SURFACE RECONSTRUCTION FROM 3D MEDICAL IMAGES BASED ON TRI-TREE CONTOURING

Seeking Geometrically Valid Surfaces

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Abstract: Surface reconstruction from 3D medical images is fundamental for bio-medical applications. Nevertheless, the generation of valid geometric surfaces is a difficult task due to the complexity of the structures necessary to represent the human body. In this paper, we describe the main strategies concerning surface reconstruction and planar contour extraction algorithms. In addition, we propose a new approach to surface reconstruction from medical images. Our approach is divided into two main parts. In the first part, contour extraction is performed using a hierarchical spatial decomposition. In the second part, these contours can be triangulated using a table of patterns in order to obtain geometrically valid surfaces.

1 INTRODUCTION

Over the years, medical images have been used for medical diagnostic. These images can be used to extract features and structures and can be also extended to three dimensions.

There are several sources to get three-dimensional datasets from medical images such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI) or Ultrasonic (US) techniques (Sachse, 2004). Medical images provide volume data and values that represent physical quantities, e.g. proton densities in MRI, and attenuation coefficients in CT. In the context of modelling, these values can be used to extract features of a patient. Furthermore, each medical image type presents special features that allow the classification of different tissue types such as bone, muscle and fat.

Lots of studies have been presented during last years in order to reconstruct three-dimensional surfaces form medical images. This enables the representation of strucures present in the human body. In this way, approaches based on iso-surfaces generation (Lorensen and Cline, 1987) are often used because of their simplicity in the implementation and because they also provide suitable results for visualization by using computer graphics techniques. There are other approaches that have been adapted from popular methods in computational geometry such as Delaunay triangulation and Voronoi diagram (Lv et al., 2009) or approaches based on Hierarchical Space Subdivision Schemes (Boubekeur et al., 2006).

Nevertheless, due to the complex structure of the human body, there are several questions to consider of these techniques. On the one hand, generating large polygonal datasets requires a high computational cost. In addition, non valid geometry can be extracted because of the presence of holes and other artefacts. Valid geometry is necessary for an appropriate interaction with the model (der Bergen, 2003). On the other hand, simplified surfaces obtained from space subdivision techniques are not well adapted in high curvature areas.

In this work, we propose an alternative oriented to seek valid geometry surfaces. This approach combines the extraction of contours, using a hierarchical spatial decomposition, and the triangulation between these contours determined by a new set of cases. We also determine the main problems of this approach and propose a new method in spite of not being empirically tested yet.

This paper is organised as follows. The next section describes the main approaches to surface reconstruction from volume data. In section 3 we mention several techniques to improve the resulting surfaces and perform different tests. Thereafter, in section 4 we propose a new surface reconstruction approach based on a hierarchical spatial decomposition. The conclusions are presented at the end.

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2 PREVIOUS WORK

Many approaches have been presented in order to reconstruct a surface from volume data. These approaches are mainly based on contouring techniques. In the following, we describe the most known techniques.

2.1 Iso-surface Reconstruction

Iso-surfaces are mainly used to rendering surfaces that represent points in $\mathbb{R}^3$ of a constant value. In case of medical images, volume data can be used to generate large polygonal sets.

One of the most utilized methods for iso-surfaces reconstruction is the Marching Cubes algorithm (Lorensen and Cline, 1987). Marching Cubes takes as input S_n (where n is the number of slices) which form a regular scalar volumetric data set. Then, lattice points in adjacent slices Sk and $S_{k+1}(1 < k < n)$ are studied in a sequential manner that considers cubes composed of eight points. Marching cubes consider 15 patterns to compare with each cube and as result can be generated until 5 triangles. In this way, Marching cubes provide a fast method to render complex structures with high resolution.

2.2 Surfaces from Contours

Generally, a contour line can be generated connecting points that have a constant value. There are two problems to solve. Firstly, how to find the equivalent value points, and secondly how to connect them.

As in the case of iso-surface reconstruction, values present on medical images make easier the classification of the different tissues and can be used to find the points to connect.

The connection of points for the contours extraction have been the subject of many works. However, two main methods are used when dealing with medical images, marching squares and edge tracking. These methods are easy to implement and take into account an iso-value to study the appearance of boundaries and generate contour lines.

Marching Squares can be considered as a two-dimensional version of the Marching Cubes algorithm. This algorithm, based on a divide-and-conquer approach, deal with four points cells that composed a slice. Then, the possible cases are reduced to 16 combinations and as result until two contour lines can be created. Nevertheless, disconnected segments can be created, hence merging operations can be required.

Edge Tracking detects edge intersections. Boundary points are detected and a contour line is generated moving across cell boundaries until the contour line closes back on itself (Zheng et al., 2008). Thus, as opposite to Marching Squares, this algorithm always provides closed contour lines.

Both the Marching Squares and the Edge Tracking algorithms use interpolation techniques to get more accurate results. On the other hand, both approaches can present ambiguity cases that have to be solved studying the contour segments continuity with their neighbour segment contours.

Numerous techniques have been proposed for reconstructing 3D surfaces from 2D contours(Ganapathy and Dennehy, 1982; Meyers et al., 1992; Klein et al., 1999). Nevertheless, it is not a trivial problem to solve considering the high complexity of the structures to be recognized as previously has been mentioned.

3 IMPROVING TECHNIQUES

We tested the Marching Cubes algorithm on a computed tomography dataset corresponding to a human head using The Visualization Toolkit (VTK) (Schroeder et al., 2006). The dataset was taken at 1 mm intervals at a resolution of 512x512 pixels. Iso-surface was reconstructed, as depicted in figure 1, considering an iso-value density of 1150 in order to detect the bone structures.

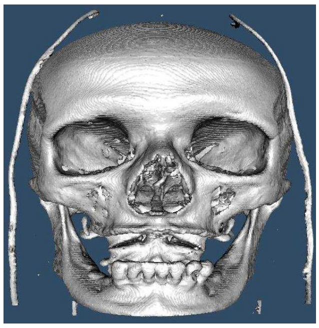

Figure 1: Iso-surface generated by using Marching Cubes algorithm and CT images.

A problem which arises is the complexity of the models. There exist many approaches in the technical literature oriented to simplify the generated geometry(Mocanu et al., 2011). We applied an algorithm based on vertex decimation (Schroeder et al., 1992) and progressive meshes (Hoppe, 1996) to reduce the total number of triangles preserving a good approximation to the original geometry. The results are shown in figure 2.

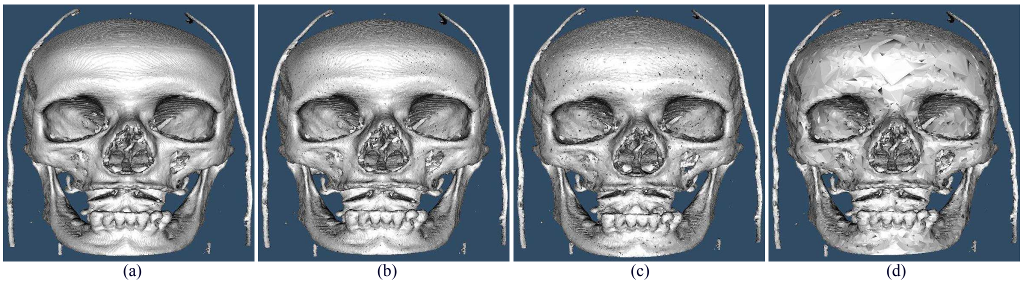

Figure 2: Simplification of geometry. a) original mesh (2.252.628 triangles). b) original mesh with decimation factor = 0.25 (1.689.471 triangles). c) original mesh with decimation factor = 0.5 (1.126.313 triangles). d) original mesh with decimation factor = 0.75 (563.157 triangles).

After that, we also tested a better adjustment of the mesh by using Laplacian smoothing (Bade et al., 2006).

In addition to the model complexity problem, the results can be erroneous because of ambiguity cases. These cases produce iso-surfaces with holes.

At this point, in spite of there are other approaches oriented to improve the Marching Cubes algorithm (Newman and Yi, 2006) and especially to solve the ambiguity problem (Gueziec and Hummel, 1995; Nielson and Hamann, 1991), we decided to test the Marching Squares algorithm to extract contours in two dimensional space.

Figure 3 shows a CT image and the contours lines which are generated through Marching Squares. Initially, the contours are composed of line segments without connectivity. Hence, these line segments must be processed to form closed polylines.

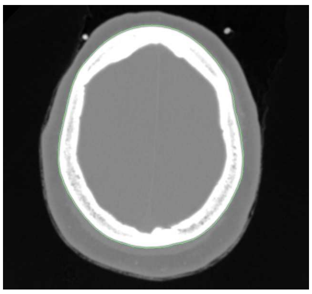

Figure 3: Contour extraction by using Marching Square algorithm and a CT image.

Nevertheless, different issues have to be considered if we want to generate surfaces from these two dimensional contours. To start with, the correspondence problem is concerned to determine the topological relationship between two planar contours that are obtained from adjacent slices. This problem arises whenever multiple contours appear in a slice. To solve it, we organize the contours into groups where each contour represents an individual object. In addition, if there are contours inside of others they are rejected in order to get only a external surface. Second, the tiling problem is concerned to generate the best geometry between the points on pairs of adjacent contours where their correspondence is assumed. In this case, we can use an approach that set the matching points in successive contours from a toroidal graph (Fuchs et al., 1977). Furthermore, it applies a divide-and-conquer technique to speed the search representing contours by ordered lists of data points. Third, the branching problem arises when there are different number of contours in adjacent sections that represent only a structure and these have to be joined. Finally, the surface-fitting problem is concerned to fit the best surface by solving the above problem. As far as this problem are concerned, we can use smooth methods, as previously showed, once triangulated surface is generated to improve the results.

To summarize, in figure 4 is shown the main stages of the process of surface reconstruction using the previously mentioned approaches.

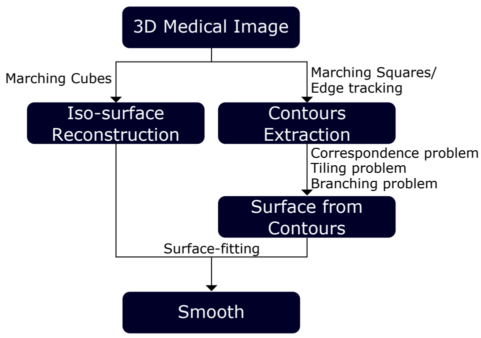

Figure 4: Stages of different approaches to reconstruct a surface from volume data.

4 SURFACE FROM CONTOURS BASED ON TRI-TREES

We have mentioned several approaches oriented to the surface reconstruction problem from medical images.

In this work, we propose a new approach that combines a contouring technique using a hierarchical spatial decomposition with a table of cases to perform the triangulation between contours.

The methodology of this approach can be divided into two main phases. First, we need to extract contours from each medical image. To achieve this, the iso-value that corresponds to the tissue to locale is set. Then, an origin point must be calculated in order to divide the image area by a tri-tree structure. This structure and the located tissues are used to extract closed contours. Second, we need to join these contours by a triangulation method based on a table of cases.

4.1 Tri-tree Structure Adaptation

A tri-tree (Jiménez et al., 2009) is an hierarchical space decomposition defined in the whole space. At its first level, the tri-tree divides the entire space into four tri-cones. In the following levels of the hierarchy, each of the tri-cones is homogeneous divided in two new tri-cones (see figure 5).

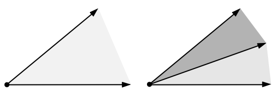

Figure 5: Representation of the division of a tri-cone.

Nevertheless, the tri-tree decomposition is slightly modified in order to cover all the image area. Considering the tri-tree centre as the midpoint of a square image, the second level tri-cones are generated reaching the corners of the source image. Finally, at deeper levels, the tri-cones are truncated to the limits of the image. In figure 6, a tri-tree applied to a medical image is shown.

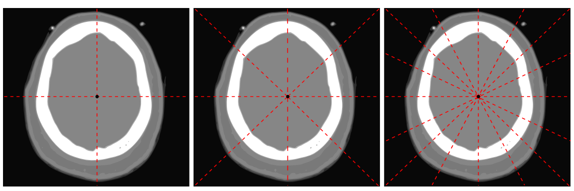

Figure 6: Tri-tree spatial decomposition over a medical image. Tri-cones of levels 1, 2 y 3 are shown.

The tri-tree is subdivided until reaching a maximum level of subdivisions. This level is previously defined. This type of spatial decomposition allows us to get contour lines with different levels of detail.

4.2 Contour Extraction

A new approach is presented to extract contour lines. To start with, we need to select a starting point from the image. This point is used to generate the straight lines which divide the image area and delimit all tri-cones. Then, the points of the image intersecting with the tri-cone lines give us information about the presence of tissues sought. Finally, these tri-cone lines are analysed in a circular direction in order to join the tissue areas and extract the contour lines.

4.2.1 Tri-tree Construction

First at all, we need to set a starting point of the image as a centre of the tri-tree.

To perform it, we consider an iso-value V_c or a range of iso-values $[V_{min}, V_{max}]$ concerning the hounsfield units that correspondent to the tissue sought. These threshold values are used to discard the rest of points.

Once tissue points has been located, tissue points are used to set the centre of the spatial decomposition. At this point, we considered two possibilities. The first possibility is to calculate the centroid of all tissue points. The main inconvenient is that the longer the distance from the points to the centre, the worse the result. Hence, a greater spatial decomposition is required for accurate results. The second possibility is to detect all regions by using an edge tracking algorithm (Zheng et al., 2008) and set a starting point for each one. This option requires the construction of a tri-tree for each region. This can also produce different number of tri-cones from adjacent medical images and it does not allow the correspondence between them. Thus, we used the first option.

The next step is the generation of the straight lines through the image. This allows us to extract an array of tissue segments for each line. These segments provide information about the starting and ending point and the tissue density. In order to generate them, we can use a rasterization algorithm as the digital differential analyzer (Foley et al., 1990).

4.2.2 Methodology

The generation of contours is based on the study of the tissue segments located through the shared lines of neighbouring tri-cones. As we mentioned, these lines are traversed circularly to join the different tissue segments. We consider a simple case when there are the same number of tissue segments located on each line.

In that case, the following algorithm summarizes the contouring process:

```
BASIC CONTOURING ALGORITHM
Input: Tri-tree lines
Output: Contours
Preconditions:
-Tri-tree lines with the same number of tissue
 segments
-Number of tissue segments > 0
FOR each tissue segment in a tri-tree line
  Create the external and internal contour
  FOR each tri-tree line
    Get final point of the segment
    Get init point of the segment
    Add final point to the external contour
    IF init point != centre of tri-tree THEN
      Add init point to the internal contour
    END IF
  END FOR
  Add external contour to the contours
  IF internal contour has points THEN
    Add internal contour to the contours
  END IF
END FOR
RETURN array of contours
```

In figure 7, a simple case and the contours generated from a medical image are shown.

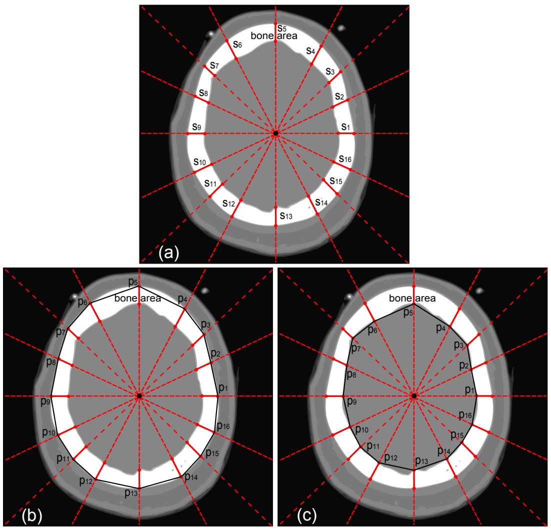

Figure 7: Contouring by using tri-tree over a CT image of the head area. a) located segments associated to bone tissue. b) external and c) internal generated contour.

Different regions and aisled structures can also appear in a medical image. To deal with it, we need to find dividing lines that separate them or abrupt changes concerning to the tissue segments located on adjacent lines. Once a dividing line is detected, we have to go back to the previous line and determine the next contour point. Finally, the tri-cones line are traversed in the opposite direction composing the contour until its first point is reached.

Complex structures can lead to many tissue segments for each tri-tree-tree line. Thus, the following issues must be studied in order to obtain the maximun information from adjacent lines: the number of tissue segments, the location of each tissue segment, the length of each tissue segment and the density of the points between neighbouring tissue segments.

4.3 Geometry Generation from Contours

Once the construction of the tri-tree is performed and contours are obtained from the 3D medical images, we need to join them by generating a geometry data set. To achieve it, we propose to compare how the contours cross the tri-cones of adjacent images. The main aim is to seek only the external contour of a region. Once its triangulation is performed, that contours are discarded and we must continue the triangulation of their internal contours.

On the one hand, we consider 5 base cases, as depicted in 8, concerning the presence of point and contour segments in a tri-cone. On the other hand, these cases can produce a lot of combinations between them. Thus, we performed a comprehensive study of different situations presented. Many cases can be simplified and reduced by using symmetry properties. As a result, we obtained a pre-calculated table of 13 patterns that can be used to determine the triangulation between tri-cone contours (see figure 9).

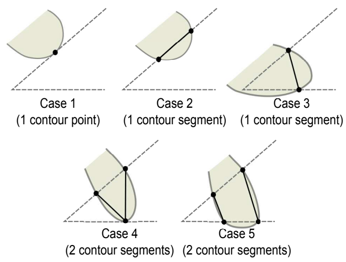

Figure 8: Table of simple cases of contours on a tri-cone.

4.3.1 Issues to Study

In the reconstruction process we have to deal with several issues. First, the branching problem arises in many structures. Thus, we need a higher spatial decomposition in order to aisle the different regions of a structure. We can also analyse the shape of the contours of adjacent images, trying to find association patterns between them. Furthermore, extra points can be generated to connect these branching structures.

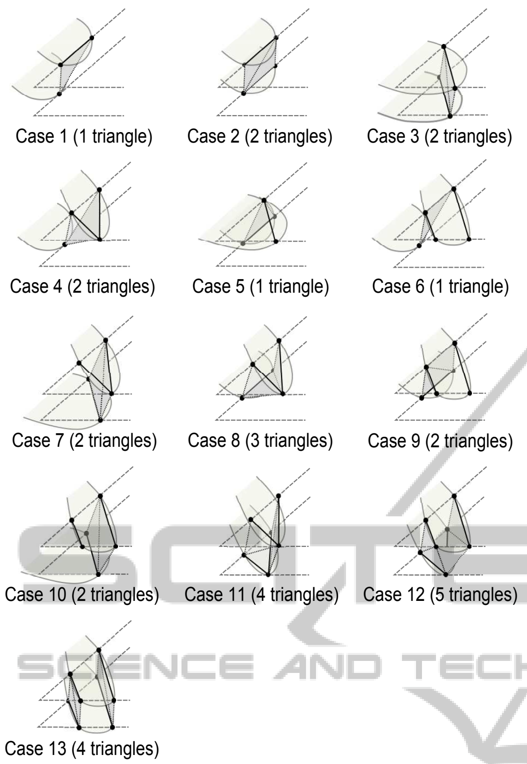

Figure 9: Table of triangulation patterns and number of triangles generated.

Second, the triangulation of contours could produce open structures in their superior and inferior ends. In some cases, we could use the centre of the tri-tree to triangulate the ends of the structures. In other cases, we could use extra points situated into the contours to triangulate and close them. Third, there are structures with internal holes. We should detect these holes and generate surfaces to represent them. Finally, we have to deal with ambiguity cases. In these cases, we need to study internal and neighbouring points of the contours in order to solve it.

5 CONCLUSIONS

We have described the main approaches used for surface reconstruction from volume data. Results of several of these techniques and improving test have been presented. The main problems of these tests have been analysed. Finally, we have also proposed a new approach oriented to reconstruct surfaces geometrically valid from volume data. This approach is based on a spatial decomposition and its main aim is to get a geometric data set easily, efficiently and robustly.

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