Collaboratively Regularized Nearest Points for Set Based Recognition

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Outline

- Why set-based recognition?
- Related work
- Regularized Nearest Points (RNP)
- Collaborative Regularized Nearest Points (CRNP)
- Experimental results
- Findings and future work
Why set-based recognition?

From single-instance recognition to set-based recognition:

Single-instance recognition

P1  P2  Pn


Set-based recognition

P1  P2  Pn

Who?  Who?  Who?
Why set-based recognition?

From single-instance recognition to set-based recognition:

- Collecting a set of images for recognition becomes increasingly convenient.
  - Taking and sharing pictures/videos gets easier
  - ...
  - ...
  - ...

Single-instance recognition

Set-based recognition

From single-instance recognition to set-based recognition:

- Collecting a set of images for recognition becomes increasingly convenient.
  - Taking and sharing pictures/videos gets easier
- The direction of set based recognition recently gets hotter and hotter.
  - Face recognition
  - Person re-identification (multiple-shot)

- Single-instance recognition

  P1  P2  Pn


- Set-based recognition

  P1  P2  Pn

  Who?
Why set-based recognition?

From single-instance recognition to set-based recognition:

Single-instance recognition

P1  P2  ...  Pn

Set-based recognition

P1  P2  ...  Pn
Who?

- Collecting a set of images for recognition becomes increasingly convenient.
  > Taking and sharing pictures/videos gets easier
- The direction of set based recognition recently gets hotter and hotter.
  > Face recognition
  > Person re-identification (multiple-shot)
- Set based recognition models have the potential to outperform single-instance based recognition approaches under the same conditions.
Related work

Existing solutions

1
2
3
Related work

Existing solutions

1. **Set-based signature generation**
   - Largely explored for person re-identification.
   - Compatible with single instance based learning algorithms.
   - Needs manual design, which is task-dependent and hard.
Related work

Existing solutions

1. *Set-based signature generation*
   -- Largely explored for person re-identification.
   -- Compatible with single instance based learning algorithms.
   -- Needs manual design, which is task-dependent and hard.

2. *Direct set-to-set matching*
   -- Uses simple minimum point-wise distance for set-to-set matching.
   -- Relies on good features for single instances.
   -- Sensitive to noises/outliers.
   -- Unsupervised.
Existing solutions

1. Set-based signature generation
   -- Largely explored for person re-identification.
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2. Direct set-to-set matching
   -- Uses simple minimum point-wise distance for set-to-set matching.
   -- Relies on good features for single instances.
   -- Sensitive to noises/outliers.
   -- Unsupervised.

3. Geometric dist. finding
   -- Mainly for face recognition.
   -- Explores set structure.
   -- Robust to noises/outliers.
   -- Unsupervised (can be supervised).
Set-to-set distance finding

Q -- Query/Probe Set
$X_i, i \in \{1, \ldots, n\}$
-- Gallery Sets

(a) Set-to-set distances
(b) Set-to-sets distance
Set-to-set distance finding

Q -- Query/Probe Set
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(a) Set-to-set distances
(b) Set-to-sets distance

(MPD, AHISD/CHISD, SANP/KSANP, SBDR, RNP)

9/12/2013  Yang Wu, et al., Kyoto University, Japan
Set-to-set distance finding

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(a) Set-to-set distances

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(MPD, AHISD/CHISD, SANP/KSANP, SBDR, RNP)

(CSA)
Regularized Nearest Points (RNP)

Regularized Nearest Points – distance finding

RNP models each image set by a regularized affine hull (RAH):

\[ \text{RAH} = \left\{ x = X_i \alpha \mid \sum_k \alpha_k = 1, \| \alpha \|_2 \leq \sigma \right\}, \]

\[ \alpha \]
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Yang et al., FG’13
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\[ RAH = \left\{ x = X_i \alpha \mid \sum_k \alpha_k = 1, \|\alpha\|_2 \leq \sigma \right\}, \]

RNP finds two nearest points from the RAH of \( Q \) and the RAH of \( X_i \), respectively by solving

\[
\min_{\alpha, \beta} \|Q\alpha - X_i\beta\|_2^2, \quad \text{s.t.} \sum_k \alpha_k = 1, \sum_j \beta_j = 1, \|\alpha\|_2 \leq \sigma_1, \|\beta\|_2 \leq \sigma_2,
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which can be solved by

$$\min_{\alpha, \beta} \left\{ \|Q \alpha - X_i \beta\|_2^2 + \lambda_1 \| \alpha \|_2^2 + \lambda_2 \| \beta \|_2^2 \right\}, \quad s.t. \sum_k \alpha_k = 1, \sum_j \beta_j = 1,$$
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where

$$\sum_k \alpha_k = 1, \sum_j \beta_j = 1 \text{ help avoiding the trivial solution } \alpha = \beta = 0$$
Regularized Nearest Points – classification

After getting the solution $\alpha^*, \beta^*$, the set-to-set distance between $Q$ and $X_i$ is defined to be

$$d_{RNP}^i = \left(\| Q^* \| + \| X_i^* \| \right) \cdot \left\| Q^* - X_i^* \beta^* \right\|_2^2,$$

where $\| Q^* \|$ is the nuclear norm of $Q$, i.e. the sum of the singular values of it.
Regularized Nearest Points – classification

After getting the solution $\alpha^*, \beta^*$, the set-to-set distance between $Q$ and $X_i$ is defined to be

$$d^i_{RNP} = \left( \|Q\|_* + \|X_i\|_* \right) \cdot \left\| Q\alpha^* - X_i\beta^* \right\|_2^2,$$

where $\|Q\|_*$ is the nuclear norm of $Q$, i.e. the sum of the singular values of it.

The nuclear norm term reflects the representation ability (related to the size) of a set, thus being able to remove the possible disturbance unrelated to the class information.
Regularized Nearest Points (RNP)

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The nuclear norm term reflects the representation ability (related to the size) of a set, thus being able to remove the possible disturbance unrelated to the class information.

Finally, $Q$ is classified by:

$$C(Q) = \arg \min_i \left\{ d_{RNP}^i \right\}.$$
Collaboratively Regularized Nearest Points

- Collaborative distance finding
Collaboratively Regularized Nearest Points (CRNP)

Collaboratively Regularized Nearest Points

Collaborative distance finding

RNP:

$$\min_{\alpha, \beta} \left\{ \|Q\alpha - X_i\beta\|_2^2 + \lambda_1 \|\alpha\|_2^2 + \lambda_2 \|\beta\|_2^2 \right\}, \quad s.t. \sum_k \alpha_k = 1, \sum_j \beta_j = 1,$$
Collaboratively Regularized Nearest Points (CRNP)

Collaboratively Regularized Nearest Points

- Collaborative distance finding

**RNP:**

\[
\min_{\alpha, \beta} \left\{ \|Q\alpha - X_i\beta\|^2_2 + \lambda_1 \|\alpha\|^2_2 + \lambda_2 \|\beta\|^2_2 \right\}, \quad s.t. \sum_k \alpha_k = 1, \sum_j \beta_j = 1,
\]

**CRNP** solves the following optimization problem:

\[
\min_{\alpha, \beta} \left\{ \|Q\alpha - X\beta\|^2_2 + \lambda_1 \|\alpha\|^2_2 + \lambda_2 \|\beta\|^2_2 \right\}, \quad s.t. \sum_k \alpha_k = 1, \sum_{i=1}^{n} \sum_j \beta_{ij} = 1,
\]

where

\[
X = [X_1, \ldots, X_n]
\]

\[
\beta = [\beta_1^T, \ldots, \beta_n^T]^T
\]
Collaboratively Regularized Nearest Points (CRNP)

Collaboratively Regularized Nearest Points

**Collaborative distance finding**

CRNP solves the following optimization problem:

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\min_{\alpha, \beta} \left\{ \|Q\alpha - X\beta\|_2^2 + \lambda_1 \|\alpha\|_2^2 + \lambda_2 \|\beta\|_2^2 \right\}, \quad \text{s.t. } \sum_k \alpha_k = 1, \sum_j \beta_j = 1,
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where

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\[ \beta = [\beta_1^T, \ldots, \beta_n^T]^T \]

RNP:

\[
\min_{\alpha, \beta} \left\{ \|Q\alpha - X\beta\|_2^2 + \lambda_1 \|\alpha\|_2^2 + \lambda_2 \|\beta\|_2^2 \right\}, \quad \text{s.t. } \sum_k \alpha_k = 1, \sum_{i=1}^n \sum_j \beta_i^j = 1,
\]
Collaboratively Regularized Nearest Points (CRNP)

Distance finding optimization

$$\min_{\alpha, \beta} \left\{ \left\| Q\alpha - X\beta \right\|_2^2 + \lambda_1 \left\| \alpha \right\|_2^2 + \lambda_2 \left\| \beta \right\|_2^2 + \gamma_1 (1 - \sum_k \alpha_k)^2 + \gamma_2 (1 - \sum_{i=1}^n \sum_j \beta_j^i)^2 \right\},$$
Collaboratively Regularized Nearest Points (CRNP)

Distance finding optimization

\[
\min_{\alpha, \beta} \left\{ \|Q\alpha - X\beta\|_2^2 + \lambda_1 \|\alpha\|_2^2 + \lambda_2 \|\beta\|_2^2 + \gamma_1 (1 - \sum_k \alpha_k)^2 + \gamma_2 (1 - \sum_{i=1}^{n} \sum_j \beta_i)^2 \right\},
\]

\[
\min_{\alpha, \beta} \left\{ \|z - Q\alpha - X\beta\|_2^2 + \lambda_1 \|\alpha\|_2^2 + \lambda_2 \|\beta\|_2^2 \right\},
\]
Collaboratively Regularized Nearest Points (CRNP)

Distance finding optimization

\[
\min_{\alpha, \beta} \left\{ \|Q\alpha - X\beta\|_2^2 + \lambda_1 \|\alpha\|_2^2 + \lambda_2 \|\beta\|_2^2 + \gamma_1 (1 - \sum_k \alpha_k)^2 + \gamma_2 (1 - \sum_{i=1}^n \sum_j \beta_j)^2 \right\},
\]

\[
\min_{\alpha, \beta} \left\{ \|z - Q\alpha - X\beta\|_2^2 + \lambda_1 \|\alpha\|_2^2 + \lambda_2 \|\beta\|_2^2 \right\},
\]

\[
z = [0_{1,m}, \sqrt{\gamma_1}, \sqrt{\gamma_2}]^T
\]

\[
Q = [Q^T, \sqrt{\gamma_1}1_{N_q,1}, 0_{N_q,1}]^T
\]

\[
X = [-X^T, 0_{N_x,1}, \sqrt{\gamma_2}1_{N_x,1}]^T
\]
Collaboratively Regularized Nearest Points (CRNP)

Distance finding optimization

\[
\min_{\alpha,\beta} \left\{ \| z - Q\alpha - X\beta \|_2^2 + \lambda_1 \| \alpha \|_2^2 + \lambda_2 \| \beta \|_2^2 \right\},
\]

Collaboratively Regularized Nearest Points
Collaboratively Regularized Nearest Points (CRNP)

Collaboratively Regularized Nearest Points

- Distance finding optimization

\[
\min_{\alpha, \beta} \left\{ \left\| z - Q\alpha - X\beta \right\|^2_2 + \lambda_1 \left\| \alpha \right\|^2_2 + \lambda_2 \left\| \beta \right\|^2_2 \right\},
\]

One-step closed-form solution? Yes!

But,

-- it is expensive,
-- the whole optimization is needed for each query/probe set.
Collaboratively Regularized Nearest Points (CRNP)

Distance finding optimization

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\[
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**One-step closed-form solution?**

Yes!

But,

-- it is expensive,

-- the whole optimization is needed for each query/probe set.

**Iterative Optimization:**

Fix \( \beta \), and optimize \( \alpha \):

\[
\alpha^* = P_q (z - X\beta), \quad \text{with} \quad P_q = (Q^T Q + \lambda_1 I)^{-1} Q^T.
\]

Fix \( \alpha \), and optimize \( \beta \):

\[
\beta^* = P_x (z - Q\alpha), \quad \text{with} \quad P_x = (X^T X + \lambda_2 I)^{-1} X^T.
\]
Collaboratively Regularized Nearest Points (CRNP)

Distance finding optimization

**Algorithm 1** Collaboratively Regularized Nearest Points (CRNP):

Require: The training/gallery sets \( \mathbf{X} \in \mathbb{R}^{m \times N_x} \), an arbitrary test/query set \( \mathbf{Q} \in \mathbb{R}^{m \times N_q} \), the pre-computed \( \hat{\mathbf{z}}, \hat{\mathbf{X}} \) and \( \mathbf{P}_x \) (using Equation 10), and four trade-off parameters \( \{ \lambda_1, \lambda_2, \gamma_1, \gamma_2 \} \).

Ensure: The representation coefficients for distance finding: \( \alpha^* \) and \( \beta^* \).

1. Construct \( \hat{\mathbf{Q}} = [\mathbf{Q}^T, \sqrt{\gamma_1} \mathbf{1}_{N_q,1}, \mathbf{0}_{N_q,1}]^T \).
2. Compute the project matrix \( \mathbf{P}_q = (\hat{\mathbf{Q}}^T \hat{\mathbf{Q}} + \lambda_1 \mathbf{I})^{-1} \hat{\mathbf{Q}}^T \).
3. Initialize \( \beta_0 = 1/N_x \).
4. while not converged or not exceeding the maximum number of iterations do
   5. Update the representation coefficients:
   6. \( \alpha_{t+1} = \mathbf{P}_q(\mathbf{z} - \hat{\mathbf{X}} \beta_t) \).
   7. \( \beta_{t+1} = \mathbf{P}_x(\mathbf{z} - \hat{\mathbf{Q}} \alpha_{t+1}) \).
5. end while
6. Return \( \alpha^* \) and \( \beta^* \).
Collaboratively Regularized Nearest Points (CRNP)

Collaboratively Regularized Nearest Points

Classification
Collaboratively Regularized Nearest Points

**Classification**

Like sparse/collaborative representation models for single-instance based recognition, here the set-specific coefficients $\beta^* = [\beta_1^*, \ldots, \beta_n^*]$ is implicitly made to have some discrimination power.
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Therefore, we design our classification model as follows.

$$C(\mathbf{Q}) = \arg \min_{i} \left\{ d_{CRNP}^i \right\},$$

where

$$d_{CRNP}^i = \left( \| \mathbf{Q}_i^* + \| \mathbf{X}_i \|_* \| \right) \| \mathbf{Q} \mathbf{\alpha}^* - \mathbf{X}_i \mathbf{\beta}_i^* \|_2^2 / \| \mathbf{\beta}_i^* \|_2^2.$$
Collaboratively Regularized Nearest Points (CRNP)

Classification

Like sparse/collaborative representation models for single-instance based recognition, here the set-specific coefficients $\beta^* = [\beta_1^*, \ldots, \beta_n^*]$ is implicitly made to have some discrimination power.

Therefore, we design our classification model as follows.

$$C(Q) = \arg \min_i \left\{ d_{CRNP}^i \right\},$$

where

$$d_{CRNP}^i = \left( \|Q\|_* + \|X_i\|_* \right) \|Q\alpha^* - X_i\beta_i^*\|_2^2 / \|\beta_i^*\|_2^2.$$

Recall that RNP doesn’t directly use the coefficients themselves which are actually also discriminative.

$$d_{RNP}^i = \left( \|Q\|_* + \|X_i\|_* \right) \|Q\alpha^* - X_i\beta_i^*\|_2^2.$$
Experimental Results

- Experimental settings -- datasets
Experimental Results

Experimental settings -- datasets

**Face recognition**

Honda/UCSD dataset and CMU MoBo dataset:

1. **Honda/UCSD** -- 20 subjects (20 specified seq. for the gallery, and the other 39 seq. for testing.);
2. **CMU MoBo** -- 24 subjects (randomly select 1 seq. out of 4 for each subject for the gallery, and the rest for testing.).
3. The gallery/probe set size for both datasets is set to be **50 or 100** (collected from the beginning of each sequence.)
Experimental Results

Experimental settings -- datasets

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Person re-identification

3 widely used datasets: iLIDS-MA, iLIDS-AA, and CAVIAR4REID.
- iLIDS-MA: 40 subjects, 1 gallery set & 1 probe set for each, set size 10;
- iLIDS-AA: 100 subjects, 1 gallery set & 1 probe set for each, set size 10;
- CAVIAR4REID : 50 subjects, 1 gallery set & 1 probe set for each, set size 5;
Experimental Results

Experimental settings -- comparisons

Methods

- MPD (CVPR10),
- SRC (TPAMI09), CRC (ICCV11),
- CHISD (CVPR10), SANP (CVPR11), KSANP (PAMI12),
- SBDR (ECCV12),
- CSA (AVSS12), RNP (FG13).
Experimental Results

Experimental settings -- comparisons

Methods

MPD (CVPR10),
SRC (TPAMI09), CRC (ICCV11),
CHISD (CVPR10), SANP (CVPR11), KSANP (PAMI12),
SBDR (ECCV12),
CSA (AVSS12), RNP (FG13).

Parameters

For CRNP: $\lambda_1 = \lambda_2 = 4, \gamma_1 = \gamma_2 = 1$

For other methods:
- default settings or originally suggested parameters were used.
Experimental Results

### Results

#### Face recognition accuracy (%) comparison on the Honda/UCSD dataset.

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</thead>
<tbody>
<tr>
<td>50 frames</td>
<td>79.49</td>
<td>76.92</td>
<td>76.92</td>
<td>79.49/82.05*</td>
<td>84.62/84.62*</td>
<td>87.18*</td>
<td>87.69*</td>
<td>84.62</td>
<td>66.67/87.18*</td>
<td>89.74</td>
</tr>
<tr>
<td>100 frames</td>
<td>87.18</td>
<td>94.87</td>
<td>82.05</td>
<td>79.49/84.62*</td>
<td>89.74/92.31*</td>
<td>94.87*</td>
<td>89.23*</td>
<td>92.31</td>
<td>92.31/94.87*</td>
<td>97.44</td>
</tr>
</tbody>
</table>

#### Face recognition accuracy (%) comparison on the CMU MoBo dataset.

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<tr>
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</thead>
<tbody>
<tr>
<td>50 frames</td>
<td>92.22</td>
<td>88.89</td>
<td>89.72</td>
<td>90.83</td>
<td>90.14</td>
<td>95.00*</td>
<td>86.25</td>
<td>91.81/91.9*</td>
<td>93.33</td>
</tr>
<tr>
<td>100 frames</td>
<td>94.31</td>
<td>92.36</td>
<td>93.06</td>
<td>94.17</td>
<td>93.61</td>
<td>96.11*</td>
<td>94.44</td>
<td>94.58/94.7*</td>
<td>94.44</td>
</tr>
</tbody>
</table>

Performance comparison for person re-identification on three benchmark datasets.

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</thead>
<tbody>
<tr>
<td>iLIDS-MA</td>
<td>50.0(75.0)</td>
<td>57.3(74.8)</td>
<td>28.5(50.0)</td>
<td>52.5(72.8)</td>
<td>46.8(74.8)</td>
<td>59.0(71.3)</td>
<td>53.3(76.0)</td>
<td>59.0(78.3)</td>
</tr>
<tr>
<td>iLIDS-AA</td>
<td>23.8(60.4)</td>
<td>36.0(68.9)</td>
<td>24.7(54.1)</td>
<td>24.6(58.2)</td>
<td>19.2(57.3)</td>
<td>22.5(59.6)</td>
<td>25.5(59.9)</td>
<td>35.4(71.6)</td>
</tr>
<tr>
<td>CAVIAR4REID</td>
<td>19.0(47.2)</td>
<td>25.4(50.8)</td>
<td>16.6(37.6)</td>
<td>25.4(51.2)</td>
<td>25.2(52.4)</td>
<td>24.6(48.8)</td>
<td>24.0(50.2)</td>
<td>26.8(63.6)</td>
</tr>
</tbody>
</table>
Experimental Results

Computational cost

For those methods which can have (parts of) their models pre-computed using the training data, the total pre-computation time (in seconds) is listed for comparison.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Honda/UCSD 50 frames</th>
<th>Honda/UCSD 100 frames</th>
<th>CMU MoBo 50 frames</th>
<th>CMU MoBo 100 frames</th>
<th>iLIDS-MA</th>
<th>iLIDS-AA</th>
<th>CAVIAR4REID</th>
</tr>
</thead>
<tbody>
<tr>
<td>SBDR[10]</td>
<td>$9.23 \times 10^3$</td>
<td>$1.46 \times 10^4$</td>
<td>$1.23 \times 10^4$</td>
<td>$3.14 \times 10^4$</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>CSA[9]</td>
<td>0.59</td>
<td>0.74</td>
<td>28.7</td>
<td>50.2</td>
<td>0.39</td>
<td>0.62</td>
<td>0.26</td>
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<tr>
<td>RNP[12]</td>
<td>0.06</td>
<td>0.20</td>
<td>0.17</td>
<td>0.64</td>
<td>0.02</td>
<td>0.05</td>
<td>0.02</td>
</tr>
<tr>
<td>CRNP</td>
<td>0.22</td>
<td>0.87</td>
<td>0.64</td>
<td>2.66</td>
<td>0.04</td>
<td>0.22</td>
<td>0.02</td>
</tr>
</tbody>
</table>

Computational cost comparison with all the related methods on all of the recognition tasks (in the \texttt{milliseconds per sample} manner, excluding the time for feature extraction).

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<td>30.8</td>
<td>8.0</td>
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</tbody>
</table>
Findings and Future Work

Findings

- **Collaborative representation** is effective for set-based recognition.
- The computationally efficient **L2-norm based regularization** works well with collaborative representation.
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Code: available soon on my personal webpage.
http://mm.media.kyoto-u.ac.jp/members/yangwu/
Thank you!

Q & A?