Collaboratively Regularized Nearest Points for Set Based Recognition

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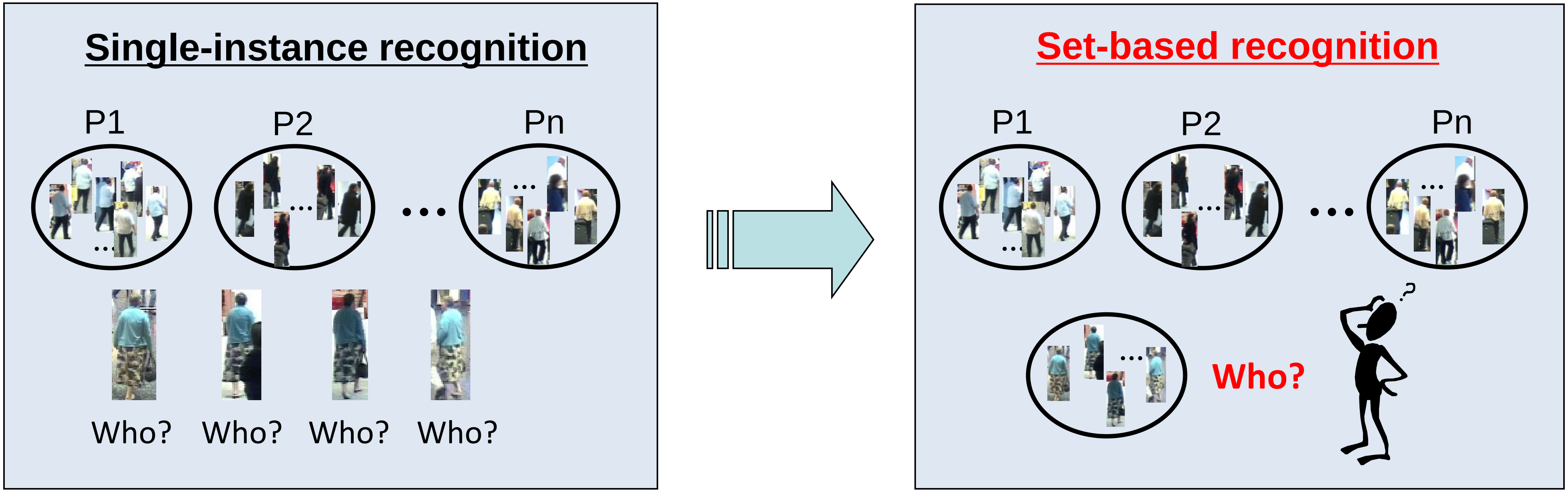
Outline

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

From single-instance recognition to set-based recognition:



Why set-based recognition?

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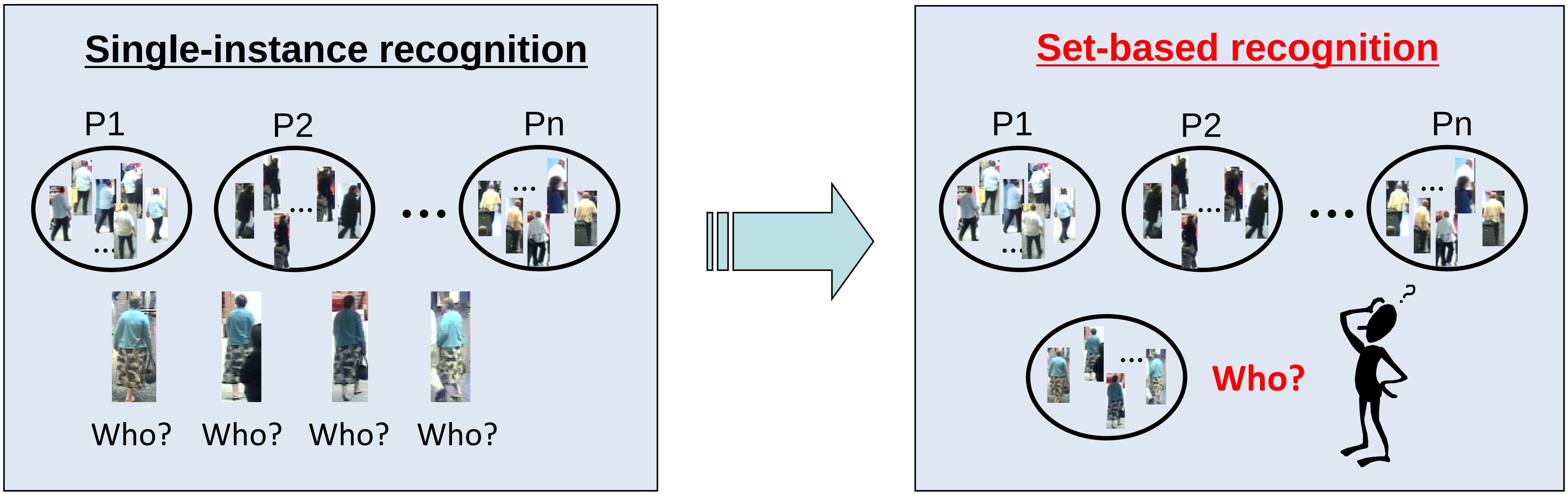

- **Collecting a set of images for recognition becomes increasingly convenient.**
  - > Taking and sharing pictures/videos gets easier

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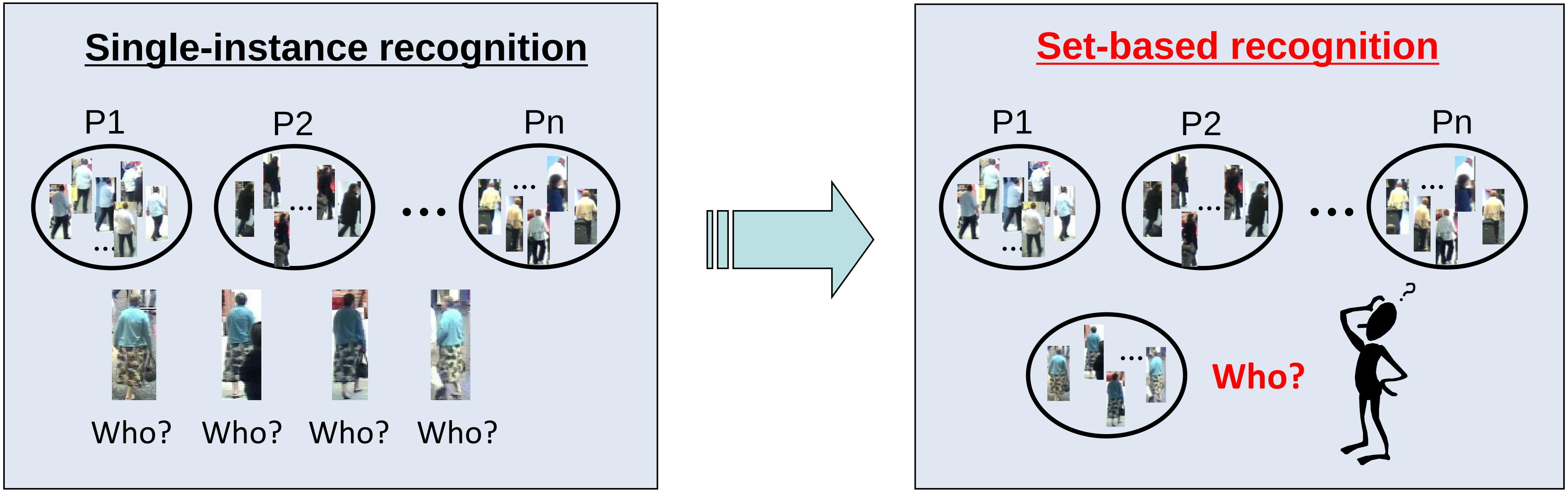

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  - > Taking and sharing pictures/videos gets easier
- **The direction of set based recognition recently gets hotter and hotter.**
  - > Face recognition
  - > Person re-identification (multiple-shot)
-

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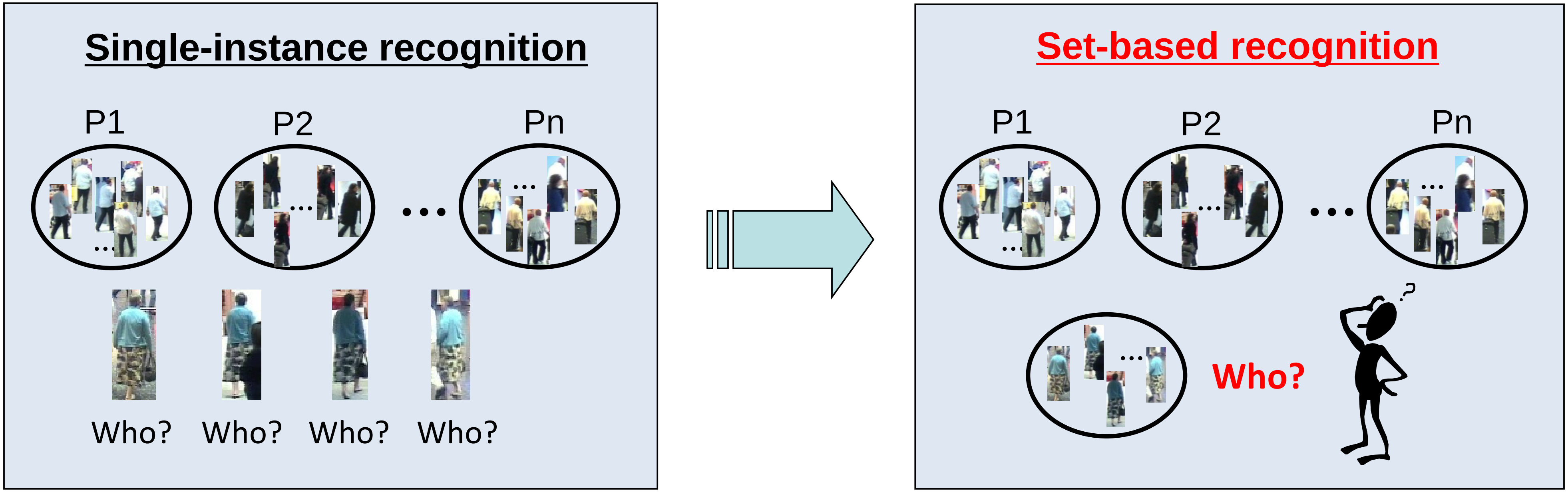


- **Collecting a set of images for recognition becomes increasingly convenient.**
  > Taking and sharing pictures/videos gets easier
- **The direction of set based recognition recently gets hotter and hotter.**
  > <u>Face recognition</u>
  > Person re-identification (multiple-shot)
- **Set based recognition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

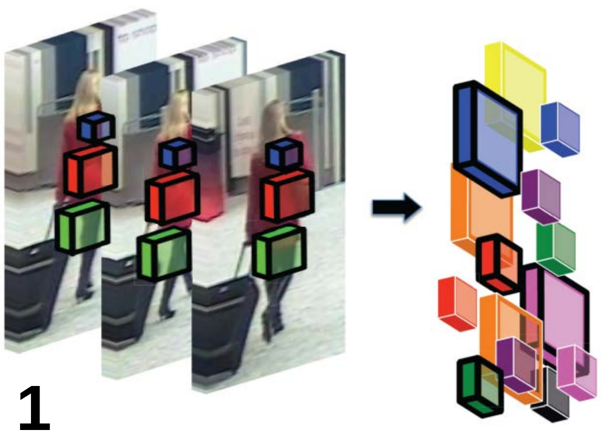
Existing solutions

1

2

3

Existing solutions



1

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

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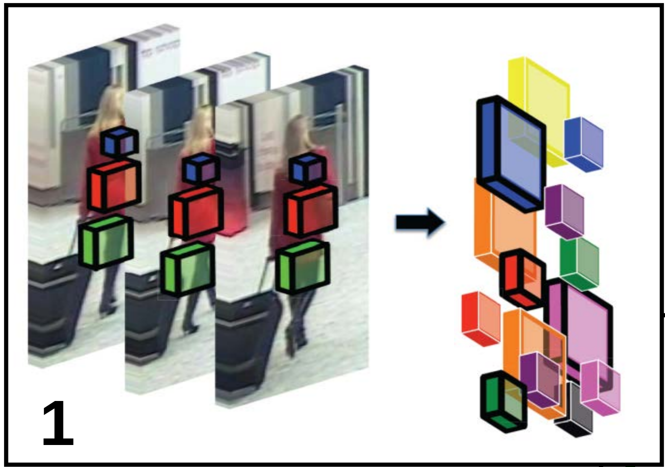
Existing solutions



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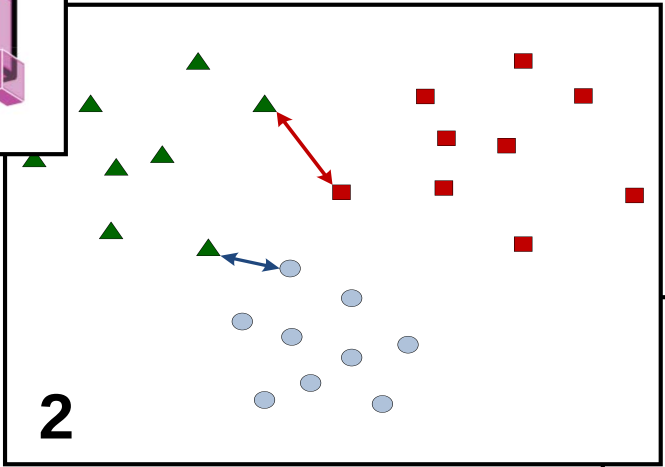


2. Direct set-to-set matching

-- Uses simple minimum point-wise distance for set-to-set matching.

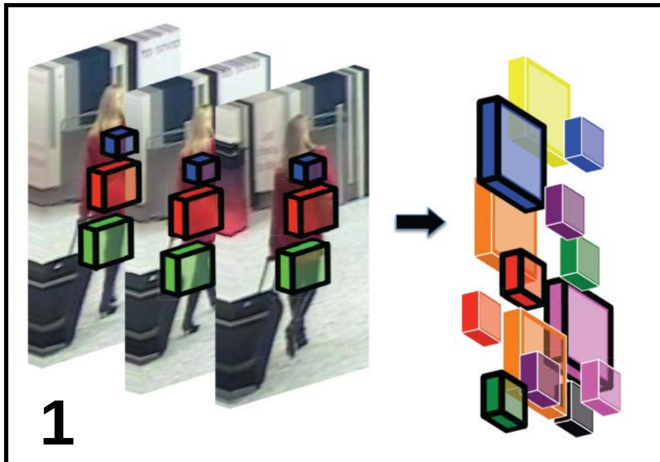
-- Relies on good features for single instances.

-- Sensitive to noises/outliers.

-- Unsupervised.

3

Existing solutions



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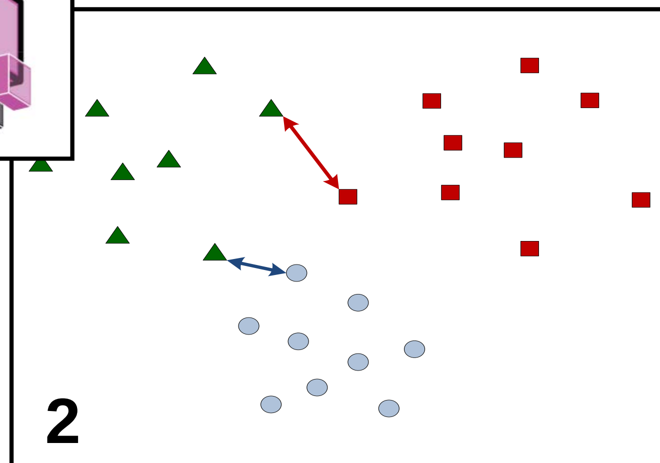

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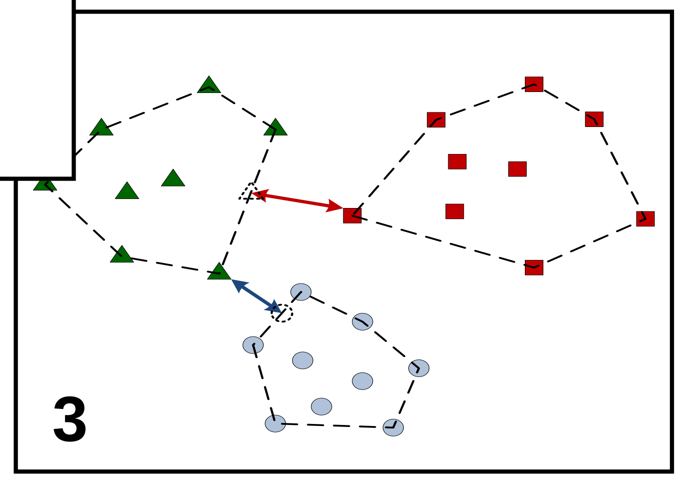
3. Geometric dist. finding

-- Mainly for face recognition.

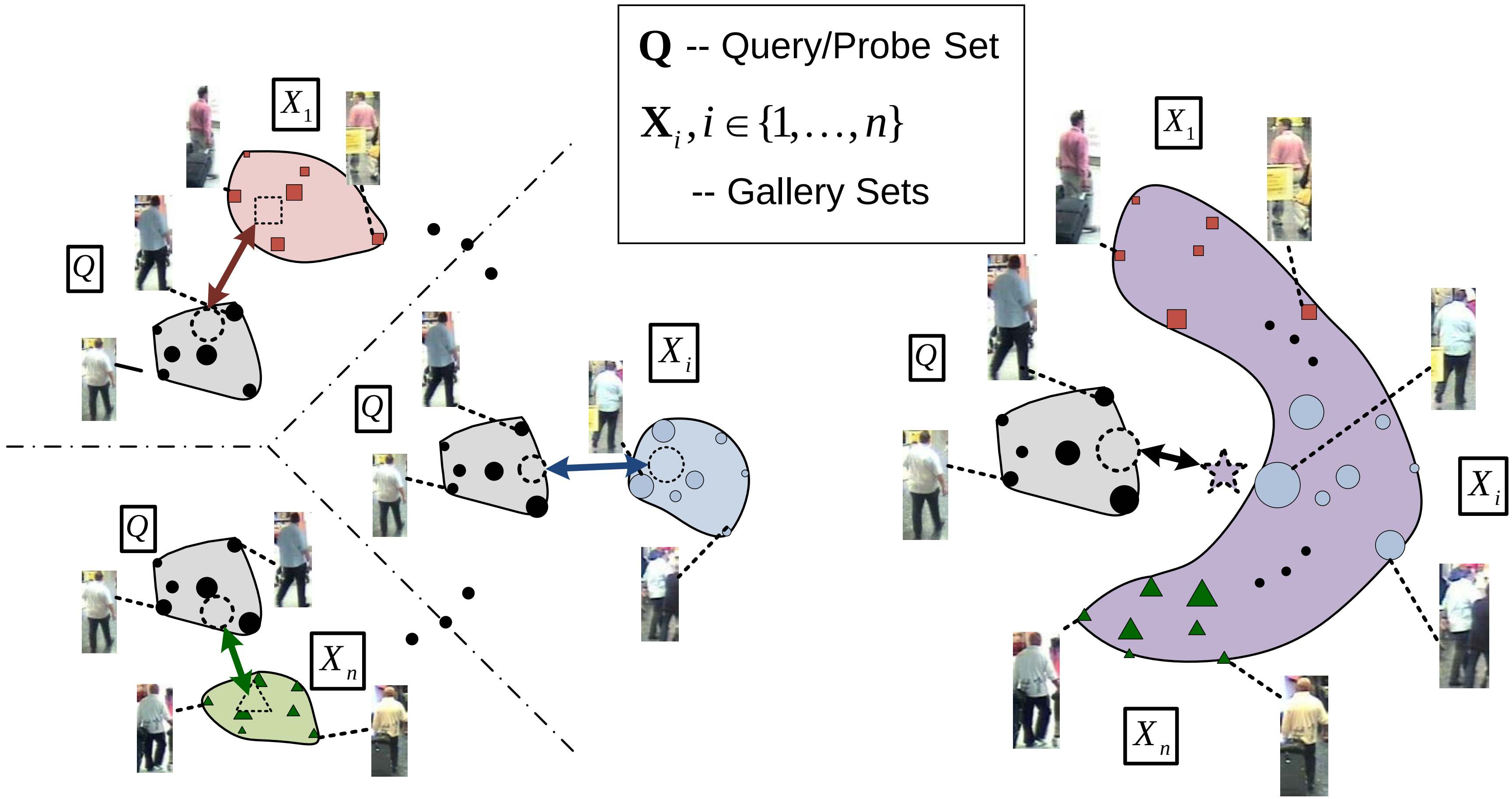
-- Explores set structure.

-- Robust to noises/outliers.

-- Unsupervised (can be supervised).



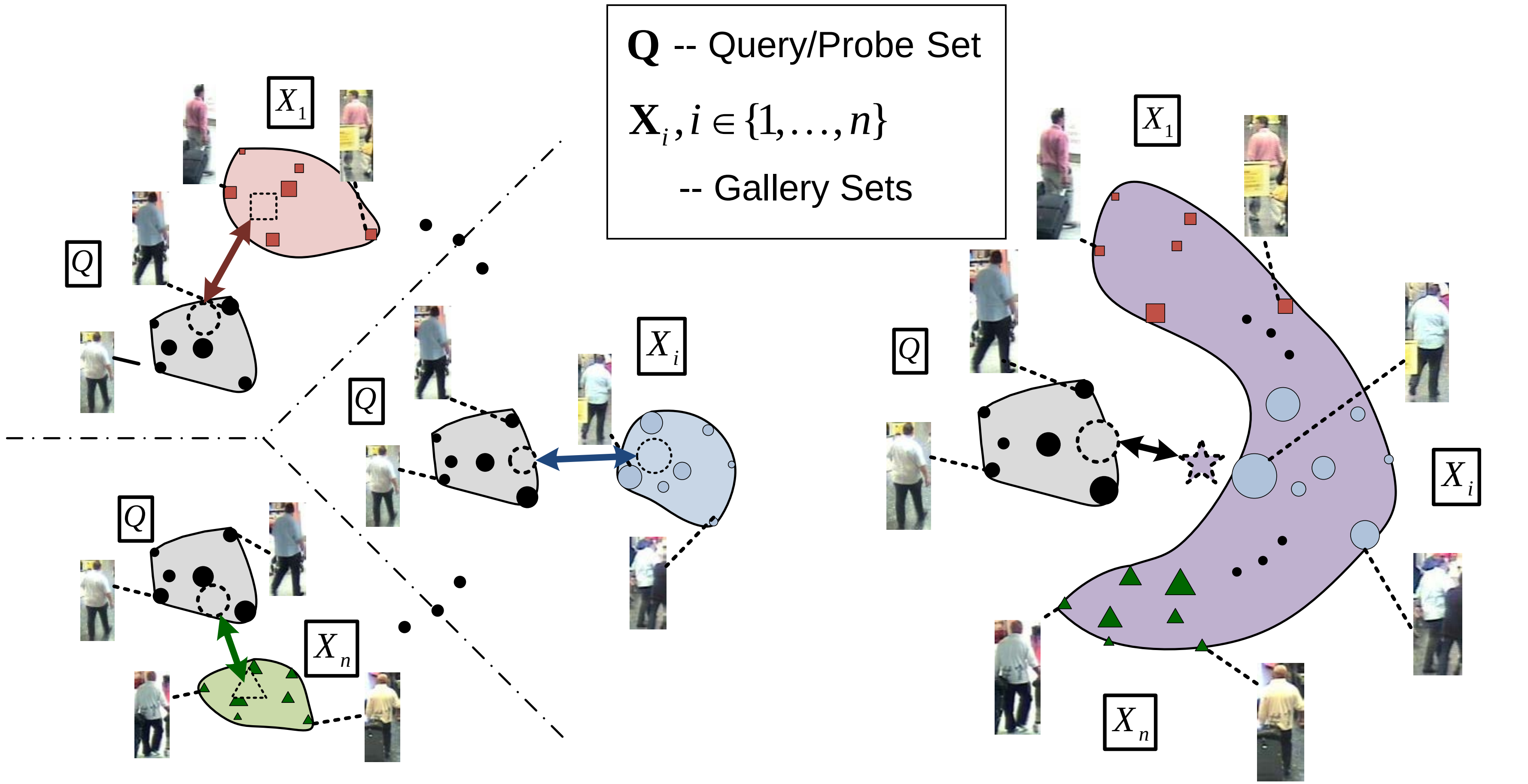
Set-to-set distance finding



(a) Set-to-set distances

(b) Set-to-sets distance

Set-to-set distance finding



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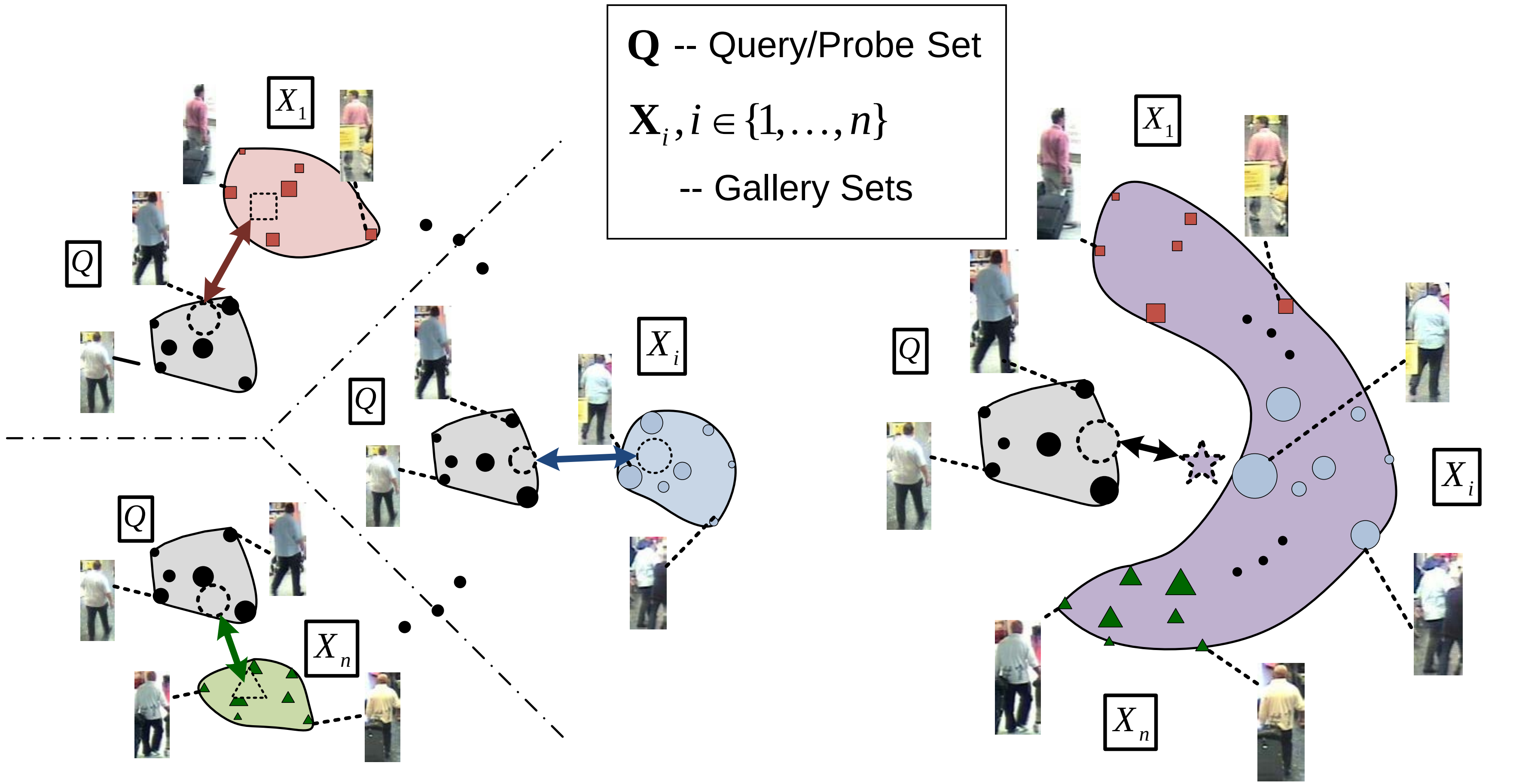

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(MPD, AHISD/CHISD, SANP/KSANP, SBDR, RNP) **(CSA)**

Regularized Nearest Points – distance finding

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

$$RAH = \left\{ \mathbf{x} = \mathbf{X}_i \boldsymbol{\alpha} \mid \sum_k \alpha_k = 1, \left\| \boldsymbol{\alpha} \right\|_2 \leq \sigma \right\},$$

Yang et al., FG'13

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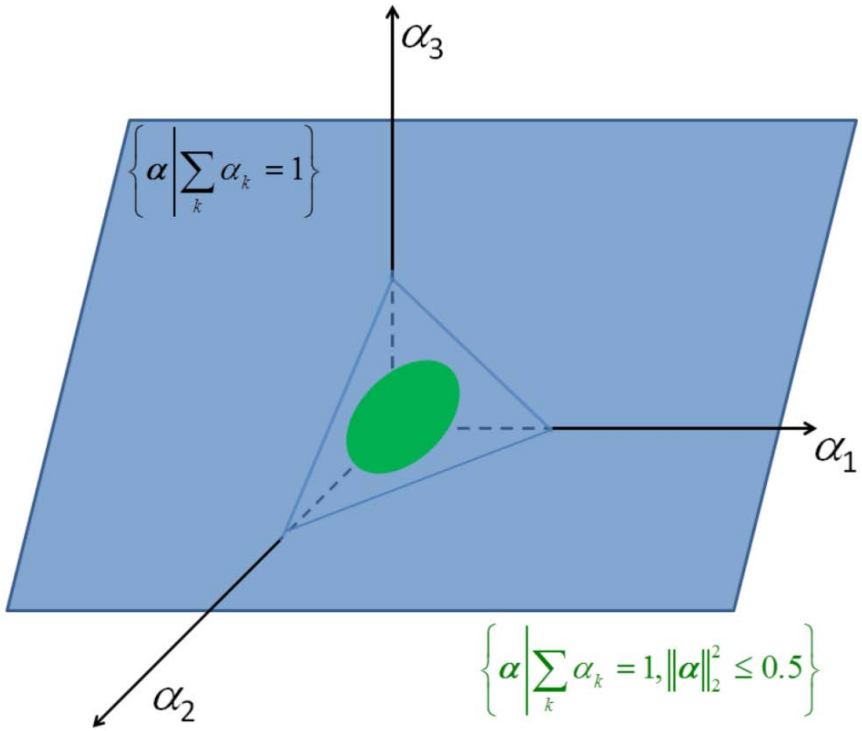

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where

$\sum_k \alpha_k = 1, \sum_j \beta_j = 1$ help avoiding the trivial solution $\boldsymbol{\alpha} = \boldsymbol{\beta} = 0$

Regularized Nearest Points – classification

After getting the solution $\boldsymbol{\alpha}^*, \boldsymbol{\beta}^*$, the set-to-set distance between $\mathbf{Q}$ and $\mathbf{X}_i$ is defined to be

$$d_{RNP}^{i} = \left(\|\mathbf{Q}\|_* + \|\mathbf{X}_i\|_*\right) \cdot \|\mathbf{Q}\boldsymbol{\alpha}^* - \mathbf{X}_i\boldsymbol{\beta}^*\|_2^2,$$

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

Minoh Laboratory

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Finally, $\mathbf{Q}$ is classified by:

$$C(\mathbf{Q}) = \arg\min_i \left\{d_{RNP}^i\right\}.$$

Collaboratively Regularized Nearest Points

- Collaborative distance finding

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RNP:

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

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CRNP solves the following optimization problem:

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where $\mathbf{X} = [\mathbf{X}_1, \ldots, \mathbf{X}_n]$

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Collaboratively Regularized Nearest Points

- Distance finding optimization

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

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$$\min_{\boldsymbol{\alpha},\boldsymbol{\beta}} \left\{ \left\| \mathbf{z} - \tilde{\mathbf{Q}}\boldsymbol{\alpha} - \tilde{\mathbf{X}}\boldsymbol{\beta} \right\|_2^2 + \lambda_1 \left\| \boldsymbol{\alpha} \right\|_2^2 + \lambda_2 \left\| \boldsymbol{\beta} \right\|_2^2 \right\},$$

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

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

$$\tilde{\mathbf{X}} = [-\mathbf{X}^T,\ \mathbf{0}_{N_x,1}, \sqrt{\gamma_2}\mathbf{1}_{N_x,1}]^T$$

Collaboratively Regularized Nearest Points

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One-step closed-form solution?

Yes!

But,

-- it is expensive,

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

Collaboratively Regularized Nearest Points

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Iterative Optimization:

Fix $\boldsymbol{\beta}$, and optimize $\boldsymbol{\alpha}$:

$$\boldsymbol{\alpha}^* = \mathbf{P}_q(\mathbf{z} - \mathbf{X}\boldsymbol{\beta}), \text{ with } \mathbf{P}_q = (\mathbf{Q}^T\mathbf{Q} + \lambda_1\mathbf{I})^{-1}\mathbf{Q}^T.$$

Fix $\boldsymbol{\alpha}$, and optimize $\boldsymbol{\beta}$:

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Collaboratively Regularized Nearest Points

- 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 $\mathbf{z}$, $\hat{\mathbf{X}}$ 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: $\boldsymbol{\alpha}^*$ and $\boldsymbol{\beta}^*$.

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 $\boldsymbol{\beta}_0 = 1/N_x$.
4: **while** not converged **or** not exceeding the maximum number of iterations **do**
5: Update the representation coefficients:
6: $\boldsymbol{\alpha}_{t+1} = \mathbf{P}_q(\mathbf{z} - \hat{\mathbf{X}}\boldsymbol{\beta}_t)$.
7: $\boldsymbol{\beta}_{t+1} = \mathbf{P}_x(\mathbf{z} - \hat{\mathbf{Q}}\boldsymbol{\alpha}_{t+1})$;
8: **end while**
9: Return $\boldsymbol{\alpha}^*$ and $\boldsymbol{\beta}^*$.

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 $\boldsymbol{\beta}^* = [\boldsymbol{\beta}_1^*, \ldots, \boldsymbol{\beta}_n^*]$ is implicitly made to have some discrimination power.

Collaboratively Regularized Nearest Points

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Therefore, we design our classification model as follows.

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

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

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

$$d_{RNP}^i = \left(\|\mathbf{Q}\|_* + \|\mathbf{X}_i\|_* \right) \cdot \left\| \mathbf{Q}\boldsymbol{\alpha}^* - \mathbf{X}_i \boldsymbol{\beta}^* \right\|_2^2 ,$$

Experimental Results

- Experimental settings -- datasets

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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.)

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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).

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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.

Method	MPD[4]	SRC[8]	CRC[14]	CHISD[2]	SANP[13]	KSANP[6]	SBDR[10]	CSA[9]	RNP[12]	CRNP
50 frames	79.49	76.92	76.92	79.49/82.05*	84.62/84.62*	87.18*	87.69*	84.62	66.67/87.18*	**89.74**
100 frames	87.18	94.87	82.05	79.49/84.62*	89.74/92.31*	94.87*	89.23*	92.31	92.31/94.87*	**97.44**

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

Method	MPD[4]	SRC[8]	CRC[14]	CHISD[2]	SANP[13]	SBDR[10]	CSA[9]	RNP[12]	CRNP
50 frames	92.22	88.89	89.72	90.83	90.14	*95.00**	86.25	91.81/91.9*	**93.33**
100 frames	94.31	92.36	93.06	94.17	93.61	*96.11**	94.44	**94.58/94.7***	94.44

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

Dataset	MPD[4]	SRC[8]	CRC[14]	CHISD[2]	SANP[13]	CSA[9]	RNP[12]	CRNP
iLIDS-MA	50.0(75.0)	57.3(74.8)	28.5(50.0)	52.5(72.8)	46.8(74.8)	**59.0**(71.3)	53.3(76.0)	**59.0**(**78.3**)
iLIDS-AA	23.8(60.4)	**36.0**(68.9)	24.7(54.1)	24.6(58.2)	19.2(57.3)	22.5(59.6)	25.5(59.9)	35.4(**71.6**)
CAVIAR4REID	19.0(47.2)	25.4(50.8)	16.6(37.6)	25.4(51.2)	25.2(52.4)	24.6(48.8)	24.0(50.2)	**26.8**(**63.6**)

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.

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

Computational cost comparison with all the related methods on all of the recognition tasks (in the ``***milliseconds per sample***" manner, excluding the time for feature extraction).

Dataset	MPD[4]	SRC[8]	CRC[14]	CHISD[2]	SANP[13]	SBDR[10]	CSA[9]	RNP[12]	CRNP
Honda/UCSD (50)	3.2	1.2×10^3	*0.28*	77.7	19.6	259	17.4	11.5	**0.32**
Honda/UCSD (100)	6.4	4.1×10^3	0.55	330	17.3	97.8	32.6	14.5	**0.46**
CMU MoBo (50)	12.4	7.6×10^3	*0.94*	89.0	47.2	85.0	29.0	3.5	**2.1**
CMU MoBo (100)	71.4	2.7×10^4	*1.8*	394	53.0	79.3	39.1	5.9	**2.5**
iLIDS-MA	3.9	741	*0.51*	58.7	121	N/A	9.6	24.5	**3.3**
iLIDS-AA	9.9	2337	*1.2*	150	344	N/A	36.8	83.4	**7.2**
CAVIAR4REID	**3.8**	214	*0.35*	55.3	249	N/A	15.8	30.8	8.0

Findings and Future Work

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- 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?