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Shared Representation Learning for Heterogeneous Face Recognition

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Heterogeneous Face Recognition

- Matching face images from different sources
- Sketch vs. VIS (Visual)
  - forensics and security applications
- NIR (Near Infrared) vs. VIS
  - An alternative way to deal with illumination problem
  - Make NIR system be compatible with legacy VIS face images

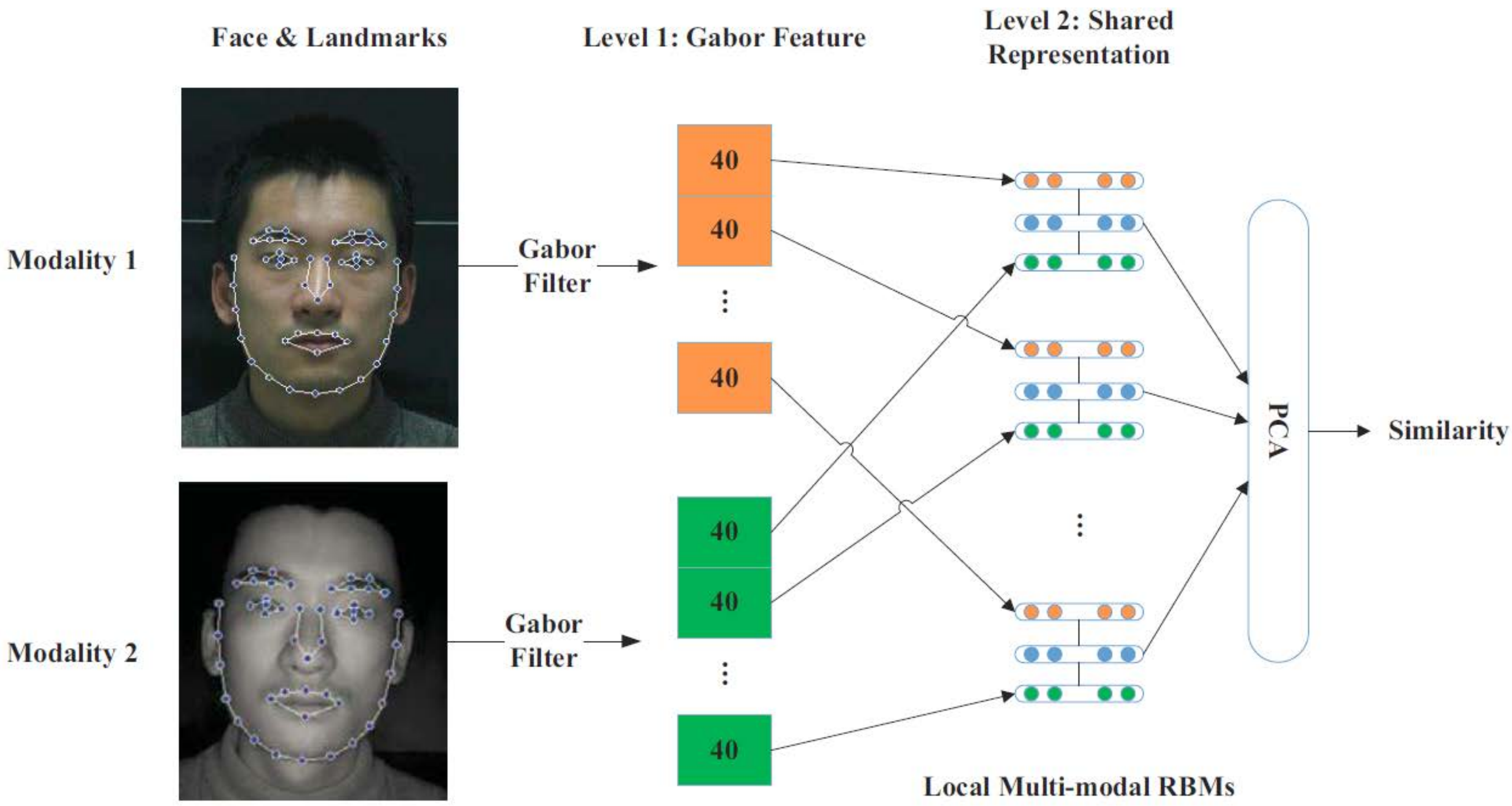
Challenges

- Ordinary VIS-VIS Face recognition is still an unsolved problem
- Nonlinear relation between face images with different modalities
- Limited training samples
- Solution: Multi-modal Restricted Boltzmann Machines (RBMs)

Related Work

- Synthesis based model
  - Eigen-transformation, CVPR 2002
  - Patch-wise LLE, CVPR 2003
  - Transforming VIS to NIR, ICB 2009
- Discriminative model
  - DoG filter, LBP, HOG, ICB 2009, PAMI 2011
  - Coupled information theoretic encoding, CVPR 2011
  - Coupled discriminant analysis, TIFS 2012

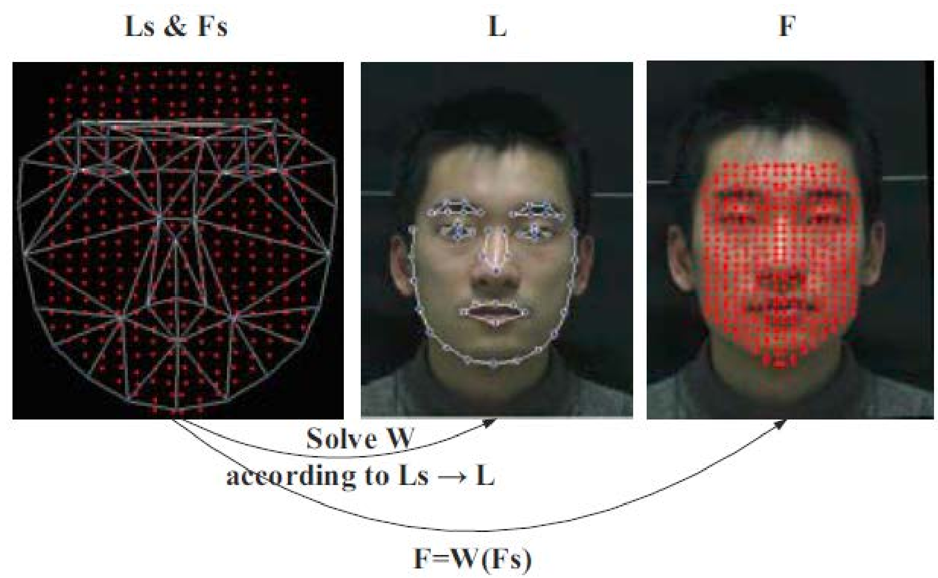
Our Method

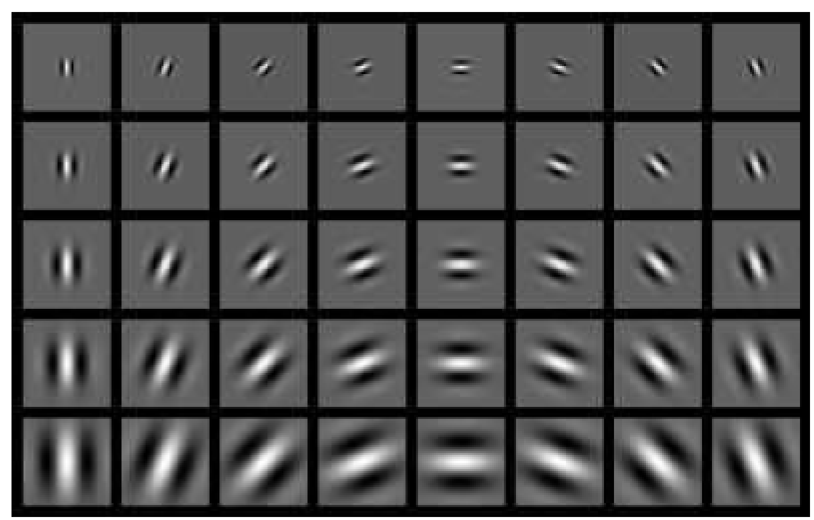


Face & Landmarks
Level 1: Gabor Feature
Level 2: Shared Representation
Modality 1
Modality 2
Gabor Filter
Gabor Filter
40
40
40
40
40
40
PCA
Similarity
Local Multi-modal RBMs

Level 1 Features

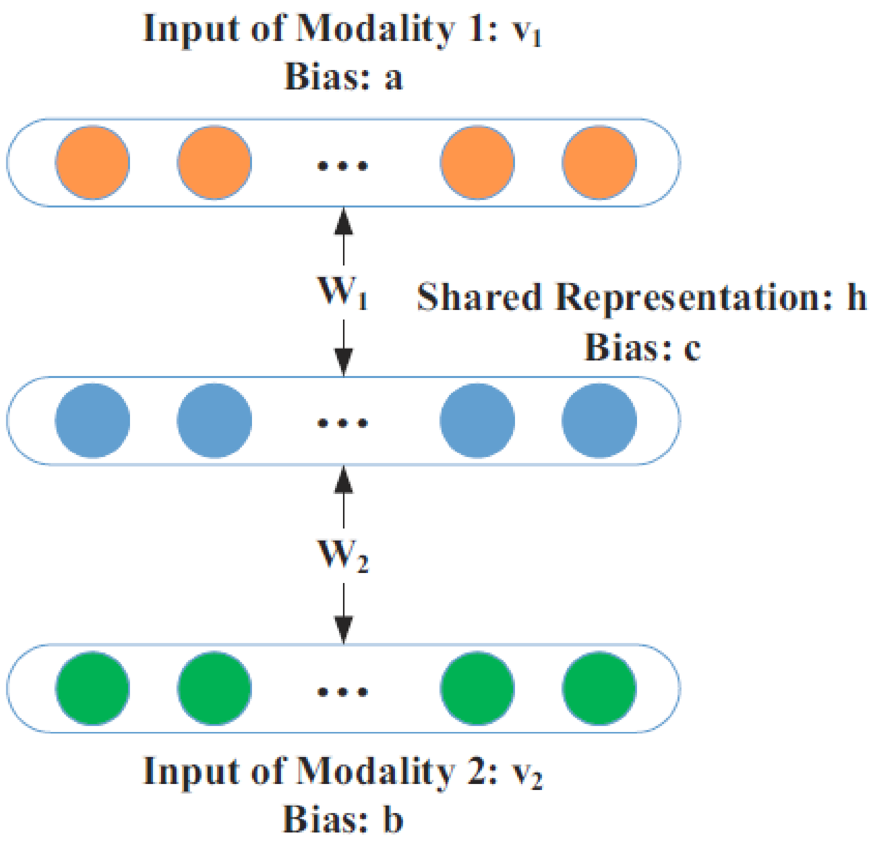
- Identity adaptive feature points
  - Localize sparse facial landmarks (48 pts)
  - Generate adaptive feature points by RBF warping (176x2 pts)
- Gabor filtering
  - 5 scales and 8 orientations
- PIE robust local features
  - 176x2x40 dimensions





Level 2 Representations

- Build the relationship between two modalities by multi-modal RBMs
- Train RBM for each feature point
- By using facial symmetry, need train 176 RBMs
- The structure of one RBM is 40-80-40
- Dimension: 176x2x80



Multi-Modal RBM

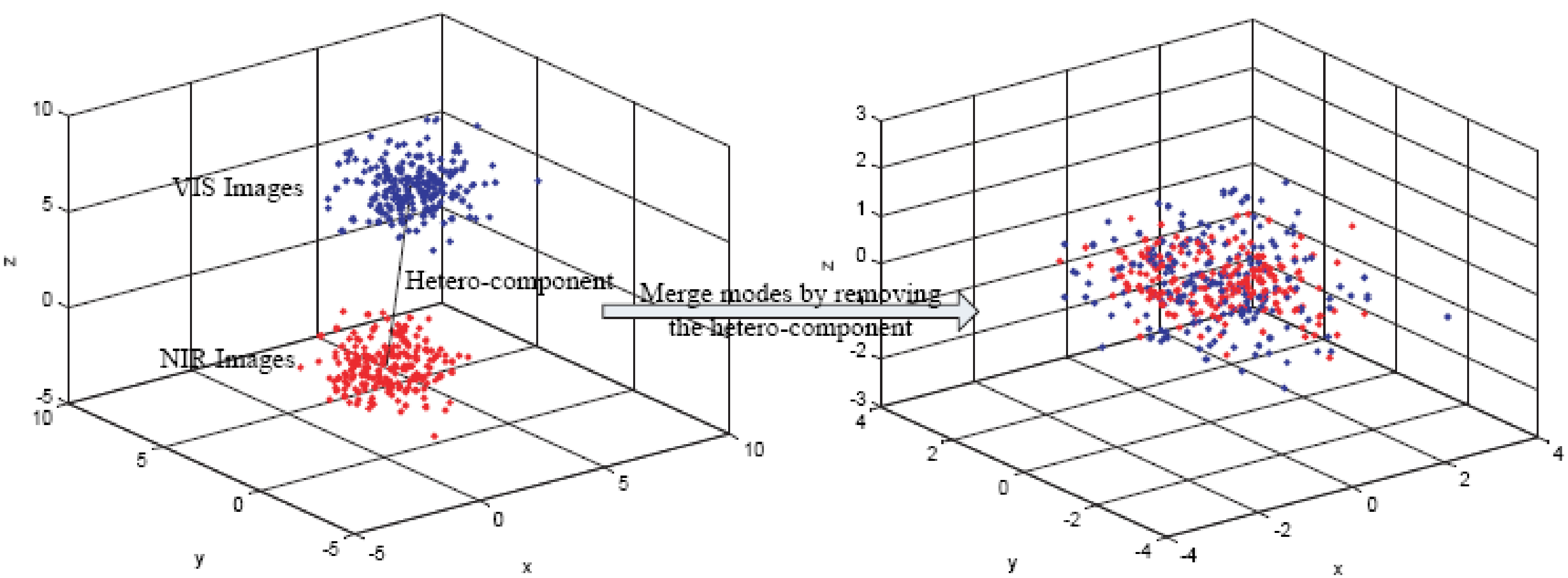
- The parameters are learned by using mean-field inference and an MCMC procedure
- Generate the hidden (shared) representation ***h*** by alternating Gibbs sampler

$$
\begin{aligned}
E(\hat{\mathbf{v}}_1, \hat{\mathbf{v}}_2, \mathbf{h}; \theta) = & \frac{1}{2}(\hat{\mathbf{v}}_1 - \mathbf{a})^T (\hat{\mathbf{v}_1} - \mathbf{a}) + \\
& \frac{1}{2}(\hat{\mathbf{v}}_2 - \mathbf{b})^T (\hat{\mathbf{v}_2} - \mathbf{b}) - \\
& \mathbf{c}^T \mathbf{h} - \hat{\mathbf{v}}_1^T \mathbf{W}_1 \mathbf{h} - \hat{\mathbf{v}}_2^T \mathbf{W}_2 \mathbf{h},
\end{aligned}
$$

- Refer: Nitish Srivastava and Ruslan Salakhutdinov. “Multimodal learning with deep boltzmann machines”. NIPS , 2012.

Removing Heterogeneous Principle Components

- The correlation factor between the first PC and $\mathbf{h} = \mathbf{m}_{NIR} - \mathbf{m}_{VIS}$ is 0.97
- Remove the first several PCs



Experiments

- Take NIR-VIS face recognition as main experiments
  - CASIA HFB dataset
  - CASIA NIR-VIS 2.0 dataset
- Sketch-VIS experiments
  - CUFS dataset
  - CUFSF dataset
- Performance: Rank1 recognition rate and ROC

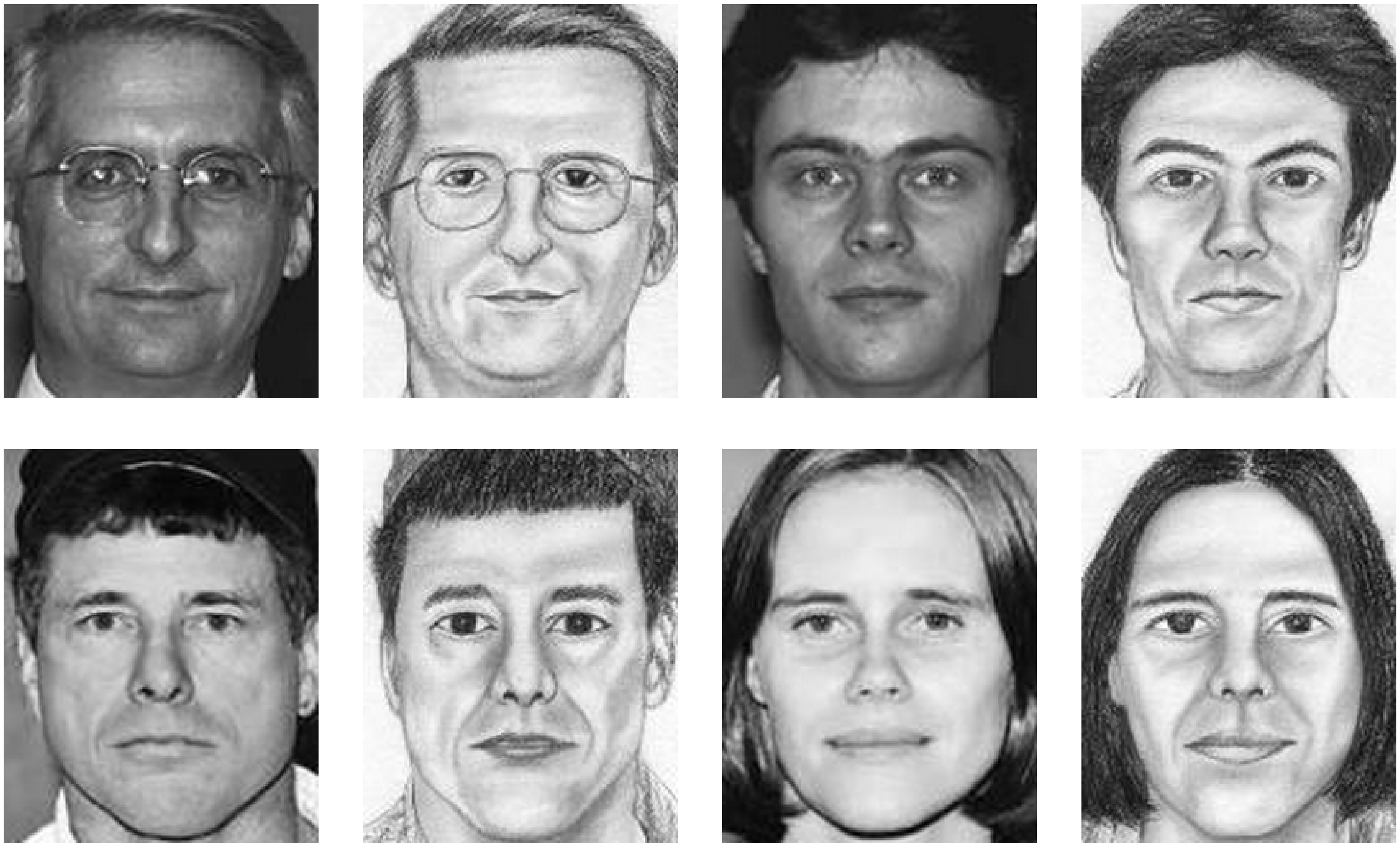
Datasets Information

Name	Modalities	No. of Subjects	No. of Images	Variations
CASIA HFB	NIR, VIS	202	5097	E, G, D
CASIA NIR-VIS 2.0	NIR, VIS	725	17580	P, E, G, D
CUFS	Sketch, VIS	606	1212	-
CUFSF	Sketch, VIS	1194	2388	-

Datasets used in our experiments. The last column denotes the main variations they addressed, *i.e.,* Pose(P), Expression(E), Eyeglasses(G), Distance(D).

Sample Images

Sample Images



Results on CASIA HFB

RANK1 RECOGNITION RATES AND VR@FAR=0.1% OF VARIOUS METHODS ON VIEW 2 OF CASIA HFB.

	Rank1	VR
Gabor	59.47±6.72%	33.51±5.70%
Gabor + Remove 20 PCs	94.87±1.72%	71.70±6.42%
Gabor + RBM	98.12±1.13%	84.50±3.75%
Gabor + RBM + Remove 11 PCs	99.38±0.32%	92.25±1.68% [1]
NN [12]	88.8%	48.78±3.87%
SR [12]	93.4%	77.56±2.96%
NN + SR [12]	92.2%	79.05±4.48%
Cognitec [12]	93.8%	85.62±2.17%
NN + SR + Cognitec [12]	97.6%	93.45±0.96%
C-DFD [15]	92.2%	65.5%
P-RS [14]	-	95.8±6.15% [2]

[1] 96.33% with z-score normalization

[2] 133 subjects for training, 67 subjects for testing

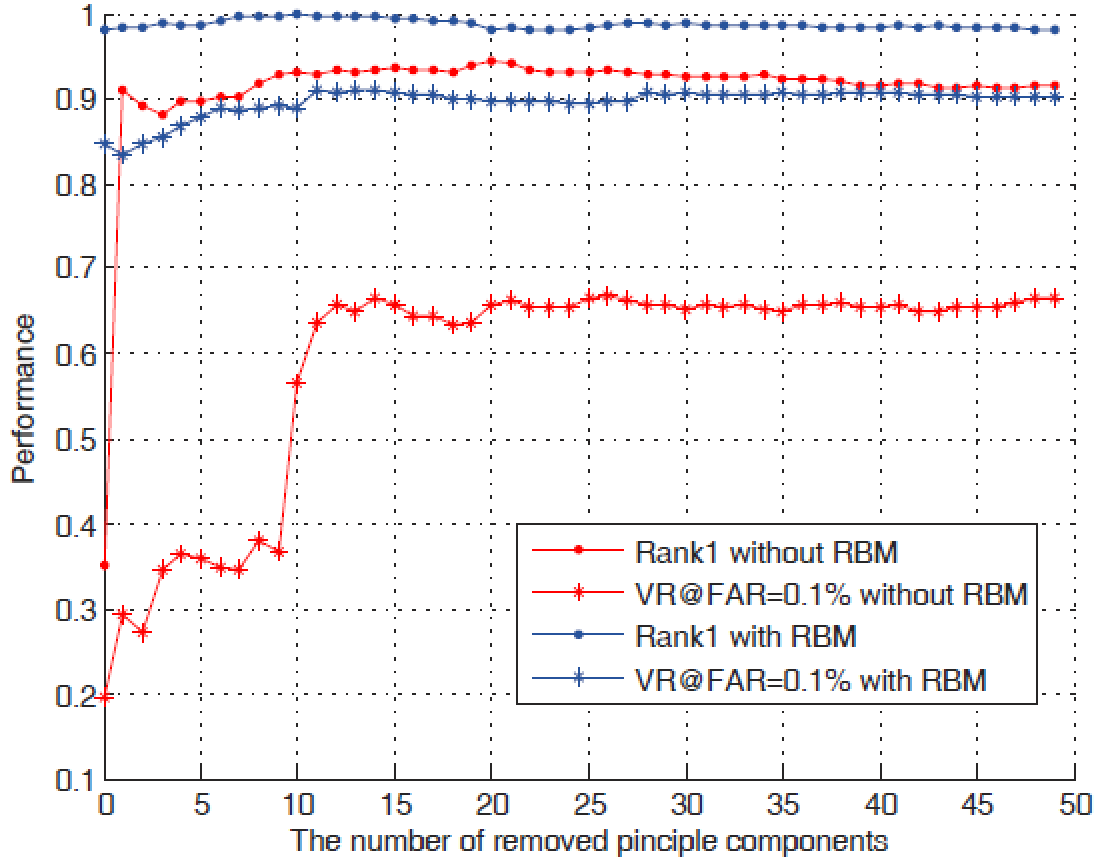
Global, Convolutional and Local RBMs

- Global: fully connected RBM
- Conv: locally connected RBM with shared weights
- Local: locally connected RBM with unshared weights

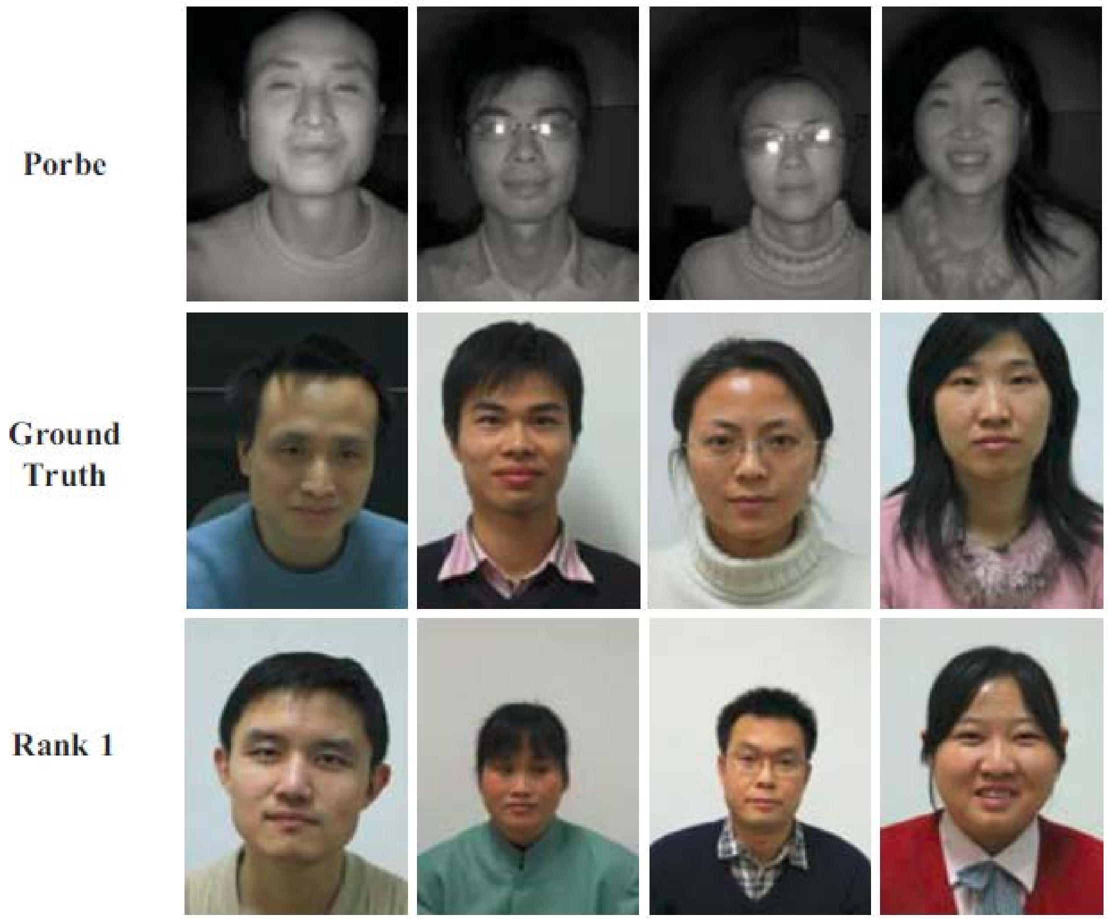
THE COMPARISON OF GLOBAL, CONVOLUTIONAL AND LOCAL RBMS ON VIEW 1 OF CASIA HFB. THE 3RD COLUMN IS VR@FAR=0.1% ON THE TRAINING SET OF VIEW 1. THE 4TH COLUMN IS VR@FAR=0.1% ON THE TESTING SET OF VIEW 1.

	Architecture	VR (Train)	VR (Test)
Global	7040-3520-7040	99.94%	1.549%
Conv.	40-80-40	73.31%	71.79%
Local	176×(40-80-40)	99.45%	90.85%

The Number of Removed PCs



Some Cases of Failure



Results on CASIA NIR-VIS 2.0

RANK1 RECOGNITION RATES AND VR@FAR=0.1% OF VARIOUS METHODS ON VIEW 2 OF CASIA NIR-VIS 2.0.

	Rank1	VR
Gabor	36.18 ± 2.56%	33.37 ± 2.29%
Gabor + Remove 20 PCs	75.54 ± 0.75%	71.40 ± 1.21%
Gabor + RBM	84.22 ± 0.86%	78.39 ± 1.45%
Gabor + RBM + Remove 11 PCs	86.16 ± 0.98%	81.29 ± 1.82%
PCA + Sym + HCA [18]	23.7 ± 1.89%	19.27%
Cognitec [5]	58.56 ± 1.19%	-
DSIFT + LDA [5]	73.28 ± 1.10%	-

Results on CUFS and CUFSF

- The first method can perform perfectly on CUFS dataset
  - Rank1 = 100%
  - VR@FAR=0.1% = 100%
- Perform good on CUFSF dataset
  - Rank1 = 98.59%
  - Rank1 = 98.70%, CITE (Coupled information theoretic encoding, CVPR 2011)

Summary

- Proposed a local to global learning framework for heterogeneous face recognition
- The first time to use multi-modal RBMs to learn shared representations of heterogeneous face images
- By plugging the local RBMs into the framework, we obtained the state-of-the-art results for NIR-VIS and Sketch-VIS problems

Thank you!

Q&A