TOSHIBA

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

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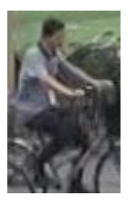
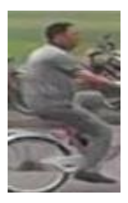
Overview

- The objective is to improve the accuracy of 1:N identification
- We proposed a metric learning method as the feature selection, as the post-processing

query  → $\boxed{-1\ \ 1}$ 1 $\boxed{-1}$ . . . $\boxed{-1}$

↕ Identify using the selected features

gallery  → -1 -1 $\boxed{1}$ 1 . . . $\boxed{1}$

Feature extraction & Binary description

Feature selection for the extracted binary description is applied

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

Target

- **Tackling to false-acceptance**

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

- **The existing methods discuss a metric space learned commonly for all the samples**

The features appropriate for the identification would differ by samples

Proposed Method

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

Approach

For each sample, calculate feature selection manner

$$\underset{\mathbf{w}_{(\mathbf{x}_i)}}{\arg\min}\ \frac{1}{K}\sum_k \left[\left(\mathbf{x}_i\circ\mathbf{w}_{(\mathbf{x}_i)}\right)^T \mathbf{y}_k^{(\mathbf{x}_i)}\right]^2 ,\qquad s.t.\quad \left\|\mathbf{w}_{(\mathbf{x}_i)}\right\|_0 \le R$$

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

$\mathbf{y}_k^{(\mathbf{x}_i)} \in \{-1,1\}^D$: 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 $\mathbf{x}_i$

If the target sample is a query, v-nearest samples are skipped, where the v-nearest samples are regarded as having the same identity as that of the query.

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

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

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

- Comparable feature selection methods were applied to the feature vector outputs of a variety of models for ReID

Model Data: train → test	Method	FRR@FAR [%] FAR=0.01%	FRR@FAR [%] FAR=0.1%	Rank1 [%]	mAP [%]
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
ResNet50 msmt→market	baseline	84.7	68.0	46.6	24.2
	Proposed	**83.8**	**66.7**	**47.2**	24.0
	ReliefF	84.8	67.5	47.1	**24.6**
	Fisher Score	85.1	68.3	46.9	24.5
ResNet50 msmt→duke	baseline	74.2	54.9	51.6	33.0
	Proposed	**71.9**	**53.5**	**52.9**	**33.6**
	ReliefF	74.1	54.8	51.2	33.1
	Fisher Score	74.3	54.9	52.1	33.3

Performances were stably improved using the proposed method

threshold@FAR=0.01%

The proposed method could discriminate quite a similar persons