Personal Recognition Using Single-sensor Multimodal Hand Biometrics

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Goals of this work

- **Introduction of a novel multimodal hand biometric system**: our proposed method combines *Hand geometry*, *Fingerprint* and *Palmprint* biometrics for reliable person authentication.
- **Employment of document scanners designed for large markets as biometric sensors**: high availability, facilitates reproducibility of experiments, sensor independence, minimizes acquisition and upkeep cost.

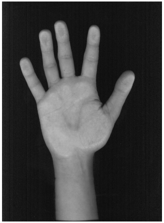
Why combining single-sensor hand-based biometrics?

- **Increased accuracy** without the need of additional sensors;
- **More flexibility** in case of failure to acquire single biometrics (e.g. single bad quality fingerprints);
- **Increased security** with respect to biometric system attacks;
- **High availability** of flatbed sensors;
- **Fair comparison** between different modalities.

Outline

Proposed method and related work

Proposed method



Sensor: Scanner
Features:

- Shape
- Minutiae
- Palmprint
- Eigenpalms+fing.

Acc.: 0.006% TER
Samples: $\approx 86 \times 5$

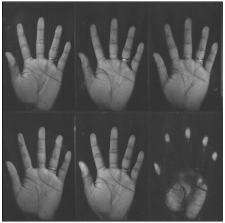
Kumar et al.

Sensor: Camera+FPR
Features:

- Hand geometry
- Minutiae
- Palmprint

Accuracy: 5.61% TER
Samples: 100×8

Rowe et al.

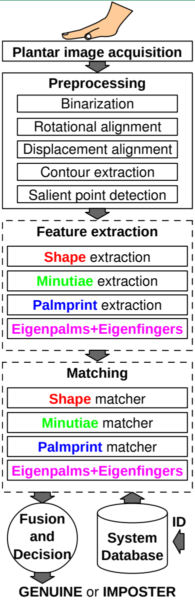


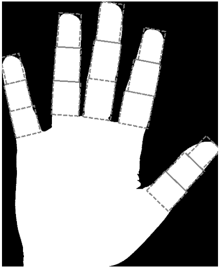
Sensor: Multispectral
Features:

- Minutiae
- Palmprint

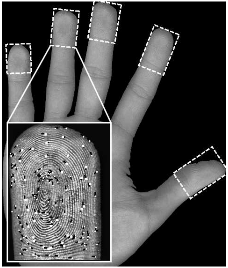
Accuracy: 0% TER
Samples: 50×12

System architecture

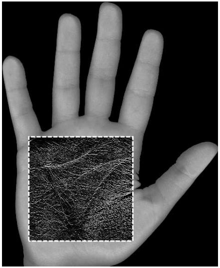




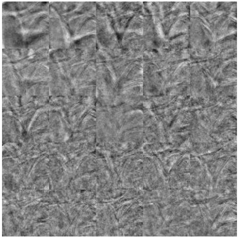
Shape: local finger widths

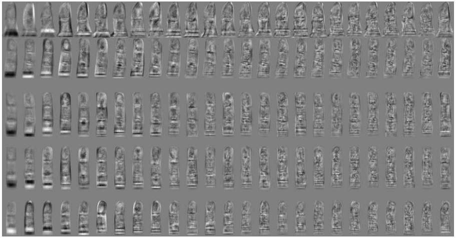


Minutiae: Galton details



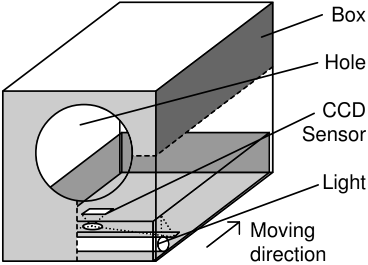
Palmprint: local block variance



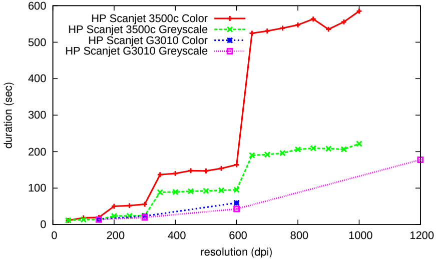


Eigenpalms+Eigenfingers: projection onto palm /finger space

Sensor and test set



(a) Employed scanning device

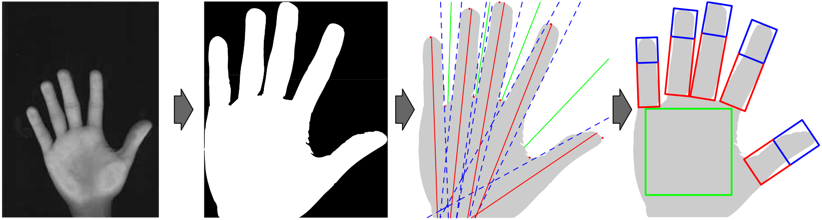


(b) Resolution-duration tradeoff.

Test database:

- **Samples**: 443 right-hand samples of 86 persons ($\approx$ 5 samples per person);
- **Gender balance**: 82.4 % male versus 17.6 % female;
- **Type**: 4250 $\times$ 5850 pixels at 500 dpi resolution, 8-bit grey-scale;
- **Conditions**: data acquisition with user sitting in front of standard HP 3500c flatbed scanning device contained in a box;
- **Recording interval**: 15 minutes.

Preprocessing



1. **Segmentation and normalization**: Otsu's thresholding, moment-based ellipse-fitting, removal of visible arm parts, hand-coordinate-system alignment (origin: valley between ring/middle finger, direction: approximated outer palm boundary);
2. **Contour extraction and salient point detection**: intra-finger valleys (and peaks) as minima (and maxima) of the *radial distance function* are refined with best-ellipse fitting of individual fingers;
3. **Region extraction**: 500 dpi fingerprint ($\frac{1}{3}$ part of finger/$\frac{1}{2}$ part of thumb) and palmprint region (size s equal to avg. finger length, Y-offset $0.2s$), both 500 dpi and 100 dpi (128×256 for thumb and little finger, others: 128×384) finger regions.

Shape feature

Feature extraction: using 500 dpi finger regions;

1. **Generation of slices**: each upright finger is divided into $c = 3$ slices $S_1, \ldots S_c$ of equal height covering the finger;
2. **Average object width**: $w(S_n)$, $1 \leq n \leq c$, with respect to the y-monotone contour extracted using a left-right scan;
3. **Concatenation** of features for all fingers.

Matching:

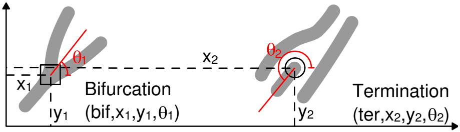
1. **Decomposition**: each feature vector is decomposed into finger-dependent parts;
2. **Manhattan distance**: between template and reference vectors for each finger;
3. **Combination**: Sum rule fusion after linear score normalization.

Minutiae feature

Feature extraction: using NIST's *mindtct* on 500 dpi fingerprints;

1. **Contrast enhancement**: using CLAHE;
2. **Generation of Image Maps**: *local ridge orientation map* (NFIS: 16 directions, 8×8 blocks), *low flow maps*, *low contrast maps*, ...;
3. **Minutiae detection**: in the binarized image by local pixel patterns;
4. **Minutiae filtering**: eliminates minutiae in malformed structures.

Matching: using NIST's *bozorth3*;



1. **Pairing**: Matching of corresponding (wrt. distance, orientation, type) minutiae yields a similarity score for each finger;
2. **Combination**: Max rule fusion after linear score normalization.

Palmprint feature

Feature extraction: using palmprint;

1. **Region normalization, edge detection**: predefined mean $\phi_d := 100$, variance $\rho_d := 400$;

$$R'(x,y) := \begin{cases} \phi_d + \lambda & \textit{if } R(x,y) > \phi, \\ \phi_d - \lambda & \textit{else.} \end{cases} \quad (1)$$

$$\lambda = \sqrt{\frac{\rho_d (R(x,y) - \phi)^2}{\rho}}. \quad (2)$$

   Edges: 7×7 Prewitt filter;

2. **Feature extraction**: variances of 144 overlapping blocks (24×24) within the resized (300×300) image.

Matching:

1. **Decomposition**: each feature vector is decomposed into finger-dependent parts;
2. **Euclidian distance**: between template and reference vectors for each finger;
3. **Combination**: Sum rule fusion after linear score normalization.

Eigenpalms+Eigenfingers feature

Eigenspaces for each finger type/ palm are precalculated by estimating most significant principal components $\mathfrak{u}_i, i \in \{1, \ldots, l\}$ from the covariance matrix of mean-normalized training samples (mean $\mathfrak{a}$).

Feature extraction: using 100 dpi finger regions;

1. **Normalization** of the palm or finger vector $\mathfrak{b}$ by subtracting the mean image $\mathfrak{n} = \mathfrak{b} - \mathfrak{a}$.
2. **Projection** onto eigenspace to get the feature vector components $\omega_i = \mathfrak{u}_i^T \mathfrak{n}$.

Matching:

1. **Decomposition**: each feature vector is decomposed into finger-dependent parts;
2. **Manhattan distance**: in feature space, result converted into similarity score;
3. **Combination**: Product rule fusion after linear score normalization.

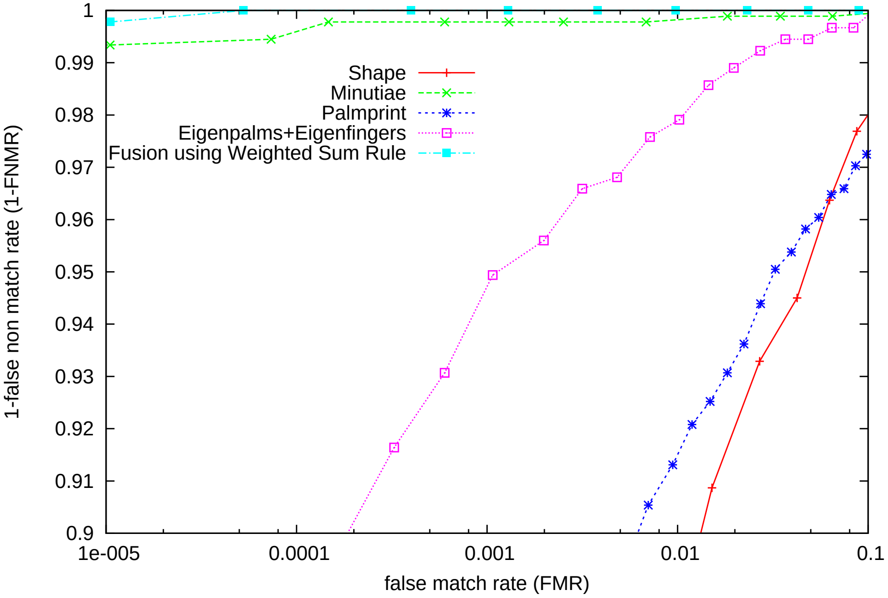
Performance evaluation

Which of the presented hand-based techniques performs best and which total performance can be achieved?

- **Comparisons**: cross-comparison of available templates resulting in 909 genuine and 95232 imposter comparisons;
- **Failure to Acquire**: 0.9% of all templates were rejected;
- **Results**: highest individual MinHTER accuracy by Minutiae, but all features contribute to the best combined feature using Weighted Sum Rule fusion (weights: 0.10 for Shape, 0.17 for Palmprint, 0.06 for Eigenpalms + Eigenfingers, and 0.67 for Minutiae).

Algorithm	MinHTER	ZeroFMR	ZeroFNMR
Shape	4.7%	70.74%	25.53%
Minutiae	0.12%	1.1%	16.44%
Palmprint	4.1%	36.19%	100%
Eigenpalms + Eigenfingers	1.44%	15.29%	10.72%
Fusion using Weighted Sum Rule	0.003%	0.33%	0.005%

Receiver Operating Characteristics



Summary and Outlook

- **Subject**: A single-sensor approach for multimodal hand-based biometric recognition has been investigated; Shape, Minutiae, Palmprint, and Eigenpalms+Eigenfingers features have been compared by their relative performance.
- **Result**:
  - Minutiae and PCA-based Eigenpalms+Eigenfingers report highest verification accuracy with 0.12% *MinHTER* and 1.44% *MinHTER*, respectively.
  - Palmprint and Shape features are less accurate (4.1% and 4.7% *MinHTER*), but contribute to the combined result;
  - Best Weighted Sum rule fusion weights were found at 0.10 for Shape, 0.17 for Palmprint, 0.06 for Eigenpalms + Eigenfingers, and 0.67 for Minutiae, resulting in $3 \cdot 10^{-3}$% *MinHTER*.
- **Future topics**: increased training set size, time lapses between recordings.

Thank you for your attention!

Selected References:

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Any Questions?