On the Persistence of Fingerprints

Soweon Yoon and Anil K. Jain

Michigan State University
http://biometrics.cse.msu.edu

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Fundamental Premise for Fingerprint Recognition

Do these two impressions come from the same finger?

- **Uniqueness**: Ridge patterns on different fingers are distinctive
- **Persistence**: Friction ridge patterns do not change over time
Persistence of Fingerprints

- Traditional perspective: Persistence of fingerprint ridge structure
- Galton compared 11 pairs of fingerprints from six different individuals; only 1 out of 389 minutiae was found to be missing

F. Galton, Finger Prints, Macmillan, 1892
Uniqueness and Persistence

“Uniqueness and persistence are necessary conditions for friction ridge identification to be feasible, but those conditions do not imply that anyone can reliably discern whether or not two friction ridge impressions were made by the same person.”

Problem Definition

Determine the persistence of fingerprints w.r.t. AFIS accuracy

Trend of genuine match scores

Trend of matching accuracy

Upward?  
Downward?  
Stable?

Decision threshold

False rejection occurs
Data Type: Longitudinal vs. Cross-Sectional

**Cross-sectional data**
A single measurement is made on each individual sampled from a population

**Longitudinal data**
Repeated measurements on a collection of individuals sampled from a population

Longitudinal data are called
- **Balanced data**: Every subject has the same number of measurements
- **Time-structured data**: Repeated measurements follow an identical time schedule across individuals
Longitudinal vs. Cross-Sectional Analysis

Cross-sectional Analysis

Long-term comparisons

Short-term comparisons

Longitudinal Analysis

Match scores decrease w.r.t. $\Delta T$

Match scores increase w.r.t. $\Delta T$

- Longitudinal fingerprint data do not satisfy the properties of balanced & time structured required for cross-sectional analysis

Longitudinal Fingerprint Database

- Repeat offenders booked by the Michigan State Police
- 15,597 subjects with at least 5 tenprint cards, minimum time span of 5-years (max. time span is 12 years) and demographics (race, gender, age)
- All genuine pairwise comparisons by two COTS matchers
- Currently, only right index finger is used in the analysis

Approach

• Fit and evaluate a multilevel statistical model with time gap as covariate to genuine match scores
  – Null hypothesis: Slope of linear model is 0
• Compare time gap with other possible covariates (i.e., subject’s age, fingerprint quality, race, and gender)
• Fit a multilevel model with time gap as covariate to binary match decisions
Multilevel Statistical Model

• Longitudinal data can be viewed as hierarchical data
  - \( j \)-th measurement (match score) for subject \( i \)
• A model in its simplest form

\[
y_{ij} = \varphi_{0i} + \varphi_{1i}x_{ij} + \varepsilon_{ij} \quad \varepsilon_{ij} \sim N(0, \sigma^2_e)
\]

Level-1 Model
(Within-person change)

\[
\varphi_{0i} = \beta_{00} + b_{0i} \\
\varphi_{1i} = \beta_{10} + b_{1i}
\]

Level-2 Model
(Between-person change)

\[
\begin{bmatrix}
b_{0i} \\
b_{1i}
\end{bmatrix} \sim N\left(\begin{bmatrix}
0 \\
0
\end{bmatrix}, \begin{bmatrix}
\sigma^2_0 & \sigma_{01} \\
\sigma_{10} & \sigma^2_1
\end{bmatrix}\right)
\]

Composite Model

\[
y_{ij} = (\beta_{00} + b_{0i}) + (\beta_{10} + b_{1i})x_{ij} + \varepsilon_{ij}
\]
Level-1 Model

\[ y_{ij} = \phi_{0i} + \phi_{1i}x_{ij} + \epsilon_{ij} \]

Subject 1

(Intercept, Slope) = (\phi_{01}, \phi_{11})

Subject 2

(\phi_{02}, \phi_{12})

Subject 3

(\phi_{03}, \phi_{13})

Subject 4

(\phi_{04}, \phi_{14})
Level-2 Model

\[ \varphi_{0i} = \beta_{00} + b_{0i} \]
\[ \varphi_{1i} = \beta_{10} + b_{1i} \]

Subject 1
\( (\beta_{00} + b_{01}, \beta_{10} + b_{11}) \)

Subject 2
\( (\beta_{00} + b_{02}, \beta_{10} + b_{12}) \)

Subject 3
\( (\beta_{00} + b_{03}, \beta_{10} + b_{13}) \)

Subject 4
\( (\beta_{00} + b_{04}, \beta_{10} + b_{14}) \)

Parameter space

Population mean

\( \varphi_{0i} \)
**Part I. Genuine Match Score Modeling**

<table>
<thead>
<tr>
<th>Level-1</th>
<th>Level-2</th>
</tr>
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<tbody>
<tr>
<td><strong>Model A (Unconditional mean model)</strong></td>
<td></td>
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</tbody>
</table>
\[ y_{ij} = \varphi_{0i} + \varepsilon_{ij} \]  
\[ \varphi_{0i} = \beta_{00} + b_{0i} \] |
| **Model B** |  
\[ y_{ij} = \varphi_{0i} + \varphi_{1i} x_{ij} + \varepsilon_{ij} \]  
\[ \varphi_{0i} = \beta_{00} + b_{0i} \]  
\[ x_{ij} = \Delta T_{ij} \quad B_T: \text{Time interval} \]  
\[ x_{ij} = AGE_{ij} \quad B_A: \text{Subject's age} \]  
\[ x_{ij} = Q_{ij} \quad B_Q: \text{Max. of NFIQ of fingerprints in comparison} \]  
\[ \varphi_{1i} = \beta_{10} + b_{1i} \] |
| **Model C** |  
\[ y_{ij} = \varphi_{0i} + \varphi_{1i} \Delta T_{ij} + \varepsilon_{ij} \]  
\[ \varphi_{0i} = \beta_{00} + \beta_{01} C_i + b_{0i} \]  
\[ \varphi_{1i} = \beta_{10} + \beta_{11} C_i + b_{1i} \]  
\[ C_i = bMale_i \quad C_G: \text{Gender} \]  
\[ C_i = bWhite_i \quad C_R: \text{Race} \] |
Model Comparisons

- **Goodness-of-Fit**
  - Smaller the value, better the model fit

- **AIC (Akaike Information Criterion)**
  - Decrease in AIC observed for Models BT, BA, BQ vs. Model A
  - $\Delta T$, AGE & Q explain the variance in genuine match scores
  - Q is the best covariate
  - AIC barely decreases for Model BT vs. Models CG, CR
  - Gender and race are not important covariates
  - Model D with $\Delta T$, AGE, and Q explains variance the best
Validation of Model Assumptions

• Normal probability plots
  – If linear, the distribution is normal

\[ \varepsilon_{ij} \sim N(0, \sigma^2) \]

Level-1

\[
\begin{bmatrix}
  b_{0i} \\
  b_{1i}
\end{bmatrix}
\sim N\left( \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix}
  \sigma^2_0 & \sigma_{01} \\
  \sigma_{10} & \sigma^2_1
\end{bmatrix} \right)
\]

Level-2

• Departures from normality are observed at tails
Parameter Estimates and Hypothesis Tests

- Bootstrap to obtain parameter estimates and confidence interval
  - Resample N (= 15,597) subjects with replacement; 1,000 bootstrap samples

- $H_0: \beta_{10} = 0$ (slope of linear model is 0)
  - $H_0$ is rejected at 0.05 level for Model B_T, B_A, and B_Q

- Genuine match scores decrease w.r.t. time interval, subject’s age, and NFIQ
Part II. Matching Accuracy Modeling

Match Score vs. $\Delta T$

- True Acceptance
- Decision threshold
- False rejection occurs

Probability of True Acceptance vs. $\Delta T$

1.0
Multilevel Model for Binary Responses
(Generalized Linear Mixed-effects Model)

**Level-1**

\[ y_{ij}^* = \begin{cases} 1, & y_{ij} > Th \smallskip \\ 0, & \text{otherwise} \end{cases} \]

\[ \epsilon_{ij} \sim N(0, \sigma_\epsilon^2) \]

\[ y_{ij}^* \sim Bin(1, \pi_{ij}) \]

\[ g(\pi_{ij}) = \varphi_{0i} + \varphi_{1i}x_{ij} + \varepsilon_{ij} \]

\[ g(\cdot) \text{ is a link function; for binary responses,} \]
\[ g(\cdot) \text{ is a logit function} \]

**Level-2**

\[ \varphi_{0i} = \beta_{00} + b_{0i} \]

\[ \varphi_{1i} = \beta_{10} + b_{1i} \]

\[ \begin{bmatrix} b_{0i} \\ b_{1i} \end{bmatrix} \sim N\left( \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_0^2 & \sigma_{01} \\ \sigma_{10} & \sigma_1^2 \end{bmatrix} \right) \]
Matching Accuracy over Time

- 400 bootstrap samples

Threshold corresponding to FAR=0.01%

- Probability of true acceptance remains close to 1 within 12-year time interval
Summary and Conclusions

- Statistical analysis with multilevel models for longitudinal fingerprint data (15,597 subjects with 12-year time span)
- Based on the results of hypothesis test and bootstrap confidence interval, we can make following inferences
  - Genuine match score tends to decrease over time
  - Matching accuracy tends to remain stable over time with high confidence
- Future work
  - Analyze longitudinal data with longer time span
  - Explore nonlinear models and interaction terms
Thank you.