# AUTOMATED UNSUPERVISED GROOVE IDENTIFICATION FROM 3D BULLET LAND SCANS

NATHANIEL GARTON, M.S., DR. HEIKE HOFMANN AND DR. ULRIKE GENSCHEL
IOWA STATE UNIVERSITY

csafe Center for Statistics and Applications in Forensic Evidence

NIST National Institute of Standards and Technology U.S. Department of Commerce

## BACKGROUND

Elimination of data from 3D bullet scans corresponding to the groove engraved area is a critical step in automated bullet mark comparison algorithms. Failure to correctly identify and remove these data can be detrimental to the accuracy of such algorithms. Currently employed solutions to the removal of extraneous data can be numerically unstable and are based on ad hoc rules of thumb [1].

We propose a principled modeling approach to identification of the edges of bullet lands, hereupon referred to as **grooves**, where the groove locations are treated as parameters in a statistical model. An advantage of our approach is that it is **unsupervised**, meaning that our model does not rely on having seen examples of correctly identified groove locations in order to make predictions about the groove locations on unseen bullet lands.

## DATA

### Data Source:

Hamby (2009) Barrel Set 44 [2]

- Ten consecutively rifled Ruger P-85 barrels
- 210 individual bullet lands (6 lands each from 35 bullets)
- 3D scans gathered from confocal light microscope at Center for Statistics and Applications in Forensic Evidence (CSAFE)
- Resolution: 0.645 $\mu$m/pixel

### Data Structure:

2D profiles generated by averages of 10 slices across the bullet land

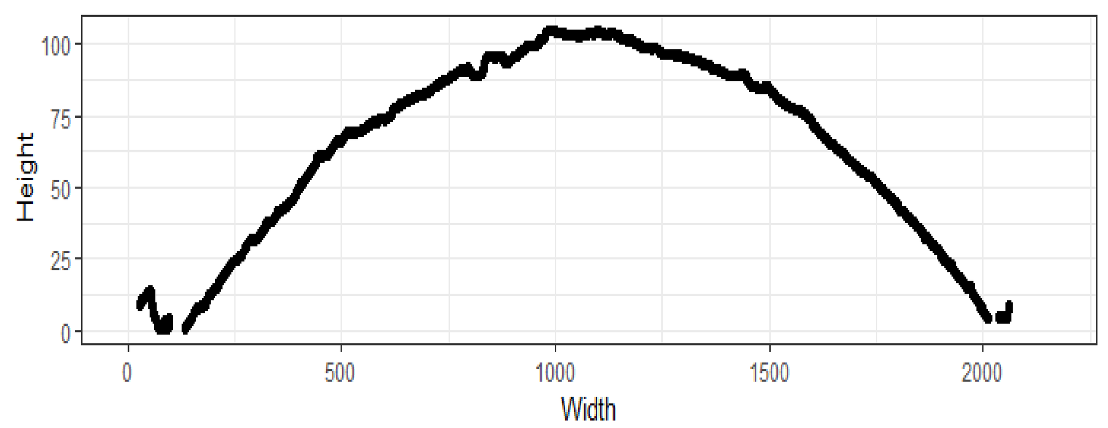
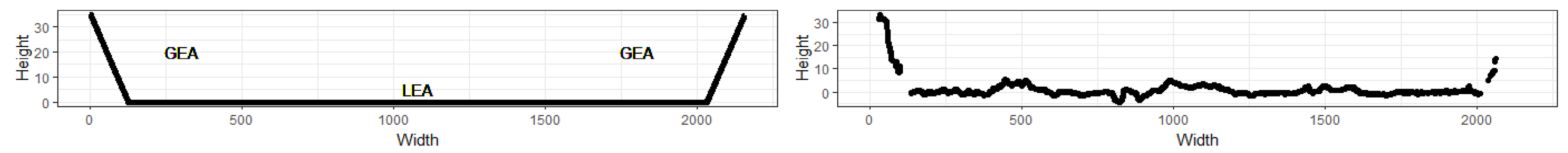



**Figure 1:** Example of a 2D profile from a 3D bullet land scan.

## METHODS

Our method relies on removal of the global curvature of the bullet. We utilize the robust LOESS procedure in order to remove this structure [3]. This results in data appearing as in Figure 2.




(a) Example of the structural assumption embedded in the mean function of the statistical changepoint model.
(b) 2D profile from a 3D bullet land scan after global structure has been removed.

**Figure 2:** Panel (a) shows the structural assumptions embedded in the mean function of the model. Panel (b) shows an example of a 2D profile after removal of the bullet curvature.

### Model:

The intuition behind our approach is that these data can now be modeled in a piecewise linear fashion plus random but highly correlated noise. Points where the piecewise components meet will be called **changepoints**. Our model can then be written as

$$(Y(x_1)...,Y(x_{k_1})) \sim N(\beta_{01}\mathbb{1} + \beta_{11}x'_{1:k_1}, \Sigma_1(\sigma_1, \ell_1)) \quad (1)$$

$$(Y(x_{k_1+1}),...,Y(x_{k_2})) \sim N(0, \Sigma_2(\sigma_2, \ell_2)) \quad (2)$$

$$(Y(x_{k_2+1}),...,Y(x_n)) \sim N(\beta_{02}\mathbb{1} + \beta_{12}x'_{k_2+1:n}, \Sigma_3(\sigma_3, \ell_3)), \quad (3)$$

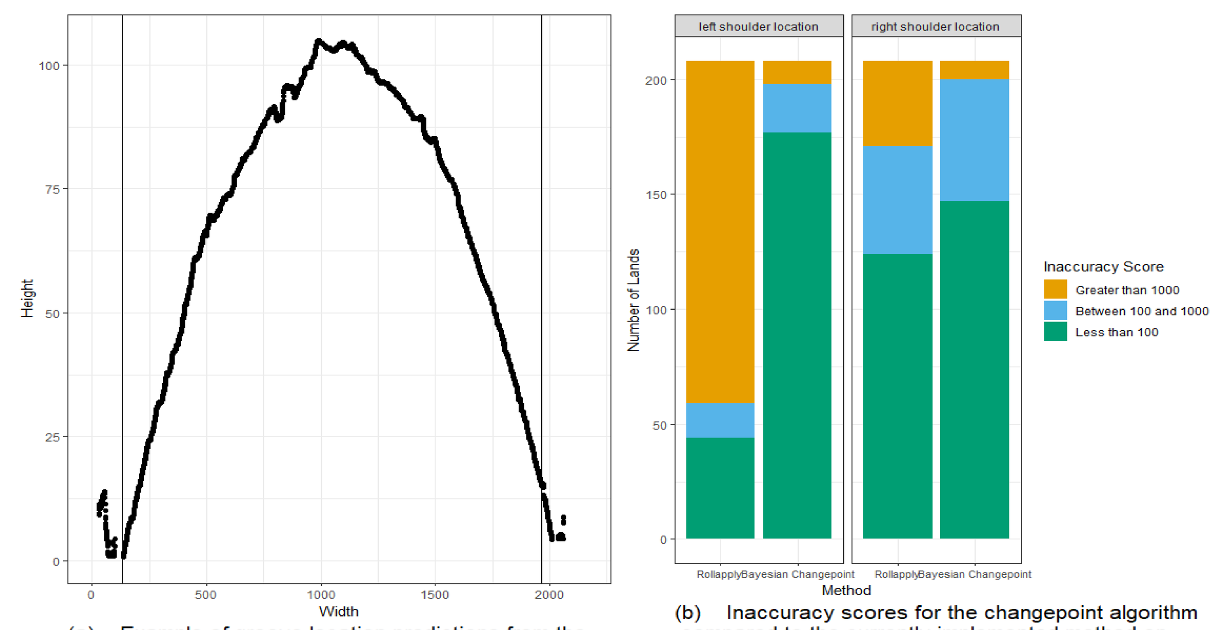
where $x_{k_1} < c_l \leq x_{k_1+1}$ and $x_{k_2} < c_r \leq x_{k_2+1}$ for changepoints $c_l$ and $c_r$, and $x'_i = x_i - \tilde{x}$ where $\tilde{x}$ is the median $x$ value. We take a Bayesian approach to analysis by putting prior distributions on model parameters, and we get predicted groove locations by taking the MAP estimate of $c_l$ and $c_r$ from several thousand runs of a Markov chain Monte Carlo algorithm.

## RESULTS 1

### Evaluating performance:

- Evaluation metric: sum of residuals (the Y-values from Figure 2(b) for example) in-between manually identified and predicted groove locations
- The larger this metric, the worse the performance.
- Figure 3(a) shows an example of groove location predictions generated by our algorithm on one of the Hamby 44 bullet lands.
- Figure 3(b) compares the performance of our method to the currently implemented method dubbed "rollapply".

## RESULTS 2




(a) Example of groove location predictions from the changepoint algorithm.
(b) Inaccuracy scores for the changepoint algorithm compared to the currently implemented method on 208 bullet lands from Hamby 44.

**Figure 3:** Panel (a) shows an example of groove location predictions on a bullet land from the Hamby 44 dataset. Panel (b) shows a plot of inaccuracy scores for 208 lands from the Hamby 44 dataset comparing the changepoint method presented here and the currently implemented groove identification algorithm.

## DISCUSSION

### Results Discussion:

- On this dataset, the Bayesian changepoint procedure is much better than the existing method for groove identification, especially for the left groove.
- As long as the overall structure of the 2D crosscuts remains consistent, this procedure should be robust to precise features that may systematically vary across types of bullets and barrels.
- A further advantage of this procedure is that it should provide the ability to quantify uncertainty about the groove locations. This means that it could be possible to identify lands where the results of the algorithm should be carefully reviewed by an expert.

### Potential Issues & Future Research:

- Improvements to computational efficiency and speed.
- Robustness study of the current method to algorithm settings and bullet/barrel types.
- Investigate more sophisticated algorithms that could be more reliablity accurate for given run times.

## REFERENCES

[1] Eric Hare, Heike Hofmann, and Alicia Carriquiry. Automatic matching of bullet land impressions. *The Annals of Applied Statistics*, 11(4):2332–2356, December 2017.

[2] James E. Hamby, David J. Brundage, and James W. Thorpe. The identification of bullets fired from 10 consecutively rifled 9mm ruger pistol barrels: A research project involving 507 participants from 20 countries. *AFTE Journal*, 41(2):99–110, 2009.

[3] William S. Cleveland. Robust locally weighted regression and smoothing scatterplots. *Journal of the American Statistical Association*, 74(368):829–836, December 1979.

This work was partially funded by CSAFE through Cooperative Agreement # 70NANB15H176 between NIST and Iowa State University, which includes activities carried out at Carnegie Mellon University, University of California Irvine, and University of Virginia