MARGIN-EMBEDDING CANONICAL CORRELATION ANALYSIS WITH FEATURE SELECTION FOR PERSON RE-IDENTIFICATION

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1. Topic and Motivations

Background: Canonical correlation analysis (CCA) is a classical subspace learning method of capturing the common semantic information underlying multi-view data. It has been used in person re-identification by treating the task of matching identical individuals across non-overlapping multi-cameras as a multi-view learning problem.

Motivation: CCA-based re-ID methods still achieve unsatisfactory results because few jointly consider discriminative margin information and selecting importantly relevant features. We propose a novel l2,1-norm regularized margin-embedding CCA (l2,1-MCCA) to address this issue.

2. l2,1-norm Regularized Margin-embedding CCA (l2,1-MCCA) Model

1. We propose to embed the margin information into CCA, termed as margin-embedding CCA (MCCA). Its merit lies in enhancing the separable ability of inter-class samples in the learned subspace.

$$(W_x, W_y) = \arg\max_{W_x, W_y} \frac{Tr(W_x^T C_{xy} W_y)}{\sqrt{Tr(W_x^T C_{xx} W_x)}\sqrt{Tr(W_y^T C_{yy} W_y)}}$$

where $C_{xx} = E\left[xx^T\right] = XX^T$, $C_{yy} = E\left[yy^T\right] = YY^T$, and $C_{xy} = \overline{C}_{xy} = XY^T + \gamma XMY^T$

where M is the learned margin weight matrix

2. We readily devise the l2,1-norm regularization term to automaticall identify relevant features for person re-ID task, termed as l2,1-regularized CCA (l2,1-CCA).

$$C_{xx} = \overline{C}_{xx} = XX^T + \alpha U_x, \quad C_{yy} = \overline{C}_{yy} = YY^T + \beta U_y, \text{ and } C_{xy} = E\left[xy^T\right] = XY^T$$

where U_* is the diagonal weight matrix $(U_*)_{ii} = \frac{1}{2\|(W_*)_{i\cdot}\|_2}$

3. Combine (1) and (2), we get the final formulation of our model (l2,1-MCCA).

$$C_{xx} = \overline{C}_{xx} = XX^T + \alpha U_x, \quad C_{yy} = \overline{C}_{yy} = YY^T + \beta U_y, \text{ and } C_{xy} = \overline{C}_{xy} = XY^T + \gamma XMY^T$$

3. Experimental Results

We compare l2,1-MCCA with other CCA-based and some baseline methods on three datasets including VIPeR, PRID and 3DPES. We measure the performance by matching rates versus different rank scores.

Table 1. The rank-n matching rate (%) of the compared methods on the VIPER dataset.(The Top-3 results: the 1st in red, the 2nd in blue and the 3rd in green).

Method	r=1	r=5	r=10	r=20
CCA [1]	16.8	41.6	55.7	69.7
PCCA [14]	19.3	48.9	64.9	80.3
EIML [15]	22	-	63	78
cAMT-DCA [16]	23.4	52.8	67.1	81.1
LF [17]	24.2	-	-	-
UMDL [18]	31.5	-	-	-
Improved DML [19]	34.4	62.2	75.9	87.2
Siamese CNN [20]	34.8	75	-	-
KCCA [2]	37.2	71.4	84.6	92.8
FT-JSTL+DGD [21]	38.6	-	-	-
kLFDA [22]	39.2	71.8	81.3	92.4
LSSCDL [23]	42.3	71.5	82.9	92.1
Ensemble Metrics [13]	45.9	77.5	88.9	95.8
AdaRSVM [24]	47.5	66.8	73.4	78.8
MCKCCA [3]	47.9	77.6	87.3	93.8
GOG+XQDA [25]	49.7	79.7	88.7	94.5
SCSP [26]	**53.5**	**82.6**	**91.5**	**96.6**
$l_{2,1}$-**CCA**	29.2	51.4	65.5	76.1
MCCA	49.2	77.7	89.1	94.0
$l_{2,1}$-**MCCA**	51.6	80.4	90.5	95.3

Table 2. The rank-n matching rate (%) of the compared methods on the PRID dataset. (The Top-3 results: the 1st in red, the 2nd in blue and the 3rd in green).

Method	r=1	r=5	r=10	r=20
CCA [1]	5.8	16.1	24.3	35.4
AdaRSVM [24]	10.4	23.0	30.7	40.3
KCCA [2]	14.7	34.2	45.7	59.3
EIML [15]	15	-	38	50
RPLM [27]	15	-	42	54
Improved DML [19]	17.9	-	45.9	55.4
Ensemble Metrics [13]	17.9	-	50	62
UMDL [18]	24.2	-	-	-
MCKCCA [3]	27.4	48.7	62.2	72.9
$l_{2,1}$-**CCA**	23.8	46.2	51.6	65.0
MCCA	27.6	44.8	57.3	71.2
$l_{2,1}$-**MCCA**	**29.7**	**49.3**	**62.9**	**75.4**

Table 3. The rank-n matching rate (%) of the compared methods on 3DPES dataset. (The Top-3 results: the 1st in red, the 2nd in blue and the 3rd in green).

Method	r=1	r=5	r=10	r=20
CCA [1]	20.1	46.6	61.7	74.9
cAMT-DCA [16]	31.9	53.5	63.9	75.1
KCCA [2]	41.5	70.6	82.3	89.8
PCCA [14]	43.5	71.6	81.8	91.0
LF [17]	45.5	69.2	-	86.1
Ensemble Metrics [13]	53.3	76.8	85.7	91.4
kLFDA [22]	54.0	77.7	85.9	92.4
FT-JSTL+DGD [21]	55.2	76.4	84.9	91.9
SCSP [26]	57.3	78.6	86.5	93.6
$l_{2,1}$-**CCA**	54.2	75.0	80.2	87.5
MCCA	59.4	79.2	86.5	91.8
$l_{2,1}$-**MCCA**	**62.5**	**82.6**	**88.3**	**93.7**

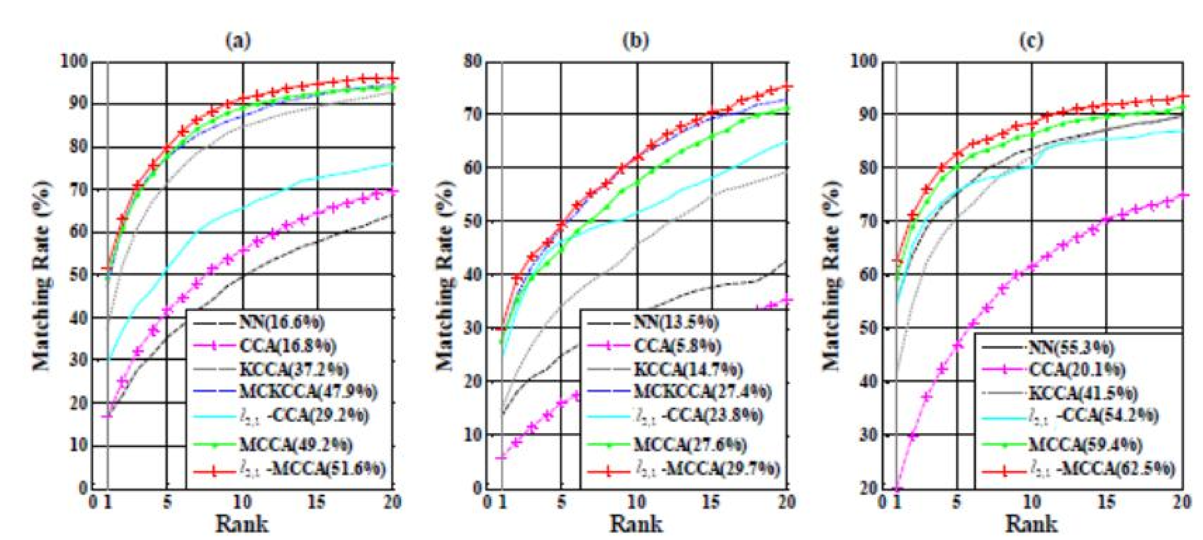

Fig. 2. The CMC curves of CCA-based re-ID methods on (a) VIPeR, (b) PRID and (c) 3DPES datasets, respectively.

Experiments on three popular datasets show the efficacy of l2,1-MCCA as compared with recently representative re-ID methods.

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