Thermal Handprint Analysis for Forensic Identification using Heat-Earth Mover’s Distance

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Outline

- Introduction
- Thermal Handprint Recognition System Construction
- Performance Evaluation
- Conclusion
Forensic Analysis

- Scientific method of gathering and examining structured data with regard to incidents of crime.

- **Forensic identification**: determination of individuality of a person

1. Complete/Total identification
   - Exact specification of an individual
2. Incomplete/Partial identification
   - Recording of certain information which will ultimately help complete or total identification

- Need of identification
  - In dead persons
  - In skeletal remains
  - In living persons
Prior Arts in Forensic Analysis

- **DNA fingerprinting**
  - Blood, skin, hair, saliva
  - Length of the strands of the DNA molecules with repeating base pair patterns by restriction fragment length polymorphism (RFLP)

- **Odor analysis**
  - Chemical analysis of perfume components by gas chromatography

- **Voice analysis**
  - Phonetic analysis and signal processing

- **Fingerprint/Handprint analysis**
  - Dactylography: a study of fingerprints as a method of identification
    - Impressions of papillary ridges of the finger tips
    - ABSOLUTE without any change of error
Problems

- DNA fingerprinting
  - Not available in all forensic scenes

- Odor analysis
  - Depends on the type of fabric containing perfume residue

- Voice analysis
  - Overlapping speech and low signal-to-noise ratio
  - Requires an audio recording device

- Fingerprint / handprint analysis
  - Most promising approach and has been adopted
  - However, it can be prevented using glove
Thermography (1/2)

- A new perspective to address problems
- **Fast, safe, and accurate non-contact** measurement of temperature and assignment of colors based on temperature.
  - Surveillance, security, and human-computer interactive systems
- **Advantages**
  - No influence from lubrication or direct contact
    - preservation of scene of investigation
  - Every object emits infrared energy/heat
    - expansion of the target
Thermography (2/2)

- Why thermal handprints?
  - Skin on human handprint contains very rich and unique biometric information
  - Handprint-based verification system (Yan et al)
    - Integrating palm geometry feature and finger-print feature
    - Accuracy of 97.00%
  - Not visible to human vision
    - Less possibility to be intentionally removed
Objectives

- To apply infrared imaging technique in extracting thermal handprints
- **To develop a system that performs a forensic identification using heat-based handprints**
  - Thermal handprint made without the glove
  - Thermal handprint made with the glove
Outline

- Introduction
- **Thermal Handprint Recognition System Construction**
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Handprint Identification Framework

-target Image X

Rotation and Batch crop

Grayscale

2-D median filter

Sobel detection

PCA rotation

Feature extraction

Transformation

EMD (Fx, Fy)

kNN & LOOCV

Sample 1  Sample 2  ...  Sample N

Training Image Y
# Experimental Details

<table>
<thead>
<tr>
<th><strong>Imaging and optical data</strong></th>
<th><strong>IRS 75</strong></th>
<th><strong>Function parameters</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>Thermal sensitivity/NETD</td>
<td>≤ 0.06°C @ +30°C</td>
<td></td>
</tr>
<tr>
<td>Image frame rate</td>
<td>60Hz</td>
<td></td>
</tr>
<tr>
<td>Focal plane array detector (FPA)/wavelength range</td>
<td>7.5-13 um</td>
<td></td>
</tr>
<tr>
<td>IR resolution</td>
<td>160 X 120 pixels</td>
<td></td>
</tr>
<tr>
<td><strong>Measurement</strong></td>
<td><strong>Temperature range</strong></td>
<td><strong>-20°C ~ +650°C</strong></td>
</tr>
<tr>
<td>Accuracy</td>
<td>± 2°C or ±2% of reading</td>
<td></td>
</tr>
</tbody>
</table>
Experimental Test

- **Set-up**
  - IRS 75 held by a 350 mm tripod
  - Blow-molded plastic surface
  - Vertical distance is 29.7 inches

- **Participants**
  - 20 subjects (17 males and 3 females)
  - Age range of 18 to 35

<table>
<thead>
<tr>
<th>Sample Type</th>
<th>Per 1 subject (#)</th>
<th>Total (#)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standard-Handprint (SH)</td>
<td>40</td>
<td>800</td>
</tr>
<tr>
<td>Glove-Handprint (GH)</td>
<td>20</td>
<td>400</td>
</tr>
</tbody>
</table>
Experimental Method

- **Leave-one-out-cross-validation** is used to estimate how accurately a predictive model will perform in practice.
  - Each 800 SH images
  - Each 400 GH images

- **Classification with k nearest neighbors**
  - HEMD is a distance function
  - K equals 5
Feature Extraction

- Thermal Input
- Grayscale
- Noise filtering
- Sobel edge detection
- PCA rotation
- Contour detection
Pre-Processing

- Thermal Input
- Grayscale
- Noise filtering
- Sobel edge detection
- PCA rotation
- Contour detection
Heat-Earth Mover’s Distance (1/3)
Earth Mover’s Distance

- A method to evaluate dissimilarity between two distributions
  - a minimal cost paid to transform one distribution into another.
  - Several supplier with each a given amount of goods supply several consumers each with a given limited capacity.

- Advantages:
  - Allows for image matching that deals with occlusions and clutter.
  - Is a true metric than other distance metrics if the total weights of two signatures are equal.
Heat-Earth Mover’s Distance (2/3)

- For each target-training pair, the cost of transporting a single point is given and is defined by Euclidean distance.

\[ \text{Target } X = \{(x_1, w_{x_1}) \ldots (x_m, w_{x_m})\}, \ 1 \leq i \leq m \]
\[ \text{Training } Y = \{(y_1, w_{y_1}) \ldots (y_n, w_{y_n})\}, \ 1 \leq j \leq n \]

Ground distance \( D = [d_{ij}] \)
Flow \( F = [f_{ij}] \)

- Our task is to find a least expensive flow of points from the target to the training that satisfies the training’s demand with subject to:

1. Allows moving points from \( X \) to \( Y \) but not from \( X \) to \( Y \)
2. Overall weight of points in \( X \) equals the overall weight of points in \( Y \)
   - Weight normalization is not required
3. Limits the clusters in \( X \) from sending points more than their weight
4. Limits the clusters in \( Y \) from receiving points more than their weight
5. Total Flow - forcefully move the maximum amount of points

\[ HEMD(X, Y, F) = \min \left( \sum_{i=1}^{m} \sum_{j=1}^{n} f_{ij} d_{ij} \right) \]
\[ f_{ij} \geq 0; \ 1 \leq i \leq m, \ 1 \leq j \leq n \]
\[ \sum_{i=1}^{m} w_{x_i} = \sum_{j=1}^{n} w_{y_j} \]
\[ \sum_{j=1}^{n} f_{ij} \leq w_{x_i}; \ 1 \leq i \leq m \]
\[ \sum_{i=1}^{m} f_{ij} \leq w_{y_j}; \ 1 \leq j \leq n \]
\[ \sum_{i=1}^{m} \sum_{j=1}^{n} f_{ij} = \min \left( \sum_{i=1}^{m} w_{x_i}, \sum_{j=1}^{n} w_{y_j} \right) \]
Heat-Earth Mover’s Distance (3/3)
Outline

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Experimental Results

- **Accuracy (ACC)**
  \[
  \frac{TP + TN}{TP + FP + TN + FN}
  \]

- **Balance accuracy metric (BAC)**
  \[
  \frac{0.5 \times TP}{TP + FN} \times \frac{0.5 \times TN}{TN + FP}
  \]
  Arithmetic mean of sensitivity and specificity

- **F-measure accuracy measure (F1)**
  \[
  \frac{Precision \times Recall}{Precision + Recall} \times 2
  \]
  Harmonic mean of precision and recall

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<tr>
<th>Sample Type</th>
<th>ACC (%)</th>
<th>BAC (%)</th>
<th>F1 (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SH</td>
<td>94.13</td>
<td>94.49±8.59</td>
<td>94.49</td>
</tr>
<tr>
<td>GH</td>
<td>92.00</td>
<td>92.50±9.09</td>
<td>92.50</td>
</tr>
</tbody>
</table>
# F-1 Measure: Confusion Matrix

| Subject | A | B | C | D | E | F | G | H | I | J | K | L | M | N | O | P | Q | R | S | T | Recall (%) |
| Left Table (SH) | 40 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 100 |
| Right Table (GH) | 0 | 38 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 95.0 |

| Subject | A | B | C | D | E | F | G | H | I | J | K | L | M | N | O | P | Q | R | S | T | Recall (%) |
| Left Table (SH) | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 100 |
| Right Table (GH) | 0 | 0 | 34 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 95.0 |

| Subject | A | B | C | D | E | F | G | H | I | J | K | L | M | N | O | P | Q | R | S | T | Recall (%) |
| Left Table (SH) | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 100 |
| Right Table (GH) | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 100 |

| Subject | A | B | C | D | E | F | G | H | I | J | K | L | M | N | O | P | Q | R | S | T | Recall (%) |
| Left Table (SH) | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 100 |
| Right Table (GH) | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 100 |

## Results Table

<table>
<thead>
<tr>
<th></th>
<th>Average Precision (%)</th>
<th>Average Recall (%)</th>
<th>F1 (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Left Table (SH)</td>
<td>94.85</td>
<td>94.13</td>
<td>94.49</td>
</tr>
<tr>
<td>Right Table (GH)</td>
<td>93.00</td>
<td>92.00</td>
<td>92.50</td>
</tr>
</tbody>
</table>
Receiver operating characteristic (ROC)

- Plot of **TPR vs. FPR** for different thresholds
  - Visual representation of how the classifier performs in the region of high sensitivity and high specificity
  - The closer the curve follows the left-top portion of the graph, more accurate the test is
  - **Area under the ROC curve (AUC)** determines how well a parameter can distinguish a targeted subject

<table>
<thead>
<tr>
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<th>AUC (%)</th>
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<tr>
<td>SH</td>
<td>95.69 ± 6.91</td>
</tr>
<tr>
<td>GH</td>
<td>98.50 ± 2.40</td>
</tr>
</tbody>
</table>

TPR: True Positive Rate, FPR: False Positive Rate
Equal error rate (EER)

- Rate at which both acceptance error (FPR) and rejection error (FNR) are equal.
- Lower the EER value, the higher the accuracy of the system
- EER of SH < EER of GH
  - Handprint without the glove is more stable and distinguishable
Discussion on Results (1/3)

- Limitation of our approach

1. **Surface material**: effect of emissivity on the clarity of raw thermal images and contour points of handprint

<table>
<thead>
<tr>
<th>Common Surface Material</th>
<th>Emissivity Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aluminum Foil</td>
<td>0.05</td>
</tr>
<tr>
<td>Paper, white</td>
<td>0.68</td>
</tr>
<tr>
<td>Cardboard, white</td>
<td>0.81</td>
</tr>
<tr>
<td>Plastic</td>
<td>0.94</td>
</tr>
<tr>
<td>Concrete, dry white</td>
<td>0.95</td>
</tr>
</tbody>
</table>

2. **Permanence**: effect of surface material on the rate of cooling for 1 minute: (a) paper (b) cardboard (c) plastic with latex glove (d) plastic (e) concrete wall

![Thermal Images](image-url)
Limitation of our approach

3. Non-flat surface: Our previous methods used the handprints made in a flat surface while a distortion of the shape of handprints may reduce an accuracy of HEMD.

1. Boiling pot

2. Box

3. Chair
Discussion on Results (3/3)

- Potential solution

1. **Surface material**
   - Unless the material is a metal, clarity of the handprint is not very sensitive to the surface materials.

2. **Permanence**
   - Motion based infrared recording technology
     - Can obtain the most original form of thermal handprints
     - Determination of time of the incident

3. **Non-flat surface**
   - Partial matching of the thermal palm geometry feature and thermal finger-print feature (Yan et al)
     - Segmentation of each features in the handprint
     - Coarse level identification ➔ fine level identification
Outline

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Conclusion

- Our system has accurately classified the data regardless of prevention. Comprehensive experiments are conducted and achieved the accuracy of 94.13%. For handprint with latex glove, the average accuracy is 92.00%. The performance results indicate that HEMD is secure and feasible biometric system.

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<td>1.07 ± 0.94</td>
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<td>92.50</td>
<td>93.00</td>
<td>92.00</td>
<td>98.50 ± 2.40</td>
<td>3.29 ± 2.49</td>
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Acknowledgement

- **Advisor**
  - Dr. Wenyao Xu

- **Laboratory**
  - Kun Woo Cho
  - Dr. Feng Lin
  - Dr. Chen Song
  - Dr. Xiaowei Xu
  - Dr. Fuxing Gu

- **Department of Computer Science and Engineering, SUNY at Buffalo**

- **Shanghai Key Lab of Modern Optical System, University of Shanghai for Science and Technology**

- **External sponsor**
  - National Science Foundation CNS-1423061