The FG 2015 Kinship Verification in the Wild Evaluation

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Introduction

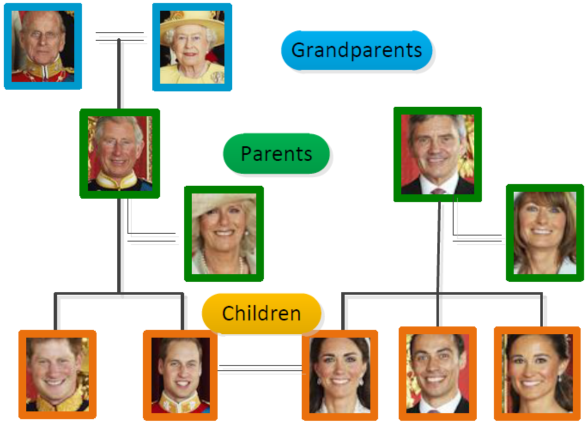
- What is *kinship verification*?

Verify whether there is a kin relation between two persons from their face images.

Introduction

- Why do we need *kinship verification*?

1) Family album organization



2) Social media analysis

Challenges

- Aging
- Ethnicity
- Expression
- Pose
- Occlusions
- Background

Motivation

- Why do we need this evaluation?
  1) Previous algorithms were only evaluated on small datasets.

     less than 200 pairs for each kin relation

  2) No standard protocol is employed to compare different methods.

     4-fold cross validation was used, difficult to reproduce

Datasets

- Four kin relations, two different sets.
- KinFaceW-I
  - Acquired from different photos
  - 156 (F-S), 134 (F-D), 116 (M-S), 127 (M-D) kinship pairs
- KinFaceW-II
  - Acquired in similar photos (most cases)
  - 250 kinship pairs for each relation.

Datasets

- Sample Images – cropped into 64x64 face image and aligned using eye coordinates

F - S

F - D

M - S

M - D

KinFaceW-I **KinFaceW-II**

Verification Protocol

- 5-fold cross validation
- Pre-specified training/testing
- Three Experiment Setting
  - *Unsupervised* – No labeled kin information
  - *Image-restricted* – Only the given kin relation information is used in training splits
  - *Image-unrestricted* – the identity information of the person is available -> more negative pairs

Baseline

- Features
  - *Local Binary Patterns (LBP)* – divide each face image in 8x8 non-overlapping blocks and extract uniform LBP for each 8x8 block → 3779 dimensional feature vector
  - *Histogram of Oriented Gradients (HOG)* – divide each face image into 16x16 (and 8x8) non-overlapping blocks and extract HOG for each 4x4 (and 8x8) blocks →2880 dimensional feature vector

Baseline

- Model
  - *Unsupervised* – Cosine similarity of LBP/HOG features
  - *Image-restricted* – apply PCA to reduce to 500 dim, apply side information based linear discriminant analysis (SILD), perform cosine similarity
  - *Image-unrestricted* - apply PCA to reduce to 500 dim, apply neighborhood repulsed metric learning (NRML), perform cosine similarity

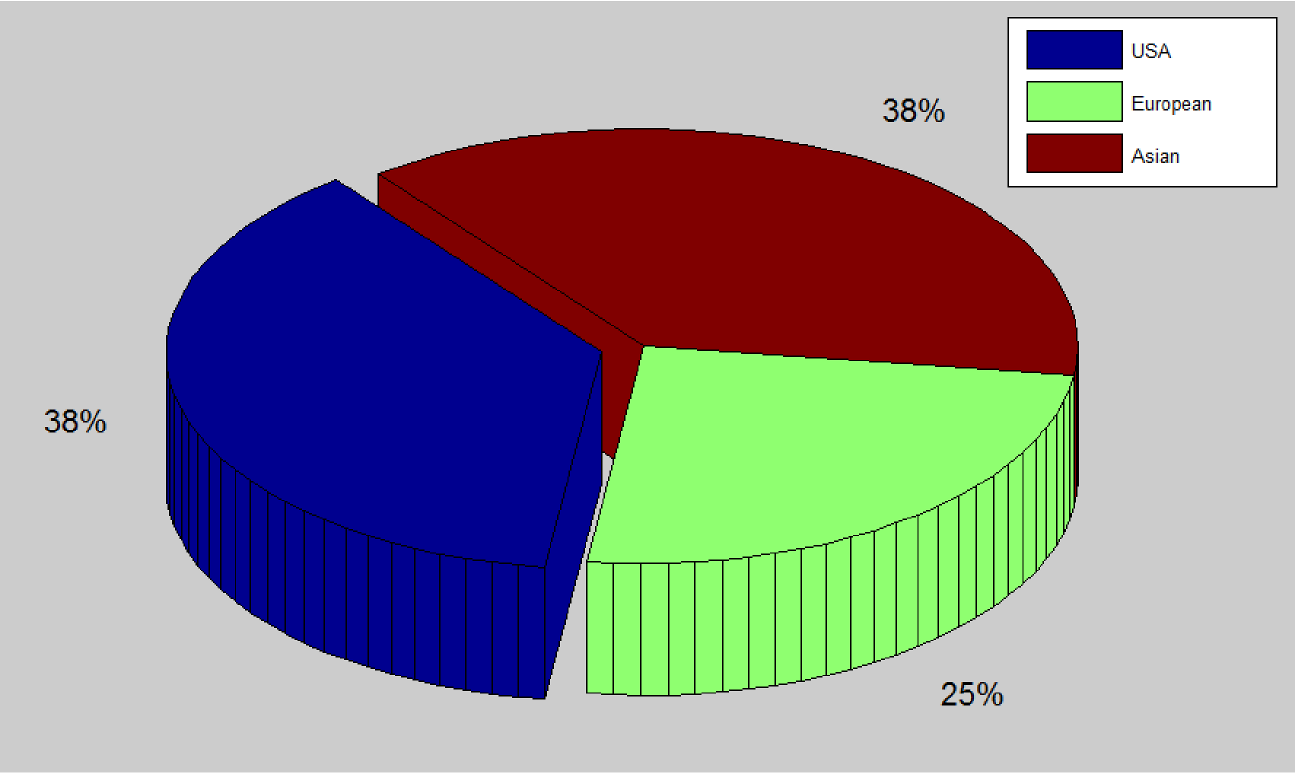
Participants and Algorithms

- 16 teams registered and downloaded our datasets.

USA: Columbia University, Michigan State University, West Virginia University

European: Delft University of Technology, University of Oulu, Politecnico di Torino,

Asian: Chinese Academy of Sciences, Indian Institute of Science, Capital Normal University



Participants and Algorithms

- 5 teams submitted their results for evaluation

  1. Bottino et al., Politecnico di Torino; Italy **(POLITO)**
  2. Zheng et al., University of Lyon; France **(LIRIS)**
  3. Castrillon-Santana et al., Universidad de Las Palmas de Grab Canaria; Spain **(ULPGC)**
  4. Qin et al., Nanjing University of Aeronautics and Astronautics; China **(NUAA)**
  5. Mahpod et al., Bar Ilan University; Israel **(BIU)**

Participants and Algorithms

- **POLITO**: feature selection-based model
  - Extract Features: Local Phase Quantization (LPQ), Three-Patch based LBP (TBLBP), Weber Local Descriptor (WLD)
  - Feature selection by ranking and obtaining optimal feature set via minimum-Redundancy Maximum Relevance (mRMR) and a modified sequential forward floating selection algorithm.
  - Classification using SVM with RBF Kernel

Participants and Algorithms

- **LIRIS**: metric learning-based model
  - Extract Features: LBP, HOG, Over-Complete LBP (OCLBP), Fisher Vector faces (FV) then reduce to 100 dimensions using WPCA.
  - Triangle Similarity Metric Learning (TSML)

$$\mathbf{a}_i = f(\mathbf{x}_i, \mathbf{A}) = \mathbf{A}\mathbf{x}_i \quad \mathbf{b}_i = f(\mathbf{y}_i, \mathbf{A}) = \mathbf{A}\mathbf{y}_i \quad \mathbf{c}_i = \mathbf{a}_i + s_i\mathbf{b}_i$$

$$J = \frac{1}{n}\sum_{i=1}^{n}[\frac{1}{2}||\mathbf{a}_i||^2 + \frac{1}{2}||\mathbf{b}_i||^2 - ||\mathbf{c}_i|| + 1] + \frac{\lambda}{2}||\mathbf{A} - \mathbf{A}_0||^2, \quad (1)$$

Participants and Algorithms

- **ULPGC**: similarity learning based model
  - Extract Features: HOG. LBP, Local Salient Patterns (LSP), Local Directional Patterns (LDP), Local Phase Quantization (LPQ), Local Oriented Statistics Information Booster (LOSIB)
  - Chi-Square Similarity measure

$$\chi^2(\mathbf{h}^A, \mathbf{h}^B) = \sum_{c=1}^{ncomps} \frac{(h_c^A - h_c^B)^2}{(h_c^A + h_c^B)}$$

  - Classification using SVM

Participants and Algorithms

- **NUAA**: Regression-based with feature selection
  - Extract Features: SIFT features
  - Regularized logistic regression objective

$$s^p(\mathbf{x}^p, \mathbf{y}^p) = (\mathbf{x}^p)^T \mathbf{W} \mathbf{x}^c.$$

$$\min_{\mathbf{W}, b} \sum_{i=1}^{N} \log \left(1 + \exp(-y_i (\mathbf{x}^p)^T \mathbf{W} \mathbf{x}^c)\right) + \lambda \|\mathbf{W}\|_*$$

  - Classification using linear SVM

Participants and Algorithms

- **BIU**: metric learning-based model
  - Extract Features: HOG and LBP
  - Asymmetric metric learning with margin maximization constraint

$$d_{\mathbf{a}}^2\left(\phi_i^o, \phi_j^y\right) = \left\|\mathbf{W}_o \phi_i^o - \mathbf{W}_y \phi_j^y\right\|_2^2$$

$$\arg\min_{\mathbf{W},b} \sum_{i,j} \max\left[1 - y_{ij}\left(b - d_{\mathbf{a}}^2\left(\phi_i^o, \phi_j^y\right)\right), 0\right]$$

  - Classification using SVM using RBF kernel

Results

- Evaluation criterion
  - Mean verification rate and ROC curve
- Unsupervised Setting

THE MEAN ACCURACY (%) UNDER UNSUPERVISED SETTING ON THE KINFACEW-I DATASET.

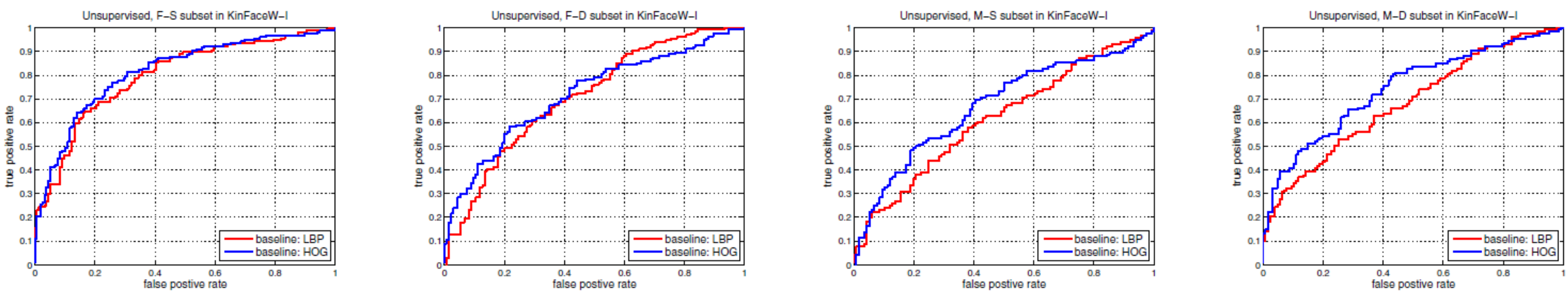
Label	F-S	F-D	M-S	M-D	Mean
(LBP)	76.92	69.05	64.24	66.59	69.20
(HOG)	79.53	70.93	67.66	72.84	72.74

THE MEAN ACCURACY (%) UNDER UNSUPERVISED SETTING ON THE KINFACEW-II DATASET.

Label	F-S	F-D	M-S	M-D	Mean
(LBP)	75.40	66.60	70.60	66.00	69.65
(HOG)	74.20	66.60	70.60	67.00	69.60

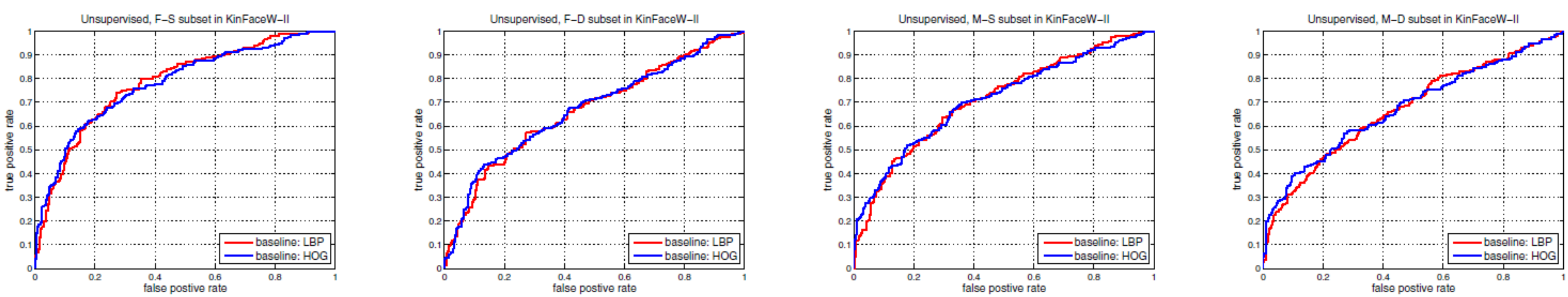
Results

- Unsupervised Setting



(a) F-S (b) F-D (c) M-S (d) M-D

Fig. 2. ROC curves of the baseline method with the unsupervised setting on KinFaceW-I.



(a) F-S (b) F-D (c) M-S (d) M-D

Fig. 3. ROC curves of the baseline method with the unsupervised setting on KinFaceW-II.

Results

- Image-Restricted Setting

THE MEAN ACCURACY (%) UNDER IMAGE-RESTRICTED SETTING ON THE KINFACEW-I DATASET.

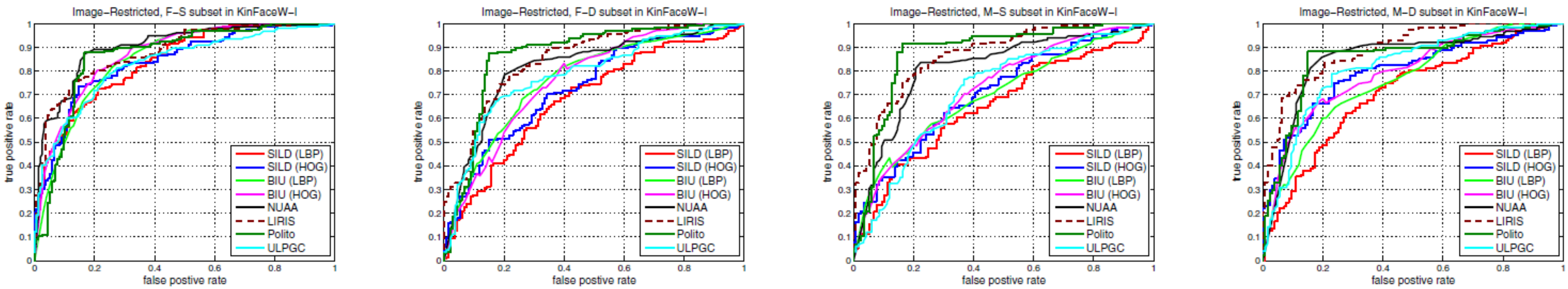
Label	F-S	F-D	M-S	M-D	Mean
Polito	85.30	85.80	87.50	86.70	**86.30**
LIRIS	83.04	80.63	82.30	84.98	82.74
ULPGC	71.25	70.85	58.52	80.89	70.01
NUAA	86.25	80.64	81.03	83.93	82.96
BIU	86.90	76.48	73.89	79.75	79.25
SILD (LBP)	78.22	69.40	66.81	70.10	71.13
SILD (HOG)	80.46	72.39	69.82	77.10	74.94

THE MEAN ACCURACY (%) UNDER IMAGE-RESTRICTED SETTING ON THE KINFACEW-II DATASET.

Label	F-S	F-D	M-S	M-D	Mean
Polito	84.00	82.20	84.80	81.20	83.10
LIRIS	89.40	83.60	86.20	85.00	**86.05**
ULPGC	85.40	75.80	75.60	81.60	80.00
NUAA	84.40	81.60	82.80	81.60	82.50
BIU	87.51	80.82	79.78	75.63	80.94
SILD (LBP)	78.20	70.00	71.20	67.80	71.80
SILD (HOG)	79.60	71.60	73.20	69.60	73.50

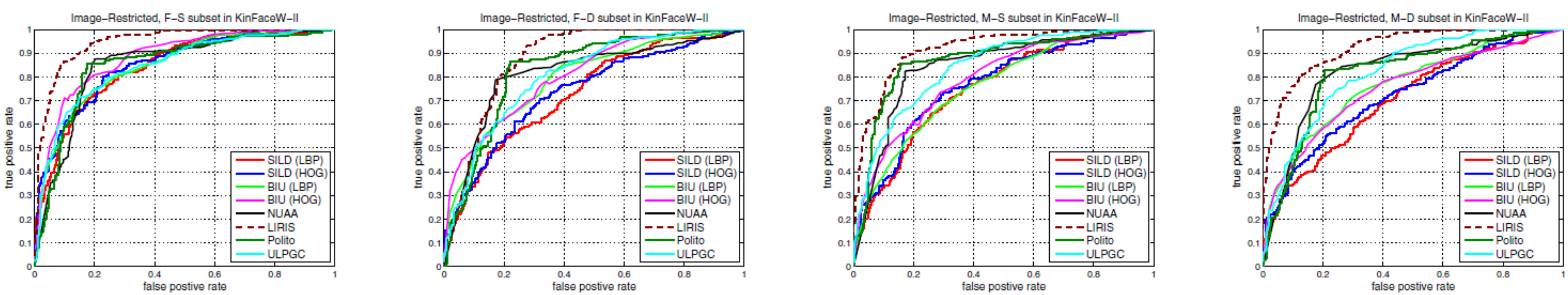
Results

- Image-Restricted Setting



(a) F-S (b) F-D (c) M-S (d) M-D

Fig. 4. ROC curves of different methods under the image-restricted setting on KinFaceW-I.



(a) F-S (b) F-D (c) M-S (d) M-D

Fig. 5. ROC curves of different methods under the image-restricted setting on KinFaceW-II.

Results

- Image-Unrestricted Setting

TABLE VII

THE MEAN ACCURACY (%) UNDER IMAGE-UNRESTRICTED SETTING ON THE KINFACEW-I DATASET.

Label	F-S	F-D	M-S	M-D	Mean
BIU (LBP)	85.51	76.54	69.93	74.36	76.59
BIU (HOG)	86.90	76.48	70.62	79.75	**78.44**
NRML (LBP)	81.43	69.76	67.23	72.87	72.82
NRML (HOG)	83.68	74.64	71.56	79.96	77.46

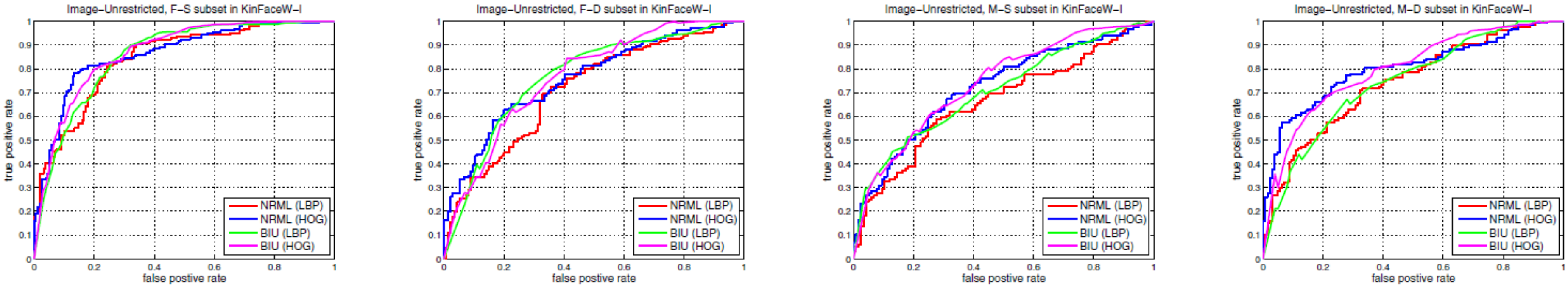
TABLE VIII

THE MEAN ACCURACY (%) UNDER IMAGE-UNRESTRICTED SETTING ON THE KINFACEW-II DATASET.

Label	F-S	F-D	M-S	M-D	Mean
BIU (LBP)	84.24	79.45	75.98	77.04	79.18
BIU (HOG)	87.51	80.82	79.78	75.63	**80.94**
NRML (LBP)	79.20	71.60	72.20	68.40	72.85
NRML (HOG)	80.80	72.80	74.80	70.40	74.70

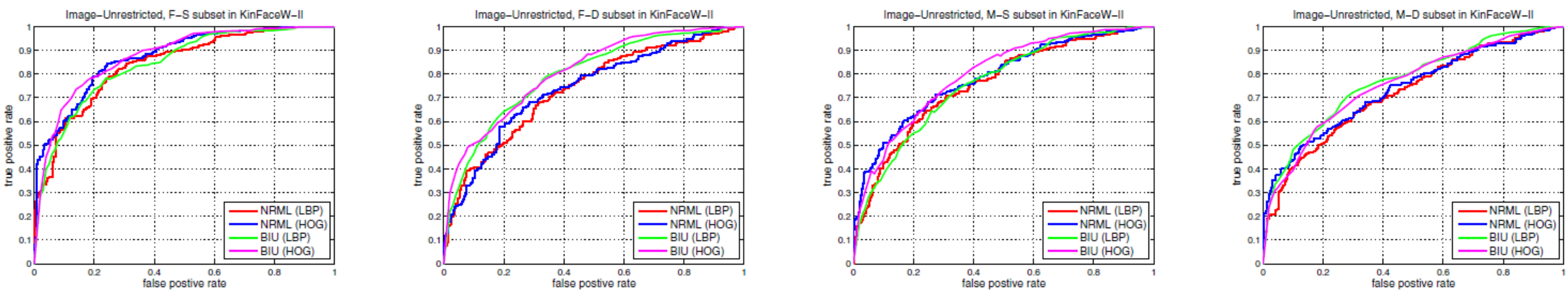
Results

- Image-Unrestricted Setting



(a) F-S (b) F-D (c) M-S (d) M-D

Fig. 6. ROC curves of different methods under the image-unrestricted setting on KinFaceW-I.



(a) F-S (b) F-D (c) M-S (d) M-D

Fig. 7. ROC curves of different methods under the image-unrestricted setting on KinFaceW-II.

Discussions

- Metric learning and feature selection can achieve better performance than other methods.
- Current technology is still not enough to produce reasonably good results and there is much space for further improvement.

Conclusion

- Established a benchmark for kinship verification for face images which will allow researcher to investigate in this problem.

Webpage

- www.kinfacew.com

KinFaceW

Home Datasets Protocol Download Results References Contact Changes

Home

Welcome to Kinship Face in the Wild (**KinFaceW**), a database of face images collected for studying the problem of kinship verification from unconstrained face images. There are many potential applications for kinship verification such as family album organization, genealogical research, missing family members search, and social media analysis.

The aim of kinship verification is to determine whether there is a kin relation between a pair of given face images. The kinship is defined as a relationship between two persons who are biologically related with overlapping genes. Hence, there are four representative types of kin relations: Father-Son (F-S), Father-Daughter (F-D), Mother-Son (M-S) and Mother-Daughter (M-D), respectively.

News!

Sep-22-2014: The detailed information of The Kinship Verification in the Wild Evaluation can be found here, which is organized as part of FG2015.

References

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4. Junlin Hu, **Jiwen Lu**, Junsong Yuan, Yap-Peng Tan, Large margin multi-metric Learning for mace and kinship verification in the wild, *Asian Conference on Computer Vision (ACCV)*, 2014.
5. **Jiwen Lu**, Junlin Hu, Xiuzhuang Zhou, Yuanyuan Shang, Yap-Peng Tan, Gang Wang, Neighborhood repulsed metric learning for kinship verification, *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 2594-2601, 2012.