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An efficient partial shape matching algorithm for 3D tooth recognition

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An Efficient Partial Shape Matching Algorithm for 3D Tooth Recognition

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Abstract— **As a new biometric strategy, tooth recognition has drawn much attention in recent years. However, most existing work focus mainly on 2D dental radiographs which are less informative and vulnerable to noise and pose variance. Although there are already several attempts on 3D tooth recognition, the results are still inaccurate and performance is inefficient. Moreover, existing methods cannot recognize precisely when the post-mortem data contains incomplete teeth. In this work, we propose an efficient and accurate partial shape matching algorithm to recognize 3D teeth for human identification. Given the ante-mortem and post-mortem teeth models which were taken from patients using a laser scanner, we first extract a series of stable and consistent feature points on the surface of 3D teeth models using a sparse feature selection method based on the saliency map. For each feature point we then establish descriptor based on Improved Spin Images (ISI), which is able to accurately describe the local region around the feature points. Due to the small number of feature points, their correspondences can be efficiently found via the ISI descriptors. Finally, the similarity of the teeth of two input samples (ante-mortem and post-mortem data) can be determined by the sum of the distances between the corresponding ISI descriptors of the feature points. We also conduct experiments to show that the proposed method can achieve state-of-art performance for both complete and incomplete post-mortem teeth data.**

Keywords— **Tooth recognition, Descriptor, Improved Spin Image, Shape Matching.**

I. INTRODUCTION

Tooth recognition has become a new biometric approach and attracted much attention in recent years. While existing biometric features such as fingerprint, palm, ear, face are vulnerable to damage by uncontrollable circumstances, teeth are the hardest bones of human body and thus can still provide information for human identification in case of natural disasters or terrorist attacks. The INTERPOL disaster victim identification protocol has also emphasized the significance of dental recognition. For example, in both of 11/9 case 2001 and Asian tsunami 2004, statistics show that dental records outperforms DNA for identification [1].

There have been several works proposed for dental biometrics most of which are based on dental radiographic records. In 2003, Jain et al. [2] propose a semi-automatic approach to manually locate each tooth from the bitewing image first. The tooth contour is extracted from the gradient image and these tooth contours are then compared to establish correct identities. Although it is shown to be feasible on a small database, it fails when the images are very blurred or the query shape is partially occluded.

In [3], another dental biometric method is presented which also used bitewing radiographs. The contours of the teeth used for matching are automatically extracted using an adaptive segmentation algorithm. Combined with the missing tooth areas, a recognition rate of 95% in the top five most similar teeth is achieved.

Tooth contours and other simple features like missing tooth area are easily affected by the poor image quality. The authors of [4] improved the previous work by adding tooth appearance which is described using a force field energy function, while the contour is represented using Fourier descriptors. The overall feature vector used for matching is the concatenation of these two features.

Rather than only dealing with bitewing radiographs, Jain et al [5] present a method to register a dental radiograph image to the atlas to determine the indices of teeth in radiographs. Their promising results show its potential for human identification.

However, all the 2D radiographs based methods suffer the limitations such as vulnerability to noise, less information, and being affected by pose variance. In recent years, 3D dental biometrics has emerged as a promising strategy[6][7]. In [6], the authors propose a pose invariant 3D dental biometrics framework, and 100% rank-1 accuracy is achieved with user interaction in segmentation. However, partial identification has not been discussed. In [7], partial identification achieves only 72.7% rank-1 accuracy.

In this paper, we present a new approach to efficiently recognize 3D partial dental data. We select feature points first, and use a discriminative descriptor to represent the local information for each feature point. Finally, tooth recognition is realized by comparison of local shape descriptors. We find that the proposed method can achieve state of art performance both in accuracy and speed. We will detail our method in Section II, and show experimental results in Section III. Finally, we conclude our method and discuss the limitations in Section IV. The major contributions of our work include:

- 3D shape descritpor is applied for dental biometrics
- State-of-art performance is achieved both in accuracy and speed.

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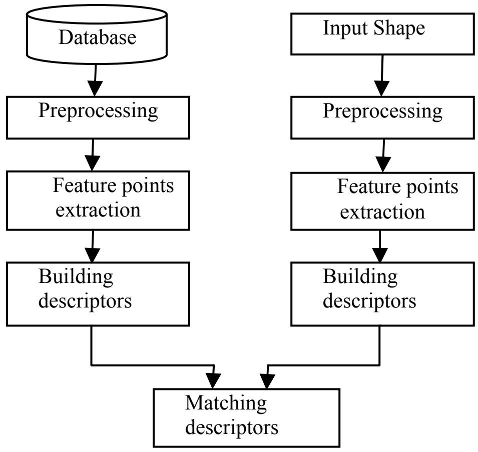

Fig. 1 Flowchart of the proposed method

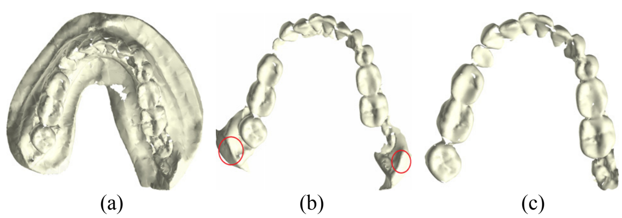

Fig. 2 Segmentation results: (a) the initial cast model, (b) automatic segmentation result, where the red circles indicate the irrelevant parts, and (c) the manual segmentation result

Fig. 3 A shape before (left) and after (right) remeshing

II. METHODOLOGY

In this section, we illustrate the proposed approach. The whole procedure is shown in Figure 1, from which we can see that preprocessing, feature points extraction and descriptors generation are the three main parts. In the following three subsections, we will describe these parts in detail.

A. Preprocessing

Preprocessing includes decimation, segmentation and remeshing. Decimation is for a faster computational speed. We only keep 10% of the original mesh using the algorithm provided in [8]. Since we aim to recognize the teeth, the irrelevant parts should be as little as possible. Hence, the models are automatically segmented using the PCA-plane segmentation [6] (see the results in Figure 2). Another preprocessing step is remeshing which is used to readjust the vertices of the mesh to make them distribute regularly. This step is important for matching, since we will construct descriptors which are sensitive to the tessellation of mesh vertices. We use the method proposed in the recent work [9], which offers much higher visual quality. We show a remeshing example in Figure 3, from which we can see the distribution of vertices become regular after remeshing.

B. Feature Points Extraction

In this step, we extract feature points for the segmented dental shapes. The feature points are expected to be salient and consistent cross different dental shapes. We choose the method proposed in [10]. It is very fast and able to deal with a shape with holes and multiple parts. This is useful as current scanners still cannot guarantee perfect outputs. Moreover, in reality post-mortem (PM) data is very likely to be partial data. In [10], every vertex is associated with the multiple Difference-of-Gaussians (DOG) operators which are used to represent the shape in multiple scales. For each scale, a scale map is computed to measure how much the vertex has been moved from its original position after Gaussian filtering. A saliency map is formed by adding all the scales, and each vertex is assigned a saliency value. Finally, the vertices which are local maximum with saliency higher than a threshold value θ are selected as feature points. Figure 4 lists a complete ante-mortem (AM) dental shape and a partial PM dental shape with their feature points detected using [10]. Feature points are indicated using blue points. We can see that AM shape has more feature points than the PM shape. This is due to fact that we want the feature points of PM shape is a subset of the feature points of AM shape. And this can be easily achieved by setting threshold as we will explain in Section III.

C. Descriptors

For all the feature points, we establish descriptors for matching. Currently, numerous shape descriptors have been proposed for shape matching and recognition [12][13][14]. One of the best local shape descriptors is Spin Images (SI) which was first proposed by Johnson and Hebert in 1997 [11] for surface registration, and has also been used in recognition problems [12][13]. Its attractive properties such as rotation, translation and pose invariance allow SI to work for many problems. However, lower descriptive power and noise sensitivity are the intrinsic deficiencies of SI. The authors of SI suggested that grouping point matches with geometric consistency should be used to enhance the robustness, but this can decrease efficiency.

In this work, we use the method proposed by [15], which is called Improved Spin Image (ISI) and is shown to be more discriminative than the traditional SI. There are mainly two improvements: first, a repeatable local Reference Frame technique is utilized to build the normals such that both uniqueness and unambiguity can be achieved. Second, one dimension of SI is replaced with signed angle which contains more information and insensitive to noise. After defining the signed angles, the local 3D surface can be mapped to 2D domain as an improved spin image using equation 1.

$$S_p : R^3 \to R^2$$

$$S_p \to (\alpha,\theta) = (\sqrt{\|x-p\|^2 - (n\cdot(x-p))^2}, D\cdot(\arccos(n\cdot n_i))) \quad (1)$$

where p is the reference point and x is a neighboring point, n and n_i are their normals, and D is the sign indicator determined by the orientation of the neighboring normal. When n_i points towards n, D is assigned +1, otherwise D is assigned -1. We show two examples of ISI in Figure 4, where the vertical axis still corresponds to the perpendicular distance from the reference point to the normal ray while the horizontal axis indicates the signed angles. In next section, we will show that by using ISI, the identification procedure can be made more efficient and accurate.

D. Dental Identification

We first train the AM dataset. For each dental model in the AM dataset, we extract feature points and build ISIs for them. Since the number of feature points is very small compared to the number of vertices of the entire model, this training process can be finished in several minutes.

For each partial PM model to be recognized, we extract sparse feature points first (Figure 4 right), and then build the ISIs using the same parameters (number of bins and bin size). Finally, we compare the ISIs of PM model with the ISIs of each AM model, and choose the AM with least sum of errors as the corresponding correct identity.

III. EXPERIMENTS AND RESULTS

A. Dataset

Ante-mortem (AM) dataset: 100 full sets of mandibular plasters taken from patients at the National University Hospital. These plasters are then digitized using Minolta VIVID 900 Surface Laser Scanner (Konica-Minolta Corporation, Osaka, Japan).

Postmortem-mortem (PM) dataset: 7 sets of mandibular plasters taken separately one year later using the same scanner. For PM dataset, we make 4 different kinds of copies: Auto-segmented Complete dataset, Auto-segmented Partial dataset, Manual-segmented Complete dataset, and Auto-segmented partial dataset. For example, Figure 4 (right) and Figure 5 comprise the Auto-segmented partial dataset.

B. Parameters Setup

There are 3 parameter values to set. The first is the threshold value θ. For AM data, we set it as 70% of the global maximum, while for PM data we set it as 80% of the global maximum. The second is the bin size for the ISI; in the following experiment it is set equal to the mesh resolution which is the mean length of all edges of the input mesh data. The last parameter is the number of the bins which is set as 16. That is the ISI is a 16 by 16 2D descriptor.

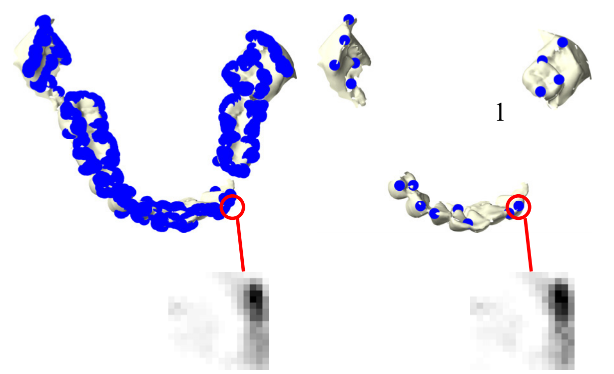

Fig. 4 An AM dental shape (left) and a partial PM dental shape (right), the blue points indicate the extracted feature points and two examples of shape descriptors are shown for two feature points on AM and PM respectively

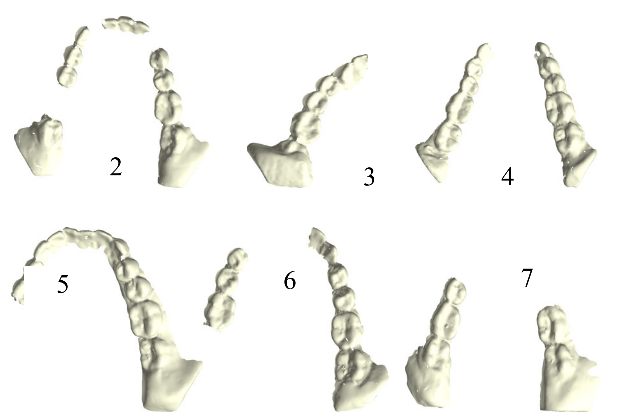

Fig. 5 Partial dental models used in this work

Table 1 Identification accuracy

Dataset	PM1	PM2	PM3	PM4	PM5	PM6	PM7
AC	Rank 1	Rank 1	Rank 1	Rank 1	Rank 1	Rank 1	Rank 1
AP	Rank 1	Rank 1	Rank 1	Rank 1	Rank 1	Rank 1	Rank 1
MC	Rank 1	Rank 1	Rank 1	Rank 1	Rank 1	Rank 1	Rank 1
MP	Rank 1	Rank 1	Rank 1	Rank 1	Rank 1	Rank 1	Rank 1

Table 2 Timing (in seconds)

Model	#Vertices(#FP)	FP detection	Matching	Total
PM1	9015(17)	2.5	458.2	462.8
PM2	9596(9)	1.9	244.6	247.3
PM3	6970(14)	1.5	378.3	380.8
PM4	10260(22)	2.0	591.5	601.9
PM5	10237(16)	2.4	432.4	436.1
PM6	9010(17)	1.8	458.4	460.7
PM7	8343(14)	1.6	374.8	376.2

C. Recognition Accuracy

We test the proposed method on Auto-segmented Complete (AC) PM data, Auto-segmented Partial (AP) data, Manual-segmented Complete (MC) data and Manual-segmented Partial (MP) data. The recognition results are shown in Table 1. We can see that for all four types of PM data, our method can always achieve 100% rank 1 accuracy.

D. Timing

The time is measure in seconds on a PC with Intel Xeon CPU X5680 3.33GHz. The time for feature detection, matching and whole procedure is summarized in Table 2.

IV. CONCLUSIONS

In this paper, we propose a new approach to identify 3D partial dental shapes. We extract a series of feature points for the input shapes and build discriminative descriptors for them. Tooth recognition is realized by comparison of the improved local shape descriptors (ISI). We also conduct experiments to show that our method is both accurate and efficient.

In this paper, segmentation is still needed to facilitate identification and achieve promising accuracy. In fact, this step can be avoided in future work by improving the algorithm for feature point detection. Furthermore, we will also enlarge the dataset, and the descriptor can be extended to 3D to make it more discriminative.

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