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Generation and Detection of Cranial Landmark

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Purpose When a surgeon examines the morphology of skull of patient, locations of craniometric landmarks of 3D computed tomography(CT) volume are one of the most important information for surgical purpose. The locations of craniometric landmarks can be found manually by surgeon from the 3D rendered volume or 2D sagittal, axial, and coronal slices which are taken by CT. Since there are many landmarks on the skull, finding these manually is time-consuming, exhaustive, and occasionally inexact. These inefficiencies raise a demand for a automatic localization technique for craniometric landmark points. So in this paper, we propose a novel method through which we can automatically find these landmark points, which are useful for surgical purpose.

Materials and Methods At first, we align the experimental data (CT volumes) using Frankfurt Horizontal Plane (FHP) and Mid Sagittal Plane(MSP) which are defined by 3 and 2 cranial landmark points each. The target landmark of our experiment is the anterior nasal spine. Prior to constructing a statistical cubic model which would be used for detecting the location of the landmark from a given CT volume, reference points for the anterior nasal spine were manually chosen by a surgeon from several CT volume sets. The statistical cubic model is constructed by calculating weighted intensity means of these CT sets around the reference points. By finding the location where similarity function (squared difference function) has the minimal value with this model, the location of the landmark can be found from any given CT volume.

Results In this paper, we used 5 CT volumes to construct the statistical cubic model. The 20 CT volumes including the volumes, which were used to construct the model, were used for testing. The range of age of subjects is up to 2 years (24 months) old. The found points of each data are almost close to the reference point which were manually chosen by surgeon. Also it has been seen that the similarity function always has the global minimum at the detection point.

Conclusion Through the experiment, we have seen the proposed method shows the outstanding performance in searching the landmark point. This algorithm would make surgeons efficiently work with morphological informations of skull. We also expect the potential of our algorithm for searching the anatomic landmarks not only cranial landmarks.

Key Words Craniometric Landmark · Localization · Statistical Cubic Model · Cubic Matching.

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Introduction

Automatic detection of anatomic landmarks

Anatomic landmarks are the standard points (or regions) which define the morphological characteristic of human body. Prior to a surgery, a surgeon tends to refer these landmarks to examine the morphological feature of patient. In the computer vision engineering, many algorithms related with automatically searching of anatomical landmarks in the human body were proposed (1-7). Subbraj and Ravi, Agarwal (1), have shown that the landmarks that are taken by automatic identification method are tend to be accurate than manually taken. Therefore, automatically searching the landmark using a computerized algorithm is suitable for the landmark identification. The proposed landmark searching algorithm in the paper is designed for a cephalometrics area.

Cephalometrics

Cephalometrics analysis is the clinical process of craniometric surgery such as orthodontic and cranioplasty. For this purpose, the cranial morphology informations of the patient is essential to the surgeon. These informations are called craniometric landmarks. Due to the development of 3D CT imaging technology, craniometric landmarks can be easily found by human with manual inspection (8). Furthermore, many recent localization techniques for craniometric points using image processing algorithms were proposed. Yue et al (2) proposed the localization method using 2D X-ray images. This method used segmentation and image transformation technique to find the best match to reference landmarks from other X-ray images. This algorithm resulted in 91% accuracy [within error distance ±2.0 (mm)] with 80 data. Cheng et al (3) used 3D CBCT images with dental landmarks area. This algorithm adopted the learning process for localization of dental landmarks. Also other efficient sub-algorithms, such as constrained search for spatial prior and random forest (9), on learning process were applied. Mean error distance of this algorithm was 3.1 (mm). There was a interesting algorithm which utilizes template matching method. Kaur and Singh (4) constructed initial landmark model with zernike moment-based global feature. With this feature, template matching process was done with expectation window. Their method yielded mean error distance as 1.84 (mm) for 18 cephalometric landmarks. Cheng et al. Ibragimov et al (5), applied the game theory to legacy random forest method for craniometric point detection. The results of their work showed 1.81 (mm) mean error distance for 19 craniometric landmarks.

In this paper, we are going to propose the method which consists of two process. One of them is construction of a statistical cubic model. The other one is cubic matching. Rotation corrected 3D CT data were used as input for our method. We assumed that if the rotation variations of 3D CT volumetric data are not significant, then the similarity function (squared difference) has a convexity with optimal point which is the center of a landmark point. Convexity of our method would be discussed in *Discussion* section.

Materials and Methods

Our method is pretty similar to Template matching (10). Several data sets are used for the creation of the statistical cubic model. Then, cubes are created at each voxel in the volume for detecting the landmark. The similarity of each cube with the created model is evaluated. After examine all similarities of cubes in the volume, we choose the voxel which is the center of the most similar cube to the statistical cubic model. The data sets used for experiments is consist of normal cranial CT vol-

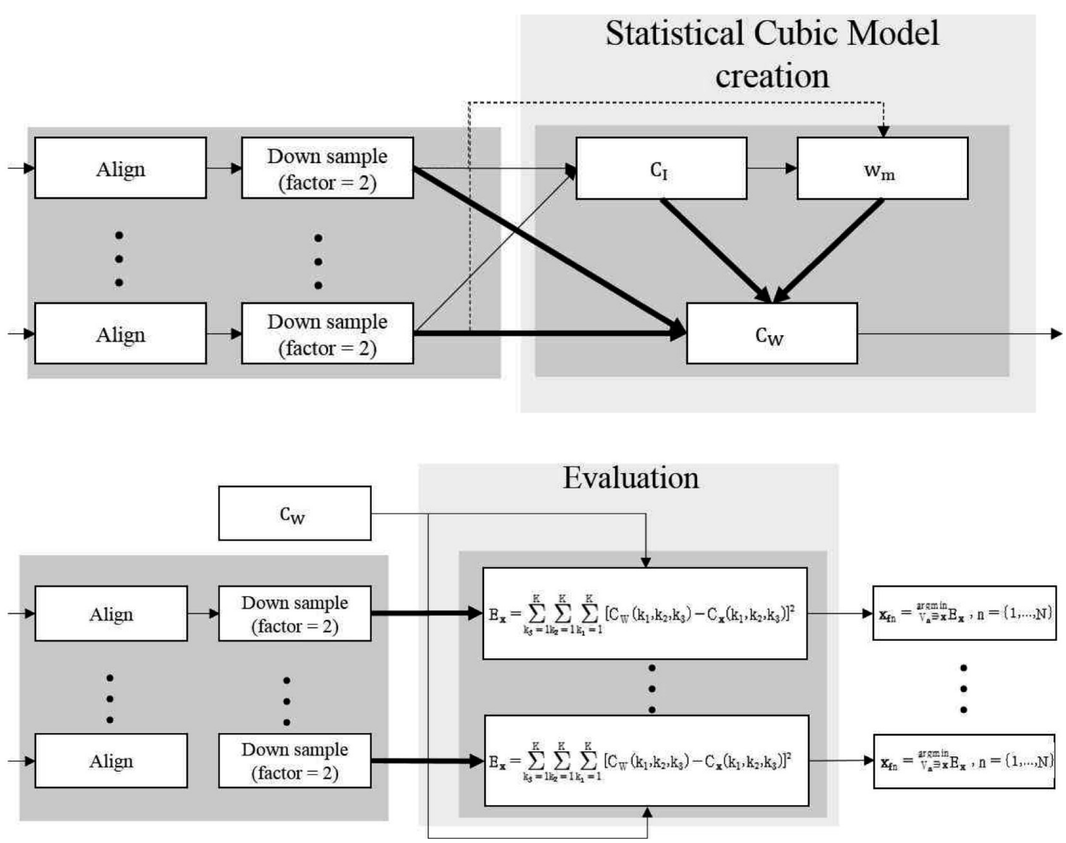

Fig. 1. Algorithm Block Diagram: Our algorithm is consist of two part, model creation stage and evaluation & detection stage. In the model creation stage, there were M input data and the other stage, whole data (N) were used.

umes of 3 to 24 months old subjects. Because of their wide variation on cranial morphology, this range seems suitable for the verification of our method. The overall processes of the proposed method are described in (Fig. 1).

Align & Down sampling

In this stage, to prevent the inconsistency by rotation of skull, we align the input data sets at first. The 5 landmarks are used for the rotation alignment (11-12). We choose the 3 landmarks (anterior nasal spine, nasion, basion) for Frankfurt Horizontal Plane (FHP). Then, the Mid-Sagittal Plane (MSP) can be set using the two points (orbitale, porion in the left side of skull) and the normal of FHP (Fig. 2). After the alignment (Fig. 3), in order to decrease the computational cost of the method, we down sample all of these aligned data volume sets by factor of 2. Since we assumed convexity of the similarity function, down sampling will not affect on the results of the method. The detected landmark location in down sampled data will be matched to the location in original data with multiplication of factor (=2).

Create Statistical Cubic Model

The generation of statistical cubic model consists of two processes. An initial average model is created firstly by averaging values of the cubes at each voxel. Then the weighted mean model is created, where the weight of each cube is determined in inverse proportion to its similarity to the initial average model. This weight strategy makes enhance the effect of the cubes similar to others, and weaken the effect of the cubes different to others. Totally N data sets are used for the experiment, denoted as V_n,. n={1, ⋯, N}. And M sets of V_n are used for the satistical model generation.

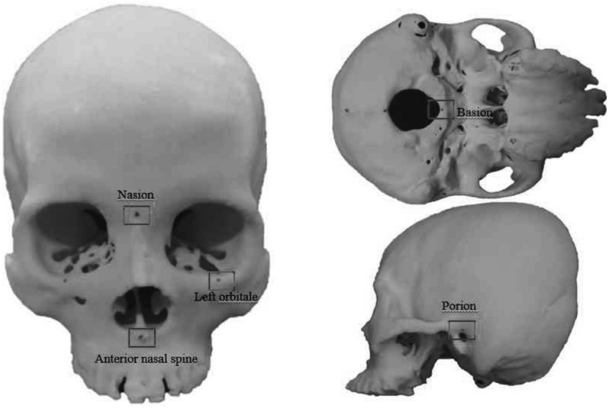

Fig. 2. Landmark points for align data: Mid Sagittal plane (MSP) was made by anterior nasal spine, nasion, and basion. Frankfurt Horizontal plane (FHP) ws made using left orbitale porion (left) and normal vector of MSP.

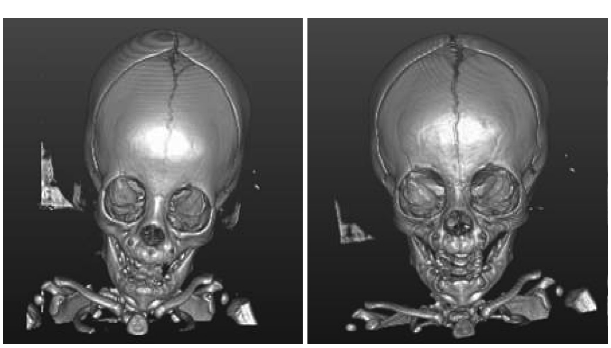

Fig. 3. Before align (left) and After align (right): FHP and MSP was used for alignment.

Initial Average Model

The initial average model C_I is made by using the cubes from M data sets, each of which is centered at the reference landmark location, denoted as $x_n = (x_n, y_n, z_n)$, n=1, ⋯, N. he reference landmark locations of V_n are denoted as x_n. Then, the landmark locations of down sampled data sets would be $x'_n = (\frac{x_n}{2}, \frac{y_n}{2}, \frac{z_n}{2})$. The cubic model is constructed by sampling cube centered at the coordinate value $x_m = (x_m, y_m, z_m)$, n={1, ⋯, M} which is the reference landmark point manually pointed by the surgeon and these cubes used in constructing model are denoted as C_m (Fig. 4). In our method, the size of cube is K^3. Averaging these cubes from M data sets yield the initial average model C_I, where

$$C_I(k_1,k_2,k_3) = \frac{1}{M}\sum_{m=1}^{M} C_m(k_1,k_2,k_3), \qquad k_1,k_2,k_3 = \{1,\dots,K\}.$$

Weighted Mean Model

The weighted mean model C_W needs the initial average model C_I and the similarity (Squared Difference, SD) E_m of each C_m, m={1, ⋯, M} with C_I. where

$$E_m = \sum_{k_1=1}^{K}\sum_{k_2=1}^{K}\sum_{k_1=1}^{K} [C_I(k_1,k_2,k_3) - C_m(k_1,k_2,k_3)]^2 .$$

Each weight W_m is calculated using E_m value. Our weighting strategy makes the most similar C_m with C_I, which has minimum E_m, dominantly affects on the weighted model, whereas the outlier, which has highest E_m, weakly affect on. This strategy enhances the robustness of our final model C_W. The weight W_m is calculated as

$$W_m = \frac{\min_{m=\{1,\dots,M\}} E_m}{E_m}.$$

Each W_m is applied to generating the weighted mean model C_W, where

$$C_W(k_1,k_2,k_3) = \frac{1}{\sum_{m=1}^{M} w_m} \sum_{m=1}^{M} C_m(k_1,k_2,k_3) w_m \ .$$

Evaluation

Experiments for testing are performed with the whole V_n including M data sets for the of model construction. In each volumetric data V_n, cubes at each voxel, denoted as C_X, are created. The similarity of each cube with C_W is calculated as,

$$E_x = \sum_{k_3=1}^{K} \sum_{k_2=1}^{K} \sum_{k_1=1}^{K} [C_W(k_1,k_2,k_3) - C_x(k_1,k_2,k_3)]^2 \ .$$

Detection

Final decision is done with E_X. The location of the landmark have the minimum E_X calculated in the previous stage. The detected landmark point x_{fn} is the center of the most similar cube to the statistical cubic model (weighted mean model), where

$$\mathbf{x}_{fn} = \underset{V_n \ni \mathbf{x}}{\operatorname{argmin}} E_{\mathbf{x}} \ , \ n = \{1, \ldots, N\} \ .$$

Results

In this paper, we examine the 20 CT data sets of 3 to 24 months subjects. Each CT data (DICOM format) has same width and height (512 pixels) with differing number of slices (depth, 400-600). As mentioned in the previous section, the down sampling factor is 2 and cube size (K) is fixed as 25. Our target landmark is anterior nasal spine (Fig. 2). The number of data sets for model construction is 5 and they are numbered as 1 to 5 (M=5). We visualized the five input cubes for the model construction and created the initial average model, and weighted average model as shown in (Fig. 5). Since we aligned the whole data sets before the experiment, it seems that there is no big outlier in the data sets. Therefore the statistical cubic model created also looks similar to each input data set of the model.

The result of test is shown in (Table 1). The all of detected landmark points using our method were very close to the reference landmark points which were manually pointed by surgeon. The detected cubes are 3D visualized in (Fig. 6). Their looks are much similar to the statistical cubic model. The most farthest

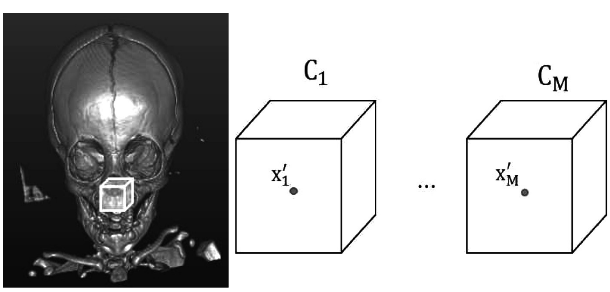

Fig. 4. Creation of Cube: is centered at the landmark center of each input data for model creation.

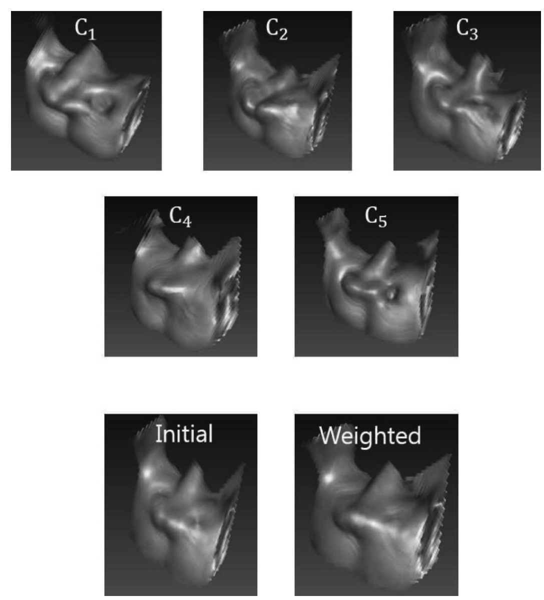

Fig. 5. Visualized Model and Model Input Data.

Table 1. Resulting error distance of whole data

Model input data					
Data Index	1	2	3	4	5
Error (mm)	0.24	0.18	0.28	0.62	0.76
Test Input data					
Data Index	6	7	8	9	10
Error (mm)	1.44	0.47	0.42	0.54	0.9
Data Index	11	12	13	14	15
Error (mm)	0.43	0.88	1.93	0.55	1.05
Data Index	16	17	18	19	20
Error (mm)	0.62	1.24	1.41	0.42	0.38
	Mean			Std	
	0.7			0.47	

location of the found landmark points is far from the reference landmark point by 1.44 (mm) in the data set 6.

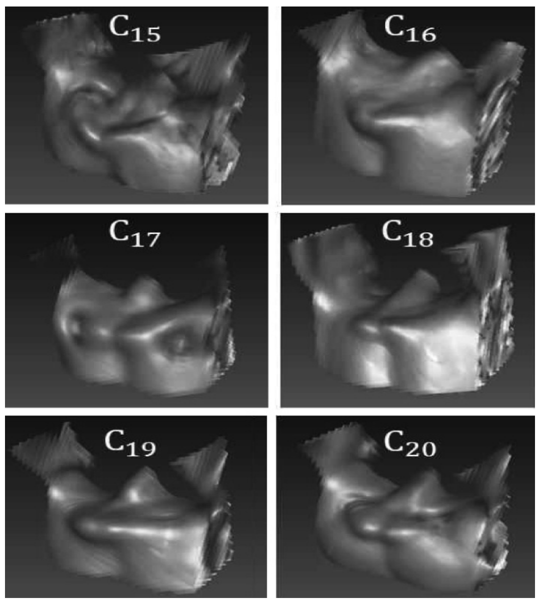

Fig. 6. Visualization of Detection result of some data.

Error distance of the test is calculated by euclidean distance between the reference landmark and the detected landmark point ($\| x_n' - x_{fn} \|$). To convert voxel distance to actual real distance, we use the pixel spacing (DICOM Tag : 0028 0010) values of dicom header. Therefore, the error distance e_n is calculated as,

$$e_n = \| x_n' - x_{fn} \| \times \textit{pixel spacing}.$$

The mean error distance is 0.7 (mm) and their standard deviation is 0.47. Despite of our calculation is done within in 3D coordinates, our results has smaller mean error distance value than other methods , even though they are calculated in 2D coordinate (Table 2).

Discussion

Convexity

Statistical cubic model based cubic matching method is much similar to template matching method. Likewise in template matching (10), the cubic matching process has to set the simi-

Table 2. Comparison to other methods

Method	Grau[6]	Saad[7]	Kaur[4]	Proposed
MES±D	0.75	2.70±1.05	1.93±1.12	0.7±0.47

ME: Mean, SD: Standard deviation

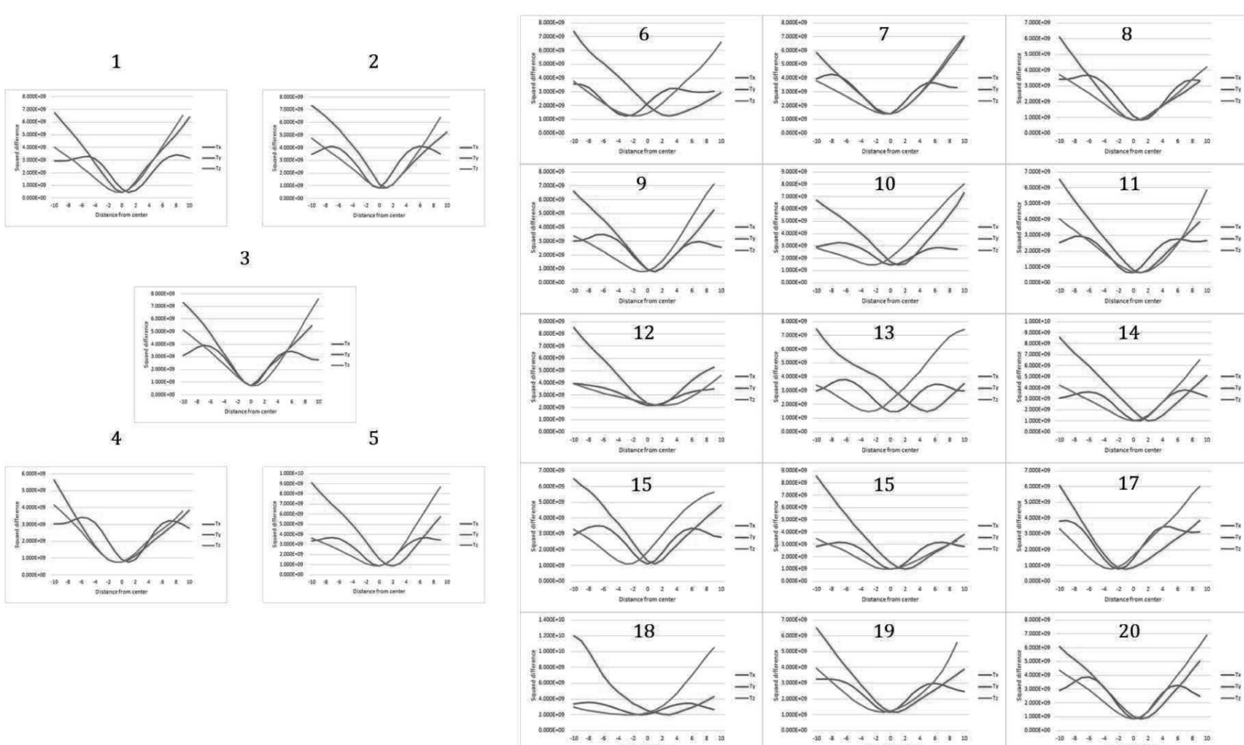

Fig. 7. Similarity function (Square Difference) variation with respect to location change from reference landmark center [(blue), (orange), (gray) with 0 to disatnce]: Minimum points would be not center of graph. This means that found centers slightly differ from reference centers.

larity function as convex function. There maybe exist the local minima, but the global minimum which is the minimum in local minima should be found in the near of the reference landmark point in the rotation corrected volume. The similarity values around the landmark should show convexity. We have assumed that squared difference function should show convexity near the global minimum. This is proven by graph (Fig. 7). In this figure, the similarity values are shown in near the reference landmark point within ±10 translation with respect to x (blue), y (orange) or z (gray). The similarity values on each data sets converge to near the reference landmark center. The detected landmark center is the convergence point on that graph. Since evaluation on the each volume is performed by intervals of 1 voxel, our assumption is proved with this graph.

Cubic matching

3D Volumetric cubic matching with statistical cubic model creation and landmark detection shows very desirable results (Table 1-2). Intuitively the cubic data has more context information than 2D window of template matching. So it is obvious the cubic matching is outstanding method than the template matching. Since the creation of the statistical cubic model is weighted averaging process of the cubes from data sets, alignment of each volume for the model creation should be performed firstly. If not, they would prone to find the undesirable location. This means that even small rotation (Almost 5 degree) of craniofacial data set may cause wrong detection in our method. This weakness is similar to that of the template matching. So if we want to create robust matching process, we should consider the rotation invariant similarity function. Some of template matching area, there are rotation invariant template matching method in 2D image processing (13). But it seems that there is no significant study on rotation invariant cubic matching method. Another solution can be exist in setting appropriate FHP and MSP plane for alignment. Cheng and Leow, Lim (12) proposed the automatic method for finding the FHP ans MSP.

Processing time issue

In this experiment, we used 512x512xDepth volumetric data sets. Since they are down sampled before detecting the landmark, exploring whole voxels in the volume can be done in some minutes. However, we should consider the improving technique for the processing time. Since our method is aimed for the clinical purpose, for a number of minutes of processing time is undesirable. So, the proposed method should be considered with various computer technological supports. One of them is big-data processing which is very hot issue in cloud computing area. And another well-known approach on computing time reduction technology is parallel processing with multiple GPUs. In the perspective of processing time, these are very helpful technologies for our method.

Conclusion

Even though the proposed method came up with a simple idea (cubic matching), this method with reducing rotation variations (alignment) shows outstanding results. The anterior nasal spine which is the target landmark point of our experiment was detected with mean error distance as 0.7 (mm). If we consider that the landmark was detected at error distance within 2.0 (mm) which was detection criterion of (2), the whole landmarks were detected appropriately in our method. Also the simplicity of our method implies that finding other anatomic landmarks, even not on cranium, can be done with our method.

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