Discriminability and Reliability Indexes: Two New Measures to Enhance Multi-image Face Recognition

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Outlines

- Multi-image Face Recognition and its problems
- The Current State of Art
- Proposed Method: Discriminability and Reliability Indexes
- Experiments and Analysis
- Conclusion and Future Work

Multi-image Face Recognition and its Problems

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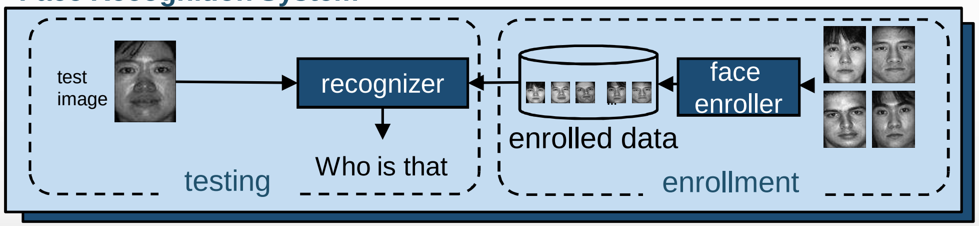
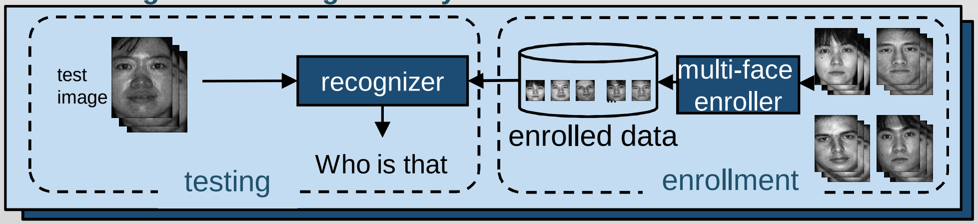
Starting with Face Recognition

- A Face Recognition (FR) system
  - Automatically recognize the identity from the input face image
  - Challenging problems
    - Lighting
    - Pose variance
    - Expression
    - Occlusion
    - Aging, make up, etc
  - Making use of multi-images (video) instead of single image
    - View based (pose)
    - Pose manifold (pose)
    - etc
  - Is every face image useful for FR?

Face Recognition System



Multi-image Face Recognition System



Problems in Multi-image Face Recognition (MFR)

Images are from ORL database http://www.cl.cam.ac.uk/research/dtg/attarchive/facedatabase.html

different images from one person

- is that all the face images are suitable for use in FR system?
  - Researchers found that the face images are not equally good for FR
    - Fontal view face always get good recognition result
    - Good quality non-frontal view also provide good features
      - [X. Liu et al. CVPR06]: profile view get better result than frontal view
      - [C.H.Liu et al. Cognition02]: the optimal view for recognition is ¾ view
  - To make use of different face images better, images should be estimated

Reference:
X. Liu, J.Rittscher and T. Chen. Optimal Pose for Face Recognition. Proceedings of IEEE International Conference on CVPR,vol:2, pp:1439-1446, 2006.
C.H Liu and A. Chaudhuri. Reassessing the 3/4 view effect in face recognition. Cognition vol:83 pp:31–48, 2002.

The Current State of Art

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The Current State of Art

Select face images from image set

- Kruger *et al.* select face images from video by clustering
- *Hadid et al.* select representative face images which minimize the error

Assign weights to face images

- Zhang *et al.* assigned weights to images based on pose and expression
- Thomas *et al.* weighted different images by a measurement called *Faceness*

Short comes

- not designed for recognition perspective
- not consider the discriminative features

Proposed measures: Discriminability and Reliability Indexes (DI, RI)

Reference:
V. Kruger and S. Zhou. Exemplar-based face recognition from video . In Proceedings of IEEE International Conference on AFGR, pages 175 – 180, 2002.
A. Hadid and M. Pietikainen. From still image to video-based face recognition: an experimental analysis. In Proceedings of IEEE International Conference on AFGR, pages 813–818, 2004.
Y. Zhang and A. Mart´ınez. A weighted probabilistic approach to face recognition from multiple images and video sequences. Image and Vision Computing, 24(6):626–638, 2006.
D. Thomas, K. W. Bowyer, and P. J. Flynn. Multiframe approaches to improve face recognition. In Proceedings of IEEE Workshop on Motion and Video Computing, pages 19–19, 2007.

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Proposed Method: Discriminability and Reliability Indexes

Discriminability Index (DI) and Reliability Index (RI)

Discriminability Index (DI)

- Measure how much discriminative the reference image is
- High DI means
  - image distinguishes from other classes' images
  - and close to images from the same class
- DI is related to not only images from the same class, but also, images from different classes.

Reliability Index (RI)

- Measure how reliable the testing image is
- High RI means
  - image has high matching quality
  - that means testing images has short distance from its own class (good match)
  - FR system has high confidence to classify such a testing image

Illustration of Discriminability and Reliability

Illustration of Discriminability

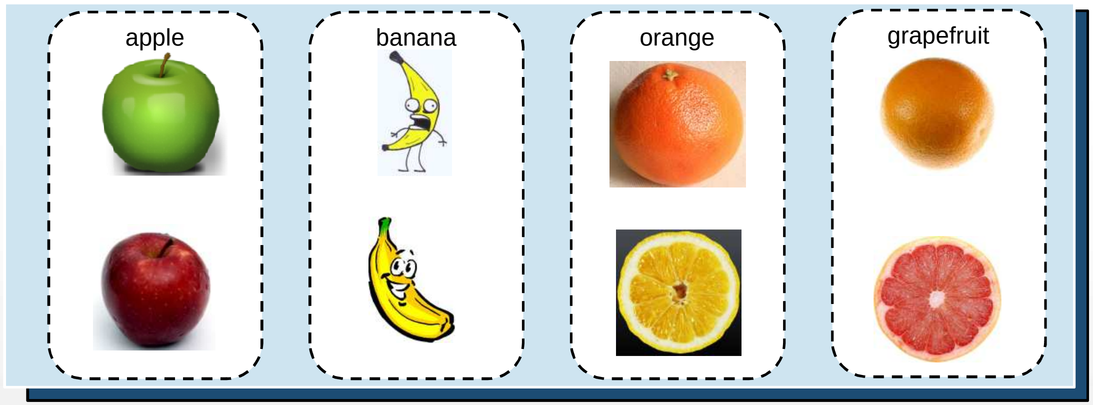
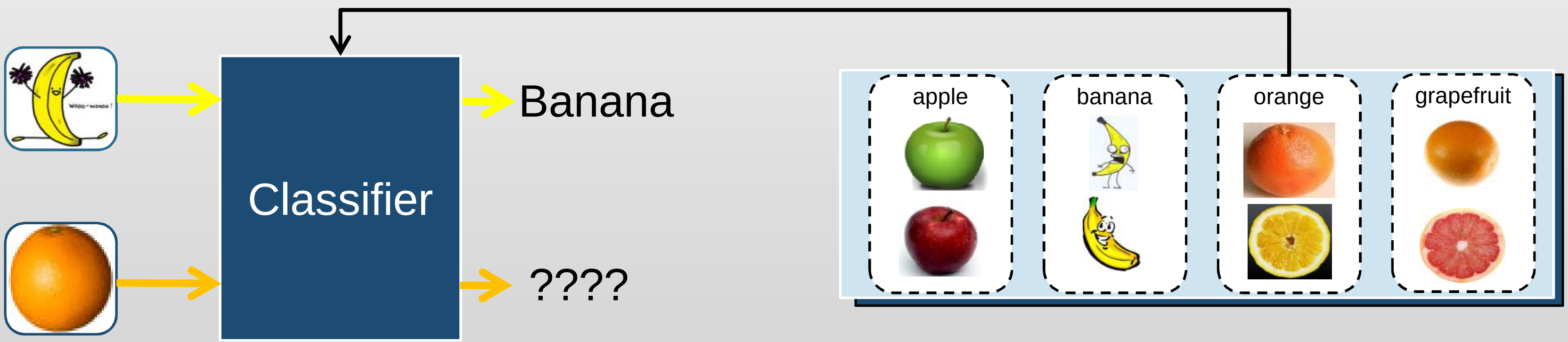


Illustration of Reliability



Note: Images of fruits are obtained by Google Image from internet.

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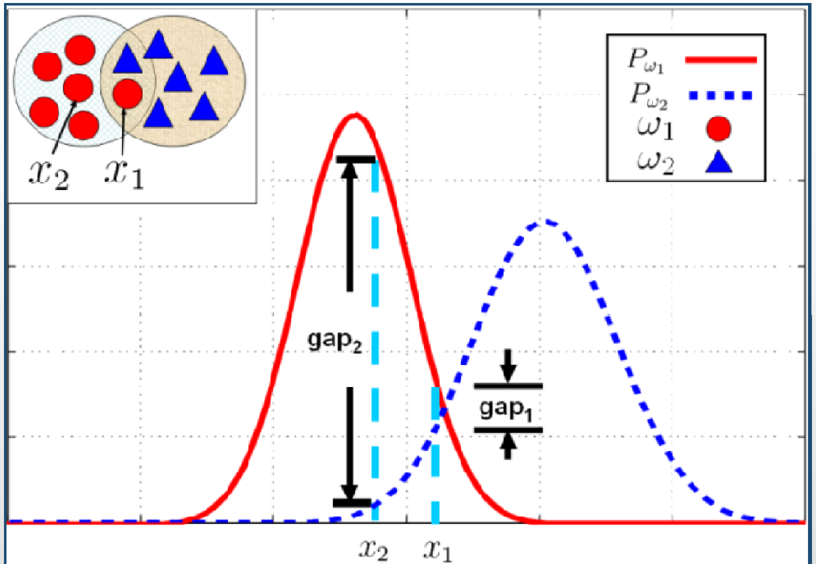
Estimation of Discriminability of reference images

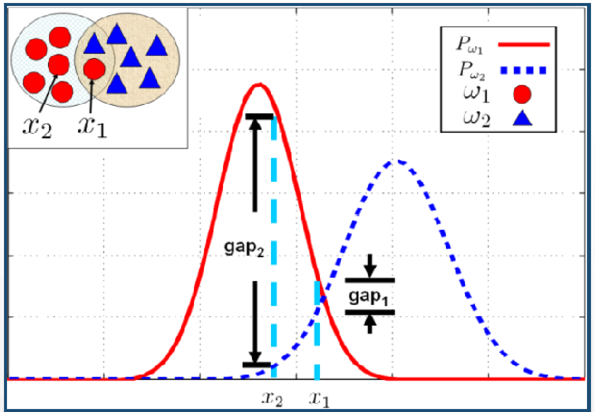


- x_1, x_2 are from same class ω_1
- x_2 has high discriminability than x_1
  - x_1 locates near the boundary
  - while x_2 locates in the center
- define gap function

  $$\text{gap}(x_i) = P(x_i|\omega_1) - P(x_i|\omega_2)$$
- higher the discriminability is, larger the gap is

$$\text{DI}_x = \text{gap}(x) = P(x|x \in \omega) - \max_i P(x|x \notin \omega_i)$$

Calculation of DI



DI: $$\mathrm{DI}_x = P(x|x \in \omega) - P(x|x \notin \omega) = C' \min_k \sum_{i=1}^{n} (\|x - y_i^k\| - \|x - y_i\|)$$

Use similarity function as Parzen window function:

$$\varphi_{\omega_k}(x, y_i) = sim(x, y_i) = \frac{C - \|x - y_i\|}{C}$$

Probability is calculated by Parzen window method:

$$P(x|\omega_k) = \frac{1}{n} \sum_{j=1}^{n} (\varphi_{\omega_k}(x, y_i))$$

Calculate DI by the gap which is defined as the Bayes discriminative function

$$\mathrm{gap}(x) = P(x|x \in \omega_1) - \max_k P(x|x \notin \omega_k)$$

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Algorithm 1: DI Calculation

Algorithm 1 DI Calculation

Input: Reference images $\mathcal{G} = \{x_{ij}\}$, threshold for termination th, number of neighbors n, number of images to be selected N
Output: DI of each image in $\mathcal{G}$
Initial: $\mathrm{DI}_{ij} \leftarrow 0$, $\mathrm{DI}'_{ij} \leftarrow 0$, $\mathrm{DI}^*_{ij} \leftarrow \phi$;

repeat
  $\mathrm{DI}'_{ij} \leftarrow \mathrm{DI}_{ij}$
  for each x_{ij} **do**
    randomly select N reference images from each class, denote as ω'_k
    search the n-nearest neighbors in each ω'_k, denote as $\mathcal{N}^k_{x_{ij}}$
    $\mathrm{DI}_{ij} \leftarrow \mathrm{DI}^*_{ij} \bigcup \{\frac{1}{n} \min_k \sum_{j=1}^{n} (\|x_{ij} - y^i_j\| - \|x_{ij} - y^k_j\|)\}$
  end for
  $\mathrm{DI}_{ij} \leftarrow avg(\mathrm{DI}^*_{ij})$
until $|\mathrm{DI}'_{ij} - \mathrm{DI}_{ij}| < th$
Output DI_{ij}

Estimation of Reliability of testing images

Discriminability → Reliability ?

- High DI → Image { close to images from same class; far away from images in other classes } → Reliable for testing → High RI
- However label information of testing is not available

Calculate RI by outlier detection

- Estimate the RI by consider the distance distributions, give a testing image p

$$D = \{d_i = d(p, y_i)\}$$

- Image has High RI iff. image has unique significant short distance
  - There are two kinds of distances, when matching an image to the references
    - one distance between images in same class $D_w = \{d | d = x' - x''\}$
    - other distances between images in different classes $D_b = \{d | d = x' - y'\}$
  - High RI → { close to images from same class; far away from images in other classes } → $d \in D_w$ is an outlier
  - Low RI → has similar distance to every image → $d \in D_w$ is not an outlier
- Estimate RI by calculate the level of $d \in D_w$ being an outlier

Determine the RI by outlier testing

d_{min} is an outlier of D ⟷ high RI ⟷ $d \in D_u$ is an outlier of D

A: high RI B: d_{min} outlier

A → B
!A → ! B → A iff. B

- High RI → $d_{min} \in D_w$ → d_{min} is an outlier of D
- Low RI →
  - $d_{min} \in D_w$ but d_{min} is not an outlier ←→ similar distances
  - $d_{min} \in D_b$ → d_{min} definitely is not an outlier
- Calculate RI by Q-test
  - Advantages: quick, effective, for extremer outlier testing (only one outlier)
  - RI is calculated as:

$$\mathrm{RI}_p = \text{Q-value} = \frac{d_{min} - \min\{d \neq d_{min}\}}{d_{min} - d_{max}}$$

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Algorithm 2: RI Calculation

Algorithm 2 RI Calculation

Input: Reference images $\{x_{kj}\}_{k=1}^{C}$, testing image y_i
Output: RI_i

for each class k **do**
  $d_k \leftarrow ||y_i - x_{kj}||$
end for
Calculate the Q-value $Q \leftarrow$ by Eq.[8]
output RI_i = Q-value

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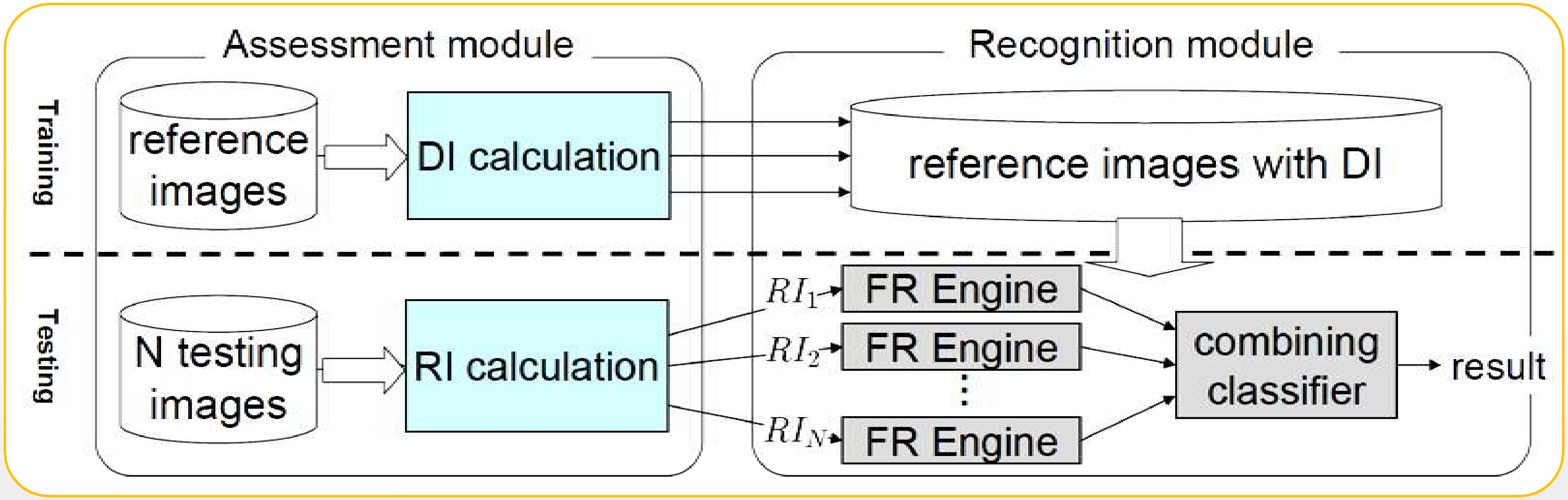
Experiments and Analysis

Methodology: Comparative Experiment



- Usage:
  - DI: assigned weights

$$\omega = \frac{1 + \mathrm{DI}}{2}$$

  - RI: select images with high RI

    90% confidence level

- FR engines:
  - *Eigenface*
  - *Kernal PCA*
- Combining classifiers

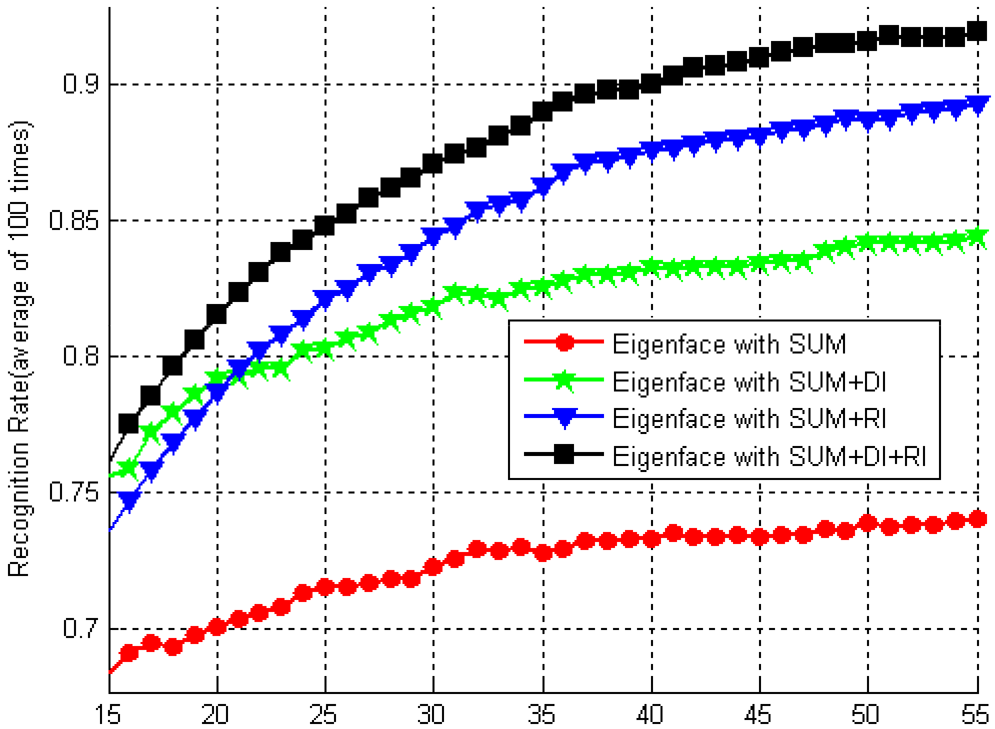
  Sum rule (SUM), Majority voting (MV), Product rule (PROD)

Experiment settings and the database

Table 1. Experiment settings

database	C	N_t	N_r	N_p	variations
CMU-PIE	68	50	10	15∼55	pose, illumination
YaleB	38	32	4	15∼32	illumination
FRGC	311	20	4	15∼30	illumination, expression, mild pose

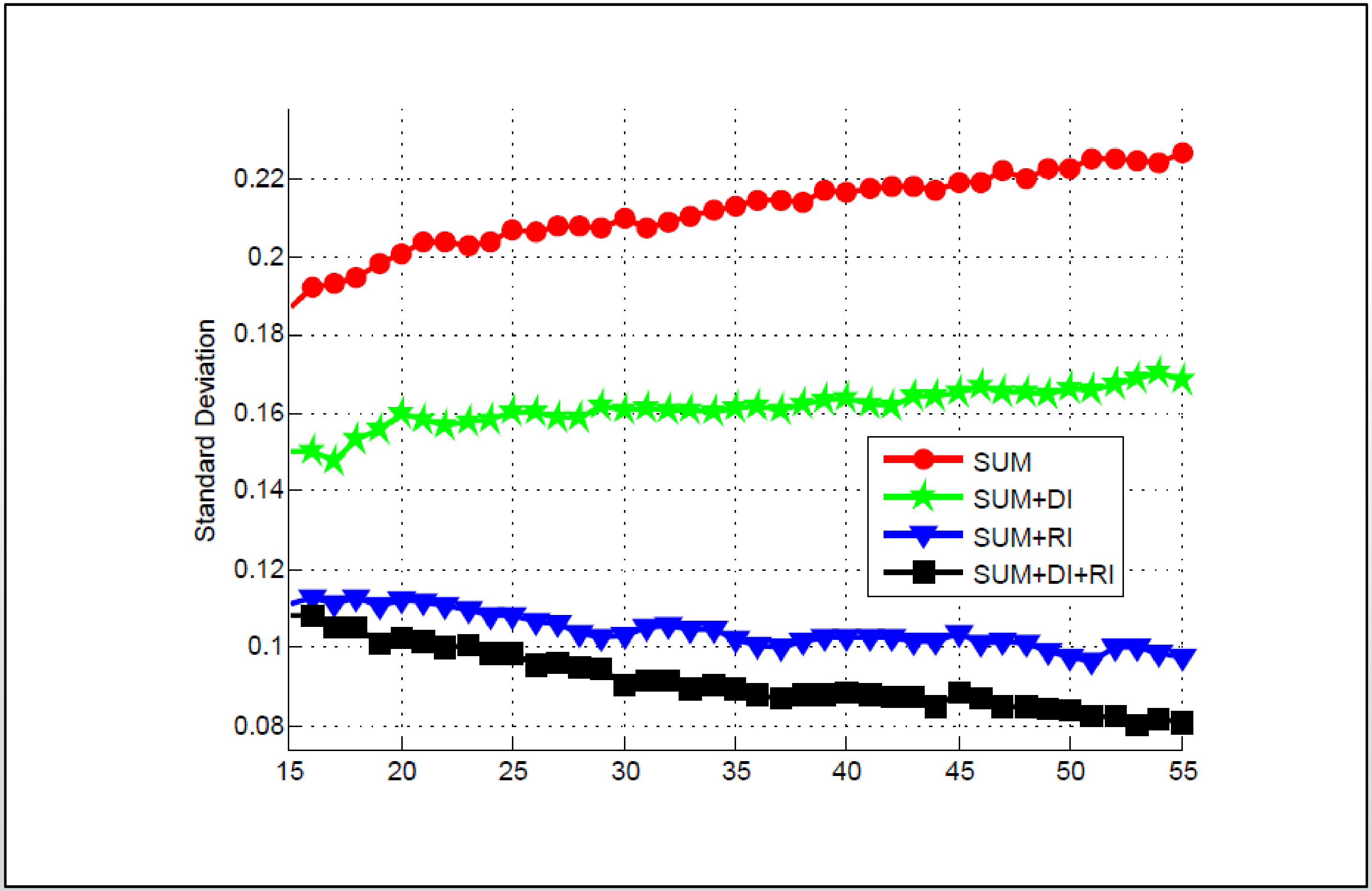
Results 1 on CMU PIE : Accuracy



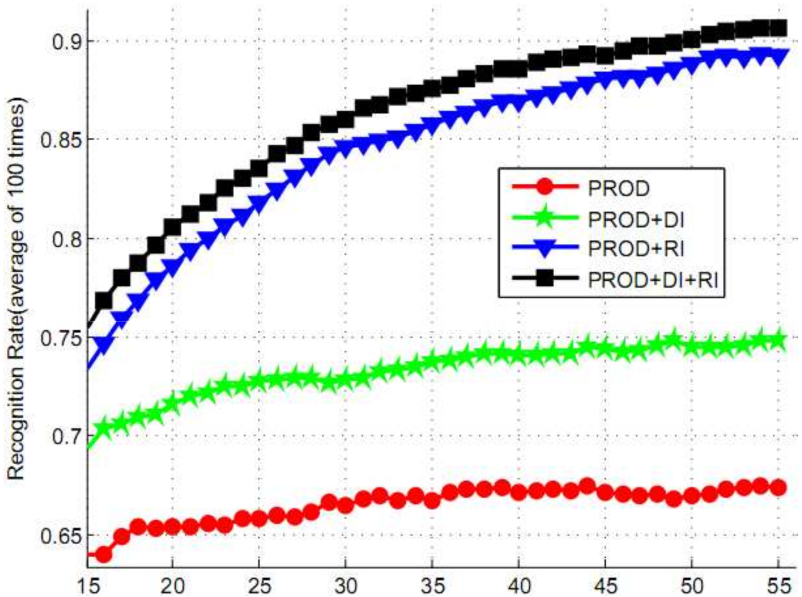
Accuracy vs. number of testing images per individual

Eigenface with sum rule

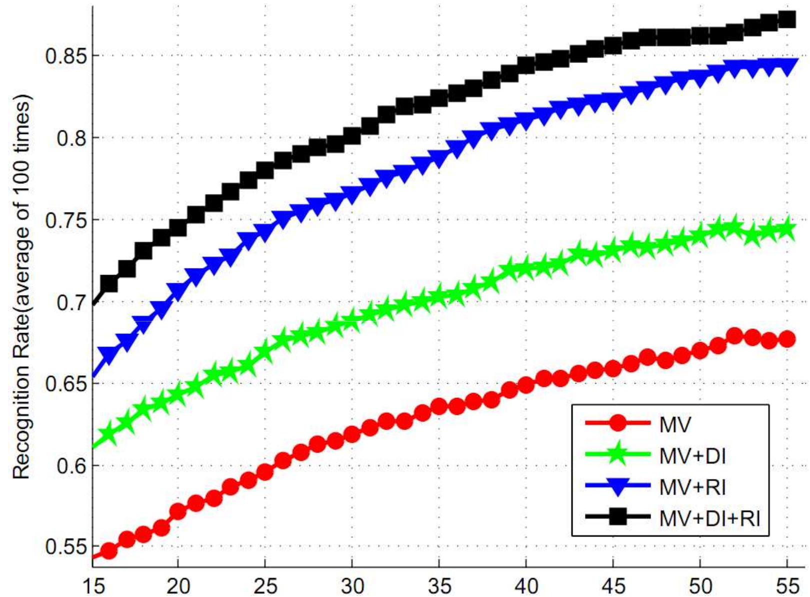
Results 1 on CMU PIE : Robustness



Results 2 on CMU PIE

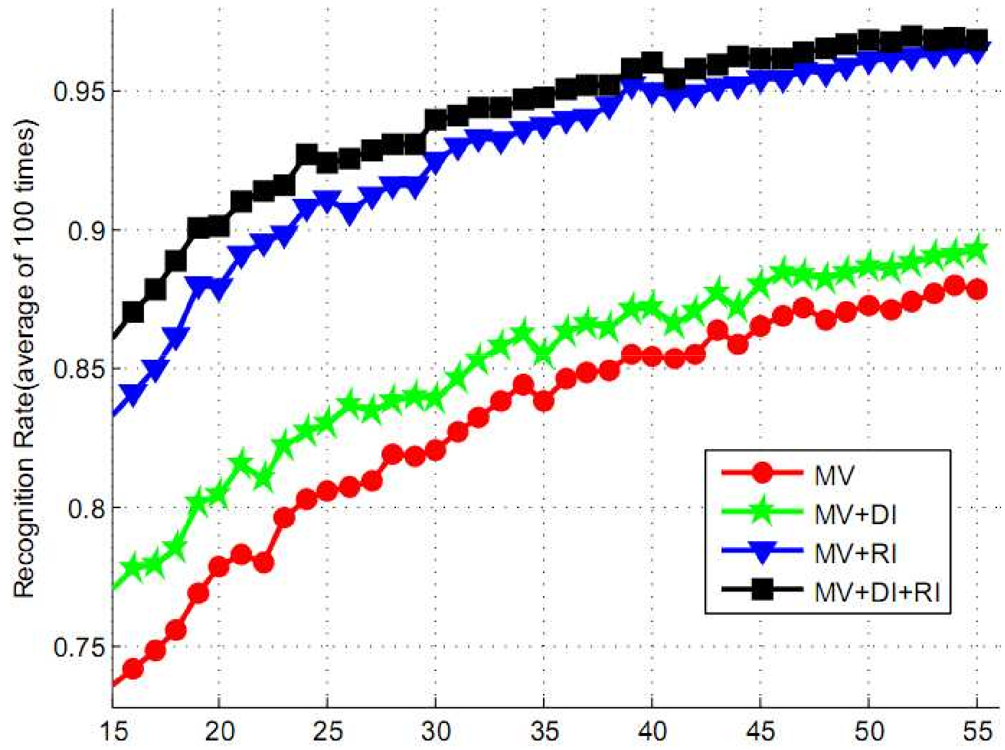


Eigenface with product rule



Eigenface with majority voting

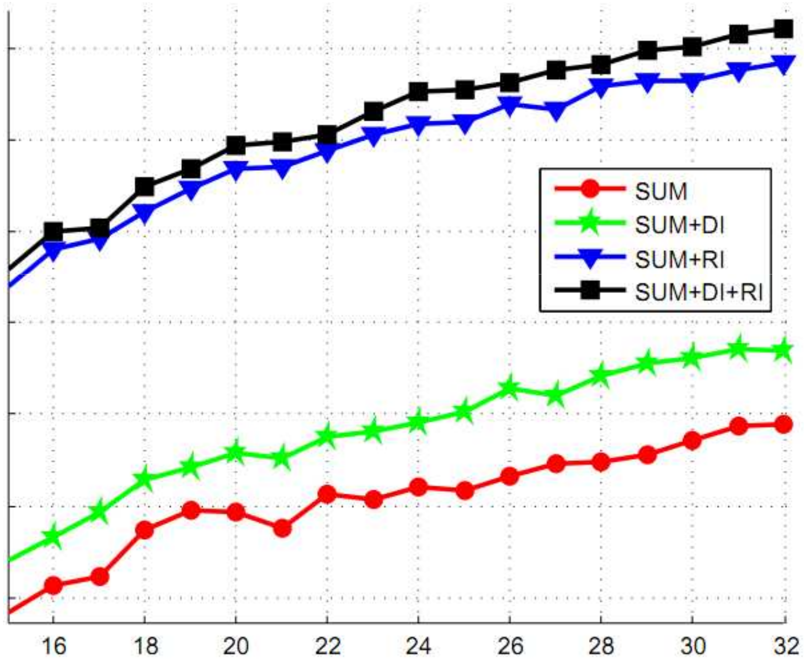
Results 2 on CMU PIE



Kernel PCA with majority voting

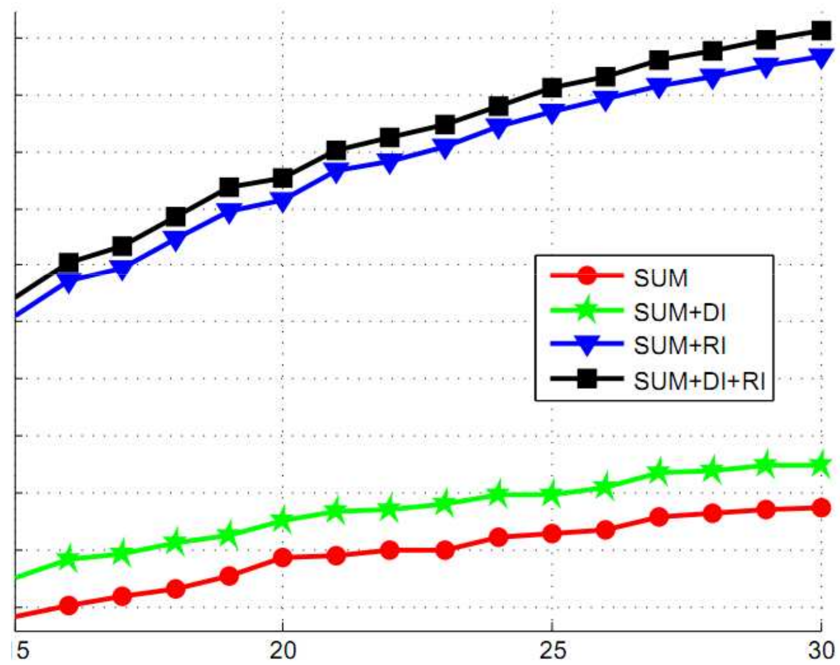
Results on YaleB and FRGC

YaleB database



Kernel PCA with sum rule

FRGC database



Kernel PCA with sum rule

Conclusion and Future Works

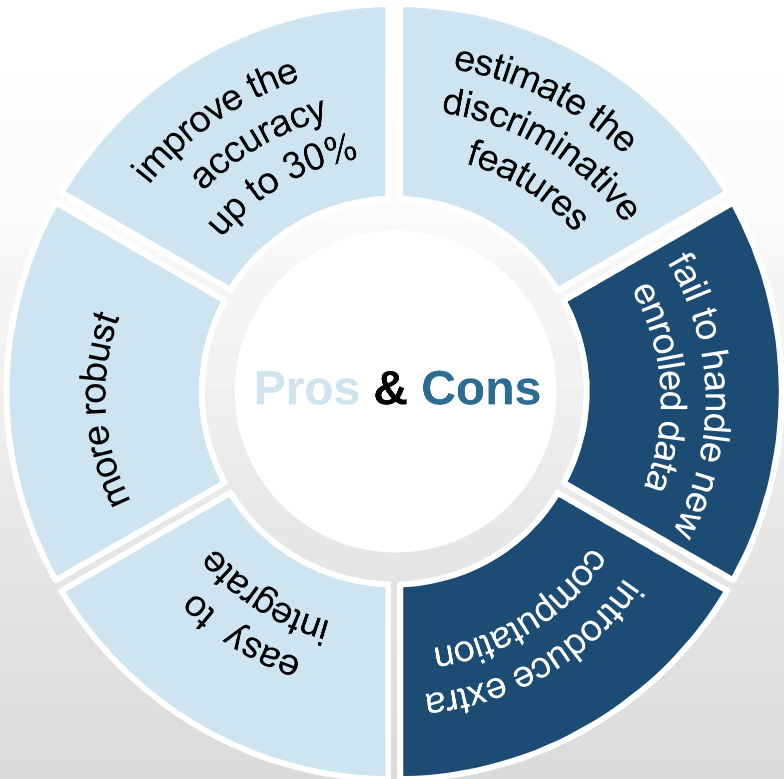
Conclusions

Advantages:

- Estimate the discriminative features of images
- DI and RI improve the recognition performance. the accuracy can be improved with 4% to 30%
- More robust performance
- DI and RI can be easily integrate with existing face recognition

Disadvantages:

- Introduce extra computation
- Cannot handle new enrolled reference data



Future works

- extended the DI RI to handle new enrolled data
- how to make use of temporal information to enhance recognition performance
- enhance face quality in video
- solve the variance, such as pose, illumination in video

THANK YOU

Q & A