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Forensic Surface Metrology: Tool Mark Evidence

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Summary: Over the last several decades, forensic examiners of impression evidence have come under scrutiny in the courtroom due to analysis methods that rely heavily on subjective morphological comparisons. Currently, there is no universally accepted system that generates numerical data to independently corroborate visual comparisons. Our research attempts to develop such a system for tool mark evidence, proposing a methodology that objectively evaluates the association of striated tool marks with the tools that generated them. In our study, 58 primer shear marks on 9 mm cartridge cases, fired from four Glock model 19 pistols, were collected using high-resolution white light confocal microscopy. The resulting three-dimensional surface topographies were filtered to extract all "waviness surfaces"—the essential "line" information that firearm and tool mark examiners view under a microscope. Extracted waviness profiles were processed with principal component analysis (PCA) for dimension reduction. Support vector machines (SVM) were used to make the profile-gun associations, and conformal prediction theory (CPT) for establishing confidence levels. At the 95% confidence level, CPT coupled with PCA-SVM yielded an empirical error rate of 3.5%. Complementary, bootstrap-based computations for estimated error rates were 0%, indicating that the error rate for the algorithmic procedure is likely to remain low on larger data sets. Finally, suggestions are made for practical courtroom application of CPT for assigning levels of confidence to SVM identifications of tool marks recorded with confocal microscopy. SCANNING 33: 1–7, 2011. © 2011 Wiley Periodicals, Inc.

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Introduction

Impression evidence is a broad category of physical evidence that is commonly found at crime scenes. It occurs when an object's morphology creates a 2- or 3-D imprint onto the surface of a softer substance (Petraco, 2011). Examples of impression evidence include: fingerprints, shoeprints, tire tracks, tool marks (impression and striation) found on bullets and cartridge cases. Although impression evidence has been used successfully for decades, it has come under attack in recent years due to the lack of a well-articulated scientific basis (Daubert, '93; Nichols, 2007).

The features found on tool mark impression evidence, that are used by forensic examiners to make "comparative examinations" and "matches," are categorized into class, subclass, and individual characteristics—with class characteristics (i.e., size, shape, brand, model) being the most inclusive and individual characteristics (i.e., the combination of nicks, dents, slashes, etc. being imparted by manufacturing methods or that accumulate with an object's use) being—in theory—unique. Considering the exclusive nature of each category, and the power of discrimination when all categories are considered together, it is believed "…that no two tools can leave tool marks that are alike" (Thompson and Wyant, 2003).

To conclude that two objects have a high likelihood of being a match, the examiner states that the "quantity and quality" of the features was such as to provide a properly drawn conclusion. The Association of Firearm and Toolmark Examiners (AFTE) have set the standards for firearm and tool mark examination. Their theory of tool mark identification (AFTE, '98; Moran, 2002), "…enables opinions of common origin to be made when unique surface contours of two tool marks are in sufficient agreement." Sufficient agreement, they clarify, "…is related to significant duplication of random tool marks by correspondence of pattern or combination of patterns of surface contours."

One can also view tool mark impressions as mathematical patterns composed of features. Numerical classification methods (Duda *et al*., 2001; Shawe-Taylor and Cristianini, 2004; Theodoridis and Koutroumbas, 2006) become useful then because they have the potential of assigning objective quantitative measures to statements like "sufficient agreement." The ultimate goal of our research is to develop standard operating procedures for the application of 3D surface metrology and machine learning to tool mark analysis that can be used by the forensic tool mark examiner community.

Biasotti is recognized as having performed the first major empirically based statistical study concerning the comparison of impression patterns (Biasotti, '59). Using a comparison microscope, the study recorded the number of matching striations between bullets fired from the same gun and bullets fired from different guns. Biasotti found that while the percentage of matching striations between these two sets of bullets could overlap, runs of 3–4 consecutive matching striations were very rare for bullets fired from different guns. Through the 1990s and early 2000s, Geradts *et al*. published database systems and algorithms for tool mark and firearms comparison which involved turning a microphotographic 2D image into a feature vector, and then applying a similarity metric to gauge similarity between patterns (Geradts *et al*., '94, '95, 2001; Geradts and Keijzer, '96). The same operating principal is used by the commercial Integrated Ballistics Identification Heritage System (Forensic Technology WAI Inc., 2001).

With the advent of confocal and interferometric microscopy for engineering applications, acquisition of an entire 3D tool mark surface can be obtained (Whitehouse, 2004). DeKinder *et al*. was the first to publish results involving automated bullet comparisons using 3D confocal laser scanning (DeKinder and Bonfanti, '99; DeKinder *et al*., 2004). They found that while the data acquisition phase was slow, comparisons could be made by taking the trace of the correlation matrix; they did not report the use of other similarity metrics. Banno *et al*. was another group to demonstrate the ability to capture and compare 3D topographies of fired bullets using a confocal microscope (Banno, 2004). Sakarya *et al*. recently published a "low cost" method which they claimed could quickly acquire 3D surface topographies of cases using a digital camera and the photometric stereo method (Sakarya *et al*., 2008). Bachrach had published some information on a system he designed called SCICLOPS for the comparison of 3D surface topographies of bullets (Bachrach, 2002). This technology seemed to be the operating principal for BulletTRAX-3D from Forensic Technologies (Bachrach, 2006). A 2006 NIST study was able to get reproducible 2D surface signatures recorded from bullets with two different types of confocal microscopes and a coordinate measuring machine; the signature differences were, also, quantified using a standard cross-correlation function (CCF) from signal processing (Song *et al*., 2006).

Chumbley *et al*. used both a stylus instrument and an optical surface metrology instrument (the operating principal was unclear but seemed to be a variant of white light confocal) to create a database of screwdriver striation profiles. The group generated profiles from 50 consecutively manufactured standard screwdriver tips held at three different angles. Employing the t-statistic as a similarity measure, they found that profiles could generally be identified 95% of the time—though trained AFTE members were able to beat this algorithm. Unfortunately, we could not make a distinction between which data sets were used in their analysis (i.e., stylus, optical profilometer or some combination thereof) (Chumbley *et al*., 2010). Recently Xie, Blunt, Jiang *et al*. reported that a stylus instrument for roundness measurements could be used for both bullet impressions and the inside of gun barrels (Xie *et al*., 2009). No optical metrology methods, however, have demonstrated the ability to scan the inside of cylindrical objects as narrow as a gun barrel.

Bachrach, Koons *et al*. recently published a study detailing a white light confocal microscopy based system on tool marks. Their system not only recorded 3D tool mark impressions for visual comparison and storage, it also, under controlled conditions, could compute estimated identification error rates (Bachrach *et al.*, 2010). They scanned striation patterns made by screwdrivers and pliers in lead and aluminum. After registering, normalizing, and computing the mean profiles—called "signatures" by the authors—a Euclidian-like "relative distance" metric was applied to gauge similarities between queried mean profiles in their database. The authors found very low estimated error rates when they used univariate empirical distributions of the similarity scores between known matching striation patterns and known nonmatching striation patterns. Interestingly, they found their estimated error rates depended strongly on the impression media (Bachrach *et al.*, 2010).

With a similar confocal system, a group at NIST developed methodology to automatically select effective areas for comparison on pristine fired bullets (Chu *et al.*, 2010). Mean profiles of the 3D striation patterns were also used as input for numerical comparisons. A maximal weighted sum of correlation scores on each land engraved area was used as the similarity metric between bullets in their database. The NIST system produced performance rates better than an unnamed "widely used" commercial system (Chu *et al.*, 2010).

Forensic firearm examiners will typically use a comparison microscope to visually align demarcated distances between the peaks and valleys of the two striation marks to make a judgment on source origin. In our study, we used high-resolution white light confocal microscopy to scan primer shear topographies on 9 mm cartridge cases, fired from four different Glock 19s. Gun-to-gun variation was recognized by utilizing multivariate statistical analysis and computational pattern recognition (i.e., machine learning).

First, principal component analysis (PCA) was used to obtain more manageably sized "synthetic" features while still containing most of the topographical information found in the original mean profiles. Next, support vector machine (SVM) algorithms and conformal prediction theory (CPT) were applied to build a supervised learning model for the classification of each profile to a particular firearm with a stated level of confidence. Both PCA and SVM methods were chosen because they were relatively free of assumptions on the statistical data on which they were used, and had been extensively applied in many industries requiring robust statistical discrimination systems. Furthermore, they had a long peer-reviewed history in the scientific literature, and produced testable (i.e., falsifiable) predictions—important issues in a case subject to the Daubert standard (Daubert, '93).

Materials and Methods

Confocal Microscopy

Primer shear marks (striation patterns) from 58 9 mm cartridge cases, fired from four Glock model 19 pistols (Glock 19s), were recorded with a Zeiss CSM-700 white light confocal microscope using a 50× objective (0.95 NA). Figure 1 shows an example of an entire head stamp and primer area. The corresponding breech face shear mark is displayed in Figure 2.

Surface Preprocessing

All surface preprocessing was performed with Mountains 5.1 Premium metrological analysis software (Digital Surf, 2010). The recorded striation

Fig 1. Primer shear. Striation pattern produced by shearing action of breech face of Glock 19 against the cartridge case primer.

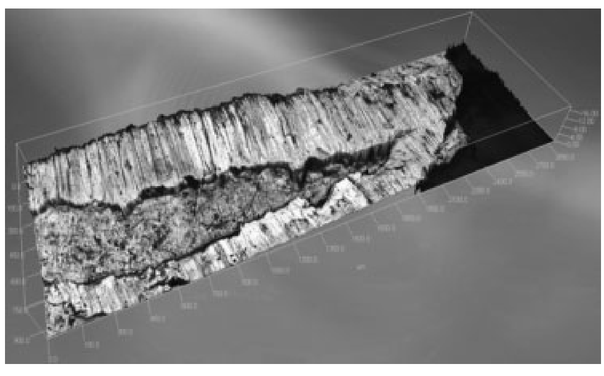

Fig 2. Confocal image of breech face shear striation pattern. Image acquired with 50× objective (0.95 NA).

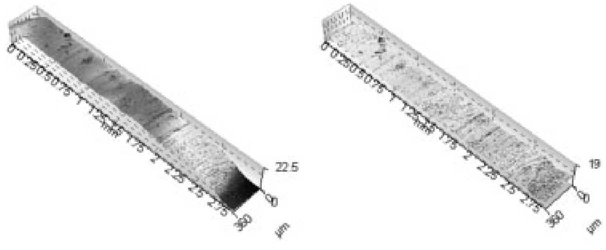

Fig 3. Unprocessed and processed (form removed) primer shear striation pattern from Glock #3, cartridge case 2.

Fig 4. Form removed primer shear from Glock #3, cartridge case 2 viewed from above. The dimensions of the surface are 2.1 mm × 250 μm but scaled to appear square for display purposes. Note the prominent striation pattern running from the top to the bottom of the figure.

patterns required form removal of a second or third order polynomial. An example of this is shown in Figure 3 with a recorded striation pattern before and after form removal. The resulting detrended striation patterns were filtered into roughness and waviness components using an areal cubic spline filter (ISO/TS 16610-22 standard) and $\lambda_{xc} = \lambda_{yc} = 0.08\,\mu\text{m}$ cut-off values (International Standards Organization, 2006).

The mean profiles of each surface for the roughness and waviness components were then computed. For striation patterns where the "lines" run vertically down the surface in the *y*-direction, there was a high redundancy of information found (cf. Fig. 4). Thus, mean profiles were used because they provide good overall summaries while having file sizes that were manageable. It is current standard practice to use the mean profile as input into the statistical discrimination algorithms instead of the entire surface (Bachrach, 2002; Faden *et al.*, 2007; Vorburger *et al.*, 2007; Bachrach *et al.*, 2010; Chu *et al.*, 2010; Chumbley *et al.*, 2010). Next, of the roughness and waviness components, we used only the recorded surfaces of the waviness component. From the profile plots in Figure 5, it was clear that almost all the "line structure"—the striation marks one would view under a comparison microscope—was contained in the waviness surface.

The waviness component of each mean profile was loaded into the R statistical program for further processing (R Core Development Team, 2009). Because each profile did not begin and end at the same points, the mean waviness profiles required alignment (i.e. registration) in order to be processed as maximally similar feature vectors in R. To register

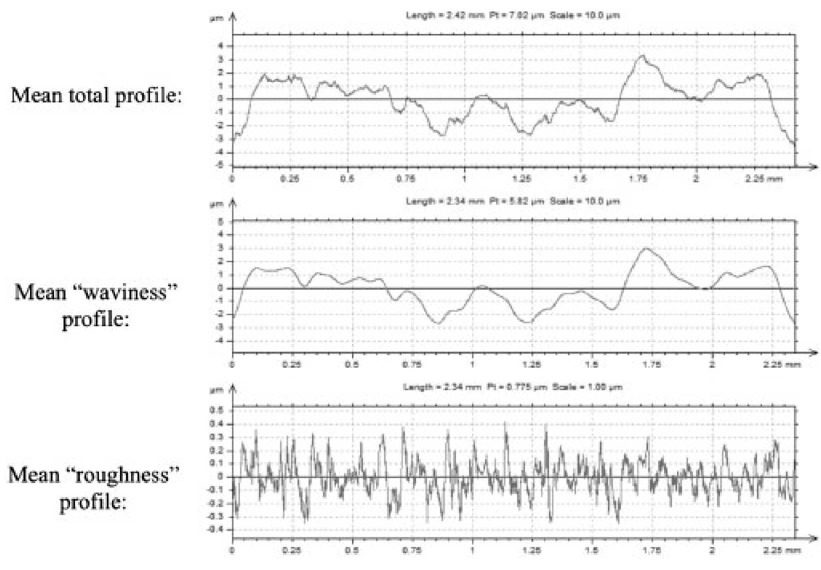

Fig 5. Mean total profile, mean waviness profile and mean roughness profile from the detrended breech face shear striation pattern of Glock #3, cartridge case 2.

the profiles, the CCF between two profiles was computed to find the shift that yielded maximum similarity. First, the mean profiles within a collection of cartridge cases fired from the same gun were registered. To do this, the longest profile of the group was chosen as a reference; the remaining profiles were then maximally aligned with respect to it via the shift that yielded the maximum of the CCF. Next, the mean profiles between guns were aligned. This was done by first computing a group-grand-mean-profile (GGMP) for each of the within-group aligned profile sets. The GGMP were then registered with respect to each other within a user defined "uncertainty window." The reason an uncertainty window was required for between-group registration was that no well-defined reference land mark was apparent in all primer shear surfaces. An ideal landmark would have been the left (or right) edge of the primer shear patterns. Unfortunately this landmark was very jagged and sometimes not so apparent. Instead, knowing that all primer shear exemplars were cropped out from the total recorded surface, 300 μm +/−100 μm from the left edge area, the GGMP were aligned within this +/−100 μm window. The shift parameters produced by the registration of group-grand-means were used to shift all the mean profiles of the groups in blocks. That is, each group of mean profiles was shifted by the amount required to register the GGMP.

Statistical Processing of Registered Waviness Profiles

Principal component analysis

PCA is a multivariate procedure that is used to reduce the dimensionality of a data set to a new data set of "derived variables" which account for successively decreasing amounts of variance (Jolliffe, 2004). The variance order of the new variables provides guidance for the reduction of the data's dimensionality while retaining an adequate representation. The native R PCA routine prcomp was used in this study to reduce the 4233-column data set down to three dimensions (3D for graphical representation) and six dimensions (6D, 95% variance retained representation).

Support vector machines for supervised tool mark identification

At present, small sample sizes are inevitable for many statistical studies of 3D tool mark surfaces. Statistical learning theory and its practical application, the SVM, was developed in response to the need for a reliable statistically based identification of object class within small sample studies (Vapnik, '98). SVMs look to determine efficient decision rules in the absence of any knowledge of probability densities by determining maximum margins of separation (Vapnik, '98; Theodoridis and Koutroumbas, 2006). This procedure produces an algorithm that determines linear decision-making rules for identification, while seeking large margins for error. In this study, a linear kernel was used with the one vs. one SVM algorithm, implemented through the R package kernlab (Karatzoglou *et al.*, 2004). The SVM penalty parameter *C* was set to 10. Finally, estimated error rates on larger sample sizes were computed through 10,000 bootstrap resampling iterations of the data set (Efron, '83; Efron and Tibshirani, '93).

Conformal prediction and confidence intervals for identification

Recently, a method which gives confidence levels to unknown pattern identification, as well as control over error rates, has emerged from the study of algorithmic randomness (Vovk *et al.*, 2005). This method, called conformal prediction, can be applied to any statistical pattern comparison algorithm and may hold a great deal of potential if applied to tool mark analysis.

The output conformal prediction regions are generalizations of confidence intervals known from textbook hypothesis testing. The Neyman–Pearson interpretation of $(1-\alpha)\times 100\%$ confidence interval, constructed from a random sample of given sample size and extended to CPT, is that the output confidence intervals will contain the true I.D. $(1-\alpha)\times 100\%$ of the time (90–92, 98). The value α is the level of significance and is typically chosen to be 5% (i.e., 95% confidence). Note that the output I.D. confidence intervals can contain multiple I.D.s for the striation pattern's identity (Vovk *et al.*, 2005). In such cases, the identity assignment (i.e. the prediction region) at the $(1-\alpha)\times 100\%$ confidence level is ambiguous. Although multi-label output is not wholly uninformative, the prediction region will contain only one label at the 5% level of significance. This means that the conformal prediction algorithm has produced a prediction region with only one label and a confidence level of at least 95%. The program for performing CPT with SVM was written using R.

Results and Discussion

Figure 6 shows the data from all profiles reduced to the first three PCs (i.e., 3D PCA, 87% variance retained). Consistent with the theory that no two tools produce the same marks, the samples are seen tightly clustered within each gun and well separated between guns. The first six PCs contained 95% of

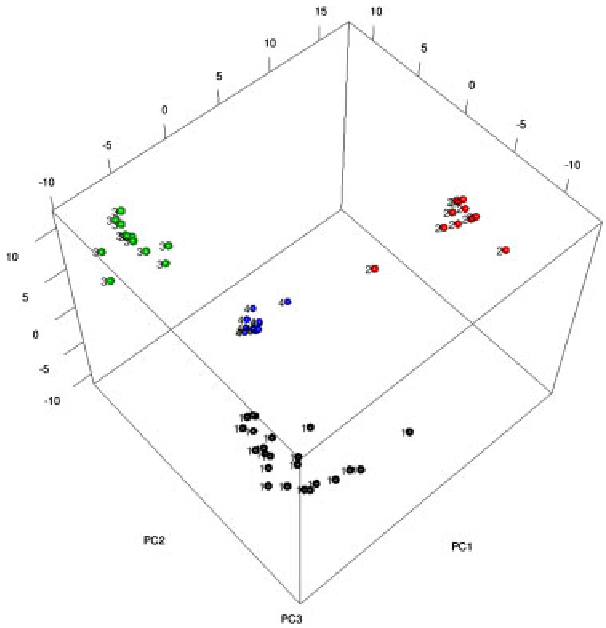

Fig 6. 3D PCA results of processed profiles from the four Glock 19s.

the data set's total variance, a typical variance benchmark used to decide how many PCs to retain (Jolliffe, 2004).

Using SVM to identify which gun generated a striation pattern (i.e., the striation patterns I.D.), the (refined) bootstrap estimated error rate was found to be 0% with 10,000 resampling iterations. The slightly more conservative 0.632 bootstrap estimated error rate was also found to be 0%. These error rates are likely a bit optimistic as our database size is still relatively small.

The 6D PCA-reduced data set was partitioned into random 50%-training 50%-testing for SVM-CPT classification at the 95% level of confidence. The CPT computation was run in ''on-line'' mode meaning that, immediately after the SVM-CPT predicts the I.D. of a test striation pattern, the data and true I.D. of this test sample are used to update the training set. The on-line mode of CPT guarantees a 5% error rate in the long run at the 95% level of confidence (Vovk *et al.*, 2005). The empirical error rate on the test set was found to be 3.5%, which is slightly lower than the theoretical long run error rate of 5%. Such a difference is to be expected, as the test set size was relatively small.

This leads us to a procedural suggestion for employing CPT with SVM in a courtroom setting. In such a setting, results of any metrological-statistical computational scheme are of paramount importance. The database of tool marks to be compared should be, at the minimum, large enough to allow resampling. The empirical error rates for each resampling iteration could then be collected and used with bootstrap-based hypothesis testing. This would give the court assurance that the empirical error rates produced by the (inevitably finite) data set are within statistical fluctuation of the CPT long run guaranteed error rate.

Conclusion

This study outlines an objective method to associate primer shear striation patterns found on cartridge cases with the guns that generated them. Three-dimensional confocal microscopy, surface metrology, and multivariate statistical methods lie at the heart of our approach. Though the sample size was small, one can see how a surface metrological–statistical scheme could provide an investigative aid to firearm and tool mark examiners.

The specific statistical methods employed in this study were selected for their generality and low reliance on distributional assumptions of the underlying data. Bootstrap-based identification error rate estimates using SVMs for discrimination, were low. Using CPT at the 95% level of confidence, the empirical identification error rates were observed to be slightly higher that the long run (large data set) gaurantee if 5%. This is likely due to the relatively small sample of firearms used. Work is underway in our laboratory to significantly increase the size of our surface database in order to further test the approach described in this paper. Also, the procedures detailed in this study should be equally applicable to any set of striation marks made by other tools.

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References

AFTE. 1998. Theory of identification as it relates to toolmarks. AFTE J 30:86–88.

Bachrach B. 2002. Development of a 3D-based automated firearms evidence comparison system. J Forensic Sci 47: 1–12.

Bachrach B. 2006. A statistical validation of the individuality of guns using 3d images of bullets. National Institute of Justice, Grant Number: 97-LB-VX-0008.

Bachrach B, Jain A, Jung S, Koons RD. 2010. A statistical validation of the individuality and repeatability of striated tool marks: screwdrivers and tongue and groove pliers. J Forensic Sci 55:348–357.

Banno A. 2004. Estimation of Bullet Striation Similarity Using Neural Networks. J Forensic Sci 49:1–5.

Biasotti AA. 1959. A statistical study of the individual characteristics of fired bullets. J Forensic Sci 4:34–50.

Chu W, Song J, Vorburger T, Yen J, Ballou S, Bachrach B. 2010. Pilot study of automated bullet signature identification based on topography measurements and correlations. J Forensic Sci 55:341–347.

Chumbley LS, Morris MD, Kreiser MJ, Fisher C, Craft J, Genalo LJ, Davis S, Faden D, Kidd J. 2010. Validation of tool mark comparisons obtained using a quantitative, comparative, statistical algorithm. J Forensic Sci 55:953–961.

Daubert V. 1993. Merrell Dow Pharmaceuticals, 509 U.S. 579.

DeKinder J, Bonfanti M. 1999. Automated comparisons of bullet striations based on 3D topography. Forensic Sci Int 101:85–93.

DeKinder J, Tulleners F, Thiebaut H. 2004. Reference ballistic imaging database performance. Forensic Sci Int 140:207–215.

Digital Surf. 2010. Mountains [computer program], 5.1th edition. France: Besançon.

Duda RO, Hart PE, Stork DG. 2001. Pattern classification, 2nd edition. New York: Wiley.

Efron B. 1983. Estimating the error rate of a prediction rule: Improvement on cross-validation. J Am Stat Assoc 78:316–331.

Efron B, Tibshirani RJ. 1993. An introduction to the bootstrap, 1st edition. Boca Raton: Chapman & Hall/CRC.

Faden D, Kidd J, Craft J, Chumbley LS, Morris M, Genalo L, Kreiser J, Davis S. 2007. Statistical confirmation of empirical observations concerning tool mark striae. AFTE J 39:205–214.

Forensic Technology WAI Inc. 2001. Integrated ballistic identification system, Côte St-Luc, QC, Canada.

Geradts Z, Keijzer J. 1996. TRAX for Toolmarks. AFTE J 28:183–190.

Geradts Z, Keijzer J, Keereweer I. 1994. A new approach to automatic comparison of striation marks. J Forensic Sci 39:974–980.

Geradts Z, Keijzer J, Keereweer I. 1995. Automatic comparison of striation marks and automatic classification of shoe marks. Proceedings SPIE.

Geradts Z, Bijhold J, Hermsen R, Murtaugh F. 2001. Image matching algorithms for breech face marks and firing pins in a database of spent cartridges of firearms. Forensic Sci Int 119:97–106.

International Standards Organization. 2006. ISO/TS 16610-22:2006 Geometrical product specifications (GPS)—Filtration—Part 22: Linear profile filters: Spline filters.

Jolliffe IT. 2004. Principal component analysis, 2nd edition. New York: Springer.

Karatzoglou A, Smola A, Hornik K, Zeileis A. 2004. Kernlab—an s4 package for kernel methods in R. J Stat Software 11:1–20.

Moran B. 2002. A report on the AFTE theory of identification and range of conclusions for tool mark identification and resulting approaches to casework. AFTE J. 34: 227–235.

Nichols RG. 2007. Defending the scientific foundations of the firearms and tool mark discipline: responding to recent challenges. J Forensic Sci 53:586–594.

Petraco N. 2011. Color atlas of forensic tool mark identification, 1st edition. Boca Raton: CRC Press.

R Core Development Team. 2009. R: a language and environment for statistical computing [computer program], 2.9.1th edition. Vienna, Austria: R Foundation for Statistical Computing.

Sakarya U, Leloglu UM, Tunali E. 2008. Three-dimensional surface reconstruction for cartridge cases using photometric stereo. Forensic Sci Int 175:209–217.

Shawe-Taylor J, Cristianini N. 2004. Kernel methods for pattern analysis, 1st edition. London: Cambridge University Press.

Song J, Vorburger T, Renegar T, Rhee H, Zheng A, Ma L, Libert J, Ballou S, Bachrach B, Bogart K. 2006. Correlation of topography measurements of NIST SRM 2460 standard bullets by four techniques. Meas Sci Tech 17:500–503.

Theodoridis S, Koutroumbas K. 2006. Pattern recognition, 3rd edition. San Diego: Academic Press.

Thompson E, Wyant R. 2003. Knife Identification Project (KIP). Ann Firearm Toolmark Exam J (AFTE) 35:366–370.

Vapnik VN. 1998. Statistical learning theory, 1st edition. New York: Wiley.

Vorburger TV, Yen JH, Bachrach B, Renegar TB, Filliben JJ, Ma L, Rhee HG, Zheng A, Song JF, Riley M, Foreman CD, Ballou S. 2007. Surface topography analysis for a feasibility assessment of a national ballistics imaging database. National Institute of Justice, Grant Number: 2003-IJ-R-029.

Vovk V, Gammerman A, Shafer G. 2005. Algorithmic learning in a random world, 1st edition. New York: Springer.

Whitehouse DJ. 2004. Surfaces and their measurement, 1st edition. London: Butterworth-Heinemann.

Xie F, Xiao S, Blunt L, Zeng W, Jiang X. 2009. Automated bullet-identification system based on surface topography techniques. Wear 266:518–522.