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Age estimation by assessment of pulp chamber volume: A Bayesian network for the evaluation of dental evidence

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Abstract

Purpose: The present study aimed to investigate the performance of a Bayesian method in the evaluation of dental age-related evidence collected by means of a geometrical approximation procedure of the pulp chamber volume. Measurement of this volume was based on three-dimensional Cone Beam Computed Tomography images.

Methods: The Bayesian method was applied by means of a probabilistic graphical model, namely a Bayesian network. Performance of that method was investigated in terms of accuracy and bias of the decisional outcomes. Influence of an informed elicitation of the prior belief of chronological age was also studied by means of a sensitivity analysis.

Results: Outcomes in terms of accuracy were adequate with standard requirements for forensic adult age estimation. Findings also indicated that the Bayesian method does not show a particular tendency towards under- or overestimation of the age variable. Outcomes of the sensitivity analysis showed that results on estimation are improved with a ration elicitation of the prior probabilities of age.

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1 Introduction

In the last few decades, the age estimation of living individuals has gained considerable importance in forensic science, mainly due to its usefulness in legal issues involving sub-adults. However, adult age assessment is equally fundamental for older adult individuals, especially in cases of specific civil proceedings [1-3]. Age estimation in adults is more complex with respect to growing subjects, whose developmental stages are much more pronounced and detectable than the degenerative processes that have to be studied in adults [4]. In this regard, the pulp-dentinal complex is one of the dental structures that show a regressive phenomenon due to aging [5]. This involves the reduction of the pulp chamber volume caused by the continual deposition of secondary dentin secreted over the years by the odontoblast along the pulp chamber walls [6]. The assessment of such regressive phenomena in teeth is actually problematic in living subjects, since most techniques require tooth extraction or section [7-10]. To cope with this constraint, a panoply of conservative imaging techniques has been proposed in scientific literature and many of these techniques involve a radiographic examination of the dentition [11-17]. Recently, an innovative method to quantify the pulpal chamber volume from a dental modeling based on 3D Cone Beam Computed Tomography (CBCT) analysis has been introduced [5]. The method uses a geometrical approximation of the different parts of the tooth, namely root, pulp and crown, which can be assimilated to elliptical based cones (root and pulp) or elliptical based truncated cones (crown). This allows a quick evaluation of the volumes of interest on the examined tooth [5]. The latter are then used to compute the ratio between the pulp volume and the hard tissue volume, namely the "Z-ratio" (or "PHr" in [5]):

$$Z = \frac{V_{pulp}}{V_{tot} - V_{pulp}} \quad (1)$$

where V_{pulp} is the volume of the pulp, V_{tot} the total volume of the tooth, and $V_{tot} - V_{pulp}$, therefore, the volume of the dental hard tissue. Z has been proved to decrease with age [5]. Considering the good inter-examiner agreement obtained (intra-class correlation coefficient of 0.99 [5]) and the practical advantages guaranteed by this innovative procedure (such as the short operating time), the method appears to be extremely interesting for the field. In a forensic framework, age-related evidence should, however, be evaluated in a coherent way in order to provide responses that fulfill the specific forensic requirements.

Usually, evidence related to the regressive phenomena due to secondary dentin deposition are treated using different kinds of regression model that consider age as the predictor variable and the volume or area of the pulp cavity as the dependent variable [5,11-13,15,16,18-29]. However, previous studies highlighted that such a statistical methodology presents some disadvantages, both statistical [30-32] and conceptual [33,34], when used in age estimation for forensic purposes. Such drawbacks can be overcome by introducing a Bayesian perspective [33,34]. In this work, a novel Bayesian framework for the evaluation of pulp-chamber volume measurements was consequently developed. This exploited a Bayesian multiple linear regression model to shape relationships between the age of a person and related pulp-chamber volume measurements to obtain appropriate distribution estimates for the underlying normal likelihood function. The final framework was implemented and applied by means of a Bayesian network (BN). The purpose is to make the interpretation procedure more rapid and straightforward in routine casework, where new evidence may continuously be collected. The full model was trained on an authentic dataset of 286 individuals and its performance evaluated against actual ages through statistical resampling procedures. Sensitivity analysis on prior probabilities was also carried out in order to study the effects of using different types of prior distribution on inferred age estimates and identify the most reliable assignment approach for real applications. To our knowledge, this is the first time that a BN based on a full Bayesian approach has been applied for the interpretation of pulp-chamber volume data (measured on a continuous scale) in a forensic perspective, and its performance evaluated on real data. It is also the first time that the influence of prior probabilities on age estimation has been thoroughly studied through sensitivity analysis in the age estimation domain.

In order to efficiently present the approach, this paper has been divided into three main parts. In the first part, the employed dataset is presented (Section 2) and the suggested full Bayesian model and Bayesian network are proposed (Section 3). The second part includes discussion of the application of the approach (Section 4) followed by sensitivity analysis on the prior distribution (Section 5) and, in the final part, an overall discussion and the conclusion are given (Sections 6 and 7).

2 Used dataset

Information from two hundred and eighty-six healthy individuals (114 males and 172 females) made up the data sample. Details recorded for each subject were sex, date of birth and date of CBCT scan. Thus, chronological ages were documented in both days and years. The same technician had taken the 286 CBCT scans by means of a Scanora Dental Cone Beam unit (Soredex, Tuusula, Finland). The images were taken at 90 kV and 5-8 mA, with a field of view selection between 60x60 or 75x100 and a scanning time of 11-13 seconds. Radiological analyses were performed in two private radiological offices, located, respectively, in Northern and Central Italy. In accordance with previous studies (e.g., [5,11,23,35,36]), values of Z-ratio were computed using the healthy upper left central incisor; all teeth presenting treatments, restorations, cavities, evident wear or attrition, or suspicious reduction/enlargement of pulp possibly due to trauma or traumatic occlusion were excluded from the study. Analyses were provided by an experienced forensic odontologist following the procedure described in [5]. Assessment of the Z-ratios was performed through a blind procedure, since the personal details of patients were masked. Table 1 describes the individuals in the data sample according to age group, whilst Figure 1 graphically illustrates this data.

3 A Bayesian approach for assessing *Z*-ratios

3.1 Suggested model

Regarding the field of the age estimation of living people, the main scope of any statistical evaluative method is to allow forensic examiners to infer an estimate on the chronological age of a specific subject based on some items of evidence collected during his/her medical examination (e.g., the measurements carried out on various age-related characteristics, such as the Z-ratio). The Bayesian approach, specifically, provides this age estimate in the form of a *posterior probability distribution* that is informed by all the items of evidence themselves, as well as by any other additional information or relevant knowledge on the examined subject (e.g. his/her sex). This distribution is called "posterior" because it is computed from a normalized combination of two antecedents, i.e. a *likelihood function* derived from a statistical model for the measured age-related characteristics and a *prior probability distribution*, through the application of the Bayes' theorem. Formally:

$$\textit{posterior probability distribution} \propto \textit{likelihood function} \times \textit{prior probability distribution} \qquad (2)$$

Consequently, the posterior probability distribution is an updated version of the initial belief[1] on the actual age of the examined individual in light of the newly measured evidence [40]. For the purpose of this work, equation (2) has been substituted with the following specific model:

$$f(a|z,s) = \frac{f(z|s,a) \times f(a)}{\int_A f(z|s,a) \times f(a)\, da} \qquad (3)$$

[1] We consider here the Bayesian (subjective) definition of probability, which states that the latter is a measure of the degree of a personal belief [37]. Such vision of probability offers a logical and coherent framework to handle uncertainty in forensic science, as widely discussed, for example, by Taroni et al. [38] or Biedermann [39].

where a is the age of the examined individual, s his/her sex and z the value Z-score observed during the individual's dental examination. Thus $f(a|z,s)$, $f(a)$ and $f(z|s,a)$ are the posterior probability distribution, the prior probability distribution and the likelihood function, respectively. In the appendix, further mathematical details of (3) are provided for interested readers.

3.2 Probability assignment

A fundamental step of the suggested approach is the assignment of the prior probability distribution and likelihood function. In most cases, prior probabilities are elicited as a uniform distribution over a given range of ages [32,41-44] in order to make the posterior distribution mainly dominated by the likelihood function. This kind of prior assignment is generally referred to as "uninformative". Other types of "informative" distributions can be used if previous knowledge on the examined individual is already available or can easily be acquired through other means. This aspect is thoroughly discussed in Section 5.

The likelihood function statistically models the relationship between the age-related characteristic (i.e., the Z-score) and chronological age. In this regard, previous works have demonstrated that the non-linearity of this relationship can be handled through a logarithmic transformation of Z (i.e., lnZ) [5] (see also Figure 1). Thus, assuming that sex also affects *lnZ*, the relationship can be assessed by means of a classical multinomial linear regression model, in which *lnZ* is the response variable and the chronological age and sex are the predictors. Formally [32,45]:

$$\begin{aligned} lnZ &= \mu_{a,s} + \varepsilon \\ &= \beta_0 + \beta_1 \times a + \beta_2 \times s + \varepsilon \end{aligned} \tag{4}$$

where β_0 is the intercept parameter, β_1 and β_2 are the slope parameters related to chronological age and sex, and ε is the error term which is assumed to be normally distributed, i.e., $\varepsilon \sim N(0, \sigma^2)$. $\mu_{a,s}$ is, furthermore, the systematic term summarizing the mean trend of the regression model.

3.3 Bayesian network (BN)

Analytically solving Bayesian models can be a tedious and time-consuming procedure, which, therefore, is unsuitable for daily practice. Nonetheless, specific statistical tools exist in order to simplify this. Examples are BNs. BNs are probabilistic graphical tools that present the dual advantage of graphically describing the relationship between the variables included in the developed inferential model, as well as of directly providing automatic computations following the rules of the probabilistic theory [46]. Therefore, they are already widely used in forensic science [47] and various disciplines [48], including age estimation [34].

The qualitative structure of a network is achieved by defining a so-called "node" for each variable to be considered in the inferential reasoning. For the purpose of this work, the main variables are the chronological age (node *A*), the sex (node *S*) and the measured logarithm of *Z*-ratio (node *lnZ*). Nodes are then connected to each other by means of directed arcs, which illustrate the direction of the probabilistic relationships between variables. In this regard, the probability of observing a given value of *lnZ* in an individual depends on his/her age and sex. Hence, the directed arcs start from nodes *A* and *S* to node *lnZ*, as illustrated in Figure 2 [34]. From a quantitative point of view, probabilities need to be assigned to each node in order to model the uncertainty related to the considered variables. Here, chronological age is inferred. Therefore, a specific prior probability distribution needs to be assigned to node *A*, whilst a Normal distribution with parameters μ and σ needs to be assigned to node *lnZ*, following the mathematical assumption discussed in the previous section. The BN can then be extended by adding further nodes in order to correctly take into account uncertainty associated with other hidden variables. Here, in particular, nodes modelling the regression analysis parameters were explicitly included (i.e., β_0, β_1, β_2, μ and σ), and probability distributions assigned according to the mathematical assumptions of regression analysis. The final retained BN structure is represented in Figure 2, whilst a full description of the nodes is presented in Table 2.

From an operational point of view, employment of the BN is extremely intuitive. By inserting observed evidence in the network, i.e., the sex of the examined individual and measured *lnZ*, the probability distributions initially associated to the other nodes in the BN are automatically updated following principles of the probability theory; the posterior probability of the chronological age can then be read in node *A*.

4 Application to dataset

4.1 Model training and evaluation

A procedure based on a leave-one-out process was developed for model training and performance evaluation. To this end, 285 subjects were used for learning the parameters implemented in the BN (Section 3) and the remaining subject was tested with the probabilistic model. The procedure was repeated for all 286 subjects. This way, each individual was tested once by maximising the data used in the learning procedure and limiting the influence of outliners. Analyses were carried out in the R environment [49]. The *R2OpenBUGS* package [50] was applied for implementing the BN presented in Section 3. A ready-to-use version of the R code is presented as Electronic Supplementary Material as an annex to this article. Parameters β_0, β_1, β_2 and σ were estimated by applying the regression model described in Section 3 to the training sets. The regression analyses were performed using the *BMLR* (Bayesian Multiple Linear Regression) code [51]. Since no background information was available about the regression parameters, an uninformative prior distribution was assigned; specifically, default distributions in the BMLR code were used. As prior probability of the chronological age, a uniform distribution between 8 and 100 years was chosen and entered in the node A. The lower limit of this interval is the age at which it could be expected that the permanent central incisors are emerged [52], whilst the upper bound models a reasonable expectation for the maximum age of an average person. The BN automatically updates this initial probability distribution, simply by entering values for *lnZ* and *S* observed on the examined subject. Convergence of the simulation procedure performed by the R2OpenBUGS machine was tested using the *Coda* package [53]. The mean of the posterior probability distribution of the chronological age was accepted as the age estimate. The performance of the method was investigated in terms of accuracy and bias. Bias is defined as the difference between the estimated and actual subject ages, whilst its absolute value corresponds to the inaccuracy [44].

4.2 Results with uninformative priors

The scatter plot in Figure 3 illustrates the comparison between the real and estimated ages of all subjects in the sample. Data are dispersed around the line of equality. Even though some punctual large deviations are observed, especially for age greater than 30 years, the method seems to provide accurate estimatations. Points under the equality line represent underestimated ages and, conversely, points above the line indicate overestimations. Interestingly, data seem equally distributed around the line, which indicates that the method does not provide systematic under- or overestimations.

Distribution of inaccuracy and bias computed for each subject in the sample (i.e., 286 values for each quantification) are summarised by descriptive statistics in Table 3, according to sex and age group. As an example, the first column in the Table (i.e., “Mean”) shows the mean of individuals’ inaccuracies computed for all subjects in the respective cohorts, whilst the second column (i.e., “Med”) reports the median of such data.

Regarding inaccuracy, the computed means were between approximately 4.80 and 9.20 years, except for female subjects between 30 and 39 years of age and those over 69 years of age, for whom the computed mean was over 10 years. Outcomes in the latter cohort may have been influenced by the small sample (8 subjects, see Table 1). Median values were generally lower than mean values and this indicates that the distribution of the computed inaccuracy was slightly skewed to the right, i.e., a larger proportion of computed inaccuracies tend to be lower than the mean. In particular, for cohorts where inaccuracy exceeds the value of 10 years, the median value is generally notably lower than the mean (except for the females in the last cohort), which suggests that the means are probably influenced by some extreme values. In order to investigate the inaccuracy variability, the interquartile range (IQR) was calculated. This statistic illustrates the zone, located around the median, which covers the values between the first and third quartiles, i.e., the central half of all values. For the central cohorts, the IQR varies between approximately 3 and 14 years, but the majority of IQR values are included in a range of approximately 6 to 9 years. The IQR statistics show that the central half of inaccuracy values tend to be dispersed in a zone close to the median; thus, extreme values are quite rare, as also shown in Figure 3, where outliers are graphically illustrated. The box plots in Figure 4 visually compare the distribution of obtained inaccuracy as a function of cohort and sex and show that differences between sexes are infrequently observed.

The mean values of bias (Table 3) are generally positive. Although this statistic appears to indicate that the method tends to overestimate age, the proportions of under- and overestimation (the last two column in Table 3) show instead that there is no uniform tendency and the studied method produced no systematic under- or overestimation. Positivity of the bias mean values is probably influenced by extreme overestimations, shown as outliers in Figure 4. In some cohorts, differences between bias found for male and female subjects can be seen but it cannot be excluded that such discrepancy arises from the sample structure.

4.3 Comparison with previous studies

An exhaustive comparison with the findings of previous studies in this field could not be performed in a satisfactory way. In fact, a large part of previous research is based on a 2D approach and used to calculate pulp area [12,54,55] (and not volumes) or linear measurements [11,14]. These works are incomparable with findings presented in this study, precisely due to the 2D radiological approach, which considers only two dimensions of the pulp extension (disregarding the pulp modification in buccal-lingual direction). Moreover, these previous works had to cope with radiological magnification and angulation that typically affect 2D X-rays and generally did not perform a validation by comparing radiological measures with real measures of extracted teeth. A comparison with studies that consider measurement of the pulp chamber volume as age-related evidence is also difficult to perform, since there are differences in the techniques used for evaluating method performance. Hence, comparison of such results may be misleading. Furthermore, most of the studies do not consider accuracy according to age group, as performed in this work. Given that, referring to an array of works that focus on pulp-chamber reduction, the method discussed in this work provides comparable or better accuracy.

Among previous works, only a few analysed central incisor as in this study. Someda et al. [16] considered the mandibular central incisor from a Japanese sample in which subjects were aged between 12 and 79 years. They reported a standard error between 8.09 and 9.24 for female subjects and between 10.09 and 11.40 for males according to the volume measured. Star et al. [23] analysed a sample collected in Belgium (from 10 to 65 years of age) and reported a root mean squared error of 12.86, whilst from a Chinese sample including subjects aged between 16 and 63 years, Ge et al. [29] observed a standard error of the estimate of 8.88 (male) and 9.51 (female) for the central incisor. For the other single-rooted teeth analysed in their study, they reported results between 8.63 and 10.20 years for male subjects and 8.80 and 10.61 years for females. Pinchi et al. [5] presented findings from an Italian sample of subjects aged between 10 and 80 years old, using the same age groups that have been investigated in the current study. Accuracy of the method was presented in terms of residuals and authors reported residual means varying between -9.92 and 13.88, with the lower residuals observed for the central cohorts (i.e., from 30 to 59 years of age). Other publications reported results obtained by analysing other types of teeth (e.g., [15,21,26,29,56]). Findings are analogous with those mentioned above. As an exception, Tardivo et al. [25] reported globally better results in terms of accuracy by analysing canines from a sample of French people between 15 and 85 years of age.

The sex dimorphism is a controversial point related to degenerative modifications of the dental tissues. A large number of previous works supported that no significant relationship between narrowing of the pulp chambers and sex can be observed [5,23,57,58]. Analysis of the current results tends to agree with these previous findings. Other studies, however, found that sex may have a non-negligible influence on pulp-chamber reduction [16,22,28,29].

5 Assignment of informative priors

5.1 Uninformative vs. informative priors

Formally, prior probability can be defined as "[…] the probability distribution one assigns to a parameter or parameters *before* performing one's experiment or observation […]" [59, p. 1] or analogously "[…] a measure of personal degree of belief about [the parameter of interest] prior to observing the data […]" [60, p. 101]. Finally, from a forensic perspective, "[t]he term "prior" encapsulates the fact that such probabilities are developed prior to any evidence specific to the instant case […]" [61, p. 40]. Prior probabilities define therefore an initial belief –expressed in the form of a probability– that one may have about a given variable of interest, based on individual experience or background knowledge, as well as specific information on the case at hand [62]. In the forensic age estimation framework, the elicitation refers to the chronological age and prior probabilities should be defined before collection and evaluation of the age-related evidence. As stated above, a so-called "uninformative" prior (or, better to say, a "uniform" prior that is a uniform distribution over a given age interval) is generally preferred [32,41-44]. Although the rationale behind this choice is to "[…][l]et the data speak for themselves […]" [32 , p. 54], this perspective needs to be well understood, since it would be misleading to state that such elicitation is "uninformative". In fact, uniform prior actually expresses a precise belief [62] that all ages included in the interval are equiprobable for the individual and he/she cannot be at an age outside the chosen range. Practitioners who choose such prior probability distributions must be aware of the significance of their decision. Furthermore, to exclude any background information from the inferential reasoning may be seen as a waste of useful knowledge. An examiner asked to express his/her expertise in an age estimation procedure is supposed to have general background knowledge, as well as specific information on the particular case, that allows him/her to specify an initial belief on the age of the individual under examination. Various strategies exist to form and formalise this initial belief. As suggested by Lucy [33], it can be based on "[…] observations of that individual and other individuals who are of known age and thought to have some underlying biological similarity with the individual for whom age is unknown […]" [33, p. 272], a psychological assessment of the examined person or, alternatively, by considering the statements expressed by the examined person. Collected information can then be summarised in terms of probability in order to be integrated in the (Bayesian) inferential reasoning as *informative* prior probability.

Taroni et al. [60] suggested an intuitive procedure to summarise a prior belief related to forensic evidence that can be adopted in the age estimation framework. Suppose that previous to any examination, and based on their own experience and knowledge, the examiner believes that the most probable age for the examined person is 40 years. Suppose also that there is no reason to assume the uncertainty about the age as non-symmetric. Thus, a Normal distribution $N(\eta, \tau)$ can be assumed as prior probability distribution on the chronological age. In this scenario, 40 years can be taken as the mean, η, of the Normal distribution. Furthermore, let's assume that the examiner considers it extremely unlikely that the age of the person is less than 30 or greater than 50 years. These boundaries can be assumed to be located symmetrically three standard deviations from the mean, since this space can be interpreted as a probability of 0.997 in the Normal distribution. Thus, standard deviation, τ, can be assigned as 10 years / 3 = ~ 3.3 years, which corresponds to the examiner's uncertainty on the most probable age. As an alternative, the expert may assign a uniform probability distribution over a given age range. As aforementioned, such an elicitation must be considered in light of the information that it provides and the chosen interval should be as narrow as rationally possible. Bolstad [63] provides other examples for formalising beliefs in terms of probability distributions. Although the designation of such informed priors is subjective and case specific, investigation of the influence of the prior choice on age estimation is a relevant, albeit relatively unexplored, task in this field (an example is provided by Sironi et al. [64]).

5.2 Sensitivity analysis

In order to test the effect of different assigned priors on age estimates, the so-called sensitivity analysis is an interesting tool [47]. Broadly speaking, sensitivity analysis involves varying one or more parameters in a probability model and exploring how such modifications affect other variables. In studies performed on data rather than individuals, a personal prior probability distribution for each subject is obviously impossible to assign, due to the lack of personal pieces of information specific to the individual case. A solution to overcome such limitation is to simulate the probability distributions for all subjects. Sensitivity analysis then varies the parameters of these simulated distributions and resultant variations in the estimation results are recorded and analysed.

Sensitivity analysis has been applied to the developed model. In particular, the simulated individual prior probabilities for each subject in the sample were elicited in form of a Normal distribution with parameters η and τ, which were also the parameters involved in the sensitivity analysis. For each subject, η and τ were varied as follows: the mean, η, was varied in an interval of ± 10 years from the real age of the individual (the central age in the interval) and the standard deviation, τ, on the contrary, was assigned as a quadratic function of η, formally, $\tau = \vartheta_1 + \vartheta_2 \times \eta^{\vartheta_3}$, with $\vartheta_1 = 2$, $\vartheta_2 = 0.001$ and $\vartheta_3 = 2$. This assignment reflects the expectation that uncertainty on the age increases with the age of an individual. Sensitivity analysis was performed by employing the BN presented in Section 3. For each subject in the sample, the simulated priors were made by varying node *A* (the chronological age variable) and then the age was estimated as described in Section 4.

5.3 Results with informative priors

The investigated outcome of the sensitivity analysis was the inaccuracy and results are graphically summarised in Figure 5. Average inaccuracies observed for each subject in an age cohort are shown according to variation of the mean parameter, η, of the simulated prior probability distribution.

Results show that inaccuracies are lower than those obtained by using a uniform prior (dashed lines in Figure 5), except for cases when the assigned value for η was lower than about -7 years the actual subject age. These findings support the use of background information in the inferential process. Inaccuracy increases with a linear proportionality according to the difference between η and the actual subject age. Moreover, underestimations were generally observed when the assigned value for η was less than the actual subject age and *viceversa*, which means that estimation biases are strictly related to prior elicitation.

Two main conclusions arise from these results. Firstly, elicitation of informed priors raises the accuracy of the estimates. Average inaccuracy for a cohort is generally lower, or similar, to that obtained by a uniform prior distribution, even for scenarios in which the most probable prior age (i.e., the mean parameter of the Normal distribution) is assigned with an error of -5 or +10 years from the actual subject age. Secondly, the posterior probability distribution seems relatively sensitive to the prior elicitation, i.e., the evidence displays low robustness towards prior elicitation. This may be related to the high variability of the observable pulp chamber volume for a given age, as illustrated in Figure 2 and Table 2. This is a notable concern, since incoherent elicitation of the priors may lead to inconsistent age estimations. It is therefore fundamental that the examiner takes into account all available information when forming their own initial belief and that such information is coherently interpreted. In cases of high uncertainty, the examiner should consider choosing priors with the most limited content of information, such as a uniform prior focused on the most logical age interval.

6 General discussion

Age estimation is usually a two-step process. At first, information is collected during the examination of a given age-related biological marker. Nowadays, the morphological changes related to pulp chamber volume can be quantified using conventional techniques and, therefore, this physical attribute can be easily exploited for age estimation of living subjects. In particular, the innovative technique based on 3D CBCT imaging presented in [5] has been shown to provide consistent results and is thus a reliable approach for quantifying tooth volumes.

The second step involves evaluation and interpretation of the collected evidence. This procedure is not only a statistical issue, but also a more general inferential problem. In a forensic context, age estimates are provided to answer legal questions of the type "what is the age of the person under examination?", which are essentially probabilistic in nature, as the actual subject age may remain unknown. In this circumstance, the Bayesian approach represents a solution to coherently deal with the uncertainty factors and provide probabilistic age estimates [40,61,65]. This has recently been recognised by the European Network of Forensic Institutes (ENFSI) [66], as well as other authors [67], who identified a Bayesian core in the evaluation and interpretation of all forensic evidence. As further benefit, the use of a Bayesian approach in age estimation allows forensic examiners to encompass some statistical limitations that affect other statistical methods employed in the field [30-33].

A criticism that has been offered against such a Bayesian approach refers to its eventual computational complexity [41]. However, the application of Bayesian methods becomes an extremely intuitive and easy task by using specific probabilistic tools, such as BNs. From an operational point of view, such probabilistic graphical tools allow users to optimise the evaluative procedure and obtain results in a rapid, easily interpretable and standardised form. In fact, once a BN has been compiled with probabilities assigned from a given reference sample, it can then be employed to evaluate evidence from all individuals related to that reference sample and rapidly provide an estimate in a coherent form. Hence, the BNs as presented in this work may provide added value to forensic daily practice by providing rapid age estimates.

In a Bayesian framework, outcomes are provided in the form of a posterior probability distribution of the chronological age, which encapsulates all uncertainty related to the problem at hand in a logical and coherent way. Both point and interval estimates can then be derived from the posterior distribution [34,44]. In adult subjects, degenerative processes assessed for collection of age-related evidence are highly variable from one individual to another. Interval estimates may therefore cover large age ranges and, consequently, result in being useless in forensic practice. In such scenarios, focusing on point estimates seems preferable, as was done in this study. Inaccuracy values were generally less than 10 years (except for a few cohorts), which is promising in terms of model performance, since errors within a 10-year range were generally observed in previous studies and considered acceptable for age estimation in adults [68-70]. Nonetheless, it seems essential to highlight that age estimates in previous literature were provided through application of regression models considering age as a dependent variable. As discussed above, this statistical methodology seems less appropriate in forensic frameworks [30-34]. Furthermore, in terms of bias, the Bayesian model suggested in this study did not show any trend towards under- or overestimation of actual ages, proving that a Bayesian method may actually overcome the inherent limitations of classical statistical tools in this specific aspect [32,42]. A Bayesian approach also provides the possibility to integrate initial expert knowledge, expressed in the form of a prior probability distribution of the chronological age.22699

Sensitivity analysis of the prior probability assignment on subject ages shows that an informed elicitation increases the quality of the estimates, although the considered evidence appears to have only a minor effect. This is a particular concern, since such scarce robustness may lead to erroneous estimates if initial expert belief is too distant from the real age of the examined individual. However, robustness may be increased by considering a multi-traits approach, i.e., by evaluating evidence collected from multiple teeth or from other physical indicators of age. From this perspective, although its influence on the reduction of the pulp chamber variable is controversial (see Section 4), the integration of the sex variable in the inferential reasoning is relevant for an eventual extension of the inferential model for the evaluation of evidence collected from physical traits that may be more affected by sexual dimorphism. BNs, again, are a flexible tool that can handle different variables and it is simple to integrate additional variables into existing graphical models.

7 Conclusion

Degenerative phenomena of teeth, such as pulp chamber narrowing in relation to secondary dentin deposition, are reliable physical markers for age estimation of adult individuals [5]. In this regard, a new technique based on an approximation procedure for quantifying dental volumes on 3D-CBCT images has previously been reported and proved to provide useful evidence for age estimation of both living individuals and unknown bodies. In this paper, for the first time, evidence collected from such a technique has been evaluated using a Bayesian network based on a full Bayesian model, in order to infer age estimates in forensic contexts. The main findings of the study are:

- pulp narrowing seems unevenly influenced by sex;
- accuracy values are generally lower than 10 years, which fulfills the criteria generally accepted for adult age estimation;
- elicitation of informed prior probability of the chronological age increases the accuracy of age estimates;
- robustness of the evidence evaluation towards the prior elicitation is low and incoherent prior assignment can led to inconsistent estimates;
- the method is not affected by systematic under- or overestimations;
- Bayesian networks optimise the evidence evaluation procedure and could provide important added value for forensic practice when evaluating this evidence type.

A ready-to-use version of the R code used for analysis in this work is available as Electronic Supplementary Material and it can be used to provide age estimation based on *Z*-ratio evidence.

8 Conflict of Interest

None.

9 Acknowledgments

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10 Addendum

From a general point of view, the Bayesian theorem applied to the assessment of continuous age-related characteristics for age estimation purposes take the following form:

$$f(a|z,s,\boldsymbol{t},\boldsymbol{g},\boldsymbol{v}) = \frac{f(z|s,a,\boldsymbol{t},\boldsymbol{g},\boldsymbol{v}) \times f(a)}{\int_A f(z|s,a,\boldsymbol{t},\boldsymbol{g},\boldsymbol{v}) \times f(a)\,da} \tag{5}$$

where a is the age of the examined individual, s his/her sex and z the value of the considered age-related characteristics (e.g., the *Z*-ratio or its logarithm, *lnZ*) computed during the individual's examination. $\boldsymbol{t}, \boldsymbol{g}$ and $\boldsymbol{v}$ are vectors, which refer respectively to the age, sex and measurements of the considered age-related characteristics of all the subjects in the reference sample (background data). Thus, the probability distribution associated with the likelihood $f(z|s,a,\boldsymbol{t},\boldsymbol{g},\boldsymbol{v})$ models the probability of observing a specific value for z on the examined individual, given his/her age and sex and the background data. Eq. (3) in Section 3 is essentially a notation-simplified form of (5), where variables concerning background data are intentionally omitted from notation.

In a parametric framework, the characteristics of the probability distribution for $f(z|s,a,\boldsymbol{t},\boldsymbol{g},\boldsymbol{v})$ can be defined based on a set of parameters $\boldsymbol{\theta}$, which can be estimated from the characteristics of the reference sample (i.e., the $\boldsymbol{t}, \boldsymbol{g}, \boldsymbol{v}$ vectors). The likelihood function in Eq. (5) is therefore a *posterior predictive distribution*, which can be further defined as follows [71]:

$$f(z|s,a,\boldsymbol{t},\boldsymbol{g},\boldsymbol{v}) = \int_\Theta f(z|a,s,\boldsymbol{\theta}) \times \pi(\boldsymbol{\theta}|\boldsymbol{t},\boldsymbol{g},\boldsymbol{v})\,d\boldsymbol{\theta} \tag{6}$$

where

$$\pi(\boldsymbol{\theta}|\boldsymbol{t},\boldsymbol{g},\boldsymbol{v}) = \frac{f(\boldsymbol{v}|\boldsymbol{t},\boldsymbol{g},\boldsymbol{\theta}) \times \pi(\boldsymbol{\theta})}{\int_\Theta f(\boldsymbol{v}|\boldsymbol{t},\boldsymbol{g},\boldsymbol{\theta}) \times \pi(\boldsymbol{\theta})\,d\boldsymbol{\theta}} \tag{7}$$

is the posterior probability distribution of the parameters, also obtained through the application of the Bayesian theorem. $\pi(\boldsymbol{\theta})$ is the prior probability distribution of the parameters and $f(\boldsymbol{v}|\boldsymbol{t},\boldsymbol{g},\boldsymbol{\theta})$ models, in probabilistic terms, the relationship between the considered age-related characteristics of the subjects in the reference sample with their chronological age and sexes. This relationship is defined as a function of the parameters $\boldsymbol{\theta}$.

In this study, the likelihood function has been modelled by means of a Normal distribution, with parameters μ and σ. The former describes the relationship between lnZ and the age and sex of an individual. Since this relationship has been found to be linear [5], a multinomial linear regression model can be used for quantifying the value of lnZ. Formally:

$$\mu_{a,s} = \beta_0 + \beta_1 \times a + \beta_2 \times s, \quad (8)$$

where β_0 is the intercept parameter, and β_1 and β_2 are the slope parameters related to chronological age and sex. The regression analysis involves uncertainty, which has to be integrated in the model. It can therefore be assumed that the observed lnZ value results from a combination of a systematic part and a random part that takes into account such uncertainty [45]. Formally:

$$lnZ = \mu_{a,s} + \varepsilon, \quad (9)$$

where the error term ε is assumed to be Normally distributed, i.e., $\varepsilon \sim \mathrm{N}(0, \sigma^2)$. The variance term σ^2 is assumed constant in the whole age range, since the logarithmic transformation reduces the heteroscedasticity of the data. Therefore, from Eq. (9) it can be inferred that $lnZ \sim \mathrm{N}(\mu_{a,s}, \sigma^2)$. Furthermore, $\boldsymbol{\theta} = \{\beta_0, \beta_1, \beta_2, \sigma\}$ and can be estimated from the reference sample by means of the Eq. (7) presented above.

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Age	**Sex**	**N**	***Z***		
			Mean	**Min**	**Max**
8-19	M	18	0.080	0.049	0.129
	F	29	0.084	0.053	0.114
20-29	M	8	0.053	0.034	0.079
	F	22	0.052	0.035	0.080
30-39	M	15	0.045	0.030	0.065
	F	24	0.041	0.021	0.065
40-49	M	22	0.034	0.022	0.051
	F	34	0.038	0.022	0.077
50-59	M	22	0.023	0.020	0.043
	F	30	0.030	0.022	0.043
60-69	M	20	0.027	0.021	0.041
	F	25	0.028	0.020	0.044
70-80	M	9	0.018	0.015	0.022
	F	8	0.023	0.015	0.032

Table 1 - Values of Z according to age cohort and sex

Node	Description
A	Chronological age of the examined individual
S	Sex of the examined individual
lnZ	Logarithm of the computed Z-ratio
$\beta_0, \beta_1, \beta_2$	Estimated regression parameters
μ and σ	Parameters of the Normal distribution on lnZ

Table 2 - Definition of the nodes in the Bayesian network structure

Age	Sex	Inaccuracy					Bias		
		Mean	Med	IQR	Min	Max	Mean	Under	Over
<20	M	4.82	3.61	3.15	0.47	14.63	4.66	0.11	0.89
	F	3.93	3.18	3.74	0.50	10.60	3.41	0.14	0.86
20-29	M	8.54	5.30	13.99	0.10	19.61	7.55	0.25	0.75
	F	9.20	6.72	9.08	0.32	20.33	7.83	0.18	0.82
30-39	M	7.48	7.11	10.41	0.39	15.72	1.02	0.60	0.40
	F	10.30	7.31	13.29	0.84	40.26	6.76	0.25	0.75
40-49	M	8.75	6.30	6.99	0.42	24.30	2.63	0.41	0.59
	F	8.19	6.56	5.62	0.17	28.16	1.11	0.47	0.53
50-59	M	7.36	6.51	8.75	0.25	19.74	0.61	0.41	0.59
	F	7.73	8.65	6.85	0.65	15.56	2.11	0.43	0.57
60-69	M	6.61	3.60	6.97	0.13	26.32	-3.31	0.45	0.55
	F	7.22	6.12	6.34	0.34	23.63	-4.54	0.76	0.24
>69	M	6.47	4.91	5.40	0.38	12.99	4.16	0.22	0.78
	F	10.39	9.76	11.53	0.60	24.16	-8.98	0.75	0.25

Med: Median; *IQR*: Interquartile range; *Min & Max*: minimal and maximal inaccuracy; *Under & Over*: proportion of under- and overestimated ages.

Table 3 - Descriptive statistics for inaccuracy and bias computed for the 286 subjects in the sample. All statistics are presented in years, except for the proportions of under-and overestimated ages.

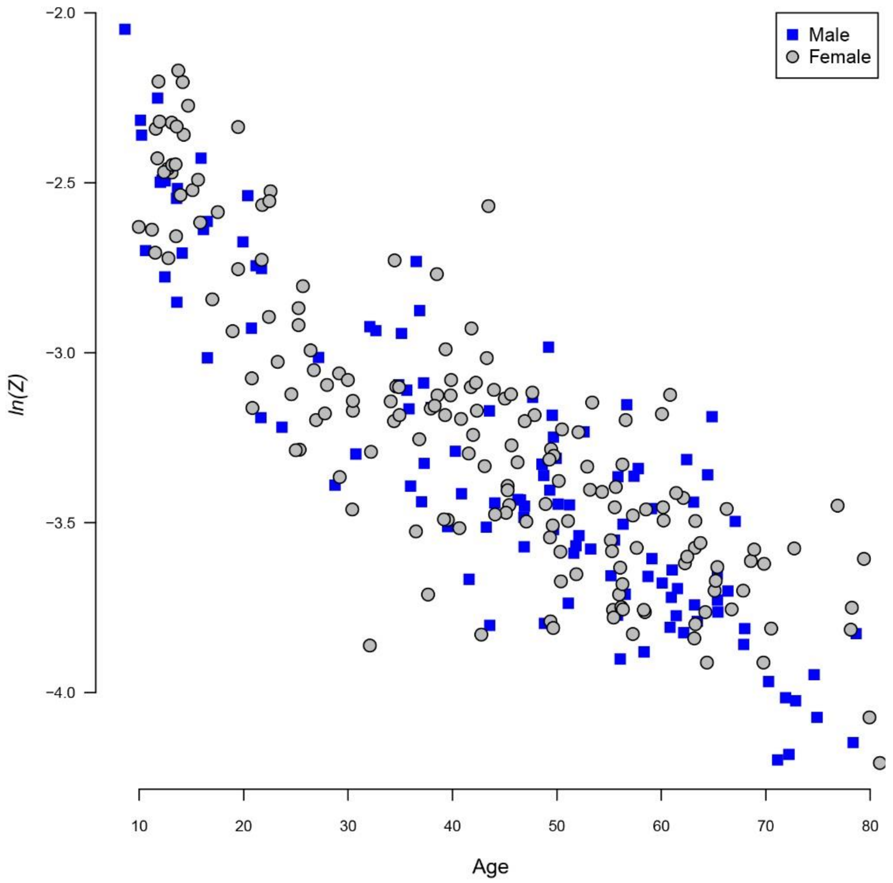

Fig. 1 - Plot of the Z-ratio (after logarithmic transformation) vs. chronological age for each subject in the considered data sample.

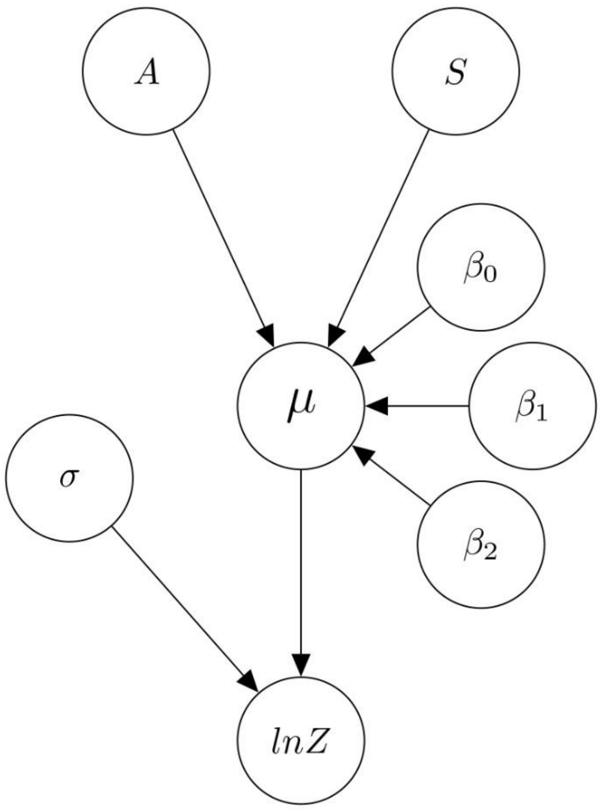

Fig. 2 - Structure of the retained Bayesian network. Nodes considered in the current scenario are: age (A), sex (S), and lnZ (lnZ), as well as the parameters related to the underlying regression model (β_0, β_1, β_2, μ and σ).

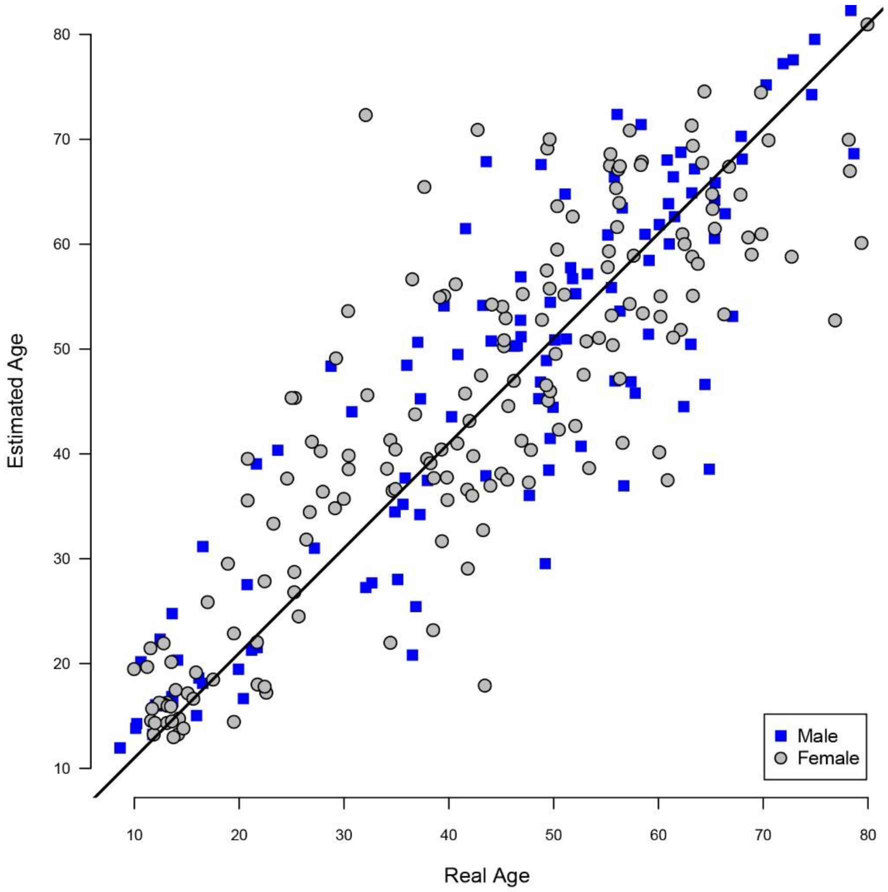

Fig. 3 - Representation of actual age (x-axis) versus estimated age (y-axis) for all subjects in the data sample. Black line represents line of equality.

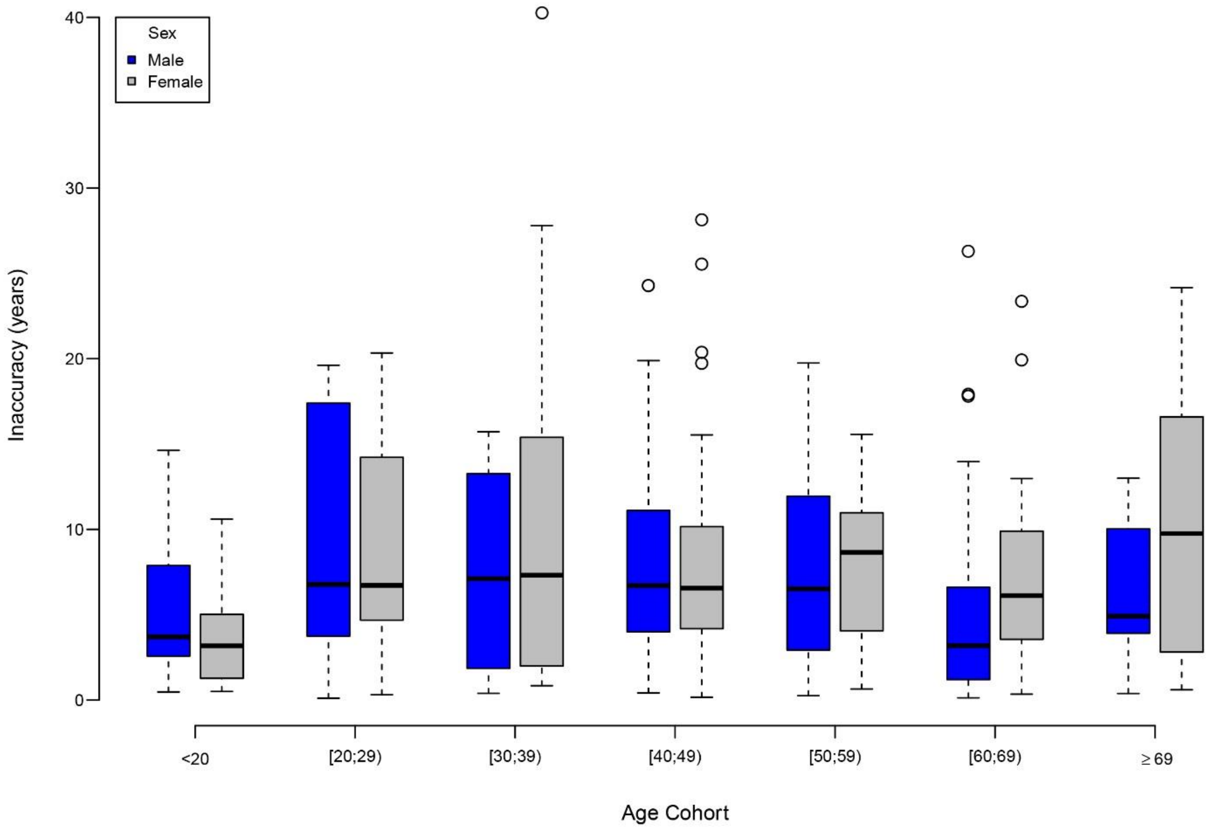

Fig. 4 - Box plots describing the distributions of computed inaccuracies.

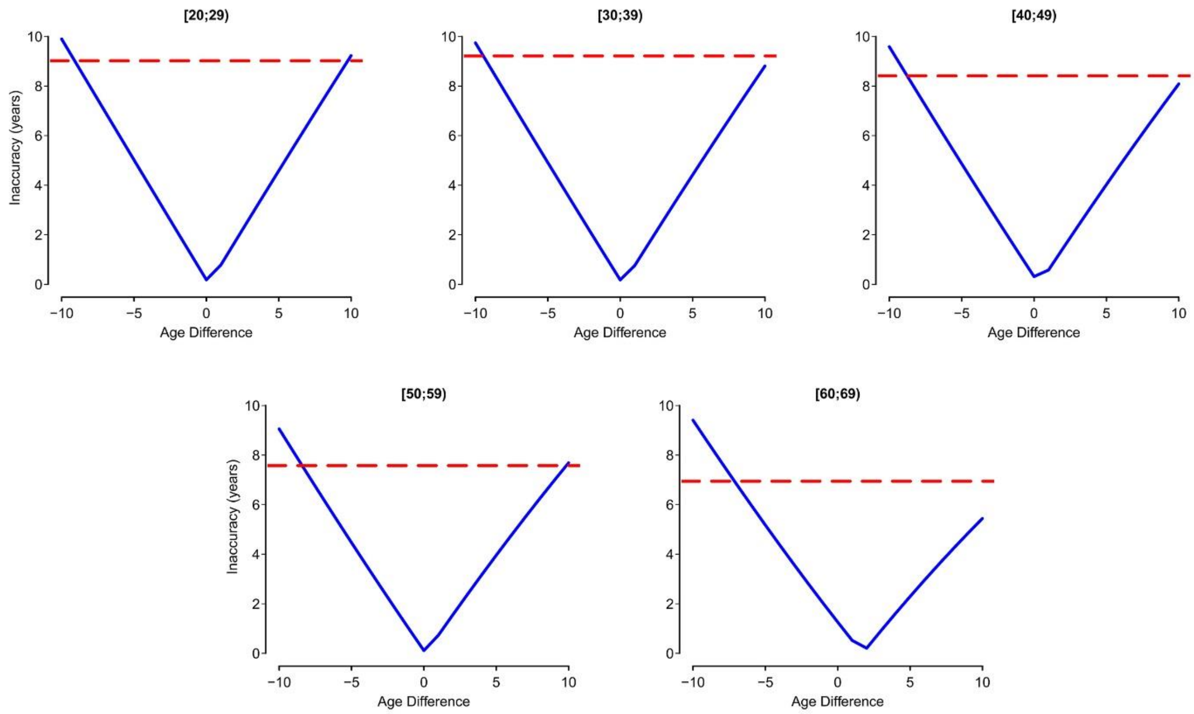

Fig. 5 - Average inaccuracy (y-axis) of estimated age observed by moving the mean parameter (η) of the prior probability distribution on the age of each subject within - 10 and + 10 years from its real age (0 thus corresponds to the case where η matches the real age for all the subjects). Data are presented by age cohorts. For the sake of comparison, dashed lines illustrate the average inaccuracy observed by using a uniform distribution (see Section 4).