Automatic Enhancement of Interoperability between Optical Fingerprint Sensors

Emanuela Marasco, Luca Lugini, Bojan Cukic

Lane Department of Computer Science and Electrical Engineering
Summary

• WVU Multi-Sensor Fingerprint Collection
• Fingerprint Interoperability Assessment
• The Proposed Enhancement Approach
• Results
Multi-Sensor Fingerprint Collection

- Data collection performed at West Virginia University
- FBI Certified livescan fingerprint sensors
- Number of participants: 500
  - Rolled individual fingerprints on right and left hands; left, right and thumb slaps per session
    - In the analysis we use right point finger only.
- Two sequential sessions for each sensor
- Inked rolled prints
## Optical Fingerprint Sensors

<table>
<thead>
<tr>
<th>Device</th>
<th>Model</th>
<th>Resolution (dpi)</th>
<th>Image Size (pixels)</th>
<th>Capture Area (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>D0 Cross Match</td>
<td>Guardian R2</td>
<td>500</td>
<td>800 x 750</td>
<td>81 x 76</td>
</tr>
<tr>
<td>D1 i3</td>
<td>digID Mini</td>
<td>500</td>
<td>752 x 750</td>
<td>81 x 76</td>
</tr>
<tr>
<td>D2 L1 Identity Solutions</td>
<td>TouchPrint 5300</td>
<td>500</td>
<td>800 x 750</td>
<td>81 x 76</td>
</tr>
<tr>
<td>D3 Cross Match</td>
<td>Seek II</td>
<td>500</td>
<td>800 x 750</td>
<td>40.6 x 38.1</td>
</tr>
</tbody>
</table>
Collection Demographics

- Provided Ethnicity, Age, Gender, Weight, Height

Diversity in Fingerprint Images

- Optical Sensors
- Image Quality: NFIQ
- Soft-Biometrics: Age / Gender
Diversity from Image Quality

- Average normalized match score vs. NFIQ image quality for all the considered devices
- The size of the square indicates the frequency

<table>
<thead>
<tr>
<th>Participant</th>
<th>Device</th>
<th>D0</th>
<th>D1</th>
<th>D2</th>
<th>D3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>Gender</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>18-29</td>
<td>Male</td>
<td>1.396</td>
<td>1.935</td>
<td>2.104</td>
<td>1.735</td>
</tr>
<tr>
<td></td>
<td>Female</td>
<td>1.526</td>
<td>2.500</td>
<td>2.513</td>
<td>1.712</td>
</tr>
<tr>
<td>30-59</td>
<td>Male</td>
<td>1.748</td>
<td>2.684</td>
<td>2.820</td>
<td>2.112</td>
</tr>
<tr>
<td></td>
<td>Female</td>
<td>2.500</td>
<td>3.222</td>
<td>3.278</td>
<td>2.778</td>
</tr>
<tr>
<td>60+</td>
<td>Male</td>
<td>3.071</td>
<td>3.476</td>
<td>3.524</td>
<td>3.095</td>
</tr>
<tr>
<td></td>
<td>Female</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

- Device Ranking by Image Quality
- Average NFIQ image quality measures

Sensor Diversity

• Impact of Sensors on Image Quality

• Impact of Sensors on Matching Algorithm

Quality distributions

![Plot of Quality distributions with NFIQ on the x-axis and Normalized Frequency on the y-axis.](image)

DET Curves Inter- and Intra-device Scenarios

![Plot of DET curves with FAR (%) on the x-axis and FRR (%) on the y-axis.](image)

© 2014 West Virginia University
Sensor Diversity

- Impact of Device Diversity on Matching

- Impact of Device Diversity and Image Quality on Matching
Diversity from Soft Biometrics

• Impact of Age / Gender on Matching Algorithms

• Impact of Age / Gender on Image Quality

• Age Groups
  • Young: 18-29
  • Elderly: 30-75

• TouchPrint 5300 device
One Identity Multiple Biometric Sources

• Can we achieve error rates in cross-device matching as good as within same-device?

• Higher intra-device genuine match scores indicate interoperability problems
Related Works

1. Image Quality (local gradients) for score calibration [1]
   • Biosecure DS2 database, 207 subjects
   • Thermal vs. Optical
   • Results: TER is reduced from 15.834% to 15.150% (at EER)
   • Weakness: association of each device with a quality cluster

2. Distortion compensation model [2]
   • Optical vs. Capacitive
   • WVU data set of 71 subjects, MSU data set of 128 subjects
   • Results: at FAR= 0.01% GAR from 35% to 75% (Verifinger)
   • Weakness: non-linear transformation of minutiae points, old sensors

The Proposed Approach

1. Training Data set
2. Feature Extraction
3. Matcher
4. Feature Selection
5. Classifier
6. Galleries
7. Feature Extraction
8. Decision
The Proposed Approach

- Compensation after matching
- Modeling qualitative information of the device and how it relates to match score
- The set of interoperability features is concatenated with the match score

Sample Interoperability Features

- Image quality (NFIQ and MITRE)
- Minutiae count
- Pattern noise
- Intensity-based statistics
- Alignment
Classification

- Random Forest-based classification
- 10-Fold Cross Validation (25% training)
Results

- Using a preliminary set of features

<table>
<thead>
<tr>
<th>Learner</th>
<th>Training</th>
<th>FMR</th>
<th>FNMR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random Forest</td>
<td>10-Fold CV 10 Trees</td>
<td>0.006%</td>
<td>3.279%</td>
</tr>
<tr>
<td></td>
<td>25% 10-Fold CV (25 Trees)</td>
<td>0.005%</td>
<td>3.741%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Baseline</th>
<th>FMR</th>
<th>FNMR</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.005%</td>
<td>6.696%</td>
</tr>
<tr>
<td></td>
<td>1.982%</td>
<td>3.741%</td>
</tr>
</tbody>
</table>

- Error rates of commercial fingerprint matchers increase when images are acquired using different devices

- Compensation after matching achieves a significant improvement of cross-device accuracy
Thanks for your attention!

Any Questions?

Emanuela Marasco, Ph.D.
WVU CITeR
Statler College of Engineering and Mineral Resources
LCSEE – PO Box 6109
395 Evansdale Drive, ESB Annex 171
Morgantown WV 26506 USA

emanuela.marasco@mail.wvu.edu
Phone: (304) 293-1455