Statistical Comparison of Tool Marks in Forensics

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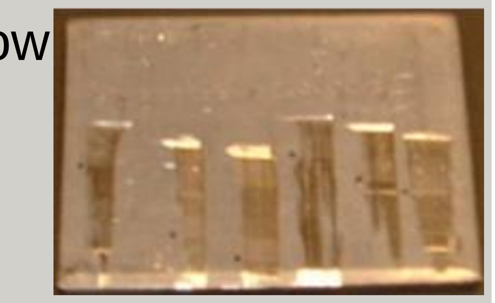
1 Motivating Problem



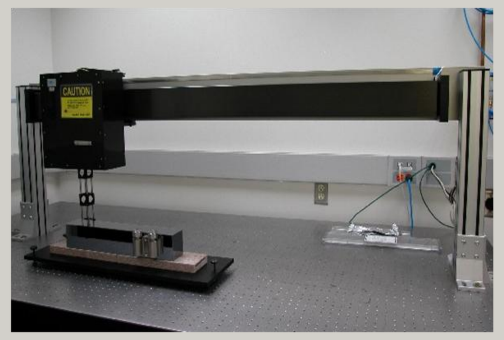
- Criminal breaks into a window using a screwdriver leaving behind a tool mark.

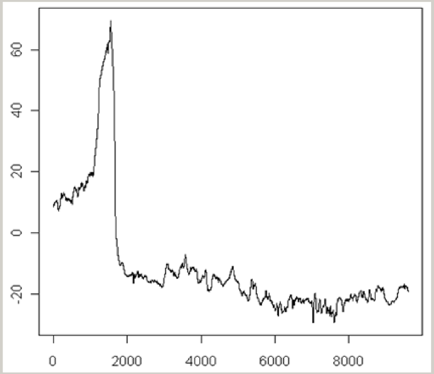
- A suspect is identified and found with a screwdriver in his possession; was that the screwdriver used in the crime?

- Grinding process of tools creates unique striae that are left behind when the tool is scraped against a hard surface, analogous to fingerprints.

2 Measurement Technique

Stylus profilometer reads across a tool mark recording the depths of the striae. The depths become a numerical dataset when read pixel-to-pixel.





Comparing two digitized tool marks results in a single numerical index value of similarity.

3 Data

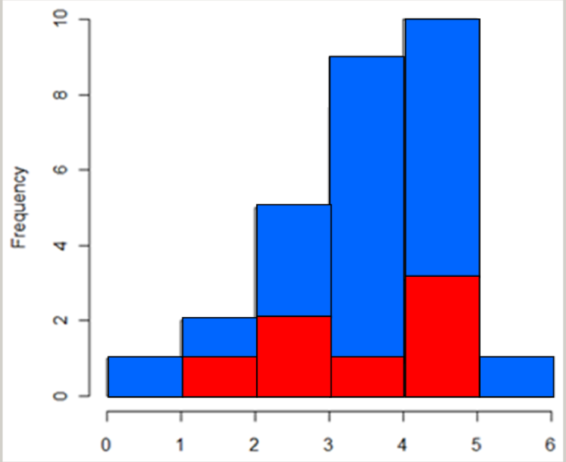
- Available tool marks
  - 1 field mark (from crime scene); x_0
  - n lab marks made by the suspect tool; $x_1, \ldots, x_n$
- y_{ij} is the comparison value from comparing x_i with x_j
- Resulting data after all pairwise comparisons are made:
  - y_{0j} for $j = 1,\ldots,n$; all comparisons of the field mark to a lab mark
  - y_{ij} for $i,j = 1,\ldots,n$ and $i < j$; all pairwise comparisons of lab marks
- Regard y_{ij} as approximately normal

4 Interpreting the Data

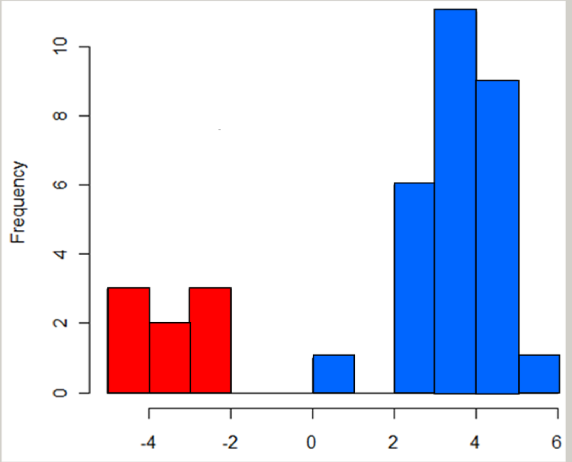
Did the suspect tool create the field mark?

i.e.: Does the field mark match the lab marks?

If y_{0j}s are comparable to y_{ij}s ➡ "no evidence" that the tool marks are different; i.e.: match



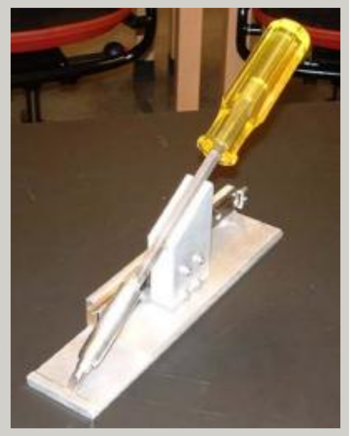
If y_{0j}s are small relative to y_{ij}s ➡ "evidence" that the tool marks are different; i.e.: no match



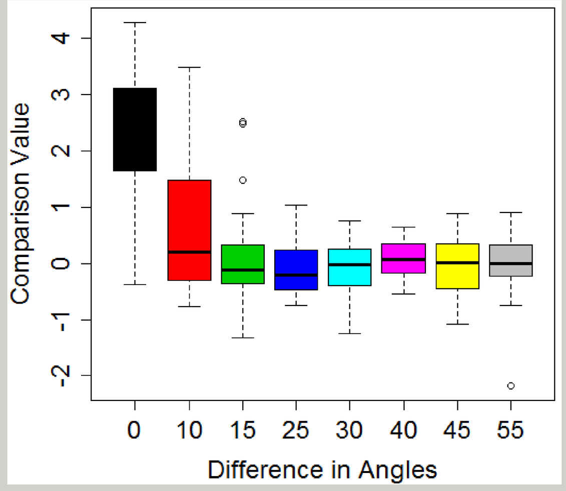
5 Basic Model

- $E(y_{0j}) = \mu_0$ for $j = 1,\ldots,n$; mean for comparison of field mark to lab marks
- $E(y_{ij}) = \mu_1$ for $i,j = 1,\ldots,n$ and $i < j$; mean for comparison of lab marks
- $Var(y_{ij}) = \sigma^2$; variance for all comparisons
- $$Corr(y_{ij}, y_{kl}) = \begin{cases} 0 \text{ if } i \neq k,\ i \neq l,\ j \neq k, \text{ and } j \neq l \\ \rho \text{ if } i = k, \text{ or } i = l, \text{ or } j = k, \text{ or } j = l \\ 1 \text{ if } i = k \text{ and } j = l \end{cases}$$
  That is, comparisons involving a common tool mark are correlated
- Parameters estimated using MLE based on weighted least squares
- Likelihood ratio test used to test H_0: $\mu_0 = \mu_1$

6 Angle Influence



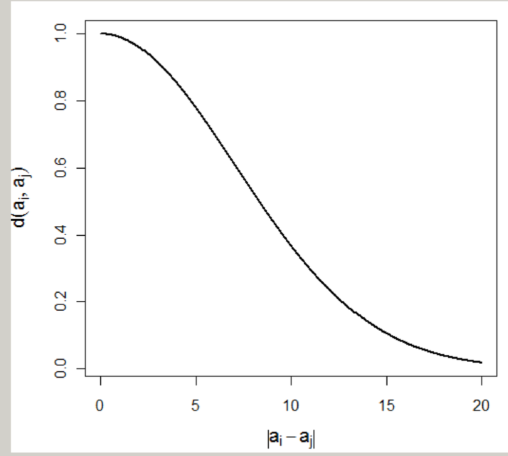
- Angle at which the tool is held when making the mark changes the appearance of the tool mark
- Boxplots show comparison values for tool marks made by the same tool at varying angles – 30°, 45°, 60°, 75°, & 85°



- Tool angles differing by more than 10° result in small comparison values indicative of non-matches
- Angle of a tool mark should be incorporated into the model

7 Model with Angle

- a_i = the tool angle (in degrees) at which tool mark x_i is made
- $d(a_i,a_j) = \exp[-\theta(a_i - a_j)^2]$, a positive similarity measure; shown in figure below



- We chose $\theta = 0.01$ so that $d(a_i,a_j) = 1$ when tool angles match, is small when $|a_i - a_j| = 10$ and approaches 0 when $|a_i - a_j| > 10$
- With more data, we would estimate θ

8 Analysis

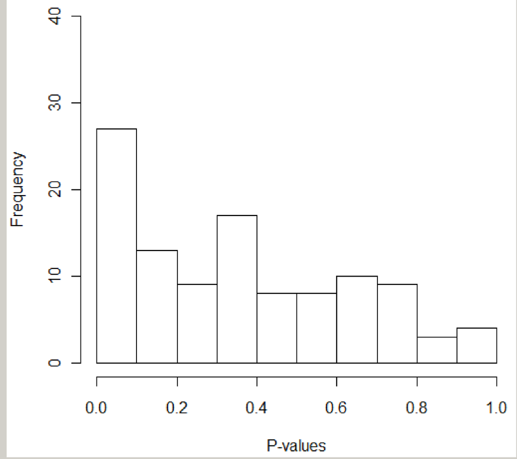
Still want to know if the same tool was used to make the field mark and the lab marks. Use a LRT with the Angle Models defined as

- Null Model
  $y_{ij} \sim N(\mu_{ij},\sigma^2)$ where
  $\mu_{ij} = \mu_0 + \alpha\, d(a_i,a_j)$ for $i, j = 0,1,\ldots,n$ and $i < j$
- Alternative Model
  $y_{ij} \sim N(\mu_{ij},\sigma^2)$ where
  $\mu_{0j} = \mu_1 + \alpha_0\, d(a_0,a_j)$ for $j = 1,\ldots,n$ and
  $\mu_{ij} = \mu_1 + \alpha_1\, d(a_i,a_j)$ for $i, j = 1,\ldots,n$ and $i < j$

Correlation structure is the same as described in **Block 5.** MLEs can be obtained for μ_0, μ_1, σ^2, α, α_0 and α_1 provided values of a_0 and ρ which are estimated using a grid search.

9 Matching Results

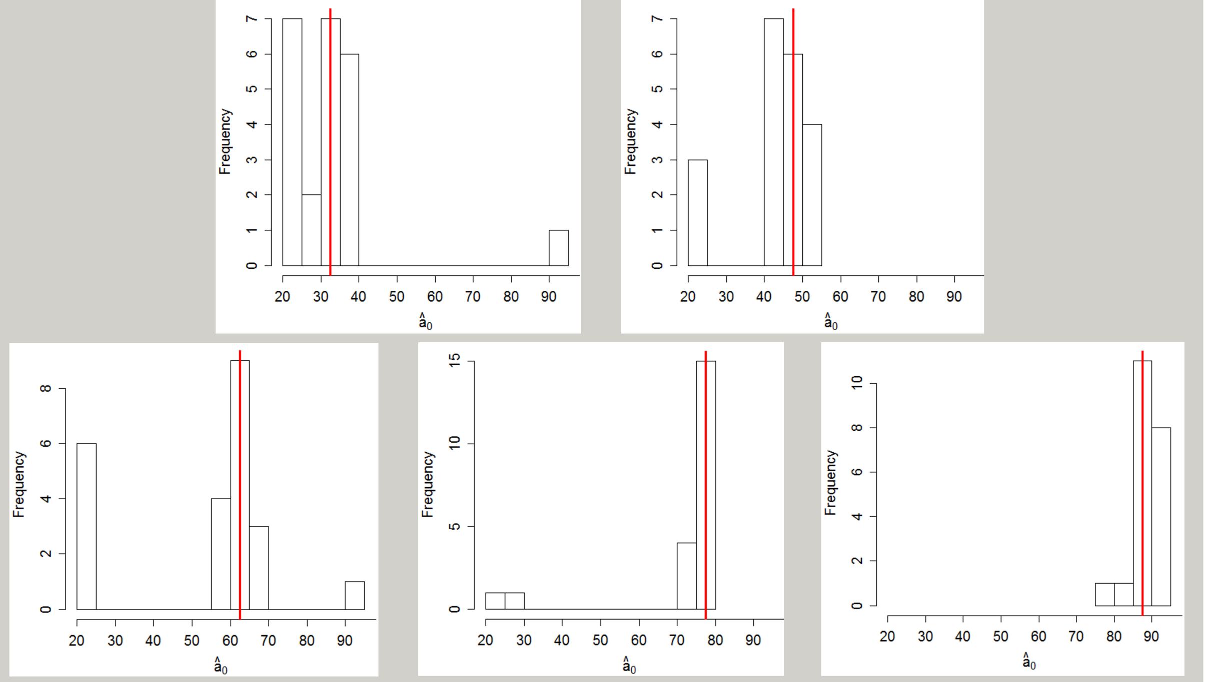
- Matching datasets consist of only tool marks made by the same tool; 20 tool marks – 4 at each of 5 angles
- Each mark chosen to be the field mark one-at-a-time
- Matches were found to be sensitive to flaws in the data and the matching process so "bad" tool marks and "bad" matches were removed
- LRT from **Block 8** was performed on remaining tool marks – total of 108 LRTs. Histogram shows the resulting p-values



- Since tool marks match, we expect most tests should FTR H_0, so p-values should be approximately uniform which is seen in the graph

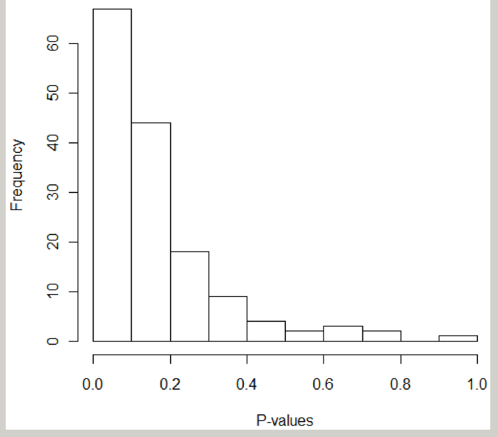
10 Estimation Results

The following histograms display the behavior of the estimate of a_0 from the matching data. Each graph shows the estimated value of a_0 for each of the five angles, the red line shows the true field angle.



11 Non-matching Results

- Non-matching datasets consist of 20 lab tool marks made by the same tool – 4 at each of the 5 angles – plus one field mark made by a different tool; one chosen from each angle from every remaining tool
- LRT from **Block 8** was performed on datasets
- Repeated for all 6 tools – total of 150 LRTs; p-values are shown in the histogram



- Since the tool marks do not match, we expect most of the tests should Reject H_0 and have small p-values which is shown in the graph

12 Conclusions

- The angle at which the tool is used can have a major effect on the similarity of tool marks
- For known matches, the field angle is predicted within 5° of the true angle in over 80% of the likelihood ratio tests
- Angle prediction is accurate as long as there are lab angles available within 10° of the field angle
- More data is necessary to include θ in the estimation process
- Correct match determination is sensitive to flaws in the tool marks as well as in the initial matching process
- The LRT based on the unknown-angle model effectively discriminates between matching and non-matching tool mark pairs

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