Multimodal Biometric Systems

BIOM 426
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Classification: Nature of Input

Four categories:

• unibiometric (single biometric)

• unimodal biometric (a single image, a single representation, and a single matcher)

• multibiometric (uses weakly correlated biometrics)

• multimodal (correlated biometric measurements)
Motivation

Drawbacks of Single Biometrics:

• Single biometric does not have enough information for discrimination

• High-security verification performance requirements (very low FMR)

• Limitations of unimodal systems are pronounced in identification mode of operation

• Combining biometrics with non-biometrics is attractive but reintroduces security problem
Motivation

Strengths:

• Improve recognition accuracy
• Universality issue – multimodal system is a solution.
• More difficult to fool than a single biometric.

Disadvantages:

• More expensive
• Inconvenience to use and requires additional verification time.
• Effective fusion schemes are needed.
Issues in Designing

1. What is the main objective?

2. What kind of system (verification or identification)?

3. Which biometrics should be integrated? Depends on application requirement and target population.

4. How many identifiers are sufficient?

Main challenge in design:

Integration of individual modalities
Performance of MMB Systems

Biometric Systems are Pattern Recognition Systems.

Facts:
- Different classifiers (of the same accuracy) often misclassify different patterns (Kittler’98). This suggests that different classifiers offer complimentary information about classification task.
- Classifiers using independent features perform better than those using correlated features.
- Same is applied to different classifiers.
- Simulations indicate that the best improvement in performance is achieved when classifiers are negatively correlated (when one classifier is wrong the other is correct).
  - Amount of improvement is directly proportional to the degree of negative correlation.
  - Positive correlation may result in degradation of performance.
- Combining two “weak” classifiers results in a large improvement.
Integration Strategies

Classification Combinations can be categorized based on:

- integration architecture
- level of fusion
- fusion strategy
- selection/training approach
Architecture

- Parallel
- Cascading (serial combination)
- Hierarchical (treelike)

Classifier 1
Classifier 2
... 
Classifier N

Fusion module

independent

Classifier 1
... 
Classifier N

Fused Data
• Cheap classifiers (low computational complexity and feature extraction cost) that have low accuracy but small false non-match rate are used first
• Followed by more accurate and expensive classifiers.
Levels of Fusion

Different combination strategies operate on different type inputs.

Categories:

- feature or measurement values
- confidence values
- rank values
- abstract level
Fusion at Confidence/Rank Level

Fusion at the Match Score Level
Fusion at Abstract Level

Biometric 1

Feature Extraction

Matcher

Decision Module

Biometric 2

Feature Extraction

Matcher

Decision Module

Class/Label

Fusion Module

Decision Level Fusion

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Summary on Fusion Levels

- Feature level is the richest in terms of information.
- Processing reduces information.
- Not much research done on biometrics fusion at feature level.
- Fusion at the abstract (decision) level is reduced to combining binary decisions.

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Ex.:   face        Y/N   Y
      handgeometry  Y/N   N   2/3-Y
      fingerprint  Y/N   Y

Majority Vote:  2/3-Y and 1/3-N
```
Summary (Continued)

Most of research is focused on fusion at the Match Score Level

Reasons:

1. Easy to access
2. Easy to combine
3. This is a compromise between feature and decision levels.
Combination Strategy

A technique used to combine the outputs of individual classifiers.

- At the abstract level: **Majority Votes** (either logical OR or logical AND is used).
  
  **Ex.** (face AND handgeometry) OR fingerprint

- At the rank level: **Class Set Reduction; Logistic Regression; Borda Counts** – class reordering methods.

- At the confidence (match score) level: **Sum, Mean, Median, Product, Minimum, Maximum Rules** (Kittler’98).

  **Steps:** (1) Map scores in common space. (2) Apply normalization. (3) Fuse.

  **Ex.:** difference score (handgeometry) and similarity score (fingerprints)

  \[
  100 - \frac{\text{Difference Score}}{\max(\text{Difference Score})} \times 100
  \]
Example

Fingerprint 10_1.tif

Image Histogram

Normalized Histogram, Mean=0 Var = 1

Histogram After Tanh(.) Transformation

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Some Theoretical Studies

• Daugman’99: Performance of a “weak” and “strong” classifiers combined at the abstract level (using OR or AND voting) degrades compared with the performance of “strong” classifier.

• Hong, Jain, Pankanti’99: AND/OR voting improves performance only under certain conditions. They showed that fusion at the Match Score level improves performance even when “weak” and “strong” classifiers are combined.

• Kittler’98: introduced sensitivity analysis to explain why sum rule outperforms other rules. Sum rule is less sensitive to the error rates of individual classifiers.
Conclusions on Strategies

- Other combination schemes and strategies:
  - Adaptive weighting
  - Stacking
  - Fuzzy integrals
  - Bagging
  - Boosting
  - Random subspaces (random forest)

- A large number of combination strategies are available to system designers.
- It is not well understood which one works better.
- Traditional selection is based either on experience or on experimental assessment of a set of schemes.
Training and Adaptability

Strategies can be distinguished based on trainability, adaptability, and requirements on the outputs of individual classifiers.

- Combinations as sum rule, voting, Borda counts are static.
- **Trainable combinations** may considerably improve performance, but require a large set of training data.
- **Adaptive combinations** adjust some parameters based on data.

- Combinations are useful if classifiers are independent. They are trained on independent data.

- Use resampling techniques to enlarge datasets
  - Bootstrapping
  - Boosting
What to Integrate?

Scenarios of operation:

1. Multiple sensors: different sensors, same biometric
2. Multiple biometrics
3. Multiple units of the same biometric
4. Multiple snapshots of the same biometric
5. Multiple representations and matching algorithms for the same biometric.
Fusion at the Match Score Level

Fusion Module

Class/Label

Decision Module
Fusion at the Match Score Level

- Fingerprint and Face modalities
- 1000 individuals
- state-of-the-art COTS systems

Goals:
- Demonstrate improvement in performance for MMB system.
- Examine well-known and novel methods of normalization and fusion.

Normalization

Ranges of different matchers have to be mapped in the same space.

Ex.: Matcher with the range of scores [100, 1000] dominates a matcher with the range [0, 1].

Denote by $s$ and $n$ match scores before and after normalization.

**Min-Max**

Let $\min(S)$ and $\max(S)$ be minimum and maximum value in the range of scores $S$. Then

$$n = \frac{s - \min(S)}{\max(S) - \min(S)}$$
Normalization

**Z-score** transforms the distribution to a distribution with zero mean and variance one

\[ n = \frac{s - \text{mean}(S)}{\text{std}(S)} \]

with \( \text{mean}(S) = \frac{1}{K} \sum_{k=1}^{K} s_k \) and \( \text{var}(S) = \frac{1}{K} \sum_{k=1}^{K} (s_k - \text{mean}(S))^2 \)

**Tanh** is known as a robust statistic. Maps the range into \([0, 1]\)

\[ n = \frac{1}{2} \left( \tanh \left( \frac{(s - \text{min}(S))}{\text{std}(S)} \right) + 1 \right) \]
Adaptive Normalization

- Verification Error is the result of overlap in Genuine and Imposter score distributions.
- The idea is to nonlinearly remap the overlapping region.
- Use min-max as a first step.

(a) Two-Quadratic:

\[ n_{AD} = \begin{cases} 
\frac{1}{c} n_{MM}^2, & n_{MM} \leq c \\
\frac{c}{1 - c} + \sqrt{1 - c} (n_{MM} - c), & \text{otherwise}
\end{cases} \]
Adaptive Normalization

(b) Logistic: similar to Two-Quadratic

\[ n_{AD} = \frac{1}{1 + A \exp(-Bn_{MM})} \]

where \( A = \frac{1}{\Delta} - 1 \) and \( B = \frac{\ln A}{c} \)

\( \Delta \) is a small constant, Ex. 0.01
Adaptive Normalization

(c) Quadratic-Line-Quadratic: leaves the overlap region unchanged and performs quadratic transformation on the remaining regions.

\[
n_{AD} = \begin{cases} 
\frac{1}{(c - \frac{w}{2})}n_{MM}^2, & n_{MM} \leq (c - \frac{w}{2}) \\
n_{MM}, & (c - \frac{w}{2}) \leq n_{MM} \leq (c + \frac{w}{2}) \\
(c + \frac{w}{2}) + \sqrt{(1 - c - \frac{w}{2})(n_{MM} - c - \frac{w}{2})}, & \text{else}
\end{cases}
\]
Fusion Rules

Traditional fusion rules: require small amount of data

(a) Simple Sum:
Consider normalized scores associated with two biometrics and $K$ users.
(Ex. Face and Hand) $(n_1^h, n_1^f), \ldots, (n_K^h, n_K^f)$

To obtain combined score simply add $n_k^h$ and $n_k^f$, that is,

$$f_k = n_k^h + n_k^f, \quad k = 1, \ldots, K.$$

(b) Min and (c) Max: choose minimum or maximum of individual scores, that is,

$$f_k = \min(n_k^h, n_k^f) \quad \text{and} \quad f_k = \max(n_k^h, n_k^f)$$
Fusion: Adaptive Rules

(d) Matcher Weighting:
- Requires more data compared to traditional rules.
- Involves EERs of individual classifiers.
- Let $e(h)$ and $e(f)$ be the EERs of the hand and face matchers.
- Let $w(h)$ and $w(f)$ be the weights associated with the hand and face matchers.

\[ w(h) = \frac{1}{1/e(h) + 1/e(f)} \quad \text{and} \quad w(f) = \frac{1}{1/e(h) + 1/e(f)}. \]

Note that $w(h) + w(f) = 1$. Then

\[ f_k = w(h)n_k^h + w(f)n_k^f, \quad k = 1, \ldots, K. \]

(e) User Weighting: the most expensive in terms of use of data but the most promising in terms of performance.