BeFIT 2011: Heterogeneous Face Recognition in VIS vs NIR modalities

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Contents

• Introduction
  – Motivation for Cross Spectral Face Recognition
  – Motivation for Standardised testing

• Dataset
  – Acquisition, sample size,
  – Protocol: Configuration I and II

• Methodology
  – Preprocessing, Feature Extraction, Dimensionality Reduction, CCA projection

• Experiments
  – Overview of algorithmic combinations

• Results

• Discussion

• Conclusions
Face Recognition

**Face Recognition (Challenges)**

- **Natural Variation**
- **Occlusion**
- **Aging**
- **Illumination Variation**

**Decision (Yes/No)**

**Probe**

**Gallery**

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Illumination Invariant Face Recognition

Spatial Methods
- 3D Re-lighting
- Photometric

2D Normalisation

Spectral Methods
- Unimodal Spectral
- Hyper-Spectral
- Cross-Spectral

Hardware Based

Software Based

• Model-based Approaches
• Algorithmic Approaches

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Cross Spectral Face Matching

- Matching NIR probe images against a set of VIS gallery images

- Scenarios – Airports, building entry points

- NIR: 800 – 1050 nm band

- Spectral Differences
  - Diffusion of features in NIR (Subsurface Scattering)
  - Light response dictating distinct facial morphology
  - Texture discrepancies

VIS face images (top) and corresponding NIR images (bottom)
Existing Heterogeneous Face Recognition Systems

- Subspace projection (Lin et al. 2006)
- Canonical Correlation Analysis as a form of feature mapping (Li et al. 2007)
- Difference of Gaussian filtering (Liao et al. 2009)
- LBP feature representation (Liao et al. 2007, Chen et al. 2009)
**Testing Procedure**

<table>
<thead>
<tr>
<th>Total Subjects</th>
<th>Vis Images</th>
<th>Nir Images</th>
<th>Database</th>
</tr>
</thead>
<tbody>
<tr>
<td>100</td>
<td>400</td>
<td>400</td>
<td>HFB</td>
</tr>
<tr>
<td>48</td>
<td>192</td>
<td>192</td>
<td>TINDERS</td>
</tr>
<tr>
<td>50</td>
<td>100</td>
<td>90</td>
<td>Chen et al. CVPR 2009</td>
</tr>
</tbody>
</table>

- Multiple protocols with several different datasets
Pose and Illumination Cross Spectral (PICS) Dataset

430 Subjects

-10 degree deviation, frontal

Fully frontal

+10 degree deviation, frontal

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Protocol

- \( V_{trn} \) – 175 subjects x 3, 525 images
- \( N_{trn} \) – 186 Subjects x 3, 558 images
- \( V_{tst} \) - 255 Subjects, 1545 images
- \( N_{tst} \) – 244 Subjects, 1563 images
**Methodology**

1. **Preprocessing**
   - Raw
   - Sequential Chain (SQ)
   - Single Scale Retinex (SSR)
   - Self-Quotient Image (SQI)

2. **Feature Extraction**
   - Local Binary Patterns

3. **Subspace Projection**
   - PCA/LDA
   - CCA

4. **Classification**
   - Nearest Neighbour
     - Chi-Squared
     - Normalised Correlation

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Mapping: Canonical Correlation Analysis

Where $C_{yy} \in \mathbb{R}^{q \times q}$ and $C_{xx} \in \mathbb{R}^{p \times p}$ are the within-set covariance matrices, while $C_{xy} \in \mathbb{R}^{p \times q}$ is the between-set covariance matrix.

$$
\rho = \frac{E[xy]}{\sqrt{E[x^2]E[y^2]}} = \frac{E[w_x^T xy^T w_y]}{\sqrt{E[w_x^T xx^T w_x]E[w_y^T yy^T w_y]}} \\
\rho = \frac{w_x^T C_{xy} w_y}{\sqrt{w_x^T C_{xx} w_x w_y^T C_{yy} w_y}}.
$$

$$
\mathbf{x} = \mathbf{w}_x^T \mathbf{x} \quad \quad \quad \mathbf{y} = \mathbf{w}_y^T \mathbf{y}
$$
## Configuration I Experiments

<table>
<thead>
<tr>
<th>Preprocessing</th>
<th>Feature</th>
<th>Classification</th>
<th>Protocol</th>
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<tbody>
<tr>
<td>SQ</td>
<td>Image space</td>
<td>LDA+NC</td>
<td>$I_a, I_b$</td>
</tr>
<tr>
<td>SSR</td>
<td>Image space</td>
<td>LDA+NC</td>
<td>$I_a, I_b$</td>
</tr>
<tr>
<td>SQI</td>
<td>Image space</td>
<td>LDA+NC</td>
<td>$I_a, I_b$</td>
</tr>
<tr>
<td>Raw</td>
<td>Image space</td>
<td>LDA+NC</td>
<td>$I_a, I_b$</td>
</tr>
<tr>
<td>SQ</td>
<td>Uniform LBPH</td>
<td>Chi-Squared</td>
<td>$I_a, I_b$</td>
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<td>$I_a, I_b$</td>
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Photometric Normalisation
Results

Photometric Normalisation

\[ I_a \]

Photometric Normalisation

\[ I_b \]
Supervised vs Unsupervised Performance
### Configuration II

<table>
<thead>
<tr>
<th>Configuration</th>
<th>Probe</th>
<th>Gallery</th>
<th>Training</th>
<th>Testing</th>
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<tbody>
<tr>
<td>$I_a$</td>
<td>NIR</td>
<td>VIS</td>
<td>$V_{trn}$</td>
<td>$V_{tst} + N_{tst}$</td>
</tr>
<tr>
<td>$I_b$</td>
<td>VIS</td>
<td>NIR</td>
<td>$N_{trn}$</td>
<td>$V_{tst} + N_{tst}$</td>
</tr>
<tr>
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<td>VIS</td>
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<td>$V_{tst} + N_{tst}$</td>
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CCA Recognition Performance

Graphs showing the rank-1 recognition rate for different algorithms and combinations.
Fusion Experiments

- Performance plateau at 5-7 algorithmic combinations
- SQ preprocessing (DoG-based) present in every single top-performing combination
- Use of more than 7-8 combinations degrades performance
Discussion

• Supervised vs Unsupervised Process chains
• Importance of Pre-processing techniques
• Over-fitting of CCA model projections
• Fusion experiments achieve peak performance
  – Importance of SQ (DoG-based) in top performing permutations
Conclusions

• Standardised testing for cross spectral datasets
• Dataset containing pose and illumination variation
• Baseline algorithms to establish a true evaluative framework
• Importance of projection model, and probe-gallery combinations
Contact Details

- [http://www.ee.surrey.ac.uk/CVSSP/Datasets](http://www.ee.surrey.ac.uk/CVSSP/Datasets) (soon!)

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  - Name
  - Organisation