Using Machine Learning to Match Striae Pattern on Land Engraved Areas of Bullets

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Inaugural Ingram Olkin S3 Forum on Gun Violence Prevention

Disclaimer

- This work has nothing directly to do with directly preventing Gun Violence
- ★ Our motive is to establish a scientific foundation for the evaluation of forensic (pattern) evidence





- ★ Background, Data, and access to it
- ★ Methodology to extract information from raw data
- ★ Results from Matching



Over-arching Objective

★ Same Source Problem: were two bullets fired through the same gun barrel?

★ Currently: Firearms and Toolmarks Examiner use visual inspection under a comparison microscope: *subject bias, error rates?*

"much forensic evidence – including, for example, bite marks and firearm and toolmark identification is introduced in criminal trials without any meaningful scientific validation, determination of error rates, or reliability testing." (National Research Council 2009)

★ Goals: (1) determine
 score as objective
 measure for the match,
 (2) establish error rates



Barrel rifling and striae



★ Barrel rifling introduces land and groove impressions on bullets

 micro-imperfections introduce striation marks



Data Sources

- NIST Ballistics Toolmarks Research Database: https://tsapps.nist.gov/NRBTD
- ★ 2d images and 3d scans of cartridge cases (firing pin and breech face impressions) and bullets (Land engraved areas)
- ★ Relatively little data on bullets, larger number of cartridge cases



Two Sensofar Confocal Light Microscopes

Four undergraduates scanning bullet lands

3d topographic images: height measurements on x-y grid





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Data from CL Microscope x-y-z files

Data captured on grid of 0.645 $\mu m \times 0.645 \mu m$

Total captured area for each land

~2.2 mm x 0.6 mm



x - y - z file

у	Z
0.000	-25.221138
0.000	-25.253155
0.000	-25.335022
0.000	-25.4 8 7
0.000	-25.477917
0.000	-25.541687
0.000	-25.673903
0.000	-25.966341
0.000	-40.070286
0.000	-40.407612
0.000	-40.587063
0.000	-33.437973
0.000	-33.691895
0.000	-39.690674
0.000	-40.3 774
	y 0.000 0.000 0.000 0.000 0.000 0.000 0.000 0.000 0.000 0.000 0.000 0.000 0.000 0.000



x3p format ISO standard ISO5436 – 2000

- **★** x3p is a container format, consisting of
 - \star a binary surface matrix
 - * an xml file with meta information (specifications of the capturing device, operator information, data specific records)
- ★ Tools for working with x3p files: OpenFMC (C, Matlab) Suite of R packages developed at CSAFE (x3ptools, bulletxtrctr)



Data collected at CSAFE

- In collaboration with Forensic Labs and Police Departments
 - ★ Srinivasan Rathinam, LAPD:
 - 4 bullets per barrel for 626 Beretta firearms
 - ★ Steve Kramer, St Louis PD:
 - 2 SigSauer barrels with 192 fired bullets each
 - Melissa McNally, Houston FSI: test sets (6 kits with 25 bullets each),
 - persistence data shots 11-50 for eight Ruger barrels
 - ★Hamby Sets 10, 36, 44, 224, and a clone (35 bullets each)
- ★ Total of > 20k scans of Land engraved areas



From raw scans to data for analysis



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Step 1: identify region suitable for matching



Region close to heel of bullet Avoid break-off



Step 1: identify region suitable for matching



Region close to heel of bullet Avoid break-off



Automatic matching score

Step 1b: from scan to crosscut

Identify matching region

000





Automatic matching score

Step 1b: from scan to crosscut

Identify matching region







Automatic matching score

Step 1b: from scan to crosscut

Identify matching region







Automatic matching score

Step 1b: from scan to crosscut

Identify matching region

000





Automatic matching score

Step 1b: from scan to crosscut

Identify matching region

000



Automatic matching score

Step 2: Identify groove locations

200 160 120 80 500 1000 1500 2000 n

Shoulders (locations outside the grooves) are removed

Identify matching region







Automatic matching score

Step 2: Identify groove locations

Pelative Location (in μm)

Shoulders (locations outside the grooves) are removed







Automatic matching score

Step 3: Fit curvature

Identify matching region









Automatic matching score

Step 3: Fit curvature

Identify matching region









Automatic matching score

Step 3: Fit curvature & get signature

Identify matching region

Identify groove locations

1000 Relative Location (in μm)







Automatic matching score

Step 3: Fit curvature & get signature



Identify matching region





Automatic matching score

Step 3: Fit curvature & get signature



Identify matching region







Automatic matching score

Step 4: Align signatures

Identify matching region











Automatic matching score

Step 4: Align signatures



Identify matching region









Automatic matching score

Step 4: Align signatures













Automatic matching score

Step 4: Align signatures



bullet - - Br1 1-5 - Br 1 2-1











Extract signature



Step 5: Extract features

Feature should distinguish between a match and a non-match

Identify matching region









Step 5: Extract features

Feature should distinguish between a match and a non-match

★ # matches/mis-matches of peaks & valleys





Identify groove locations

Relative Location (in um)



Step 5: Extract features

Feature should distinguish between a match and a non-match

matches/mis-matches of peaks & valleys
 # consecutive matches/mis-matches(cms)







Step 5: Extract features

Feature should distinguish between a match and a non-match

- ★ # matches/mis-matches of peaks & valleys
- ★ # consecutive matches/mis-matches(cms)
- \star depth of peaks/valleys







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Feature should distinguish between a match and a non-match

- ★ # matches/mis-matches of peaks & valleys
- ★ # consecutive matches/mis-matches(cms)
- depth of peaks/valleys
- \star area between the signatures











Step 5: Extract features

Feature should distinguish between a match and a non-match

- # matches/mis-matches of peaks & valleys
- ★ # consecutive matches/mis-matches(cms)
- depth of peaks/valleys
- \star area between the signatures
- \star cross-correlation function







mismatches non_cms matches barrel2 barrel1 bullet1 bullet2 land2 land1 cms ccf 2 10 0.26 2.16 0.54 8.19 3 0.00 20.49 4 1 1 2 1 2 1 2 0.30 0.00 2.31 19.41 0.58 8.25 4 0.58 0.00 3.48 Unk G 1 4 2 1 18.94 1.74 8.42 0.85 2 0.00 6.14 16.41 2.23 4.24 1 3 4 1 4 0.38 6.86 2 2 0.00 2.37 18.61 1.18 4 1 10 5 2 6 2 6 0.32 0.00 4.01 16.43 2.29 4 1 4.98 cStats.org 2 5 2 4 1 2 0.24 0.00 2.24 18.02 0.56 5.00

Features & comparisons

									S	tches		ns	
	barrel1	bullet1	land1	barrel2	bullet2	land2	ccf	Ω	matche	misma	cms	non_cr	Known match
	4	2	1	10	1	3	0.26	0.00	2.16	20.49	0.54	8.19	FALSE
	4	2	1	2	1	2	0.30	0.00	2.31	19.41	0.58	8.25	FALSE
	Unk	G	1	4	2	1	0.58	0.00	3.48	18.94	1.74	8.42	FALSE
	4	1	3	4	2	1	0.85	0.00	6.14	16.41	2.23	4.24	TRUE
	4	2	1	10	2	5	0.38	0.00	2.37	18.61	1.18	6.86	FALSE
	4	2	1	6	2	6	0.32	0.00	4.01	16.43	2.29	4.98	FALSE
	4	2	1	5	2	2	0.24	0.00	2.24	18.02	0.56	5.00	FALSE

Features & comparisons

Features & comparisons

All features show distinction between known matches and known non-matches



Combining Features Decision Tree

★ Decision Tree (1984 Breiman)





Combining Features Decision Tree

★ Decision Tree (1984 Breiman)



Combining Features Decision Tree

★ Decision Tree (1984 Breiman)



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Combining Features Random Forest

★ Combination of 500 Decision Trees



- one false match (score too high) for tree,
 several false non-matches (scores too low)
- ★ no errors for Random Forest score, good separation



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Automatic matching of bullet land impressions, Annals of Applied Statistics, Eric Riemer Hare, Heike Hofmann, and Alicia Carriquiry

Algorithmic approaches to match degraded land impressions Eric Hare; Heike Hofmann; Alicia Carriquiry Law, Probability and Risk, Volume 16, Issue 4, 1 December 2017, 203–221, https://doi.org/10.1093/lpr/ mgx018



Case validation



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Validating the RF score Random Forest

★ Phoenix PD Study (Tyler Klep)

* known matches: eight barrels with three test fires each

\star ten questioned bullets



Validating the RF score Random Forest

★ Houston Test 1 (Melissa McNally)

 \star known matches: five barrels with three test fires each

★ eight questioned bullets



Conclusions

- ★ Preliminary results are promising
- **★** Rewarding to work on project with obvious high impact
- ★ Challenges at every step:
 - data collection, data wrangling, feature extraction, modeling
 - ★ theoretical foundations, knowledge transfer to labs



Why is this Data Science?

Result is combination of

★ Data management:

scans are large (~15 MB each), organizational structure for quality checks, re-scans, ...

- ★ Computationally intensive data processing, supervised learning methods
- ★ Applied Statistics: exploratory analysis, feature extraction, distributional properties, error analysis



Thank You!

Questions?

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