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PAPER

ANTHROPOLOGY; ODONTOLOGY

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An Evaluation of Statistical Methods for the Determination of Age of Death Using Dental Root Translucency and Periodontosis

ABSTRACT: Lamendin and colleagues (1992) proposed to assess age-at-death from root translucency and periodontosis. Several teeth from the same individual were included in their study. In our work, we evaluate the reliability of their formulas without introducing this bias. Our sample was constituted of 214 individuals (114 males and 100 women) selected from the Terry collection (U.S.A.). The R^2 between age and both indicators is equal to 0.33 and 0.08 ($p < 0.001$). Based on linear regression, the mean of standard error for individual age prediction was equal to 13.67 years, and the mean interval length is equal to 53.89 years. Multinomial logistic regression and Bayesian approach failed to give satisfactory results when classifying the individuals in age categories. Therefore, the use of root translucency and periodontosis may lead to incorrect age-at-death assessment, and it is thus necessary to complement this approach with other techniques to assess age-at-death.

KEYWORDS: forensic science, root translucency, periodontosis, age-at-death, regression, Bayes theorem

Age-at-death assessment is an important issue in the identification of human remains, both in a forensic context and in anthropology. Teeth are the hardest organs in the human body; they are durable and sometimes the only evidence available.

For many decades, scientists depended on Gustafson's method to assess adult age-at-death using six dental features (gingival attachment level, transparency of the root apex, wear of occlusal surfaces, amount of secondary dentine, apposition of cementum, and resorption of the root). Modifications of this method were later proposed, including the technique of Lamendin and colleagues (1), which used two parameters easily measured on the dental surface: periodontosis and root translucency. Since its publication and despite subsequent criticism, this method is used commonly (2). The methodology is easy to apply and uses accessible and easily extracted single-rooted teeth that need no preparation. Moreover, the interobserver variability is low (1,3–5).

From a statistical point of view, however, the correlation between the combined features is poor. In the original publication of Lamendin et al. (1), R^2 reaches 0.33. Applying Lamendin's technique, Prince and Ubelaker (6) obtained an R^2 of 0.49 ($p < 0.001$). In both studies, several teeth of a single individual were included in the sample, introducing a non-negligible bias because of the violation of nonindependent observations hypothesis of linear regression. Gonzalez-Colmenares et al. (7) produced an R^2 value 0.488 from the multiple regression model for the new formula on a population of Colombian remains.

The aim of this study is to investigate the value of several statistical prediction systems relating root periodontosis and translucency and age-at-death using a single tooth: ordinary least squares regression, multinomial logistic regression, and Bayesian method. We also consider the relation between the two dental criteria separately considering age and sex.

Material

The osteological material used has been described in the study of Martrille et al. (8): 214 skeletons from the Terry Collection were examined (114 males and 100 females). This skeletal series is housed at the National Museum of Natural History, in Washington, D.C. The collection was developed between 1900 and 1965, and consists of over 1600 disarticulated individuals of known sex, age-at-death, and in most cases, cause of death. Most of the specimens have a nonquestionable age-at-death, and we excluded specimens with a question mark after the indicated age in the collection. However, in a few cases, specific date of birth was not know by the next of kin, and most likely age estimations were made. This is demonstrated in the Terry Collection by the presence of spikes in the "multiple of 5" age categories (9). Excluding individuals, as far as possible, reduces the significance of this artifact from collecting.

Because root translucency develops later in life, this method cannot be used with young individuals (2,8). The known age ranges varied between 26 and 91 years, with an average age 53.1

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(standard deviation: 16.7). Thirty percent were between 26 and 40 years old, 35% from 41 to 60 years old, and 35% between 61 and 91 years old.

The consideration of ancestry population affinities (previously referred to as "race") is a question that one must face when developing methodologies for age-at-death assessment. If cranial and infracranial variation in different groups living under different biocultural conditions through time and space is a reality, it is a far more complex matter than simply clustering individuals into several ethnic categories or by continent. A racial approach "ignores the heterogeneous pattern of phenotypic variation in the highly plastic species *H. sapiens*. It runs contrary to the genetic evidence that there is a great deal of genetic homogeneity in this species. It ignores that both phenotypic and genotypic variations are continuous" (10, p. 309).

Furthermore, a second aspect should be pointed out. It has been demonstrated that rates of age-related changes in both root translucency and periodontosis vary among population samples from different geographic regions (4,7,11,12). The interpretation of those results focuses on difference between populations suggesting that specific population standards may provide higher reliability. The low correlation coefficients between age and the two dental criteria reflect the marked variation in biological aging changes in the teeth of different individuals. Thus, it is difficult to state whether the variation observed comes from inter- or intra-population variability (13). Moreover, when a skeleton is discovered and identified in the legal context, the attribution to a specific population is far from being reliable as demonstrated in several recent studies (10,14,15). As a consequence, if ancestry is not available, general standards should be applied. In the present study, "white" and "black" individuals were pooled together.

Methods

Dental Criteria and Measurements

Because of degeneration of the soft tissues surrounding the tooth, gingival regression progresses from the neck to the apex of the root. Periodontosis is defined as the maximum distance between the cementoenamel junction and the line of soft tissue attachment.

With aging, normal dentin is altered to form what is known as transparent or sclerotic dentin. The tubules gradually fill up with a mineral phase over time, beginning at the apical end of the root and often extending into the coronal dentin (16). Transparency of the root is because of the deposit within dentin tubules of hydroxyapatite crystals. It corresponds to the maximum height of this feature measured on the labial surface on the tooth from the apex. Root height is the distance between the apex of the root and the cementoenamel junction.

Measurements were carried out using a square caliper. Each measurement (periodontosis, translucency, root length) was made on the same side of each tooth as it is recommended in the Lamendin's method (1). Use of the root translucency index (*100/root length) and root periodontosis index (*100/root length) compensates for differences because of tooth position or variation in root length (17). T and P denote respectively root translucency and root periodontosis.

Statistical Approach

All statistical tests and estimations were computed with SAS® Software (version 9.1; SAS Institute Inc., Cary, NC), specifically through use of the following procedures: PROC TTEST, PROC GLM, PROC REG, and PROC LOGISTIC.

To test whether the mean of different dental characteristics is determined by sex, Student's *t*-tests were performed. Several estimation methods were used to take into account the correlation between the two criteria and age-at-death: ordinary least squares regression, multinomial logistic regression, and Bayesian approach. For each analysis, estimations were first made for the whole sample and then according to sex.

For the ordinary least squares regression, the Lamendin's method was applied to the study sample.

For the multinomial logistic regression, we wanted to transpose Lamendin's methodology with the two criteria into a qualitative dependent variable model. We first conducted an ordinal logistic analysis using cumulative logits where the dependent variable represents the age group into three homogeneous categories: <41 years old, between 41 and 60 years old, and 61 or older, as proposed by Martrille and colleagues (8) who tested the Lamendin's technique on the same sample. The *p*-value for the score test of the proportional odds assumption performed by the LOGISTIC procedure was equal to 0.089 and led us to reject the parallel regression assumption at the 10% level. This test being anticonservative (because it too often rejects the assumption) (18), we compared the ordinal model (where the modeled probability was the fact of being in a higher age group) with the two binomial models to determine whether the slopes were meaningfully different. For P, the slope changes direction. Thus, a multinomial logistic regression was performed. In such a model, $P(y_i = j|x_i)$ refers to the probability of obtaining the response value j for the i_{th} response and j_0 refers to the reference category. The predicted probability for each category of the dependent variable can be written as follows:

$$P(y_i = j|x_i) = \frac{e^{(\beta_j' x_i)}}{1 + \sum_{k \neq j_o} e^{(\beta_k' x_i)}} \forall j \neq j_o$$

$$P(y_i = j_o|x_i) = \frac{1}{1 + \sum_{k \neq j_o} e^{(\beta_k' x_i)}}$$

where the vector $\beta_{i0} = 0$.

In our study, multinomial logistic regression compares the highest age group with the lowest one (<41 years old) and the middle age group with the lowest one.

We noted that the proportion of well-classified events was slightly higher in the multinomial logistic regression (54.7% versus 50.9% in the ordinal logistic regression). The Akaiké's information criterion (AIC), computed as *-2 (log-likelihood) +2* (number of estimated parameters in the model)* where the number of estimated parameters in a multinomial logit model is equal to $k(s + 1)$—where k is the total number of response levels minus one, and s is the number of explanatory effects—allowed us to compare different models. As a lower AIC indicates a better model fit, the retained model is the multinomial logit model with the two dental criteria. In each version of the model, two generalized R^2 measures, because of Cox and Snell, and Nagelkerke for the fitted model are supplied. To evaluate the predictive ability of the model, we have been led to compare predicted probabilities and observed probabilities. More precisely, we computed the individual predicted probabilities and chose the predicted category with the highest probability. Then, we could obtain well-classified events rates.

Bayes theorem is commonly used in forensic science (19–21). We applied a Bayesian prediction for individual age-at-death assessment on the two dental criteria. To calculate posterior probabilities, each of the two dental criteria was divided into quartiles;

therefore, we obtained two-four-class homogeneous size indexes. Table 1 gives the thresholds used to divide each of these two criteria into four categories. Figure 1 shows the mean age within each category for both indexes.

The use of Bayes theorem led us to calculate the probability that an individual belongs to age category I after taking into account both prior information (e.g., the probability of an individual belonging to a defined age group given no information from the reference sample and observed evidence from the indexes variables).

Let I be the number of categories of the variable age group (AG), J be the number of classes of the root translucency rate index, and K be the number of classes of the root periodontosis rate index.

$$\forall i \in \{1, ..., I\}, \forall j \in \{1, ..., J\}, \forall k \in \{1, ..., K\} :$$

$$\mathrm{P}(age \in AG_i | \{T = j; P = K\}) = \frac{p(\{T = j; P = k\} | age \in AG_i) \times p(age \in AG_i)}{\Sigma_{i=1}^{I} p(\{T = j; P = k\} | age \in AG_i) \times p(age \in AG_i)}$$

In our case, J = K = 4.

Results

Descriptive Statistics

The descriptive statistics of the Terry Collection study sample are shown in Table 2. We found no evidence of a significant difference in T and P between men and women at the 5% level (Table 3). Descriptive statistics reveal that root translucency rate increases with age and show a smaller tendency for P to increase with age (Fig. 2).

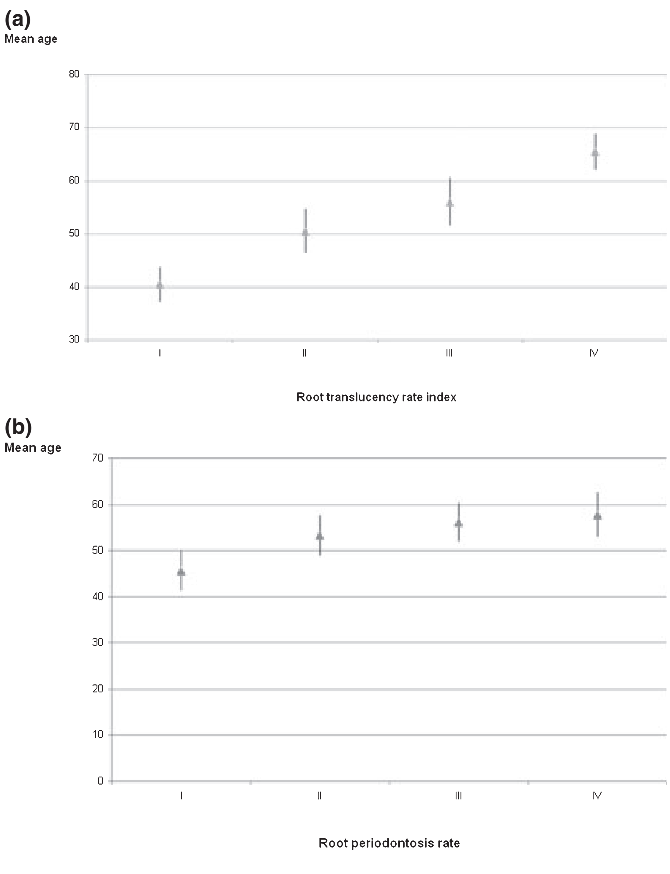

FIG. 1—*a. Mean of age-at-death depending on root translucency rate index; for each index, an ANOVA test was performed and showed a significant statistical difference in mean age (p < 0.001) between the four groups. b. Mean of age-at-death depending on root translucency rate index; for each index, an ANOVA test was performed and showed a significant statistical difference in mean age (p < 0.001) between the four groups.*

TABLE 1—*Supplementary criteria characteristics.*

	Min	Max	First Quartile	Median	Third Quartile	Interquartile Interval
Root translucency rate	10.7	88.9	38.5	51.5	64.0	25.5
Root periodontosis rate	0.0	48.4	13.5	17.2	22.2	8.7

TABLE 2—*General characteristics of the study sample (n = 214).*

	Min	Max	Mean	Standard Deviation	Median
Age-at-death (years)	26	91	53.1	16.7	52.0
Translucency height (mm)	1.5	20	7.8	3.0	7.5
Periodontosis height (mm)	0	8	2.7	1.2	2.5
Root translucency rate	10.7	88.9	51.2	17.3	51.5
Root periodontosis rate	0	48.4	18.1	7.9	17.2

TABLE 3—*Comparison of means depending on gender or group.*

Characteristic	Total (n = 214)	Men (n = 114)	Women (n = 100)	p*
Age-at-death (years)	53.1 (16.7)	55.4 (17.8)	50.45 (15.2)	0.032
Translucency height (mm)	7.8 (3.0)	8.0 (3.4)	7.5 (2.6)	0.226
Periodontosis height (mm)	2.7 (1.2)	2.9 (1.4)	2.6 (1.0)	0.069
Root translucency rate	51.2 (17.3)	50.5 (18.4)	52.0 (16.0)	0.529
Root periodontosis rate	18.1 (7.9)	18.2 (8.6)	17.9 (7.0)	0.755

*p-value associated with Student's t-test, standard deviation in parenthesis.

Estimation Strategies

Our main results for each of the three proposed estimation strategies can be summarized as follows. In the ordinary least squares regression, the squared correlation coefficient R^2 between age and the T (resp. age and P) is equal to 0.33 (resp. 0.08), with a p-value <0.001.

The following equation was obtained:

$$Age = 20.591 + 0.516T + 0.336P$$

Judging by Table 4 results, the two dental criteria clearly appear to be statistically positively associated with age. Each supplementary point of T (resp. point of P) contributes to increase the age-at-death. However, the model does not seem to be reasonable. The scatter plot of residuals against the dependent variable age (Fig. 3) highlights the tendency of this model to overestimate the age of young adults and to underestimate one of the older age group. A comparison between chronological age and calculated age from the analogous Lamendin's method, among the three age groups, confirms this remark. For the group below 41 years old, the estimated age was indeed significantly overestimated by more than 12 (p < 0.001), and for the group above 60 years old, the estimated age was significantly underestimated by 12 (p < 0.001). On the other hand, among individuals aged between 41 and 60, there was no evidence of significant difference between the chronological age and the estimated age (p = 0.382). Moreover, the mean of the

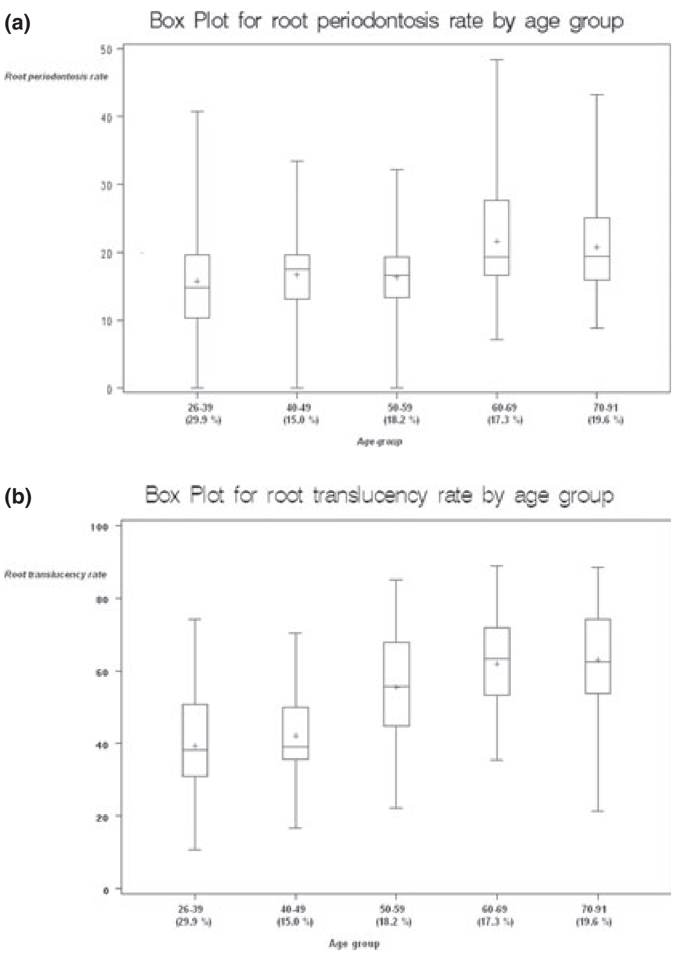

FIG. 2—*a. Box plot for root translucency rate and periodontosis rate, by age group. Groups means are depicted by crosses. b. Box plot for root translucency rate and periodontosis rate, by age group. Groups means are depicted by crosses.*

standard error of individual prediction coming from our sample was equal to 13.67 and the mean interval length is equal to 53.89.

In Table 5, the multinomial logistic model with the two dental criteria is compared with analog models with only one dental criterion. In this model, the global p-value of T was lower than 0.001 and the one associated with P was equal to 0.002, indicating that these variables are significantly related to age-at-death. We see that T has a quite large and statistically significant effect on the odds ratios comparing the fact of being in the higher age group to the lowest (OR = 1.114 per each percentage point of root translucency rate; $p < 0.001$). The retained model is presented in model (3) of Table 5. In part (1) of this table, it is interesting to notice the large

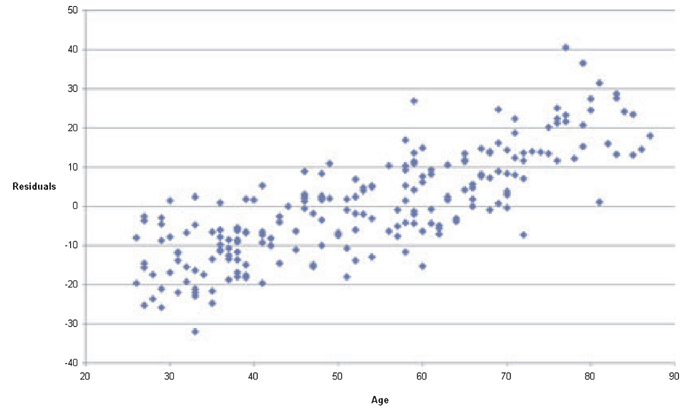

FIG. 3—*Scatter plot of residuals against the dependent variable age. Residuals are defined as the difference between observed values and predicted values.*

p-value associated with the second dental criterion; it indicates insufficient evidence to reject the null hypothesis that P has no significant effect on the age-at-death. In part (2), such a criterion has a significant effect on the probability of being aged more than 61 compared to people aged >40. Table 5 shows that, for the same value of P, a person with a supplementary single unit change of T for the first criterion, is 11.4% more likely to be in the highest category than the lowest one. A change of 10 points of percentage in the root translucency rate variable multiplies by 1.73 ($=e^{0.055\times10}$) the chances of being in the middle age category rather than the lowest category and by $2.95 = (e^{0.1083\times10})$ those of being in the highest category rather than the lowest category.

Resolution of multinomial logit equations led us to the following predicted probabilities formulas:

$$p(26 \leq ageatdeath \leq 40) = \frac{1}{1 + e^{(-2.3249+0.055\times T+0.00065\times P)} + e^{(-7.0787+0.1083\times T+0.0915\times P)}}$$

$$p(41 \leq ageatdeath \leq 60) = \frac{e^{(-2.3249+0.055\times T+0.00065\times P)}}{1 + e^{(-2.3249+0.055\times T+0.00065\times P)} + e^{(-7.0787+0.1083\times T+0.0915\times P)}}$$

$$p(61 \leq ageatdeath \leq 91) = \frac{e^{(-7.0787+0.1083\times T+0.0915\times P)}}{1 + e^{(-2.3249+0.055\times T+0.00065\times P)} + e^{(-7.0787+0.1083\times T+0.0915\times P)}}$$

The global p-value of T for men (respectively for women) was lower than 0.001 (resp. <0.001) and the one associated with P was equal to 0.002 (resp. 0.301). The two criteria have nearly the same

TABLE 4—*Ordinary least squares (OLS) estimation of age-at-death (*n *= 214).*

	Whole Sample (N = 214)			Men (N = 114)			Women* (N = 100)		
	Coefficient	95% CI	p	Coefficient	95% CI	p	Coefficient	95% CI	p
Constant	20.591	[14.128; 27.055]	<0.001	20.934	[12.799; 29.070]	<0.001	22.013	[11.554; 32.473]	<0.001
Root translucency rate	0.516	[0.407; 0.625]	<0.001	0.510	[0.363; 0.658]	<0.001	0.519	[0.358; 0.679]	<0.001
Root periodontosis rate	0.336	[0.096; 0.576]	0.006	0.476	[0.160; 0.792]	0.003	0.083	[−0.283; 0.448]	0.655
R^2	0.345			0.415			0.303		
Adjusted R^2	0.343			0.404			0.288		

*Because of the null hypothesis that the errors were homoscedastic is rejected at 5% level (p = 0.014), this model must be interpreted with caution.

TABLE 5—*Different multinomial logistic models of estimated age group (*n *= 214), adjusted odds ratios.*

	Aged 41–60 Years Versus <41* (1)				More Than 61 Years Versus <41* (2)					
	Estimated Parameter	OR	95% CI	*p*	Estimated Parameter	OR	95% CI	*p*	Global *p*	AIC
Model 1										
Root periodontosis Rate	0.0177	1.018	[0.970. 1.068]	0.47	0.1027	1.108	[1.053. 1.166]	<0.001	<0.001	454.9
Constant	−0.1445									
Model 2										
Root translucency rate	0.0548	1.056	[1.029; 1.084]	<0.001	0.1092	1.115	[1.081; 1.150]	<0.001	<0.001	402.8
Constant	−2.303				−5.3938					
Model 3										
Root translucency rate	0.0550	1.057	[1.029; 1.084]	<0.001	0.1083	1.114	[1.080; 1.250]	<0.001	<0.001	392.3
Root periodontosis rate	0.00065	1.001	[0.952; 1.052]	0.98	0.0915	1.096	[1.033; 1.162]	0.002	<0.001	
Constant	−2.3249				−7.0787					

*Reference category.
AIC, Akaiké's information criterion.

TABLE 6—*Multinomial logistic regression (*n *= 214), according to sex, adjusted odds ratios.*

	Aged 41–60 Years Versus <41*			More Than 61 Years Versus <41*		
	Total (N = 214)	Men (N = 114)	Women (N = 100)	Total (N = 214)	Men (N = 114)	Women (N = 100)
Root translucency rate	1.057†	1.072†	1.047‡	1.114†	1.125†	1.119†
Root periodontosis rate	1.001	1.011	0.989	1.096†	1.125†	1.054
Generalized R^2	0.34	0.41	0.29			
Max-rescaled R^2	0.38	0.46	0.33			

*Reference category.
†Significant at 1% level.
‡Significant at 5% level.

effect for men (an odds ratio equal to 1.125) on the probability to be in the highest age category rather than the lowest. For women, there is no evidence that P has a significant effect on the probability to be in the highest category (resp. middle category) rather than the lowest one. Multinomial logistic models on female subsample and male subsample are presented in Table 6.

Concerning the predictive ability of the model, the proportion of well-classified events is equal to 54.7% in the whole sample, 60.5% among men, and 51% among women. It is also useful to know how well the predicted values match the actual values. It is also useful to know how the discordant results are discordant. We compared the predicted age group (that is, the age group with the highest predicted probability) with the actual age group; it is obvious that the model predicts reasonably well for the highest age group but not that well for the middle age group (a little more than one-third is well classified). Table 7 shows that a multinomial logistic analysis should help to get a better prediction for men than for women (a difference of nearly 10%). In addition, the generalized R^2 is greater on men subsample than on women subsample.

Bayesian approach results are given in Tables 7 and 8. First, posterior probabilities were computed on the whole sample (Table 8). For example, on the whole sample an individual with a combining indicator equal to III-III has a 46.2% chance of being aged between 41 and 60, a 38.5% chance of being aged between 61 and 91, and only a 15.4% chance of being aged <41. But, as it would have been incorrect to make estimates for individuals, who also appeared in the reference sample, we used a Jackknife re-sampling strategy (22). Each individual was removed in turn when its

TABLE 7—*Proportion of well-classified individuals: results coming from multinomial logistic regression and Bayesian approach, according to gender and age group.*

	Total (N = 214)	Men (N = 114)	Women (N = 100)
		Multinomial logistic regression	
Whole sample	54.7%	60.5%	51.0%
<41 years	58.5%	58.1%	58.8%
[41–60] years	37.3%	42.2%	36.8%
More than 61 years	68.9%	76.1%	60.7%
		Bayesian approach	
Whole sample	42.5% (13.6%)*	44.7% (14.9%)	41.0% (16.0%)
<41 years	44.6% (9.2%)	45.2% (12.9%)	52.9% (20.6%)
[41–60] years	20.0% (20.0%)	10.8% (16.0%)	26.3% (7.9%)
More than 61 years	64.4% (6.8%)	71.7% (15.2%)	46.4% (21.4%)

*Proportion of not classified individuals is in parenthesis.

TABLE 8—*Posterior probability distribution and estimation computed on the whole sample, men sample, and women sample.*

Combining indicator (T and P)	Whole Sample (N = 214)				Men (N = 114)				Women (N = 100)			
	26–40	41–60	61–91	Estimation	26–40	41–60	61–91	Estimation	26–40	41–60	61–91	Estimation
I–I	0.737	0.263	0.000	26–40	0.769	0.231	0.000	26–40	0.667	0.333	0.000	26–40
I–II	0.533	0.267	0.200	26–40	0.500	0.125	0.375	26–40	0.571	0.429	0.000	26–40
I–III	0.400	0.600	0.000	41–60	0.200	0.800	0.000	41–60	0.600	0.400	0.000	26–40
I–IV	0.700	0.300	0.000	26–40	0.667	0.333	0.000	26–40	0.750	0.250	0.000	26–40
II–I	0.333	0.600	0.067	41–60	0.500	0.500	0.000	26–40 or 41–60	0.143	0.714	0.143	41–60
II–II	0.429	0.500	0.071	41–60	0.429	0.571	0.000	41–60	0.429	0.429	0.143	26–40 or 41–60
II–III	0.182	0.455	0.364	41–60	0.000	0.500	0.500	41–60 or 61–91	0.286	0.429	0.286	41–60
II–IV	0.231	0.231	0.538	61–91	0.000	0.250	0.750	61–91	0.600	0.200	0.200	26–40
III–I	0.400	0.267	0.333	26–40	0.286	0.286	0.429	61–91	0.500	0.250	0.250	26–40
III–II	0.333	0.250	0.417	61–91	0.000	0.333	0.667	61–91	0.667	0.167	0.167	26–40
III–III	0.154	0.462	0.385	41–60	0.200	0.200	0.600	61–91	0.125	0.625	0.250	41–60
III–IV	0.214	0.214	0.571	61–91	0.250	0.125	0.625	61–91	0.167	0.333	0.500	61–91
IV–I	0.000	0.500	0.500	41–60 or 61–91	0.000	0.667	0.333	41–60	0.000	0.333	0.667	61–91
IV–II	0.000	0.385	0.615	61–91	0.000	0.429	0.571	61–91	0.000	0.333	0.667	61–91
IV–III	0.050	0.350	0.600	61–91	0.000	0.333	0.667	61–91	0.091	0.364	0.545	61–91
IV–IV	0.000	0.143	0.857	61–91	0.000	0.100	0.900	61–91	0.000	0.250	0.750	61–91

posterior probabilities were calculated on the basis of the other cases. In Table 7, the proportions of well-classified, misclassified or nonclassified individuals obtained from the jackknife re-sampling strategy are given.

Like the multinomial logistic model, a well-classified individual means that the highest posterior probability corresponds to the interval including age. A nonclassified individual corresponds to the case where the highest of the three posterior probabilities is obtained for more than one age category (these ones have exactly the same posterior probability). Like the multinomial logistic model, the Bayesian approach seems to predict reasonably well for the highest age group with at least 64.4% of well classified on the whole sample and at least 71.7% on men sample.

Discussion

While comparison between sexes failed to show any significant difference, there was a clear effect on age estimation on a sample of the same osteological collection (6). On the French population on which the method was developed, Lamendin and colleagues (1) found no statistical difference between sexes. Similarly, on Spanish and Colombian samples, Gonzalez-Colmenares et al. (7) found no difference. This discrepancy between results may be related to a lack of statistical power on the samples showing no significant difference.

Root translucency increases with age but periodontosis shows a smaller tendency. This difference was also noted in the other studies (1,7). It is well established that periodontosis has no correlation with chronological age in when periodontal disease is present (3). Periodontal disease is the result of several factors, including exposure to oral bacteria, physiological response to those bacteria, and tissue structure. There is evidence that some of the inter-individual variations have a genetic basis (23). As a consequence, this pathology constitutes a major bias in age assessment with the Lamendin's method. Thus, although it plays an important role, periodontal disease is not taken into account in this method.

The relation between age and root transparency varies from one population to another. The R^2 extends from 0.40 to 0.9 (4,7,11,12).

The results obtained by multiple linear regression show a low adjusted R^2 (0.34), as observed in other studies in which the value varies between 0.33 and 0.49 (1,6,7). The mean error in this study was as high as 13.7 years whereas another sample of the collection, including several teeth of the same individuals, gave a mean error of 8.11–11.9 years (6) and 10 years in the initial study on a French population (1). Besides, for example, if we focus on an individual with average characteristics, the prediction interval coming from the above fitted model is equal to [26.3; 79.9]. Large age ranges are also produced when useful phase-aging method is used (Suchey-Brooks female Phase V: 25–83 years, male Phase VI: 34–86 years; 24).

Based on our sample, established equations for the determination of age-at-death tend to overestimate the age of young adults, and underestimating one of older individuals known as the "mean attraction" typical of the linear regression with low R^2 (25,26).

In their article in 1990, Lamendin and colleagues argued that it was impossible to determine a prediction interval around a predicted value in multiple regressions. To test the reliability of their technique, they calculated the mean error between actual and estimated age for the whole sample as well as for each decade. Many tests on known age and sex samples of Lamendin's method used this approach (6–8,27). Statistical software has developed considerably in the last 15 years; today, with SAS 9.1 software, for example, the limits of the confidence interval for an actual individual response can be obtained and it is even possible to generate them for new individuals. We observed that the confidence interval around the predictive value could reach as much as 54 years. In death investigation, experts should keep this parameter in mind when considering the accuracy of the prediction. To avoid false exclusions in forensic practice, anthropologists and pathologists should avoid narrow age ranges and prefer reliable chronological interval (8).

Multinomial logistic regression let us classify individuals into three age categories : <41 years, 41–60 years, and >60 years. Only 55% of the subjects were properly classified, 10% of men being more accurately classified than women. Classification was most accurate in the oldest age group. This statistical model allows us to avoid the frequent underestimation of age of older individuals that typically results from linear regression.

There are alternatives to regression analysis. If the probability is not evenly distributed about the mean, the regression has to adopt a wider confidence interval whereas Bayesian prediction gives age ranges which vary according to the empirical case-by-case approach to the estimation of error (19).

However, the results obtained by this nonparametric approach did not provide satisfactory results when compared to the multinomial logistic regression. It may be related to the transformation of quantitative data into an ordinal scale which results in loss of information. However, the individuals for which age is included in the proper category are those belonging to the ">60 years." Accuracy in classification was significantly higher in the male group than in the female group. In a recent publication (28), the authors applied the Bayesian analysis on a Balkan population. They found that the Bayesian approach offered the most appropriate statistical analysis for their sample. They determined that there was a significant difference between real and estimated age, with an absolute mean error of 9.01 years. Consistent with our findings, they demonstrated that application of the Bayes theorem tended to minimize age underestimation in older individuals. However, as their statistical criteria were different from ours, the results between their study and ours cannot be compared in more detail.

Conclusion

Our goal was to establish a new formula to assess age-at-death by evaluating root translucency and periodontosis using a single tooth, instead of including several teeth of the same subject in the sample of reference as Lamendin et al. (1) and Prince and Ubelaker (6) did in their respective studies. Whereas our results show that the correlation between the two associated criteria and age is low, when linear regression is applied, the mean of the standard error of individual prediction is 13.67 years which is slightly higher than the results of Lamendin et al. (1), Prince and Ubelaker (6), and Prince and Konigsberg (28). Other statistical prediction tools—the multinomial logistic regression and the Bayesian method—were utilized. The percentage of individuals correctly classified into the three age groups is higher with the parametric approach, but is still unsatisfactory in comparison with results derived by the linear regression. The main drawback of the two dental criteria we studied is the low correlation between both indicators and age. Besides, the variation in the biological aging process has profound effects on age-at-death assessment. However, the simplicity and rapidity of the method make it a useful tool for quick estimation at the autopsy table, or in mass disaster situations, and we recommend it in current practice. However, while analysis based on root translucency and periodontosis is still useful in the forensic setting, particularly for individuals between 40 and 60 years old (2), it should be complemented by a strong clinical experience to obtain reliable results.

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