FACIAL EXPRESSIONS IN THE WILD

Databases and Experiment Protocols

Emotion Recognition In The Wild Challenge and Workshop (EmotiW 2013)

Partial Least Squares Regression on Grassmannian Manifold for Emotion Recognition

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Outline

- Problem
- Related work
- Our Method
- Experiments
- Conclusion

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Emotion recognition in the wild

- Challenges
  - Large data variations
    - head pose, illumination, partial occlusion, etc.
  - Lack of labeled data
    - Manual annotation is hard as spontaneous expression is ambiguous in the real world.

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Video-based emotion recognition

- Acoustic information based
  - Time domain and frequency domain
    - e.g. pitch, intensity, pitch contour, Low Short-time Energy Ratio (LSTER), maximum bandwidth, …
- Vision information based
  - Spatial space and temporal space
    - e.g. Optical flow, 3D descriptor (LBP-TOP, HOG 3D), tracking based (AAM, CLM), probabilistic graph model (HMM, CRF), …

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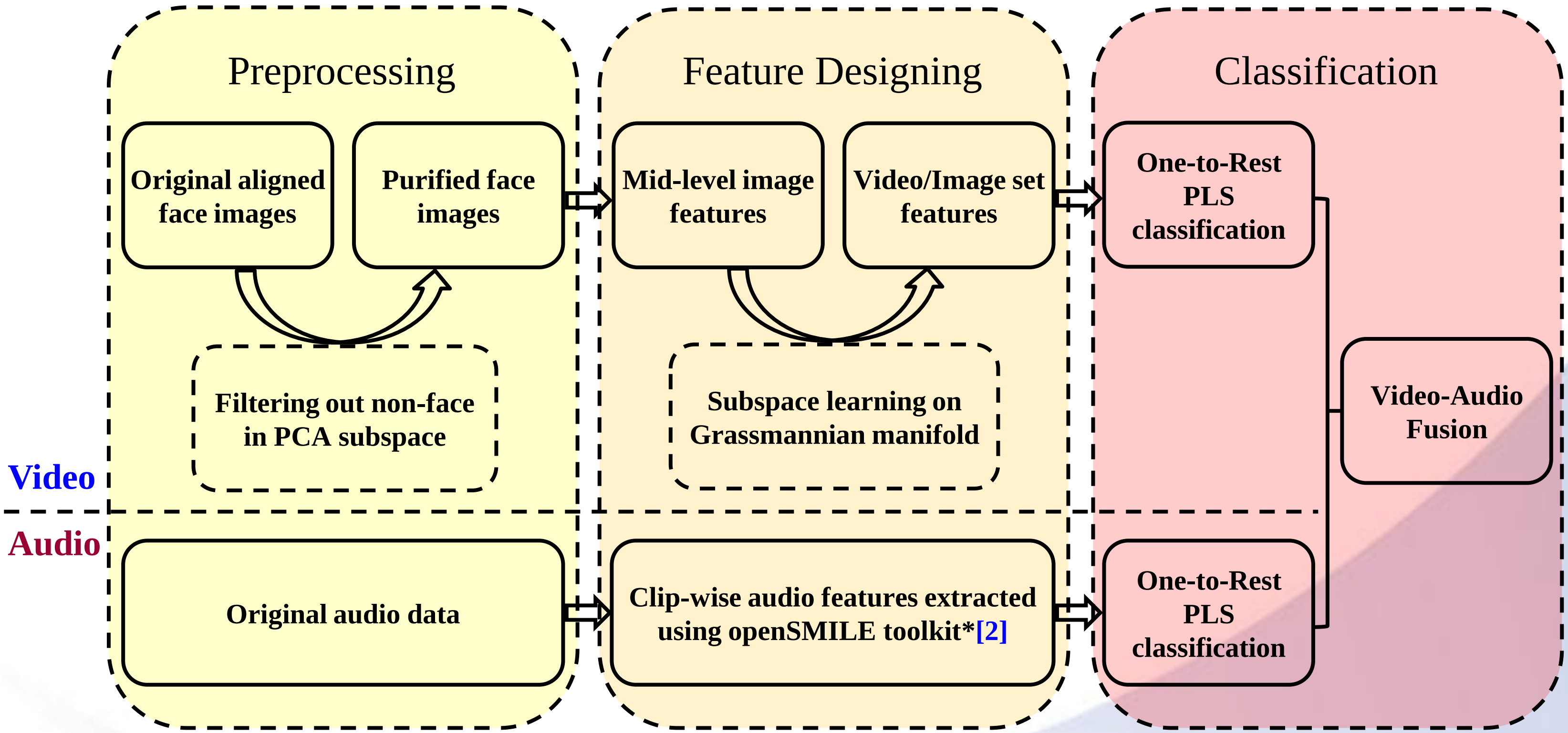
Our method

- Key issue
  - How to model the emotion video clip?
- Motivation
  - Alleviate the effect of mis-alignment of facial images
  - Encode the data variations among video frames
- Basic idea
  - Inspired by recent progress of image set-based face recognition [1]
  - Treat the video clip as an image set, i.e., a collection of frames
  - Linear subspace for video (image set) modeling

[1] R. Wang, H. Guo, L. S. Davis, and Q. Dai. Covariance discriminative learning: A natural and efficient approach to image set classification. CVPR, 2012.

Our method

- An overview



[2] F. Eyben, M. Wollmer, and B. Schuller. Opensmile: the munich versatile and fast open-source audio feature extractor. ACM MM, 2010.

Our method

- Preprocessing
  - Original face alignment using MoPS [3] (*provided by organizer*)
  - Purification of face images
    - Original aligned face images set: $X = \{x_1, x_2, \dots, x_n\}, x_i \in R^D$.
    - PCA projection learned on X by preserving low energy: W.
    - Mean reconstruction error of each image:

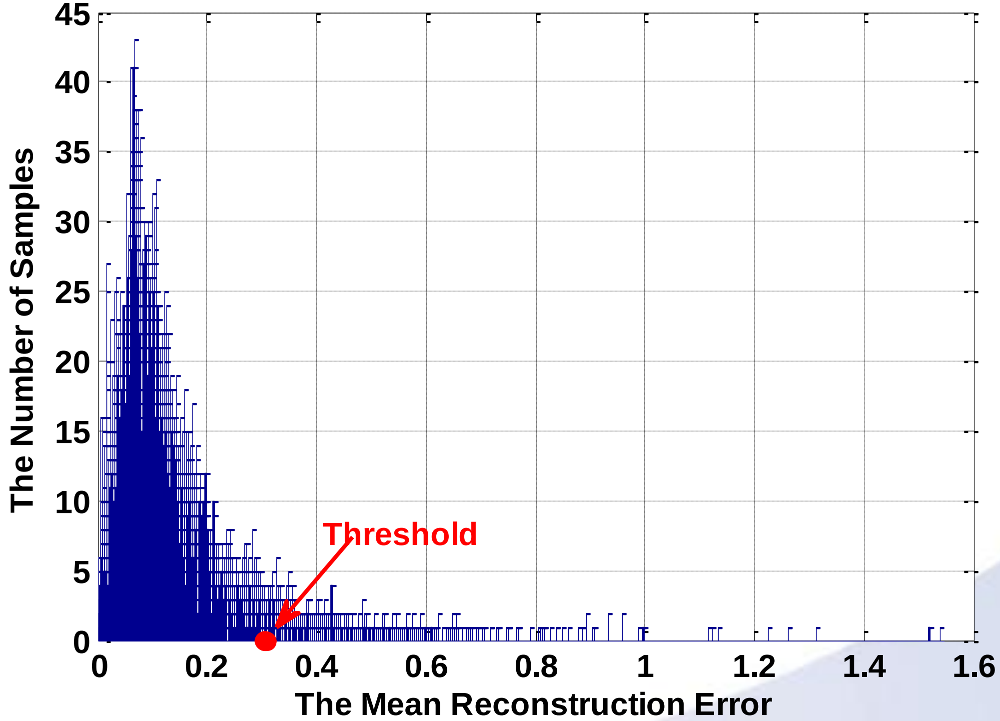
$$MeanErr_t = \frac{1}{D} \left|\left| x_t - W^T W x_t \right|\right|^2$$

    - Non-face/Badly-aligned face images tend to have large $MeanErr_t$.

[3] X. Zhu, and D. Ramanan. Face detection, pose estimation, and landmark localization in the wild. CVPR, 2012.

Our method

- Preprocessing
  - The distribution of $MeanErr_t$ on training set in EmotiW2013.



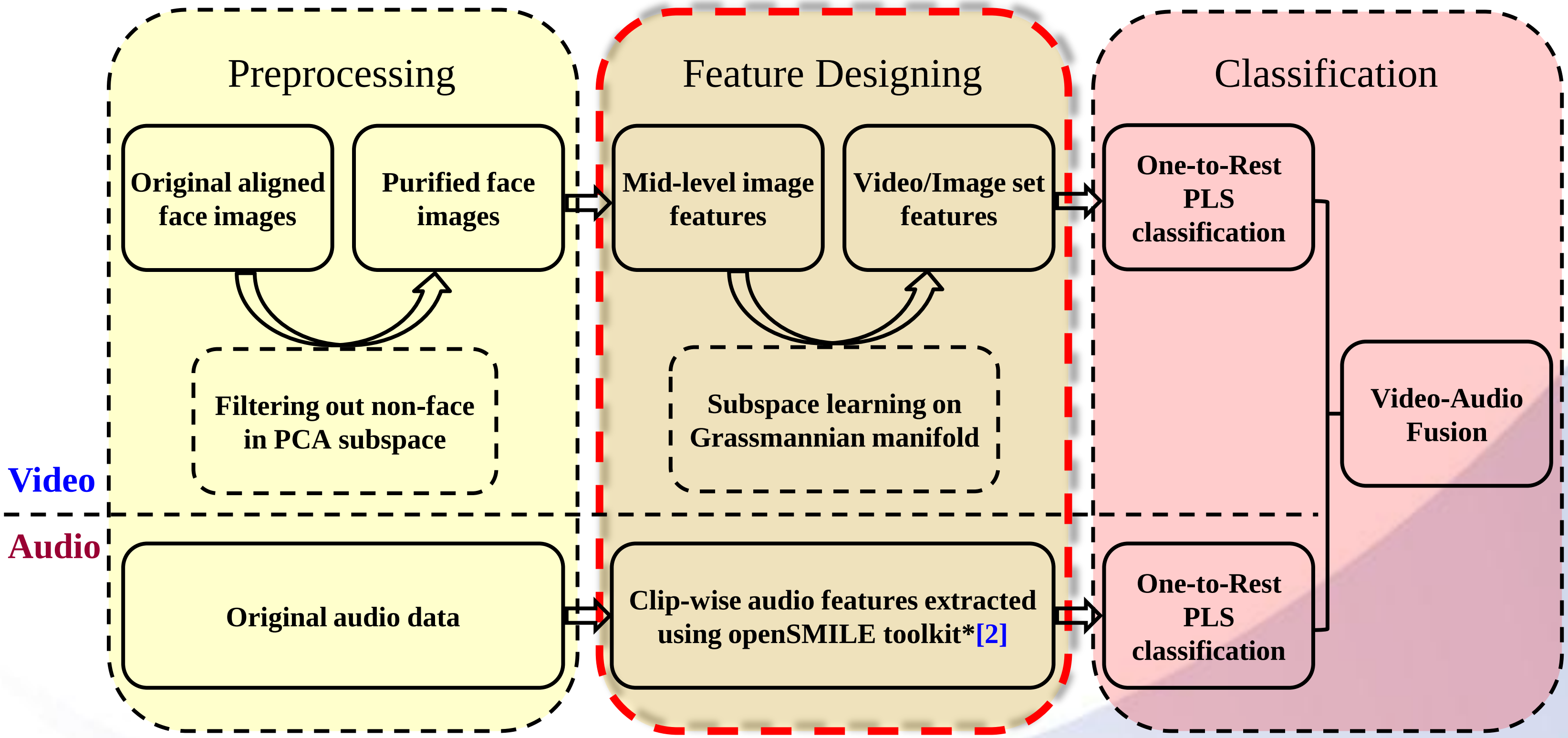
* Threshold is for filtering out non-face in PCA space.

Our method

- Preprocessing
  - An example of 100 samples with largest mean reconstruction error. Most are non-face images or mis-alignment results.

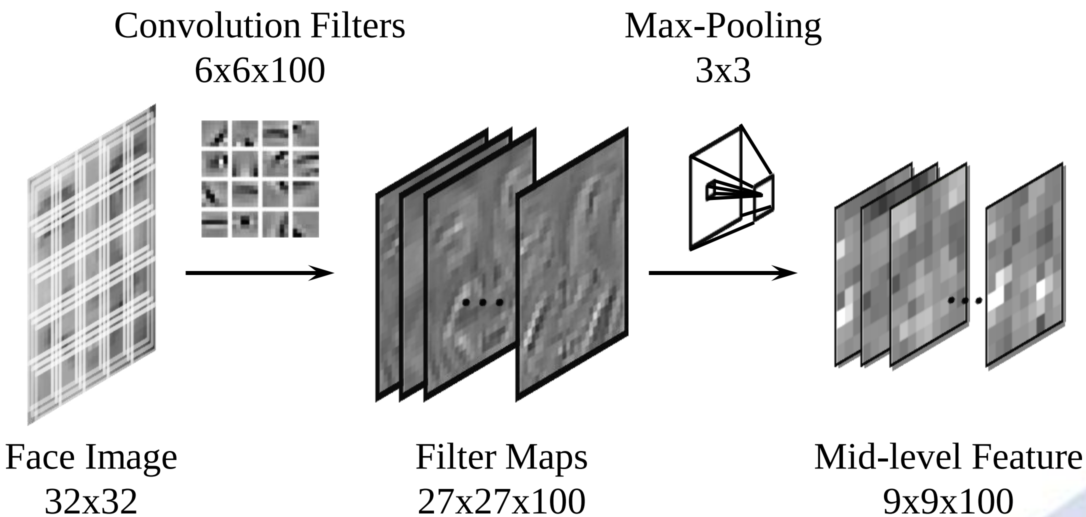
Our method

- An overview



Our method

- Feature designing
  - Image feature [4]



[4] M. Liu, S. Li, S. Shan, X. Chen. AU-aware Deep Networks for Facial Expression Recognition. FG, 2013.

Our method

- Feature designing
  - Video feature
    - Each video clip is a set of images, denoted as $S_i \in R^{f \times n_i}$, where f is the dimension of image feature, and n_i is the number of frames.
    - The video S_i can be represented as a linear subspace P_i, s.t.
      $$S_i S_i^T = P_i \Lambda_i P_i^T$$
    - Thus all the video clips can be modeled as a collection of subspaces, which are also the points on Grassmannian manifold.

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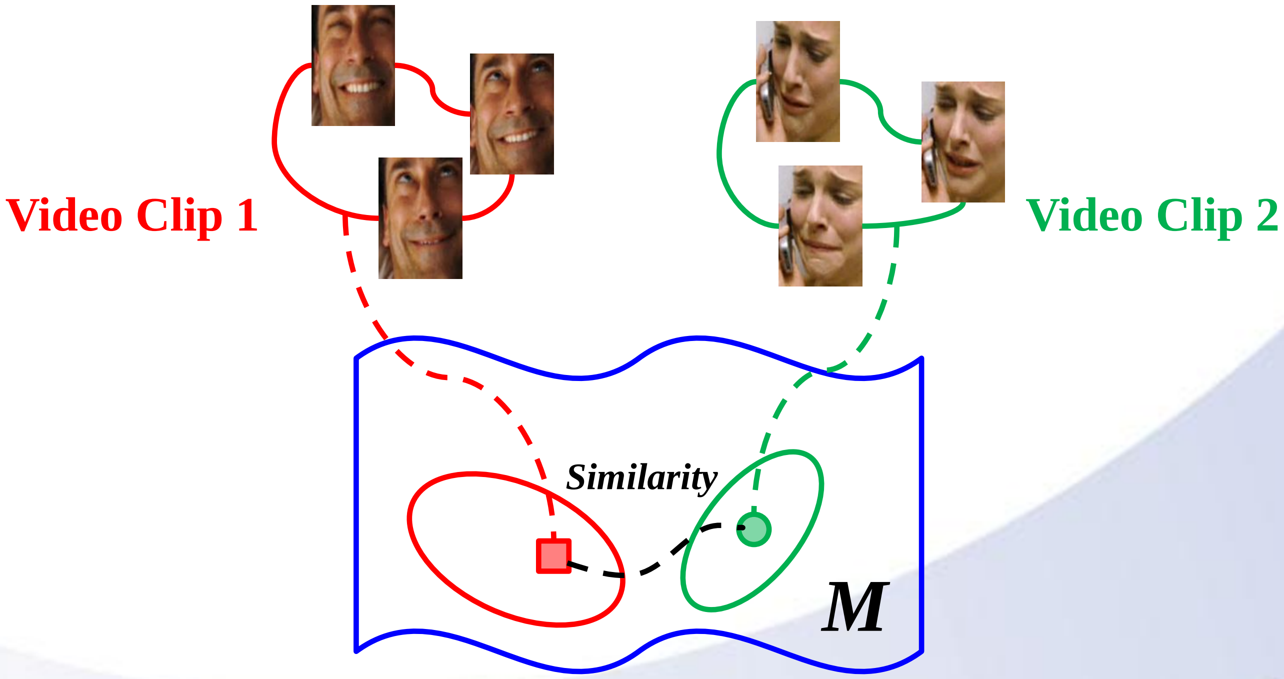
Our method

- Feature designing
  - Video feature
    - An illustration of subspaces on Grassmannian manifold



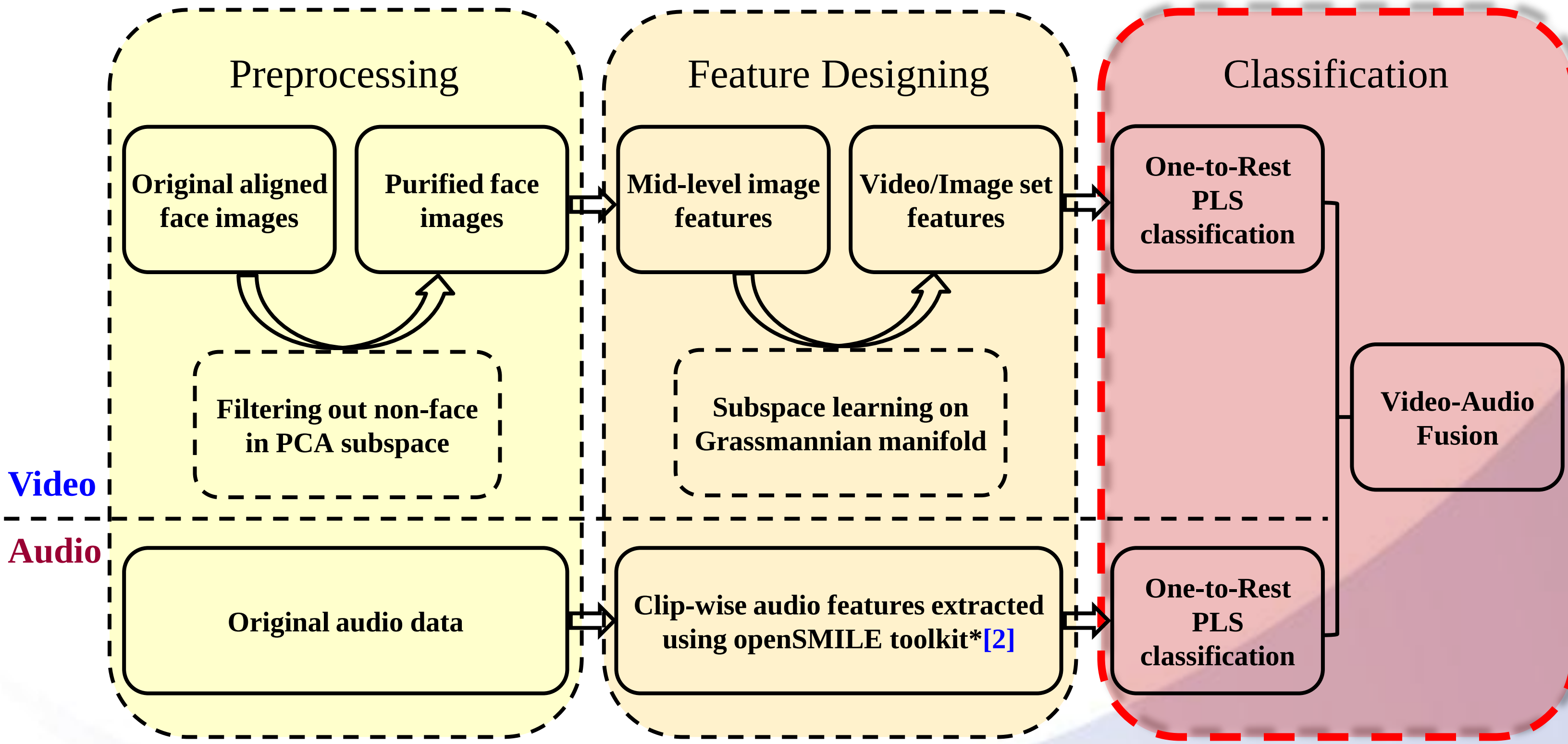
Our method

- Feature designing
  - Video feature
    - The similarity between two points $\boldsymbol{P_i}$ and $\boldsymbol{P_j}$ on manifold M can be measured by a linear combination of Grassmannian kernels.
      - Projection kernel[5]: $k_{ij}^{[proj]} = ||P_i^T P_j||_F^2$.
      - Canonical correlation kernel[6]: $k_{ij}^{[CC]} = max_{a_p \in span(P_i)} max_{b_q \in span(P_j)} a_p^T b_q$.
      - Linear combination: $k_{ij}^{[com]} = k_{ij}^{[proj]} + \alpha k_{ij}^{[CC]}$.
    - The kernels of each point (i.e., each video) to all training points serve as its final feature representation for classification.

[5] J. Hamm, D. Lee. Grassmann discriminant analysis: a unifying view on subspace-based learning. ICML, 2008.
[6] M. Harandi, C. Sanderson, S. Shirazi, B.C. Lovell. Graph embedding discriminant analysis on Grassmannian manifolds for improved image set matching. CVPR, 2011.

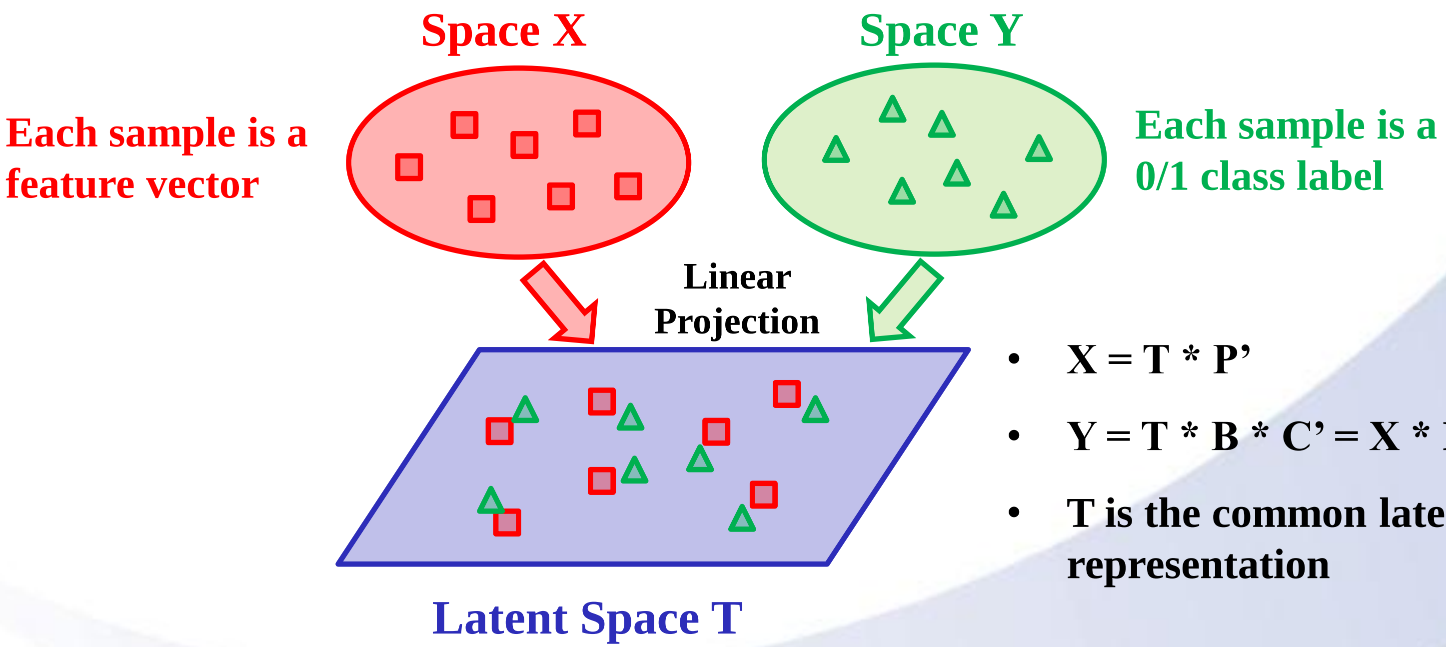
Our method

- An overview



Our method

- Classification
  - Partial Least Squares (PLS) for classification [1]
    - Maximize the covariance between observations and class labels

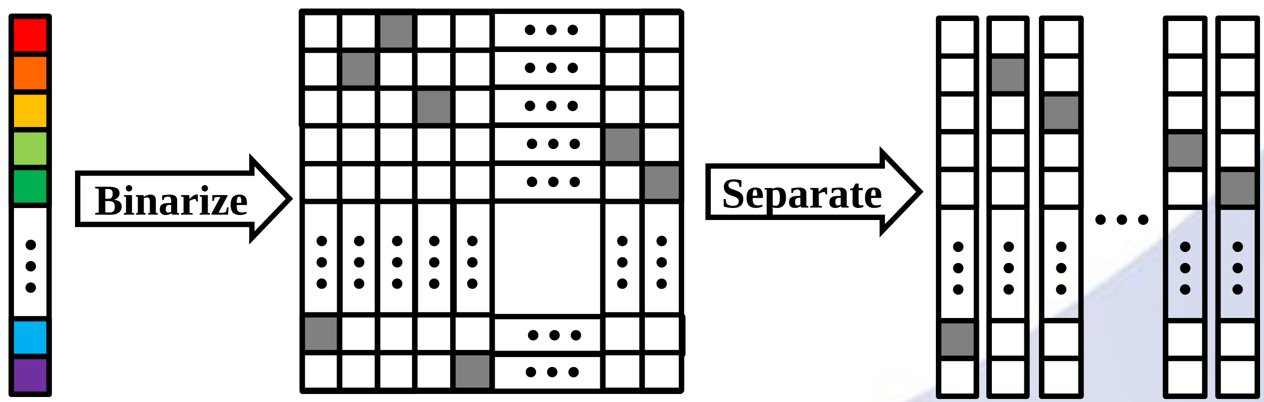


- $X = T * P'$
- $Y = T * B * C' = X * B\_pls$
- T is the common latent representation

[1] R. Wang, H. Guo, L. S. Davis, and Q. Dai. Covariance discriminative learning: A natural and efficient approach to image set classification. CVPR, 2012.

Our method

- Classification
  - One-to-Rest PLS
    - Suppose there are ***c*** categories and ***N*** training samples, we train ***c*** One-to-Rest PLS classifiers to predict each class simultaneously.
    - Effectively to handle the hard classes, e.g. “*Sad*” vs. “*Disgust*”



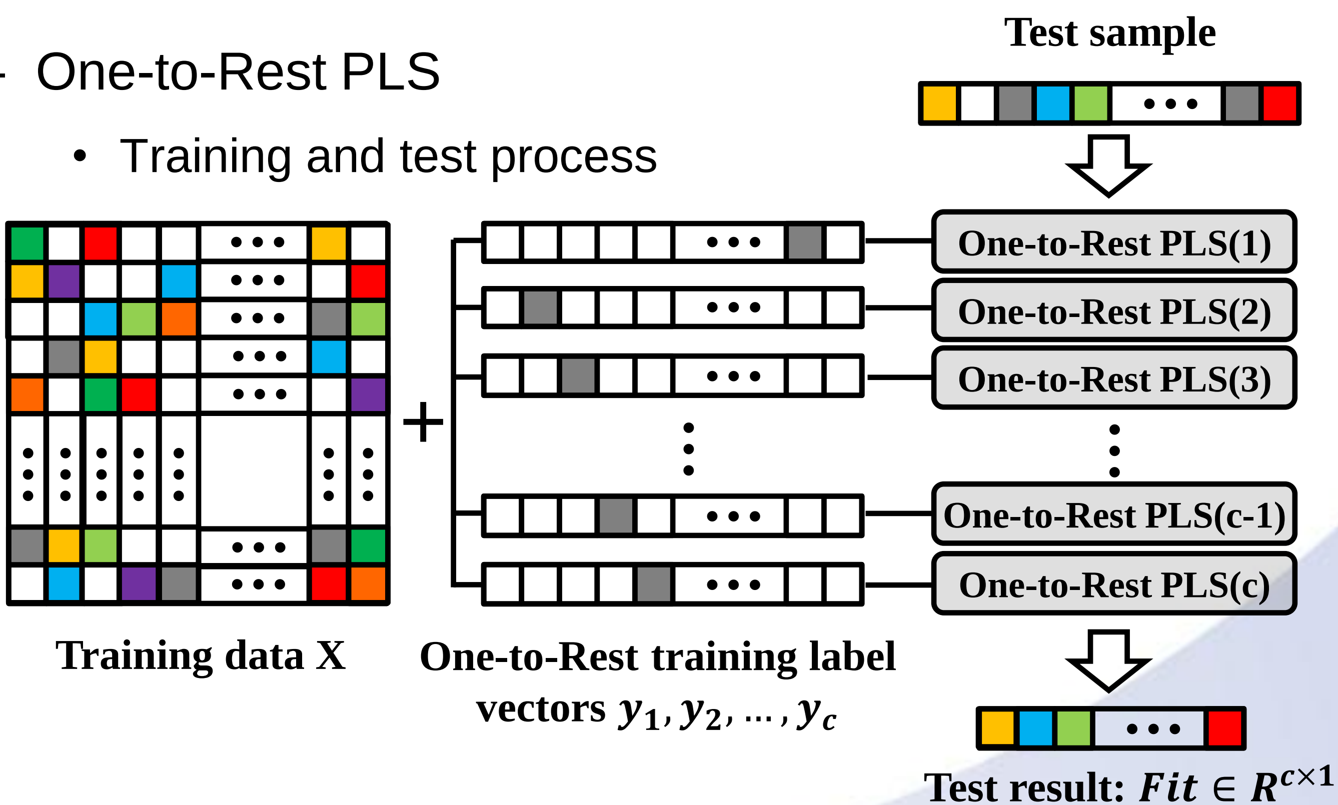
Original training label vector $\boldsymbol{Y} \in \boldsymbol{R}^{N\times 1}$

Binary training label matrix $\boldsymbol{Y} \in \boldsymbol{R}^{N\times c}$

One-to-Rest training label vectors, $\boldsymbol{y}_1, \boldsymbol{y}_2, \ldots, \boldsymbol{y}_c \in \boldsymbol{R}^{N\times 1}$

Our method

- Classification
  - One-to-Rest PLS
    - Training and test process



Our method

- Classification
  - Video-Audio fusion for final test output
    - For a given test video, using the *c* PLS classifiers for video and audio respectively, we obtain two prediction vectors $Fit^{video}, Fit^{audio} \in R^{c\times 1}$.
    - We conduct a linear fusion at decision level using weighted parameter λ

$$Fit^{fusion} = (1-\lambda)\, Fit^{video} + \lambda Fit^{audio}.$$

    - The category corresponding to the maximum value in $\boldsymbol{Fit^{fusion}}$ is determined to be the recognition result.

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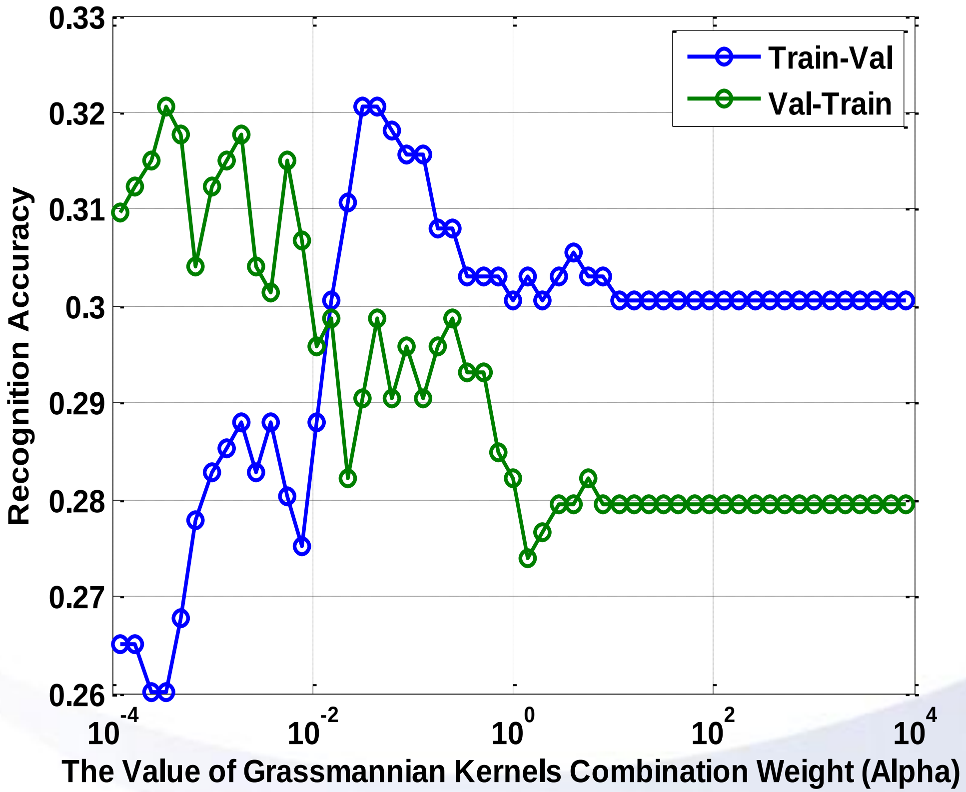
Experiments

- Discussion of Parameters
  - The fusion weights of Grassmannian kernels



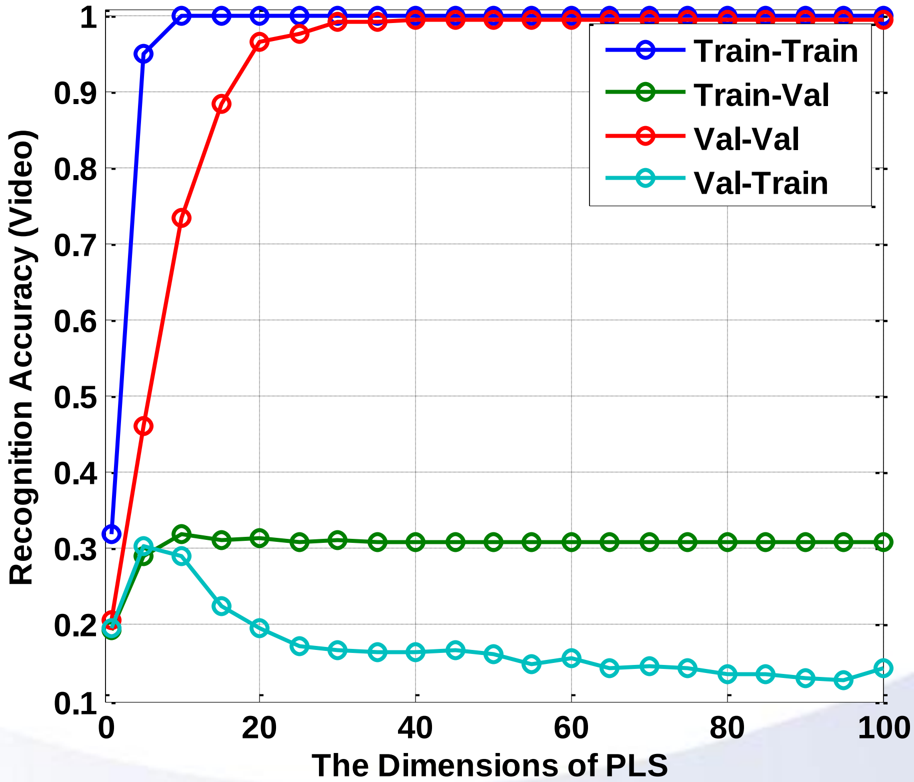
$$k_{ij}^{[com]} = k_{ij}^{[proj]} + \alpha k_{ij}^{[CC]}$$

Train-Val: $@\alpha = 2^{-6}, 2^{-5}$

Val-Train: $@\alpha = 2^{-10}$

Experiments

- Discussion of Parameters
  - The dimension of One-to-Rest PLS (video)

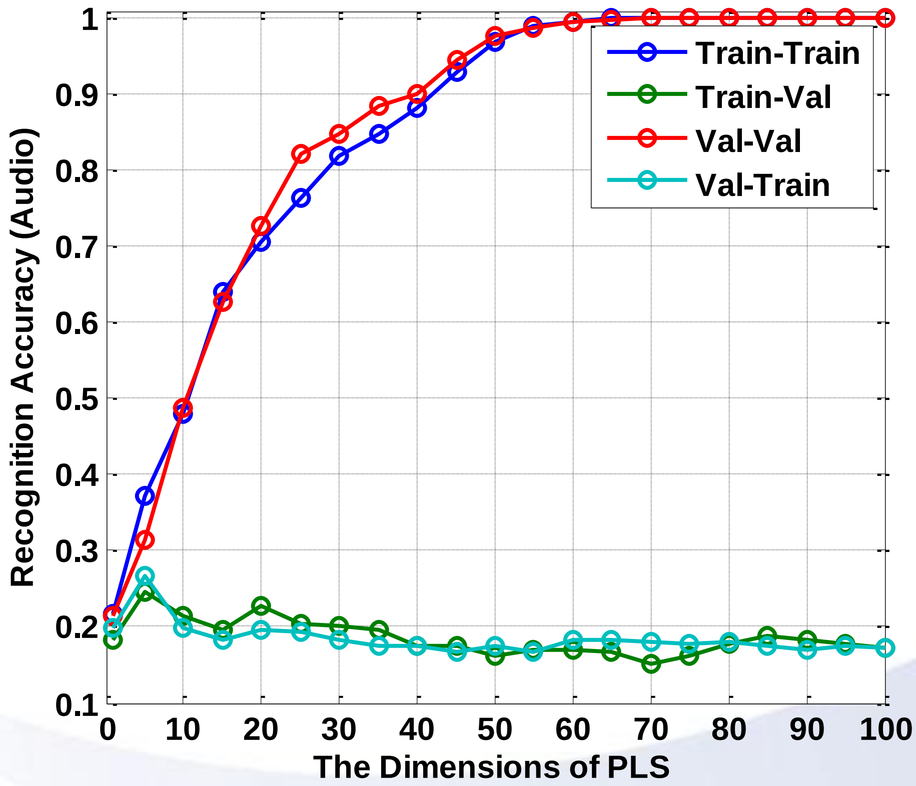


Train-Val: $@dim = 10$

Val-Train: $@dim = 5$

Experiments

- Discussion of Parameters
  - The dimension of One-to-Rest PLS (audio)

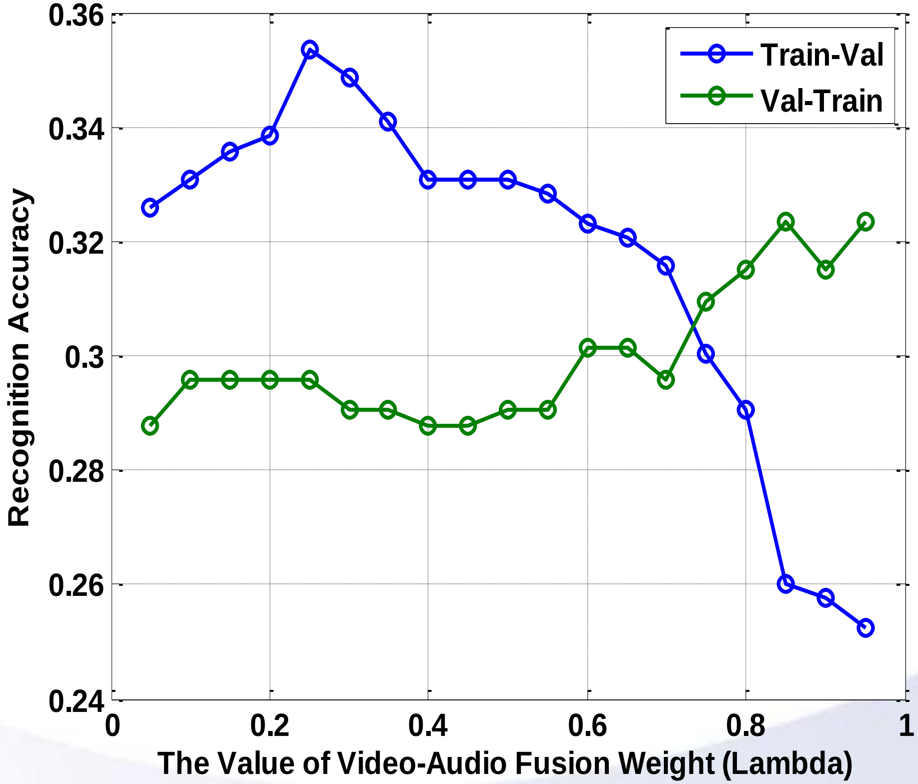


Train-Val: @$dim = 5$

Val-Train: @$dim = 5$

Experiments

- Discussion of Parameters
  - The fusion weights of video and audio modalities



$$Fit^{fusion} = (1 - \lambda) Fit^{video} + \lambda Fit^{audio}$$

Train-Val: @$\lambda = 0.25$

Val-Train: @$\lambda = 0.85$

Experiments

- Results comparison

Performance Comparison		Audio only	Video only		Audio + Video			
					Original data			Purified data
					Feature-level fusion		Decision-level fusion	Decision-level fusion
		One-to-Rest PLS	Grassmannian Discriminant Analysis [6]	Grassmannian Kernels + One-to-Rest PLS	Multi-class LR	One-to-Rest PLS	One-to-Rest PLS	One-to-Rest PLS
Ours	***Val***	24.49 %	30.81%	32.07%	22.48%	24.24%	34.34%	**35.86%**
	Test*	--	**24.04%**	--	--	**26.28%**	**33.01%**	**34.61%**
Baseline	***Val***	19.95%	27.27%		22.22%			
	Test	22.44%	22.75%		27.56%			

[6] M. Harandi, C. Sanderson, S. Shirazi, B.C. Lovell. Graph embedding discriminant analysis on Grassmannian manifolds for improved image set matching. CVPR, 2011.

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Conclusion

- Key points of the current method
  - PCA-based data purifying to filter out mis-alignment faces
  - Linear subspace modeling of video data variations
  - Multiple video features fusion by Grassmannian kernels combination
  - Multi-modality fusion at decision level of video and audio
- Issues to further address
  - Exploration of video temporal dynamics information
  - More sophisticated video modeling
  - More effective fusion at feature level
  - …

Thank you.

Question?