Efficient PSD Constrained Asymmetric Metric Learning for Person Re-identification

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Introduction

- **Problems with existing metric learning methods**
  - Applying PSD: expensive
  - No PSD: noisy
  - pos/neg samples: largely unbalanced
- **Contributions**
  - APG solution to the PSD constrained logistic metric learning problem
  - Asymmetric pos/neg sample weights to balance pos/neg costs
- **Advantages**
  - PSD+APG leads to low rank and smooth metric
  - APG solution is fast in convergence
  - PSD and asymmetric weights lead to notable improvements

Cross-view Logistic Metric Learning

- **Formulation**
  - Mahalanobis distance : $D^2_{\mathbf{M}}(\mathbf{x},\mathbf{z}) = \|\mathbf{x}-\mathbf{z}\|^2_{\mathbf{M}} = (\mathbf{x}-\mathbf{z})^T\mathbf{M}(\mathbf{x}-\mathbf{z})$
  - Loss function : $f_{\mathbf{M}}(\mathbf{x},\mathbf{z}) = log\left(1+e^{y(D^2_{\mathbf{M}}(\mathbf{x},\mathbf{z})-\mu)}\right)$
  - Full loss : $F(\mathbf{M}) = \sum_{i=1}^{n}\sum_{j=1}^{m} \underline{w_{ij}} f_{\mathbf{M}}(\mathbf{x}_i,\mathbf{z}_j)$ asymmetric pos/neg sample weighting
  - Problem : $\min_{\mathbf{M}} F(\mathbf{M}), \quad s.t.\ \underline{\mathbf{M} \succeq 0}$ PSD constraint, smooth the solution
- **APG Solution**
  - Gradient : simplified matrix computation $\nabla F = \mathbf{X}\mathbf{A}_t\mathbf{X}^T - \mathbf{X}\mathbf{G}_t\mathbf{Z}^T - (\mathbf{X}\mathbf{G}_t\mathbf{Z}^T)^T + \mathbf{Z}\mathbf{B}_t\mathbf{Z}^T$
  - Proximal operator : $P_{\eta_t}(\mathbf{M},\mathbf{V}_t) = F(\mathbf{V}_t) + \langle \mathbf{M}-\mathbf{V}_t, \nabla F(\mathbf{V}_t)\rangle + \frac{1}{2\eta_t}\|\mathbf{M}-\mathbf{V}_t\|^2_F$
  - Update rule : $\mathbf{C}_t = \mathbf{V}_t - \eta_t\nabla F(\mathbf{V}_t) = \mathbf{U}_t\mathbf{\Lambda}_t\mathbf{U}_t^T$

    $\mathbf{M}_t = \mathbf{U}_t\mathbf{\Lambda}_t^{+}\mathbf{U}_t^T$
  - Dimension reduction : $\mathbf{P}_t = \mathbf{U}_t^{+}(\mathbf{\Lambda}_t^{++})^{1/2}$

    $D^2_{\mathbf{P}_t}(\mathbf{x},\mathbf{z}) = \|\mathbf{P}_t^T\mathbf{x} - \mathbf{P}_t^T\mathbf{z}\|^2_2$

Experiments

- **Analysis： low rank and individual improvement**

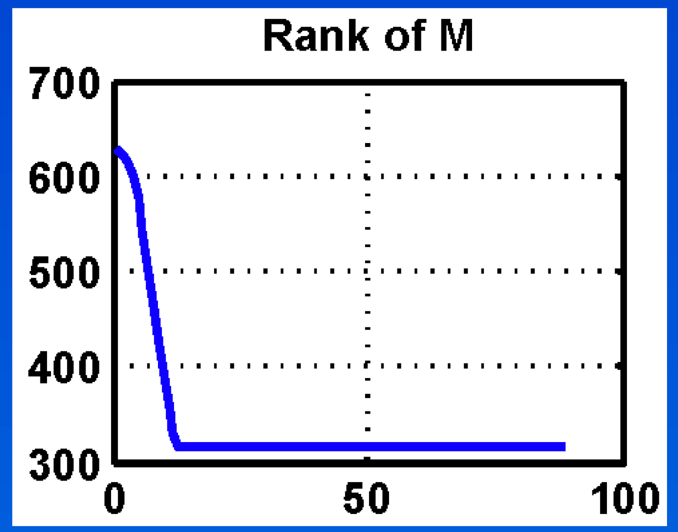

Fig. 1. Fast rank shrinkage.

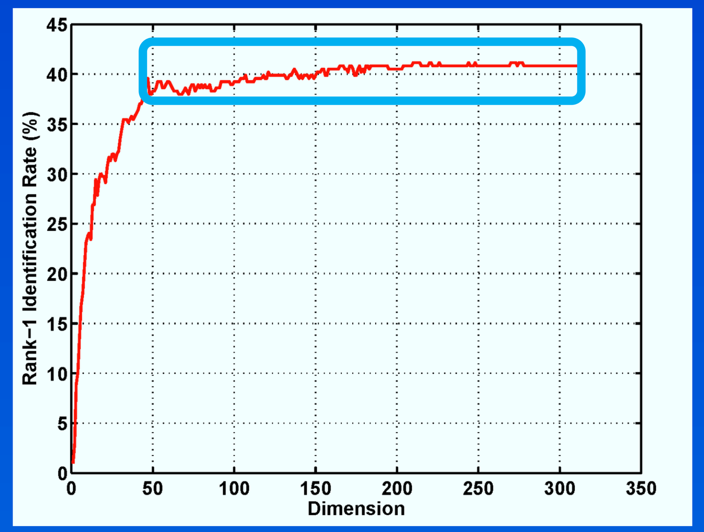

Fig. 2. Low rank selection.

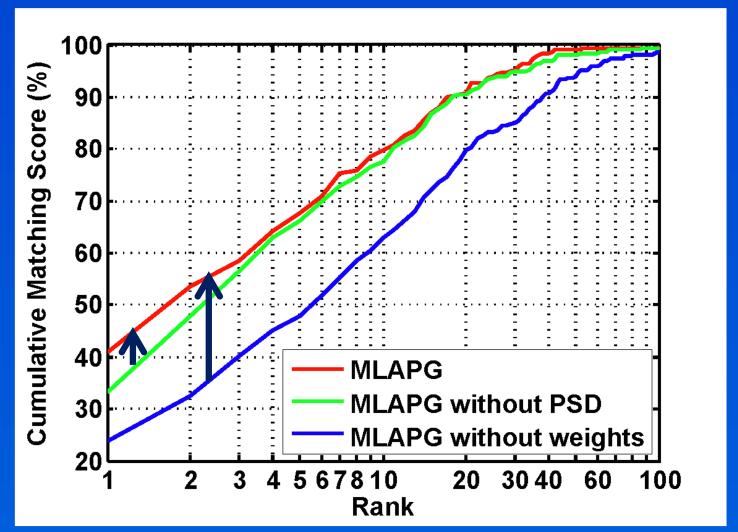

Fig. 3. Improvements by PSD and weighting.

- **Comparison of metric learning methods with the same LOMO feature**

Method	rank = 1	rank = 10	rank = 20
MLAPG	**39.21**	**81.42**	**92.50**
XQDA	38.23	81.14	92.18
KISSME	33.54	79.30	90.47
LMNN	28.42	72.31	85.32
LADF	27.63	75.47	88.29
ITML	19.02	52.31	67.34
LDML	13.99	38.64	48.73
PRDC	12.15	35.82	48.26

Fig. 4. On the VIPeR database.

Method	rank = 1	rank = 10	rank = 20
XQDA	**16.56**	**41.44**	**52.48**
MLAPG	15.60	40.48	**52.48**
LMNN	10.80	34.24	45.76
KISSME	10.64	31.60	43.20
ITML	9.44	27.04	35.20
LDML	8.16	22.24	27.36
PRDC	7.52	23.84	31.44
LADF	6.00	27.36	41.28

Fig. 5. On the QMUL GRID database.

- **Comparison to the published results**

Method	rank=1	rank=10	rank=20	Reference
MLAPG	**40.73**	**82.34**	**92.37**	Proposed
XQDA	40.00	80.51	91.08	2015 CVPR [14]
SCNCD	37.80	81.20	90.40	2014 ECCV [29]
Kernel Ensb 2	36.1	80.1	85.6	2014 ECCV [28]
kBiCov	31.11	70.71	82.45	2014 IVC [18]
LADF	30.22	78.92	90.44	2013 CVPR [13]
SalMatch	30.16	65.54	79.15	2013 ICCV [30]
Mid-level Filter*	29.11	65.95	79.87	2014 CVPR [32]
MtMCML	28.83	75.82	88.51	2014 TIP [19]
RPLM	27.00	69.00	83.00	2012 ECCV [9]
SSCDL	25.60	68.10	83.60	2014 CVPR [15]
LF	24.18	67.12	82.00	2013 CVPR [22]
SDALF	19.87	49.37	65.73	2013 CVIU [1]
KISSME	19.60	62.20	77.00	2012 CVPR [10]
PCCA	19.27	64.91	80.28	2012 CVPR [20]
PRDC	15.66	53.86	70.09	2013 TPAMI [33]
ELF	12.00	44.00	61.00	2008 ECCV [6]

Fig. 6. On the VIPeR database.

Method	rank=1	rank=10	rank=20
MLAPG	**16.64**	41.20	52.96
XQDA [14]	16.56	41.84	52.40
MtMCML [19]	14.08	**45.84**	**59.84**
MRank-RankSVM [16]	12.24	36.32	46.56
MRank-PRDC [16]	11.12	35.76	46.56
RankSVM [23]	10.24	33.28	43.68
PRDC [33]	9.68	32.96	44.32
L1-norm [16]	4.40	16.24	24.80

Fig. 7. On the QMUL GRID database.

Method	rank=1	rank=10	rank=20
MLAPG	**64.24**	**90.84**	**94.92**
XQDA [14]	63.21	90.04	94.16
Mid-level Filter [32]	34.30	64.96	74.94
SalMatch [30]	28.45	55.67	67.95
GenericMetric [11]	20.00	56.04	69.27
eSDC [31]	19.67	40.29	50.58

Fig. 8. On the CUHK Campus database.

	Labeled	Detected
LOMO+MLAPG	**57.96**	**51.15**
LOMO+XQDA [14]	52.20	46.25
DeepReID [12]	20.65	19.89
KISSME [10]	14.17	11.70
LDML [7]	13.51	10.92
eSDC [31]	8.76	7.68
LMNN [26]	7.29	6.25
ITML [3]	5.53	5.14
SDALF [1]	5.60	4.87

Fig. 9. On the CUHK03 database.

Project Website and MATLAB Source Code

- http://www.cbsr.ia.ac.cn/users/scliao/projects/mlapg/

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