SURFACE MATCHING ALGORITHMS FOR COMPUTER AIDED RECONSTRUCTIVE PLASTIC SURGERY

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ABSTRACT

High energy traumatic impact of the craniofacial skeleton is an inevitable consequence of today's fast paced society. The work presented in this paper leverages recent advances in computer vision, computer visualization and computer-aided manufacturing/design to reduce the fractures and reconstruct the craniofacial skeleton in silico. First, two popular surface matching algorithms namely the Iterative Closest Point (ICP) algorithm and the Data Aligned Rigidity Constrained Exhaustive Search (DARCES) algorithm are applied individually to the problem of craniofacial reconstruction. The potential benefits and shortcomings of both these algorithms are explored. A synergetic combination of the DARCES and ICP algorithms where the output of the DARCES algorithm is fed as input to the ICP algorithm is shown to result in improved performance in terms of both, reconstruction accuracy and execution time.

Keywords: - *Surface Matching, Computer-aided Reconstructive Surgery, Computer Tomography.*

1. INTRODUCTION

High energy traumatic impact of the craniofacial skeleton is an inevitable consequence of today's fast paced society. The plastic surgeon restores the form and function of the fractured bone elements in the craniofacial skeleton typically by first exposing all the fragments, then returning them to their normal configuration, and finally maintaining these reduced bone pieces with rigid screws and plates. However, there are several critical and inherent limitations to this current, standard approach. To visualize the fragments in order to reduce them necessitates their exposure which consequently reduces the attached blood supply. To improve the blood supply, one can decrease the extent of dissection. However this means not being able to visualize the entire fracture, which could lead to potential mal-alignments of the bone fragments. We seek to solve the above dilemma by developing an enabling technology that leverages recent advances in computer vision, computer visualization and computer-aided design and manufacturing (CAD/CAM) to reconstruct the craniofacial skeleton and reduce the fractures *in silico.* The reconstruction of the craniofacial skeleton from broken fragments is achieved by using the ICP and DARCES algorithms. Eventually, a synergetic combination of the two algorithms, where the output of the DARCES algorithm is fed as input to the ICP algorithm, is shown to result in an improved surface matching algorithm with a substantial reduction in the mean squared error (MSE) as well as reduction in the execution time for the reconstruction of the craniofacial skeleton.

2. IMAGE PRE-PROCESSING

Fig.1: A typical sequence of 2D CT Images

The input to the system (Fig.1) is a sequence of 2D grayscale images of a fractured human mandible, generated via Computer Tomography (CT). Each of the slices has dimensions 150 mm x 150 mm and has an 8-bit color depth. A series of image pre-processing tasks are undertaken before using the surface matching algorithms to obtain the desired goal of image registration. The software resulting from the implementation of the surface matching algorithms and image pre-processing tasks is currently integrated into a JAVA-based package called *InSilicoSurgeon* (© The University of Georgia Research Foundation Inc., 2004) for computer-assisted reconstructive plastic surgery. A brief description of the image pre-processing tasks is as follows:

2.1 Thresholding

For the given set of CT images, the bright components represent the broken mandible fragments and the dark areas represent soft tissue. Hence, the threshold for the binarization is not difficult to select and simple thresholding is sufficient. Based on a priori knowledge, we classify a pixel with gray-scale value above 250 to belong to the object of interest and represent it using the color black (as shown in Fig. 2b). Thus we have a binary image B(i, j) for a gray scale CT image slice G(i, j) given by:

$$B(i,j) = \begin{cases} 0 & if\,(G(i,j) > 250 \\ 1 & otherwise \end{cases} \tag{1}$$

2.2 Connected Component Labeling

Binarization by itself cannot distinctly represent the two fractured fragments, as can be seen from Fig. 2(b). This is because we still need to filter out some undesired artifacts so that only the broken fragments are used for the purpose of surface matching. A 2D Connected Component Labeling (CCL) in conjunction with an area filter is used to remove these unwanted artifacts (which are typically small in size). The threshold value for the area filter is chosen to be 1000. Connected components with area less than the threshold value are deleted. The result of these operations is illustrated in Fig. 2(c). The results of the 2D CCL are propagated across the CT image slices, resulting in a 3D CCL algorithm.

2.3 Interactive Contour Detection

After applying the thresholding, CCL and size filtering operations on all the 2D CT slices, the task of interactive contour detection is performed on the result. The interactive contour detection algorithm requires the user to click on the end points of the fracture contour in each of the CT slices. The intervening contour points are automatically generated using a contour tracing algorithm. The contour points from the CT image stack are assembled to form the 3D surface point data set. A 3D surface point data set is generated for each fracture surface.

(a) (b) (c)

Fig. 2: (a) A typical 2D CT slice, (b) The result of binary thresholding on (a) and (c) The result of CCL and size filtering on (b).

3. SURFACE MATCHING USING ICP

The task of the ICP algorithm [1] is to establish a correspondence between two surface point sets to be matched as well as to compute the 3D transformation that brings the two sets into registration. In the present problem, the cardinalities of the two data sets to be matched are different. We denote the fragment/data set to be matched as the sample fragment/data set and the fragment/data set to which the sample fragment/data set is to be matched as the model fragment/data set.

3.1 The ICP algorithm

The ICP algorithm consists of the following steps:-

(a) The matching points in the model data set corresponding to points in the sample data set are determined. This new set of matching points in the model data set, which represents a subset of the original model data set, is called the closest set.

(b) The 3D rigid body transformation (3D translation and 3D rotation) that brings the two surfaces into registration is computed. The transformation is obtained using the Theory of Quaternions [1].

(c) The computed transformation is applied to the original sample data set and the MSE between the transformed sample data points and the corresponding closest points is calculated. The MSE (ε^2) is given by:

$$\varepsilon^2 = 1/N \sum_{i=1}^{N} \left\| c_i - (Rs_i + T) \right\|^2 \tag{2}$$

where R denotes the rotation, T denotes the translation, s_i denotes a point of the sample data set and c_i represents the corresponding point in the closest set. Steps (a)-(c) are repeated with an updated sample set (generated by applying R and T obtained at the current iteration to the current sample set) until a pre-specified error convergence criterion is reached.

3.2 Closest Set Computation

To compute the closest set, which is the most crucial step in the ICP algorithm, the matching point pairs are determined using the *Maximum Cardinality Minimum Weight Bipartite Matching* algorithm based on the Hungarian method proposed by Kuhn [2]. For the *Bipartite Graph* G(V, E), the 3D sample and model data sets correspond to the two disjoint vertex sets (V1, V2). The *edge-weight* (W_{ij} ε E) between any two nodes i and j (such that i ε V1 and j ε V2) is deemed to be the Euclidean distance between them. Note that the Euclidean distance is invariant to a 3D rigid body transformation. Thus, the edge weights are given by:

$$W_{ij} = \left[(x_i - x_j)^2 + (y_i - y_j)^2 + (z_i - z_j)^2 \right]^{1/2} \qquad (3)$$

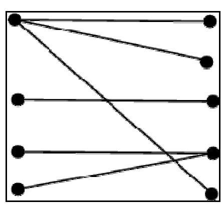

Fig.3: A typical Bipartite Graph

4. SURFACE MATCHING USING DARCES

The DARCES algorithm [3] is widely used for solving the partially overlapping 3D registration problem efficiently and reliably. The method requires no local feature detection and no initial transformation estimation for the matching of two 3D data sets, and thus differs from any feature-based approach or iterative approach for the 3D registration problem.

4.1 The DARCES Algorithm

The main steps in the DARCES algorithm are:
(a) Reference points are selected in the sample data set from the overlapping region of the sample data set and the model data set. Note that the sample data set and the model data set have the same meaning as in the case of the ICP algorithm.
(b) From the set of reference points, 3 control points are chosen.
(c) Based on certain geometric constraints, the corresponding 3 matching points on the model data set are determined. For the 3 reference points, there will be many such sets of 3 matching points in the model data set.
(d) For each set of 3 pairs of corresponding points (i.e. the 3 control points and one set of 3 matched model points), a 3D rigid body transformation is obtained. Note that 3 pairs of corresponding points are sufficient to determine a 3D rigid body transformation.
(e) Each transformation is then applied to all the reference points other than the 3 control points. If the distance between a transformed point and its nearest model point is below a certain threshold, then this reference point is considered to have been successfully aligned on the model surface. Thus the number of successfully aligned sample data points is computed for each transformation.
(f) The transformation which has successfully aligned the maximum number of data points is deemed to be the solution to the registration problem.

4.2 Some important implementation issues

For determining the rotational component of the 3D rigid body transformation, the Singular Value Decomposition (SVD) technique [4] is employed. For choosing the control points an improvised Random Sample Consensus (RANSAC)-based approach is used. The 3 control points are determined in such a way that they form an equilateral triangle. The length of a side of the triangle is varied between 25% - 35% of the maximum spread of the reference data set. The alignment thresholds are chosen to be different along each coordinate axis. Along each of the x, y, z axes, the alignment thresholds are simply chosen to be equal to the respective voxel resolutions.

5. DARCES – ICP COMBINATION

The DARCES algorithm helps in outlier rejection but the resulting transformation is only approximate. The ICP algorithm, on the other hand, yields a more accurate 3D rigid body transformation but is sensitive to outliers in the input data. Moreover, the pairs of matched points generated by the DARCES algorithm also help in reducing the cardinalities of the two data sets to be matched (using Bipartite Graph Matching [5]) in the ICP algorithm. Thus the dense bipartite graph used to determine the closest set in the ICP algorithm can be reduced to a sparse bipartite graph [6] with fewer nodes and edges. The subsequent *Maximum Cardinality Minimum Weight Matching* algorithm has a much reduced computational complexity when run on a sparse bipartite graph. Simultaneously, a much lower MSE can be achieved for the matching of the two surfaces, since the DARCES algorithm provides a better starting point to the ICP algorithm by virtue of outlier removal. Thus, the synergetic combination of the DARCES and ICP algorithms, where the inputs to the ICP algorithm are the original model set and the sampled set transformed by the DARCES algorithm, results in an improved surface matching algorithm with higher reconstruction accuracy and reduced execution time.

6. EXPERIMENTAL RESULTS AND FUTURE RESEARCH

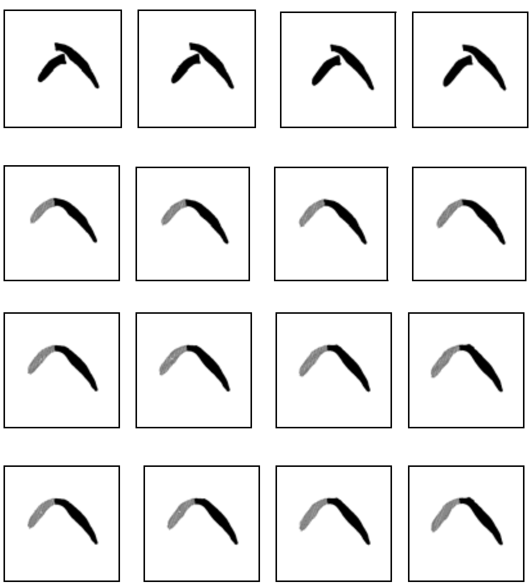

Fig. 4: The first row represents a sequence of 2D slices representing the two 3D volumes (corresponding to the two fragments) to be matched. The second, third and fourth row shows the result of the ICP algorithm, the DARCES algorithm and the combined DARCES-ICP algorithms respectively.

Fig. 4 shows the surface matching results from the ICP, DARCES and DARCES-ICP algorithms. Table 1 compares the MSE metric for the matched surfaces for each of the above algorithms. As can be seen, the DARCES-ICP hybrid algorithm yields a lower MSE metric than both the ICP and DARCES algorithms. The DARCES and ICP algorithms are purely data driven. In practice, in addition to obtaining a locally optimal solution, the preservation of the global 3D shape of the human mandible is very much desirable. Future enhancements will incorporate a model-driven search which will achieve a more accurate matching of the 3D fracture surfaces as well as ensure preservation of the global 3D shape of the human mandible. The current version of *InSilicoSurgeon*© can be used as a plug-in for the JAVA-based image processing package called *ImageJ* which is developed and distributed by the National Institutes of Health (NIH), Bethesda, MD.

Table 1: Comparison of the MSE for the ICP, DARCES and DARCES-ICP algorithms.

Algorithm	MSE (mm^2)
ICP	0.91
DARCES	0.33
DARCES-ICP	0.25

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