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PAPER

PHYSICAL ANTHROPOLOGY

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Validation of Tool Mark Analysis of Cut Costal Cartilage*,†

ABSTRACT: This study was designed to establish the potential error rate associated with the generally accepted method of tool mark analysis of cut marks in costal cartilage. Three knives with different blade types were used to make experimental cut marks in costal cartilage of pigs. Each cut surface was cast, and each cast was examined by three analysts working independently. The presence of striations, regularity of striations, and presence of a primary and secondary striation pattern were recorded for each cast. The distance between each striation was measured. The results showed that striations were not consistently impressed on the cut surface by the blade's cutting edge. Also, blade type classification by the presence or absence of striations led to a 65% misclassification rate. Use of the classification tree and cross-validation methods and inclusion of the mean interstriation distance decreased the error rate to *c*. 50%.

KEYWORDS: forensic anthropology, tool mark analysis, cut marks, costal cartilage, method validation

Researchers have shown that the striation pattern impressed in costal cartilage during the creation of a cut mark is an adequate representation of the tool's cutting edge and can be used to identify class and individual characteristics of the tool (1–7). Bonte (1,2) focused his research on the variation in striation patterns made in costal cartilage by various types of cutting edges. He examined experimental cut marks made in costal cartilage with 12 morphologically different serrated knives and concluded that each blade resulted in a characteristic striation pattern (1). Watson examined impression evidence made from two consecutively manufactured Buck knives and found that each produced a unique striation pattern (4). Rao and Hart (5) compared a striation pattern observed in a costal cartilage cut mark to the striation pattern observed in test marks made with a suspect weapon and concluded "within reasonable scientific certainty" a match between the fine and coarse striae, which result from the class and individual characteristics of the tool. Based on the published research, the current generally accepted method of tool mark analysis in cut costal cartilage is to infer the type characteristics of a blade using the configuration of striations observed on the cut surface. The presence and organization of striations are the qualitative variables utilized during the analysis.

In spite of this research, the subjective association of a tool mark in costal cartilage with a particular knife has been ruled inadmissible as evidence (8). In *Ramirez v. State of Florida,* the Florida Supreme Court ruled that the state was aware of no scientific predicate in the literature for the specific theory used by the tool mark examiner in the case to identify a specific knife from a knife mark left in costal cartilage (8). The court suggested that the method used by the analyst in this case departed from the generally accepted method of tool mark examination significantly enough to make this particular method novel, and thus inadmissible. The distinction between the structural composition of costal cartilage relative to the traditional media to which tool mark methods are applied, the lack of photographic and written records associated with the method, and the consequent inability to test the theory were considered significant departures from the generally accepted tool mark methods that have been upheld in the courts. The method itself was deemed inadmissible in repeated retrials.

A series of recent Supreme Court rulings, including *Daubert v. Merrill-Dow Pharmaceuticals* (9), have developed and refined the criteria for the admissibility of expert testimony. The result is that the existing 1975 Federal Rules of Evidence (10) was chosen as the standard for the determination of admissibility of forensic testimony. The *Daubert* ruling provided the following as guidelines for use by the courts in evaluating expert testimony, that: (i) the theory is testable by the scientific method; (ii) it has been peer-reviewed; (iii) it is associated with an established reliability with a known error rate; and (iv) it is generally accepted within the relevant scientific community (10).

In light of the recent inadmissibility of tool mark analysis of cut costal cartilage specifically, and more generally the increased attention levied on expert testimony, we designed the following study with the purpose of validating the current method through independent testing and measurement of the potential error rate. The goals of the study are to evaluate: (i) the repeatability of the impressed striations by the blade into the cut costal cartilage and (ii) the probability of correctly classifying the blade type based on the striation pattern observed on the cut surface.

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Research Design

To test the repeatability of striations impressed into the costal cartilage by a tool's cutting edge, experimental cut marks were made using three knives with markedly different cutting edges: smooth, serrated, and micro-serrated. The smooth-edged knife was an 8″ Chef Knife of a Hampton Forge Epicure Cutlery Collection four piece cutlery set (Hampton Forge, LTD., Eatontown, NJ). The serrated-edged knife was a 5″ Serrated Utility Knife of a J.A. Henckels International four piece paring knife set (J.A. Henckels International, Hawthorne, NY). The micro-serrated-edged knife was an 8″ Chef knife of the Chefmate three piece knife set (Nestle Professional, Rogers, MN). No serrations were cut into the cutting edge of the smooth blade. A pattern of scalloped serrations with points measuring 4 mm apart was machined into the cutting edge of the serrated blade. A primary and secondary pattern consisting of 5-mm regions without striations separated by 7-mm regions with striations was machined into the cutting edge of the micro-serrated blade. The regions of striations consisted of linear ridges spaced 1 mm apart (see Figs 1–3).

The knives were unused prior to the study. Each knife was used to make 30 cut marks in the costal cartilage of pig spare ribs (*Sus scrofa).* Three portions of spare ribs were used; only one knife was used per portion. The spare ribs were placed on a penetrable surface, a Styrofoam cooler. Each knife was held perpendicular to the spare ribs then forced through the costal cartilage in a ventral to dorsal direction to generate the cut marks. The cut marks were made by an individual other than the analysts.

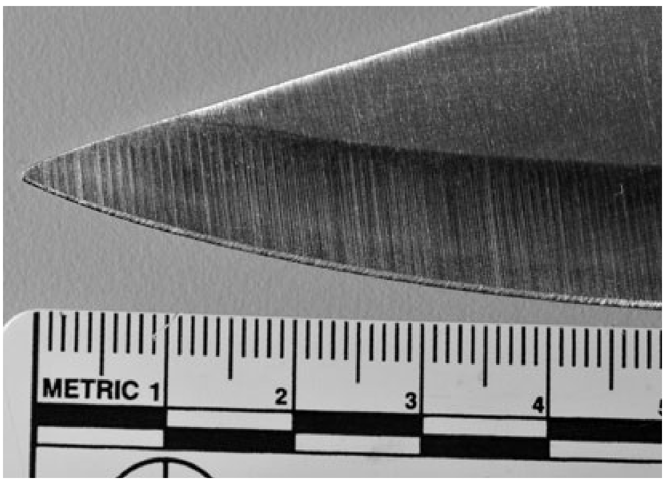

FIG. 1—*Smooth-edged blade (scale in cm). Note the linear defects along the beveled edge resulting from the machining of the blade.*

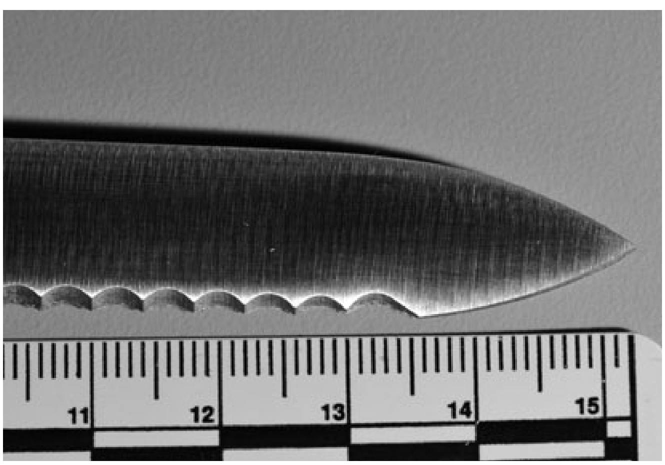

FIG. 2—*Serrated-edged blade (scale in cm).*

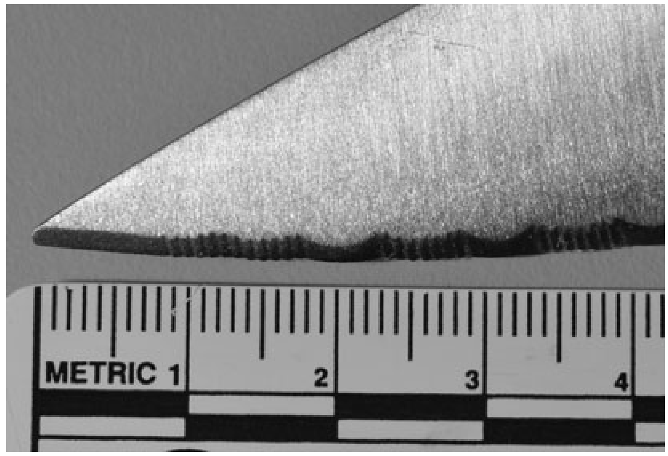

FIG. 3—*Micro-serrated-edged blade (scale in cm).*

To prepare the cut marks for analysis, a section of costal cartilage containing each cut mark was excised from the spare ribs and placed in 10% formalin solution for an extended period of time. A specimen number of 1–90 was randomly assigned to each cut mark. Once fixed, one analyst prepared each cut surface for casting. When the knife incompletely transected the cartilage, a scalpel cut was made at an acute angle from the tip of the cut mark through the uncut cartilage to open the two experimentally cut surfaces. The scalpel cut surfaces were scored to differentiate the processing cut surface from the experimental cut surface. Experimentally cut surfaces were cast with Mikrosil Casting Material (Kjell Carlsson Innovation, Sundbybberg, Sweden). Each cast was labeled with the specimen number and either A or B, corresponding to the two surfaces of each cut mark. The length and width of the cut surfaces were measured. Each cast was photographed using an Olympus DP72 digital camera attached to an Olympus SZXY Stereomicroscope (Olympus America Inc., Melville, NY). The magnification of the cast was dependent on the size of the cast and the field of view. The digital camera was calibrated daily.

Each cast was analyzed by three analysts. Each analyst was a doctorate level practicing forensic anthropologist who performs tool mark examination of cut costal cartilage during regular laboratory analysis. Each analyst examined the cut surface and recorded: (i) if striations were present; (ii) if the striations occurred at regular intervals; and (iii) if the striations were organized into a primary and secondary pattern. Striation was defined as linear marks that crossed the cut surface. Regular striations were defined as striations that appear to occur at regular intervals. Irregular striations were defined as striations that appear to occur at highly variable intervals. Primary and secondary striation pattern was defined as areas of regularly spaced striations separated by regular intervals devoid of striations. Prior to analysis, each variable was defined, and the definitions were discussed among the analysts to ensure full understanding. Each analyst was blind to the blade type at the time of the analysis.

Using the measurement function of the digital camera software (DP2-BSW; Olympus America Inc.), the analysts measured the distance between the striations. Expression of the striations throughout the cut surface was variable and ranged from well demarcated to

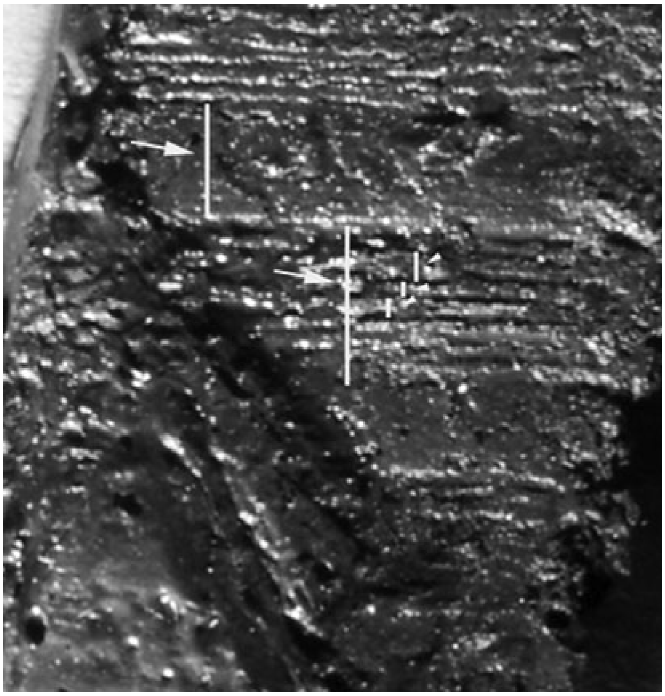

FIG. 4—*Photograph of the cast of the cut surface. The lines represent interstitial measurements.*

TABLE 1—*List and definitions of variables.*

Variable	Definition
Categorical variables	
Specimen	Specimen number and side designation (e.g., 82a or 82b)
Striations	Yes—two or more linear ridges or grooves cross the cut surface, No—one or no linear ridge or groove crosses the cut surface
Striation type	Regular—the striations occur at regular intervals; Irregular—the striations occur at irregular intervals; None—no striations are observed
Striation pattern	Yes—the striations are organized into a primary and secondary pattern; No—the striations are not organized into a primary and secondary pattern, or no striations are observed on the cut surface
Cut type	Yes—the costal cartilage was completely transected by the knife; No—the costal cartilage was incompletely transected by the knife
Blade type	The type of the blade used to create the cut mark: smooth, serrated, or micro-serrated. (This variable was added to the record after the analysis was completed.)
Numeric variables	
Interstriation distance	The distance between each striation measured in mm
Mean interstriation distance (MID)	The mean interstriation measurement found on a single cut surface.
Width	Width of the experimentally cut surface (mm)
Length	Length of the experimentally cut surface (mm)
Area	Length*Width of the experimentally cut surface (mm^2)

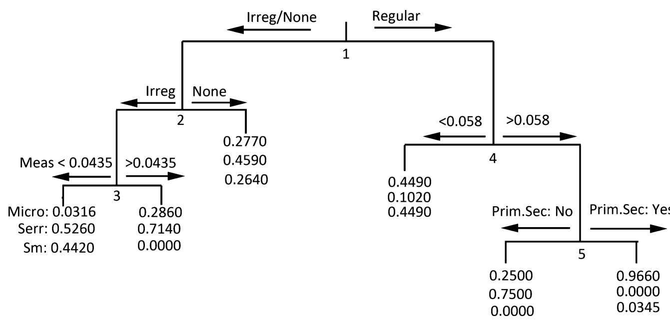

FIG. 5—*Classification tree modeled on variations' striation, striation type, striation pattern, and mean interstriation distance (MID). The classification tree is used to guide the analyst through the analytical process of identifying blade type based on striation configuration. The top Node 1 requires the analyst to decide if striations are present and if so are they regularly or irregulary spaced (None, no striations; Irreg, irregular striations; Regular, regular striations). Node 2 divides surfaces with irregular striation (Irreg) from surfaces devoid of striations (None). Node 3 and 4 divide surfaces based on MID. Node 5 divides surfaces based on striation pattern (Prim.Sec: No, primary and secondary striation pattern absent; Prim.Sec: Yes, primary and secondary striation pattern present). At each terminal node the probabilities of the cut surface resulting from each blade type are listed in order, from top to bottom, as micro-serrated, serrated, and smooth.*

barely perceivable. The analysts measured the interstriation distance between each striation he/she identified as well demarcated. When a primary and secondary pattern was observed, measurements were taken to capture the interstriation distance of both patterns (Fig. 4). The mean distance between the striations for each surface was identified, and the variable was termed mean interstriation distance (MID). The qualitative variable of primary and secondary striation pattern was not considered when establishing the MID. When no striations were present, the MID was recorded as zero. Table 1 lists and defines each variable.

Each analysis resulted in a record. A record consisted of the qualitative results of the examination: presence or absence of striations (striations); regularity or irregularity of the striations (striation type); and presence or absence of a primary and secondary striation pattern (striation pattern). Also included in each record were the MID, the length, width, and approximate area of the cut surface.

The data were then analyzed using classification trees constructed with the Tree library in the open-source data analysis package R (11). Misclassification rates were estimated by repeating a cross-validation procedure in which half the cut surfaces are randomly selected as training data for designing the classification tree and the remaining half are used as test data. The cross-validation procedure was repeated 500 times to obtain an empirical distribution of error rates. This should give a reasonably accurate picture of the distribution of error probabilities in classifying new data with training data sampled from knife blades similar to those used in the study.

First, a classification tree was developed that modeled all variables. The resulting tree included the variables: area, MID, length, striation type, width, and cut type, in order of importance. All other variables were excluded. The tree was then pruned from 29 to 24 terminal nodes (see Discussion for details regarding tree pruning). After pruning, the splitting branch immediately above 16 of the 24 terminal nodes was based on variables reflecting the dimensions of the cut surface: length, width, or area. A second classification tree was developed that modeled variables striations, striation type, striation pattern, and MID. The resulting tree included only the striation type and MID variables. The number of terminal nodes was six. This tree is shown in Fig. 5 as an example of the output of the classification tree methodology. It is not intended as a prescription for operational use.

To compare classification accuracy with interstriation measurements to accuracy without them, we used a cross-validation procedure. First, one analyst for each of the 180 cut surfaces was randomly selected. Using this subset of records, 500 replications of the cross-validation procedure were performed. The procedure randomly split the surfaces into two halves: the training surfaces and the test surfaces. The resulting test data consisted of 90 records. The classification tree was developed with the training data (training data included *c*. 270 records). Each record of the test data was passed down the tree and classified as belonging to the blade type that had the highest frequency at the terminal node of the tree. The procedure was repeated 500 times, and the misclassifications were counted.

Results

The study design resulted in 180 cut surfaces. Each analyst independently analyzed each cut surface. After deleting records with obvious data entry errors and one inadvertently overlooked cut surface by one analyst, the sample consisted of 535 records. Table 2 lists the occurrence of several categorical variables within the sample.

The first step of the analysis was to examine the accuracy of blade classification using the current accepted method of cut mark analysis. Following the current method, a cut surface was identified as correctly classified under the following circumstances. A surface was cut with a smooth blade and was found to have no striations or irregular striations. A surface was cut with the serrated blade and was found to have regular striations that were not organized into a primary and secondary pattern. A surface was cut with the micro-serrated blade and was found to have regular striations organized into a primary and secondary pattern. Based on these parameters, 66% of the cut surfaces were misclassified. The misclassification rate for each analyst was 65%, 66%, and 68%, respectively. Table 3 shows the variables on which the misclassifications were based by blade type and the percentage of the sample that was misclassified for each variable.

The second step was to evaluate the error rate of the blade type classification using the classification tree. A histogram of the misclassification results of the cross-validation procedure is shown as Fig. 6. Tables 4 and 5 summarize the empirical distributions of error rates obtained during the cross-validation procedure, and Figs 7 and 8 indicate that there is a small but real improvement in accuracy when MID is included among the classifying variables. In Figs 7 and 8, the nonoverlapping notches on the sides of the boxes indicate that the difference in medians is significant at the 5% level.

TABLE 2—*Occurrence of categorical variables.*

	Number of Records	Percent of Sample
Striations absent	159	29
Regular striations	260	49
Irregular striations	116	22
Primary/secondary pattern	80	15

TABLE 3—*Cut surface misclassification by blade type and variable.*

Blade Type	Variable and Percent of Inaccurate Classification
Smooth	Regular striations—51
	Primary and secondary pattern—22
Serrated	No striations—41
	Irregular striations—36
	Primary and secondary pattern—4
Micro-serrated	No striations—24
	Irregular striations—5
	Regular striations, no primary/secondary pattern—42

Discussion

The results of the study indicate a very high potential error rate when analyzing a cut mark in costal cartilage using the current generally accepted method. Striations were observed on nearly all the cut surfaces regardless of the blade type, 70%. Of the cut surfaces without striations, 42 were cut with the micro-serrated blade, 73 with the serrated blade, and 44 with the smooth blade. Contrary to current methods, the presence of striations was shown in this study not to be an informative variable. However, the serrated and micro-serrated blades have an 18- and 9-mm smooth-edged tip, respectively. Some of the surfaces cut with the serrated blade that lack striations may be explained by this nonserrated area. Furthermore, the striations observed on the surfaces cut with the smooth-edge blade most likely resulted from the defects along the beveled edge as a result of machining (Fig. 1).

The accuracy of the analysis improved when the classification tree method was used. The classification tree method is a well-established approach that when applied to these data enables an analyst to decide which blade type made a given cut surface or associate probabilities with each of the given blade types for a given cut surface. The decision or probability assessment is based on the observed values of variables such as those described earlier: striation pattern, striation type, and MID. These variables separately convey information about blade type. However, they leave open the question of how to optimally combine the variables to derive a decision rule or estimation procedure for new cases.

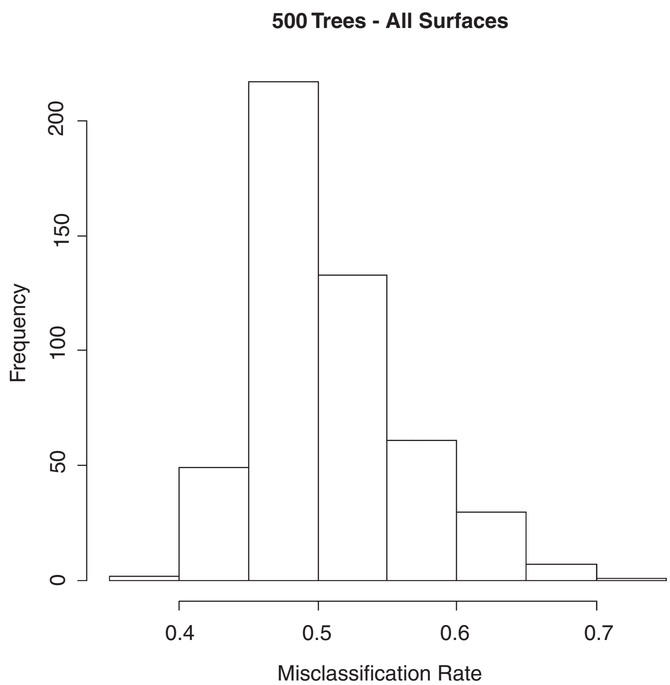

FIG 6—*Histogram showing the frequency of misclassification rates for the 500 repetitions of the cross-validation procedure. All surfaces, both with and without striations, are included.*

TABLE 4—*Error rates for the full data set (500 replications of cross-validation procedure).*

	Minimum	1st Quartile	Median	Mean	3rd Quartile	Maximum
W/Measurements	0.3226	0.4407	0.4754	0.4760	0.5106	0.6552
W/O Measurements	0.4375	0.5301	0.5574	0.5614	0.5934	0.7593

TABLE 5—*Error rates for surfaces with striations (500 replications of cross-validation procedure).*

	Minimum	1st Quartile	Median	Mean	3rd Quartile	Maximum
W/Measurements	0.3333	0.4386	0.4762	0.4777	0.5161	0.6935
W/O Measurements	0.4462	0.5312	0.5614	0.5630	0.5932	0.7213

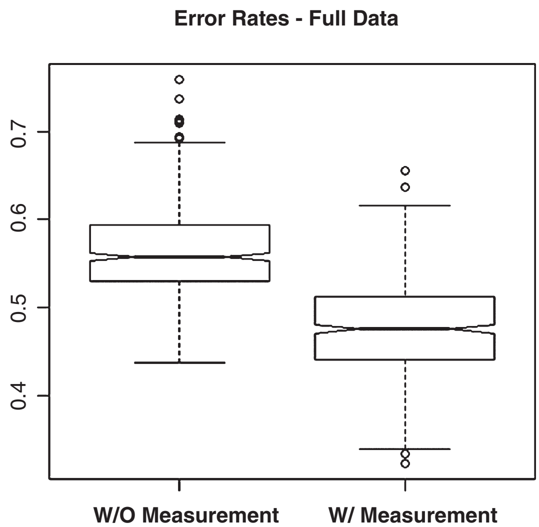

FIG. 7—*Box and whisker plots of the distributions of misclassification rates from 500 replications of a cross-validation procedure. All surfaces are included. The three horizontal lines in the central boxes mark the quartiles and the median. The whiskers extend to the most extreme value or to a distance of 1.5 times the interquartile range from the nearest quartile. Individual outliers above or below the whiskers are marked with circles. Nonoverlapping notches in the sides of the boxes indicate highly significant differences in the medians.*

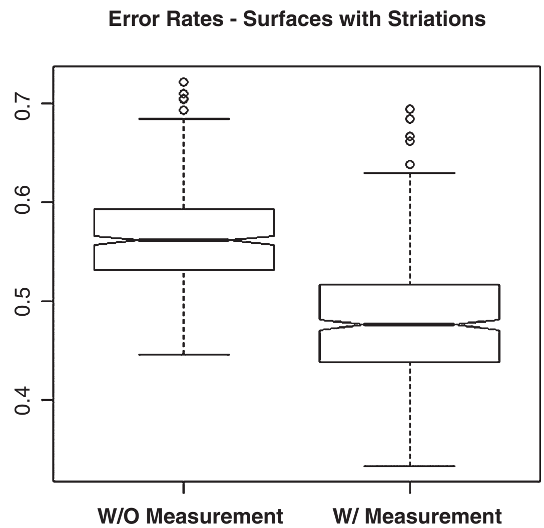

FIG. 8—*Box and whisker plots of the distributions of misclassification rates from 500 replications of a cross-validation procedure. Surfaces with striations only. The three horizontal lines in the central boxes mark the quartiles and the median. The whiskers extend to the most extreme value or to a distance of 1.5 times the interquartile range from the nearest quartile. Individual outliers above or below the whiskers are marked with circles. Nonoverlapping notches in the sides of the boxes indicate highly significant differences in the medians.*

The rapid development of classification and regression tree methods began with the paper by Breiman et al. (12). These methods are implemented in the tree library (13) of the open-source data analysis package R (11). Excellent discussions of the mathematical, statistical, and computational aspects of the classification tree procedures in R are given by Clark and Pregibon (14) and Venables and Ripley (15). For completeness, we briefly describe the main principles of binary tree construction.

Each classification tree begins with a root node, at which all the training values of the class response variable (in this case, the blade type) are collected. For simplicity, we shall assume that the number of levels of the class variable is three, as in the present case. In general, it could be any fairly small number. Let N denote the number of training cases, and let p_1, p_2, and p_3 denote the relative frequencies (empirical probabilities) of the classes at the root node. A measure of the uniformity of the distribution of classes at the node is the deviance.

$$D = -N \sum_i p_i \log p_i$$

The deviance has a minimum value of zero when all the training cases belong to the same class and a maximum value of $N \log 3$ when the proportions are all equal. The goal in constructing the tree is to obtain nodes as pure as possible with respect to the class membership of cases assigned to those nodes. Thus, small deviances are desirable.

Suppose the root node is split into two daughter nodes having N_1 and N_2 cases assigned to them. It can be shown that $D \geq D_1 + D_2$, where the terms on the right are the deviances at the daughter nodes.

$$D_j = -N_j \sum_i p_{ij} \log p_{ij}$$

Hence, the reduction in total deviance obtained by splitting the parent node is $D - D_1 - D_2$. The precise rule for the split depends on only one of the covariates, and it is chosen to achieve the greatest reduction in total deviance. For numeric covariates x, one daughter corresponds to the rule $x \leq c$ and the other corresponds to $x > c$, where c is a threshold value. For categorical covariates x, one daughter corresponds to a subset of the levels of x, and the other corresponds to the complementary subset. Starting with the root node, the tree is grown by splitting nodes until a stopping rule is encountered. The stopping rule can be a minimum size for nodes or a minimum reduction in total deviance.

After growing the tree, the common practice is to prune the least important terminal branches using a cross-validation procedure. This procedure aims at a compromise between complexity of the tree and classification accuracy and is a guard against overfitting. The hope is that the pruned tree will be more robust in classifying new data.

Finally, we mention that classification trees do not lend themselves to formal testing and estimation in the way that log-linear multinomial response models do, for example. The basic methodology of tree fitting involves almost no distributional assumptions. Validation of fitted trees usually depends on bootstrap or cross-validation methods.

The initial classification tree built on all the variables collected during the study resulted in a low misclassification rate, 12%. However, the tree directed the analyst to base the majority of the decisions on the dimensions of the cut surface. The authors were skeptical of the tree and felt that the dimensions of the cut surface reflected the size of the costal cartilage as opposed to the type of blade.

The second classification tree was constructed on all variables, except the variables that reflected the dimensions of the cut surface. The resulting tree excluded all variables except the striation type, striation pattern, and MID. The tree is shown in Fig. 5. The misclassification rate of the second tree was high (*c.* 50%), but the probabilities associated with each classification were informative.

Additionally, we elected to use the MID rather than the median interstriation distance. The interstriation distances were not normally distributed. However, the mean captured the large distances measured on the surfaces with primary and secondary striations better than the median. Also, we compared the median and the MIDs, and there was minimal difference between the two. In the end, we decided to use the mean, although the data were not normally distributed, because it better reflected the range of measurements observed on the cut surface.

An important note is that the classification tree included in this paper is created from the analysis of cut marks made from only three blades. The detail included in this publication as to how to utilize a classification tree is presented to thoroughly demonstrate the statistical analysis. The authors do not recommend the classification tree for operational use. The goal of the study was to evaluate the error rate associated with the method of tool mark analysis of cut marks in costal cartilage; it was not to develop a method or alter the current generally accepted method. The median interstriation distance appears to be a contributory variable to the tool mark analysis of costal cartilage cut surfaces, but a larger study must be conducted before the true value is appreciated.

The study results paint a cautionary tale of tool mark analysis of cut marks in costal cartilage. The results show that the current method of classifying a blade type based on the presence/absence and regularity of striations has a very high potential error rate. Following the current accepted method of tool mark analysis on cut costal cartilage led to a misclassification rate of 66% of the cut surfaces analyzed during the study. Using the tree classification method and including the MID increased the accuracy of the method, but the error rate remained high.

Conclusion

The application of current accepted method for tool mark analysis of cut costal cartilage resulted in >65% misclassification rate when applied to the study sample. The results indicate that serrations in the blade were not consistently impressed in the cut surfaces of costal cartilage as striations. Using the classification tree method and including the MID increased the accuracy of the analysis; however, the error rate remains around 50%.

Acknowledgments

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