Adaption of the Chumbley Score to matching of bullet striation marks

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1 Introduction and Results

Compairing pairs of toolmarks with the intention of matching it to a tool has been studied relatively more in the past as compared to bullets, and Chumbley et al. (2010) have described in their paper an algorithm and a deterministic method that compares two toolmarks and come to the conclusion if they are from the same tool or not. The method also determines the error rates, reduces subject bias and designate the two toolmarks as matches or non-matches with respect to a source. This project tries to adapt the Chumbley algorithm as modified by Hadler & Morris (n.d.), to bullets which are much smaller in length, width, are not flat and curved in the cross-sectional topography as opposed to tools like screw driver tips which produces longer and pronounced markings. The majority of Bullet profiles and signatures extracted by procedures mentioned by Hare et al. (2016) are almost 1/4 th the size of toolmarks as used by Chumbley et al. (2010) or even smaller. Striations on Bullets are made on their curved surfaces, whereas the algorithm developed by Chumbley et al. (2010) and Hadler & Morris (n.d.) has only been tested for flatter and wider surfaces which have negligible curvature. Therefore, using methods proposed for toolmarks may need adaptation in order to give tangible results for bullets. Moreover, in order to to get flat bullet signatures and remove the curvatures some kind of smoothing needs to be applied as a pre-step. This needs further investigation as to whether the level of smoothing does effect the working of the algorithm on Bullets. Another important aspect of adapting the algorithm is to find the sizes of the two comparison windows Hadler & Morris (n.d.) that minimizes the associated errors. This identification is not obvious as, if we go too small in the comparison windows, the unique features of the trace segments are lost and seem similar, while too large sizes vastly reduces the weight of small features that would otherwise uniquely classify a signature and hence identify the region of agreement.

An objective analysis of signatures (pre-processed markings) and profiles (raw markings) of bullet lands for all Hamby-44 and Hamby-252 scans pairwise land to land comparisons (a total of 85,491 comparisons)(Hamby et al. 2009) made available through the NIST ballistics database (Zheng 2016) was done to identify the effects of the two comparison windows and coarseness parameter on the error rates in as proposed in the adjusted chumbley algorithm for toolmarks by Hadler & Morris (n.d.). The results suggested that the Nominal type I error α value shows dependency on the size of the window of optimization and the window of validation. For a given window of optimization the actual Type I error is comparable the nominal level only for only a select few validation window sizes. A Test Fail, which is the percentage of incorrect classifications, depends on whether known-match or known non-matches has predictive value, with test results from different sources having a much higher chance to fail. On conducting an analysis of all known bullet lands using the adjusted chumbley algorithm, Type II error was identified to be least bad for window of validation 30 and window of optimization 120. In case of unsmoothed raw marks (profiles), Type II error increases with the amount of smoothing and least for LOWESS smoothing coarseness value about 0.25 or 0.3. In an effort to identify the level of adaptiveness of the algorithm, comparisons were made between signatures and profiles. Their comparison with respect to validation window size for a fixed optimization window side suggeted that, profiles have a total error greater than or equal to the total error of signatures for all sizes of validation window. Profiles also fail (i.e. incorrectly classify known-matches and known non-matches) more number of times than signatures, which lets us conclude that the behaviour of the algorithm for the profiles instead of pre-processed signatures is not better. Finally it needs to be noted that the current version of the adjusted chumbley algorithm seems to falls short when compared to other machine-learning based methods Hare et al. (2016), and some level of modification to the deterministic algorithm needs to be identified and tested that would reduces the number of incorrect classifications.

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