Annals of Clinical and Medical Case Reports

Research Article ISSN 2639-8109 |Volume 13

Application of Anatomical Feature Principal Component Distance in Skull-Face Matching

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Received: 01 July 2024

Accepted: 09 July 2024

Published: 14 July 2024

J Short Name: ACMCR

Citation:

Dafeng J,Application of Anatomical Feature Principal Component Distance in Skull-Face Matching. Ann Clin Med Case Rep. 2024; V13(21): 1-6

Keywords:

Anatomical features; Principal component coefficient; Euclidean distance; Face restoration; Database

1. Abstract

1.1. Objective: To explore the application value of the principal component distance of anatomical features in skull-face matching. Materials and Methods50 cases of human head CT data, including 25 males and 25 females. The skull and facial tissue of each case were reconstructed and stored in the skull and head databases respectively. Six anatomical features in the skull were determined, the coordinate points were recorded, and the covariance and principal component coefficients of the coordinate points were calculated. The principal components of the marked points were obtained by marking the coordinates of the marked points, and then the mean and standard deviation of the principal components were calculated. The mean and standard deviation of the principal components were saved in the database in order as the digital mapping of the skull and face. The Euclidean distance between the principal component coefficient of the skull to be matched and the principal component coefficient of the skull model in the database was compared, and the facial model with the minimum distance mapping was used as the facial simulation result of the skull. The anatomical feature points of 40 skulls in the model library were re-marked and matched with the skull models in the database to verify the reliability and robustness of the data algorithm.

1.2. Results: The number of correct cases of skull substitution matching in the database was 37 cases (92.5%).

1.3. Conclusion: The principal component distance based on anatomical features can effectively match the facial data corresponding to the skull.

2. Introduction

Human face restoration technology based on skull bones has always been a hot topic in archaeology and forensic medicine [1]. Traditional restoration technology obtains human head data through CT scanning, reconstructs it, and then uses 3D printing or plaster model to obtain a skull model, and then performs soft tissue simulation on the model to achieve the effect of facial restoration. This type of restoration requires a high time cost, a large amount of material, a low restoration effect compliance rate, and cannot be digitally stored or modified. In response to the above shortcomings, this study intends to establish a digital skull-face database, combine the spatial distance of the principal component coefficient of anatomical features, and optimally match the skull, thereby mapping the facial features of the skull.

3. Information

3.1. General Information

50 cases of human head CT data, including 25 males and 25 females; scanning range: from the top of the skull to the entire mandible; scanning voltage: 120kV; resolution: 0.49mm×0.49mm×0.5mm; scanning machine: Philips; workstation: HOST-32348. DICOM (Digital Imaging and Communications in Medicine) data were provided by the Imaging Center of Nantong Traditional Chinese Medicine Hospital.

3.2. Software Platform

Image processing platform: 3DSlicer 5.6.1 (www.slicer.org); data processing and programming: MATLAB R2016a (Mathworks corp., USA).

4. Methods

This study is based on the CT data of the skull, locates six anatomical feature points, and matches the three closest skulls and faces in the database through the principal component coefficient distance of the feature points. The specific experimental process is shown in the figure below.

4.1. Anatomical Landmark Positioning

Volume rendering was performed on the data in 3DSlicer, and a set of marker points were created using Create new Point List. The left zygomatic bone, nasal root, end of nasal bone, right zygomatic bone, maxillary central incisor gap, and mandibular chin were marked to create a set of 6 marker points (Figure 1) .

After positioning, copy the coordinates in the Markups module and import them into Excel for numbering.

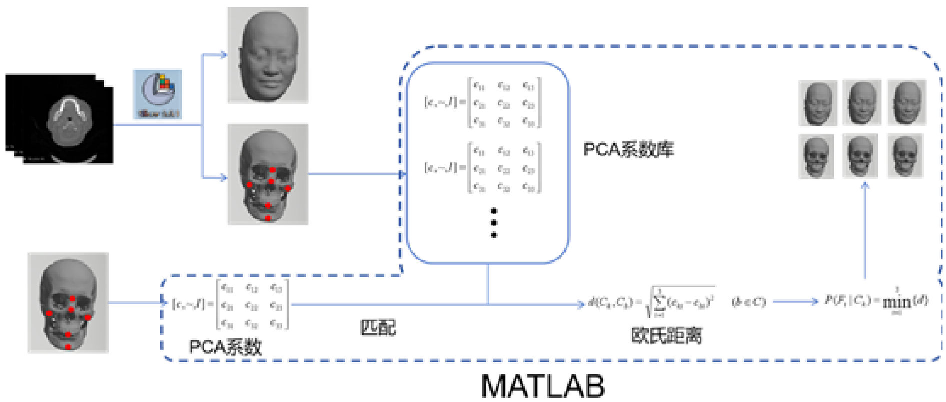

Figure 1: The process of skull-face matching based on anatomical feature points

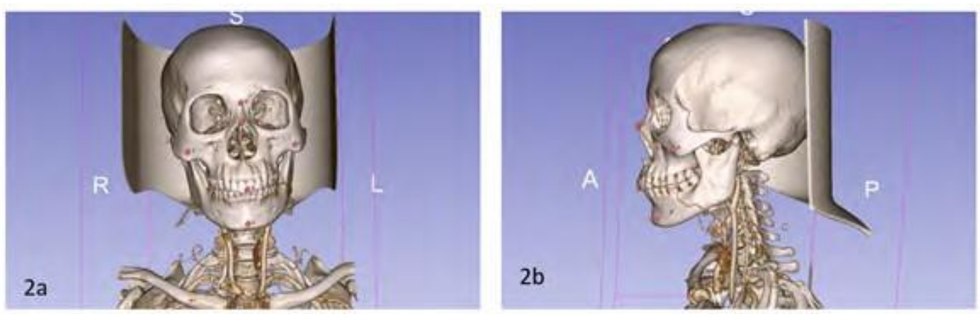

Figure 2: Positioning of 6 anatomical feature points (a front; b side)

4.2. Model Reconstruction and Export

Use the threshold to reconstruct the skull and face, cut off the excess parts, open the Surface Toolbox, select the model, adjust the optimization rate to 0.9 in the Decimate module, and optimize the model to reduce the number of vertices and polygons and increase the extraction efficiency. The optimized skull model and facial model are exported as stl (stereolithography) to form a model database, which includes a skull model library and a facial model library, in which the corresponding skull and facial models have the same number.

4.3. Digitization of Anatomical Features and Formation of Feature Database

Import the coordinates in 2.1 into MATLAB, calculate the covariance matrix (Formula 1), and use the covariance matrix to calculate the principal component coefficients.

$$S_{jk} = \frac{1}{n-1}\sum_{i=1}^{n}(x_{ij}-\bar{x}_j)(x_{ik}-\bar{x}_k) \qquad (i=1,2,\cdots,n;\ j,k=1,2,\cdots,p)$$

---------------(Formula 1)

Where n is the number of feature points, n = 6, p is the feature dimension, p = 3, represents the X-axis coordinate, Y-axis coordinate and Z-axis coordinate respectively, x_{ij}, x_{ik} represent the coordinate values of the corresponding axes respectively, $\bar{x}_j$, $\bar{x}_k$ represent the mean of the coordinates of the corresponding axes respectively, and S_{jk} is the covariance matrix of the coordinate matrix. Find the eigenvalues and eigenvectors of the covariance matrix, and find the first principal component coefficient under the condition of the maximum eigenvalue.

The MATLAB commands used in the above process are:

S=cov(Coordinates);% Calculate the covariance matrix of the coordinate matrix

[C,~,lam]=pcacov(S);% Calculate the principal component coefficient coeff and variance contribution lam of the covariance matrix. Thus, a 3×3 symmetrical square matrix is obtained. The square matrix is saved in order in a txt file as a feature database. The cumulative contribution rate of the principal components was calculated from the variance contribution, and the cumulative contribution rates of the first two principal components were > 90%.

Formula 2 is used to calculate the first and second principal components of the marker points and record them in the digital feature library.

$$Y_{ni} = F_n * C_i \qquad (i = 1,2) \text{ ----------------(Formula 2)}$$

Where n is the number of samples, i is the principal component number, Yni is the principal component of the sample, Fn is the coordinate of the sample marking point, and C_i is the principal component coefficient.

4.4. Digital Feature Distance Calculation

According to the cumulative contribution rate of the principal components in 2.3, the first principal component coefficient, the mean and standard deviation of the second principal component are used as digital features, and the Euclidean distance (Formula 3) between the mark to be matched and the digital feature library is calculated as the skull similarity evaluation index.

$$d(Y_k, Y_b) = \sqrt{\sum_{i=1}^{2}(Y_k - Y_b)^2} \text{ ------------------(Formula 3)}$$

Where *Yk is* the principal component digital feature of the skull to be matched, and Y_b *is the principal component* digital feature in the principal component coefficient library.

The three smallest distances are selected as the reference model output (Formula 4).

$$P(F_i \mid Y_k) = \min_{i=1}^{3}\{d\} \text{ ------------------ (Formula 4)}$$

Where *Yk* is the principal component coefficient of the skull to be matched, and F_i *is* the three matched faces with the smallest distance.

4.5. Model Rotation Verification

By rotating the existing model along the X, Y, and Z axes, the digital features at different angles are calculated and then their similarities are compared.

4.6. Program Testing and Packaging

A graphical user interface was designed, and appropriate buttons, graphic display axes, options and other components were defined (Figure 3). Coordinate recording tables and principal component coefficient calculation and display functions were embedded in the software.

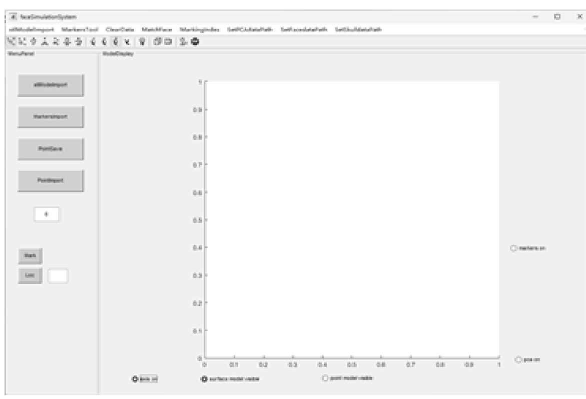

Figure 3: The program's graphical user interface

4.7. Pass Misjudgment Rate

Using 40 skull models in the database, we re-marked their feature points, and then conducted a matching accuracy test to calculate the matching success rate. The matching results were recorded as matching results if the minimum, mean, and maximum Euclidean distance judgment results had the same number more than twice. The back-alteration misjudgment rate was calculated using Formula 5.

$$E = \frac{n^*}{n} \times 100\% \text{ -----------------(Formula 5)}$$

Where n^* is the number of false positives, n is the total number of cases, here n = 40, and E is the back-alternative false positive rate.

5. Results

5.1 Calculation Results of Feature Marker Coordinates and Principal Component Coefficients

Skull model No. 4 in the database was selected for matching verification, and (Figure 4) shows the coordinates and principal component coefficients of the selected data points. It can be seen from (Table 1) that the order of feature point coordinates has changed, but the difference in principal component coefficients is small. It can be seen from Table 2 that the digital features of the markers of the same model change little at different angles.

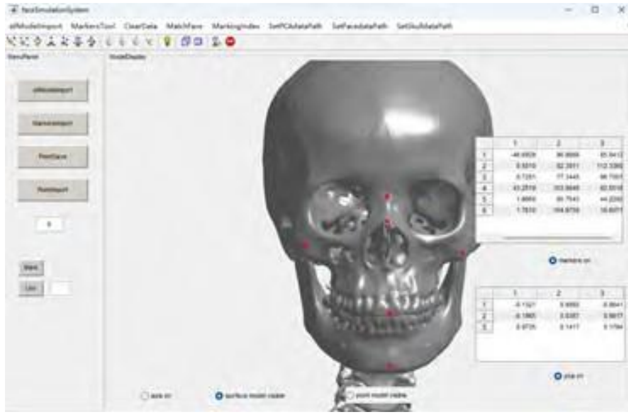

Figure 4: Feature markers (red dots) , coordinates (①) and principal component coefficients (①)

Table 1: shows the original feature coordinates and principal component coefficients of the database skull, and the re-labeled feature coordinates and principal component coefficients and principal component coefficients of original features and relabeled features

	Original feature coordinates	Relabel feature coordinates
Feature 1	-46.02,95.40,87.98	-46.70,96.87,85.84
Feature 2	0.35,81.73,114.45	0.50,82.38,112.34
Feature 3	44.81,103.21,85.80	0.73,77.34,96.75
Feature 4	1.02 ,76.84 ,96.11	43.25,103.98,82.65
Feature 5	0.15 ,85.14,44.77	1.67,85.75,44.23
Feature 6	-1.09 ,104.67 ,16.52	1.78,104.98,16.61
The first principal component coefficient	-0.03,-0.18,0.98	-0.13,-0.19,0.97
The second principal component coefficient	1.00,0.08,0.04	0.99,0.04,0.14
The third principal component coefficient	-0.08,0.98,0.17	-0.06,0.98,0.18

5.2 Verification Results

According to the first and second principal component features in (Table 2), the corresponding three minimum distances in all samples are selected, and the corresponding face and skull models are extracted and displayed through the principal component digital feature library mapping. In this example, skull model No. 4 is used for verification, and (Figure 5) shows the matching results. As shown in (Figure 4), among the three matches, the order of similarity and distance of the minimum match is 15(0.00315), 12(0.04292), 4 (0.05555), the order of similarity of the average match is 4 (0.08984), 11(0.11736), 15 (0.12741) and the order of similarity of the maximum match is 4 (0.12413), 11 (0.17435), 10 (0.23217). Therefore, it is considered that the skull model is matched successfully. According to Formula 4, after verification of 40 data sets, 37 were successfully matched with the original skulls, with a matching success rate of 92.5%.

Table 2: Digital features of the same skull model at different angles

Angle (X, Y, Z)	The mean of the first principal component	Standard Deviation	The second principal component mean	Standard Deviation
0, 0,0	33.45	43.8 6	16.47	29.84
30,0,0	32.89	43.7 7	16.94	30.21
30,30,0	33.0 2	43. 60	16.38	29.42
30,30,30	32.48	43.1 5	15.78	29.59

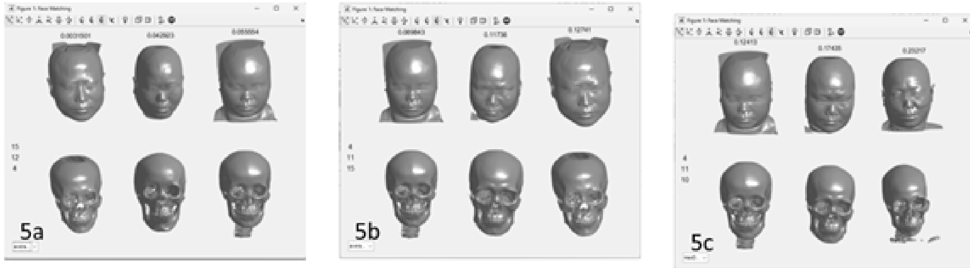

Figure 5: Matching results based on the Euclidean distance model of principal component coefficients (a minimum value matching; b mean matching; c maximum value matching)

6. Discussion

Skull physiognomy restoration is of great significance for archaeology, forensics and biological species attributes. In two-dimensional images, face restoration using block similarity [2] and fuzzy face restoration based on the Da Vinci platform [3] are currently used to restore missing faces. However, there has been relatively little research on three-dimensional face restoration. The reason is that soft tissues vary greatly and the correspondence between skull and soft tissue is unclear. Since the anatomical characteristics of the skull play an important role in CT-MRI image fusion [4-6] and the skull is also the basic structure of the soft tissue of the head and face, it is theoretically feasible to use the anatomical characteristics of the skull to evaluate the similarity of different skulls. The more obvious anatomical characteristics of the skull include the anteroposterior diameter, transverse diameter, petrosal angle, internal occipital protuberance and height of the ethmoid crest [7]. These features play an important role in intracranial image fusion, but cannot be used for craniofacial data fusion or matching. In terms of the application of surface structures, the positioning error of anatomical features based on CT is smaller than that of anatomical features based on MRI, and the applied features include eight structures such as the center of the eyebrows, the helix, and the external occipital protuberance [8]. According to the research of Zhou et al., the features based on expression key points have a higher recognition accuracy than the universal full-face Hausdorff distance, and the feature data is more concentrated [9]. The corresponding calculation amount is also significantly reduced, indicating that facial expressions have a significant correlation with anatomical features, but these temporary facial features [10] cannot be used as key points for cranio-facial matching. Therefore, it is necessary to find anatomical features that match the personalized face before they can be applied to cranio-facial matching data.

According to Elena et al., the zygomatic bone can be used as a three-dimensional evaluation feature for facial soft tissue defects [11]. The zygomatic bone is also the widest part of the face, and it is the feature point with the largest variance on the coronal axis. The frontonasal angle, which is the angle between the line between the glabella-upper end of the nasal bone (nasal root) -end of the nasal bone and the frontal bone, varies greatly among different races or individuals [12] . The frontonasal angle can be regarded as the maximum variance of the feature point on the sagittal axis and can be used as a marker for skull-skull matching. The chin protuberance is divided into round, square and pointed shapes, and there are also large differences among different races or different periods of human beings [13]. Therefore, it can also serve as a marker for skull-skull matching. Among the differences in skull structure, the genetic influence rate of the permanent dental arch is as high as 72.92% [14] . Therefore, the distance between the nasal root and the chin protuberance can be regarded as the maximum variance of the feature point on the vertical axis and can also be used as a marker for skull-skull matching. The difference of the principal components of the matrix is mainly based on its eigenvalues and eigenvectors, the latter of which represents the main direction of the distribution of the three-dimensional point cloud and is the basis for calculating the principal component coefficient. Based on the above anatomical features, the basic structures of skull matching include the zygomatic bone, nasal root, nasal bridge, dental arch and mandibular chin protuberance. Principal component analysis is a dimensionality reduction analysis technique that can reduce the dimensionality of complex facial point clouds [15] , thereby calculating the principal component distance and using it as feature similarity [16]. The advantage of principal component analysis coefficients is that they are not affected by the scaling, rotation, and translation of the original coordinate points. The principal component analysis is essentially a linear fit of multivariate data. Therefore, too many dimensions can easily lead to overfitting. In the preliminary experiment of this study, it showed obvious overfitting when there were 9 feature points. Based on the above foundation, this study used the six craniofacial anatomical features of the skull CT sequence to obtain the principal component coefficients and matched the most similar skull by calculating the Euclidean distance, combined with the existing craniofacial data, to map the most suitable facial structure. The reliability of the matching was analyzed from the back-substitution error of the known model library. As shown in Table 1, the principal component coefficients obtained in different feature coordinates were very close. Furthermore, by solving the principal components, the mean and standard deviation of the first principal component and the mean and standard deviation of the second principal component were obtained. This was used as the digital feature of the model. Combined with the Euclidean distance, the similarity between the model to be matched and the model in the database can be evaluated. As shown in (Figure 5), the matched model is consistent with the model to be tested. Through the back-substitution test of 40 cases of data, the accuracy rate reached 92.5%.

7. Conclusion

The principal component distance based on anatomical features can effectively match the facial data corresponding to the skull.

8. Support Fund

Nantong Social Welfare Project - Development and Application of Medical Image Positioning System in Minimally Invasive Orthopedics (MS12021089)

References

1. Hongen D. Research on the technology of facial realism in skull restoration. Chang'an University, 2012.
2. Tingting Su, Wang Na. Face restoration algorithm based on image block similarity and completion generation. Science Technology and Engineering. 2019; 19(13): 171-176.
3. Xuefei W, Jianming L. Implementation of a fuzzy face restoration algorithm on the Da Vinci platform[J]. Television Technology. 2013; 37(7): 9-12.
4. Tengfei X. Application of three-dimensional reconstruction of CT-MRI fusion images in three-dimensional display of sinus-skull base surgical navigation. PLA Medical College, 2012.
5. Rong Y, Qingxiang L, Chi M. Multimodal imaging fusion technology and diagnosis and treatment of skull base-inferior temporal tumors. Journal of Peking University (Health Sciences). 2019; 51(1): 53-58.
6. Zhiqiang L, Xiaoshu L, Jiyong X. Application of 3DSlicer multimodal image fusion technology in meningioma surgery. Chinese Journal of Clinical Neurosurgery. 2021; 26(10): 758-760.
7. Li G, Xiaohua Z, Baojun X. Correlation analysis between Chinese skull morphology and skull-related anatomy. Journal of Wuhan University. 2004; 25(3): 292-294.
8. Dafeng J, Zhongbin M. Dual-modality fusion of computed tomography and magnetic resonance images of the human head based on surface anatomical features. Acta Anatomica Sinica. 2019; 50(5): 638-644.
9. Zhou Y, Liang YW, Tan PP. Design of an intelligent laboratory facial recognition system based on expression keypoint extraction. IEEE Access, 2023; 11: 129805-129817.
10. Hong K. Facial expression recognition based on anatomaly feature. Optical Review, 2022; 29(3):178-187.
11. Elena GO, Federica M, Sandro M. Three-dimensional evaluation of soft tissue malar modifications after zygomatic valgization osteotomy via geometrical descriptors. J. Personalized Med.2021; 11(3): 205.
12. Wei T, Yaqiong G, Xianlu W. Clinical effect and experience of comprehensive rhinoplasty with autologous rib cartilage. Anhui Medical Journal, 2021; 42(10): 1155-1158.
13. Chengping D, Haijun L. Variation of mandibular chin shape in modern humans and comparison with fossil humans. Acta Anatomica Sinica, 2014; 45(6): 847-850.
14. Jing L, Jinghui Z, Yichao Q. Study on the heritability of dental crowns and dental arches in adolescents. Chinese and Foreign Medical Treatment. 2015; 9:15-17.
15. Sharma R, Patterh MS. A new hybrid approach using PCA for pose invariant face recognition[J]. Wireless Personal Communications. 2015; 86(3): 1561-1571.
16. Chung ST, Seongwon C. Robust face recognition based on 2D PCA face distinctive identity feature subspace model. Signal Processing, 2010; 47(1): 35-44.