Journal of Network Intelligence ©2022 ISSN 2414-8105 (Online)
Taiwan Ubiquitous Information Volume **7**, Number **4**, November **2022**

Research on Two Interpolation Algorithms for Anthropometric Data Completion – a Case Study on the Data of Elderly Males in Fujian, China

Keke Sun

School of Design Art
Xiamen University of Technology
Xiamen, China
sunkeke@xmut.edu.cn

Min Gao

School of Design Art
Xiamen University of Technology
Xiamen, China
2122041075@s.xmut.edu.cn

Bi Li

School of Mechanical and Automotive Engineering
Xiamen University of Technology
Xiamen, China
bili@stu.xmut.edu.cn

*Corresponding author: Keke Sun

Received August 20, 2022, revised September 27, 2022, accepted October 24, 2022.

Abstract. *The static dimensions of human anthropometric are prone to missing data during the measurement process, which leads to increased costs while building anthropometric databases. To this end, a thin-plate sample interpolation (TPS) method is proposed for completing missing data. First, 54 groups of anthropometric data of older males aged 60 to 87 years were obtained according to the measurement criteria and categorized into common data and vulnerable to missing values data according to the degree of missing data. Then, correlation analysis was performed. The fitting performance of the linear interpolation and the TPS methods was analyzed using the data with higher correlations as a reference for the missing data. Finally, three samples were taken for experimental validation, and an error mean E was proposed to quantify the prediction performance of the algorithm. The results showed that (1) the error mean of the linear interpolation method for the three samples with small missing data was 1.16 times, 2.79 times, and 1.07 times that of the TPS method. (2) The mean error of the linear interpolation method for the three samples with medium missing data was 1.22 times, 1.80 times, and 1.14 times that of the TPS method. (3) The errors of the linear interpolation method for the three samples with large missing data were 1.24 times, 2.58 times, and 1.79 times those of the TPS method. In summary, the mean values of the errors obtained by the TPS method were lower than those of the linear interpolation method, indicating that the proposed TPS method can provide better prediction results.*
Keywords: Anthropometry of the elderly, Data completion, Thin-plate spline interpolation, Linear interpolation.

---

1. **Introduction.** The growing trend of an aging world population has brought the design of products and services for aging individuals into focus. As a basis for such products and services, an anthropometric and ergonomic database for the elderly is essential. At present, there is a lack of anthropometric data of people over 60 years of age in China. This paper establishes a comprehensive and effective anthropometric database of the elderly and provides a reference for research on and practice regarding the physiological health and social life of the elderly.

Easton et al. [1] used Kaplan-Meier curves and Cox regression models for anthropometric measurements (body mass index [BMI], height, waist-hip ratio, and calf circumference [CC]) of 1298 frail people aged 50 years or older within a group of older Mexicans at risk of death for survival analysis. Their conclusions suggested that calf circumference is potentially valuable in predicting negative health outcomes. Kamide et al. [2] used intraclass correlation coefficients (ICCs) and 95% limits of agreement (LOAs) to analyze the concordance between self-reported and measured BMI values in 420 older adults aged 65 years or older and living independently in the community. The results showed that the ICC was 0.964 for men and 0.970 for women; the 95% LOA was relatively wide, and the BMI assessment for Japanese older adults should be based on the measured values. Sampaio et al. [3] tested the association between anthropometric markers and frailty in 316 older adults using logistic regression techniques to identify predictors of frailty in older adults. This was also assessed by the parameters provided by the receiver operating characteristic (ROC) curve. The results showed that calf circumference, BMI, and corrected arm muscle area were inversely correlated with frailty. The metrics showed good sensitivity and were easy to measure. Zhang et al. [4] statistically analyzed the height, weight, waist circumference (WC), fasting glucose, and triglyceride levels in 4985 elderly people using the Chi-square test, logistic regression analysis, and ROC curves. The conclusions showed that lipid accumulation product was closely associated with nonalcoholic fatty liver disease, and it can be an effective screening and treatment tool for nonalcoholic fatty liver disease in the elderly. Dhana et al. [5] assessed the association of BMI, WC, and BMI with fat-free mass (FFM) and fat mass (FM) in 3612 participants using multivariate models adjusted for confounders. The results showed that BMI and WC were positively correlated with fat mass index (FMI) and fat-free mass index (FFMI) in men and women. The above literature focused on the association of anthropometric data and the physical health of older people. It has some value in predicting the health of older people.

Pasalich et al. [6] used paired t-tests, correlation coefficients, and Bland-Altman plots to assess the variability and consistency of self-reported anthropometric data with technician measurements in 103 Australian older adults aged 60-70 years. The results showed that the consistency correlation coefficients were generally high, except for the waist-to-hip ratio, which had a small mean difference. Goes et al. [7] used linear mixed regression models to analyze age-related changes in the longitudinal changes in height, weight, and WC in 1702 older adults between the ages of 70.6 and 80 years. Their conclusions indicated that behavioral variables were associated with current height, weight, and WC but neither behavioral variables nor the presence of chronic disease affected anthropometric changes. Guo et al. [8] analyzed BMI and muscle mass and CC and mid-arm circumference (MAC) data of 2155 elderly subjects aged 60 years without dementia using a linear mixed-effect models stratified by age. The results showed that vigorous physical activity slowed the decline in BMI and CC and vascular disease accelerated the decline in BMI and MAC. Bhowmik et al. [9] used linear discriminant analysis and principal component analysis. Two baseline algorithms were tested to develop an efficient algorithm to address the difficulties in automatic face recognition. They created a new face database (DeitY-TU) based on facial images and anthropometric data of 524 individuals from different nontribes and

Mongolian tribes of north-east India. Elsamny et al. [10] used the Rhinobase software and CorelDraw software to analyze the mean nasal anthropometric values of 300 Egyptian men to derive the ethnic differences in their external nasal anthropometric values as a reference standard for nasal reconstruction and aesthetic rhinoplasty. The above literature studies illustrate that anthropometric site data are correlated with anthropological characteristics of different geographical and ethnic groups. Cheng et al. [11] measured basic body data and structural and postural dimensions of 5772 preschool children in Taiwan using an electromagnetic motion analysis system, tape measure, electronic scale, and electronic calipers. The differences in body size and weight between Japanese and American children of the same age were compared to develop a large-scale anthropometric database of preschool children. Dawal et al. [12] measured 60 body dimensions of 107 Malaysian elderly individuals to develop an anthropometric database for the Malaysian elderly population to provide a reference for the design of home facilities for older Malaysians and older people in other countries. Shahida et al. [13] used a professional standard anthropometer and a dynamometer to measure body dimensions and handgrip strength (HGS) in 38 elderly subjects aged 60 years and older and analyzed the correlation between anthropometric dimensions and handgrip strength. The results showed that stature, sitting hip width, wrist circumference, hand circumference and heel circumference, and ankle circumference were significantly correlated with handgrip strength. Tessari et al. [14] used multiple linear regression to analyze the effect of anthropometric data from 2009 to 2013 on BMI and WC as well as absolute BMI and WC changes over the same period. The results suggested that maintaining body weight and WC within normal ranges during aging can help maintain quality of life. Rezende et al. [15] studied a representative probability sample for cross-sectional analysis and assessed weight, height, girth (waist, hip, calf, and arm), BMI, body obesity index, waist-hip ratio, and waist-to-stature ratio in 621 older adults by gender and age. The results showed that the elderly subjects had lower body weight. There was no difference in the rate of central obesity between the male and female age groups. Saghazadeh et al. [16] used Dream GP Incorporated's 3D foot scanner Footstep PRO to measure foot variables in sitting and standing positions in 151 elderly Japanese men and used the independent samples t-test and analysis of covariance. The results showed that truncated foot length, instep, belly button height, foot length, ball circumference, ball width, heel width, and instep circumference had a significant effect on sitting and standing positions and could serve as a reference for making shoes for older adults. Kaewdok et al. [17] utilized descriptive statistics, independent t-tests, and percentile values data analysis applied to 32 body dimensions measured in 240 elderly subjects in Thailand. The results showed that the majority of anthropometric dimensions were larger in men than in women. Design-meaningful anthropometric values were provided for the elderly to create a database for an elderly friendly environment. Dawal et al. [18] designed an ergonomic bathing area for the disabled and elderly based on Muslim preferences. They measured anthropometric dimensions of 20 elderly and disabled respondents. They proposed a solution to improve the comfort and accessibility of elderly and disabled people in Malaysian mosques. Amaral et al. [19] using descriptive statistics, obtained anthropometric and hand grip strength values for 1609 adults and elderly residents at maximum performance and analyzed the Pearson correlations between these variables. The values were a reference for HGS behavior in healthy adults and older adults, and the authors explored their potential application in the assessment of health status in adults and older adults. The above literature studies analyzed methods of creating anthropometric databases for different populations and analyzed anthropometric data of older people.

The present author's related research [20] used mathematical analysis, fitting functions, and length calculation formulas derived from large sample measurement experiments to analyze the relevant curve patterns of young Asian female bodies and developed a 2D-3D non-contact anthropometric and calculation method applicable to daily dressing states to obtain the chest, waist, and hip dimensions under natural daily dressing conditions.

Different algorithms are used to fit measurement data and analyze the fitting performance. First, common data with high correlation are used as a reference for missing data to analyze the missing data in anthropometric measurements. Then, the algorithm with better fitting performance is selected for the missing data of the elderly anthropometric data for the remediation of the data. This study addresses the problems of the high cost of establishing an anthropometric database for the elderly and imputation of missing data.

2. **Experiment.** In the anthropometric data collection experiment, measurements were taken in Fujian, China, on elderly males between the ages of 60 and 86 years for a period of approximately 3 weeks. Martin's rulers, including long Martin's rulers, medium Martin's rulers, and short Martin's rulers, right angle gauges, vernier calipers, circumference rulers, foot length meters, fingertip distance rulers, and tape measures were used. During the measurement process, field measurements were taken in groups of two. The measurement parts and measurement methods were based on ISO 7250-1:2008, which contains 55 items, such as height, weight, and other common body data, as well as other relevant body size data. To ensure the quality and efficiency of the measurement experiments, the measurement personnel were trained in advance and the subjects were given gifts to increase their cooperation. The experimental measurement tools and measurement environment are shown in Figure 1.

(a) Martin scale (b) Measurement scenarios

Figure 1. Measurement data acquisition

3. **Correlation analysis.** The correlation between different types of anthropometric data and common data was analyzed, and the common data with higher correlation were selected as a reference of the missing data and used for subsequent data completion. Three correlation metrics are commonly used: Pearson correlation coefficient, Kendall correlation coefficient, and Spearman correlation coefficient. In this paper, the Spearman correlation coefficient was used for the anthropometric data correlation analysis.

3.1. **Correlation analysis method.** Spearman's correlation coefficient refers to the method of calculating correlation using the ranks of two sets of elements within their respective sets. The correlation calculation process is as follows.

(1) Analyze the ranks of elements x_i and y_i within the two sets of data X and Y in their respective sets and denote them as $G(x_i)$ and $G(y_i)$ $(i = 1, 2, \ldots, n)$.

(2) The correlation between the data is

$$\gamma_s = 1 - 6\frac{\sum_{i=1}^{n} \left[G(x_i) - G(y_i)\right]^2}{n(n^2 - 1)}. \tag{1}$$

3.2. **Classification of database data.** The database data are divided into common anthropometric data and relatively likely to be missing anthropometric data. Common anthropometric data refer to the body data that are generally accessible to the public and not likely to be missing. The specific common anthropometric data types are shown in Table 1. The remaining 55 measured sites were rearranged and divided into seven groups based on the body parts that are relatively vulnerable to missing data. This is shown in Tables 1 to 7.

Table 1. Common anthropometric data types

No.	1	2	3	4	5	6	7
Name	Age	Weight	Height	Sitting height	Chest	Waist	Hip

Table 2. Types of anthropometric data that are prone to missing values (basic body height)

No.	8	9	10	11	12
Name	High fingertips	Calf plus foot height (popliteal height)	High tibial points	Elbow height	Perineal height
+ No.	13	14	15	16	17
Name	Anterior superior iliac spine	Waist height	Shoulder height	Standing cervical vertebra	High eye

Table 3. Types of anthropometric data that are prone to missing values (sitting position)

No.	18	19	20	21	22
Name	Thick thighs	Hip Width	Abdominal width	Waist thickness	Abdominal thickness
No.	23	24	25	26	27
Name	Elbow height	Knee height	Shoulder height	Cervical point height	Eye height

3.3. **Correlation analysis results.** Figure 2 shows the results of the correlation analysis between the common anthropometric data.Figure 3 shows the results of the correlation analysis between the basic body height and the common anthropometric data. Figure 4 shows the results of the correlation analysis between the body sitting data and the missing anthropometric data. Figure 5 shows the correlation between the body standing data and the missing body data. Figure 6 shows the correlation between the body circumference

Table 4. Types of anthropometric data that are prone to missing values (standing position)

No.	28	29	30	31	32
Name	Hip-knee distance	Hip-popliteal distance	Body Thickness	Chest Thickness	Chest width
No.	33	34	35	36	37
Name	Waist width	Hip Width	Shoulder width	Maximum shoulder width	Elbow and shoulder width

Table 5. Types of anthropometric data that are prone to missing values (body circumference)

No.	38	39	40	41	42
Name	Neck Root Circumference	Neck circumference	Head circumference	Abdominal circumference	Wrist circumference

Table 6. Types of anthropometric data that are prone to missing values (top length)

No.	43	44	45	46	47	48	49
Name	Wingspan	Back length	Elbow wrist distance	Shoulder elbow distance	Elbow span	Upper limb length	Straight forward upper limb extension

Table 7. Types of anthropometric data that are prone to missing values (length of limbs)

No.	50	51	52	53	54	55
Name	Foot width	Foot length	Hand width	Hand length	Head width	Head length

data and the missing body data. Figure 7 shows the results of the correlation analysis between the upper body length data and the missing body data. Figure 8 shows the results of the correlation analysis between the limb length data and the missing body data. The colors represent the level of correlation of the data, with the best correlation in the yellow band.

As can be seen from Figure 2, among the common anthropometric data types, the correlation coefficient distribution between data 1 and common data is -0.216 to 1, and its highest correlation is with common data 7. The correlation coefficient distribution between data 2, 6, 7 and common data is 0.077 to 1, -0.160 to 1, and 0.195 to 1, respectively, all of which have the highest correlation with common data 5. The correlation coefficients between data 3, 5, and the common data are -0.216 to 1 and 0.182 to 1, respectively, with the highest correlation with common data 2. Data 4 has a correlation coefficient distribution of -0.081 to 1 with the common data, and it has the highest correlation with common data 3. Data 1 to 7 all have the highest correlation with themselves.

As can be seen from Figure 3, among the prone to be missing human anthropometric data types (basic human height), the correlation coefficients between data 8 to 12 and the common anthropometric data are -0.195 to 0.902, -0.008 to 0.723, -0.170 to 0.660, -0.203 to 0.560 and -0.201 to 0.325, respectively, and the correlation coefficients between data 14-16 and the common anthropometric data distribution are -0.206 to 0.056, -0.202

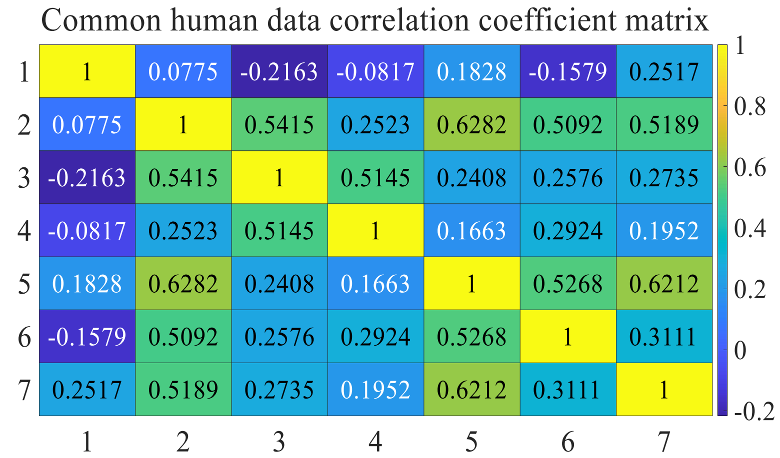


FIGURE 2. Common anthropometric data correlation coefficient matrix

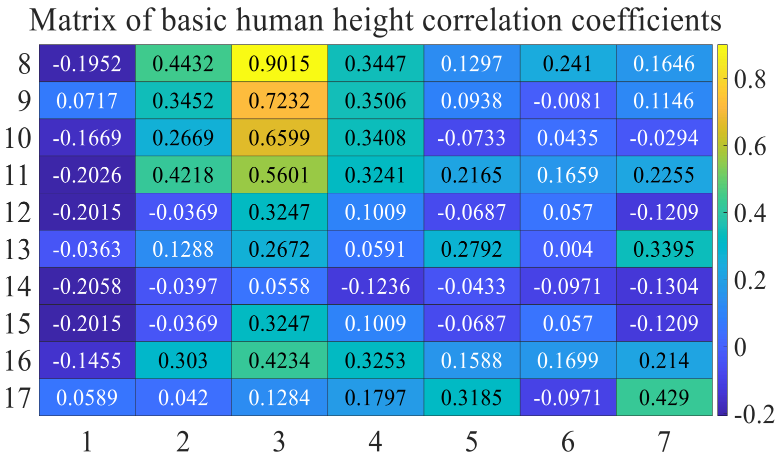


FIGURE 3. Correlation coefficient matrix (basic human height)

to 0.325, and -0.146 to 0.423, respectively, and all have the highest correlation with common anthropometric data 3. The correlation coefficients between data 13 and 17 and the common anthropometric data are -0.036 to 0.340 and 0.060 to 0.430, respectively, with the highest correlation being with common anthropometric data 7.

As can be seen in Figure 4, among the missing body data types (sitting position), the correlation coefficients between data 18 and the common data are -0.218 to 0.125 , with the highest correlation being with common data 1. The correlation coefficients between data 19 and common data range from -0.213 to 0.348, with the highest correlation being with common data 7. Data 20, 24, 25, and 27 have correlation coefficients of -0.192 to 0.080, -0.140 to 0.346, 0.135 to 0.333, and -0.142 to 0.645 with the common data, respectively, and have the highest correlation with common data 3. The distribution of correlation coefficients between data 21 and common data range from 0.051 to 0.360, and it has the highest correlation with common data 2. The distribution of correlation coefficients between data 22 and common data range from 0.041 to 0.674, with the highest correlation with common data 5. The correlation coefficient distribution between data 23 and common data is -0.115 to 0.119, with the highest correlation with common data 6. The distribution of correlation coefficients between data 26 and common data is 0.115 to 0.546, with the highest correlation with common data 4.

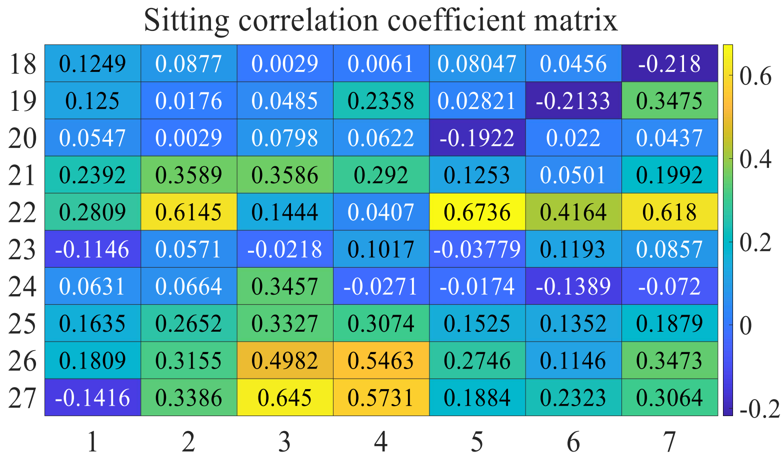


Figure 4. Correlation coefficient matrix (seated)

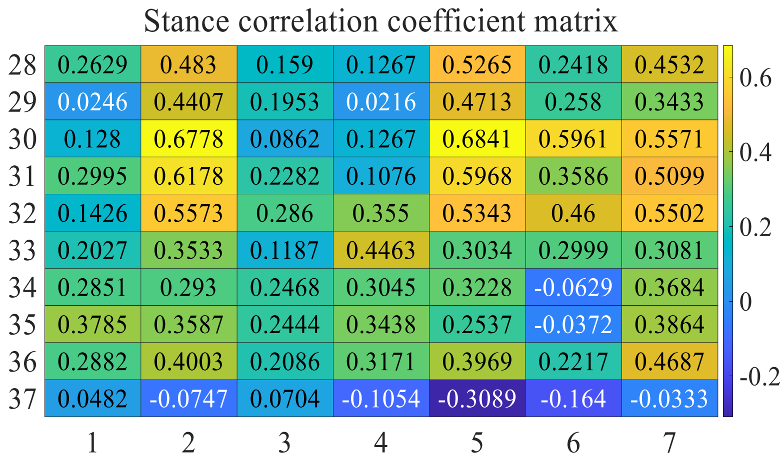


Figure 5. Correlation coefficient matrix (upright position)

As can be seen from Figure 5, among the missing body data types (stance), the correlation coefficients between data 28, 29, and 30 and the common data are 0.127 to 0.527, 0.022 to 0.47 , and 0.127 to 0.684, respectively, with the highest correlation with common data 5. The distribution of correlation coefficients between data 31 and 32 and common data is 0.108 to 0.618 and 0.143 to 0.557, respectively, with the highest correlation with common data 2. Data 33 has a correlation coefficient distribution of 0.119 to 0.446 with the common data and has the highest correlation with common data 4. Data 34, 35, and 36 have correlation coefficients of -0.062 to 0.368, -0.037 to 0.386, and 0.222 to 0.469, respectively, with the common data and have the highest correlation with common data 7. The distribution of correlation coefficients between data 37 and common data is -0.309 to 0.070, with the highest correlation with common data 3.

As can be seen in Figure 6, among the missing body data types (human circumference), the correlation coefficients between data 38, 41, and 42 and the common data are 0.056 to 0.506, 0.182 to 0.743, and 0.042 to 0.493, respectively, with the highest correlation with common data 7. The distribution of correlation coefficients between data 39 and common data range from 0.036 to 0.518, with the highest correlation with common data 5. Data 40 has a correlation coefficient distribution of -0.080 to 0.279 with common data and the highest correlation with common data 1.

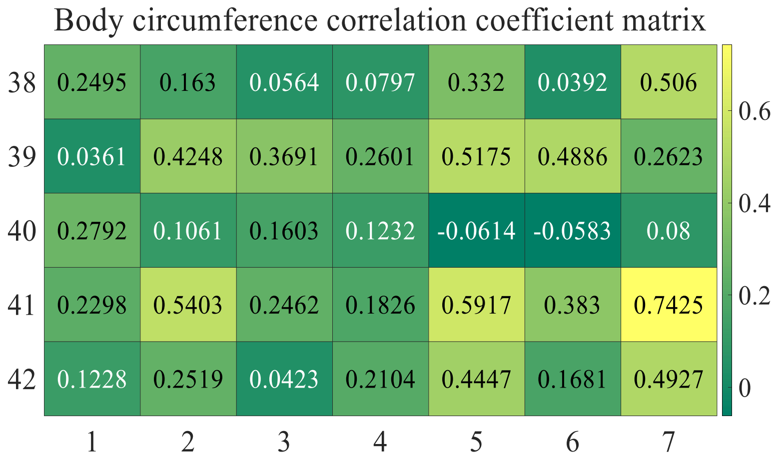


Figure 6. Correlation coefficient matrix (body circumference)

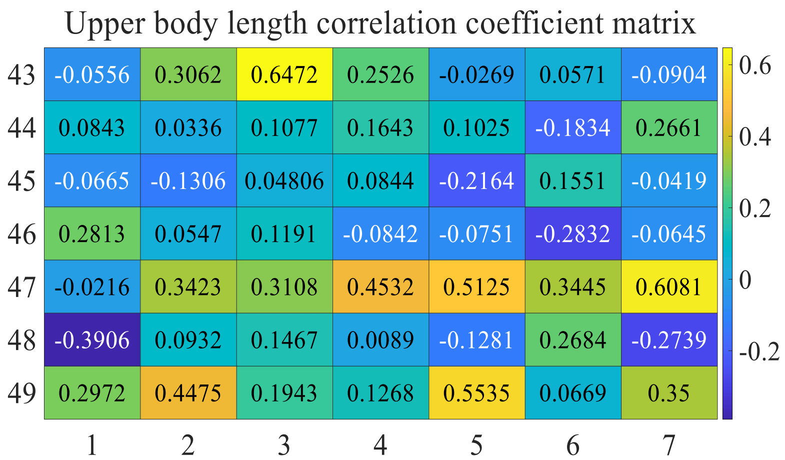


Figure 7. Correlation coefficient matrix (upper body length)

As can be seen from Figure 7, among the easily missing anthropometric data types (upper body length), data 43 has a correlation coefficient distribution of -0.090 to 0.647 with the common data 3. The correlation coefficients between data 44 and 47 and common data are -0.183 to 0.266 and -0.021 to 0.608, respectively, with the highest correlation being with common data 7. Data 45 and 48 have a correlation coefficient distribution of -0.130 to 0.155 and -0.390 to 0.268, respectively, with the common data, and the highest correlation is with common data 6. The distribution of correlation coefficients between data 46 and the common data is -0.283 to 0.281, with the highest correlation being with common data 1. Data 49 has a correlation coefficient distribution of 0.070 to 0.554 with the common data, with the highest correlation being with common data 5.

From Figure 8, it can be seen that among the easily missing anthropometric data types (limb length), data 50, 51, 53, and 55 have correlation coefficient distributions of -0.403 to 0.212, -0.304 to 0.307, -0.082 to 0.472, and -0.244 to 0.258, respectively, with the common data, and the highest correlation is with common data 3. The distribution of correlation coefficients between data 52 and common data is -0.181 to 0.270, with the highest correlation being with the common data 7. Data 54 has a correlation coefficient distribution of -0.146 to 0.291 with the common data, with the highest correlation being with common data 1.

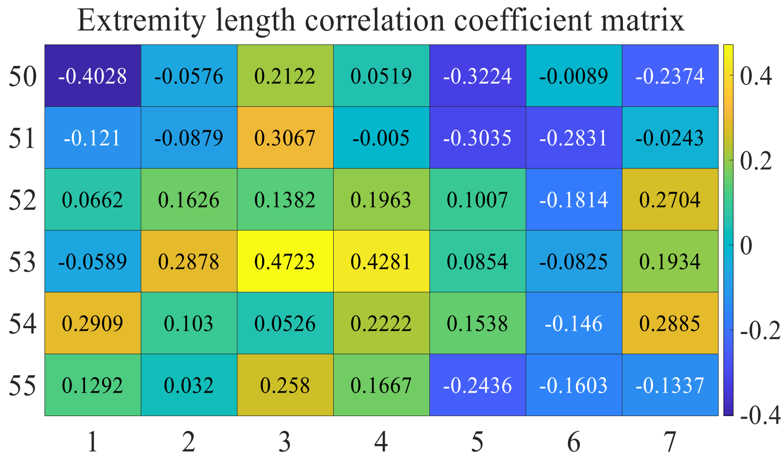


FIGURE 8. Correlation coefficient matrix (limb length)

To judge the correlation more intuitively, the correlation coefficients for each common anthropometric data were averaged, and the results are shown in Figure 9.

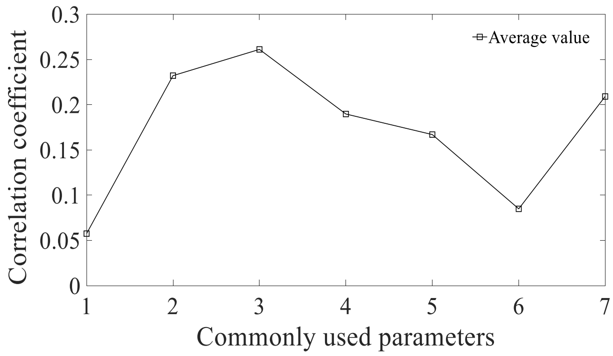


FIGURE 9. Results of the correlation analysis (average correlation coefficient)

The average correlation coefficient for age is 0.058; for weight is 0.232; for height is 0.261; for sitting height is 0.190; for chest is 0.167; for waist is 0.085; and for hip is 0.209. The data distribution shows that: (1) the mean correlation coefficients of the anthropometric data are all greater than 0, and the overall correlation is positive. The average correlation coefficient for age is the lowest, and the average correlation coefficient for height is the highest. (2) The mean correlation coefficients for data 2 and 3 are the highest among the missing data, at 0.232 and 0.261, respectively, which are greater than that for the other data. This indicates that height and weight are more suitable references for missing data.

4. **Data Completion.** Height (data 1) is the x-axis coordinate; weight (data 2) is the y-axis coordinate; and the missing data are the z-axis coordinate. The missing data of the database are predicted using the fitting algorithm, and the fitting performance is analyzed.

4.1. **Correlation analysis results.** Height (data 1) is the x-axis coordinate; weight (data 2) is the y-axis coordinate; and the missing data are the z-axis coordinate. The missing data of the database are predicted using the fitting algorithm, and the fitting performance is analyzed.

Definition of 3D linear interpolation: A linear interpolation method is used to calculate other points in a 3D cube from the values of the cube vertices, as shown in Figure 1, where the coordinates of the other six vertices can be derived from the point (x_0, y_0, z_0) and the point (x_1, y_1, z_1).

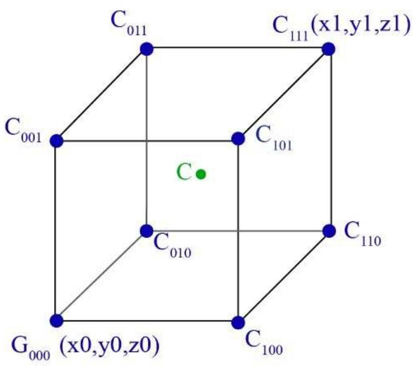


FIGURE 10. Three-dimensional linear interpolation

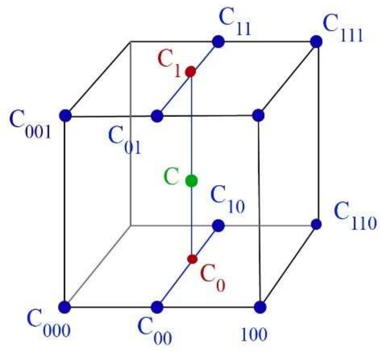


FIGURE 11. Algorithm resolution diagram

Related algorithm calculation process:

(1) Calculate the weights of the predicted points in the X, Y and Z directions.

$$\begin{cases} x_d = \dfrac{x - x_0}{x_1 - x_0} \\ y_d = \dfrac{y - y_0}{y_1 - y_0} \\ z_d = \dfrac{z - z_0}{z_1 - z_0}. \end{cases} \tag{2}$$

(2) c_{00}, c_{10}, c_{11}, and c_{01} are obtained by interpolating the eight vertices along the x-axis, as shown in Figure 10. The relevant equations are

$$\begin{cases} c_{00} = (x_0(1 - x_d) + x_1 x_d, y_0, z_0) \\ c_{01} = (x_0(1 - x_d) + x_1 x_d, y_0, z_1) \\ c_{11} = (x_0(1 - x_d) + x_1 x_d, y_1, z_1) \\ c_{10} = (x_0(1 - x_d) + x_1 x_d, y_1, z_0). \end{cases} \tag{3}$$

(3) c_0 and c_1 are obtained by interpolating the four interpolation points along the y-axis direction, as shown in Figure 11. The relevant equations are

$$\begin{cases} c_0 = (x_0(1 - x_d) + x_1 x_d, y_0(1 - y_d) + y_1 y_d, z_0) \\ c_1 = (x_0(1 - x_d) + x_1 x_d, y_0(1 - y_d) + y_1 y_d, z_1). \end{cases} \tag{4}$$

(4) The prediction point c is obtained by interpolating the interpolation points c_0 and c_1 along the z-axis direction, as shown in Figure 11. The relevant equation is

$$c = (x_0(1 - x_d) + x_1 x_d, y_0(1 - y_d) + y_1 y_d, z_0(1 - z_d) + z_1 z_d). \tag{5}$$

4.2. **Thin plate strip interpolation (TPS).** TPS is a robust spatial data interpolation and smoothing technique based on splines. Let the input points be $(\dot{x}_i, \dot{y}_i, \dot{z}_i)$ $(i = 1, 2, \cdots, n)$ and the interpolation points be (x_i, y_i, z_i). Then, the TPS objective is to find a function f that makes $z_i = f(x_i, y_i)$ and satisfies the bending energy function minimum. The specific procedure is as follows.

(1) Considering the deformation function as bending a thin steel plate through a given number of n points, the energy required to bend the plate is

$$E(f) = \iint \left[\left(\frac{\partial^2 f}{\partial x^2} \right)^2 + 2 \left(\frac{\partial^2 f}{\partial x \partial y} \right)^2 + \left(\frac{\partial^2 f}{\partial y^2} \right)^2 \right] dxdy. \tag{6}$$

(2) The required f is a function of the minimum bending energy.

$$z_i = a_0 + a_1 x_i + a_2 y_i + \sum_{j=1}^{n} w_j U(s_{ij}), \tag{7}$$

U is the basis function:

$$U(s_{ij}) = \begin{cases} s_{ij}^2 \log(s_{ij}), & s_{ij} \neq 0 \\ 0, & \text{otherwise} \end{cases}, \tag{8}$$

$$s_{ij} = \sqrt{(x_i - \dot{x}_j)^2 + (y_i - \dot{y}_j)^2}. \tag{9}$$

(3) Analysis shows that the coefficients to be solved in the equation are a_0, a_1, a_2, and $\sum_{j=1}^{n} w_j$. Then, $n+3$ equations are needed. As equation (1) has n equations, three constraint equations need to be introduced:

$$\begin{cases} \sum\limits_{i=1}^{n} w_i = 0 \\ \sum\limits_{i=1}^{n} x_i w_i = 0 \\ \sum\limits_{i=1}^{n} y_i w_i = 0. \end{cases} \tag{10}$$

From equations (6) and (9), the variables a_0, a_1, a_2, and $\sum_{j=1}^{n} w_j$ can be found by substituting back into equation (6) to obtain the equation of the function being sought.

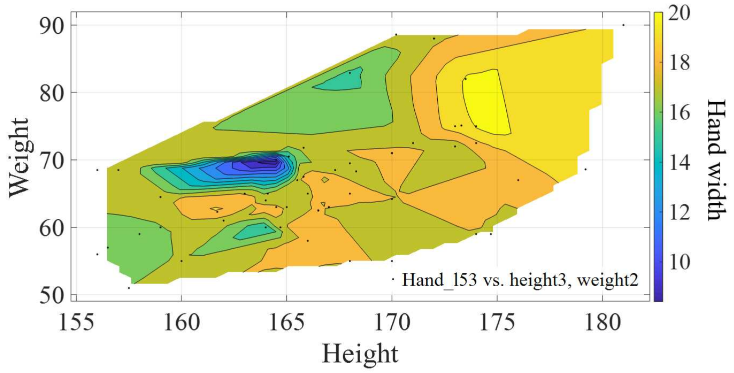
4.3. **Algorithm performance.** A comparative analysis of the fitting performance of the two algorithms, linear interpolation and TPS, was first carried out, and data 53 (hand length) was selected as the experimental data (Figure 12).

Figure 12(a) shows the linear interpolation method, and Figure 12(b) shows the TPS method. Analysis shows that (1) the linear interpolation method connects adjacent data points with a straight line; the TPS method connects data points with a polynomial curve. (2) The linear interpolation method has only continuous function values at the interpolation nodes, and the fitting range is smaller, while the fitting range of the thin-slab strip interpolation (TPS) method is larger than that of the interpolation nodes.

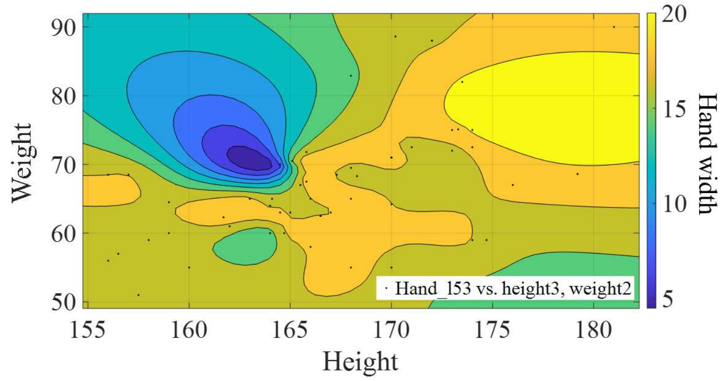
As mentioned above, the fitted line of TPS method is smooth and continuous, and the smoothness is higher than that of linear interpolation method. At the same time, the fitting range of data points of TPS method is larger than that of linear interpolation method. The data can be fitted to the range beyond the interpolation nodes. The results show that the TPS method is better than the linear interpolation method in terms of the rationality of the data fitting and the fitting range.

4.4. **Fitting experiment.** To compare the relationship between the predicted values and the original data, the mean value of the fitting error E is presented.

$$E = \frac{\sum_{k=1}^{n} \frac{e_i}{y_i}}{n} \times 100\% = \frac{\sum_{k=1}^{n} \frac{|\widehat{y}_i - y_i|}{y_i}}{n} \times 100\%, \tag{11}$$



(a) Linear interpolation



(b) Thin plate strip interpolation (TPS)

FIGURE 12. Comparison of fitting results

n is the total number of data in the sample; i is the ith data in the sample; e_i is the difference between the predicted value and the original data; y_i is the original data; and $\hat{y}_i$ is the predicted data.

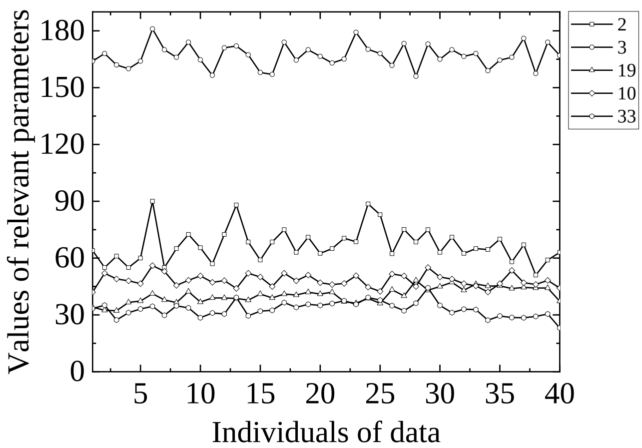
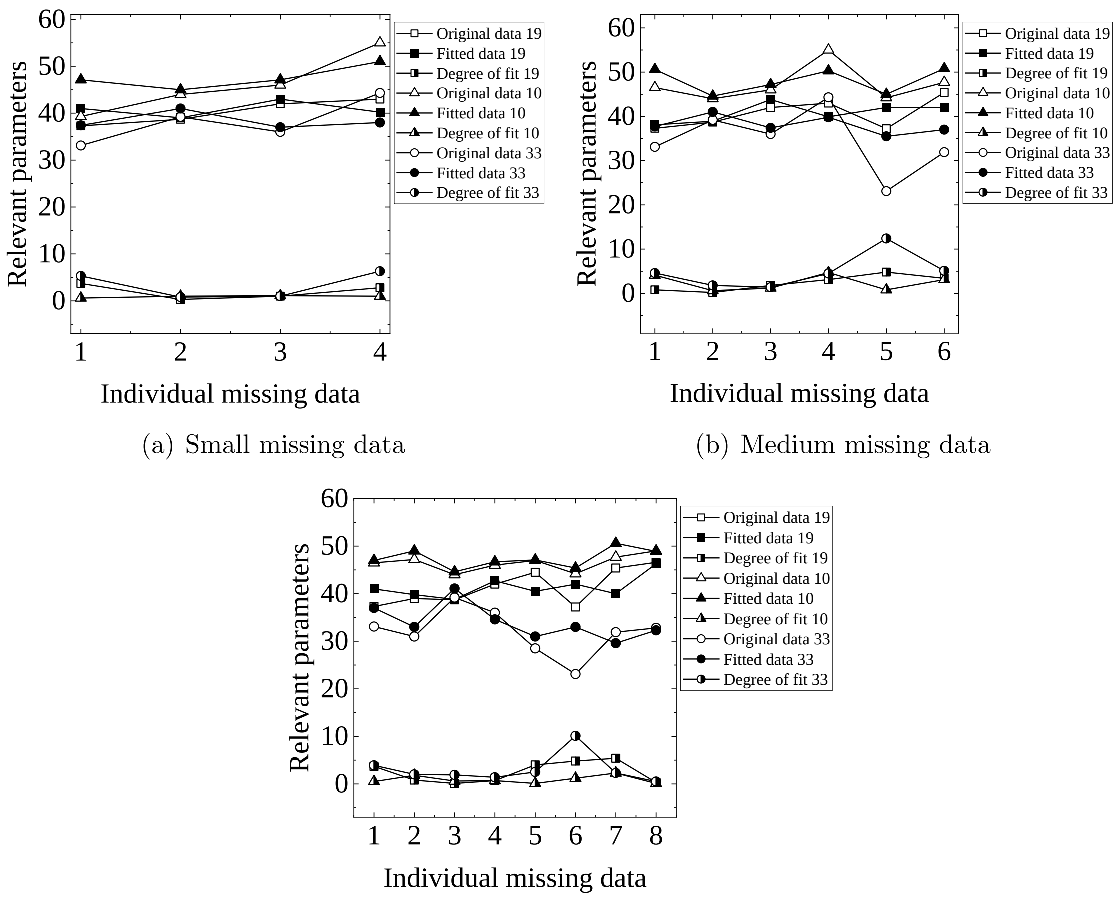


FIGURE 13. Original data

Three sets of data, namely hip width (sitting position) (data 19), tibial point height (data 10), and waist width (data 33), were selected as the sample data from 39 elderly women, and two sets of data, namely weight (data 2) and height (data 3), were selected as the reference data, as shown in Figure Figure 13 shows the raw measurements for the three datasets: hip width (seated) (data 19), tibial point height (data 10), and waist width (data 33).

The above three sets of data were treated as missing data and were classified as small, medium, and large missing data, according to the extent of the missing: small missing data is defined as less than 8% missing data; medium missing data, 8% to 12%; large missing data, more than 12%, respectively. Height and weight were also used as references for comparative analysis. The data for the three different missing cases of small, medium, and large were fitted by two different algorithms: the linear interpolation method and the TPS method. The fitted results of the data were compared with the original data, as shown in Figure 14.



(a) Small missing data

(b) Medium missing data

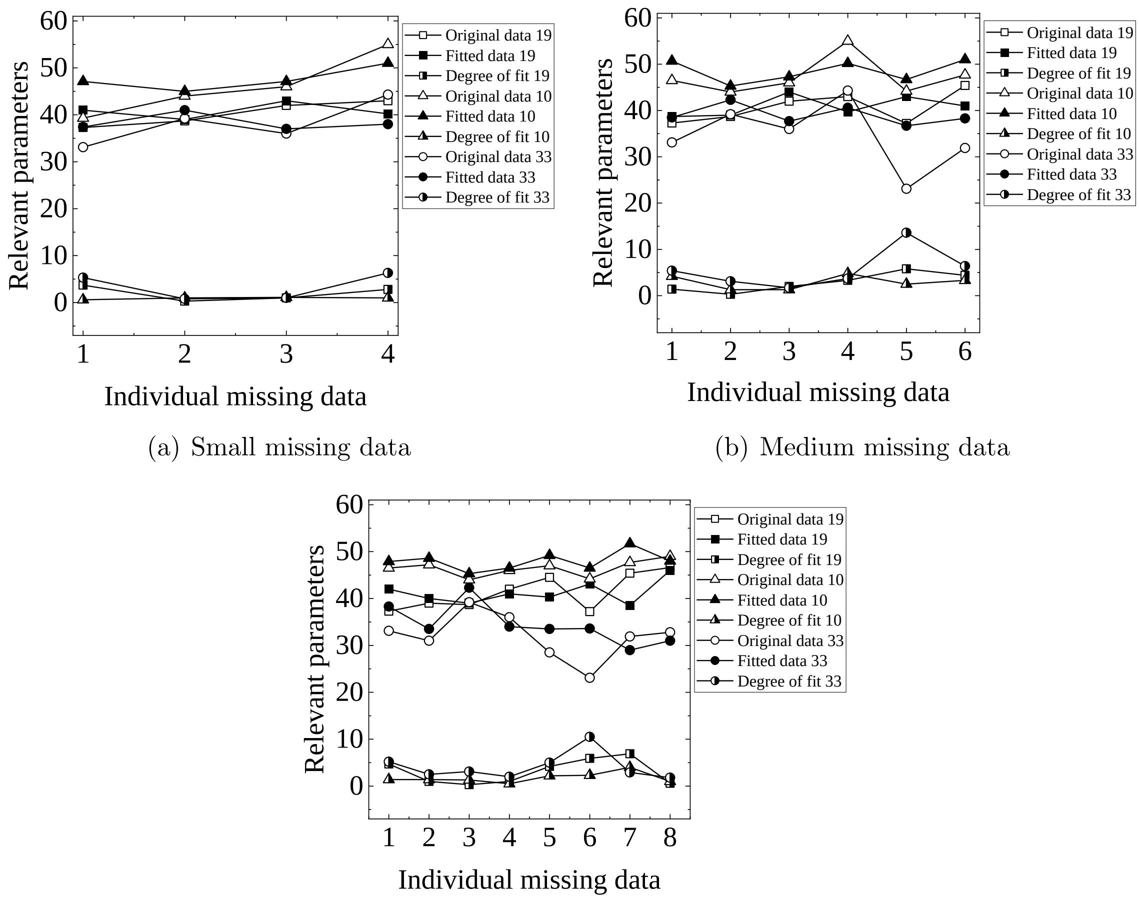
(c) Large missing data

Figure 14. Linear interpolation method

Figure 14 shows a comparison of the fitting performance of the linear interpolation method.The data were fitted using the linear interpolation method, and the fitted data were analyzed against the original data. The degree of fit of the data was expressed by calculating its difference.

From the small missing data in Figure 14(a), the best-fitting differences between the original data and the fitted data for hip width (sitting) tibial point height, and waist width are 0.4, 1.4, and 0.6, respectively. From the medium missing data in Figure 14(b), the best-fitting differences between the original data and the fitted data for hip width (sitting), tibial point height, and waist width are 0.3, 1.3, and 1.7, respectively. From

Figure 14(c), showing large missing data, the best-fitting differences between the original data and the fitted data for hip width (sitting), tibial point height, and waist width are 0.3, 0.5, and 1.8, respectively.



(a) Small missing data

(b) Medium missing data

(c) Large missing data

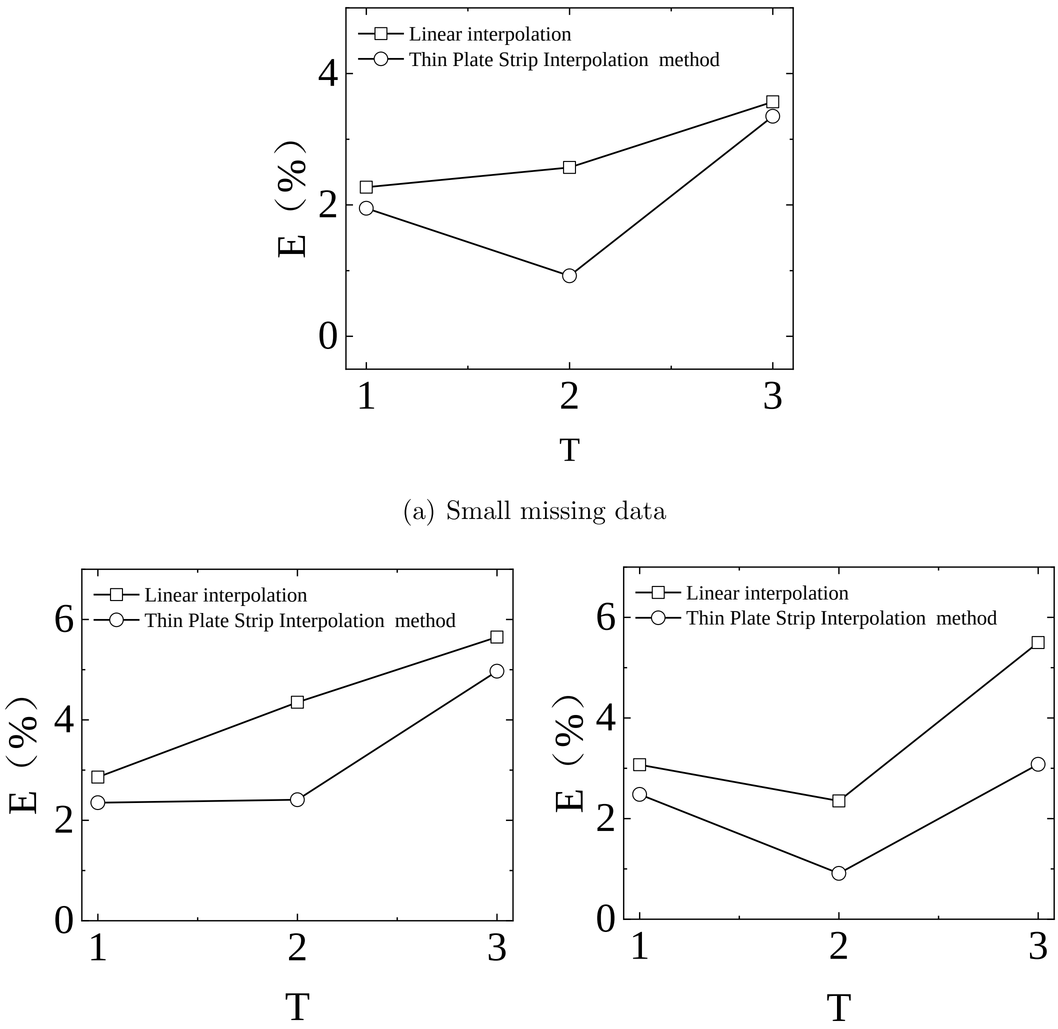
Figure 15. Thin plate strip interpolation (TPS)

Figure 15 shows the comparison of the fitting effect of the TPS method. The data were fitted using the TPS method , and the fitted data were analyzed against the original data to show how well the algorithm fitted the data by calculating the difference.

From the small missing data in Figure 15(a), the best-fitting differences between the original data and the fitted data for hip width (sitting), tibial point height, and waist width are 0.3, 0.6, and 0.08, respectively. From the medium missing data in Figure 15(b), the best-fitting differences between the original data and the fitted data for hip width (sitting), tibial point height, and waist width are 0.2, 0.6, and 1.4, respectively. Figure 15(c), (large missing data) shows that the best-fitting differences between the original data and the fitted data for hip width (sitting), tibial point height, and waist width are 0.1, 0.1, and 0.5, respectively.

The variance analysis of Figure 14, Figure 15 shows that there is a decline in the fitted data in the experimental comparison. between the linear interpolation method and the TPS method in the medium missing data 5 and in the large missing data 6 when comparing the fitted data with the original data, which is mainly due to the excessive difference in height and body size of the male data samples in the data selection, which causes the difference between data 5 and data 6 corresponding to the fitting of the waist width of data 33 to be too large, and therefore There is a decrease in the data fitting results. This situation is more common in the statistics of anthropometric data, so the data fluctuation caused by the difference in body size should also be considered when fitting the data. The algorithm should also take this situation into account when comparing experiments.

A comparison of the fit between the fitted data and the original data based on the linear interpolation method and the TPS method was performed. The original data, located in the same part, and the fit of the two algorithms, located in the same part, were averaged, and the average of the two sets of data was then compared and analyzed, as shown in Figure 16. T represents the sample number. $T = 1$ represents sample 1 (hip width [sitting]); $T = 2$ represents sample 2 (tibial point height); and $T = 3$ represents sample 3 (waist width).



(a) Small missing data

(b) Medium missing data

(c) Large missing data

FIGURE 16. Algorithm performance validation

The mean values of the fitted data were compared with the original data fit in the three groups of missing data: small missing, medium missing, and large missing, as shown in Figure 16. From the small missing data in Figure16(a), it can be seen that the mean values of the errors for the three samples (hip width [sitting], tibial point height and waist width) of the linear interpolation method are 5%, 5.3%, and 9.3%, respectively, and the mean values of the errors for the three samples of the TPS method are 4.8%, 1.9%, and 8.8%, respectively. The mean values of the degree of fit of the TPS method are smaller than those of the linear interpolation method. From the missing data in Figure 16(b), it can be seen that the mean values of the errors for the three samples of the linear interpolation method are 7.0%, 9.3%, and 16.3%, respectively, and the mean values of the errors for the three samples of the TPS method are 5.8%, 5.0%, and 14.3%, respectively. The mean values of the degree of fit of the TPS method were smaller than those of the linear interpolation method. From the large missing data in Figure 16(c), it can be seen that the mean values of the errors for the three samples of the linear interpolation method are 7.4%, 5.0%, and 17.2%, respectively, and the mean values of the errors for the three samples of the TPS method were 6.0%, 1.9%, and 9.6%, respectively. The mean value of the degree of fit of the TPS method was smaller than that of the linear interpolation method. The analysis shows that the prediction error values of the TPS method are always smaller than those of the linear interpolation method, which indicates that the TPS method has better prediction results.

5. **Conclusion.** This study used a sample of 54 older male adults as a measurement sample to analyze the missing data in their body measurements. The TPS method was also proposed for solving the problem of missing anthropometric body database for the elderly. The database data were first divided into common body data and relatively likely to be missing anthropometric body data, and the correlations between them were analyzed. Then, the data with higher correlation (height and weight) were used as reference data, and the fitting performance of linear interpolation and TPS was analyzed with the relatively likely to be missing data.

Finally, three of the 54 experimental samples were taken for fitting experiments: (1) the three experimental samples were treated for missing data and categorized into small missing data ($< 8\%$), medium missing data (8% - 12%), and large missing data ($> 12\%$) for validation experiments. (2) The two algorithms were used to predict the three samples of data with three degrees of missingness, and an error mean E was proposed for quantifying the prediction performance of the algorithms. (3) The mean value of the error E of the fitted values calculated using the thin plate strip interpolation (TPS) method was compared with that obtained using the linear interpolation method. The conclusions suggest that the mean error values of the TPS method for the three datasets of hip width (sitting), tibial point height, and waist width in the small missing data were 4.8%, 1.9%, and 8.8%, respectively, which were smaller than those of the linear interpolation method, which were 5%, 5.3%, and 9.3%, respectively. The TPS method's mean error values for the three datasets of hip width (sitting), tibial point height, and waist width in the medium missing data were 5.8%, 5.0%, and 14.3%, respectively, which were smaller than the 7.0%, 9.3%, and 16.3% of the linear interpolation method, respectively. The mean error values of the TPS method for the three datasets of hip width (sitting), tibial point height, and waist width in the large missing data were 6.0%, 1.9%, and 9.6%, respectively, which were smaller than the 7.4%, 5.0%, and 17.2% of the linear interpolation method, respectively. In summary, the mean values of the errors obtained by the linear interpolation method were consistently higher than those obtained by the TPS method, and it can be concluded that the TPS method is better at predicting the results in data fitting. Data Availability

Data Availability. The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest. The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgment. This study was funded by the Natural Science Foundation of Fujian Province (Project No. 2020J01286) and the Graduate Technology Innovation Project of Xiamen University of Technology (Project No. YKJCX2021223).

REFERENCES

[1] J. F. Easton, C. R. Stephens, H. Román-Sicilia, M. Cesari, and M. U. Pérez-Zepeda, "Anthropometric measurements and mortality in frail older adults," *Experimental Gerontology*, vol. 110, pp. 61–66, 2018.

[2] N. Kamide, M. Sakamoto, Y. Shiba, and H. Sato, "Accuracy of body mass index measurements in community-dwelling older Japanese people based on self-reported anthropometric data," *European Geriatric Medicine*, vol. 10, no. 1, pp. 151–154, 2018.

[3] L. S. Sampaio, J. A. O. Carneiro, R. da Silva Coqueiro, and M. H. Fernandes, "Anthropometric indicators as predictors in determining frailty in elderly people," *Ciência & Saúde Coletiva*, vol. 22, no. 12, pp. 4115–4124, 2017.

[4] Y. Zhang, B. Li, N. Liu, P.-X. Wang, and J.-H. He, "Evaluation of different anthropometric indicators for screening for nonalcoholic fatty liver disease in elderly individuals," *International Journal of Endocrinology*, vol. 2021, p. 6678755, 2021.

[5] K. Dhana, C. Koolhas, J. Schoufour, F. Rivadeneira, A. Hofman, M. Kavousi, and O. H. Franco, "Association of anthropometric measures with fat and fat-free mass in the elderly: The Rotterdam study," *Maturitas*, vol. 88, pp. 96–100, 2016.

[6] M. Pasalich, A. H. Lee, L. Burke, J. Jancey, and P. Howat, "Accuracy of self-reported anthropometric measures in older Australian adults," *Australasian Journal on Ageing*, vol. 33, no. 3, pp. 27–32, 2013.

[7] V. F. Goes, E. Wazlawik, E. d'Orsi, A. Navarro, and D. A. González-Chica, "Do sociodemographic, behavioral or health status variables affect longitudinal anthropometric changes in older adults? population-based cohort study in Southern Brazil," *Geriatrics & Gerontology International*, vol. 17, no. 11, pp. 2074–2082, 2017.

[8] J. Guo, Y. Shang, L. Fratiglioni, K. Johnell, A.-K. Welmer, A. Marseglia, and W. Xu, "Individual changes in anthropometric measures after age 60 years: a 15-year longitudinal population-based study," *Age and Ageing*, vol. 50, no. 5, pp. 1666–1674, 2021.

[9] M. K. Bhowmik, K. Saha, P. Saha, and D. Bhattacharjee, "DeitY-TU face database: its design, multiple camera capturing, characteristics, and evaluation," *Optical Engineering*, vol. 53, no. 10, p. 102106, 2014.

[10] T. A. Elsamny, A. N. Rabie, A. N. Abdelhamid, and E. A. Sobhi, "Anthropometric analysis of the external nose of the Egyptian males," *Aesthetic Plastic Surgery*, vol. 42, no. 5, pp. 1343–1356, 2018.

[11] I.-F. Cheng, L.-C. Kuo, C.-J. Lin, H.-F. Chieh, and F.-C. Su, "Anthropometric database of the preschool children from 2 to 6 years in Taiwan," *Journal of Medical and Biological Engineering*, vol. 39, no. 4, pp. 552–568, 2018.

[12] S. Z. M. Dawal, Z. Ismail, K. Yusuf, S. H. Abdul-Rashid, N. S. M. Shalahim, N. S. Abdullah, and N. S. M. Kamil, "Determination of the significant anthropometry dimensions for user-friendly designs of domestic furniture and appliances – experience from a study in Malaysia," *Measurement*, vol. 59, pp. 205–215, 2015.

[13] M. S. N. Shahida, M. D. S. Zawiah, and K. Case, "The relationship between anthropometry and hand grip strength among elderly Malaysians," *International Journal of Industrial Ergonomics*, vol. 50, pp. 17–25, 2015.

[14] A. A. Tessari, M. W. C. Giehl, I. J. C. Schneider, and D. A. González-Chica, "Anthropometric measures change and quality of life in elderly people: A longitudinal population-based study in Southern Brazil," *Quality of Life Research*, vol. 25, no. 12, pp. 3057–3066, 2016.

[15] F. A. C. Rezende, "Anthropometric differences related to genders and age in the elderly," *Nutrición Hospitalaria*, vol. 32, no. 2, pp. 757–764, 2015.

[16] M. Saghazadeh, N. Kitano, and T. Okura, "Gender differences of foot characteristics in older Japanese adults using a 3D foot scanner," *Journal of Foot and Ankle Research*, vol. 8, no. 1, 2015.

[17] T. Kaewdok, S. Sirisawasd, S. Norkaew, and S. Taptagaporn, "Application of anthropometric data for elderly-friendly home and facility design in Thailand," *International Journal of Industrial Ergonomics*, vol. 80, p. 103037, 2020.

[18] S. Z. Dawal, W. N. L. Mahadi, M. Mubin, D. D. I. Daruis, S. Mohamaddan, F. A. Abdul Razak, N. I. Abd Rahman, M. H. Mohd Abd Wahab, N. Adnan, S. A. Anuar, and R. Hamsan, "Wudu'

workstation design for elderly and disabled people in Malaysia's mosques," *Iranian Journal of Public Health*, vol. 45, suppl. 1, pp. 114–124, 2016.

[19] C. A. Amaral, T. L. M. Amaral, G. T. R. Monteiro, M. T. L. Vasconcellos, and M. C. Portela, "Hand grip strength: Reference values for adults and elderly people of Rio Branco, Acre, Brazil," *PLOS ONE*, vol. 14, no. 1, p. e0211452, 2019.

[20] K.-K. Sun, Y.-J. Chiu, Y.-C. Chen, and Y.-X. Wang, "A 2D-3D non-contact anthropometric method for daily dressing state-takes young Asian women as example," *Journal of Measurements in Engineering*, vol. 5, no. 3, pp. 161–175, 2017.