Biometric Covariate Analysis using Partial Area Under Curve

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Collaborative Effort

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Why perform covariate analysis?

• It is important to understand the influence of various factors (covariates), such as image quality metrics, population demographic factors and environmental conditions on the performance of biometric recognition systems.

• This knowledge can profoundly influence how biometric systems are designed and implemented in real-world operational scenarios.

• To demonstrate our Area-Under-Curve method for performing covariate analyses, we explore matching performance for three iris datasets from Authenti-Corp’s IRIS06 study using the Daugman 2007 algorithm.
Covariate Analysis Challenges

- Biometric systems are used for many different types of applications, which necessarily operate at different points on an ROC curve.
  - For example, for admission to Disney World, the higher false match rates associated with lower false non-match rates (higher true match rates) would be tolerable
    - Convenience to the customer is more important than some level of monetary loss
  - At a high-security facility, the lower true match rates associated with lower false match rates would be required
    - Security is more important than convenience.

- The influence of covariates is typically analyzed at one or multiple operating points
  - For example, FMR=10^{-3}, 10^{-4}, 10^{-5} or Threshold Score=0.32, 0.34, 0.36 (Hamming distance)
  - Analysis at multiple points can be difficult, time consuming and cumbersome
    - Results can be difficult to convey and understand

- It is desirable to perform a generalized covariate analysis that is independent of threshold ⇒ Area Under ROC Curve (AUC)
Why use Area Under Curve (AUC)?

- Easy to understand
  - Represents the probability of a correct decision given a genuine image and an impostor image
  - Overall probability of a correct answer
  - The larger the AUC value, the better the overall performance of the system
    - AUC=1 is perfect performance

- Serves as a single figure of merit that characterizes the performance of the system
  - Threshold independent
  - Accounts for all thresholds

- The statistical properties of AUC are well characterized
  - Determining statistical significance of AUC differences straightforward using Wilcoxon estimate

- The analysis space is reduced from a multi-point ROC curve to a single metric
  - The influence of various covariates on system performance can be systematically studied as a function of the AUC figure of merit

Score Distribution

ROC Curve

AUC

0.9763
Limitations of AUC

- Single metric from an inherently multi-objective problem
  - While problem is simplified, nuances may be overlooked
- AUC is heavily weighted by portions of the ROC curve where systems most certainly will not operate, that is at false match rates above a certain value, for example, FMR>0.1%
Partial AUC (p-AUC)

- To address limitations of AUC, we propose to look at partial AUC (p-AUC), which is restricted to a range of false match rates that are operationally feasible.
- Selecting the range of the ROC curve that is operationally relevant depends upon the modality and scenario.
  - For facial recognition, we have seen implementations that operate successfully at false match rates as high as 10%.
  - For single-fingerprint systems, acceptable false match rates might be at or below $10^{-3}$.
  - For iris recognition, operational false match rates below $10^{-4}$ are typical.

<table>
<thead>
<tr>
<th>FMR</th>
<th>AUC</th>
<th>p-AUC</th>
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<tr>
<td>1</td>
<td>0.972292</td>
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<tr>
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<tr>
<td>0.01</td>
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</table>

Area Under Curve (probability of correct decision)

FMR ≤ 1.0, AUC=0.972292
FMR ≤ 0.1, p-AUC=0.093847
FMR≤0.01, p-AUC= 0.009219
AUC Statistical Analysis

• Need error bars to draw conclusions
• Borrow image assessment approach from radiology
  – Probabilistic Multiple Reader, Multiple Case (MRMC) model
    • Normal cells ⇒ Genuine scores
    • Abnormal cells ⇒ Impostor scores
  – References
Variance (AUC) = $\sigma^2 = \frac{\alpha_1}{N_{gen}} + \frac{\alpha_2}{N_{imp}} + \frac{\alpha_3}{N_{gen}N_{imp}}$

- Can directly compute each alpha term and predict variance from genuine and impostor scores
- Third term accounts for correlations between impostors and genuines
- OneShot freeware application computes $\alpha$ terms without resampling techniques and is unbiased
  \[\text{http://www.radiology.arizona.edu/CGRI/IQ/page2/page7/page7.html}\]
- Methods and software extended to account for p-AUC

Statistical Properties of AUC & p-AUC
Statistical Significance “p-value”

• Use Wilcoxon signed-rank statistical hypothesis test to determine statistical significance between two AUC values
• Non-parametric equivalent to t-test
• Assume null hypothesis \( \Rightarrow \) two AUCs equal
• p-value is the probability that the null hypothesis explains the result
  – Computed from the variances of the two AUCs
  – Small p-value (e.g., \( p < 0.05 \)) indicates a significant difference between the AUC values and thus a statistically significant performance difference between the two cases under investigation
• To perform the significance test for partial AUC, we assume that partial AUC is normally distributed
  – Normal assumption has been shown to be valid for as few as 10 subjects (i.e., 10 x 10 matrix of scores)
• Caution
  – p-value indicates statistical significance
  – p-value does not indicate that the hypothesis is correct
p-value Illustration

Score Distributions

Camera A
- Genuine Comparisons (4301)
- Impostor Comparisons (1212867)

Camera B
- Genuine Comparisons (4765)
- Impostor Comparisons (1313303)

Camera C
- Genuine Comparisons (5164)
- Impostor Comparisons (1342752)

ROC Curves

AUC ± σ

0.9905 ± 0.0012
0.9730 ± 0.0018
0.9763 ± 0.0016
Calculating p-value

Distribution of Measured AUC Difference
(assuming true difference is 0)

\[ \Delta = |AUC_1 - AUC_2| \]

\[ \Delta_{\text{Camera B-Camera C}} = 0.003245, \quad p = 0.1897 \quad \text{Not statistically significant} \]

\[ \Delta_{\text{Camera A-Camera B}} = 0.01751, \quad p = 0.0000 \quad \text{Statistically significant} \]

Is the measured AUC difference unlikely?

Integral form:

\[ p = 2 \int_{\Delta}^{\infty} \frac{1}{\sqrt{2\pi\sigma_{\Delta}^2}} \exp \left[ \frac{-1}{2\sigma_{\Delta}^2} x^2 \right] \, dx \]

Numerical form:

\[ p = 2 \left[ \frac{1}{2} - \frac{1}{2} \operatorname{erf} \left( \frac{\Delta}{\sqrt{2\sigma_{\Delta}^2}} \right) \right] \]

probability of measuring observed difference if \( \Delta = 0 \)
GLMM Covariate Analysis Approach

• Generalized Linear Mixed Effect model is used to relate probability of verification to subject and image covariates
  – Ross Beveridge’s group at Colorado State University
• Pros:
  – Uses empirical performance and covariate data associated with people and imagery to fit a model relating covariate values to probability that a person will be correctly verified
  – Model quantifies how changes in covariates alter the probability that a person will be correctly verified
• Cons:
  – GLMM modeling complex
  – Requires parameter tuning
  – Performed at a selected operating point on the ROC, i.e., FMR=0.001

Figure from Beveridge, et. al., “Focus on Quality, Predicting FRVT 2006 Performance,” 2008 8th IEEE International Conference on Automatic Face and Gesture Recognition
AUC Covariate Analysis Approach

• To demonstrate utility of AUC & p-AUC figures of merit and Wilcoxon signed-rank statistical hypothesis test, we evaluate the influence of three covariates on iris recognition performance:
  – Camera
    • A, B & C
  – Gender
    • Male & Female
  – Eye
    • Left & Right
## AUC & p-value Nomenclature

### Probability of Correct Decision
- Camera A: 99%
- Camera B: 97%
- Camera C: 98%

### P-value Legend
- p > 0.05, Not Statistically Significant
- p ≤ 0.05, Statistically Significant

### Direction of Arrow Indicates Higher AUC Value

#### Camera Table

<table>
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<tr>
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<td>A</td>
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<tr>
<td>C</td>
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</table>
Cameras A, B & C

- Camera A performs significantly better than Cameras B & C

- Camera C performs better than Camera B for AUC (FMR ≤ 1.0) but Camera B performs better than Camera C for p-AUC (FMR ≤ 0.1)
  - ROC curves cross
Gender – Cameras A, B & C Combined

For Cameras A, B & C combined, there is no significant performance difference between men and women.
Gender – Camera A

For Camera A, performance for men is significantly better than for women.
Gender – Camera B

For Camera B, there is no significant performance difference between men and women.

FMR $\leq 1.0$

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<th>Female</th>
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<tbody>
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<tr>
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FMR $\leq 0.1$

<table>
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<tbody>
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<tr>
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</tbody>
</table>

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International Biometric Performance Conference

4 March 2010
Gender – Camera C

For Camera C, performance for women is significantly better than for men.

AUC and p-AUC figures of merit reveal performance variations between covariates.

In this example:

- If population is predominantly male, use Camera A.
- If population is predominantly female, use Camera C.
- Can investigate origin of performance differences.
Eye – Cameras A, B & C Combined

For Cameras A, B & C combined, performance for right eyes is significantly better than for left eyes.
Eye – Camera A

For Camera A, performance for right eyes is significantly better than for left eyes.
Eye – Camera B

For Camera B, performance for right eyes is significantly better than for left eyes.
Eye – Camera C

For Camera C, statistical significance is different for full AUC (FMR=1.0) and p-AUC (FMR=0.1):

- For full AUC, there is no significant performance difference between left and right eyes.
- For p-AUC, performance for left eyes is significantly better than for right eyes.

p-AUC figure of merit reveals statistical significance for operational region of interest.

In general, better to use p-AUC than AUC.
Conclusions (1 of 2)

• Covariate analysis is an important tool for understanding the influence of various factors (covariates) and for enhancing the performance of biometric recognition systems
  – Identify which covariates matter and quantify how they affect performance for situations of interest
  – Useful to algorithm and hardware system developers
    • Facilitate system designs that are less sensitive or insensitive to significant covariates
  – Useful to system integrators
    • Implement systems to minimize influence of significant covariates

• Area Under Curve (AUC)-based covariate analysis approach is simple and fast to perform and easy to understand
  – AUC represents overall probability of a correct answer
  – Currently used in medical imaging field
  – System performance characterized with a single, threshold-independent metric
  – Re-sampling techniques not used
  – Produces unbiased estimates of components of variance
  – No modeling required, no parameters to tune
Conclusions (2 of 2)

- We propose a new metric, partial AUC (p-AUC), which is limited to an operationally-feasible portion of the ROC curve.
- AUC and p-AUC are measures that give the probability of a correct decision when presented with both an impostor and a genuine image.
- Statistical significance easy to determine using Wilcoxon p-values:
  - Distribution of AUCs determines statistical significance of results.
  - Small p-value indicates a significant difference between the metrics.
- We have demonstrated the utility of AUC & p-AUC metrics and the Wilcoxon signed-rank statistical hypothesis test for performing covariate analyses using iris recognition data:
  - The approach is effective, informative, straightforward and easy.
- Open-source code available for AUC:
  - [http://www.radiology.arizona.edu/CGRI/IQ/page2/page7/page7.html](http://www.radiology.arizona.edu/CGRI/IQ/page2/page7/page7.html)
Two-Reader Variance

\[ \sigma^2 = \frac{\alpha_1}{N_{gen}} + \frac{\alpha_2}{N_{imp}} + \frac{\alpha_3}{N_{gen}N_{imp}} + \frac{\alpha_4}{2} + \frac{\alpha_5}{2N_{gen}} + \frac{\alpha_6}{2N_{imp}} + \frac{\alpha_7}{2N_{gen}N_{imp}} \]

\[ \sigma_{12} = \frac{\alpha_5}{2N_{gen}} + \frac{\alpha_6}{2N_{imp}} + \frac{\alpha_7}{2N_{gen}N_{imp}} \]