Real-time Simulation of Deformable Soft Tissue Based on Mass-Spring and Medial Representation

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Abstract. In this paper, we present a novel deformable model for soft tissue simulation in a real-time manner. The innovative model consists of two sub-models: the surface one and the internal one, which are based on Mass-Spring system and Medial Representation respectively. This proposed model is more accurate and efficient than the pure surface Mass-Spring one by taking advantages of Medial Representation to reflect inner attributes of soft tissue. We also optimize the Mass-Spring system in order to refine the appearance of soft tissue movement and reduce its complexity. A real clinical model using a segmented left-kidney is presented as an example in our case study.

1 Introduction

For years, real-time modeling of deformable objects has become increasingly significant in biomedical domain. More and more novices and students practice surgical operations on the virtual objects instead of living animals and cadavers.

Many authors proposed various models in the past decades. Finite Element Method (FEM) [1] and Mass-Spring [2] are considered the most popular methods among them. Meanwhile, M-Rep [3], a sort of model basing on Medial Representation [3], was proposed to represent the global deformation of the objects. However, an ideal soft tissue deforming simulation is still a challenging task due to the complex internal structure and surface appearance of the deformable objects. FEM is the most accurate method for simulating, but it hardly satisfies the real-time requirement because of its high complexity and large numbers of parameter definitions. Surface Mass-Spring System could have acceptable response-time if we limit the number of mass points of the model. Nevertheless, this model contains few internal features of soft tissue [4], which results in low accuracy when to simulate the global deformation. M-rep is applied to simulate the deformation based on medial structure implying the internal information of soft tissue. However, it is limited in the rough appearance of surface and poor efficiency. The novel approach proposed in this paper addresses the problems mentioned above by introducing a hybrid model integrating the advantages of Mass-Spring and Medial Representation.

In order to implement the context mentioned above, the hybrid model is designed as follow. From the medical image data of soft tissue, two types of models are generated which represent the surface Mass-spring system and the internal model respectively. After that, we will establish a relationship between the two separate models to transfer forces from outside to inside. The strategy is attractive because it reserves both surface information and internal structure. Contrasting to the standard techniques, it can not only simulate the local deformation appropriately, but also reflect the global deformation reasonably.

The paper is organized as follows. In section 2, we provide the methods to obtain the surface Mass-Spring model and the internal model, and then we introduce the hybrid model consisting of them. Some results of the hybrid model are shown in section 3. Finally, we will discuss future work and come to our conclusion in section 4.

2 Soft Tissue Modeling

The complete methodology of soft tissue modeling consists of two core modules: Image Data Processing and Mathematical Modeling, each of which contains two submodules. The former includes Balloon Segmentation and Skeleton Extracting, while the latter consists of Surface Modeling and Internal Modeling (Fig. 1).

The whole procedure of the modeling is described here: firstly, Balloon Segmentation is employed to extract the specific soft tissue from medical image dataset; secondly, it establishes the surface model of soft tissue using Mass-Spring System; thirdly, the skeleton of soft tissue is calculated; fourthly, the medial atoms [3] on the skeleton shoot out many spokes implying the boundary information, after which the internal model composed with skeleton and spokes is created; finally, the hybrid model of soft tissue is generated by composing the surface Mass-Spring model and the skeleton structure according to specialized relations. The detail of these steps will be illuminated in the following sections, especially the surface modeling, the internal modeling and the hybrid modeling (Fig. 1).

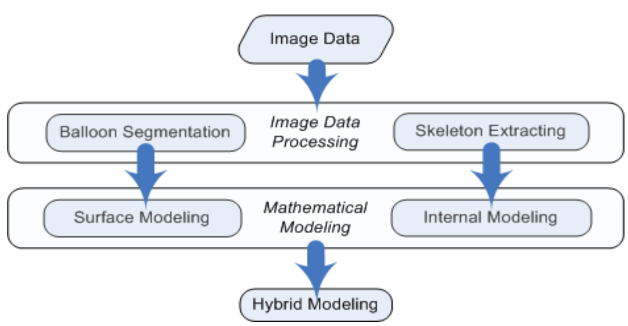

Fig. 1. The flow chart of the whole procedure to model the soft tissue.

2.1 Balloon Segmentation for Surface Mesh

Balloon Segmentation is a volumetric Segmentation algorithm based on dynamic deformable meshes [5]. This algorithm is preferred because the data structure of the segmentation's result is appropriate to establish the surface Mass-Spring model as well as its connection with the internal model.

The basis idea of balloon algorithm is to add image-force [5] on an initial mesh object, which could make the object expand or shrink towards the surface of soft tissue. The mesh object will adjust its shape to meet with the boundary of soft tissue as closely as possible after iterating the calculation for specified times, just like a balloon inflated or deflated. Fig. 2 shows the effect while the algorithm is applied on the medical image of a left kidney.

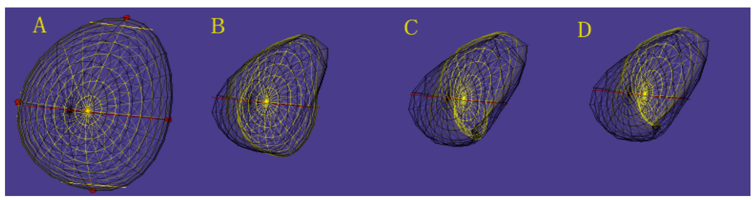

Fig. 2. Balloon Segmentation applied on the medical image of a left kidney. (A) The initial mesh. (B) Iterate for 50 times. (C) Iterate for 100 times. (D) Iterate for 150 times.

2.2 Surface Mass-Spring Modeling

The Mass-Spring system is widely used in simulating the deformation of non-rigid object. The system models an object as a set of masses connected by corresponding springs. The springs' topology used here is based on Balloon Segmentation, which means that each mass connects with its six neighboring points through corresponding springs (Fig. 3(A)).

Spring is a fundamental unit in Mass-Spring model. Fig. 3(B) presents two essential parts of the unit: the elastic equipment and the damper [2]. The former generates elasticity force proportional to the alteration of the springs' length, and the latter engenders damping force proportional to the velocity of mass-points.

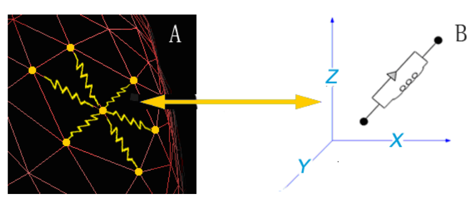

Fig. 3. (A) The springs' layout of the surface model. (B) The basic unit of the spring in the 3D coordinate-system. The triangular module is the damper.

Mass-Spring employs a differential equation to simulate the process of deformation:

$$m_i \ddot{x}_i(t) + c_i \dot{x}_i(t) + \sum_{j \in \sigma(i)} (k_{i,j} * \Delta l_{i,j}) = F_i^{extern} \quad (1)$$

Where x_i, m_i and c_i is the displacement, mass and damping factor of the ith point respectively; $\sigma(i)$ represents the neighboring points of the ith point; $k_{i,j}$ is the elastic coefficient of the spring ij; Δl donates the difference between original length and current length of spring ij.

During the implementation, we improve the structure of traditional Mass-Spring system in order to refine the effect of simulation. Firstly, we add a curvature force. Curvature force controls the degree of bending and twisting of soft tissue. We imitate the force by bringing in an assistant spring: angular spring [2]. As shown in Fig. 4(A), P_1, P_2 and P_3 are the surface points of soft tissue. The angular spring links point A with the *mid point* of P_2P_3. Secondly, we induct a concept of fixed position [6] in order to prevent soft tissue from escaping from the original location. Here, we presume that each point has a corresponding fixed spot located in the original position of the point, and the point connects with the spot through springs named return-springs. As a result, soft tissue always has a tendency to go back to the original position. For example, P_1P_1', P_2P_2', P_3P_3' and P_4P_4' are the return-springs whose initial length is zero in Fig. 4(B).

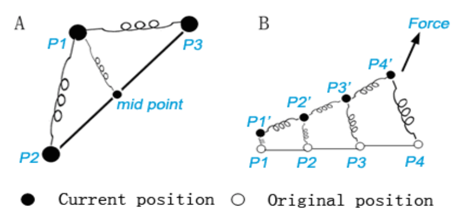

Fig. 4. (A) The angular-spring between *P1* and *mid point*. (B) The return-spring between the original position (*P1, P2, P3, P4*) and the current position (*P1', P2', P3', P4'*).

2.3 Internal Skeleton Modeling

Stephen M. Pizer [3] introduced the "M-Rep" concept, a type of Medial Representation, based on Blum's medial axes. This model uses medial atoms and a particular tuple ($\{x, r, F(\vec{b}, \vec{n}), \theta\}$) [7] [8] to imply the positions of boundary (Fig. 5(A)). Here medial atom represents an interior section of a figure [7]. As a result, M-rep is a sound approach to reflect the internal structure.

In order to establish the internal model, Distance Mapping Method [9] is employed to calculate the skeleton, along which media atoms are selected evenly. Then we simplify M-Rep with the purpose of reducing the model's complexity. We reset the topology of medial atom and implied boundary just like hub and spokes (Fig. 5(B)).

Each medial atom (or hub) on the skeleton shoots out several spokes evenly, and the angle between each single spoke and skeleton is a constant value θ. The corresponding tuple is altered to $\{x, r, F(V, \overline{AB}), \theta\}$, where x is the coordinate of the medial atom B; r is the length of the spoke; F is the plane determined by V and $\overline{AB}$; V is the Orientation-Vector of boundary C which links media atom A to boundary C; θ is the angle between skeleton BA and spoke BC.

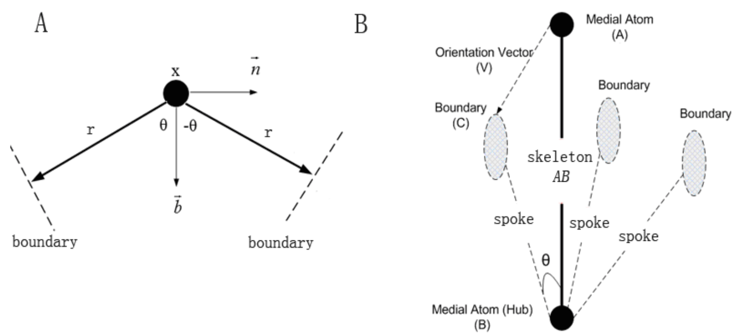

Fig. 5. (A) M-rep in 2D. (B) Simplified Medial Representations in 3D.

The simplified Medial Representations (Fig. 5(B)) are different from M-rep in several ways. Firstly, each tuple in M-rep corresponds with a medial atom, while the one of the simplified corresponds with a spoke. Secondly, the r in M-rep is the radius of corresponding medial atom and the r belonging to the same medial atom should be identical to each other, whereas the one in the simplified model is the length of the relevant spoke and they could be unequal to each other. According to the data of the tuple, we can calculate the position of implied boundary C:

$$\underline{C} = x + R_{V,\overline{AB}}(\theta)\overline{AB} * r_{\overline{BC}} / |\overline{AB}| \tag{2}$$

Where $R_{v,\overline{AB}}(\theta)$ denotes an operator rotating its operand ($\overline{AB}$) by the argument angle in the plane spanned by v and $\overline{AB}$; $|\overline{AB}|$ is the length of the vector $\overline{AB}$.

Other spokes connecting with media atom B are calculated by rotating spoke BC around axis BA and scaling BC to the length of corresponding spoke. All implied boundaries could be obtained by iterating the approach described above.

2.4 The Hybrid Model

The boundaries implied by spokes might not just the points on the surface Mass-Spring model, so the application will relate spokes with surface points by repeating the following step: calculating the coordinate of an implied boundary by formula (2) and finding out its closest point on the surface model. Then, a new spoke, which links the closest surface point and the corresponding medial atom, is established and replaces the old one. The new spoke will be removed if the closest surface point has already related to another spoke. Fig. 6 displays an instance of each model.

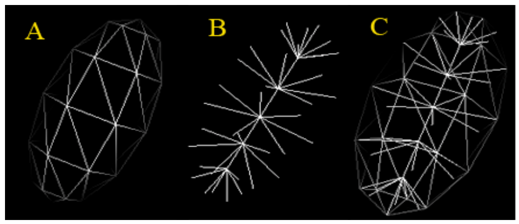

Fig. 6. An example of ellipsoid represented by the three models. (A) Surface Mass-Spring model (B) Internal model with skeleton and spokes (C) The hybrid model

The hybrid model is established after the above processes. Then the skeleton and spokes are considered to be springs. Finally, we should set the parameters of the model appropriately in order to simulate soft tissue effectively and efficiently. An automatically recursive approach is employed to set these parameters. Firstly, we initialize such parameters as the damping factor (c), the mass (m) of the points and the elastic coefficient (k) of springs on the surface as well as at the inside manually. Here the values of the internal parameters are set much larger than the ones of the surface parameters because the interior of soft tissue is more difficult to deform than the surface. Secondly, a specified force is applied on a surface point. If the displacement of the surface point excesses the maximum threshold determined previously, all of these parameter values on the surface would increase 0.5 times. These values would decrease 0.5 times if the displacement were less than the minimum threshold. The same criterion is also applicable for the internal parameters. After iterating for several times, the program terminates with suitable values for these parameters. By comparing numerous generated parameter values engendered from different initial values and observing the deformation effect using these values, we choose one group of the most appropriate values as the optimum parameters

3 Experiment Results

The hybrid model application is performed on the computer with an Intel Pentium IV-2.60 GHz CPU and 1.0GMbyte of memory. Visual C++ 7.0 is used as the integrated development environment. There are 458 points on the surface and 24 points on the skeleton. Each atom shoots out 18 spokes ($\theta = 90$ degrees).

The stable state of the left kidney model is showed in Fig. 7(A). The model achieves a reasonable result when deforming on global level (Fig. 7(B)), while the surface Mass-Spring model corrupts under the same large-scale force. The model also gets a refined appearance on local-region deformation (Fig. 7(C) and Fig. 7(D)).

In order to meet the real-time requirement, the deformation should be determined at rates of 15-20 times per second. In our application simulating the left kidney employing the hybrid model, the update rate is 25-40 times per second, which means that the hybrid model satisfies the real-time requirement. Moreover, the surface Mass-Spring model with the same surface structure as the hybrid one is updated at rates of 28-45 times per second, so the hybrid model does not markedly increase its complexity when introducing the internal structure and achieving sound global deformation effect.

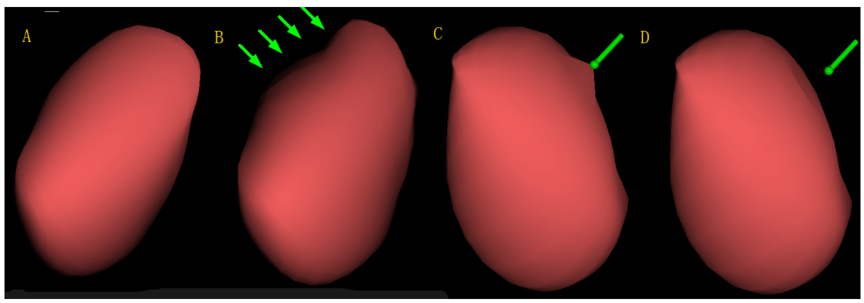

Fig. 7 (A) The left-kidney (B) Global deformation caused by applying large-scale force. (C) Nip the kidney. (D) Release the forceps.

4 Conclusion

In this paper, we present a hybrid model ensuring a sound effect without increasing the computation-time when deformation is applied on either the global level or the local region. We also briefly introduce the Balloon Segmentation appropriate to obtain the mesh structure of soft tissue. Using Balloon algorithm could generate mesh arrangement automatically as well as conveniently. However, it also results in the uneven distribution of springs and points. The density of springs and points near the two acmes is much higher than are others (Fig. 2(D)), which influence the accuracy of simulation. In addition, the method employed to exact the skeleton has some flaws [9]. It could not obtain a precise result when the structure of soft tissue contains some branches.

In future, we endeavor to model a more complex soft tissue, such as heart. We also attempt to improve the accuracy of the current model and reduce the response-time, which is significant in virtual surgery. Moreover, we need to ameliorate the program for generating the mesh structure as well as the algorithm for exacting the skeleton. The recent task is programming on the force feedback mouse, which could make users feel actual about soft tissue.

5 Acknowledgement

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