CLASSIFICATION WITH CLASS-INDEPENDENT QUALITY INFORMATION FOR BIOMETRIC VERIFICATION

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Presentation outline

• What is class-independent quality information in biometrics?

• How can class-independent information help in pattern classification?

• How to systematically improve biometric verification with quality information?

• Conclusions
Quality measures in biometrics

Images from the Extended Yale B corpus

Subject A

$qm=1$

$qm=2$

Subject B

$qm=1$

$qm=2$

Quality information is class-independent
Motivation of this work

- Biometric data is **rarely** of constant, controlled quality
- Inconsistent data quality \(\Rightarrow\) classification **ERRORS**
- Current understanding of the role of quality measures is **more intuitive than systematic**
- Existing approaches are mostly **heuristic and ad-hoc**

**OBJECTIVE**

Create a **systematic method** of classification with **quality measures**, **generalizable** to single-, multi-classifier and multimodal systems.
Why errors occur?

\[ x = x' + \Delta x = \Phi(n, x') \]
Why errors occur?

Distribution/model shift observed in face, fingerprint, speaker verification etc.

Score distribution shift
Shift in score distributions

\[ \Downarrow \]

Scores \( x \) and signal quality are DEPENDENT

\[ \Downarrow \]

Scores \( x \) and quality measures \( qm \) are DEPENDENT

Why errors occur?
Improving classification with class-independent information

Evidence space $e = [\text{scores } x, \text{ quality measures } qm]$

In the context of $x$, irrelevant $qm$ becomes relevant.
Improving classification with quality measures

Properly collected quality measures are relevant, class-independent classification features.

Stronger dependence between quality measures and baseline classifier scores can lead to better class separation.

Class-independent quality features can help improve classification.
Q-stack: motivation

• Scores and quality measures can be considered as classification features
• Stronger dependence between quality measures and baseline classifier scores can lead to improved class separation
• Actual dependencies are hard to model analytically
• Data-driven approach: dependencies learned from data

Q-stack: a generalized stacking-based framework of classification using quality measures
How to use quality measures?

• Introducing **Q-stack**
• Based on the concept of **classifier stacking**
How to use quality measures?

**Q-stack**: multiple classifier application
How to use quality measures?

**Q-stack**: multiple quality measures
Q-stack: synthetic example

Score threshold, ER=0.13

Stacked classifier: LDA
ER=0.05

Stacked classifier: SVM
ER=0.03
Q-stack as a generalized framework

- Seeks an **optimal decision boundary** in the evidence space
- One **stacked classifier**
- Modality-independent
- Accepts **multiple quality measures**
- **Generalizable** to existing approaches
Generalization example – multiple classifier systems

Fusion function with quality parameter

Example of a multi-classifier fusion function

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

Heuristic approximation of optimal Q-stack decision boundary
Experimental design

Goal of the experiment:
To demonstrate that quality measures bring a **systematic improvement** over baseline systems.

Used modalities: face, fingerprint

Used stacked classifiers in the Q-stack framework:
- SVM-rbf
- SVM-lin
- Bayes/GMM
Experimental evaluation: face verification

Baseline: HTER=0.27

**Q-stack** SVM-lin: HTER=0.214

**Q-stack** SVM-rbf: HTER=0.217

**Q-stack** Bayes: HTER=0.212

Matcher:
PCA/Mahalanobis

Quality Measure:
Corr. coef. with average face template
Experimental evaluation: fingerprint verification

Baseline:
HTER=0.0086

**Q-stack** SVM-lin:
HTER= **0.0047**

**Q-stack** SVM-rbf:
HTER= **0.0051**

**Q-stack** Bayes:
HTER= **0.0039**

Matcher:
NIST (NFIS2)

Quality Measure:
NIST (NFIQ)
Experimental evaluation: multimodal fusion

**Baseline fusion**

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<tr>
<th>Method</th>
<th>HTER</th>
<th>ER_A</th>
<th>ER_B</th>
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<tr>
<td>SVM-lin</td>
<td>0.0076</td>
<td>0.0033</td>
<td>0.0118</td>
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<tr>
<td>Bayes</td>
<td>0.0056</td>
<td>0.001</td>
<td>0.0013</td>
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**Q-stack**

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<tbody>
<tr>
<td>SVM-lin</td>
<td>0.0026</td>
<td>0.0029</td>
<td>0.0022</td>
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<tr>
<td>Bayes</td>
<td>0.0027</td>
<td>0.0038</td>
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</table>
Conclusions

• Quality measures can be treated as classification features
• Class-independent quality measures can help separate between classes, given their dependence on the baseline classifier scores
• Proposed method Q-stack is a general framework of classification with quality measures in
  - single classifier systems
  - multi-classifier/multimodal systems
• Theoretical findings are supported by experiments with real biometric data
• Parts of presented results can be found in:


**Q – stack: uni- and multimodal classifier stacking with quality measures**, K. Kryszczuk, A. Drygajlo, 7th International Workshop on Multiple Classifier Systems 2007, Prague, Czech Republic