Statistical Analysis of Kinematic Measurements on Signatures for Forgery Detection

Emily Allen, Alicia Carriquiry, Danica Ommen

Iowa State University

Center for Statistics and Applications in Forensic Evidence

Introduction

As our world becomes more technologically centered, the increased use of digital signatures will heighten the demand for digital signature analysis and forgery recognition. Digital signatures are commonly written on signature pads at various places such as banks and pharmacies. In addition to digitally written signatures, a software called MovAlyzeR can be used to aid non-digital forgery cases by collecting signature samples from a genuine writer and suspect.

This project aims to develop a statistical approach to differentiate a genuine signature from a forged one. The dataset used was obtained using MovAlyzeR. The MovAlyzeR software extracts dynamic information from a signature as it is written. The signatures are segmented into strokes, and each stroke's attributes are measured and recorded (Fig. 1). The variables collected for each stroke include **size, duration, velocity, jerk, and pressure**. This information is used to compute Hotelling's T^2 test statistics, which are then implemented into a score-based likelihood ratio. This analysis helps identify forgery and can supplement court cases that involve the crime of forgery.

Data & Methods

Forgery Types

Two test statistics were calculated separately for two forgery types: disguised with model (DWM) and disguised no model (DNM). The DWM signatures were written by forgers who were provided a model signature of the signature they are forging. The DNM signatures were written by forgers who were only provided a name to forge without a model (Fig. 2). The analysis on this poster uses the forged with model signatures.

Hotelling's Test Statistics

To compute one Hotelling's T^2 test statistic, we compared five questioned signatures to five known genuine signatures. The questioned signatures fall into two categories: known forgeries and known genuine signatures. One known match statistic and known non-match statistic was computed for 92 subjects. This resulted in 92 test statistics for the known match distribution and 92 test statistics for the known non-match distribution. The test statistics can be interpreted as dissimilarity scores, with low scores being more similar and high scores being less similar.

Kernel Density Estimation

Corresponding test statistic scores for the known genuine comparisons are used to approximate the known-match score distribution via kernel density estimation and similarly for the non-known-match distribution under each forgery condition. Findings are promising, in that the overlap between the two sets of scores in each case is moderate. Thus, the Hotelling's T^2 metric can help discriminate between genuine and forged signatures.

Score-Based Likelihood Ratio

For each new comparison, the test statistic is computed and compared to each reference distribution. The ratio of these two values is the score-based likelihood ratio for that comparison. The score-based likelihood ratio is a statistically based objective method for assessing the value of evidence towards forgery. Higher ratios indicate increased similarity between signature samples, and lower ratios indicate decreased similarity between samples.

Data & Results

Figure 1

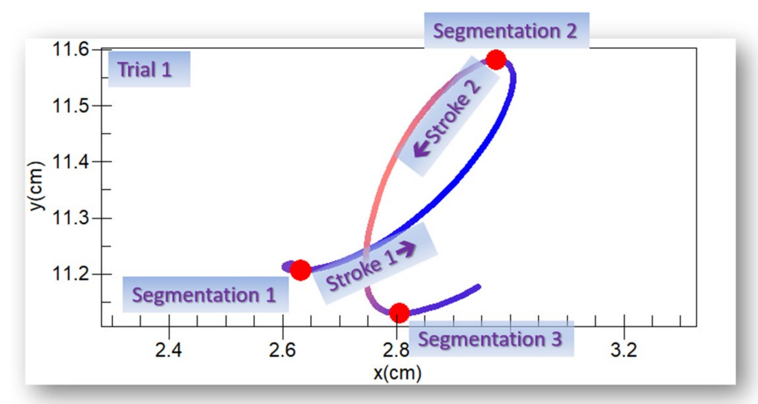


Figure 2

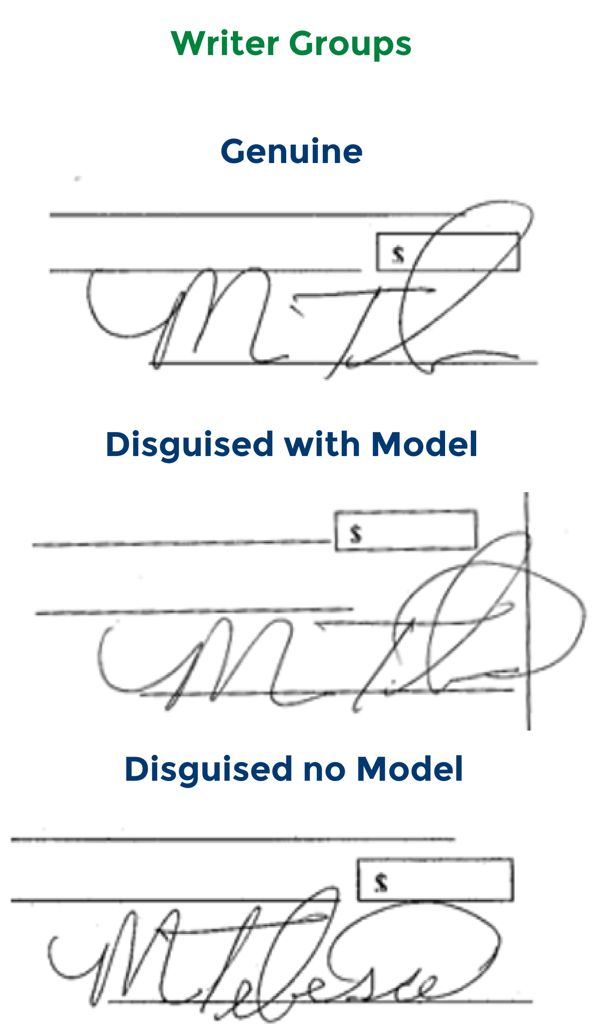


Figure 3

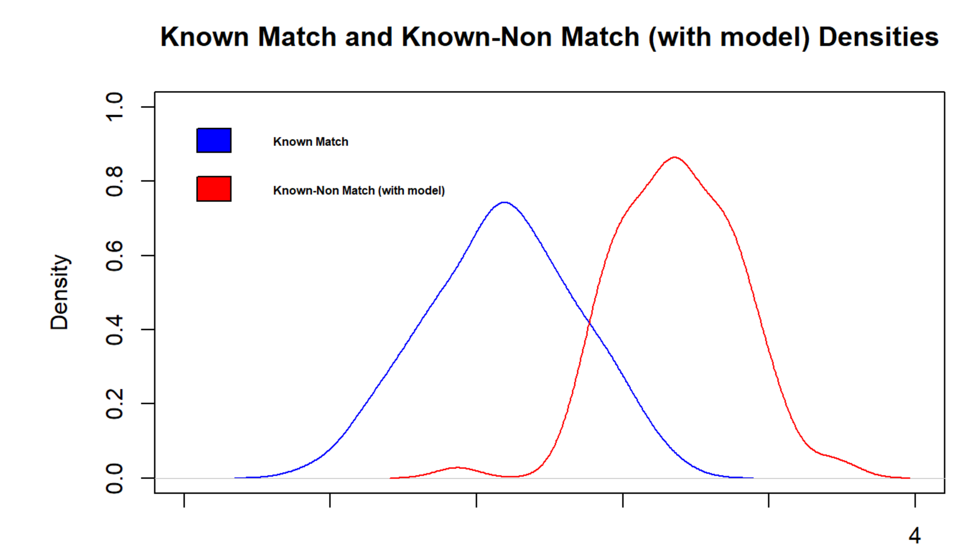


Figure 4

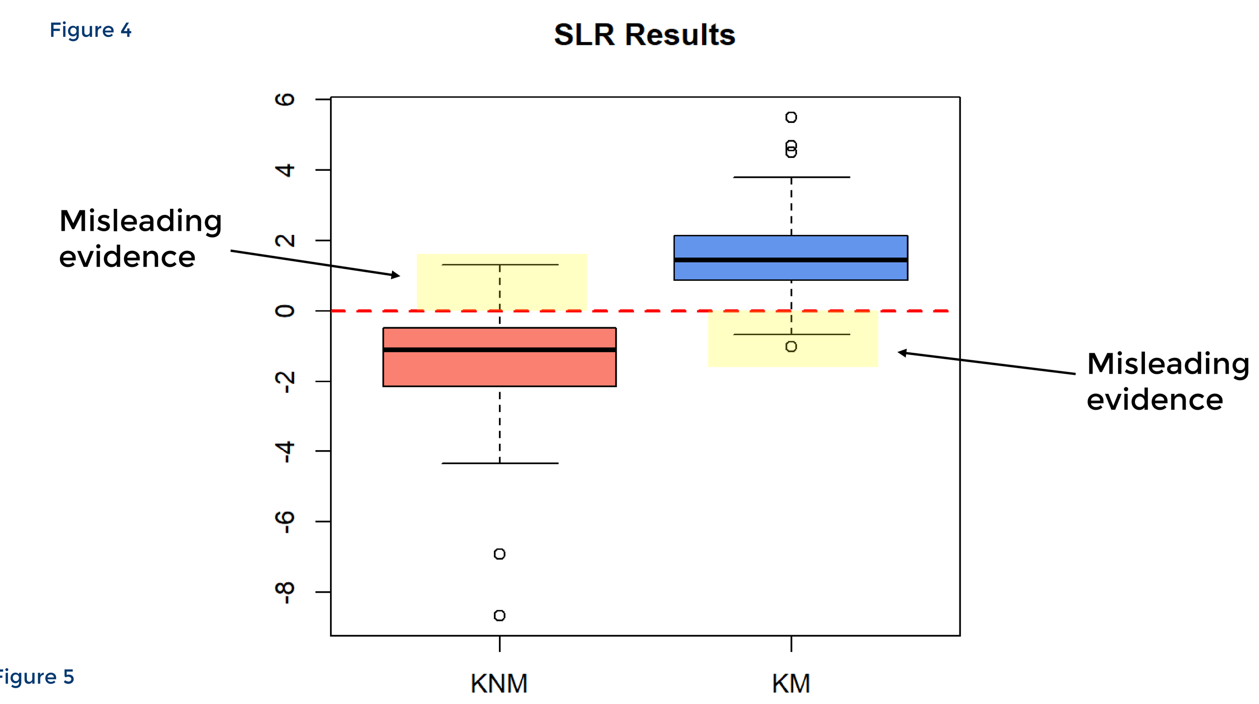


Figure 5

Confusion Matrix	Known Match	Known Non-Match
SLR ≥ 0	79	4
SLR <0	13	88

Rates of Misleading Evidence: KM: 14% KNM: 4%

Overall Model Accuracy: 91%

Implementation and Interpretation

Figure 6

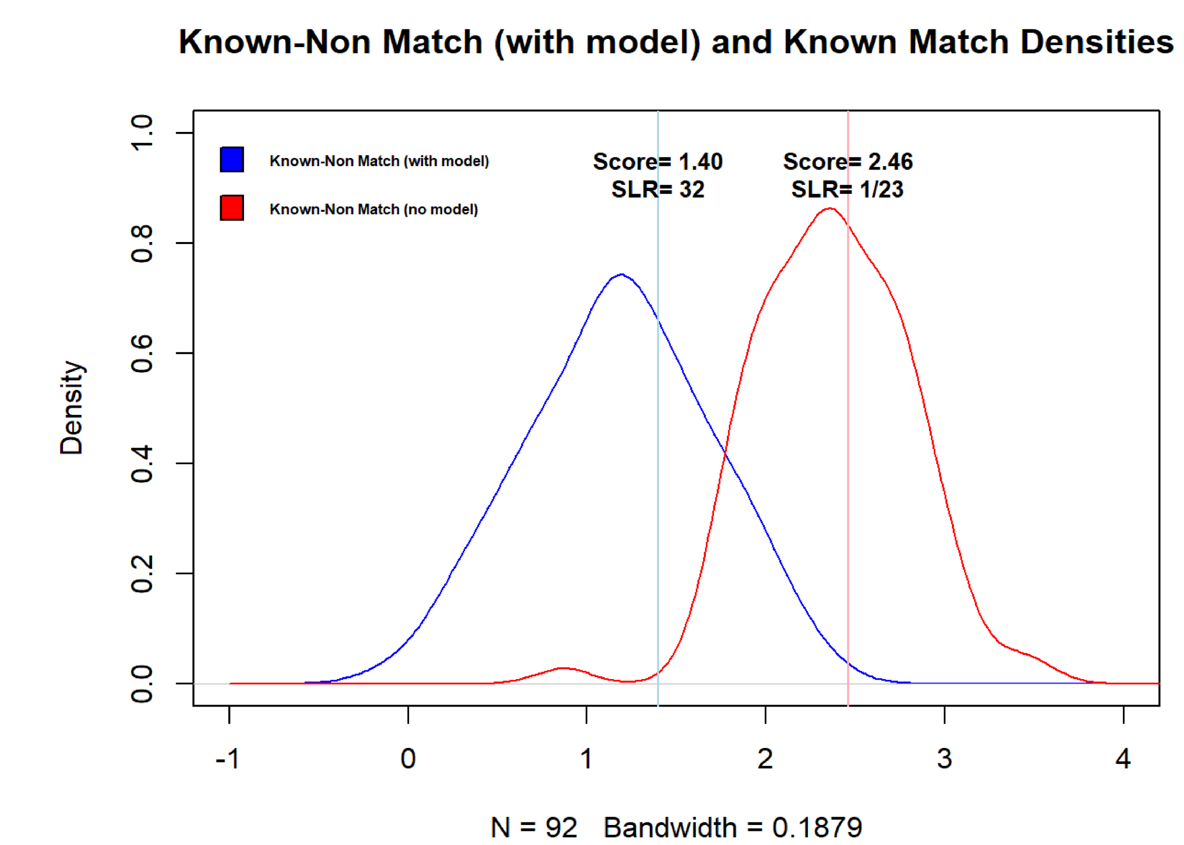


Figure 7

SLR of 32:	SLR of 1/23:
We are **32** times more likely to observe this degree of similarity if the signatures **are** from the same writer.	We are **23** more times more likely to observe this degree of similarity if the signatures **are not** from the same writer.

Results & Discussion

Figure 1: The data is collected and analyzed for each stroke of writing. A stroke is indicated by a change in direction.

Figure 2: The data is categorized into writer groups: genuine, disguised with model, and disguised no model. "Model" refers to an image of the genuine signature.

Figure 3: Figure 3 shows the kernel density estimations for the known match and known non-match distributions. These densities are used when computing the score-based likelihood ratio.

Figure 4: Figure 4 contains two boxplots made up of all score-based likelihood ratios computed for both known non-matches and known matches. The highlighted yellow parts of the boxplot show the misleading evidence, and the non highlighted portion shows comparisons that were correctly deemed as genuine or forged.

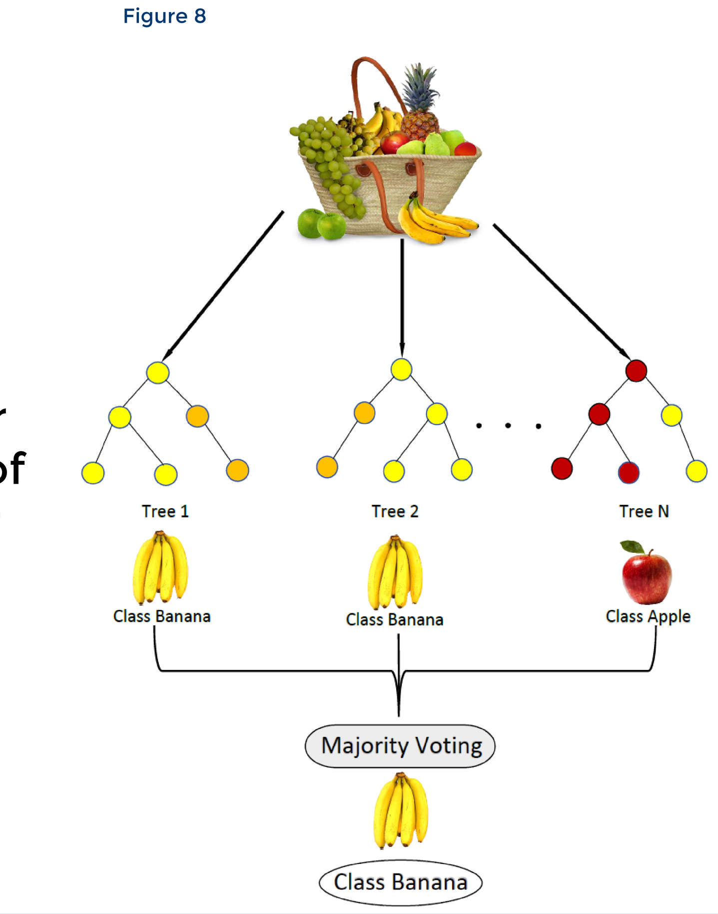
Figure 5: The confusion matrix shows the rates of misleading evidence for known matches and known non-matches. The rate of misleading evidence is 14% for known matches, and 4% for known-non matches, meaning that this method is more accurate when comparing known non-matches.

Implementation and Interpretation: Figure 6 shows the comparison of a set of questioned signatures compared to a group of forgeries and a group of genuine signatures. The two vertical lines show the corresponding test statistic dissimilarity scores. The ratio of the two densities at this specific score location is used to compute the score-based likelihood ratio. The interpretations, or final court evidence, is shown in Figure 7.

Future Directions: Random Forest Classification

Since January of 2023, I have been using a random forest to classify each pair of signatures as either a match or a non-match. A random forest is an ensemble machine learning method based off multiple decision trees. Currently, the preliminary model is performing at about 92% accuracy, which is higher than the Hotelling model. The rate of misleading evidence is about 9% for known matches and 13% for known non-matches. This method is very promising for increasing classification accuracy. Figure 8 is a simple representation of how a random forest is used for classification.

Figure 8



Resources & References

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