Metric learning method for subspace-based image-set recognition

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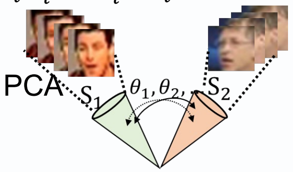
(1) Introduction

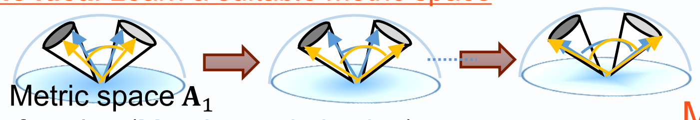
- *Image-set recognition*:
  - ➢ Efficient approach for object recognition.
  - ➢ Utilizing multiple images (multi-view, video) as an input.
- *Subspace-method*:
  - ➢ General approach for the image-set recognition.
  1. Representing an image-set by a low-dimensional subspace.
  2. Classifying an input image-set by the subspace-similarity
- ***Our objective***: improving performance of subspace-based methods
- ***Approach***: constructing a metric learning method with subspaces

(2) Proposed method

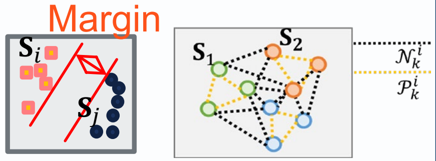
- Subspace similarity with a metric
  - $\mathrm{sim}(\mathbf{S}_1,\mathbf{S}_2) = \|\hat{\mathbf{S}}_1^T\mathbf{A}\hat{\mathbf{S}}_2\|_F^2 = \sum_j \cos^2\theta_j$, $\hat{\mathbf{S}}_i = \mathbf{S}_i\mathbf{U}_i\Sigma_i^{-1/2}$, $\mathbf{U}_i\Sigma_i\mathbf{U}_i^T = \mathbf{S}_i^T\mathbf{A}\mathbf{S}_i$.
  - θ_j: j-th canonical angle
  - $\mathbf{S}_i$: Basis of a subspace generated by PCA



- **Basic idea: Learn a suitable metric space**



- Cost function (Margin maximization)

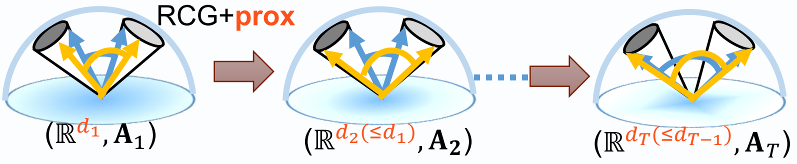


- $\mathbf{A}^* = \min_{\mathbf{A}} J(\mathbf{A}) = J_b(\mathbf{A}) + J_w(\mathbf{A}) + \lambda\left(1 - \|\mathbf{A}\|_F^2\right)^2$,
- $J_b(\mathbf{A}) = \frac{1}{kN}\sum_{i=1}^N \sum_{j\in\mathcal{N}_k^i} \mathrm{sim}(\mathbf{S}_i,\mathbf{S}_j)$,
- $J_w(\mathbf{A}) = \frac{1}{kN}\sum_{i=1}^N \sum_{j\in\mathcal{P}_k^i} d^2(\mathbf{S}_i,\mathbf{S}_j) = \frac{1}{kN}\sum_{i=1}^N \sum_{j\in\mathcal{P}_k^i}(r - \mathrm{sim}(\mathbf{S}_i,\mathbf{S}_j))$
- $\mathcal{N}_k^i$/ $\mathcal{P}_k^i$:k-neighborhood of the i-th subspace
- Optimization:
  - Use Riemannian conjugate gradient, RCG. ($\mathbf{A}$ must be a SPD matrix)
  - Need a gradient of sim().
    - Reformulate

$$\begin{aligned}\mathrm{sim}(\mathbf{S}_i,\mathbf{S}_j) &= \|\hat{\mathbf{S}}_i^T\mathbf{A}\hat{\mathbf{S}}_j\|_F^2 = tr(\hat{\mathbf{S}}_j^T\mathbf{A}\hat{\mathbf{S}}_i\hat{\mathbf{S}}_i^T\mathbf{A}\hat{\mathbf{S}}_j) = tr(\hat{\mathbf{S}}_j\hat{\mathbf{S}}_j^T\mathbf{A}\hat{\mathbf{S}}_i\hat{\mathbf{S}}_i^T\mathbf{A})\\ &= tr(\mathbf{S}_j\mathbf{U}_j\Sigma_j^{-1/2}\Sigma_j^{-1/2}\mathbf{U}_j^T\mathbf{S}_j^T\mathbf{A}\mathbf{S}_i\mathbf{U}_i\Sigma_i^{-1/2}\Sigma_i^{-1/2}\mathbf{U}_i^T\mathbf{S}_i^T\mathbf{A})\\ &= tr(\mathbf{S}_i^T\mathbf{A}\mathbf{S}_j(\mathbf{S}_j^T\mathbf{A}\mathbf{S}_j)^{-1}\mathbf{S}_j^T\mathbf{A}\mathbf{S}_i(\mathbf{S}_i^T\mathbf{A}\mathbf{S}_i)^{-1}).\end{aligned}$$

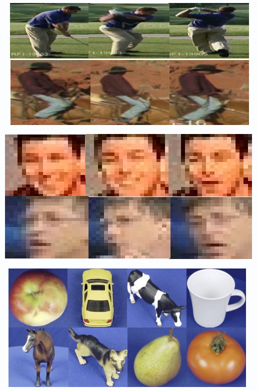
(3) Extension method

- Rank($\mathbf{A}$)=dim. of the metric space→can estimate the optimal dim automatically by low-rank constraint
- Cost function: $\min_{\mathbf{A}} J(\mathbf{A}) + \eta\|\mathbf{A}\|_*$, $\|\ \|_*$trace norm.
- Optimization: RCG + proximal gradient method
  - The trace norm constraint is not differentiable.
  - Apply the following operation after RCG step
  - $\mathrm{prox}_\eta^{tr}(\mathbf{A}) = \mathbf{U}\max(\mathbf{\Sigma} - \eta\mathbf{I},\mathbf{0})\mathbf{U}^{\mathrm{T}}, \mathbf{U}\mathbf{\Sigma}\mathbf{U}^{\mathrm{T}} = \mathbf{A}$



(4) Results

- Datasets:1. UCF sport(10 actions) 2. YTC(47 faces) 3.ETH(8 objects)



model	method	UCF	YTC	ETH
Affine hull	AHISD[1]	53.33	56.31±4.61	70.25±4.78
subspace	GGDA[2]	47.33	47.45±8.06	93.75±4.75
	PML[3]	72.67	54.82±4.63	93.75±3.17
	RMML[4]	59.33	54.96±4.96	90.25±4.16
	Proposed	71.33	59.29±2.72	**95.28±3.21**
	+$\|\mathbf{A}\|_*$	**74.00**	**59.85±3.53**	95.25±2.82

(5) Conclusion

- We introduced a metric space into a subspace-method and constructed metric learning frameworks by efficiently handing subspaces.
- We showed that our methods can achieve competitive results compared with various previous methods.

[1] Cevikalp, H. and Triggs, B. "Face recognition based on image sets", CVPR 2010.

[2] Harandi, M.T. et al, "Graph embedding discriminant analysis on Grassmannian manifolds for improved image set matching", CVPR 2011.

[3] Huang, Z. et al, "Projection metric learning on Grassmann manifold with application to video based face recognition", CVPR 2015.

[4] Zhu, P. et al, "Towards Generalized and Efficient Metric Learning on Riemannian Manifold. IJCAI 2018.