}, \mathbf{x}^{B,v}; \mathbf{p}^{u,v})\}_v$ in descending order.

Experimental Results

Learned Human Salience

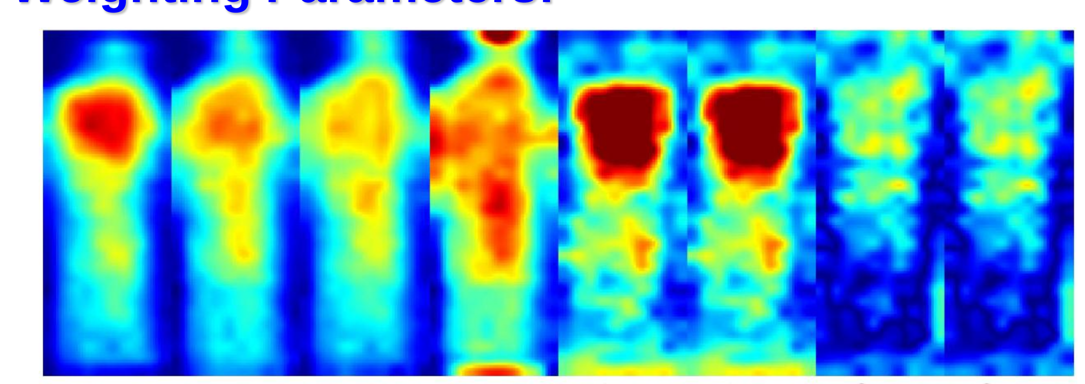


(a) VIPeR dataset



(b) CUHK Campus dataset

Learned Weighting Parameters:

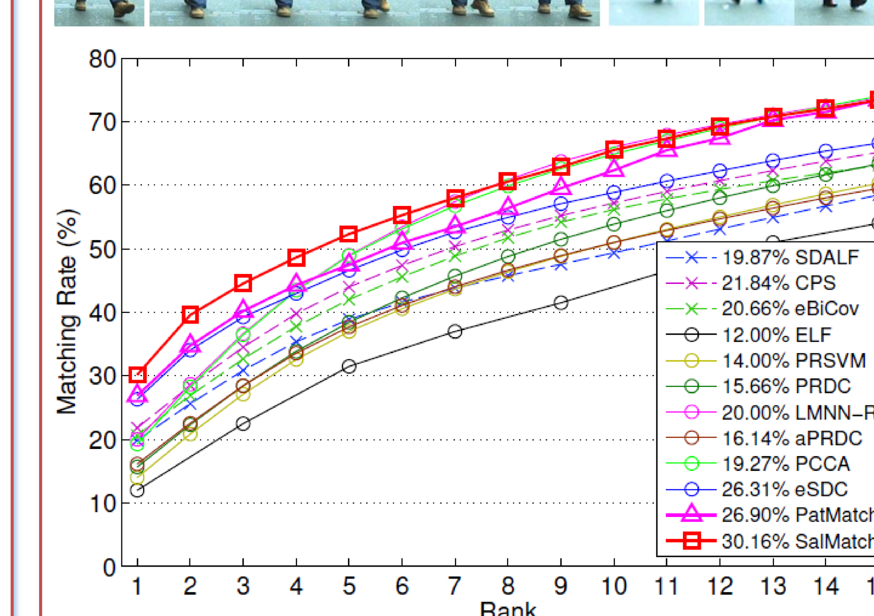


$\{\alpha_{p_i,k}\}_{k=1,2,3,4}$ correspond to the first four terms of matching features based on salience matching with visual similarity, and $\{\beta_{p_i,k}\}_{k=1,2,3,4}$ correspond to the last four terms only depending on salience matching.

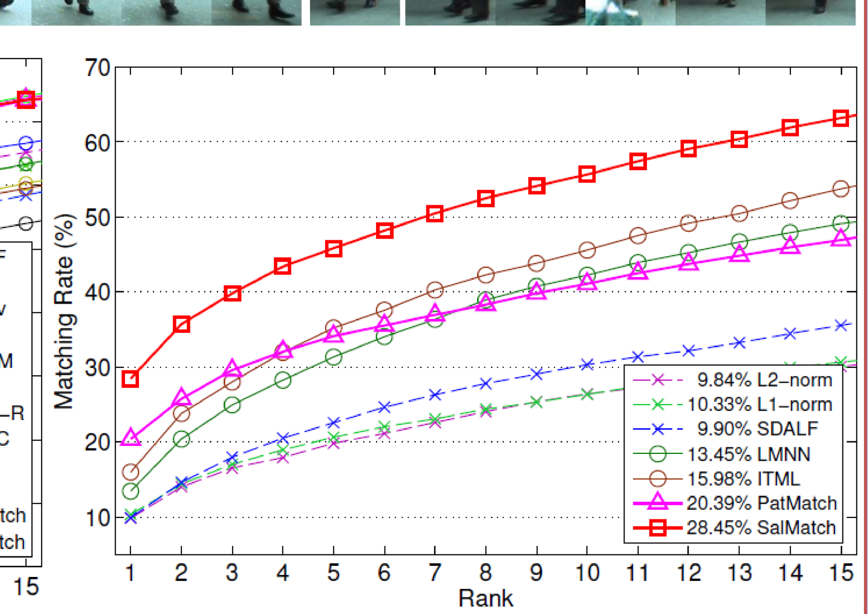
Comparison with Sate-of-the-Arts:

VIPeR dataset

CUHK Campus dataset



(a) VIPeR dataset



(b) CUHK Campus dataset