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Lyle W. Konigsberg,[1] *Ph.D.; Nicholas P. Herrmann,*[2] *Ph.D.; Daniel J. Wescott,*[3] *Ph.D.; and Erin H. Kimmerle,*[4] *Ph.D.*

Estimation and Evidence in Forensic Anthropology: Age-at-Death

ABSTRACT: A great deal has previously been written about the use of skeletal morphological changes in estimating ages-at-death. This article looks in particular at the pubic symphysis, as it was historically one of the first regions to be described in the literature on age estimation. Despite the lengthy history, the value of the pubic symphysis in estimating ages and in providing evidence for putative identifications remains unclear. This lack of clarity primarily stems from the fact that rather *ad hoc* statistical methods have been applied in previous studies. This article presents a statistical analysis of a large data set (n = 1766) of pubic symphyseal scores from multiple contexts, including anatomical collections, war dead, and victims of genocide. The emphasis is in finding statistical methods that will have the correct "coverage." "Coverage" means that if a method has a stated coverage of 50%, then approximately 50% of the individuals in a particular pubic symphyseal stage should have ages that are between the stated age limits, and that approximately 25% should be below the bottom age limit and 25% above the top age limit. In a number of applications it is shown that if an appropriate prior age-at-death distribution is used, then "transition analysis" will provide accurate "coverages," while percentile methods, range methods, and means (±standard deviations) will not. Even in cases where there are significant differences in the mean ages-to-transition between populations, the effects on the stated age limits for particular "coverages" are minimal. As a consequence, more emphasis needs to be placed on collecting data on age changes in large samples, rather than focusing on the possibility of inter-population variation in rates of aging.

KEYWORDS: forensic science, pubic symphysis, probit analysis, likelihood ratio

Human osteological remains are routinely used in forensic anthropology either to estimate various characteristics of individuals to aid in identification, or to serve as evidence in a putative identification. Either pursuit should have a Bayesian underpinning. In the estimation setting it is necessary to have a prior distribution for the estimate, while in the evidentiary setting it is necessary to have the probability of getting the observed osteological data for a case from the population at large. This probability comes fairly directly from the prior distribution characterizing the population at large, or it can come directly from the observed distribution of the osteological data in the population at large.

This paper is the second in a four part series on estimation and evidence in forensic anthropology. The first paper (1), which formed a chapter in an edited volume, examined the use of long bone data both in estimating stature within a Bayesian setting and in presenting evidence when stature is "known" for a "positive" identification. The current paper examines the use of the Suchey–Brooks (2–4) pubic symphyseal system both in age estimation and in the presentation of evidence for putative identifications. The planned third paper will present comparable estimation and evidence problems for categorical variables such as sex and "race," while the final paper in this series will present the estimation and evidence problem for time-since-death.

[1]University of Illinois, Department of Anthropology, 109 Davenport Hall, 607 South Matthews Avenue, Urbana, IL 61801.

[2]University of Tennessee, Department of Anthropology, 250 South Stadium Hall, Knoxville, TN 37996.

[3]University of Missouri, Department of Anthropology, 107 Swallow Hall, Columbia, MO 65211.

[4]University of South Florida, Department of Anthropology, Soc 107, 4202 E. Fowler, Tampa, FL 33620.

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The focus here on a single ordinal categorical variable (the six Suchey–Brooks stages) in a discussion of methods for age estimation and presentation of evidence is perhaps unfortunate. While such staged systems from the pubic symphysis have received considerable attention in their own right (2–12), methods that are based on multiple "indicators" (13–20) naturally provide more information. In this paper the focus is on a single staged (i.e., ordinal categorical) system for three reasons. First, there are now a considerable amount of data for the Suchey–Brooks system on known age individuals from a number of different populations and contexts. The current paper uses data on over 1700 known age-at-death males. Second, it has been suggested in a number of places (20,21) that populations may vary in the timing of their progression through the Suchey–Brooks stages. As the current data are from a number of different populations, it is possible to examine the practical effect of such possible timing differences. And finally, it is necessary in a methodological paper such as this to focus on a single "indicator" of age because the multiple "indicator" method adds considerable analytical complexity.

Materials and Methods

The Samples and Data

The sample consists of 1766 males with known ages-at-death (see Table 1). Of these individuals, sub-samples come from (in order from largest to smallest sample size) the Los Angeles Coroner's Office (2), the Terry Anatomical Collection, U.S. Korean War Dead (22), Balkan genocide victims, and the Department of Anatomy of the University of Chiang Mai, Thailand (10). Some comments are in order here concerning the documentation for ages-at-death in each sub-sample. Of the sub-samples, the L.A. Coroner's Office sample is one of the better documented, as birth certificates were available and time of death was known. The data

TABLE 1—*Samples used in the current study.*

Collection	*n*
Los Angeles Coroner	737
Terry Anatomical Collection	422
Korean War	358
Balkans	212
University of Chiang Mai Anatomical Collection	37
Total	1766

used here were obtained from a handout accompanying a poster presented by Suchey (personal communication) at the AAFS meetings on February 14, 1986 in New Orleans. The Terry Anatomical Collection is much more poorly documented. Ages-at-death were reported when individuals were entered into this dissection-room collection, but the source for these ages is not documented. There is "age heaping" on ages ending in zeros and fives, so it seems most likely that the ages were either self-reported prior to death or were taken from information provided by relatives or friends. The Korean War Dead sample is primarily composed of those killed in action, in which case the exact birth date and death date are known (age-at-death is then known to within a day). Some of the Korean War Dead remains were from individuals who died as POWs, in which case the date of death was sometimes only known to within a month or two. The ages-at-death for the University of Chiang Mai sample are taken from Schmitt's (10) Figure 2 using "DataThief" (http://www.datathief.org/). Because these are read from a scan of Schmitt's graph, the ages may be slightly inaccurate. Table 2 lists the ages within Suchey–Brooks stages for the Thai sample used within this study.

Of the five sub-samples, the Balkan sample is one of the more difficult to work with in terms of documentation. The identification of remains was made by relatives, usually based on personal effects and clothing. The ages-at-death are those reported by relatives and so may be inexact. Djurić (23) previously noted in a study of 39 Kosovars that: "After recognition of associated material (clothes and personal belongings) by the family of the victims, and comparison of antemortem and postmortem data by the anthropologist, the 12 positive identifications were made." These comparisons apparently did not involve DNA analysis, which raises the question of validity of such identifications. Because of this concern, in some analyses reported here, the Balkan sample is treated as a "test case" with unknown ages. If there are a considerable number of misidentifications, then ultimately the estimated ages would be only randomly associated with the reported ages.

The Suchey–Brooks (2) scores for pubic symphyseal development were recorded for all samples. These scores represent a six-stage ordinal categorical scale that grew out of lumping Todd's (12) 10-phase system. The Los Angeles Coroner's Office sample was scored by Judy Suchey using the original 10-phase system and was later collapsed into the six-stage Suchey–Brooks system. The Terry Anatomical Collection was scored by Herrmann again using the original Todd system, while the Korean War Dead sample was similarly scored by Herrmann, Wescott, and Konigsberg. The Balkan sample was scored by Kimmerle using the Suchey–Brooks six-stage system. The Thai sample was scored by Aurora Schmitt (10). Because the Thai sample size is so low ($n = 37$), this sample is not used for any direct estimation problems, but is included to examine a point made in Schmitt (10). She has argued that the 95% ranges given in Katz and Suchey (2) for age within stage include much less of the age distribution for the Thai sample than one would expect.

TABLE 2—*Age distribution within Suchey–Brooks pubic symphyseal stages for the University of Chiang Mai Anatomical Collection males.*

Stage	Ages
2	20, 22, 30, 39, 58
3	49, 51, 59, 68, 75
4	41, 42, 46, 46, 47, 49, 51, 57, 75, 79, 82
5	42, 43, 45, 51, 53, 56, 58, 59, 59, 66, 76
6	34, 60, 62, 71, 82

Ages are from "DataThief" (http://www.datathief.org/) applied to Schmitt's (10) Figure 2.

Percentile Method

There is a long history in forensic and physical anthropology of using sample statistics of age within stage to estimate age. For example, Katz and Suchey (2) gave a table that lists the sample sizes within their six stages of the pubic symphysis, as well as the mean age, the standard deviation of age, and the 95% range of age within stage. The application to a target sample or case of mean age and standard deviation within stage from a reference (known age) sample is a perilous exercise. There is little reason to expect that the age distribution within skeletal stages will be Gaussian, or even that it will be symmetric. It is for this reason that the use of percentiles of age within stage, as advocated in Katz and Suchey (2), is the better approach. Their use of the "95% range" amounts to listing the 2.5 and 97.5 percentiles of age. But even the percentile method has considerable disadvantages over "transition analysis," which is described below. First, the percentile method, when used, should include standard errors on the percentiles. This is necessary because when a sample is subdivided by stages, the individual stages may contain relatively few individuals. As a consequence some percentiles themselves may have substantial sampling variances. A second problem is that the listing of a few sample percentiles provides a rather incomplete description. If authors provide, for example, the 95% range this will be of little help to researchers who may only need a 50% range (the bottom 25th and top 75th percentiles). Both of these problems can be addressed graphically by producing complete Kaplan–Meier (24) plots of survivorship within stage and including confidence intervals on the survivorship. But a final problem with any method that conditions on stage to estimate age is that all of these methods contain an implicit prior distribution for age. This implicit prior is the actual age distribution of the reference sample itself. Much ink has needlessly been shed both in forensic and physical anthropology on the need for "population specific" estimators, when in fact many of the perceived differences in aging between samples derive from the different age structures of the study populations.

Transition Analysis

Extensive use is made here of what Boldsen et al. (19) have referred to as "transition analysis." Transition analysis is a parametric method for modeling the passage of individuals from a given developmental stage to the next higher stage in an ordered sequence. In the current example, there are six ordered phases within the Suchey/Brooks (2,12) pubic symphyseal system, so five transition distributions must be modeled (one between phase I and II, one between II and III, one between III and IV, one between IV and V, and one between V and VI). If there were longitudinal data, it would be a quite simple task to characterize these distributions, as one could look at the empirical distributions for, say, the day at which individuals changed from a Suchey–Brooks phase II to a Suchey–Brooks phase III. As the Suchey–Brooks system represents a continuum of morphology by a six-phase ordered system, it would be quite difficult to decide on what given day the morphology "switched," so the task would be simpler if the data were more coarsely sampled (say at yearly intervals or so). But in the real-world case data are sampled cross-sectionally so that there is a solitary observation on each individual, and consequently one cannot "see" the distributions of transition ages. Instead, it is necessary to assume a distributional form for the transitions and then fit the transition analysis model by the method of maximum likelihood.

The method can be introduced starting with a simplified version and then elaborated to account for the actual complexity of analyzing age progression in pubic symphyseal development. As a very crude first example, the pubic symphyseal phases can be collapsed into two very broad stages. The first stage is composed of Suchey–Brooks phases I and II and the second stage contains phases III to VI. Phase III in the Suchey–Brooks system represents the point at which the oval outline of the symphyseal face is complete, so the crude two-stage system contrasts incomplete with complete pubic symphyseal faces. A probit model (25,26) was fit to the 1766 males using the glm function in "R" (27,28). ("R" scripts for all of the Figures and analyses in this paper can be obtained from https://netfiles.uiuc.edu/lylek/www/JFS08.htm.) Probit regression fits an intercept and regression slope much like an ordinary regression, but these can be converted to the average age and standard deviation of age at which individuals move from stage 1 to stage 2 (or from Suchey–Brooks phase II to phase III). In the current example, the average age is 27.30 years and the standard deviation is 7.41 years.

Transition analysis can be represented graphically, so before looking at the extension to more than two stages it is useful to look at graphical representations. Rather than work in the straight scale for age, one can use age in the natural log scale so that the transition distribution is log normal. Figure 1 shows the transition

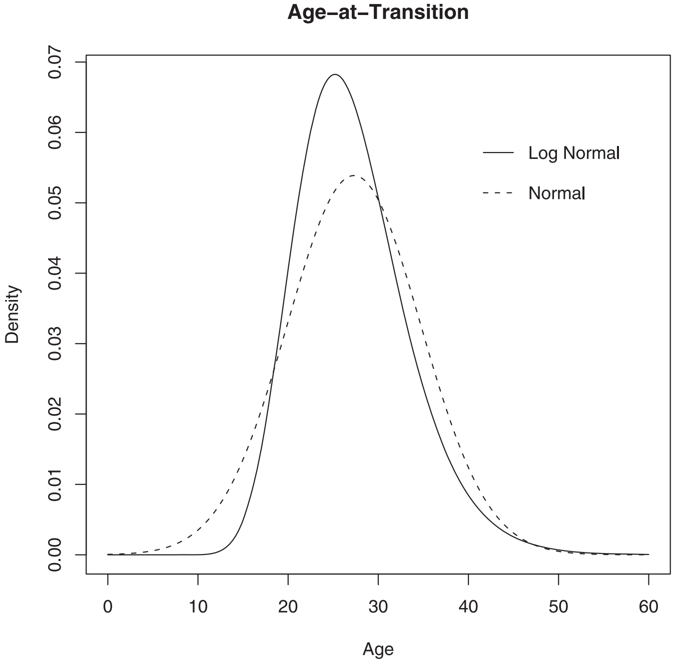

FIG. 1—*Age-at-transition distributions (log normal and normal) between Suchey–Brooks stages I to II and III to VI based on 1766 known age males.*

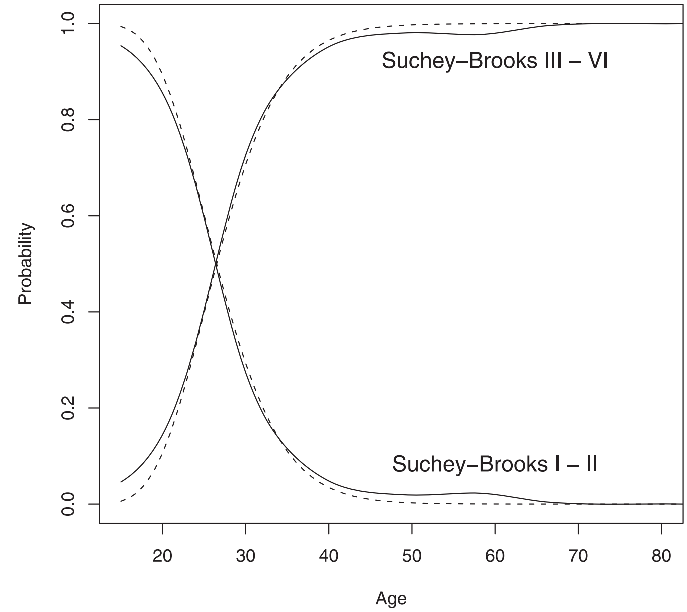

FIG. 2—*Probabilities of being in Suchey–Brooks stage I or II as versus stages III to VI. The solid lines are from a (nonparametric) kernel density while the dashed lines are from the log-normal transition analysis.*

distribution both in the straight scale and in the log scale. For the log normal the mean age-at-transition is 26.52 which is 0.78 years less than for the normal distribution. An advantage of the log-normal distribution is that because it is not symmetric it generally will not include ages-at-transition that are extremely young, while in some settings the normal transition distribution may even include negative ages-at-transition. The transition analysis method can also be compared graphically to (nonparametric) kernel density estimation (13,29,30). This provides a graphical check on the reasonableness of the parametric transition analysis method. Figure 2 shows the probability across age of being in Suchey–Brooks stages I or II as versus stages III–VI. These probabilities are shown using both the log-normal transition model and kernel density estimation. As can be seen from Fig. 2, these very different methods produce rather similar probabilities.

Building on the previous example, a cumulative probit model can be applied to age on a log scale thus representing more than one transition. The cumulative probit, also sometimes referred to as the proportional odds model with a probit link or ordered probit, has been covered extensively in the literature (19,25,26,31–42). Figure 3 shows the age-at-transition distributions between the six stages. For comparison, the log-normal distribution between stages I–II and III–VI that was previously calculated (see Fig. 1) is also shown in Fig. 3. An attractive feature of the cumulative probit is that it will provide similar results when stages are collapsed. Figure 4 shows the probability from the cumulative probit of being in each stage at a given age as well as the kernel density estimates. As the probit and kernel density methods do not agree well for Suchey–Brooks stage V and VI, Fig. 5 shows how a simple collapsing of these last two stages into one stage can bring the two methods into agreement.

Age Estimation from Transition Analysis and a Prior Age Distribution

If one adopts a Bayesian approach to age estimation then a prior age-at-death distribution must be specified. Lucy et al. (14)

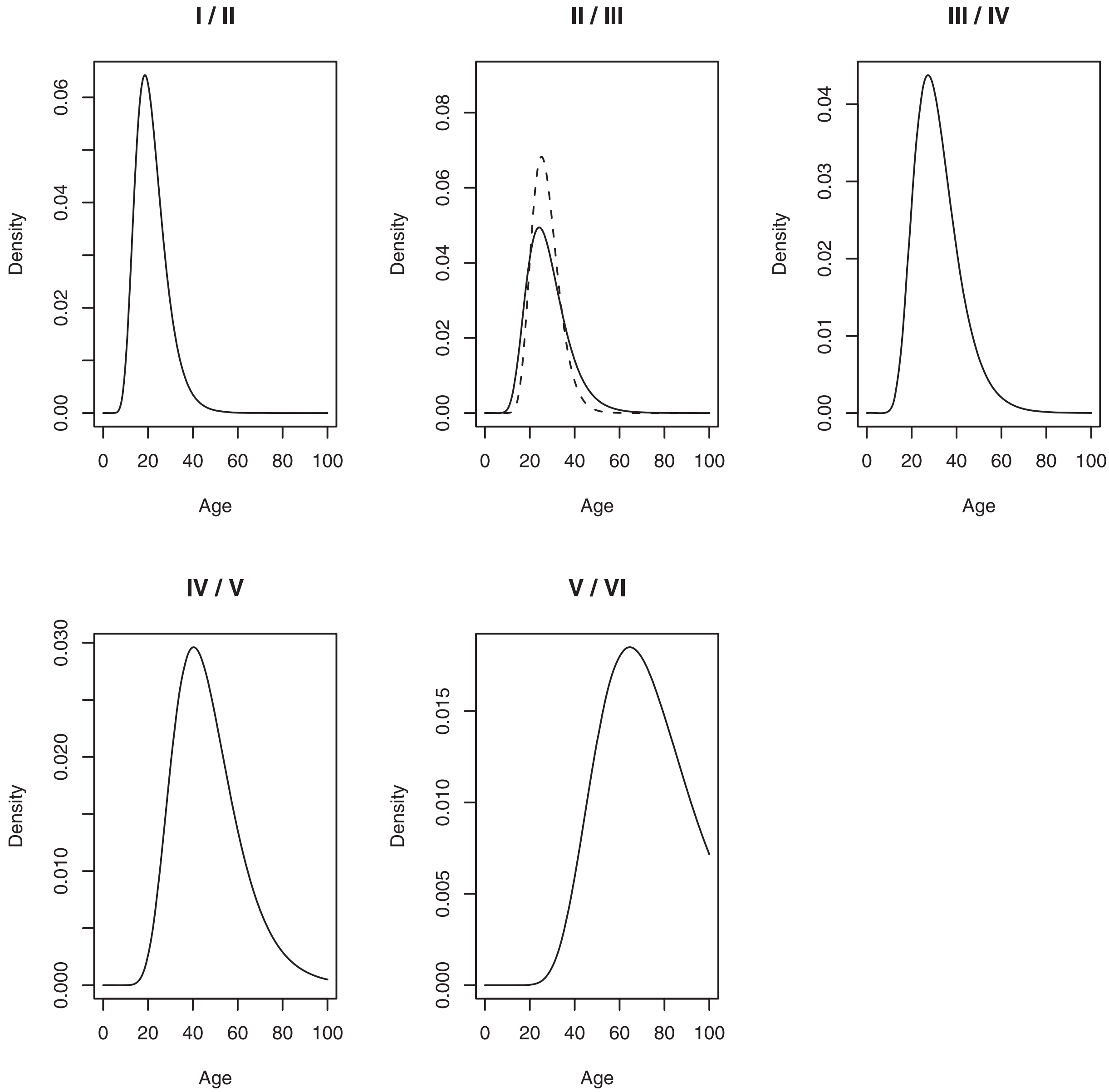

FIG. 3—*Log-normal age-at-transition distributions between the six Suchey–Brooks stages calculated from a cumulative probit model on 1766 males. In the second panel (for transition between stage II and III), the log-normal distribution from Fig. 1 is shown as a dashed line.*

argued for using the reference sample both to obtain likelihood functions (which is what transition analysis provides) as well as the prior age-at-death distribution. In many contexts, including the current article, it may not be at all reasonable to use the reference sample to obtain a prior age-at-death distribution. In the current context the L.A. Coroner's Office sample age-at-death distribution may be representative of "individuals dying from accidents, suicides, homicides or unexpected natural deaths" (3) in Los Angeles County, California, but it would not form a reasonable prior for deaths from conventional wars or from acts of genocide. The Terry Anatomical Collection sample used here represents only about half of the available males, and was selected to approximate a uniform age-at-death distribution, so it would be a poor choice for a prior age-at-death distribution. The Korean War dead sample represents mortality from a conventional war, and would not form a reasonable prior in most forensic anthropology contexts.

Prior age-at-death distributions should be specified so that they are reasonable guesses at what the possible age should be for an individual case prior to an osteological analysis. In the results section of the paper, two main examples of age estimation are presented, one using the Balkan sample and the other using the Thai sample. For the Balkan sample it would be reasonable to use an "age-at-missing" distribution reported in Komar (43), but as shown in the results section, this distribution does not match the age-at-death distribution for the 199 Balkan individuals with ages-at-death between 20 and 75 years. As a consequence, a Gompertz model is used to fit the 212 Balkan individuals as a prior age-at-death distribution, and similarly a Gompertz model is used for the 37 Thai individuals. Combining these prior age-at-death distributions with the probabilities from the transition analysis of being in the observed Suchey–Brooks stages yields a function that is proportional to the posterior density of age. Dividing through by the integral across age gives the probability density function

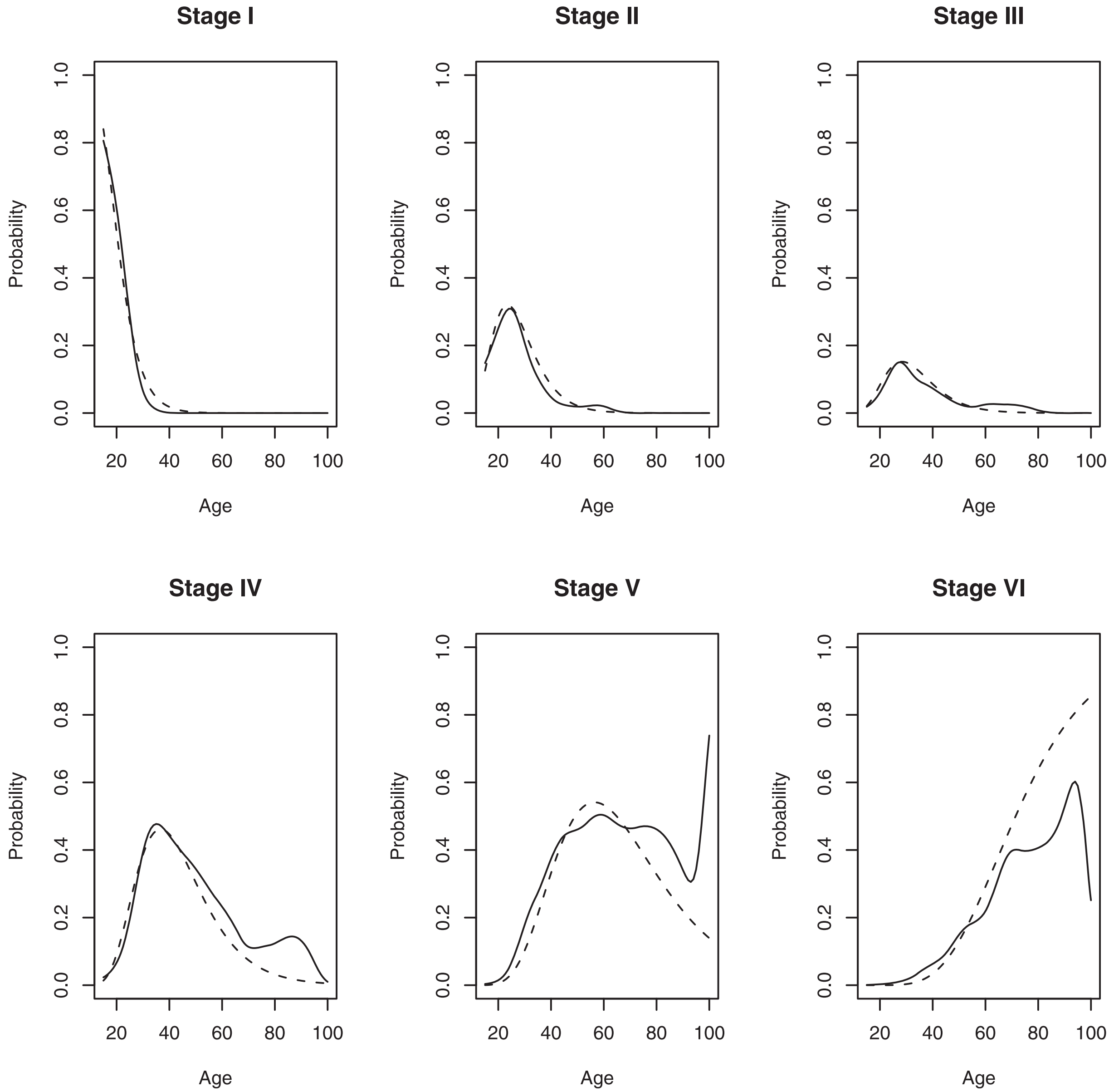

FIG. 4—*Probabilities of being in each of the Suchey–Brooks stages. The solid lines are from a (nonparametric) kernel density while the dashed lines are from the log-normal transition analysis.*

(PDF) of age conditional on Suchey–Brooks stage. From this PDF one can find the highest posterior density region (44) (HPDR) for any specified level of coverage. "Coverage" here refers to the percentage of individuals expected to fall within the specified HPDR. In the current example only 50% coverage is used, as this optimizes one's ability to find deviations from the expected level of coverage. For comparison, the mean age by stage plus and minus 0.674 standard deviation units from Suchey and Katz's (3) Table 1 (p. 211) is used. This later tabling of values was based on a rescoring of the L.A. Coroner's sample using the six-stage Suchey–Brooks system, the same system that was used to score both the Balkan and Thai samples. If ages-at-death are normally distributed within stage for the L.A. Coroner's sample, then ±0.674 standard deviations should give a 50% confidence interval. The correctness of coverage for the HPDR and confidence interval approaches are examined using a cumulative binomial test. The cumulative binomial is also used to test if the HPDR and confidence intervals are appropriately centered on the age distributions within stages.

Pubic Symphyseal Stages as Evidence in "Positive Identification" Cases

Steadman et al. (45) have already discussed the use of both pubic symphyseal and auricular surface stages in calculating the likelihood ratio for a "positive identification." As Konigsberg et al. (46) have noted, it is the likelihood ratio that should be reported when building the evidentiary basis for identifications. The likelihood ratio in the current setting is calculated as the probability that an individual would be in the observed Suchey–Brooks stage conditional on the known (if the identification is correct) age divided by the probability of obtaining the observed Suchey–Brooks stage from the "population at large." As likelihood ratios will be calculated for a number of different samples,

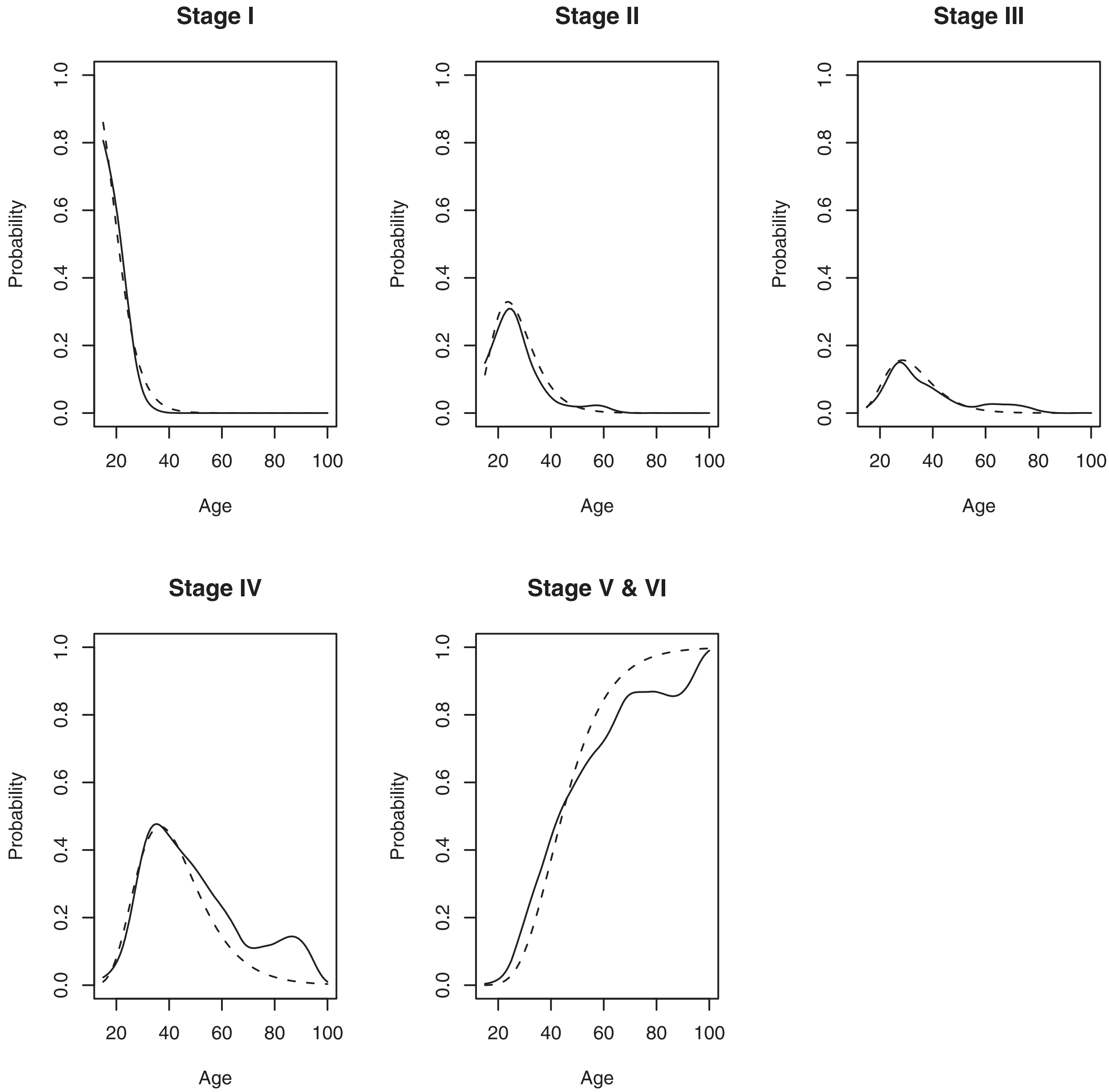

FIG. 5—*Probabilities of being Suchey–Brooks stages I, II, III, IV, and V/VI combined. The solid lines are from a (nonparametric) kernel density while the dashed lines are from the log-normal transition analysis.*

the probability of obtaining particular Suchey–Brooks stages can be estimated by the observed frequencies in each sample. The probability that an individual would be in an observed Suchey–Brooks stage conditional on "known" age is found from the transition analysis.

For ease of interpretation the likelihood ratio can be converted to a base 10 logarithm. A score of zero then represents "evens" or the case where the observed Suchey–Brooks stage is as likely to come from the identified individual as from an individual selected at random. Similarly a score of 1.0 represents a likelihood ratio of 10, so that the Suchey–Brooks stage is 10 times more likely to be observed in the identified case than in an individual from the population at large. Because the evidentiary value of the Suchey–Brooks system is sample specific, one needs to examine plots of the log-likelihood ratio distributions for each of the four largest samples (the Los Angeles Coroner's Office sample, the Terry Anatomical Collection, The Korean War Dead sample, and the Balkan sample). These likelihood ratios are calculated using transition analysis from the total sample less each of the particular samples under study. In each plot the average distribution from 1000 permutations across the sample is shown to indicate the expected distribution under random "positive identifications."

Results

Percentile Method

Figures 6–9 show the Kaplan–Meier (24) survivorship estimates and 95% confidence intervals within the six Suchey–Brooks pubic symphyseal stages for the Los Angeles Coroner's samples, the Terry Anatomical Collection, the Korean War Dead sample, and the Balkan sample. Table 3 lists sample sizes within stages for each sample, as well as the 2.5th, 25th, 50th, 75th, and 97.5th percentiles of age within stage. The percentiles were found using "method 7"

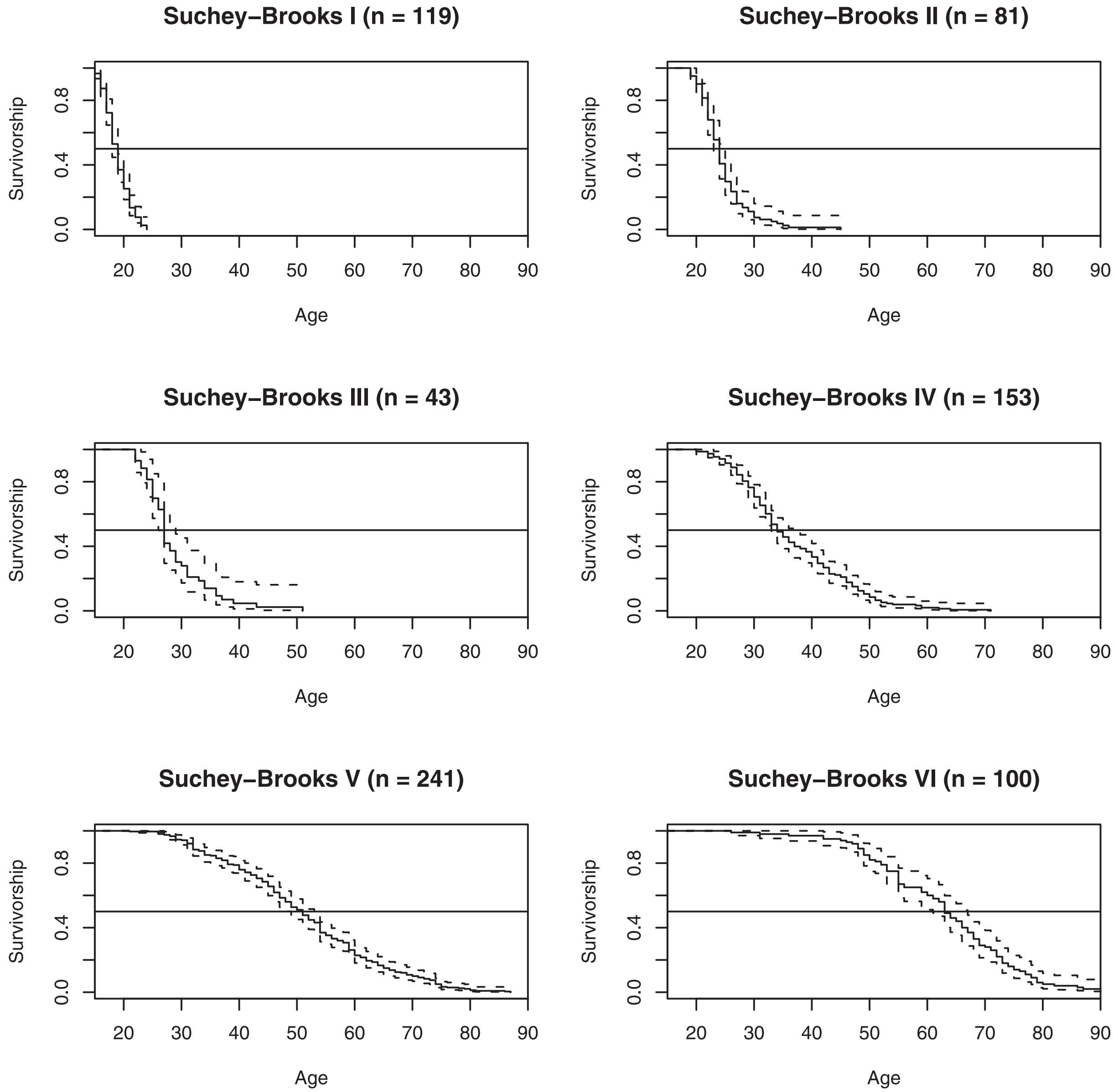

FIG. 6—*Survivorship within Suchey–Brooks pubic symphyseal stages for the Los Angeles Coroner's sample. The central horizontal line in each panel is at 0.5 survivorship, which is the median age within each stage. The dashed lines represent the 95% confidence intervals around the Kaplan–Meier estimates of survivorship.*

from Hyndman and Fan (47), and the ages were rounded to the nearest integer. The 2.5th and 97.5th percentiles for the Los Angeles Coroner's sample agree with the "95% range" published in Katz and Suchey's (2) Table 8, except for the bottom age of 36 years for stage VI given in Katz and Suchey. A value of 39 years was obtained here; presumably the value of 36 years was a typographical error. Additionally, there are two less individuals in the first stage as compared to Katz and Suchey because two individuals under 14 years were excluded here.

Table 3 provides the 50th percentile of age within stage across samples as a quick summary of the central tendencies for age within stage. The 50th percentile is the median age within stage, and could also be read from the survivorship graphs in Figs. 6–9 where the 95% confidence interval on the median is also shown. Survivorship by stage is a function of both the total sample survivorship and the aging/senescence pattern for the age "indicator." As a consequence, the contrast of Fig. 8 for the Korean War Dead sample with Figs. 6, 7, and 9 illustrates the often cited example where a direct application of "age-by-stage" information from the young Korean War Dead sample would underestimate ages for more typical forensic or anatomical samples which contain older adults.

Transition Analysis

Some graphical results from transition analysis have already been provided in the methods section to explain the method. In this section more detailed results are provided in tabular form so that the method can be applied to future samples. Table 4 contains the transition analysis parameters (mean and standard deviation of the log age of transition) between each of the six Suchey–Brooks stages for all individuals in the study ($n = 1766$), for all except the Balkan sample ($n = 1554$), and for just the Balkan ($n = 212$), Los Angeles Coroner's Office ($n = 737$), Terry Anatomical ($n = 422$), and

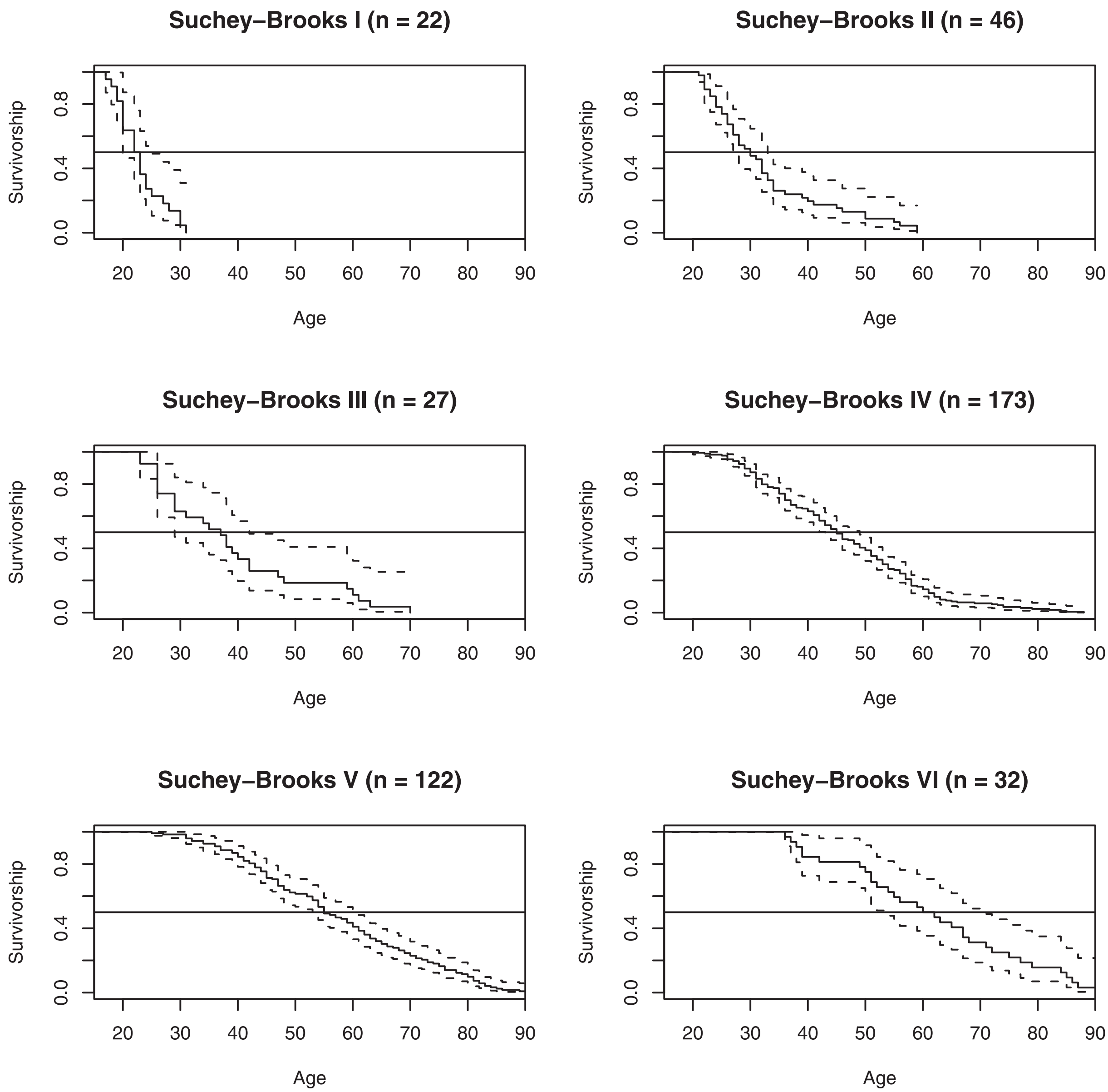

FIG. 7—*Survivorship within Suchey–Brooks pubic symphyseal stages for the Terry Anatomical Collection, drawn as in Fig. 6.*

Korean War (n = 358). The table also gives the standard errors for all parameters and the mean age-at-transition converted back to the original straight scale of years.

From the standard errors and parameter values in Table 4, it may be tempting to test for differences in rates of aging between the samples. Plus and minus 1.96 times the standard error gives an approximate 95% confidence interval for a given parameter. Using such a basis for comparison one might surmise, for example, that individuals from the Balkans enter a Suchey–Brooks stage III from stage II significantly earlier than individuals from other regions. But while it is true that the Balkan confidence interval for the mean age-at-transition between stages II and III does not overlap the comparable transition for individuals from other samples, this does not directly address the question of how well "non-Balkan standards" would apply to individuals from the Balkans. To look at this question, Fig. 10 plots the transition distributions based on the 1554 non-Balkan individuals and the 212 Balkan individuals. Figure 11 shows a comparable plot of what are known as normed likelihoods (48). These normed likelihoods are the probabilities of being in each Suchey–Brooks stage (based on the transition analyses) but scaled such that the maximum probability (or really, the maximum likelihood) is equal to 1.0. Figure 11 also shows dotted horizontal lines at normed likelihoods of 0.7965 and 0.1465. From a frequentist standpoint, the 95% confidence set for age conditional on Suchey–Brooks stage consists of all ages with normed likelihoods greater than 0.1465 (from equation 7.20 in Shao [49] and see Konigsberg and Frankenberg [50]). Similarly, the 50% confidence set for age conditional on Suchey–Brooks stage consists of all ages with normed likelihoods greater than 0.7965.

Age Estimation from Transition Analysis and a Prior Age Distribution

As a test for transition analysis, the parameters have been applied to estimate age ranges for the 212 Balkan individuals and the 37 Thai individuals. In both analyses, the transition analysis parameters were calculated for the entire male sample but excluded the Balkan sample when testing on the Balkans, and similarly

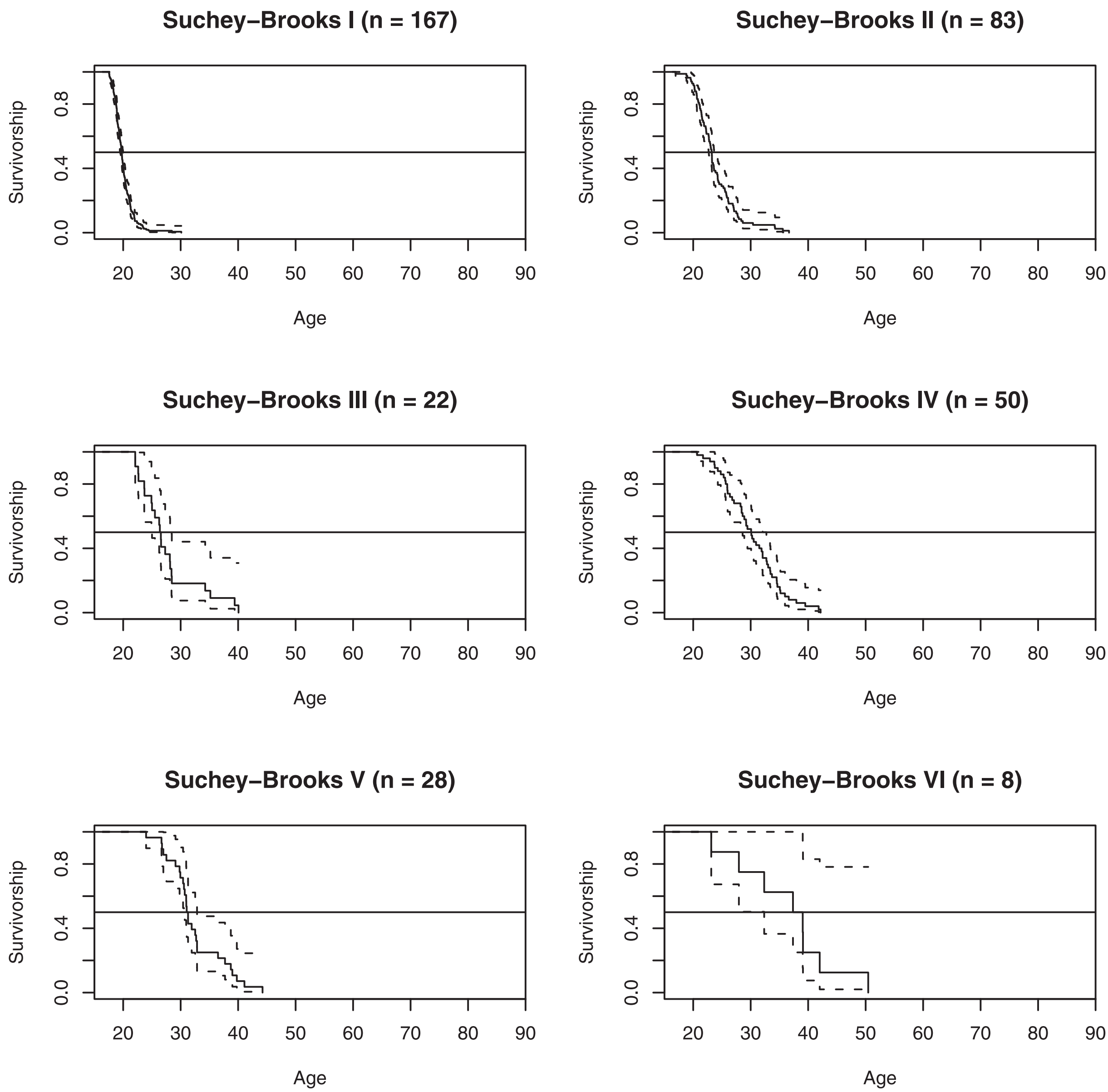

FIG. 8—*Survivorship within Suchey–Brooks pubic symphyseal stages for the Korean War Dead sample, drawn as in Fig. 6.*

excluded the Thai sample when testing for Thailand. For both samples, it is necessary to have a prior age distribution, for which Gompertz models are used here. The youngest individual in the Balkan sample was 17 years old and for the Thai sample the youngest individual was 20 years old, so the Gompertz models begin at ages 17 and 20, respectively. Figure 12 compares the age distribution from Komar's (43) Srebrenica age-at-missing data with the age-at-death data for 199 Balkan individuals in the current study with ages between 20 and 75 (inclusive). As these age distributions are quite dissimilar, a Gompertz model fit to the current data is used to represent the prior age-at-death distribution. Figure 13 shows the 95% confidence intervals for the Kaplan–Meier and Gompertz model for the Balkan sample, while Fig. 14 shows a comparable graph for the Thai sample.

Figure 15 shows a plot of coverage for the Balkan sample comparing the Suchey–Brooks confidence intervals to the transition analysis HPDRs. The stages have been randomly "jittered" to reduce overlap of the points, and the HPDRs from the transition analysis are plotted above the points and the Suchey–Brooks confidence intervals below. The intervals shown in Fig. 15 are supposed to represent 50% coverage. For transition analysis 108 of the 212 individuals (50.9%) fall within the nominal 50% regions. On a cumulative binomial test this is not significantly different from the expected coverage (p = 0.8368). Of the 104 individuals who fall outside of the 50% HPDRs, 53 are below the HPDR and 51 are above. This does not differ significantly from the expected 1:1 ratio on a cumulative binomial test (p = 0.9219). For the Suchey–Brooks confidence intervals, 90 of the 212 individuals (42.5%) fall within the nominal 50% regions. On a cumulative binomial test, this does differ significantly at the 0.05 level from the expected coverage (p = 0.0330). Of the 122 individuals who fall outside of the 50% Suchey–Brooks confidence interval, 36 are below the confidence interval and 86 are above. This does differ significantly from the expected 1:1 ratio on a cumulative binomial test ($p < 0.0001$).

Figure 16 shows a coverage plot for the Thai sample. For transition analysis, 17 of the 37 individuals (45.9%) fall within the

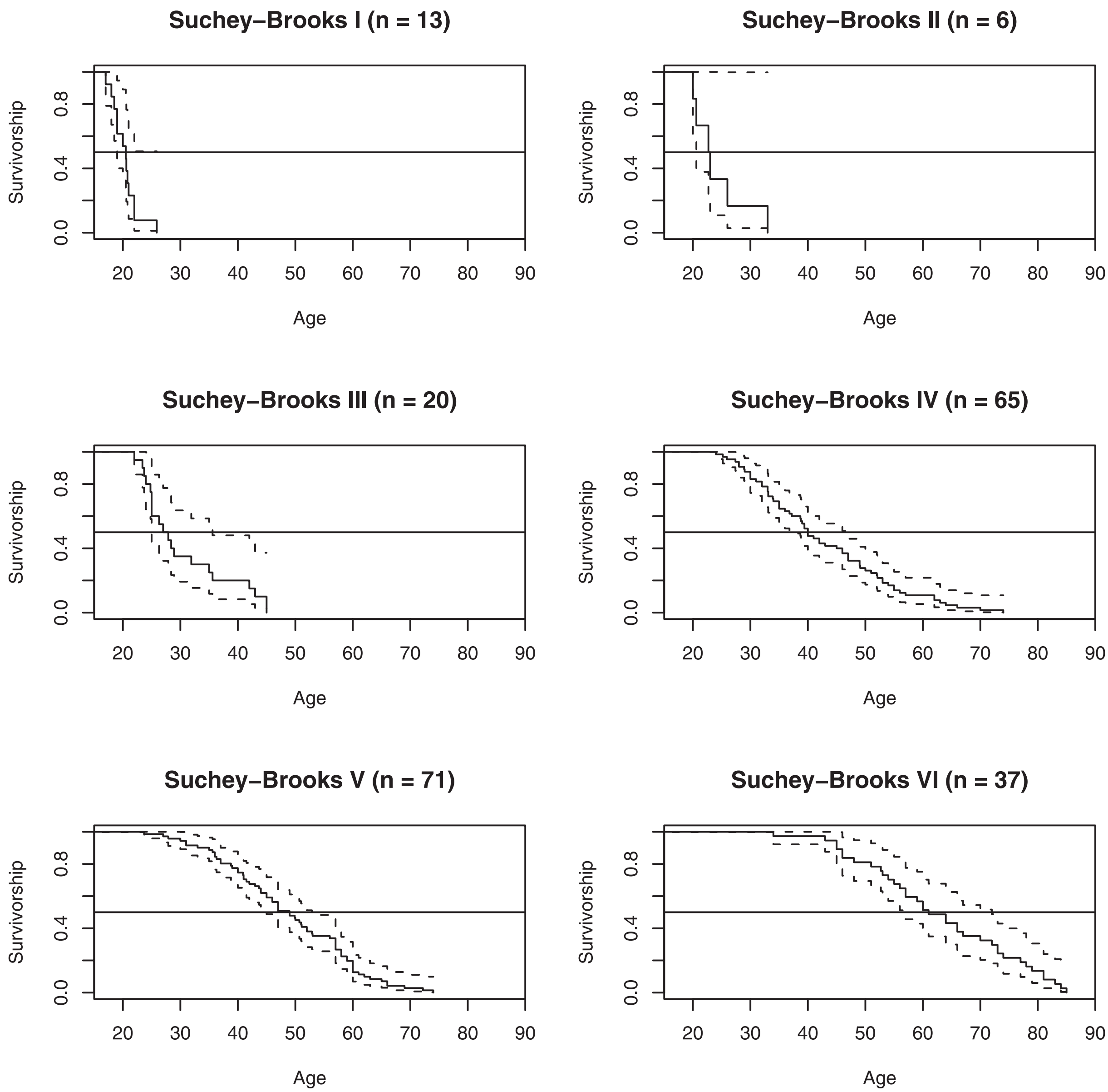

FIG. 9—*Survivorship within Suchey–Brooks pubic symphyseal stages for the Balkan sample, drawn as in Fig. 6.*

nominal 50% regions. On a cumulative binomial test, this is not significantly different from the expected coverage ($p = 0.7428$). Of the 20 individuals who fall outside of the 50% HPDRs, six are below the HPDR and 14 are above. This does not differ significantly from the expected 1:1 ratio on a cumulative binomial test ($p = 0.1153$). For the Suchey–Brooks confidence intervals, eight of the 37 individuals (21.6%) fall within the nominal 50% regions. On a cumulative binomial test, this does differ significantly at the 0.001 level from the expected coverage ($p = 0.0007$). Of the 29 individuals who fall outside of the 50% Suchey–Brooks confidence interval, two are below the confidence interval and 27 are above. This does differ significantly from the expected 1:1 ratio on a cumulative binomial test ($p < 0.0001$).

Figures 17–20 show the cumulative distributions of log-likelihood ratios for the four largest samples: the Los Angeles Coroner's Office sample, the Terry Anatomical Collection, the Korean War Dead sample, and the Balkan sample. In each of these figures, the transition analysis parameters are calculated from the entire sample but excluding the sample of interest. The Los Angeles Coroner's Office sample shows the highest evidentiary value, with 84.80% of the cases having log-likelihood ratios greater than zero. This means that for 84.80% of the cases the likelihood ratio is greater than 1.0, which in turn means that the Suchey–Brooks stage is more likely to be seen if the identification is correct than it is to be seen if the individual is randomly drawn from the sample. For the Terry Anatomical Collection the evidentiary values are generally lower, such that only 52.84% of the sample has likelihood ratios greater than 1.0. The Korean War sample is intermediate with 73.18% of the cases having likelihood ratios greater than 1.0, and finally the Balkan sample has a slightly higher percentage than the Korean War sample, with 75.47% of the cases from the Balkans having likelihood ratios greater than 1.0. For comparison, Figs. 17–20 also show the average distribution of likelihood ratios from 1000 permutations of the Suchey–Brooks stages against the known ages. In the Los Angeles Coroner's Office sample, 45.05% of the randomized cases had likelihood ratios greater than 1.0, for the Terry

TABLE 3—*Sample sizes within Suchey–Brooks stages and the 2.5th, 25th, 50th (median), 75th, and 97.5th percentiles of age within stage.*

Stage	*n*	2.5%	25%	50%	75%	97.5%
Los Angeles Coroner's Office						
I	119	15	17	19	20	23
II	81	19	22	24	26	35
III	43	22	25	27	31	43
IV	153	23	30	34	43	59
V	241	28	41	51	60	78
VI	100	39	54	63	72	87
Terry Anatomical Collection						
I	22	18	20	22	25	30
II	46	22	25	30	36	59
III	27	23	28	37	44	65
IV	173	26	35	45	56	78
V	122	31	45	55	69	85
VI	32	37	51	61	73	88
Korean War Dead						
I	167	18	19	20	21	24
II	83	19	21	23	26	34
III	22	22	24	26	28	40
IV	50	22	26	30	33	41
V	28	26	30	31	34	42
VI	8	24	31	38	40	49
Balkans						
I	13	17	19	20	21	25
II	6	20	21	23	25	32
III	20	23	25	27	35	45
IV	65	26	33	40	51	68
V	71	28	40	49	58	70
VI	37	42	53	61	73	84

Anatomical Collection this percentage was 35.54%, for the Korean War sample the percentage was 46.93%, and for the Balkan sample the percentage was 44.81%.

Discussion

The discussion in this paper is framed around a number of particular methodological issues that often arise in attempting to estimate age-at-death or presenting osteological evidence that may help confirm identifications. The first problem to be dealt with is that of how to model the progression of individuals through an ordered (staged) system such as the Suchey–Brooks pubic symphyseal stages. The use of the term "model" reveals a predilection for parametric methods. While the use of nonparametric kernel density regression or estimation (13,51) is an extremely useful tool for checking the reasonableness of a parametric model, nonparametric methods are difficult to generalize across different studies. Such methods typically require access to raw data. Kernel density estimation (a nonparametric method) was used for Figs. 2, 4, and 5, and indeed the method demonstrated a departure from unimodality for the probability of being in stage V (see Fig. 4). This departure could be corrected by combining stages V and VI as shown in Fig. 5. The departure from unimodality for the probability of being in stage V is perhaps none too surprising given that there was a major reclassification of stage V and VI when Brooks and Suchey (3,4) rescored symphyses that had previously been scored on the Todd 10 phase system. As the data for the current analysis consist of some samples that were scored with reference to the Suchey–Brooks stages and others that were scored on the Todd system (and then "collapsed" to Suchey–Brooks), there is internal heterogeneity.

Among parametric models for ordinal categorical data, a simple one has been adopted here, using cumulative probit analysis with age measured on a log scale. The fact that the nonparametric kernel method and the cumulative probit provide very similar probabilities for being in each Suchey–Brooks stage conditional on age (see Figs. 4 and 5) is a clear sign that the cumulative probit is a reasonable model. Konigsberg and Herrmann (52) have used an unrestricted cumulative probit to model progression through the Suchey–Brooks stages, Boldsen et al. (19) have used a continuation ratio approach, and Samworth and Gowland (53) have suggested using a shifted exponential. All of these models add a level of complexity that seems unnecessary in the current context. In the case of continuation ratios, there is the additional problem that stages which are combined can produce different transition parameters depending on whether the continuation ratios are "forward" or "backward" ratios. As Figs. 1 and 3 show, the cumulative probit provides a very similar transition distribution regardless of whether that transition is between stages I and II combined to stages III through VI combined, or between stages II and III.

An additional benefit of using a relatively simple parametric model to represent progression through the Suchey–Brooks stages is that one can provide all of the relevant information in simple tabular form (see Table 4). The percentile method, which was applied graphically in Figs. 6–9 and summarized in Table 3 cannot be presented as compactly. Furthermore, the percentile method takes essentially a "hidden Bayesian" approach where the reference sample prior age distribution influences the calculated percentiles. The use of percentiles or any percentile-based method such as the "95% range" consequently cannot be recommended.

TABLE 4—*Transition analysis parameters.*

Parameter	Estimate	Standard Error	exp(Est.)	Estimate	Standard error	exp(Est.)	Estimate	Standard error	exp(Est.)
	All males (*n* = 1766)			Without Balkans (*n* = 1554)			Balkans (*n* = 212)		
I–II	3.0240	0.0158	20.6	3.0339	0.0161	20.8	2.9177	0.0684	18.5
II–III	3.2860	0.0136	26.7	3.3019	0.0141	27.2	3.0436	0.0600	21.0
III–IV	3.4077	0.0129	30.2	3.4162	0.0135	30.5	3.3147	0.0455	27.5
IV–V	3.7982	0.0123	44.6	3.8099	0.0130	45.1	3.7612	0.0313	43.0
V–VI	4.2688	0.0181	71.4	4.2731	0.0187	71.7	4.1916	0.0434	66.1
Standard deviation	0.3175	0.0084	—	0.3174	0.0088	—	0.3118	0.0265	—
	Los Angeles (*n* = 737)			Terry Collection (*n* = 422)			Korean War (*n* = 358)		
I–II	3.0172	0.0208	20.4	2.7887	0.0757	16.3	3.1024	0.0133	22.3
II–III	3.2457	0.0184	25.7	3.2064	0.0492	24.7	3.2977	0.0155	27.0
III–IV	3.3541	0.0176	28.6	3.3554	0.0419	28.7	3.3615	0.0167	28.8
IV–V	3.6785	0.0163	39.6	4.0115	0.0352	55.2	3.5363	0.0216	34.3
V–VI	4.1818	0.0200	65.5	4.6079	0.0647	100.3	3.7220	0.0357	41.3
Standard deviation	0.2462	0.0098	—	0.4512	0.0337	—	0.1590	0.0098	—

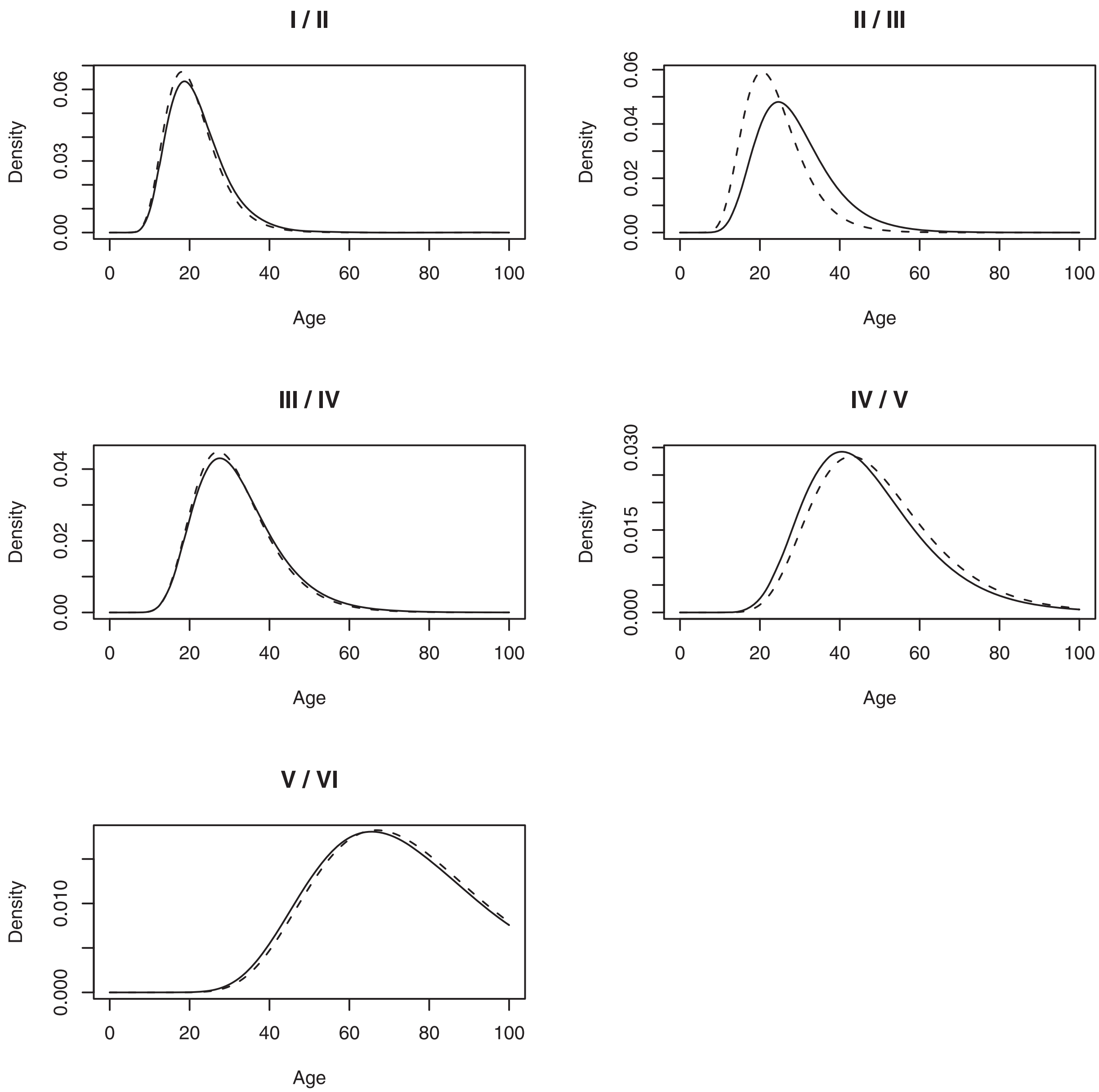

FIG. 10—*Log-normal age-at-transition distributions calculated for the 1554 non-Balkan males (sold lines) and for the 212 Balkan males (dashed lines).*

Some of the transition analysis parameters provided in Table 4 indicate significant differences between samples for mean ages-at-transition. For example, it has already been mentioned that the mean age-at-transition between stage II and III is significantly lower for the Balkan sample as versus a conglomeration of all other samples. But as has also already been mentioned, such significant differences do not necessarily translate into appreciable differences in likelihoods, and consequently would have little impact on the posterior density of age. In Fig. 10, which compares the age-at-transition distributions for the Balkans versus all other samples, it is clear that there is very substantial overlap in the distributions for any given transition. In Fig. 11, which shows the normed likelihood with a uniform prior for age-at-death, it is also clear that the differences between the Balkans and all other samples has no appreciable effect on confidence intervals for age-at-death.

Because the percentile method does not allow for different prior age-at-death distributions, while maximum likelihood (i.e., non-Bayesian) estimation of age-at-death uses an unreasonable uniform prior (as in Fig. 11), it is better to use explicit priors when estimating age-at-death. Figure 12 shows that the age-at-missing distribution from Komar's Srebrenica data (43) does not match the age-at-death distribution for the current sample of 199 Balkan males with ages-at-death between 20 and 75. This departure is likely due to the fact that the Srebrenica data are from reported missing persons' ages, which may depart from ages for individuals who were missing, recovered, and identified. It is unlikely that such a departure would arise from misidentifications, because a systematic difference such as observed in Fig. 12 would only arise if misidentification rates are correlated with age-at-death. Figures 13 and 14 show that a Gompertz model of mortality can be adequately fit to the sample of Balkan and Thai males, respectively, while Figs. 15 and 16 show that the 50% coverage from transition analysis is accurate in its coverage and placement. Specifically, the 50% coverage includes approximately 50% of the ages-at-death by Suchey–Brooks stage and approximately as many ages are below the 50% coverage as are above. Such is

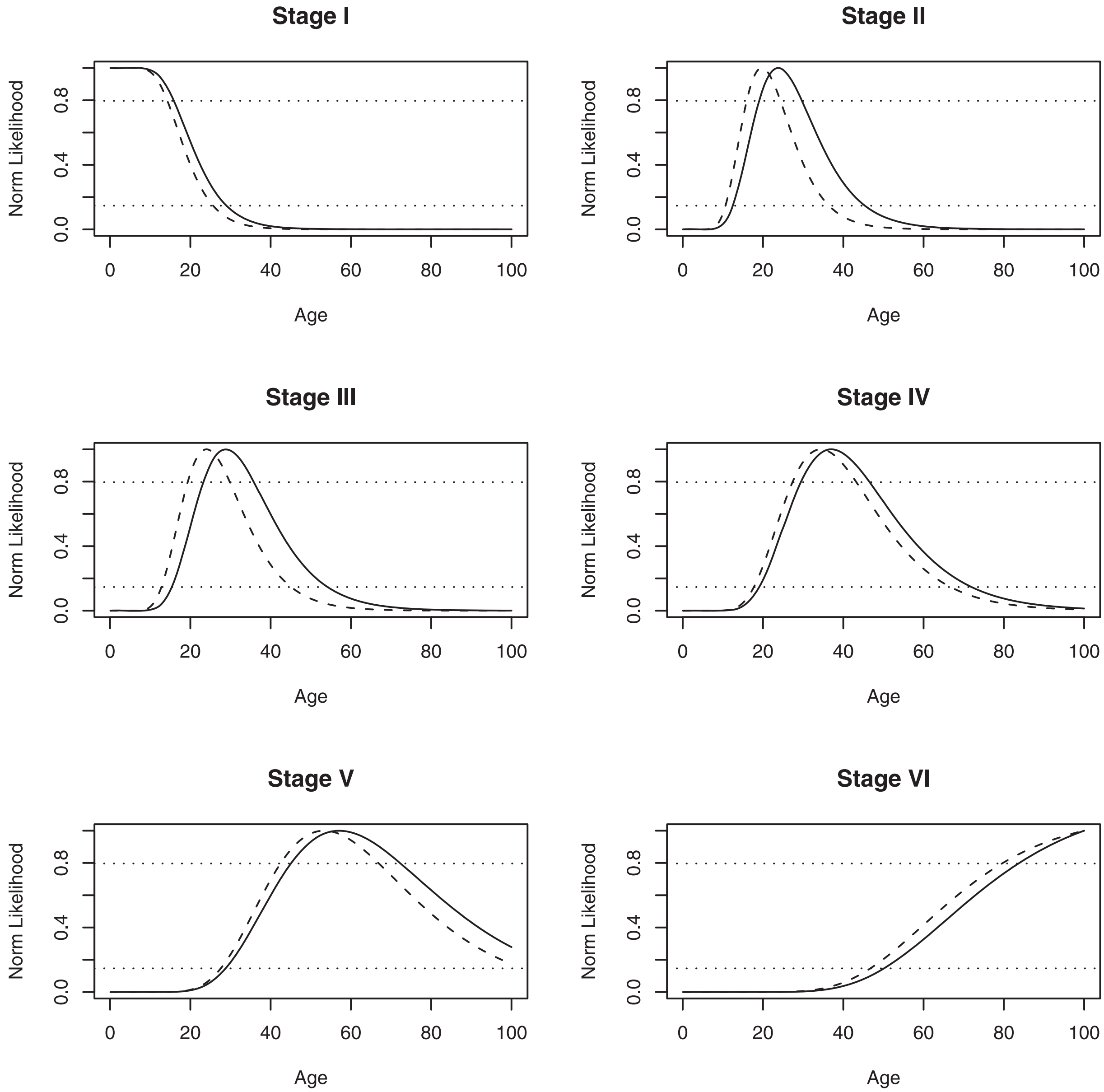

FIG. 11—*Normed likelihoods for age against stage for the 1554 non-Balkan males (solid line) and 212 Balkan males (dashed line). The upper dotted horizontal lines represent the 50% confidence set, so that normed likelihoods above this line represent ages in the 50% confidence set. The lower dotted lines represent the 95% confidence set.*

not the case for the confidence intervals taken directly from Suchey's data assuming a normal distribution for age within stage. For both the Balkan and Thai samples these confidence intervals include less than the stated coverage and tend to underestimate age-at-death.

On the evidentiary value of the Suchey–Brooks stages, a rather different tack from those previously explored has been taken here. From the statistical literature on ordinal categorical data, it is common to see some summary measure of the fit of a model, usually referred to as a pseudo R^2 (31,54–56). The preference in this article in using transition analysis is to look at the "evidentiary value" provided by log-likelihood ratio statistics rather than any R^2 based measure. The latter provide a measure of the proportion of variation in one variable, in this case Suchey–Brooks stage that is explained by another variable, in this case age. Such a measure of association, while potentially of academic interest, tells little about the utility of the method in actual forensic applications. For example, were it the case that the standard deviations for transition ages between Suchey–Brooks stages were remarkably small, say on the order of a few days, then the R^2 would be equal to one. Similarly, this would provide probabilities of being in each of the six stages that are zero when individuals were not between the relevant two transition age means, and that were equal to one when they were between the relevant two transition age means. In other words, once one knew the age of an individual one would know with complete certainty the Suchey–Brooks stage of the individual, and similarly if one knew the Suchey–Brooks stage for an individual one would exactly know the individual's possible age range. However, the system would in most contexts still have relatively low evidentiary value for the simple fact that there are only six stages. The extent to which the Suchey–Brooks system is informative for a particular identification

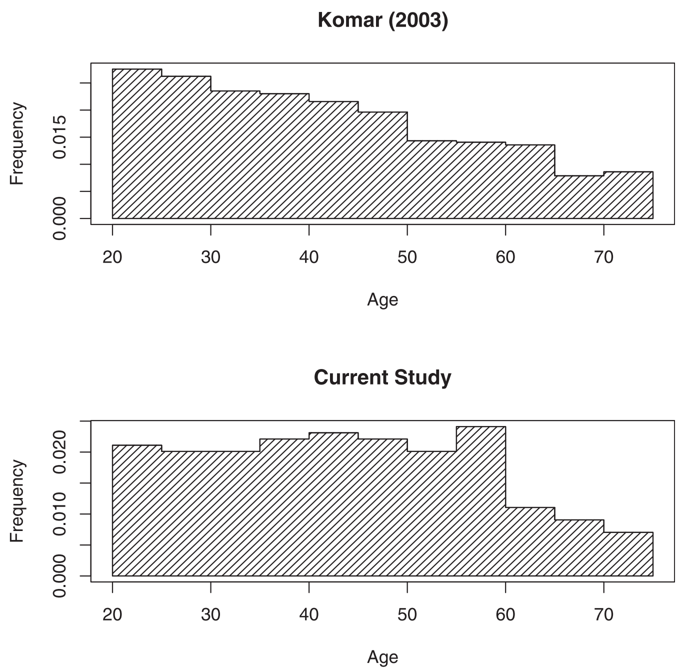

FIG. 12—*Comparison of Komar's (43) age-at-missing data from Srebrenecia and the age-at-death distribution for the 199 Balkan males (current study) with ages between 20 and 75 years (inclusive).*

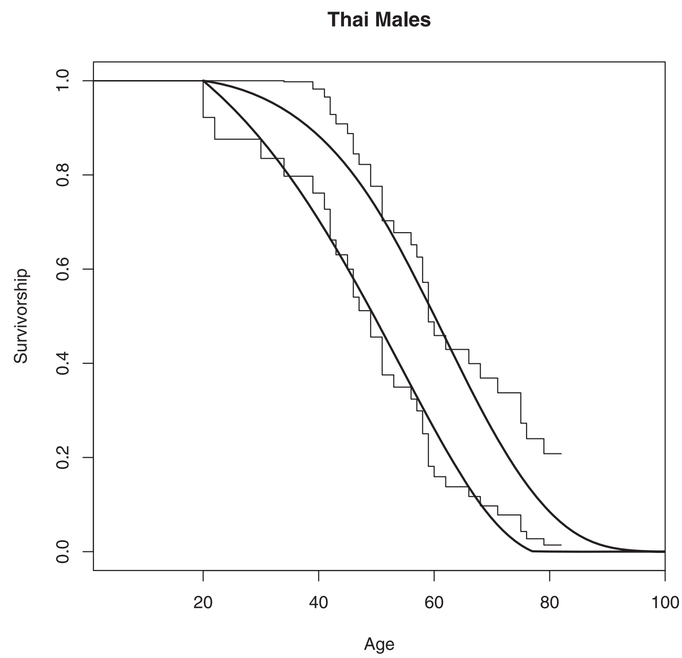

FIG. 14—*The 95% confidence interval on survivorship (Kaplan–Meier method, shown as step functions) for the 37 Thai males and the 95% confidence interval on a Gompertz mortality model (shown as smooth functions) fit to the same age-at-death data.*

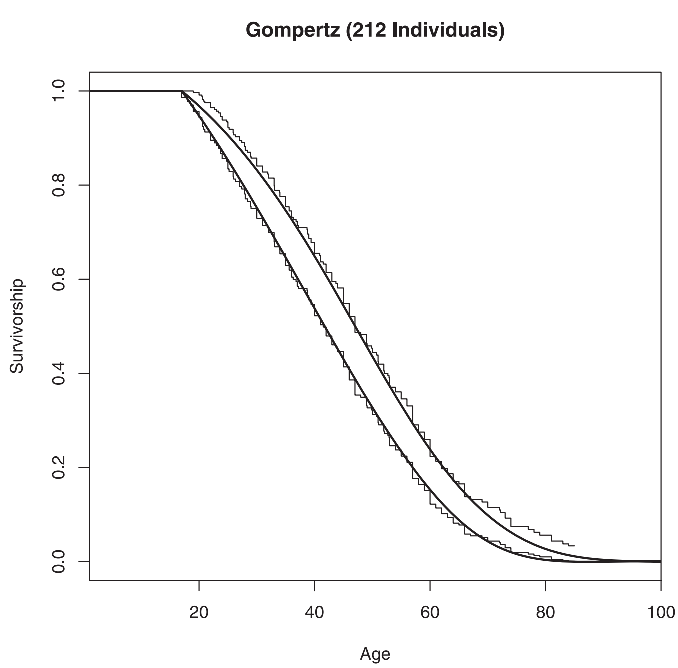

FIG. 13—*The 95% confidence interval on survivorship (Kaplan–Meier method, shown as step functions) for the 212 Balkan males and the 95% confidence interval on a Gompertz mortality model (shown as smooth functions) fit to the same age-at-death data.*

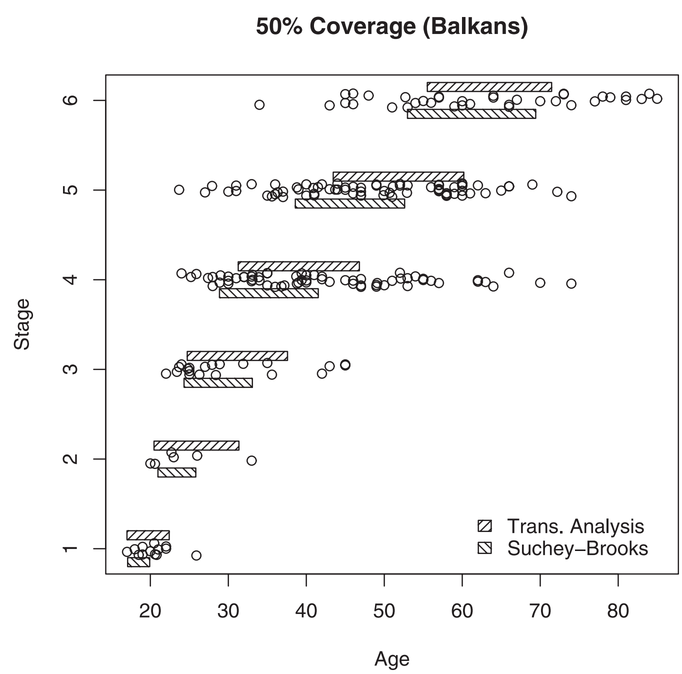

FIG. 15—*Plot of 50% coverage for the 212 Balkan males. The stages have been randomly jittered to reduce overlap of points. The upper hatched rectangles represent the transition analysis 50% regions where the transition analysis parameters are from the 1554 non-Balkan males and the prior age-at-death distribution is from the Gompertz model shown in Fig. 13. The lower hatched rectangles are from the assumption of a normal distribution of age within each stage and are based on summary statistics in Suchey and Katz (3).*

in such an unlikely setting depends on the rarity of a given stage, which in turn depends completely on the age-at-death structure for the population at large.

The graphs shown in Figs. 17–20 show, as one would generally expect, that the evidentiary value of the Suchey–Brooks system is rather lower. The system certainly operates better than expected at random, even for the Balkan sample in which identifications are not based on paper records or DNA. However, with only six stages the system cannot be expected to provide much information for identification purposes. When combined with other osteological or

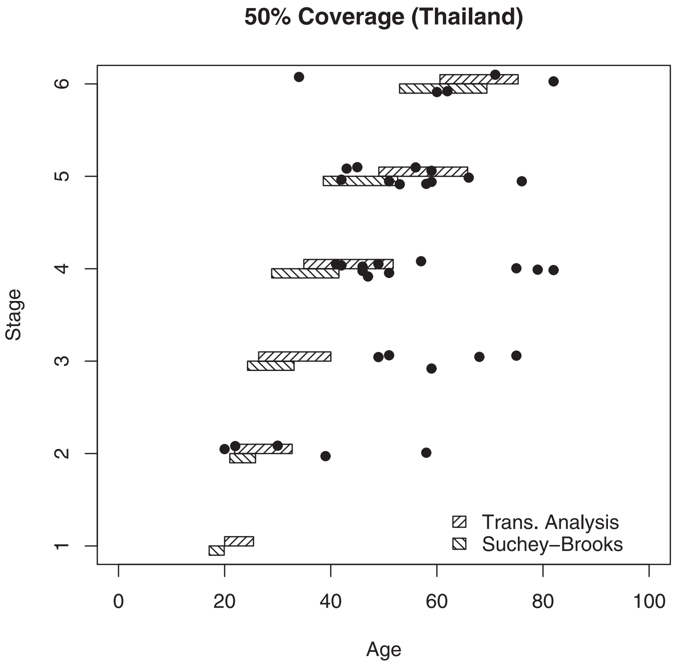

FIG. 16—*Plot of 50% coverage for the 37 Thai males. The stages have been randomly jittered to reduce overlap of points. The upper hatched rectangles represent the transition analysis 50% regions where the transition analysis parameters are from the 1729 non-Thai males and the prior age-at-death distribution is from the Gompertz model shown in Fig. 14. The lower hatched rectangles are from the assumption of a normal distribution of age within each stage and are based on summary statistics in Suchey and Katz (3).*

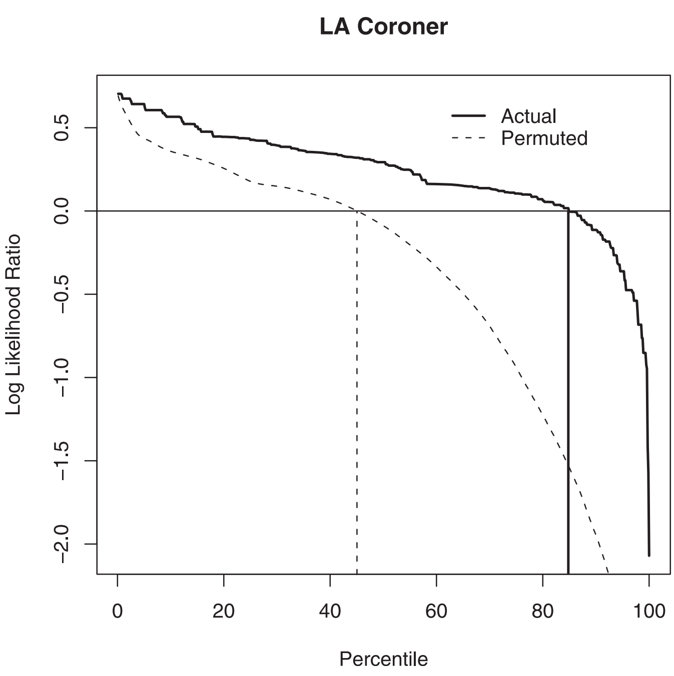

FIG. 17—*Percentiles of log-likelihood ratios across 737 Los Angeles Coroners' Office cases. Transition analysis parameters are from the 1029 individuals in the Korean War Dead, Terry, Balkan, and Thai samples, while the probability of a person being in a particular stage from the "population at large" is taken from the frequencies among the 737 cases. The permuted set is from averaging 1000 runs where individuals' ages are randomized against stage for the 737 cases. In the actual data, 84.80% of the log-likelihood ratios are greater than zero (i.e., better than "evens"), while in the permuted data 45.05% are greater than zero.*

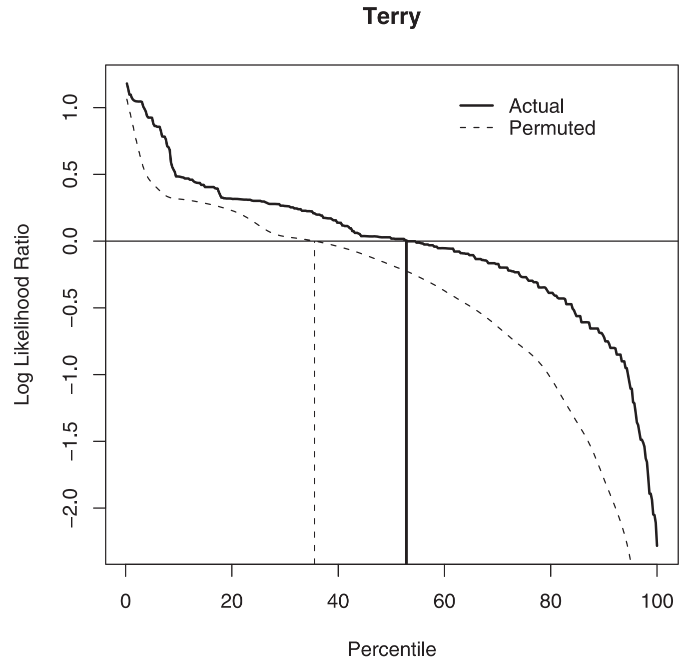

FIG. 18—*Percentiles of log-likelihood ratios across 422 Terry Anatomical Collection cases. The graph is drawn using the same methods as given in the caption for Fig. 17 but with the transition analysis parameters taken from the 1344 individuals in the LA Coroner's, Korean War Dead, Balkan, and Thai samples. In the actual data, 52.84% of the log-likelihood ratios are greater than zero, while in the permuted data 33.54% of the log-likelihood ratios are greater than zero.*

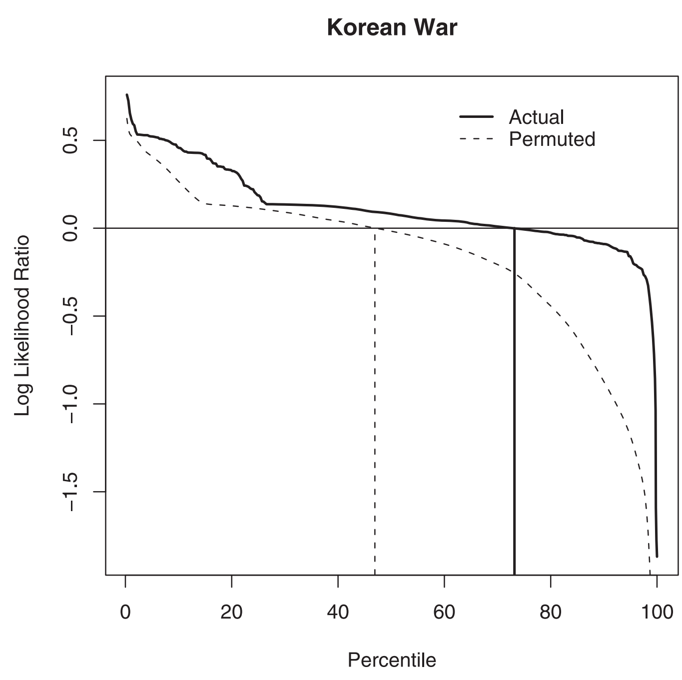

FIG. 19—*Percentiles of log-likelihood ratios across 358 Korean War Dead cases. The graph is drawn using the same methods as given in the caption for Fig. 17, but with the transition analysis parameters taken from the 1408 individuals in the LA Coroner's, Terry, Balkan, and Thai samples. In the actual data, 73.18% of the log-likelihood ratios are greater than zero, while in the permuted data 46.93% of the log-likelihood ratios are greater than zero.*

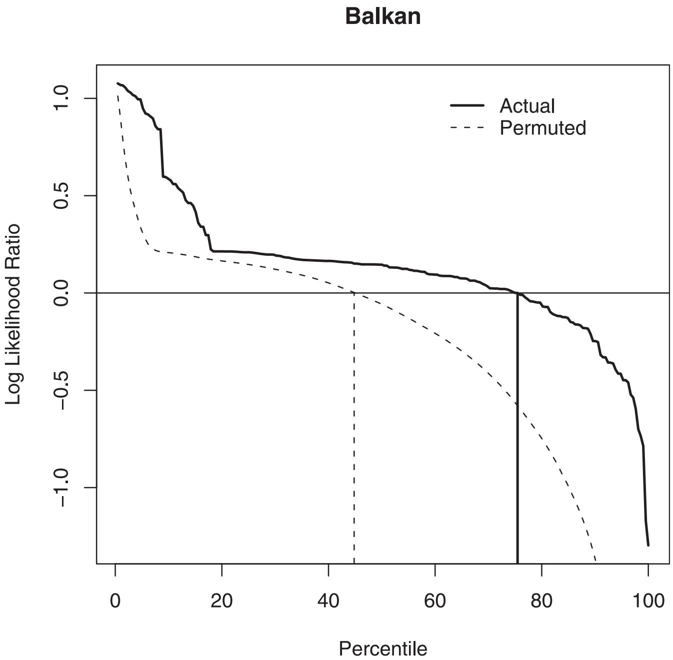

FIG. 20—*Percentiles of log-likelihood ratios across 212 Balkan cases. The graph is drawn using the same methods as given in the caption for Fig. 17, but with the transition analysis parameters taken from the 1554 individuals in the LA Coroner's, Terry, Korean War Dead, and Thai samples. In the actual data, 75.47% of the log-likelihood ratios are greater than zero, while in the permuted data 44.81% of the log-likelihood ratios are greater than zero.*

dental information (45), the Suchey–Brooks system may raise the log-likelihood ratio for an identification. As "multifactorial" methods for age estimation are preferable to the use of a single ordinal categorical system, it logically follows as well that multiple lines of osteological and dental evidence should be explored when establishing the likelihood ratio for a "positive identification."

Disclaimer

This study does not represent in whole or in part the views of the United Nations but those of the authors.

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Additional information — Reprints not available from author:
Lyle W. Konigsberg, Ph.D.
Department of Anthropology
University of Illinois
109 Davenport Hall
607 South Matthews Avenue
Urbana, IL 61801
E-mail: lylek@utk.edu