Quantification of Teeth in CT Images Using Statistical Shape Model Based on Geometrical Complexity

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***Abstract*— Quantification and visualization of three-dimensional (3D) tissue shapes are the main components of computer-aided treatment procedures. In this paper, we quantify 3D structure of different teeth from Computer Tomography (CT) images using statistical shape models. Then we will evaluate the constructed models based on the geometrical complexity of their shapes. The proposed method consists of four stages: initial data extraction from raw CT images, preprocessing, corresponding landmark extraction and statistical shape model construction. Corresponding landmarks are extracted automatically using image registration and marching cubes algorithms. The statistical shape model is obtained using point distribution model and principal component analysis for three different teeth: canine, premolar and molar. The results show that the generality of the model decreases and reconstruction error increases with incrementing complexity of the tooth geometrical shape. Also the number of variation modes required to reach desired cumulative variability of the statistical model increases.**

Keywords- statistical shape models; rigid and nonrigid registration; point distribution model; dental CT scan;

I. Introduction

Teeth are the most important anatomical structures in the mouth. Computer assisted procedures in common clinical procedures such as tooth restoration, mechanized dental implants, orthodontic planning and maxillofacial surgery are getting more attention in modern dentistry. Accurate knowledge of the 3D shape of teeth is very important in many maxillofacial surgical application and treatment simulations.

Among different medical imaging techniques, computerized tomography of teeth leads to more accurate results. Therefore, CT scan images are used to create three dimensional statistical shape models in this paper. Nowadays, tomography methods used for tooth imaging are micro CT and Cone-Beam CT. Due to lowest radiation dosage of Cone-Beam CT scan images, this technique gradually substitutes traditional CT scan imaging [1]. Axial CT images are used in this paper to generate an accurate statistical atlas of teeth.

Segmentation is the most important stage of preprocessing for 3D visualization and quantification in medical application. Till now, several methods have been used to segment teeth in medical images. In this paper, we use one of the latest works in this field that utilizes variational level-set to accurately segment teeth in CT images [2].

3D visualization of teeth and jaw helps dentists in diagnosis and treatment procedures [1]. In computer assisted surgery, only visualization is not sufficient and a quantified measure of the given tissue is required. Finite element model (FEM) is one of the examples of quantification methods that is used in biomechanical evaluation of tissues and studying the stresses on their surface and volumes [3]. Statistical shape modeling (SSM) is the other quantification technique which analyzes anatomical shape variations of tissues [4]. Buchilard et al. [5] used statistical shape model of tooth to reconstruct one imperfect specimen surface from its partial observed information. They performed initial image registration manually that reduces the accuracy of reconstructed model.

In this paper we intend to reconstruct a more accurate model by improving the previous works and also improve the accuracy of generating model procedure utilizing automatic algorithms. We will also evaluate and compare different generated models with regard to geometrical shape complexity of different teeth.

This paper is organized as follows. Section 2 describes the suggested method and construction of statistical shape model. Section 3 analyzes experimental results and simulations. Finally, Section 4 presents conclusion and future steps.

II. Proposed Method

The method used in this article consists of four main stages: extraction of initial data from CT-images, preprocessing, automatic landmark extraction and generating statistical shape model. These stages are further explained in the following parts.

A. Data extraction from raw CT images

Manual Segmentation is a very time consuming task due to large number of required training datasets for generating a statistical model and the number of teeth in each slice. So, an automatic way is needed for segmentation of teeth in CT images. To do so, in this paper we use variational level-set method [2].

In the next step, tissue pixels and background pixels are labeled "1" and "0" respectively. The result is a set of binary masks for each slice that should be placed in a three dimensional matrix to form a binary volume of the given tooth. To remove the surface noise, Laplasian smoothing method [6] is used. Data preparation steps are shown in Fig. 1.

B. Preprocessing for landmark extraction

Statistical models can be acquired based on various features of the object. Since we want to model 3D shape and the surface of the tooth, here we use the distribution of surface points. The points should be equivalent in number and have correspondence with each other for each individual tooth. An automatic method introduced in [7] is used to extract corresponding landmarks. At the outset, volumetric 3D shapes are registered with rigid and affine registration [8]. The original shape of volumes do not change in this stage; only the size and spatial direction of shapes vary due to scaling and rotation nature of these types of registration. The training shapes should be coincided in this step as much as possible.

One of the teeth is chosen as initial reference shape and others should be registered on it. The initial atlas is generated using a distance based shape blending method. With considering the i-th shape as B_i, Euclidian distance map $DT(B_i)$ of the boundary is obtained [9]. The atlas mean shape is calculated from:

$$DT(B_{av}) = \frac{1}{N_t}\sum_{i=0}^{N_t-1} DT(B_i) \tag{1}$$

where N_t is the number of datasets. B_{av} is initial atlas shape which is obtained by tresholding on $DT(B_{av})$. The model should be independent of the initial chosen shape. Therefore an iterative algorithm should be used, so that all data are again registered on the mean atlas and shape blending process is performed. This process should be done until a stop condition is satisfied: similarity of the constructed atlas with one obtained in the former step. The initial atlas obtained in this stage is considered as a reference for extraction of corresponding landmarks. The data preprocessing and initial reference atlas reconstructing levels are shown in Fig. 2.

C. Landmark Extraction

Initial reference atlas obtained in the previous section is a labeled binary volume and must be transformed to surface. We use marching cubes algorithm [10] to triangulate its surface. The matrix which contains surface triangles information is saved in this stage for further using in visualization procedure. Only the triangles vertices matrix is used for statistical analyzing. The number of surface points is extremely high and is reduced with a decimation method proposed in [11]. The advantage of this method is its intelligence for choosing the points so that their density is higher in uneven and complicated surfaces.

The datasets are registered on the reference atlas using iterative closest points algorithm [12]. In this stage nonrigid registration is used and transformation matrices for each dataset should be saved. Therefore the same number of points in correspondence with each other is obtained for each dataset. The stages of automatic landmark extraction are shown in Fig. 3.

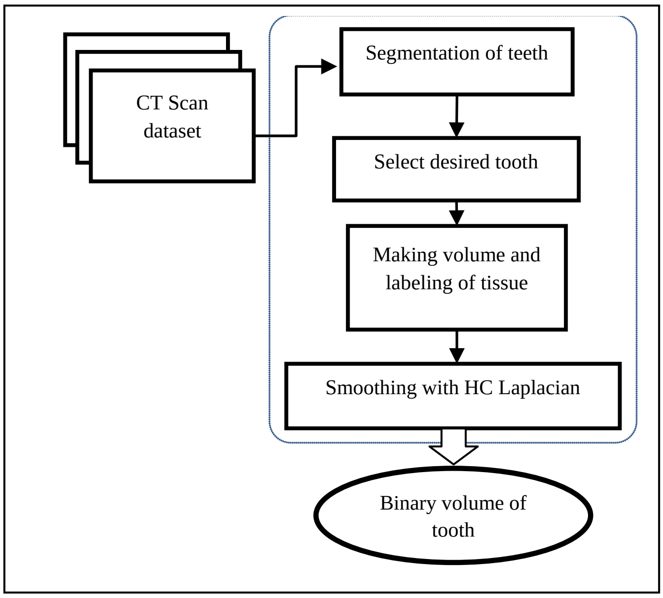

Figure 1. Flowchart of data preparation from raw CT images

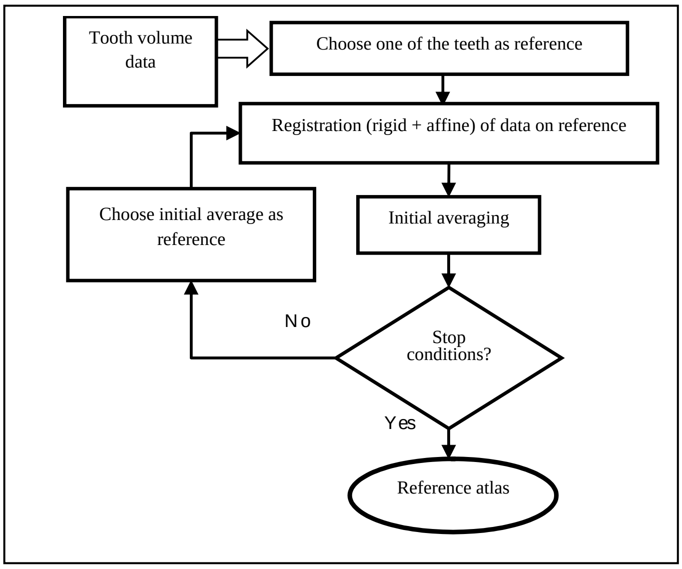

Figure 2. Preprocessing of data for landmark extraction

D. Statistical shape model

After extracting the corresponding landmark for each dataset, there will be N points for each tooth. These points are used for analyzing variation of data shapes in three dimensional space. In order to obtain the statistical model of a specific data, its coordinates in Cartesian system should be put in a (1×3N) vector as: $m = (x_0, y_0, z_0, \ldots, x_{N-1}, y_{N-1}, z_{N-1})$. The statistical model is calculated through the mean and variance of the shape using principal components analysis. The mean shape $\overline{m}$ for N_t datasets is calculated from:

$$\overline{m} = \frac{1}{N_t}\sum_{i=0}^{N_t-1} m_i \tag{2}$$

The modes of variations represent variation of landmarks in relation with each other in the statistical model. In order to calculate them, we need the covariance matrix (R) of data points that is obtained from:

$$R = \frac{1}{N_t - 1}\sum_{i=0}^{N_t-1}\left(m_i - \overline{m}\right)\left(m_i - \overline{m}\right)^T \tag{3}$$

The eigenvalues of matrix R are sorted in descending order and called λ_i. The eigenvectors corresponded to these eigenvalues are considered e_i. Each shape related to the datasets can be approximated by superposition of the mean shape with linear combination of N_{pc} principal modes of variations as follow:

$$m = \overline{m} + \sum_{i=0}^{N_{pc}-1} \omega_i e_i \tag{4}$$

where ω_i is the weight corresponding to eigenvalue e_i. The reconstructed shape can be changed by varying these weights. By applying limitation of $-3\sqrt{\lambda_i} \le \omega_i \le +3\sqrt{\lambda_i}$ for these weights, we ensure that the shape reconstructed is similar to those in the original training set [4].

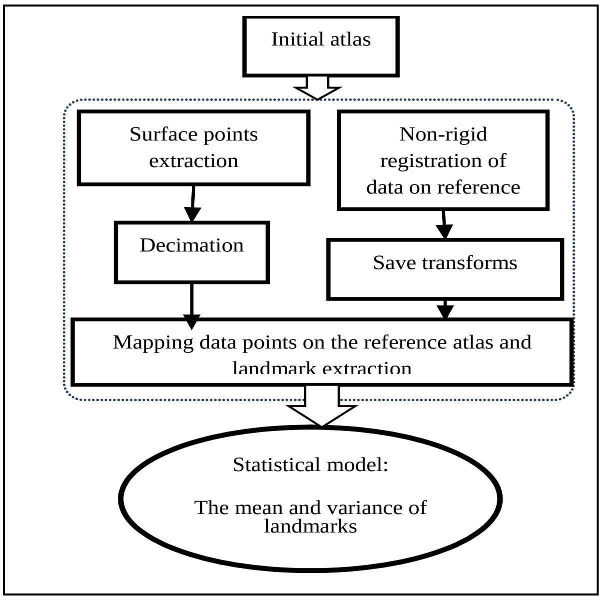

Figure 3. Automatic landmark extraction and generating statistical model

Principal component analysis is used here since all modes of variations are not necessary for creating the model. It means that the number of efficient components for reconstructing the 3D shape is limited. The cumulative variability is a good measure of representing the impact of each mode in the generated model.

III. EXPERIMENTAL RESULTS

In this paper, eleven dental CT-scan datasets are used as input training data. The images are in DICOM format and dimensions of 256 × 256. Images have 3×3×3 voxel size that is reduced to 1×1×1through interpolation to increase the accuracy of calculations.

The number of tooth roots is considered as the complexity measure of tooth geometrical shape. Canine, premolar and molar have one, two and three roots respectively. Therefore we extract statistical models only for these three teeth from CT datasets. The eigenvalues of covariance matrix for all modes are sorted in descending order in Fig. 4. As can be seen, the extent of these values is increased with increment the complexity of teeth geometrical shapes and reached zero with a higher number of input datasets.

The percent of cumulative variability for each mode of variation is shown in Fig. 5. The minimum number of input samples for creating a desired statistical model can be obtained according to the diagram of cumulative variability. For example, according to Fig. 5, we need at last 6, 7, and 9 first modes to gain 90% of variability for canine, premolar and molar respectively. There is a meaningful relation between this diagram and the one in Fig. 4. It can be seen that the required number of input datasets for training the model increases with increment of the complexity of teeth shape. This criterion is directly dependent on the eigenvalues of the covariance matrix. Therefore, it would be possible to analyze the variation of model and principal components of different teeth through the extent of eigenvalues.

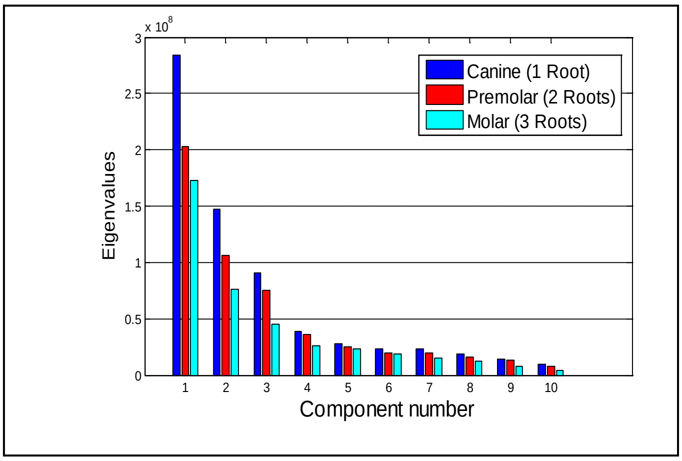

Figure 4. The extent of eigenvalues of all modes for each tooth

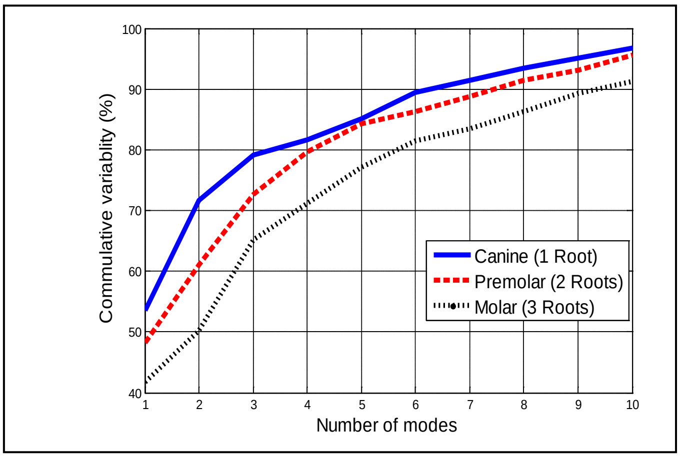

Figure 5. The percentage of cummulative variability of each variation mode

The generality measure for each tooth is defined as the model reconstruction error for each of the data. We use leave-one-out to evaluate the variability of reconstructed model for each tooth. First, one of the input data is chosen and the statistical model is built with other input data. Then 3D shape is reconstructed with the most important variation modes and the mean square error of it with the chosen data is calculated. This is repeated for all input datasets. The mean and variance of this error is shown in Fig. 6 for all variation modes. It could be seen that both error mean and error variance increases with increment of complexity of the tooth shape. So the variability of the model decreases and the required variation modes increases for creating a statistical model of a more complex shape.

The mean shape and the reconstructed shape considering only the first (the most important) mode of variation for each of the three teeth is shown in Fig. 7. The teeth on the right show the new shape when the first mode is added by a coefficient +3 $\sqrt{\lambda_1}$, whereas the teeth on the left show the new shape when the first mode is added by a coefficient -3 $\sqrt{\lambda_1}$.

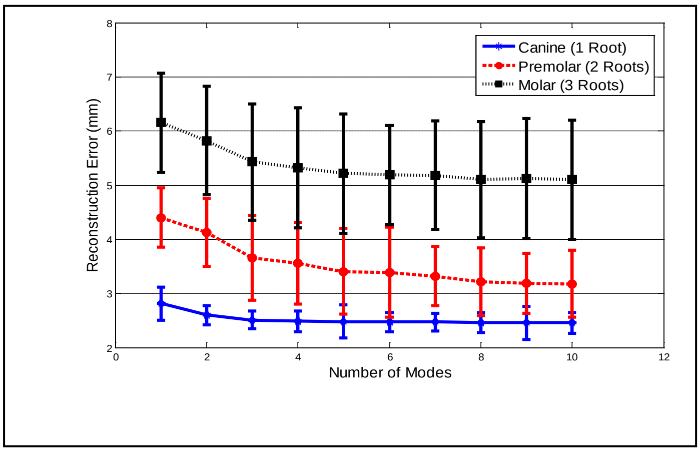

Figure 6. Reconstruction error for each tooth

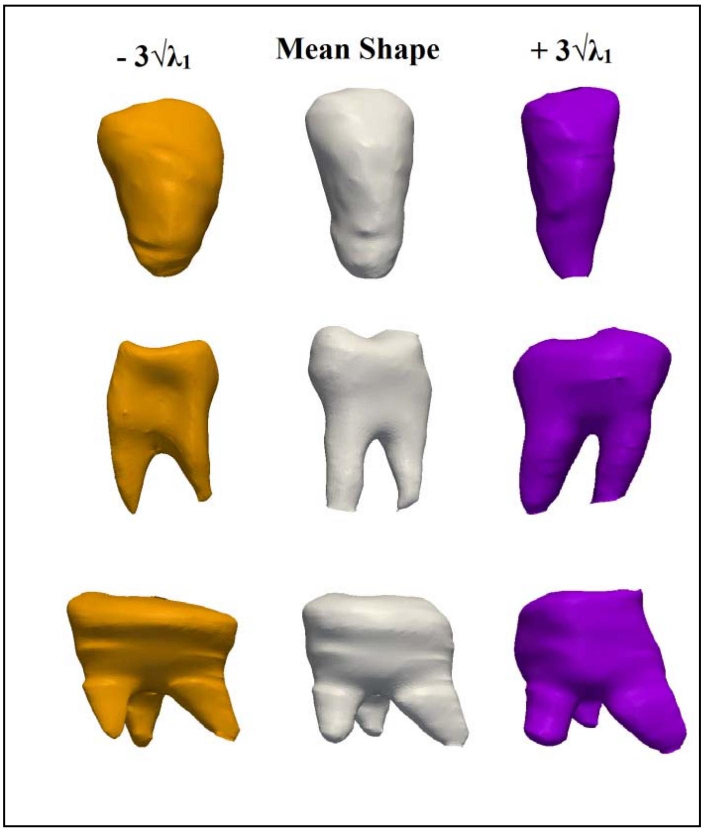

Figure 7. The results of statistical shape model: mean shape and variation of the first mode with coefficient ±3 $\sqrt{\lambda_1}$ (upper row: Canine, middle row: Premolar, bottom row: Molar)

IV. Conclusion

In this paper, 3D shape of teeth in CT-scan images were analyzed using statistical shape models. First, the procedure of preparing volumetric data from raw CT-scan images is explained. Then, corresponding surface landmarks were extracted using non-rigid registration and marching-cubes algorithm. Statistical model of canine premolar and molar teeth were obtained using these landmarks. The number of tooth roots is considered as complexity measure of their geometrical shape. In order to evaluate the constructed model, generalization and the percentage of cumulative variability criteria are used. Studying these criteria, it is concluded that the number of principal components increases and the generality of the system decreases with increment of geometrical complexity of teeth shape.

Statistical shape models represent useful anatomical information of three-dimensional structure of tissues that can be used in medical image analysis. In future works, we will use these statistical shape models in estimation of teeth shapes.

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