AUTOMATIC MESH SEGMENTATION USING ATLAS PROJECTION AND THIN PLATE SPLINE

Application for a Segmentation of Skull Ossicles

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Abstract: Mesh segmentation has become a crucial step in many computer graphics applications. This paper provides new method for three dimension Atlas based mesh segmentation using thin plate spline approach (TPS) and a new FNN algorithm. This method consists of three steps: first, we apply a rigid registration between two meshes the atlas and the mesh to segment. The second step is the application of an elastic registration using thin plate spline method. The last step is the identification of the different regions to segment the mesh using our FNN algorithm. We tested the performance of our method on synthetic images and on a real human skull and found that the preliminary results obtained are satisfactory.

1 INTRODUCTION

In medical imaging, the use of three- dimension shape has greatly facilitated the disease diagnosis. Segmentation is an important and difficult step in medical images analysis. The segmentation of polygonal meshes can divide the mesh into multiple segments in order to simplify or change the mesh representation to another representation more meaningful and easier to analyze.

There was a wealth of research focused on methods for polygonal meshes segmentation we can classify them into two categories: methods based on geometric features, and methods based on semantic approaches.

In the first case, the shape is segmented into a number of uniform patches with respect to some surface properties, while in the second one the segmentation is aimed at identifying relevant features of the shape. In patch segmentation methods, shapes are dividedinto regions that have certain geometric features such as flatness, convexity, approximation to a primitive bend (Shamir, 2008).

Among the most frequently used algorithms, we cite the growth of regions, watershed, deformable models, hierarchical partitioning, spectral partitioning and skeletonization.

Segmentation into meaningful parts: This type of segmentation can divide the object into meaningful components. This segmentation is mainly based on human perception. Thus, some researchers propose to use primitive specifying the 3D shape such as boundaries to break down a scene or object (Lon, 2007).Others use models (Atlas) to project the predefine segmentation of the atlas to the object to be segmented (Commowick, 2010). The atlas based segmentation has become a standard method for brain segmentation Oliver (Oliver, 1998) summarizes the segmentation of the brain atlas in three stages. The first step is to match the image overall patient and image atlas for which they are located in the same repository. The second step is to apply a local deformation to bring the two images perfectly.

Finally a transformation will be applied to the atlas image.

An illustration showing figure1 the difference between the two method (surface patches and significant parts).

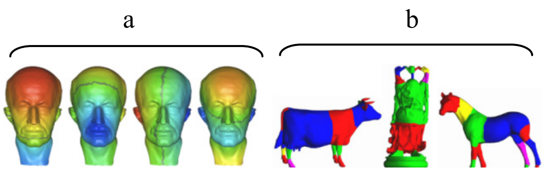

Figure 1: (a) Segmentation using patch approaches (Shamir, 2008), (b) Segmentation into meaningful parts (Katz, 2006).

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The areas of use of mesh segmentation are numerous. Among them, we cite: the texture mapping (Delest, 2008), the mesh parameterzation remeshing, mesh simplification, meta morphosis (Delest, 2007), mesh compression (Karni, 2000), collision detection, pattern Recognition and reverse engineering.

In this work, we propose a automatic segmentation method based on atlas projection and thin plate mesh deformation. Details of the method will be discussed later. We also present some experimental results obtained on synthetic meshes and other real skull shapes.

2 PROPOSED METHOD

We propose a segmentation method in the relevant parts of triangular meshes by atlas projection. The main purpose of this method is to identify the various bones of the human skull. The method consists of three stages: The first step is to apply a rigid registration between two shapes as input, the thin plate algorithm is then applied to minimize the distortion between the atlas shape and the patient one. During the third step, we apply our "FNN" (finding nearest neighbors) algorithm to classify all the bones composing the skull.

Since there is no literature in about pre-segmented human skull, we had to manually segment atlas shape to make it as anatomical atlas. Figure 2 illustrates the different stages of the proposed method.

2.1 Creating an Anatomical Atlas

To create an atlas for the human skull, we manually segmented a reference mesh in nine different regions representing nine bones using real skull atlas. We have developed a tool to manually segment a shape. Once we have identified a set of nodes that represent a logically related region we labeled the different region with different colors figure 3.

This tool provides high accuracy in the classification stage of the various vertex of the mesh.

2.2 Rigid Registration

Mesh registration is a technique used to find a transformation for mapping a source mesh known as a reference mesh and a target mesh. Note here that a change of scale is required if the difference between the size of two meshes is important. This step is performed before applying the registration between two images. In this study, we targeted the rigid registration between two different meshes using the ICP algorithm (Iterative Closest Point) (Zheng, 1992).

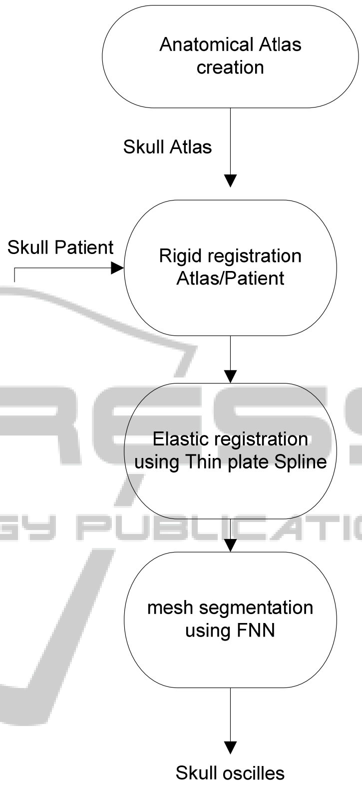

Figure 2: Proposed Method.

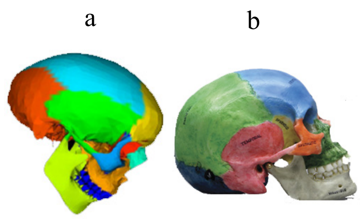

Figure 3: (a) Reference 2d images, (b) 3d anatomical mesh.

Each region will contain points belonging to the same skull ossicle.

The principle of ICP is to iterate between a step of mapping data and another step of optimization of rigid transformation until convergence.At each iteration,the Algorithm provides a list of matched points and an estimate of the transformation, the algorithm converges when the error in distance between matched points is below a certain threshold. The transformation used for registration is composed of a rotation and a 3D translation.

Algorithm 1.

1. for each region *OSi* representing a skull
2. Repeat
3. Manual selection of a point compatible with *e OSi*.
4. Issuance of the color *Ci* in point *e* in the image
5. Choosing a Surrounding number of neighbors at this point that belongs to the same ossicle
6. Retrieving neighbors *IDs* in a list *L*
7. While $L \neq \emptyset$

Remove the next element *s* of *L*

Save the coordinates of *s* Provide color *Ci* at the point *s*

8. If the neighbors are not all compatible with *OSi* then back into
9. Until browned all points of *OSi*

We chose to represent 3D rotation by the technique of quaternion as it offers much more flexibility algorithmic and numerical stability.

If we represent the quaternion by a vector: $q_R = [q_0, q_1, q_2, q_3]^t$, such that $q_{02}+ q_{12}+q_{22}+ q_{32} = 1$, then the rotation matrix R (q_R) can be written as a linear combination of these terms. If moreover, we denote by q_T translation vector as $q_T = (q_4, q_5, q_6)$, then the rigid transformation used by the ICP algorithm is as follows:

$$q = [q_R \mid q_T] = (q_0, q_1, q_2, q_3, q_4, q_5, q_6) \qquad (1)$$

If we denote by CP_1 and CP_2 two sets of points to be matched by ICP, then we have:

$$R(q_R) * CP_1(i) + q_T \approx CP_2(i) \qquad (2)$$

The registration problem amounts to minimizing the following quadratic error:

$$err(q^k) = \frac{1}{N_p}\sum_{i=1}^{Np}\left\| CP_1(i)^k - (R(q_R^k) * CP_2(i) + q_T^k)\right\|^2 \qquad (9)$$

With Np is the number of points CP_1 and CP_2 and k is the index of current iteration. Thus the ICP algorithm can be formulated as follows (Delest, 2008).

Algorithm 2.

1.Begin

2.Initialize $k = 1$, $T_k = T_i$,

convergence = 0

3.While (k <*kmax* or convergence == 0)

-Compute for each point of the set of D'_2 ($D'_2 = Tk.D_2$) the nearest point across D_1 (or vice versa). The result matched the list of issues [CP_1, CP_2].

-Calculate the transformation *T* with the use of quaternion

whose input CP_1, CP_2 and T_k and minimizing the error:

$$\varepsilon = \frac{1}{N}\left\| T_k * CP_2(i) - CP_1(i)\right\| \qquad (4)$$

NisthenumberofpointsCP$_1$and CP$_2$.

- Update $T_k = T$, $k = k+1$
- If convergence condition satisfied =>convergence = 1

End While

End

2.3 Elastic Registration using Thin-plate Spline

Mesh elastic registration is a mesh deformation process; one of the transform -ations that are able to represent elastic deformations is the thin-plate spline (TPS). Thins plate spline were introduced by Bookstein, in (Bookstein,1989) for geometric design. In two dimension images the TPS model describes the transformed coordinates (x^T,y^T) both independently as a function of the original coordinates (x, y):

$$(x^T,y^T)=(f_x(x,y),f_y(x,y)) \qquad (5)$$

Algorithm begin with given a displacements of a number of landmark points, the TPS model interpolates those points, while maintaining maximal smoothness. For each landmark point (x,y), the displacement is represented by an additional z-coordinate, and, for each point, the thin plate is fixed at position (x, y, z). The strain energy is calculated by integrating the second derivative over the entire surface that can be minimized by solving a set of linear equations.

$$\iint_{R2}\left(\left(\frac{\partial^2 z}{\partial x^2}\right)^2 + 2.\left(\frac{\partial^2 z}{\partial x \partial y}\right)^2 + \left(\frac{\partial^2 z}{\partial y^2}\right)^2\right)dxdy \qquad (6)$$

The TPS model for one of the transformed coordinates is given by parameter vectors a and D:

$$F(x^T,y^T)= a_1+ a_2x+a_3y+...+\sum_{i=1}^{n} D_i F(\left| L_i - (x,y)\right|) \qquad (7)$$

Where $F(r)= r^2\log(r)$ is the basis function, $a = [a_1\ a_2\ a_3\ a_4]^T$ defines the affine part of the transformation, D gives an additional non-linear deformation, and the L_i are the landmarks that the TPS interpolates figure 4.

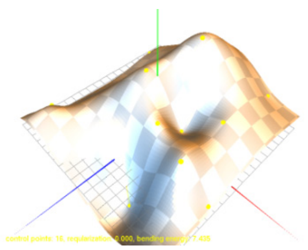

Figure 4: Thin plate spline interpolation of 15 points.

Algorithm 3.

1. Given a set of source landmark we define P matrix of (3xn) n number of vertex

$$P = \begin{bmatrix} 1 & x_1 & x_1 \\ 1 & y_2 & y_2 \\ . & . & . \end{bmatrix}$$

2. Using the basis function we define matrix K (n x n)

$$K = \begin{bmatrix} 0 & F(r_{12}) & \dots & F(r_{12}) \\ F(r_{12}) & 0 & \dots & F(r_{12}) \\ \dots & \dots & 0 & \dots \\ F(r_{12}) & F(r_{12}) & \dots & 0 \end{bmatrix}$$

3. Define M combination of K and P matrix

$$M = \left[\begin{array}{cc} K & P \\ \hline P^T & O \end{array}\right]$$

Where O is a 3x3 matrix of zeros

4. Inverse M matrix on to another Z matrix defined as

$$M^{-1}Y = (D|a_1\ a_2\ a_3)^T$$

5. Define a function $F(x^T, y^T) = a_1 + a_2x + a_3y + \dots + \sum_{i=1}^{n} D_i F(|L_i - (x,y)|)$

Every were in the plane

(Rohr, 1999) proposed a method to estimate thin plate splines. The method interpolates some of the points using smoother transfor-mation controlled by a parameter μ, which weights the optimization of landmark distance and smoothness. For $\mu = 0$, there is full interpolation, while for very large μ, there is only an affine transformation left. In our methods the landmarks used in the TPs algorithm are the entire atlas mesh vertex.

2.4 Mesh Segmentation

At this level, we must label the resulting mesh vertex from the previous step using the atlas mesh. Clustering of vertex in specific classes is done according to the following algorithm

Algorithm 4.

1. Repeat
2. For *P1* a vertex of the patient skull
   Make
   - Identify the point *P2* in the mesh of the atlas that is as close as possible to the point *P1* through the Calculation of a Euclidean distance.
   -Identify *RAi* region is located in the *P*2, which corresponds to an ossicle *i*
   -Classify *P1* in the region that corresponds to *the RPi ossicle i*
   EndFor
Until term of the entire patient mesh vertex.

The "FNN" algorithm starts with the creation of regions representing the various bones of the skull. Then, it identifies the entire vertex that exists in the mesh to segment. For each point, it searches the closest point in the mesh atlas. Finally, as a result all vertex of the classified mesh is segmented into regions, each one of them represent ossicles of the skull.

3 EXPERIMENTAL RESULTS

Validation is a fundamental step to enhance the robustness and effectiveness of our method. For this reason, we begin by validating our method on synthetic meshes before doing it on real human skull. We have also proposed a validation tool, providing additional flexibility to the user deal with the selection of algorithm parameters.

Subsequently, we present preliminary results of this work.

3.1 Automatic Segmentation of Simple Shapes

The objective of this validation is to study the performance of our algorithm on simple shapes with limited number of vertex. A sample result is given in Figure 5 illustrating the various steps of our method.

Indeed, we have manually created a synthetic 3D model as the anatomical atlas, as shown in Figure 5(b).

The result of application of rigid registration between the mesh Figure 5(b) and the model is given in Figure 5(c).

Finally, accurate identification of each homogeneous region, which is based on "FNN" and elastic registration, is shown in Figure 5(d).

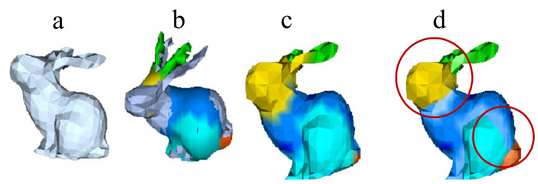

Figure 5: (a) Synthetic model to be segmented, (b) Rigid registration, (c) Synthetic model segmentation without elastic registration, (d) Synthetic model segmentation after elastic registration.

These results are very satisfactory, which proves the effectiveness of the method. Nevertheless, it is important to check the robustness of the algorithm on real images.

3.2 Segmentation of Skull Bones

We are interested in the detection of various human skull bones. Figures 5(c) and 6 show the results of applying our method on the mesh of a patient who is shown in Figure 5(b). Thus, the mesh is segmented into nine areas that represent the different bones.

Following this experience, we noted the existence of a limited number of mesh points that were not labeled at the frontal bones and mandible, while the other bones have been correctly detected. We can therefore estimate that qualitatively the results are satisfactory.

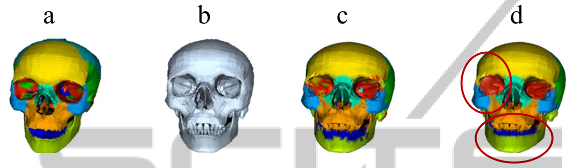

Figure 6: (A) Human skull atlas, (b) patient skull, (c) segmentation result of the patient skull before rigid registration, (d) Final segmentation result of the patient skull.

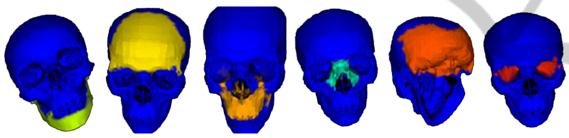

Figure 7: Result of the segmentation of the skull in 6 ossicles.

4 CONCLUSIONS

Mesh segmentation are one of the major problems in 3d image analysis. In this context, we proposed a solution to divide a given shape into meaningful parts using atlas projection. It uses a rigid registration and the elastic registration with TPS to minimize distortion and uses a proposed "FNN" algorithm to identify the final mesh parts. The results are qualitatively very interesting

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