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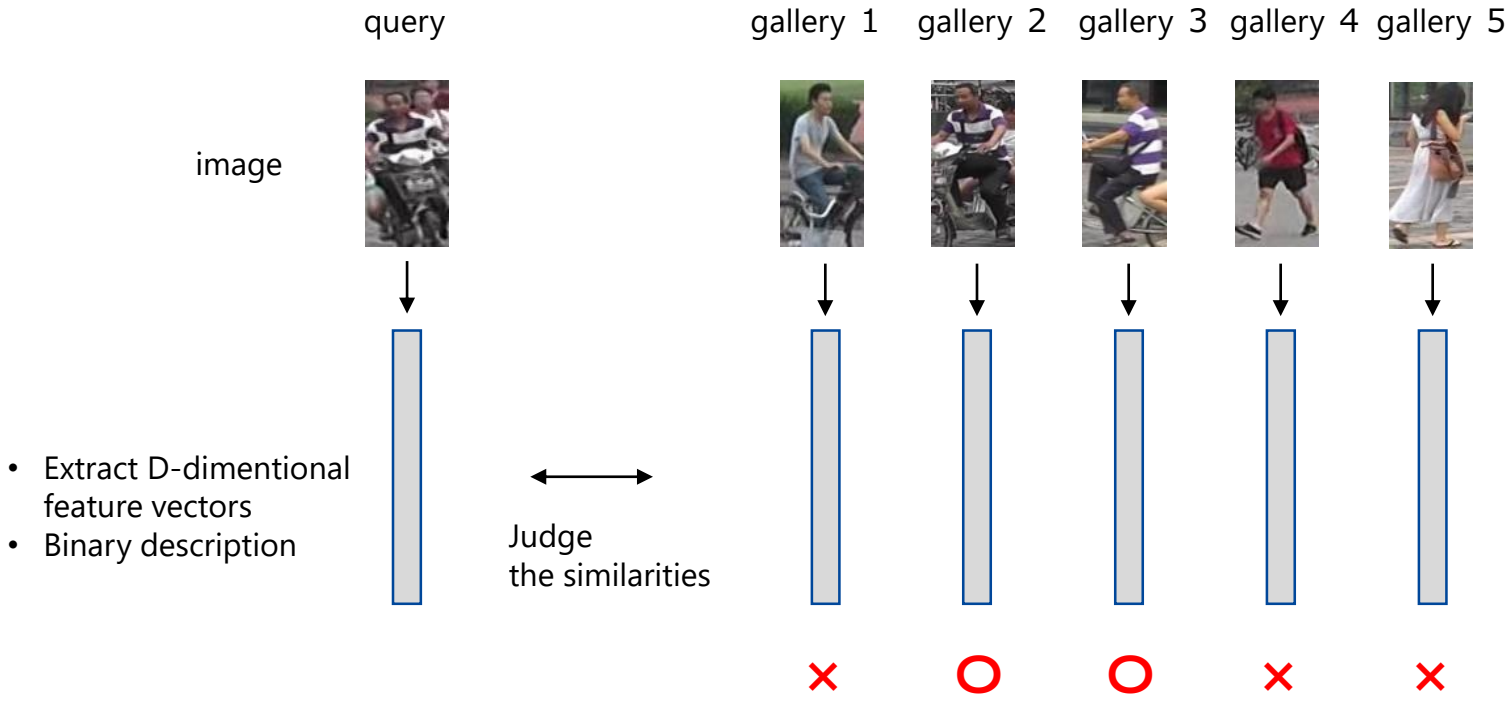
Sample-Dependent Distance for 1 : N Identification via Discriminative Feature Selection

Naoki Kawamura and Susumu Kubota

Corporate Research and Development Center, Toshiba Corporation

Objective：Improving accuracy of identification

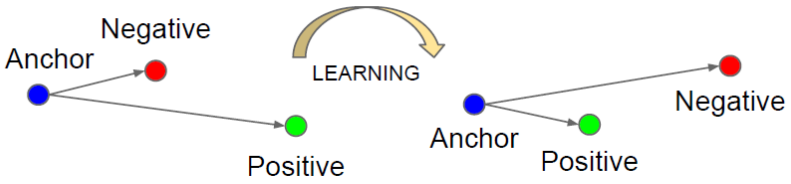
Collate a query with the registered N galleries

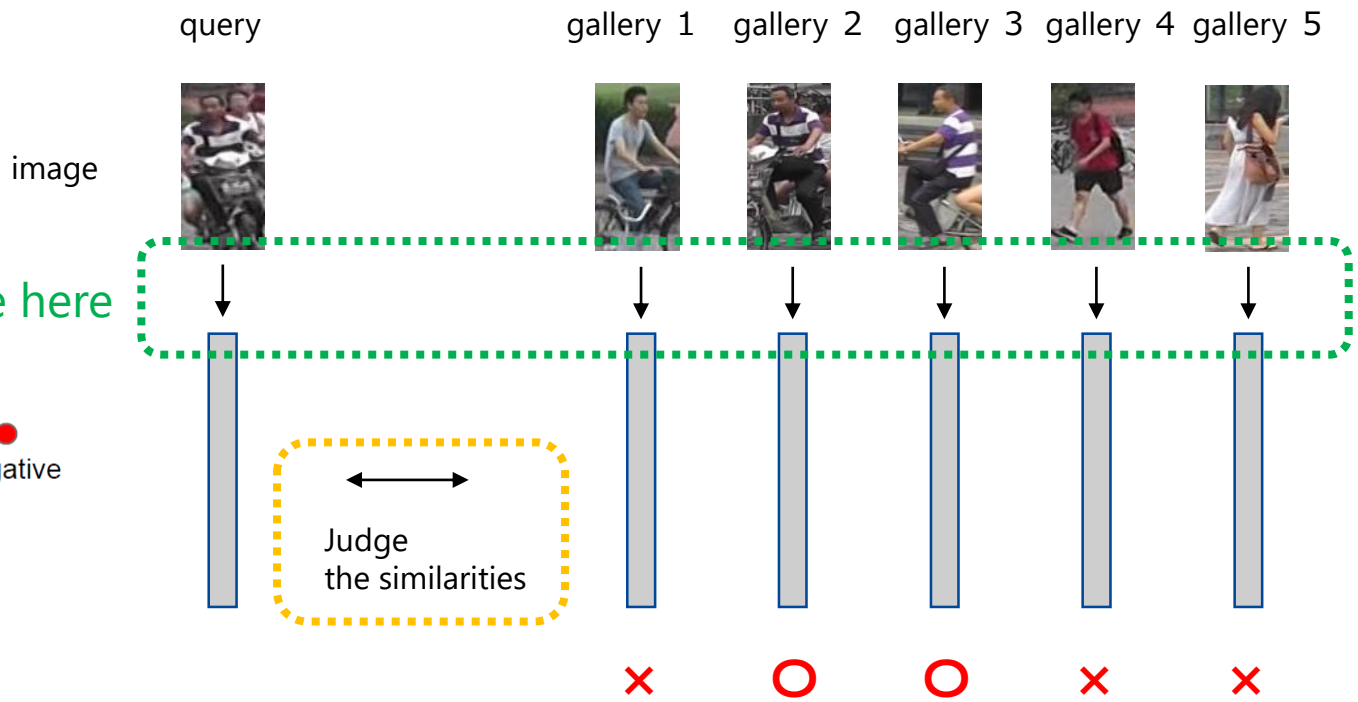


For the acceleration, feature vectors are often binarized in a high dimensional space in collating a query and galleries.
We focus on the post-processing with the binary description.

Related Works

- Metric learning (e.g. Triplet loss*, Arcface loss**)





General metric learning modules are here

We focused on the post processing

* F. Schroff, et al., Facenet, CVPR2015 ** J. Deng, et al., Arcface, CVPR2019

Subject：Tackling to false-acceptance

Extracted future vectors potentially includes misleading factors even after deep metric learning

in case where common features among different similar persons

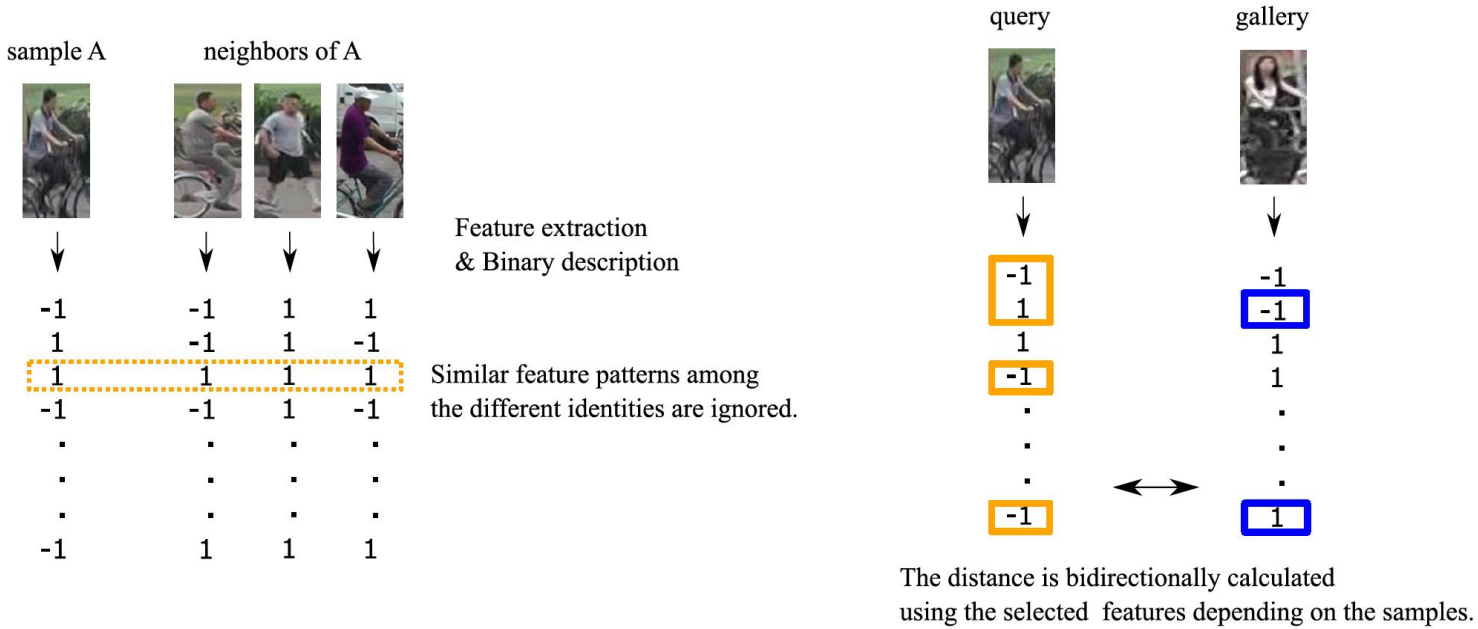
➡ The misleading features should be ignored in identification

The features appropriate for the identification would differ by samples

➡ The selected features should be determined for every sample

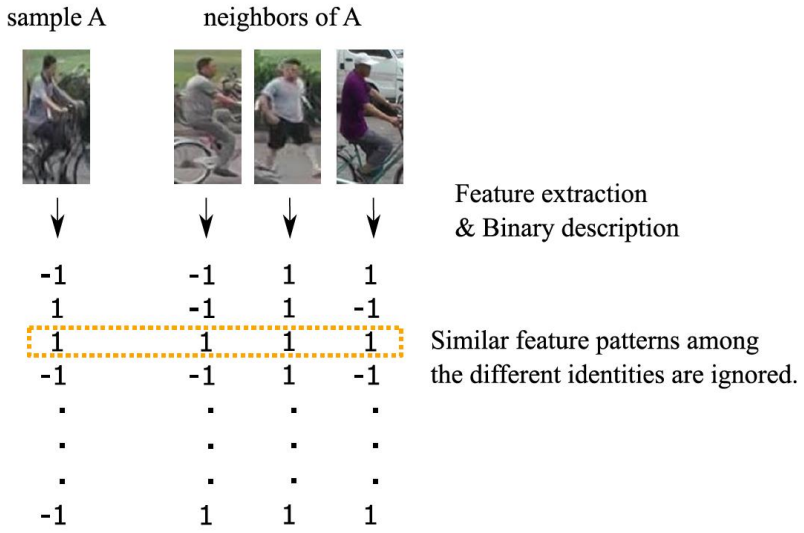
Approach : Sample-dependent feature selection

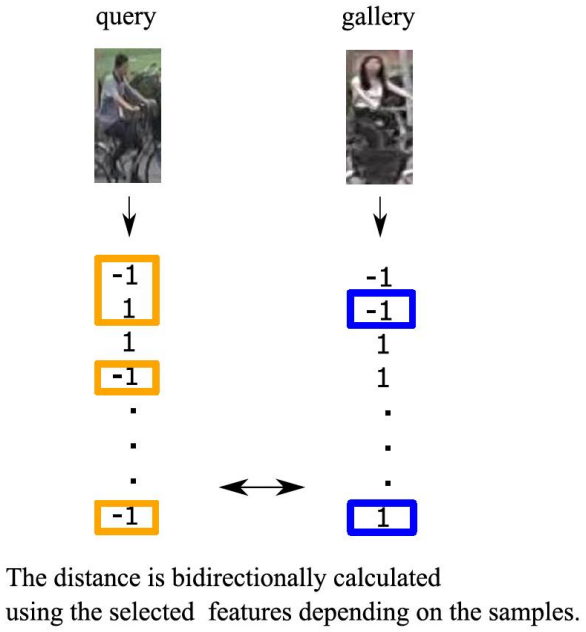
We proposed a metric learning method as the feature selection, as the post-processing, for the binary description



Approach : Sample-dependent feature selection

- Select feature factors so that different but very similar identities can be well discriminated
- Each pair of a query and galleries are collated using the feature selection manner different by the samples





Approach : Sample-dependent feature selection

For each sample of a query and galleries,
calculate feature selection manner

$$\arg\min_{\mathbf{w}_{(x_i)}} \underbrace{\frac{1}{K}\sum_{k}\left[\left(\mathbf{x}_i \circ \mathbf{w}_{(x_i)}\right)^T \mathbf{y}_k^i\right]^2}_{\text{Orthogonalization between a sample and the similar other identities}} ,$$

$$s.t. \quad \underbrace{\left\|\mathbf{w}_{(x_i)}\right\|_0 \leq R}_{\text{Select } R \text{ of } D \text{ futures}}$$

$\mathbf{x}_i \in \{-1,1\}^D$: feature vector of the i -th sample

$\mathbf{y}_k^{(x_i)} \in \{-1,1\}^D$: k-nearest gallery sample of the different identity of $\mathbf{x}_i$

$\mathbf{w}_{(\mathbf{x}_i)} \in \{0,1\}^D$: feature selection mask of $\mathbf{x}_i$

Approach : Sample-dependent feature selection

Sample-dependent feature selection is bi-directionally employed in collating a query $\boldsymbol{p}$ and a gallery $\boldsymbol{g}_i$

$$\mathrm{h}(\boldsymbol{p}, \boldsymbol{g}_i) = \frac{D - \boldsymbol{p}^{\mathrm{T}} \boldsymbol{g}_i}{2}$$

Hamming distance in usual cases

$$\mathrm{h}_{\boldsymbol{w}_{(\boldsymbol{p})}}(\boldsymbol{p}, \boldsymbol{g}_i) = \frac{R - (\boldsymbol{w} \circ \boldsymbol{p})^{\mathrm{T}} \boldsymbol{g}_i}{2}$$

Hamming distance
under the feature selection of $\boldsymbol{p}$

$$\mathrm{h}_{\boldsymbol{w}}(\boldsymbol{p}, \boldsymbol{g}_i) = \frac{1}{2R}\left(\mathrm{h}_{\boldsymbol{w}_{(\boldsymbol{p})}}(\boldsymbol{p}, \boldsymbol{g}_i) + \mathrm{h}_{\boldsymbol{w}_{(\boldsymbol{g}_i)}}(\boldsymbol{p}, \boldsymbol{g}_i)\right)$$

proposed distance metric
for the identification

Experimental Results

- Comparison with the other methods of feature selection as the post-processing
- Comparable feature selections are applied to the outputs of various deep person-ReID models [***]

Dataset	# IDs (classes)		# images	
	Query	Gallery	Query	Gallery
Market1501	750	751	3368	15913
Dukemtmcreid	702	1110	2228	17661

Model Data: train → test	Method	FRR@FAR [%]		Rank1 [%]	mAP [%]
		FAR=0.01%	FAR=0.1%		
OSNet market→market	baseline	36.8	13.9	94.5	84.4
	Proposed	**29.7**	**10.1**	**95.0**	**86.0**
	ReliefF	36.9	13.9	94.5	84.3
	Fisher Score	37.1	13.9	94.6	84.5
OSNet duke→duke	baseline	43.1	22.3	87.3	73.3
	Proposed	**36.0**	**19.2**	**88.3**	**75.6**
	ReliefF	42.9	22.5	87.2	73.3
	Fisher Score	43.3	22.3	87.4	73.4
OSNet msmt→market	baseline	79.7	57.2	68.0	42.1
	Proposed	**77.1**	**53.6**	**69.4**	**42.9**
	ReliefF	79.4	56.9	68.4	42.3
	Fisher Score	80.2	58.0	68.3	42.3
OSNet msmt→duke	baseline	62.3	40.4	67.2	49.3
	Proposed	**58.3**	**38.3**	**68.0**	**50.2**
	ReliefF	62.0	40.2	67.5	49.5
	Fisher Score	62.3	40.3	67.5	49.7

Performances were stably improved using the proposed method

*** K. Zhou, et al.,OSNet, ICCV2019

Experimental Results

green : positive
red : negative

threshold@FAR=0.01%

Accuracy is also improved at very low FAR

The proposed method could discriminate quite a similar persons

Conclusion

- We focused on metric learning as the post-processing based on the feature selection
- Sample-dependent feature selection is employed so that each sample can be discriminated from the similar samples of different identities
- Our method stably improved the accuracy for a variety of 1:N-identification models

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