Automated Groove Identification in 3D Bullet Land Scans (we'll change the title)

Kiegan Rice *

Department of Statistics, Iowa State University

and

Nate Garton

Department of Statistics, Iowa State University

and

Ulrike Genschel

Department of Statistics and CSAFE, Iowa State University

and

Heike Hofmann

Department of Statistics and CSAFE, Iowa State University

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Abstract

Keywords: 3 to 6 keywords, that do not appear in the title

1 Background

Thanks to (1), we can do stuff. Hamby et al. (1)

2 Data Source

3 Methodology

We first need to remove the global structure of the bullet land.

3.1 Global Structure Removal

The non-traditional data structure necessitates employing non-traditional methods to model and remove the global structure. The data are made up of two competing structures: the LEA data, of which we would like to model the global structure, and the GEA data, which we would like to consider as outlying data. Traditional statistical modeling techniques minimize the least squared vertical distance from each data point to a fit line; this results in undue influence by GEA points, which pull any fit lines towards their unusual points.

While bullets are traditionally circular, it is unwise to use a rigidly quadratic model to fit the global structure. We cannot assume that fired bullets will retain a neatly circular shape, especially at the level of detail scans are captured. The significant amount of physical pressure that acts upon bullets as they are fired through a barrel also can lead to some warping or slight deformations *(find a citation from JFS or AFTE about warping/deformation of bullets?)*. Finally, the placement of the land relative to the plane of reference when a 3D scan is being captured can vary slightly, meaning that the 2D crosscuts can be slightly tilted or rotated. This will not translate into a clean quadratic-shaped(?) crosscut.

To avoid the potential risks arising from using a quadratic linear model, we instead use a locally weighted regression (LOESS) which fits linear regression models on small pieces of the data and combines predictions to result in a non-parametric predicted fit of the data structure.

However, since LOESS is still rooted in traditional regression techniques, it is unable to adequately identify and address the separation between GEA and LEA data structures. To address this, we implement a robust version of LOESS which iteratively downweights unusual data points and re-fits a LOESS model to each land. This robust LOESS is an adapted version of the robust LOESS proposed by (2).

This model is fit as follows: (add more formulaic language here...)

1. Fit a LOESS model (span = 1) to an entire crosscut to predict y using values of x.

2. Obtain predicted values of y from the model fit in step 1.

3. Calculate residual values using the predicted y values.

4. Calculate bisquare weights for each residual value using the following formula:

$$max(1 - (residual/(6 * mar))^2, 0)^2$$

5. Assign weights to each data point according to its residual value. If the residual value is positive, assign the bisquare downweight. If the residual is negative, leave the weight at 1.

6. Repeat steps 1-5 with updated weights at each iteration for k iterations, with 20 iterations as the default.

7. After k iterations of updating the weight vector, fit a LOESS model (span = 1) and obtained predicted and residual values.

The subsequent prediction methods for shoulder location are based on the residuals calculated from the fit to the global structure of each land. One method uses penalized two-class classification techniques to classify each data point into "LEA" or "GEA", while the second uses Bayesian changepoint analysis to predict the data points at which the shoulders begin on either side.

3

3.2 Two-Class Classification

3.3 Bayesian Changepoint Analysis

4 Results

5 Conclusions

6 References

References

1. Hamby JE, Brundage DJ, Thorpe JW. The Identification of Bullets Fired from 10 Consecutively Rifled 9mm Ruger Pistol Barrels: A Research Project Involving 507 Participants from 20 Countries. AFTE Journal 2009;41(2):99–110.

2. Cleveland WS. Robust Locally Weighted Regression and Smoothing Scatterplots. Journal of the American Statistical Association 1979;74(368):829–836.