Efficient collision detection for soft tissue simulation in a surgical planning system

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Abstract

In the field of cranio-maxillofacial surgery, there is a huge demand from surgeons to be able to automatically predict the post-operative face appearance in terms of a pre-specified bone-remodeling plan. Collision detection is a promising means to achieve this simulation. In this paper, therefore, an efficient collision detection method based on a new 3D signed distance field algorithm is proposed to accurately detect the contact positions and compute the penetration depth with the moving of the bones in the simulation, and thus the contact force between the bones and the soft tissues can be estimated using penalty methods. Thereafter, a nonlinear finite element model is employed to compute the deformation of the soft tissue model. The performance of the proposed collision detection algorithm has been improved in memory requirements and computational efficiency against the conventional methods. In addition, the proposed approach has the superior convergence characteristics against other methods. Therefore, the usage of the collision detection method can effectively assist surgeons in automatically predicting the pos-operative face outline.

Keyword: Signed distance field, collision detection, soft tissue prediction, surgical simulation

1. Introduction

Many cranio-maxillofacial surgical planning systems (CSPSs) appear to be widely in use by surgeons in computing an optimal plan and training for the purpose of repeatedly practicing surgical procedures. However, in the existing systems[1][2][3][4], the boundary conditions of the biomechanical model, which affects the accuracy and stability of the soft tissue deformation, must still be defined manually by measuring the displacements of the bones in terms of the bone-related planning developed by the surgeon. Therefore, automatically estimating the boundary conditions and predicting soft tissue deformations with respect to pre-specified bone remodeling plans becomes highly desirable in the CSPSs. Collision detection is a promising means to achieve this simulation. Currently, deformable continuous collision detection has been studied widely with the development of surgical simulation, robotics and games. Some methods based on bounding volume hierarchies(BVHs) or spatial sub-division were successfully applied to the detection of the contact between surgical tools and an organ in the surgical simulation[5][6][7][8].

However, for the craniofacial surgical simulation presented in this work, collision detection is not simply to detect the touch of objects, instead, precise collision information, e.g. penetration depth and normals, is required. Furthermore, intersection regions between the bones and the soft tissues are generally large. Therefore, the methods that have been widely used in the surgical simulation are not appropriate for this work, and an effective and efficient collision detection algorithm is highly desired. Fortunately, the distance fields, free from these limitations, can be applied in collision detection, and the estimation of the penetration depth and the normals needed for the biomechanical model of the soft tissues is extremely fast and independent of the geometric complexity of the object[7]. Fuhrmann[9] proposed a rapid collision detection method based on the partial distance field. This method is suitable to detect the contact between rigid objects and highly deformable objects. However, it used the uniform grid data structures resulting in huge memory requirements. Frisken[10] proposed the adaptive distance field technique. Their contribution is to reduce memory requirements and represent complex shape in diverse scales. However, this method increased the cost of more complex storage and retrieval. These drawbacks hamper the distance field from being applied in collision detection. Therefore the efficient computation of the distance field for a given surface representation is still a research topic. In this work, we present an efficient method for computing the signed distance field by combining Fuhrmannn's algorithm[9] and the adaptive sampling method[10], and an efficient collision detection algorithm based on the proposed distance field is employed to automatically estimate the penetration depth and the contact force after the moving of the bones. The proposed algorithm can help to achieve efficiently collision detection between the bones (rigid objects) and the soft tissues (deformable objects).

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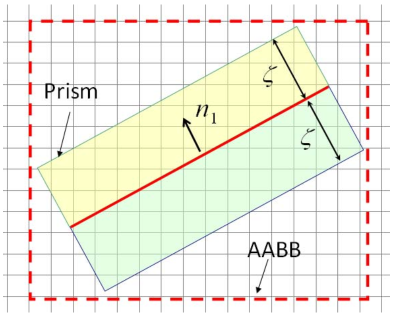

Figure 1. Prism of a triangle mesh and the AABB of the prism

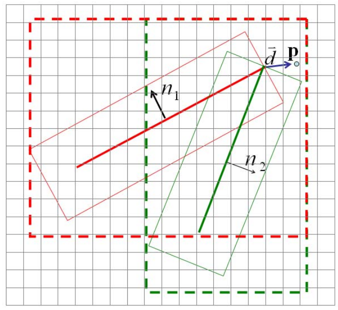

Figure 2. The mesh feature closest to $\mathbf{p}$ is a vertex of the triangle or a point at the edge of the triangle

2. Method

2.1. 3D Signed distance field

An efficient signed distance field algorithm is designed by combining the partial distance field algorithm[9] and the adaptive sampling algorithm[10]. It can generate a signed distance field for the geometry with oriented triangle meshes, and does not require a closed and 2-manifold surface. The algorithm that is used to generate a signed distance field for triangular geometrical model is summarized as follows:

(1) For each triangle of the surface of the geometrical model, a prism is generated by moving its vertices along the surface normal by an amount of ζ in negative and positive direction (ζ is the assumed thickness of the distance field), as shown in Figure 1.

(2) For each prism generated in step (1), the axis-aligned bounding box(AABB) enclosing this prism is determined, as shown in Figure 1.

(3) For all grid points inside the corresponding bounding volume, the distances to the triangle of the surface are computed, and the sign of the distance values are determined by the sign of the angle weighted pseudo-normal. If the calculated absolute value is less than the current value of the distance field, the current value is set to a new value.

(4) A hierarchical octree is constructed to organize the cartesian grid points of the distance field, and subsequently an adaptive distance field is generated using adaptive, detail-directed sampling method.

In the above algorithm, steps (1) and (2) are straightforward, while steps (3) and (4) relate to two key problems which are the sign computation of the distance value and the generation of the adaptive distance field. We describe the efficient methods to address these two problems in this section.

For a given point $\mathbf{p}$, the minimum distance from $\mathbf{p}$ to a triangle mesh can be calculated using the voronoi regions of the features of the triangle. However, if the sign which determines whether a point is inside or not simply results

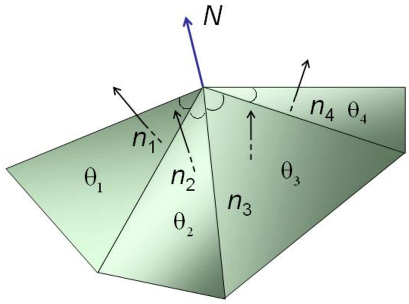

Figure 3. The angle weighted pseudo-normal $\mathbf{N}$

from the sign of the inner product of the face normal and the direction vector (from point $\mathbf{p}$ to the closest point $\mathbf{c}$ on the surface), which is presented by Fuhrmannn[9], it does not work in many cases, because in some cases the closest feature is a vertex or an edge, there is the same distance to two or more triangles but the dot product of $\vec{d} \cdot \vec{n_1}$ and $\vec{d} \cdot \vec{n_2}$ have different signs, as shown in Figure 2. In this work, therefore, the angle weighted pseudo-normal, which is guaranteed to have a positive dot product with the direction vector whenever the point is outside and a negative dot product whenever the point is inside[11], is employed to address this problem. As shown in Figure 3, for a given vertex $\mathbf{v}$, the angle weighted pseudo-normal is defined as

$$\vec{N}_v = \frac{\sum \vec{n}_i \theta_i}{\| \sum \vec{n}_i \theta_i \|} \tag{1}$$

where$\{\theta_1, \theta_2, \theta_3, \cdots\}$ are the incident angles of point $\mathbf{c}$, and $\{\vec{n}_1, \vec{n}_2, \vec{n}_3, \cdots\}$ are the normals of the incident faces.

In addition, for a given edge $\mathbf{e}$, the pseudo-normal is straight defined as $\vec{N}_e = \sum \vec{n}_i$. Let there be a given grid point $\mathbf{p}$, the distance to the triangle mesh is $d = \inf_{\mathbf{x} \in M} ||\mathbf{p} - \mathbf{x}||$, and assume that $\mathbf{c}$ is a closest point in the triangle mesh M, so that the distance is $d = ||\mathbf{p} - \mathbf{c}||$, and the direction vector is $\mathbf{r} = \mathbf{p} - \mathbf{c}$. Thus, the sign of the distance value is given by $s_d = sgn(\vec{N}_v \cdot \vec{r})$ or $s_d = sgn(\vec{N}_e \cdot \vec{r})$, which means that $s_d > 0$ if $\mathbf{p}$ is outside the surface, and

$s_d < 0$ if $\mathbf{p}$ is inside.

In order to perform the adaptive sampling approach, an octree-based hierarchical data structure is used to store the sampled data so as to process the sample data more efficiently. First, an octree is built to store the regularly sampled distance field generated in step 3, and then the bottom-up approach is used to unite recursively leaf cells within a specified error tolerance. Specifically, a group of adjacent cells, starting with the smallest in the octree, is coalesced as long as none of them has child cells and the sampled distance of the eight cells can be reconstructed from the sample values of their parent cells to a specified error tolerance. Upon considering all the cells for coalescing at a given level in the hierarchy, the group of cells at the next level is considered. The adaptive distance field generation is completed when the coalescence is finished at a given level or the root node is reached.

2.2. Collision Detection and Penetration Depth Computation

Collision detection between different objects is carried out pointwise when using distance field. Vertices on the internal surface of the deformable object (the soft tissue model) are compared against the distance field of other objects (bones). A collision occurs if the distance(D) is a negative value. An adaptive distance field stores distance values at cell vertices of an octree data structure and uses trilinear interpolation for reconstruction and gradient estimation.

2.3. Penalty Force

We assume that the contact between the bones and the soft tissues is frictionless, and thus the contact force is normal to the surface. In the paper, the penalty-potential energy is defined as a function of imposed displacements(penetration depth d)

$$\phi(d) = k_c d^2 \tag{2}$$

The external contact force is therefore computed as follows:

$$\mathbf{F}_a^{ext} = \int_{\partial V^{(c)}} \frac{\partial \phi}{\partial \mathbf{x}} N_a da \tag{3}$$

3. Results

3.1. Prototype Implementation

The prototype system was performed on a workstation with a Dual-Core AMD Opteron CPU 3.0GHz, with 4G of RAM and a NVIDIA Quadro FX 5500 GPU. For concreteness, the case of craniofacial dysostosis is used to describe the prototype applied in the experiments, the objective of which is to simulate correction of the craniofacial dysostosis

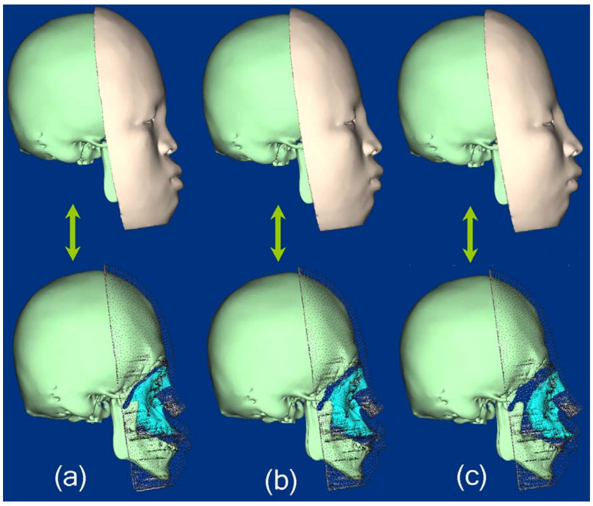

Figure 4. Results of soft tissue deformation based on mixed-element modeling (a) pre-operative face configurations, (b) the predicted face configurations with the bones of the mid-face moving 6mm forwards, (c) the predicted face configurations with the bones of the mid-face moving 12mm forwards and 5mm downward.

with mid-face distraction osteotogenesis. The implementation workflow consists of the following steps:(1) the 3D geometric models, including the bone tissue models and the soft tissue models, are reconstructed from CT data sets, and the signed distance field of the skull-model is generated following the proposed signed distance field algorithm; (2) the bone cuts (osteotomies) are modeled with the help of a craniofacial surgeon, and the required cut surfaces for defining the bone regions are interactively generated following the anatomy structures. Thereby, the skull-remodeling plan and the moving paths of the bones are computed; (3) the bones move automatically following the moving path of the bone-related plan. When the collision occurs, the contact nodes and the penetration depth between the moved bones and the soft tissues are computed using the proposed collision detection algorithm, and thus the penalty force of the soft tissue model is computed in terms of the penetration depth of the contact nodes; (4) the geometrical model and the boundary conditions serve as input for our simulator, and We used the nonlinear finite element method base on hyper-elastic material model to simulate the behavior of the facial soft tissue and to predict the new facial configurations. Figure 4 shows the predictive results under different displacements of the bones.

3.2. Performance Evaluation

3.2.1. Collision detection. We compared our collision detection approach to the two conventional methods: the

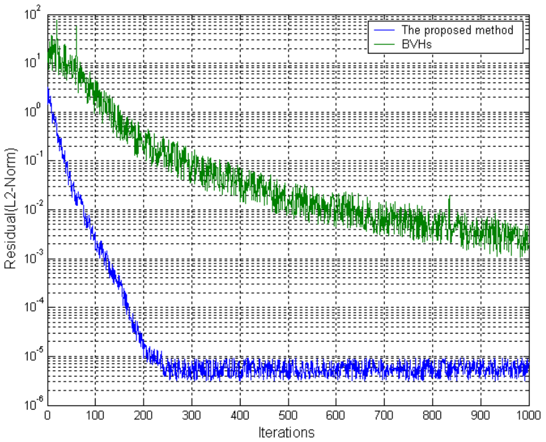

Figure 5. Comparison of Convergence rates.

fast partial distance field computation method using uniform grid data structure[9], and the adaptive distance field technique[10]. A skull model with 96190 triangles is employed to test the performance of these methods. Table 2 shows the performance comparison results of the distance field computation. The average memory requirements of our algorithm decrease by 73% against the uniform grid method (Fuhrmann's method). Although, the distance field computation time is slightly greater than Fuhrmann's method, the average computation time improves by 77% against the adaptive distance field.

3.2.2. Numerical comparison of convergence. We compared the convergence characteristics of the collision detection algorithm based on bounding volume hierarchies and the proposed algorithm based on the signed distance field. The surgical simulation, as shown in figure 4, is used to test the convergence rates of the two algorithms. Figure 5 shows the comparison results of convergence rates of the two algorithms. For the former, oscillation is evident and the convergence speed is very slow. That is because the contact forces change discontinuously in many cases. Instead, for the latter, since the new adaptive signed distance field can represent complex shapes with arbitrary precision, the residual quickly converges to low states.

4. Discussion

The proposed method is successfully demonstrated in a preliminary application to complex cranio-maxillofacial surgery. Since the nonlinear finite element is much more sensitive to the boundary conditions and the material parameters, the definition of boundary condition is a key factor for the nonlinear finite element model. However, it is difficult to define the boundary conditions for the facial soft tissue model using such conventional methods as manual measurement, registration due to the complexity of the facial geometric structures, which is why many research works[3] concluded that the nonlinear finite element did not enhance significantly accuracy of the soft tissue deformation. However, we employ an accurate collision detection algorithm to estimate the penetration depth and the penalty force, which successfully define boundary conditions automatically. Therefore, the superior computational strategy of the boundary conditions presented in this paper has great significance to promote the development of the soft tissue prediction systems based on bone-related planning. It not only helps us estimate the contact forces between the bones and the soft tissues automatically, but also improves the accuracy and the efficiency of the surgical planning system.

5. Conclusion

This paper presents a novel method for assisting surgeons in automatically predicting the new face configurations based on a pre-specified bone-related plan. An accurate collision detection method using the signed distance field is the key technique in automatically predicting the cranio-facial surgery. It performs the accurate contact handling between the bones and the soft tissues. When the bones move following a pre-specified bone-related plan, this method can automatically and dynamically detect the inter-penetration depth and the contact normals between the moved bones and the soft tissues. These inter-penetration depth and the contact normals are needed for the biomechanical model of the soft tissues. Moreover, the signed distance field computation method is improved in both the computational efficiency and the memory requirements. In addition, this work employed a nonlinear biomechanical model for enhancing accuracy and simulation realism required in the cranio-maxillofacial surgical simulation.

For future work, we will further improve our method. Although reducing the simulation time is not the goal of the CSPS, it is necessary to optimize and improve the efficiency of the biomechanical model analysis and collision detection. Of course, the accuracy has been a key issue to enable the clinic practice of this method. Therefore, the biomechanical model will be further investigated. Moreover, much more qualitative validation for the biomechanical model is necessary for further studies.

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Table 1. Performance comparison of distance field computation (triangles: $96,190$)

Resolution	Error tolerance	Fuhrmann et al[9]		Frisken et al[10]		Our algorithm	
		memory(M)	time(s)	memory(M)	time(s)	memory(M)	time(s)
128×128×128	5.0×10^{-5}	8.4	3.12	3.2	11.78	2.9	4.26
256×256×256	1.0×10^{-5}	67.1	13.15	19.9	107.54	18.1	16.75
512×512×512	1.0×10^{-6}	536.9	60.62	99.5	965.83	95.1	68.15

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