Adapted Fusion Schemes for Multimodal Biometric Authentication

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Outline

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6. Multi-Algorithm Fingerprint Verification (Q-Based Fusion)
7. Multimodal Authentication Sign + Finger (UD Fusion)
8. Conclusions and Future Work
Introduction to Biometrics

Biometric system: Automatic pattern recognition system that makes use of personal biometric traits to recognize individuals

- Enrollment
- Verification (Authentication): 1-to-1 matching
- Identification: 1-to-N matchings

Biometric systems
Verification errors

- Biometric verification is a detection task:
  - Type I Error, False Rejection (FR): a genuine user is rejected
  - Type II Error, False Acceptance (FA): an impostor is accepted
    - Casual impostors (no imitations, random forgeries)
    - Real impostors (imitations, skilled forgeries)
- Equal Error Rate (EER): error rate for the decision threshold where FA=FR

![Graph showing False Rejection Rate (%) vs False Acceptance Rate (%)](image)

Verification errors

- Comparison of verification systems: ROC (left) and DET (right) curves

![Graph comparing ROC and DET curves for System A and System B](image)
### Biometric modalities

- **Any human characteristic that satisfy these requirements:**

<table>
<thead>
<tr>
<th>Biometric</th>
<th>Universality</th>
<th>Distinguishiveness</th>
<th>Permanence</th>
<th>Collectability</th>
<th>Performance</th>
<th>Acceptability</th>
<th>Circumvention</th>
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<tr>
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<tr>
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<td>M</td>
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<td>H</td>
<td>M</td>
<td>H</td>
<td>M</td>
<td>M</td>
</tr>
</tbody>
</table>

- **Comparative market share by biometric modality**
Limitations of single biometric modalities

- **Noise in the acquisition**: due to the sensors or to the acquisition conditions
- **Intra-user variability**: due to the interaction with the sensor, due to the variability of the biometric
- **Limited distinctiveness** of the biometric
- **Limited universality**: some users may not be enrolled in the system
- **Limited resilience to attacks**: use of artificial biometrics (gummy fingers)

Limitations in fingerprint verification: FVC (1/6)

- Recent fingerprint technology evaluations:
  - Fingerprint Vendor Technology Evaluation (FpVTE2003)
    - Organized by NIST
    - Organized by BioLab (University of Bologna), National Biometric Test Center (San Jose State Univ.) and PRIP Lab. (Michigan State Univ.)

*We focus on Fingerprint Verification Competition 2004*
Limitations in fingerprint verification: FVC (2/6)

- Development data: 10 fingers x 8 impressions x 4 sensors
- Sequestered data: 100 fingers x 8 impressions x 4 sensors
- Image quality is low to medium due to exaggerated plastic distortions, artificial dryness, wet fingers, ...

Limitations in fingerprint verification: FVC (3/6)

- FVC2000 (natural acquisition, 11 algorithms):
  - Winner 1.73% EER, average of first 5 systems 4.52% EER
- FVC2002 (natural acquisition, 31 algorithms):
  - Winner 0.19% EER, average of first 5 systems 0.52% EER
- FVC2004 (exaggerated distortion, 41 algorithms):
  - Winner 2.07% EER, average of first 5 systems 2.36% EER
Performance improves with the fusion of up to 7 systems.
Performance deteriorates when combining more than 10 systems.
The largest improvement is obtained for the fusion of 2-3 systems.

Some interesting examples:

<table>
<thead>
<tr>
<th>Participant</th>
<th>Ranking on DB1 (EER)</th>
<th>EER on DB1</th>
<th>Participant</th>
<th>Ranking on DB2 (EER)</th>
<th>EER on DB2</th>
<th>Participant</th>
<th>Ranking on DB3 (EER)</th>
<th>EER on DB3</th>
<th>Participant</th>
<th>Ranking on DB4 (EER)</th>
<th>EER on DB4</th>
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<tr>
<td>047</td>
<td>1st</td>
<td>1.97</td>
<td>039</td>
<td>1st</td>
<td>1.58</td>
<td>047</td>
<td>1st</td>
<td>1.18</td>
<td>071</td>
<td>1st</td>
<td>0.61</td>
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<tr>
<td>101</td>
<td>2nd</td>
<td>2.72</td>
<td>047</td>
<td>1st</td>
<td>1.97</td>
<td>1.20</td>
<td>027</td>
<td>1.20</td>
<td>027</td>
<td>1st</td>
<td>0.61</td>
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<tr>
<td>101</td>
<td>2nd</td>
<td>2.72</td>
<td>047</td>
<td>1st</td>
<td>1.97</td>
<td>071</td>
<td>1st</td>
<td>0.61</td>
<td>039</td>
<td>1st</td>
<td>0.39</td>
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<tr>
<td>004</td>
<td>6th</td>
<td>4.10</td>
<td>039</td>
<td>1st</td>
<td>1.58</td>
<td>101</td>
<td>2nd</td>
<td>1.29</td>
<td>071</td>
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<td>2nd</td>
<td>2.72</td>
<td>047</td>
<td>1st</td>
<td>1.97</td>
<td>075</td>
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<tr>
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<td>6th</td>
<td>4.10</td>
<td>101</td>
<td>7th</td>
<td>3.50</td>
<td>004</td>
<td>6th</td>
<td>1.39</td>
<td>039</td>
<td>4th</td>
<td>1.07</td>
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<tr>
<td>052</td>
<td>19th</td>
<td>8.41</td>
<td>103</td>
<td>14th</td>
<td>4.99</td>
<td>002</td>
<td>13th</td>
<td>3.82</td>
<td>075</td>
<td>31th</td>
<td>5.99</td>
</tr>
</tbody>
</table>

Matching Strategy
Based on:
- Ridge correlation
- Minutiae Local
- Minutiae Global

Limitations in fingerprint verification: FVC (5/6)
Some changes with respect to previous editions:

- DATA: Larger DBs, 150 fingers, 12 impressions per finger
- DATA: Most difficult fingers from a larger pool of fingers (NFIQ) extracted from BIOSEC DB
- PLANNED STUDIES: Interoperability, Quality

**IMPORTANT DATES:**
- Participant registration deadline: June 30, 2006
- Development databases available online: July 1, 2006
- Algorithm submission deadline: October 31, 2006
- Expected publication of the results: January, 2007

For further information, please visit: [http://bias.csr.unibo.it/fvc2006](http://bias.csr.unibo.it/fvc2006) or send an e-mail to: fvc2006@csr.unibo.it

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**Multibiometric systems**

- **Various biometric evidences are combined in order to improve the performance** (or other requirements) **of the system**
- When combining different biometric modalities (multimodal biometrics), the **population coverage improves significantly**
- **The security improves significantly** due to the difficulty to fool several evidences
  
  ...but the complexity and acceptability of the system may deteriorate
### System model and previous works

#### Work | Modalities | M | Arch. | Level | Gain
--- | --- | --- | --- | --- | ---
Brunelli and Falavigna [1995] | Speaker, face | 5 | P | C | ID:17—2 (TE)
Duc et al. [1997] | Speaker, face | 2 | P | C | VER:6.7—0.5 (TE)
Kittler et al. [1998] | Speaker, face | 3 | P | C | VER:1.4—0.7 (EER)
Hong and Jain [1998] | Face, fingerprint | 2 | S | R/C | ID:6.9—4.5 (FR/0.1%FA)
Jain et al. [1998] | Speaker, finger | 3 | P | C | VER:15—3 (FR/0.1%FA)
Ben-Yacoub et al. [1999] | Speaker, face | 3 | P | C | VER:4—0.5 (EER)
Choudhury et al. [1999] | Speaker, face | 3 | P | C | ID:16.5—6.5 (TE)
Chatzis et al. [1999] | Speaker, face | 4 | P | C | ID:6.7—1.07 (TE)
Verlinden et al. [2000] | Speaker, face | 3 | P | C | VER:3.7—0.1 (TE)
Ross and Jain [2000] | Face, finger, hand | 3 | P | C | VER:16—2 (FR/0.1%FA)
Kumar and Zhang [2003] | Face, palmprint | 2 | P | C | VER:3.6—0.8 (EER)
Wang et al. [2004] | Speaker, finger | 2 | P | C | VER:2—0.7 (EER)
Poh and Bengio [2006] | Speaker, face | 8 | P | C | VER:2.2—0.7 (TE)

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### The Thesis and Related Contributions

- [Image of fingerprints and pen]
Motivations and main related works

- Performance drop of single biometrics under degraded Q (FVC campaigns [Cappelli et al., 2006]), which may affect the different modules of a multibiometric system in a different way [Jain and Ross, 2004]
  → Incorporating biometric Q in multibiometrics [Bigun et al., 1997; Chatzis et al., 1999]

- Strong user-dependencies in the score distributions of some biometric traits, such as voice (NIST SRE campaigns [Doddington et al., 1998]), or signature (SVC evaluation [Yeung et al., 2004]).
  → User-dependent fusion in multibiometrics [Jain and Ross, 2002; Toh et al., 2004]

The Thesis

The adaptation of the fusion functions at the score level in multimodal biometric authentication can report significant verification performance improvements. Examples of input information for this adaptation include a reduced number of scores from individual users and signal quality measures of the input biometrics. This statement also applies to other problems in multibiometrics such as multi-algorithm fusion.
Research contributions

• **Literature reviews**: score fusion strategies; score normalization

• **Theoretical frameworks**: score normalization

• **Novel methods**: user-dependent score normalization; user-dependent score fusion (Bayesian and SVM); quality-based score fusion (Bayesian and SVM)

• **Biometric systems**: improvement of the ATVS function-based signature system; new feature-based signature system (with J. Lopez); new ridge-based fingerprint matcher (with L.M. Muñoz)

• **Biometric data**: contribution to the acquisition and management of the MCYT bimodal database

• **Experimental studies**: score normalization in signature; multi-algorithm signature, speaker and fingerprint; multimodal signature and fingerprint

Adapted fusion schemes: user-dependent fusion

- **Contribution**: combined used of global and local information for training the user-dependent fusion functions. This is commonly done in speaker verification [Reynolds et al., 2000] but it is applied for the first time to multibiometric fusion. Existing user-dependent fusion approaches only consider local information [Jain and Ross, 2002; Toh et al., 2004]

**GLOBAL**: Set of training scores from a pool of users (genuine and impostor)

**LOCAL**: Set of training scores from the user at hand (genuine and impostor)

→ **Bayesian** and **SVM** user-dependent fusion algorithms
Bayesian adaptation of the fusion functions

Multilevel score:  
\[ x = [x_1, \ldots, x_F] \]  
Fused score:  
\[ s_T = f(x_T) = \log p(x_T|\omega_1) - \log p(x_T|\omega_0) \]

Fusion training set:

\[ X = (x_i, y_i)_{i=1}^N \]
\[ y_i \in \{\omega_0, \omega_1\} = \{\text{Impostor, Client}\} \]
\[ p(x|\omega_0) = N(x|\mu_0, \sigma_0^2) \]
\[ p(x|\omega_1) = N(x|\mu_1, \sigma_1^2) \]

Global training set:

\[ X_G \xrightarrow{\text{ML}} \{\mu_{G,0}, \sigma_{G,0}^2\}, \{\mu_{G,1}, \sigma_{G,1}^2\} \]

Local training set:

\[ X_{j,L} \xrightarrow{\text{ML}} \{\mu_{j,L,0}, \sigma_{j,L,0}^2\}, \{\mu_{j,L,1}, \sigma_{j,L,1}^2\} \]

\[ \mu_{j,A,k} = \alpha_k \mu_{j,L,k} + (1 - \alpha_k) \mu_{G,k} \]
\[ \sigma_{j,A,k}^2 = \alpha_k (\sigma_{j,L,k}^2 + \mu_{j,L,k}^2) + (1 - \alpha_k) (\sigma_{G,k}^2 + \mu_{G,k}^2) - \mu_{j,A,k}^2 \]

Adapted fusion schemes: quality-based fusion

- **Contribution:** Although some existing theoretical frameworks for multibiometric fusion describe confidence measures [Bigun et al., 1997; Bengio et al., 2002], they were not related to the input biometric quality. This is the first experimental work on quality-based fusion.

  → **Combination, Bayesian** and **SVM** quality-based fusion algorithms
Quality-based adaptation of the fusion functions

SVM learning:

$$
C_i = C \left( \prod_{r=1}^{R} q_{i,r} \right)^{\alpha_i} 
$$

$$
\min_{w, w_0, \xi_1, \ldots, \xi_N} \left( \frac{1}{2} \|w\|^2 + \sum_{j=1}^{N} C_j \xi_j \right) 
$$

$$
y_i (\langle w, \Phi(x_i) \rangle + w_0) \geq 1 - \xi_i, \quad i = 1, \ldots, N 
$$

$$
\xi_i \geq 0, \quad i = 1, \ldots, N 
$$

SVM-based score fusion:

$$
s_T = f(x_T) = \langle w, \Phi(x_T) \rangle + w_0 
$$

$$
f_{SVM,Q} (x_T) = \beta_1 \sum_{r=1}^{R} \frac{\beta_r}{\sum_{j=1}^{R} \beta_j} f_{SVM,r} (x_T^{(r)}) + (1 - \beta_1) f_{SVM} (x_T) 
$$

MCYT Bimodal Biometric Database
MCYT bimodal biometric database

- Acquired within the Spanish MCYT TIC00-1669 project
- Fingerprints and handwritten signatures

FINGERPRINTS:
- 330 donors x 10 fingers x 12 samples x 2 sensors (optical and capacitive) = 79200 fingerprint images
- 3 levels of control

QMCYT fingerprint subcorpus:
- 75 donors x 10 fingers x 12 impressions (optical sensor) = 9,000 images
- All images labeled manually according to the image quality [0,9]
SIGNATURE:

- Acquisition procedure:
  - WACOM Intuos pen tablet
  - Ink pen over paper templates → on-line and off-line corpora
  - Restricted size guidelines
- Acquisition protocol:
  - 330 subjects
  - 25 genuine signatures (in groups of five) + 25 skilled forgeries (from five impostors) → 16,500 signatures
MCYT bimodal biometric database: signature

Multimodal biometric databases: ongoing work

**BioSec** (FP6 IP), **Biosecur-ID** (CICYT TIC2003), **Biosecure** (FP6 NoE):
Face, Voice, Iris, Fingerprint, Hand, ...
### BIOSEC DB

**Acquisition sites:**
- **UAM, UPC, TID, MIFIN**
  
**Collaborators:**
- **UCOL, UTA (usability and acceptance study)**
- **KULRD (legal issues)**

**Acquisition protocol (in each session):**
- 4 frontal face images (neutral pose)
- 4 utterances of a PIN (8 digits) + 3 repetitions of other users’ PINs (x 2 microphones x 2 languages)
- 4 iris images (x 2 eyes)
- 4 fingerprint images (x 4 fingers x 3 sensors)

**Two releases:**
- **Baseline (available from mid-2005):**
  - 200 subjects, 2 acquisition sessions (1 to 2 weeks between them)
- **Extended (available from late-2006):**
  - 250 subjects, 4 acquisition sessions (1 week to 1 month)

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### BIOSECURE DB: Call for Participation

**Llévate 30 € por la cara**

Participa en un proyecto de investigación europeo dando de forma anónima tus rasgos biométricos

**2 sesiones** de 40 minutos entre noviembre de 2006 y marzo de 2007

**Abierto a todos:** alumnos, personal, familiares y amigos

Más información en el laboratorio **B203**, Escuela Politécnica Superior, UAM
**EQUIPMENT:** low-cost webcam, e.g., Philips SPC 900NC

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**PHILIPS SPC 900NC + PLANTRONIC S Voyager 510**

**LG IrisAccess EOU3000**

**BIOMETRIKA FX2000**

**YUBEE (Atmel FingerChip)**

**WACOM Intuos A6 + Inking Pen**

**CANON EOS 30D + Ring Flash**
BIOSECURE DB: Dataset 3

HP iPAQ hx2790
Fingerprint and Signature

SAMSUNG Q1 + WebCam
Face and Voice

• SETUP:
(Indoor/Outdoor Acquisition)

Multi-Algorithm Signature Verification
On-line signature

- On-line signature verification → dynamic information: $x, y, \text{pressure}, ...$

- Off-line signature verification:

**Advantages of on-line signature**

- User-friendly
- Well accepted socially and legally
- Non invasive
- Already used in a number of applications (e.g., points of sales)
- Acquisition hardware already integrated in some devices (Tablet PC, PDA, ...)

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### Challenges of on-line signature

- Intra-class variability
- Temporal (inter-session) variability
- Impostors may produce (skilled) forgeries
- Not appropriate for previously acquired off-line signature images

### On-line signature methods

**Global:**
- Representation: global feature vector
- Similarity: distance computation between vectors (e.g., Mahalanobis, Euclidean, Neural Networks, ...)

**Local:**
- Representation: sequence of vectors (e.g., strokes, segments, spatial windows, ...)
- Similarity: matching of vectors considering the spatio-temporal structure of the sequence (e.g., DTW, HMM, ...)
Milestones related to our work

1989: State-of-the-art, by Leclerc and Plamondon (PR)
1994: Feature-based system, by Nelson et al. (IJPRAI)
1995: Stroke-based HMM system, by Prasad et al. (PR)
1996: Feature-based system, by Lee et al. (T-PAMI)
2000: State-of-the-art, by Plamondon (T-PAMI)
2005: Function-based HMM system, Fierrez-Aguilar et al. (T-SMC-C)
2005: Feature-based system, by Fierrez-Aguilar et al. (AVBPA)

SVC 2004: Organized by Yeung et al. (ICBA)
→ ATVS ranked 2nd (1st for random forgeries)

Research significance

- A combined set of novel, adapted and existing global features
- Sorting of features according to discriminative capability
- Novel machine expert based on global information
- Fusion of the global system with a competitive local system based on HMMs
- Usage of MCYT DB (330 subjects: 8,250 genuine signatures and 8,250 skilled forgeries)
- 6,600 genuine matches; 8,250 skilled forger matches; 108,570 random impostor matches
Local system: feature extraction and matching

FEATURE EXTRACTION:
- 3 basic functions (100 Hz):
  - $x, y, p$
- Geometric normalization:
  - position, rotation
- 4 extended functions:
  - path-tangent angle
  - path velocity magnitude
  - log curvature radius
  - total acceleration magnitude
- First-order time derivative functions $\Rightarrow$ 14 time-functions.

MODELING AND MATCHING:
- HMM (2 states, 32 mixtures).

Local system: comparison with the state-of-the-art

SVC2004, TASK 2 ($x, y, p$)
- 1st place for random forgeries
- 2nd place for skilled forgeries
Global system: feature extraction

Features ranked according to individual inter-user class separability

<table>
<thead>
<tr>
<th>Ranking</th>
<th>Feature Description</th>
<th>Ranking</th>
<th>Feature Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>signature total duration $T_s$</td>
<td>2</td>
<td>$N$(pen-ups)</td>
</tr>
<tr>
<td>3</td>
<td>$N$(sign changes of $dx/dt$ and $dy/dt$)</td>
<td>4</td>
<td>average jerk $j$</td>
</tr>
<tr>
<td>5</td>
<td>standard deviation of $a_y$</td>
<td>6</td>
<td>standard deviation of $v_y$</td>
</tr>
<tr>
<td>7</td>
<td>(standard deviation of $y$)/$\Delta y$</td>
<td>8</td>
<td>$N$(local maxima in $x$)</td>
</tr>
<tr>
<td>9</td>
<td>standard deviation of $a_x$</td>
<td>10</td>
<td>standard deviation of $v_x$</td>
</tr>
<tr>
<td>11</td>
<td>$j_{\text{rms}}$</td>
<td>12</td>
<td>$N$(local maxima in $y$)</td>
</tr>
<tr>
<td>13</td>
<td>$t$(2nd pen-down)/$T_s$</td>
<td>14</td>
<td>(average velocity $v$)/$v_{x,\text{max}}$</td>
</tr>
<tr>
<td>15</td>
<td>$A_{\text{min}} = \frac{(y_{\text{max}} - y_{\text{min}})(x_{\text{max}} - x_{\text{min}})}{(\Delta x - \sum_{i=1}^{\text{pen-down}} (x_{\text{max}} - x_{\text{min}}(i)))\Delta y}$</td>
<td>16</td>
<td>$(x_{\text{last pen-up}} - x_{\text{max}})/\Delta x$</td>
</tr>
<tr>
<td>17</td>
<td>$(x_{\text{1st pen-down}} - x_{\text{min}})/\Delta x$</td>
<td>18</td>
<td>$(y_{\text{last pen-up}} - y_{\text{min}})/\Delta y$</td>
</tr>
<tr>
<td>19</td>
<td>$(y_{\text{1st pen-down}} - y_{\text{min}})/\Delta y$</td>
<td>20</td>
<td>$(T_w v)/(y_{\text{max}} - y_{\text{min}})$</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>99</td>
<td>$\theta$(before last pen-up)</td>
<td>100</td>
<td>$(2nd t(y_{\text{max}}))/T_w$</td>
</tr>
</tbody>
</table>

Global system: feature selection

For each feature $k$ with $k = 1, \ldots, 100$

\[
S(k) = \sum_i \sum_j |d_{i,k} - d_{j,k}|
\]
Global system: matching

\[ \lambda_{\text{parzen}} \]

\[ p(o_T | \lambda_{\text{parzen}}) \]

Global system: feature extraction example

Genuine Signatures (All)
Skilled Forgeries (All)
Genuine Signatures (Shown)
Skilled Forgery (Shown)
Experimental protocol

- MCYT Signature DB
- Number of signers: 330
- Training:
  - GENUINE: either 5 or 20 signatures
- Testing:
  - GENUINE: the remaining 20 or 5 signatures
  - RANDOM FORGERIES: first signature of the remaining users
  - SKILLED FORGERIES: the 25 forgeries available

Results: feature selection

<table>
<thead>
<tr>
<th>5 training signatures</th>
<th>20 training signatures</th>
</tr>
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<tbody>
<tr>
<td>EER (%)</td>
<td>EER (%)</td>
</tr>
<tr>
<td>SKILLED</td>
<td>SKILLED</td>
</tr>
<tr>
<td>RANDOM</td>
<td>RANDOM</td>
</tr>
</tbody>
</table>

Graphs showing EER (%) for Global (Parzen) and Local (HMM) for 5 and 20 training signatures, for SKILLED and RANDOM categories.
Conclusions

- Novel set of ranked global features for signature verification
- New system based on global information
- Fusion of the global system with a competitive local system based on HMMs
- Experiments on a large dataset (330 subjects; 16,500 signatures) both on random and skilled forgeries
- Experimental findings:
  - Global better than local for small training set size
  - Local improves faster than global for increasing training set size
  - User-dependent thresholds significantly improve the performance, specially for local
  - Local and global provide complementary information
- Best EERs:
  - 5 training signatures: 2.39% (skilled) and 0.41% (random)
  - 20 training signatures: 0.55% (skilled) and 0.0% (random)
Ongoing work in signature verification: DTW

**FUNCTIONAL FEATURE EXTRACTION:**
- 3 Functions (100 Hz): $\delta x$, $\delta y$, $p$
- Geometric Normalization: position, size

**MATCHING:**
- DTW:
  $$D(i, j) = \min \begin{cases} 
  D(i-1, j-1) + d_E(i, j) \\
  D(i-1, j) + d_E(i, j) \times c \\
  D(i, j-1) + d_E(i, j) \times c \\
  d_E(i, j) < \text{thresh} \rightarrow 0 
\end{cases}$$

$D$ serves to define the optimal alignment between point $i$ in the input signature and point $j$ in the template, which is computed via **dynamic programming**.

A constant factor $c$ multiplied by the Euclidean distance between the two feature vectors is used instead of constant penalties.

No penalty if the Euclidean distance is small.

Applications of signature verification: BBVA

[Images of secure encryption and web-based access examples]
Q-Based Multi-Algorithm Fingerprint Verification

Introduction: fingerprint verification

- Advantages:
  - Permanence, uniqueness and distinctiveness
  - Large experience in the forensic environment
  - Small and cheap sensors that can be easily embedded
  - Growing demand for civilian applications
Introduction: fingerprint verification

- Challenges:
  - Universality (subjects unable to use fingerprints)
  - Intra-class variability (skin or weather conditions, technology of the sensor, user cooperation, ...) → image quality

  
  Higher ↔ **Cost and size of the sensor** → Lower

  
  3D OPTICAL SOLID STATE

  
  Higher ↔ **Image quality** → Lower

Introduction: fingerprint verification

- Multi-algorithm fingerprint recognition:
  - A number of works have shown the benefits of combining multiple approaches for fingerprint recognition
  - Different levels of combination: sensor-level, feature-level, score-level, decision-level

  
  We focus on **score-level fusion**
Milestones related to our work

1997: Bayesian Expert Conciliation by Bigun et al. (AVBPA)
1997: Minutiae-Based Fingerprint Matcher by Jain et al. (T-PAMI, P-IEEE)
2000: Ridge-Based Fingerprint Matcher by Jain et al. (T-IP)
2003: State-of-the-Art by Maltoni et al. (Handbook)
2003: Q-Based Mulimodal Fusion by Bigun et al. (ICIAP, MMUA)
2005: Q-Based Multimodal Fusion by Fierrez-Aguilar et al. (PR)
2005: Global Quality Measure, by Chen et al. (AVBPA)

ICB 2006: Q-Based Fusion for Multi-Level Fingerprint Verification

Motorola Best Student Paper Award

Research significance

- First published work on quality-based fusion for biometrics using real multi-level data and automatic quality measures
- Comparison of minutiae- and ridge-based matching performance for different image quality groups
- Usage of a large DB (QMCYT) including 7,500 images from 750 fingers (6,750 genuine and 561,750 impostor matchings, respectively)
System architecture

Assumptions:
- Matching scores $s_M$ and $s_R$ are already normalized to the range $[0,1]$
- Performance of one matcher (minutiae) drops significantly as compared to the other under image quality degradation

$$s_Q = \frac{Q}{2} s_M + \left(1 - \frac{Q}{2}\right) s_R$$

NOTE: More general formulations ($n$ matchers) using Bayesian theory and SVMs are developed in Chapter 3 of the Thesis

Fingerprint image quality

- Measure of separability of ridges and valleys
- Extractability of fingerprint features (minutiae, core points...)

Fingerprint Image Quality Computation Methods

- **Based on Local Features**
  - Orientation Field
  - Gabor filter responses
  - Pixel intensity

- **Based on Global Features**
  - Orientation Field
  - Power spectrum

- **Based on Classifiers**
  - Neural Networks

*We use a Global Image Quality based on the Power Spectrum*
Automatic fingerprint quality assessment

- Based on global features:
  - A global measure of quality is computed for each image
  - The quality is related to the energy concentration in ring-shaped regions of the power spectrum

Q = 0.05  Q = 0.36  Q = 0.92

NOTE: Method developed by Yi Chen et al. (AVBPA 2005)

Minutiae-based matcher

- Normalization
- Orientation field
- ROI
- Ridge extraction & profiling

- Minutiae alignment
- Pattern matching (edit distance)

Ridge-based matcher

**PREPROCESSING**
- <NONE>

**FEATURE EXTRACTION**
- Energy responses of Gabor filters in different directions
- FingerCode

**SIMILARITY**
- Correlation-based alignment
- Matching based on Euclidean Distance


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**Database: QMCYT**

- Scanner: UareU from Digital Persona
- Fingerprint image: 500dpi, 400 x 256 pixels
- Fingerprint corpus: 750 fingers (75 subjects) x 10 impressions
### Experimental protocol

- Enrollment: one impression of each finger
- Genuine matchings: remaining 9 impressions (9 x 750 trials)
- Impostor matchings: 1 impression from all the remaining fingers (750 x 749 trials)

- All fingers are classified into 5 equal-sized disjoint quality groups, based on a quality ranking
- The quality ranking is based on the average quality of the genuine matchings corresponding to each finger:

\[
Q_{\text{matching}} = \sqrt{Q_{\text{enrolled}} \cdot Q_{\text{test}}}
\]

where \( Q_{\text{enrolled}} \) and \( Q_{\text{test}} \) are global image quality measures.

### Performance comparison for quality groups

Observations:
- The performance of the minutiae-based matcher drops significantly under degraded image quality
- The performance of the ridge-based matcher is robust to the global image quality measure considered
- Sum fusion outperforms the best system only for good quality images
- Quality-based fusion outperforms the best system in all cases
**Fusion results**

![Graph showing performance](image)

**Observations:**
- Due to large differences in performance between the two systems, sum fusion improves the performance only in a region of the DET curve.
- Incorporating the image quality in the sum fusion leads to improved performance in all cases.

**Conclusions**

- Quality-based fusion of ridge- and minutiae-based matchers.
- Usage of a global quality measure based on power spectrum, and a large corpus comprising 7500 images from 750 fingers.
- Experimental findings:
  - The ridge-based approach outperforms the minutiae-based approach in low quality image conditions.
  - Both approaches obtain similar performance for good image quality.
  - The ridge-based approach is more robust to quality image degradation (almost independent of image quality) while the minutiae-based approach experiments a large performance drop.
  - Quality-based fusion overcomes the problem of performance drop of one component in multi-algorithm fingerprint verification.
Applications of fingerprint verification: TID

User-Dependent Multimodal Authentication
User-dependent multimodal fusion: experiments

- Function-Based Signature System + Minutiae-Based Fingerprint System
- GLOBAL, LOCAL, and ADAPTED fusion (and decision) are compared
- Bayesian and SVM-based (RBF kernel) fusion algorithms

User-dependent multimodal fusion: experimental protocol

- Database used in the experiments:
  - 75 subjects from QMCYT
  - 10 impressions of one finger (lowest Q finger for 10% of the subjects, and highest Q finger for the remaining subjects)
  - 17 genuine signatures per user
- Experimental setup based on worst-case scenario:
  - 3 fingerprints for enrollment
    - 7 genuine matchings
    - 10 impostor matchings (with the best 10 impostor fingerprints from a pool of 750 different fingers)
  - 10 signatures for enrollment
    - 7 genuine matchings
    - 10 impostor matchings (skilled forgeries from 5 skilled imitators)

\[
\begin{align*}
\text{75x7 genuine} & \\
\text{75x10 impostor} & \\
\text{Real bimodal test trials in a worst-case scenario}
\end{align*}
\]
GLOBAL FUSION: $M$ users are randomly selected with replacement 200 times. Each time, the selected matching scores are used to train a user-independent fusion function, which is tested on the remaining users. Errors are finally averaged after the 200 iterations.

- Large performance improvement for $M < 10$, stable results for $M > 20$
- SVM more robust to small training set sizes

LOCAL FUSION: For each user, $N$ scores are randomly selected without replacement and forcing half of them in each class client/impostor, 50 times. Each time, a user-dependent fusion function is trained, which is tested on the remaining scores of the given user.

- Trained fusion is better than trained decision on summed scores
- SVM much more robust to small training set sizes
User-dependent multimodal fusion: results

**ADAPTED FUSION**: Users are sampled as in the GLOBAL case. Each time, all the remaining users are sampled and tested as in the LOCAL case but using the background information provided by users in the GLOBAL dataset from which the given user was left out.

- Incorporating global information in user-dependent fusion is specially helpful for small user-dependent training set sizes.
- **Bayes** (0.53%) outperforms **SVM** (0.79%) in the best operating point.

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Conclusions and Future Work
**Conclusions**

SIGNATURE:
- Fusion of a new feature- with an enhanced function-based approach
- Outstanding EERs, one of the largest DB in the literature (16,500 signs.)
- User-dependent decision thresholds significantly improve the performance

FINGERPRINT:
- Comparison and fusion of ridge- and minutiae-based matchers based on Q
- Q-based fusion outperforms the standard sum rule approach

MULTIMODAL FUSION:
- User-dependent fusion: SVM, Bayes
  - The incorporation of background information in user-dependent fusion schemes is demonstrated to enhance the verification performance
  - SVM more robust to small training set sizes, best results for Bayes with large training set sizes
- Quality-based fusion: Combination, SVM, Bayes

**Ongoing and Future Work**

SIGNATURE:
- Development and fusion of DTW approach [M. Martinez]
- Application to different scenarios: Tablet PC, PDAs, ...
- Cryptobiometrics using written signatures [M. Freire]
- Study of vulnerabilities: skilled forgeries, hill-climbing attacks, ... [J. Galbally]

FINGERPRINT:
- Development and fusion of image correlation approach [F. Alonso]
- Match-on-card
- Cryptobiometrics using fingerprints [M. Freire]
- Study of vulnerabilities: gummy fingers, hill-climbing attacks, ... [J. Galbally]

MULTIMODAL FUSION:
- Application of adaptive kernel methods
- User-dependent and Q-based fusion
- Exploitation of the new MM DBs to study time lapse effects, image Q effects, ...
- Quality measures for common biometrics (signature Q?) [F. Alonso]
- Application-independent evaluation [D. Ramos]
- Evaluation methodologies (CC, ISO/IEC JCT1/SC27/SC37)
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