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Assessing the Quality of Force Feedback in Soft Tissue Simulation

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***Abstract*— Many types of deformable models have been proposed for simulation of soft tissue in surgical simulators, but their realism in comparison to actual tissue is rarely assessed. In this paper, a nonlinear mass-spring model is used for real-time simulation of deformable soft tissues and providing force feedback to a human operator. Force-deformation curves of real soft tissue samples were obtained experimentally, and the model was tuned accordingly. To test the realism of the model, we conducted two human-user experiments involving palpation with a rigid probe. First, in a discrimination test, users identified the correct category of real and virtual tissue better than chance, and tended to identify the tissues as real more often than virtual. Second, users identified real and virtual tissues by name, after training on only real tissues. The sorting accuracy was the same for both real and virtual tissues. These results indicate that, despite model limitations, the simulation could convey the feel of touching real tissues. This evaluation approach could be used to compare and validate various soft-tissue simulators.**

I. INTRODUCTION

Deformable soft tissue modeling is an essential part of most surgical simulators. The model should be realistic, but simple enough to be rendered in real time. Many approaches have been taken by researchers to model deformable bodies in real-time simulations [1]. Most existing models are linear elastic and hence are valid in only a small linear stress-strain region. Furthermore, the challenge of tuning model parameters based on experimental data has received limited attention; examples of such studies include [2], [3]. An arguably important judgement of the quality of a soft tissue simulation is its success in immersing users in the virtual environment by convincingly providing them with the feel of touching real tissues; something that has rarely been addressed in the literature. In [4], the fidelity of force feedback in deformable models was assessed by comparing the feel of real and virtual models of linear elastic silicone objects.

In this paper, we develop a simple nonlinear mass-spring virtual model of soft tissue to represent tissue deformations and calculate force feedback during real-time simulations. Parameter tuning was conducted to match the behavior of our model to that of real soft tissues. The main focus of our study was to evaluate the realism of the model in conveying the feel of touching real tissues to users. We present two human-user studies to evaluate the realism of the simulations. The preliminary experimental results provide an indication of the realism of the simulation.

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II. METHODS

The methods include the development of the model and simulation, tuning of model parameters, and two human-user experiments to evaluate the simulator. The evaluation method (Section II-C) is independent of the modeling scheme; the particular modeling scheme invoked was selected because the parameters can be tuned based on experimental data.

A. Deformable Tissue Model and Simulation

We chose the mass-spring representation for modeling soft objects. Mass-spring models can be implemented easily and solved in real time. Also, forming complicated geometries is fairly straightforward with the mass-spring method. In a conventional mass-spring network, the object is modeled as point masses connected with linear springs. Displacements of points as a result of external loads are then computed. To simulate nonlinear force-displacement behavior of soft organs, the linear springs were replaced with biphasic, non-linear ones, as described in [5]. However, in order to improve realism and computational efficiency, some modifications were implemented. The modified force-deflection function of the spring connecting nodes i and j is:

$$F_{ij}(\Delta l_{ij}) = \begin{cases} (K_1 \Delta l_{ij} + K_2 \Delta l_{ij}^3) l_{ij}^0 & \left|\frac{\Delta l_{ij}}{l_{ij}^0}\right| \leq \Delta l_c \\ (A + B(|\Delta l_{ij}| - l_{ij}^0 \Delta l_c)) \operatorname{sgn}(\Delta l_{ij}) & \left|\frac{\Delta l_{ij}}{l_{ij}^0}\right| > \Delta l_c \end{cases} \tag{1}$$

where K_1 and K_2 are constants, Δl_{ij} is the spring deformation from its rest length l_{ij}^0, and Δl_c is the critical strain, below which the spring is nonlinear. This formulation was inspired by real soft tissue behavior, which exhibits a highly nonlinear force-deformation curve at small strains and a linear one at higher strains [6]. A and B are defined to make the transition C^1 continuous. The spring forces were scaled according to the springs' initial lengths, so the smaller springs become softer as recommended in [7]. To add visco-elasticity to the system, a damping force was applied to every node in the model, in the form of a force proportional and opposite to their velocity. Thus, the equations of motion for the entire system take the form of:

$$M_i \ddot{\mathbf{r}}_i + b_i \dot{\mathbf{r}}_i + \sum F_{ij} \frac{\mathbf{r}_i - \mathbf{r}_j}{|\mathbf{r}_i - \mathbf{r}_j|} = \mathbf{F}_i^{ext} \tag{2}$$

where M_i, b_i, $\mathbf{F}_i^{ext}$, $\mathbf{r}_i$ are the mass, damping, external force vector, and position vector of node i, respectively, and F_{ij} is found from (1). Finally, the equations of motion were solved using the implicit central difference numerical integration scheme.

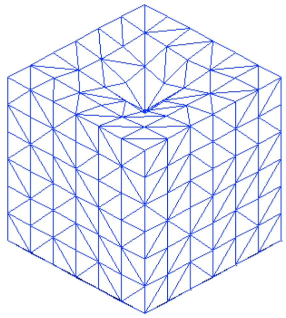


Fig. 1. Cubic model used for simulations.

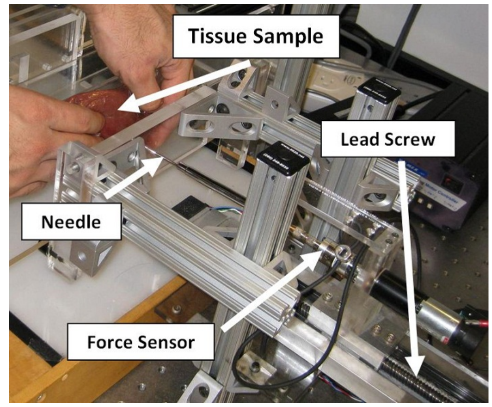


Fig. 2. The setup used for tissue parameter acquisition.

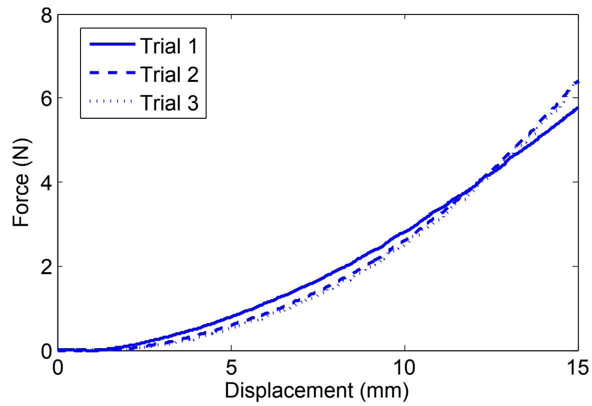


Fig. 3. Force-displacement data measured from goat heart tissue at 5mm/s.

Figure 1 shows the cubic model used for both parameter tuning and real-time simulations. The model has an edge length of 6cm and consists of 343 nodes and 1296 tetrahedron elements. The tetrahedron mesh was preferred because of its numerous advantages over other methods of spring arrangement [7]. All facial nodes except the ones on the top surface were anchored to the ground to prevent rigid body motion in the simulations. The interaction point was the middle point of the top face and its motion was restricted to the vertical direction. The cube was used for tuning the spring and damping constants (Section II-B), as well as for real-time simulations.

In real-time interactions, a virtual tool was introduced in the environment and its motion was related to the vertical movements of a Phantom Premium 1.5 haptic device (SensAble Technologies Inc., Woburn, MA). After contact, the mid-point of the tissue surface was moved along with tool. The vertical component of the external force vector acting on the node was then sent to the haptic device. For the output force of the model to match that of the real data in the tuning process (Section II-B), a scaling factor had to be used to scale the forces to the desired level. Very stiff springs make the model unstable, so achieving the desired force level was impossible by only increasing the spring constants. The model was run on a Windows PC with a 2.0GHz Pentium processor. The haptic update rate was maintained at 300Hz, the fastest achievable speed of solving the differential equations with our system.

B. Parameter Tuning

To tune the spring and damping parameters, data was acquired from real tissue samples using a probe attached to a motorized force sensor setup (described in [8]). The diameter of the probe was 1.9mm. Three tissues were tested: goat kidney, liver, and heart. Samples were held fixed on the device while the probe moved toward the tissue with one of three speeds: 2, 5 or 10mm/s. The force and displacement data were then recorded at a 500Hz sampling rate, and the experiment continued until the probe punctured the tissue sample (Figure 2). The experiment was repeated three times for each tissue. A representative plot is shown in Figure 3. After filtering and averaging the data, the plots were used to empirically tune the parameters of the model for each tissue. The data after the puncture was truncated, since they were not useful for developing a pre-puncture deformation model. Also, since the differences between the plots obtained at different speeds were not significant, only the spring constants could be tuned. The damping constant was set manually to a large enough value to ensure stability during the real-time simulations, but not too large to create artificial sluggishness.

C. Realism Evaluation

To evaluate the quality of force feedback in real-time simulations of the model, two experiments were carried out. Seven users, 3 male and 4 female, participated in two experiments. Their ages varied from 22 to 35 years with an average of 26 years, and all were right-handed with no injuries or disorders of the dominant hand. All had little or no experience with haptic devices and real tissues. Users were blindfolded and pink noise was played through a pair of closed headphones in order to eliminate cues other than the haptic feedback. For the experiments, the stylus of the haptic device was replaced by an attachment that allowed only vertical movements. Also, the movement stroke was limited with the aid of an adjustable mechanical stop. Real tissue samples were placed inside a cup in front of the haptic device (Figure 4).

At the beginning of the experiments, users were asked to place the index finger of their dominant hand at a designated

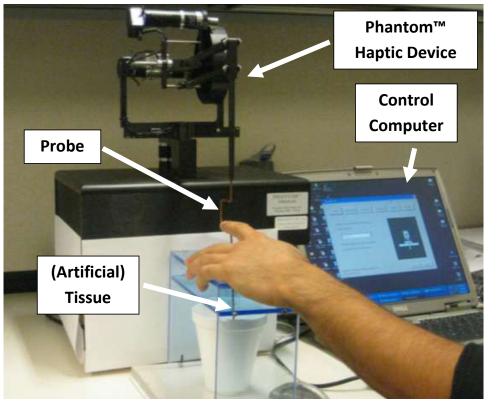


Fig. 4. Experimental setup for realism evaluation.

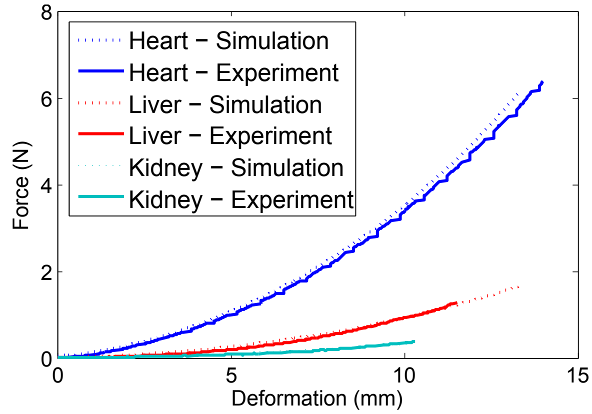


Fig. 5. Measured and simulated force-displacement curves for three types of tissues.

point on the attachment and perform slow vertical movements to touch the real/virtual tissue samples. For the virtual samples, an empty cup was used. Also, since the weight of the stylus of the haptic device was removed, for both the real tissue palpation and virtual tissue simulation, a gravity compensation force was added. The vertical movement of the tool was restricted to 30mm, 15mm of which was in contact with the real/virtual tissue samples. The limit was intended to prevent the virtual models from becoming unstable as a result of large deformations, and the real tissues from being punctured due to excessive pressure.

In the first experiment, users attempted to discriminate between the real and virtual tissue samples. The experiment involved training and testing phases. In the training phase, users were presented with the three real tissue samples and palpated them in order to familiarize themselves with the force-displacement behavior. For the testing phase, virtual and real tissues were presented to the users in random order and the users were asked to determine whether each sample was real or virtual. Each tissue was presented 5 times, resulting in 30 trials in total for the real and virtual samples. No veridical feedback was provided to the users. At the end of the experiment, users were asked to provide their opinions about the difficulty of performing the task and their feeling of forces and clues that helped them make their decision.

The second experiment was material identification. Users were presented with the real and virtual models in two series of trials and were asked to respond with the tissue names. Training on real tissues was carried out before each trial series (real and virtual tissues). Each tissue sample was presented 5 times to the users, which resulted in two 15-trial experiments. The combination of the two experiments took one hour on average.

III. RESULTS AND DISCUSSION

Figure 5 shows the result of parameter tuning for the three tissue samples. The jagged shape of the curve obtained from the heart tissue is a result of the filtering and averaging the somewhat noisy data obtained from the experiment. This, however, did not affect the tuning process. The simulation curves closely track the data obtained from the real tissues.

In the first experiment, the average rate of incorrect answers (reporting the wrong category of virtual or real tissue) was 29.5% (SD 28.2%). Figure 6 shows the average errors in detecting the right category. The larger the errors are, the more successful the simulation is in presenting realistic tissues. Although the errors for the kidney tissue (realistic softest one) were larger than the other two tissues, there was no statistically significant difference between the three tissue types. Users expressed difficulty recognizing the tissues, especially for the kidney. Some vibrations were reportedly felt during the heart tissue simulation, although this was negligible most of the time and hence not a cue for most users.

We calculated sensitivity and bias based on a method adapted from the signal detection theory [4]. First, the hit (H) and false alarm (F) rates were found for all the users. The hit rate is an indication of recognizing the real tissues correctly, and the false alarm rate is the rate of reporting a virtual tissue as a real one. The mean values of hit and false alarm rates were 76.2% and 35.2%, respectively. Figure 7 shows the H and F distribution and also the sensitivity and bias for all the users. The mean sensitivity is 0.73, which indicates that the ability of category detection is above chance level (0.5), but is still far from 1, the perfect category detection. The mean bias value is -0.35, which means that the users had some tendency to report the real tissues instead of the virtual ones. This also indicates that the model was, to some extent,

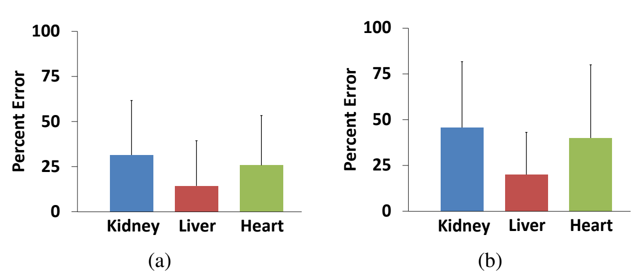
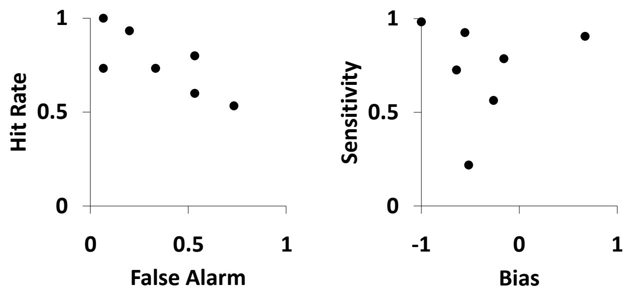


Fig. 6. (a) Real perceived as virtual, and (b) virtual perceived as real, errors. The errors are averaged over all users.



(a) (b)

Fig. 7. (a) Hit rate versus false alarm and (b) sensitivity versus bias for all users.

successful in presenting the feel of touching real tissues to the users. We also checked whether users' performance improved or worsened during the course of experiment, but there was no significant difference between the two halves of the first experiment.

Users performed the material identification task with almost the same accuracy for both real and virtual tissue samples. The mean accuracy for the real and virtual tissues were 63.8% (SD 18.4%) and 61.0% (SD 23.9%), respectively. There was no significant difference between the two categories. This was also another indication of the virtual model having acceptable fidelity in simulating real tissues. For both real and virtual samples, confusing kidney with the heart occurred in significantly fewer times than other errors ($p < 0.005$ for both), which was expected because of the large stiffness difference between the two tissues.

Although users were asked to apply small forces at slow speeds and there was also a mechanical hard stop to prevent the tissues from being punctured, during the palpation of the kidney tissue there was an occasional puncture, which was a strong clue for the users. This was one of the main drawbacks of the experiment. In a post-experiment survey, users reported that the simulation was compelling and realistic for all the three tissue types.

IV. CONCLUSIONS AND FUTURE WORK

In this study, we investigated the quality of haptic feedback from a real-time simulation of virtual soft tissues. We used real tissue samples to measure the force-deformation curves and tune a nonlinear mass-spring model based on that data. The results of preliminary tests show that, although users were able to detect virtual tissues with an accuracy higher than chance, they had some difficulty in doing so. Also, users identified real and virtual tissues with the same accuracy.

There were some limitations in the modeling and experiment which, if overcome, could lead to better results. The speed of the probe during force-displacement data acquisition was limited; higher speed and sampling rate, could enable improved tuning of model viscosity. The achievable haptic update rate was 300Hz, resulting in the small vibrations mentioned earlier. Force interpolation or extrapolation [9] could be employed to separate the deformation calculation and force feedback loops in the simulations and run the haptic feedback in a higher rate. This would further reduce the vibrations and make the model more realistic.

In this preliminary study, only seven users were recruited for the experiments. Increasing the number of users could lead to lower variance in the data and more confidence in the statistical results.

Ideally, the average hit rate for the users should be closer to 100%, which might be achieved with users who had experience with soft tissue palpation. This can be addressed by recruiting experienced srugeons or using longer training sessions for novices.

The palpation method in the experiments is a very limited form of palpation. It is different from palpation performed with bare hands, but not so different from that occuring during minimally invasive surgery (MIS). The simulation approach evaluated in this paper, therefore, is promising for use in a surgical simulator for MIS where training on cadavers, real patients or animals can be challenging, unrealistic, or not ethically acceptable. The evaluation method described in this paper is general and independent of the modeling scheme. Therefore, the model can be replaced by a more appropriate one if mandated by a particular application.

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