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A Novel Feature Point Matching Method for Skull

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A Novel Feature Point Matching Method for Skull

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Abstract. Skull feature points play an important role in computer-aided craniofacial restoration. An improved relative angle histogram algorithm is proposed to match the feature points of the skull, aiming at the low positioning accuracy of the existing skull feature point matching algorithm and the difference of the number of points and the difference of the distribution of the model points. First, the Iterative Closest Point (ICP) algorithm is used to register the original skull model. Then, a new spindle is established for the model after registration. The relative angle of the model points is calculated and the phase diagonal distribution of the model points is calculated. Finally, the model points which are most similar to the histogram distribution of the model feature points are selected as the matching points. Experiments show that the algorithm has achieved good results in the matching of feature points of the skull model.

1. Introduction

With the rapid development of 3D acquisition system, 3D models have been widely applied in many fields, and the research on 3D models has become a hot topic. Feature point extraction is the foundation and premise of most 3D models. The feature points of three-dimensional skull model have important research significance in forensic and biological fields, and have been widely used, such as craniofacial restoration, virtual surgery, focus location and so on.

In recent years, many researchers have studied the feature extraction technology of 3D skull model deeply. Luiz et al. [1] proposed a method for automatically detecting feature points based on skull images. The method assumes that the skull image is facing forward, and the major axis is determined by calculating the centroid point of the skull, and other feature points are determined by morphological analysis. Lucia et al. [2] proposed to extract feature points from 3D skull data by extracting peak lines from 3D models. However, this method can only locate the edge connection curve near the upper orbit of the skull, and can not precisely locate the feature points. Liu et al. [3] used the topological relationship between the feature points and SUSAN operator to automatically determine other key feature points in the skull image. However, this method requires higher image quality and must be a frontal image of the skull with poor anti-interference ability. Feng et al. [4] used the method of partition statistical variable model and model similarity matching to calibrate skull feature points. However, this method uses the model similarity and mapping relationship to indirectly obtain the feature points of the model to be tested, so the error is large and the accuracy is not good enough. Lai et al. [5] proposed a three-dimensional skull feature point calibration method based on knowledge base. This method relies on prior knowledge, and the search is time consuming when determining the final feature point.

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In view of the above problems, this paper proposes an improved relative angle histogram matching method for the feature points of the skull. First, the ICP algorithm is used to register the skull model. Then, a new spindle is established for the model after the registration, the spherical mapping is performed, the relative angle of the model points is calculated and the phase diagonal distribution of the model points is statistically analyzed. Finally, the model points which are most similar to the histogram distribution of the model feature points are selected as the matching points. The algorithm flow is shown in Figure 1.

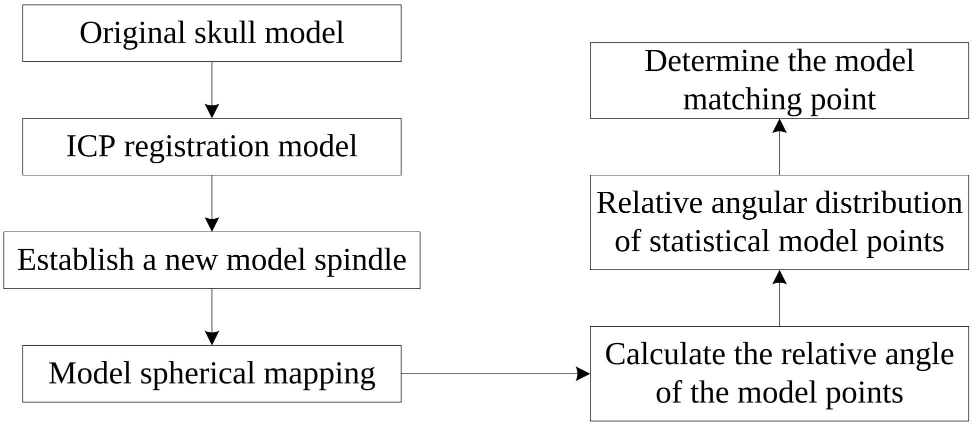

Figure 1. Algorithm flow in this paper

2. Skull Model Registration

In order to solve the problem that the coordinate system of the skull model is not uniform and the spatial position is different, it is necessary to register all the models, try to eliminate the spatial position difference between the models, and make the model data in the unified Frankfurt coordinate system [6]. Model registration is a relatively automated method with a set of data as a baseline template, and other models are transformed into a baseline template. In this paper, the classical ICP registration algorithm [7] is used to register the skull model. The result is shown in Figure 2.

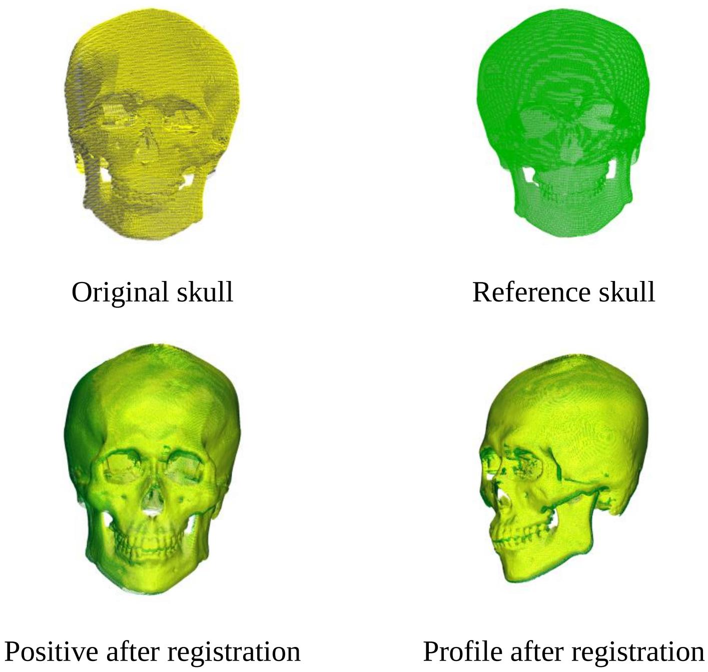

Figure 2. Model registration results

3. Improved Relative Angle Histogram Algorithm

In view of the shortcomings of the traditional relative angle histogram algorithm [8], an improved relative angle histogram algorithm is proposed. The improvement measures are as follows: (1) The X axis, the Y axis and the Z axis in the Euclidean space coordinate system are selected as the main axis, that is, the orthogonal vector basis calculated in the traditional algorithms, namely, vector (1,0,0), (0,1,0), (0,0,1), respectively, is taken as the main axis of the Euclidean space coordinate system. (2) The spherical mapping is used to transform [9] the model by spherical mapping to reduce the influence of the complex structure of the model.

3.1 Establish a new model spindle

The relative angle histogram algorithm [8] uses PCA to calculate the covariance matrix of the model points, thus determining the model spindle, but the PCA algorithm has its own shortcomings. The algorithm is sensitive to the discrete, far away from the center data, and thus has a great influence on the computation of the eigenvector. The distribution of the skull model is not uniform, and the number of each model point is not consistent, which leads to the main axis direction obtained by the PCA algorithm, which is very different in each model. But even if the same model, if the number of points in the model difference or distribution difference, then the calculated main shaft will also appear very different, which will inevitably lead to the error of the matching results. Therefore, this paper selects the X-axis, Y-axis, and Z-axis in the Euclidean space coordinate system as the main axis, and replaces them with vectors (1,0,0), (0,1,0), (0,0,1). The orthogonal vector basis calculated in the traditional algorithm.

3.2 Model spherical mapping

The physiological structure of the skull model is complex. The uneven structure on the surface has an important influence on the calculation of relative angles. In this paper, spherical mapping is used to transform the model [9] to reduce the influence of the complex structure of the model.

In this paper, a spherical mapping of a three-dimensional skull model is performed. The number of model points is n, the coordinates of three dimensional points are v, and the central coordinates are used to represent c. The origin of coordinates after ICP registration is selected as the center c of the model.

Taking the center c as the starting point, the length of the farthest point from the distance c is the sphere radius r, that is, $r = \max\|v_i - c\|$. Using c as sphere center and r as the radius, we can establish the mapping sphere of the skull model, and we can easily get the model coordinates after mapping to the sphere. Let the point v_i maps to the sphere is $v_i^{'}$, then $v_i^{'} = \frac{r}{\|v_i - c\|}(v_i - c) + c$.

3.3 Relative angular distribution of skull model points

For any point v_i in model V, the angle between $n-1$ vector $v_i v_j (1 \le j \le n, j \ne i)$ originating from v_i and e_1 in spindle direction is calculated, that is, the relative angle between point v_i and model V.

$$\theta_j(\theta_i) = \arccos\left(\frac{\overrightarrow{v_i v_j} \cdot \overrightarrow{e_1}}{|\overrightarrow{v_i v_j}||\overrightarrow{e_1}|}\right) \tag{1}$$

According to the formula (2)

$$\theta_j(\theta_i) = \begin{cases} \theta_j(\theta_i) & if\ e_3^{\mathrm{T}} \cdot v_i > 0 \\ -\theta_j(\theta_i) & if\ e_3^{\mathrm{T}} \cdot v_i < 0 \\ \theta_j(\theta_i) & if\ e_3^{\mathrm{T}} \cdot v_i = 0\ \ \& e_2^{\mathrm{T}} \cdot v_i > 0 \\ -\theta_j(\theta_i) & if\ e_3^{\mathrm{T}} \cdot v_i = 0\ \ \& e_2^{\mathrm{T}} \cdot v_i \le 0 \end{cases} \tag{2}$$

Using the formula (3)

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$$R_{i,j} = \begin{cases} \theta_j(\theta_i) & if \quad \theta > 0 \\ 2\pi + \theta_j(\theta_i) & if \quad \theta \le 0 \end{cases} \tag{3}$$

The angle can be converted to between $(0^\circ \sim 360^\circ)$, and the converted angle is the relative angle of point v_i. The $n-1$ angle can be obtained at each point.

The relative angular distribution of the model points describes the geometric features of the point on the global model. The algorithm regards the relative angle as a random variable and statistics the distribution of $n-1$ components. The probability density function of the variable is as follows:

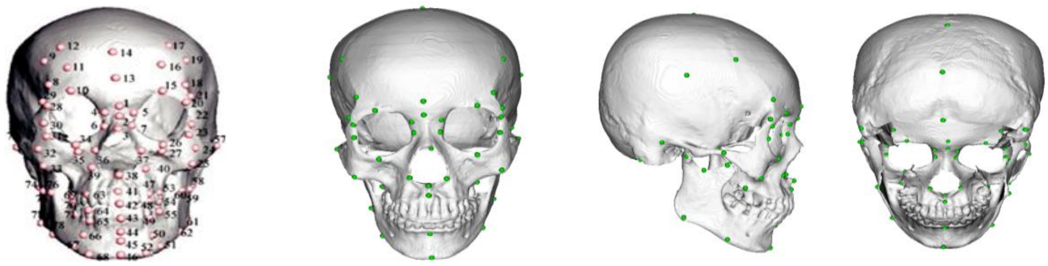
$$p_k(v_i) = \frac{1}{N}\sum_{j=1}^{N}\phi_j^k(v_i) \tag{4}$$

Where $\phi_j^k(v_i) = \begin{cases} 1 & if \ |Rang_{i,j} - k| \le \delta \ \& \ k \in [0, 2\pi] \\ 0 & otherwise \end{cases}$. δ is the sampling interval of the angle. The distribution curve is called the correlation angle distribution histogram of model points.

4. Experimental Result

It is carried out on a database of 267 whole skull CT scans(153 females and 114 males) on voluntary persons that mostly come from Uighur ethnic group in North of China, age 18-88 years for females and 20-84 years for males. The images of each subject are restored in DICOM format with a size of approximately 512 × 512 × 250. Each 3D skull surface is extracted from the CT images and represented as a triangle mesh including about 220,000 vertices. All the skulls are substantially complete; that is, each skull contains all the bones from calvarias to jaw and has the full mouth of teeth.

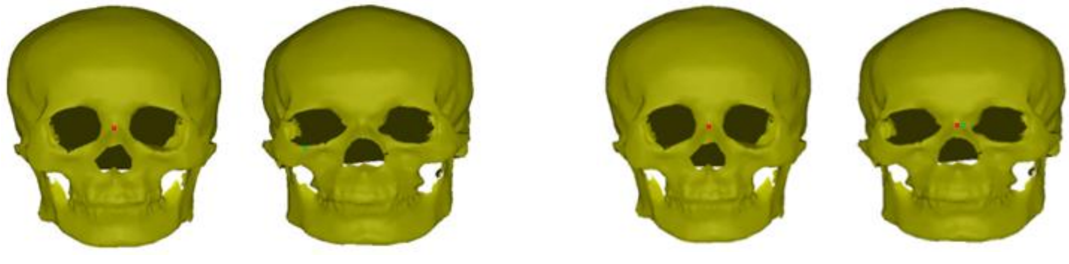
There is no uniform standard for the definition of skull feature points. In this paper, 78 feature points are defined based on reference [10]. As shown in Figure 3.



Feature point definition Positive profile Behind

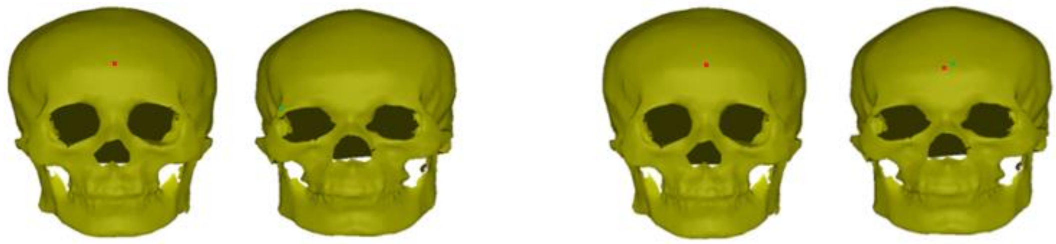
Figure 3. Skull feature point definition and calibration results

In this paper, the traditional relative angle histogram algorithm and the improved relative angle method are applied to the registration model respectively. The results are shown in Figures 4 and 5.



Traditional relative angle histogram algorithm Improved relative angle histogram algorithm

Figure 4. 2th feature point matching results



Traditional relative angle histogram algorithm Improved relative angle histogram algorithm

Figure 5. 13th feature point matching results

The matching result of feature point No.2 is shown in Figure 4. Figure 5 is the matching result of feature point No.13. Figure 4 (a) and figure 5 (a) use the traditional relative angle histogram algorithm to match the feature points. Figure 4 (b) and figure 5 (b) are the improved relative angle histogram algorithm for feature point matching. From Figure 4 (a) and figure 5 (a), it can be seen that the traditional relative angle histogram algorithm is far away from the hand-made feature points, and the error is very large. From Figure 4 (b) and figure 5 (b), we can see that the improved relative angle histogram algorithm is very close to the hand calibrated feature point, and the error is very small. Compared with the traditional relative angle histogram algorithm, the localization effect of this method has been greatly improved. Experimental results show that the effect is still good for other feature points.

In order to evaluate whether the feature point location is accurate, we define the Euclidean distance between the feature point and the manual calibration point. Let the coordinates of the manually calibrated points be (x, y, z), and the coordinates of the feature points extracted by the algorithm are $(x^{'}, y^{'}, z^{'})$, and calculate the Euclidean distance between the two points. That is,

$$d = \sqrt{(x-x^{'})^2 + (y-y^{'})^2 + (z-z^{'})^2} \tag{5}$$

Give the point threshold ε, if $d \le \varepsilon$, the feature point is said to be positioned accurately. Otherwise, the positioning is incorrect and the calculation is in pixels. The 267 sets of skull models used in the experiment were between 600 and 700 pixels and the width was between 400 and 500. By setting multiple thresholds for multiple tests, the positioning effect is best when the threshold is 35, and the positioning accuracy of 53 feature points in the 78 feature points is 100%, accounting for 68% of the total, and the location accuracy of the remaining points is also more than 80%.

5. Conclusion

The method proposed in this paper has a good effect on matching the feature points of the skull model with complicated structure and irregular geometry. The algorithm has the following three advantages: (1) The coordinate axis of Euclidean space coordinate system is used as the main axis to eliminate the uneven distribution of the skull model and the inconsistency of the number of model points. (2) Since the uneven structure of the skull model has an influence on the calculation of the relative angle, the spherical mapping method is used to transform the model, which can reduce the influence of the complex structure of the model on the matching points. (3) The location accuracy of the feature points is high, and 68% of the feature points have a positioning accuracy of 100%. Of course, this algorithm is not only limited to the skull model, but also applies to other models. In the next step, we will continue to expand the dataset to verify the algorithm and improve the location accuracy of feature points, so as to provide reference for practical applications.

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