Haptic Modeling and Rendering Based on Neurofuzzy Rules for Surgical Cutting Simulation[1)]

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Abstract This paper combines image processing with 3D magnetic tracking method to develop a scalpel for haptic simulation in surgical cutting. First, a cutting parameter acquisition setup is presented and the performance is validated from soft tissue cutting. Then, based on the acquired input-output data pairs, a method for fuzzy system modeling is presented, that is, after partitioning each input space equally and giving the premises and the total number of fuzzy rules, the consequent parameters and the fuzzy membership functions (MF) of the input variables are learned and optimized via a neurofuzzy modeling technique. Finally, a haptic scalpel implemented with the established cutting model is described. Preliminary results show the feasibility of the haptic display system for real-time interaction.

Key words Cutting force acquisition, image processing, fuzzy neural network, haptic modeling, haptic display, surgery simulation

1 Introduction

As a new training method, surgery simulation attracts more and more research interests due to its flexibility, convenience and low cost. Most of the present prototypes only emphasize on visualization of the soft tissue, and cutting is visualized by geometry models[1,2]. Apart from the visual effect, the haptic can also give additional information about the physiological state of the cutting tissue, especially in various kinds of minimally invasive surgery (MIS), hence the ability of haptic rendering for cutting simulation is important.

Since there is no direct correlation between the parameters of tissue and the control points of the geometry models, it is difficult to simulate haptic. The physical models[3,4], on the other hand, have been used to demonstrate the dynamic behaviour of soft objects or organs, and can run in real-time by introducing preprocessing or condensing method[5,6]. However, they are sensitive to tissue parameters, or the topology of the tissue should be updated when cutting, therefore, the haptic display of cutting is not considered or simply taken as the elastic force from the tissue.

Recently, the cutting force has been measured by installing a force sensor in a scalpel[7,8], but without modeling the cutting depth and the cutting force. The interacting force was analysed for surgery scissor cutting and needle puncturing[9,10], and used to model the surgery gestures from the *in vivo* measurement[11,12]. However, they are limited to modeling the cutting process indirectly, and the idea of modeling is still a conventional one. To achieve the haptic display, which needs at least 1KHz of refresh frequency to get a natural feeling, a "haptic recording" rendering approach was proposed by directly displaying the acquired haptic data[10]. But this method lacks flexibility and there are several limitations to the usage of "acquired haptic". Previously we presented a similar model by fitting the acquired data[13], but it lacks continuity and has to change between different cutting phrases.

This paper aims to provide a new modeling method and a prototype hardware implementation for haptic display in surgical cutting simulations. As the tissue-cutting mechanism is very complex and its dynamic characters are difficult to achieve[14], we exploit the fuzzy characteristics of the tissue cutting, which may embody the essence of this phenomenon, by working with a fuzzy model (FM) instead of mathematical one. Developing an FM is usually easier and cheaper than developing a mathematically based model, and it offers some advantages over conventional one in robustness and fidelity. Also, FMs have already been successfully applied to a number of systems[15]. The T-S fuzzy modeling method[16], characterized by its high efficiency and easy combination with adaptive optimization methods[17], was chosen for this purpose. Based on an input-output data set, the adaptive neural fuzzy inference system

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(ANFIS) is an universal approximator that allows a fuzzy inference system to learn by using a back-propagation algorithm[18]. Given enough fuzzy rules, the model could approximate any real continuous function and the output surface is continuous[19]. Compared with the conventional models, the fuzzy haptic model presented in this paper could achieve more realistic and smooth haptic display and could be easily implemented by hardware as well. Preliminary results from our haptic scalpel have shown that realistic simulations are possible. Simplicity is the main advantage of the system.

The arrangement of this paper is as follows. In Sections 2 and 3, a new cutting parameter acquisition system is presented, and cutting experiments are performed. After preprocessing of the acquired data, a haptic model is established based on fuzzy inference method in Section 4. Following the identification, the fuzzy model is then used for developing a haptic display device and preliminary experiments are given in Section 5. Finally, Section 6 details the conclusions.

2 Cutting parameter acquisition setup

The cutting force acquisition device is adapted from a surgery stainless scalpel[20]. An alloy sheath without ferromagnetism is installed outside the scalpel that revolves on the axis of the scalpel. A three dimensional and six degrees of freedom magnetic tracking device (FASTRACK 3SPACE, Polhemus Com.) is attached to the outside of the sheath to acquire the position and orientation information of the scalpel (the static accuracy is 0.005mm and 0.025° in the range of 1m), and the cutting velocity is calculated from the distance travelled and the time spent. A force sensor (FSL05N2C, Honeywell) is attached to the upper end of the handle inside the sheath (with nominal sensitivity of 0.12mV/g). After amplified by 100 times, the output voltage of the sensor is sampled with a 12bits A/D card (KH–9251) at a sampling frequency of 10KHz, then sent to a personal computer for recording. The cutting force from the scalpel edge can be calculated after calibration and unit conversion. In order to reduce the interference of ferromagnetism material with the magnetic tracking device, a wood board is chosen as the cutting platform. The interference of the stainless scalpel can be ignored, since the cutting process is within the effective tracking range (1.5m), and the material of the scalpel is hard steel and the volume is small. In the cutting process, the scalpel′s length outside the tissue is recorded from the digital video camera (ExwaveHead, Sony Com.) and image capture card (DH-CG300, DaHeng Image Com.) based on color identification. The handle and sheath of the scalpel are painted black for easy differentiation between the cutting tissue and the scalpel. The cutting force of the system is calibrated with an electrical scale with a precision of 0.5g at different cutting conditions, and the output voltage of the A/D acquisition card is 1240mv/N, which is in accordance with the nominal accuracy. The calibration of cutting depth is given by measuring the image pixels of the scalpel (47.5mm) and the image pixels (400), so the measured precision is 0.118mm/pixel. The setup is shown in Fig. 1.

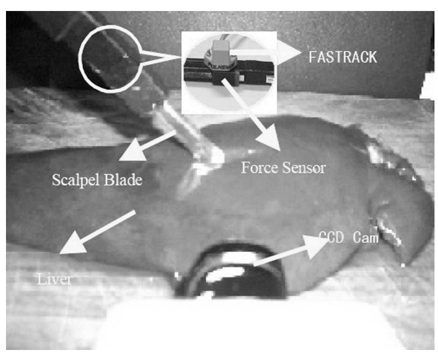


Fig. 1 The cutting parameter acquisition experimental setup

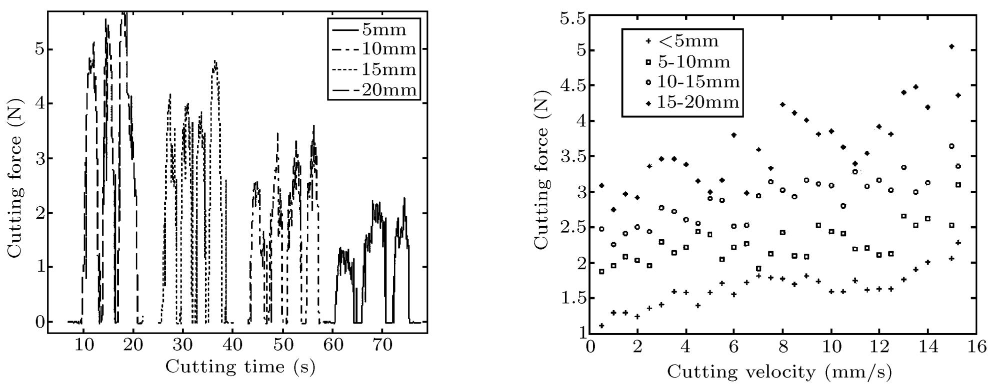
3 Material preparation and cutting experiments

A pair of freshly-slaughtered swine′s livers are prepared for the cutting experiment. First, one end of the liver is fixed on the testing table with a nail, while the other end is left free, just to mimic the actual tissue boundary as much as possible. 27° salt solution is sprayed occasionally in the process of the experiment in case of tissue dehydration and hardness, which would influence the biomechanical property of the tissue. The wood cutting table is chosen to minimize the interference with the magnetic tracking device. Then, the liver is cut from the fixed end to the free end, and the cutting force and cutting velocity and cutting depth are recorded with the acquisition system. Fig. 2 (a) shows the original unfiltered liver cutting forces at different depths (5mm, 10mm, 15mm, 20mm) for different cutting times (3, 4, 4, 3 corresponding to each of the above cutting depths). The cutting force heavily depends on the cutting depth, that is, the deeper the penetration of the scalpel blade, the higher the cutting force. But even for identical penetration depth, there exists a distinctive difference. The possible reason might be the tissue boundary condition variance in the cutting process. We can also observe a saw-type cutting force curve, which indicates the tissue experiences a repeated process from elastic deformation to abrupt fracturing.

4 Identification of the haptic model

4.1 Data preprocessing

In order to identify the nonlinear cutting model, specifications should be given in terms of input-output pairs. Because of the nonlinearity, viscoelasticity and time dependency of the soft tissue[21], different cutting processes vary greatly. Even in the same cutting process the cutting force shows nonlinearity with the boundary conditions of the tissue changing. In order to minimize the randomicity of a single experiment, a preprocessing method is adopted from the collected data: The cutting forces are averaged for different cutting experiments at each given cutting depth and each cutting velocity. The processed data are shown in Fig 2 (b). Then, the fuzzy modeling process based on the filtered input-output data can begin.



(a) (b)

Fig. 2 The original unfiltered (a) and the pre-processed (b) cutting force

4.2 Structure identification

Although Sugeno′s approach is still in continuous development, it comes closer to the qualitative reasoning. The identification method tries to determine all elements: variables, fuzzy sets, and consequent coefficients. This approach uses hybrid learning that can be combined with adaptive optimization methods easily. The only information specified by the user is the number and the type of membership functions and the training sequence. Given enough fuzzy rules, it can approximate any precision, so we choose it as the base of our model. The structure identification of the fuzzy system is to partition the input variable space equally and then to estimate the precondition parameters. After choosing the Gaussian function as the MF of the input variables, the consequent parameters are estimated and the parameters (m_{ij}, σ_{ij}) of the input MFs are optimized. The procedure stops at a certain step when the performance is less than a desired value.

Suppose the system function to be identified is $F(X, Y)$, where (X, Y) are n pairs of experimental data, and the vector X is the input cutting depth and cutting velocity, while the vector Y is the output cutting force. This paper only concerns with the multi-input single-output (MISO) system, and the fuzzy structure of the cutting force can be identified through the following steps.

1) Fuzzy partition of input space. The input spaces (x_1, x_2) are divided into five (NB, NS, Z, PS, PB) and four (NB, NS, PS, PB) fuzzy subspaces equally by the center of each MFs (Chosen as Gaussian

function) respectively, and the output cutting force (y) is the linear combination of each input variable, and need not be partitioned.

2) Fuzzy rule inference. First order T-S structure is adopted and the biggest membership is assigned to a given point according to the known MF and the collected data pairs (x_{i1}, x_{i2}, y_i). The total number of fuzzy rules is 20 (5×4), as

$$R_i: \text{ if } x_1 \text{ is } A_{l1} \text{ and } x_2 \text{ is } A_{l2} \text{ then } y_i = p_{i0} + p_{i1} \cdot x_1 + p_{i2} \cdot x_2 \tag{1}$$

where the subscript $i = 1, 2, \cdots, 20$ is the index of the fuzzy rule, R_i is the ith fuzzy rule, x_j and y_i are the jth input variables and the output of the ith fuzzy rule, respectively, and p_{ij} is the parameter to be identified. A_{ij} is the fuzzy subset of the input variable x_j for the ith rule, whose MF is

$$A_{ij}(x) = \exp\left[-(x_i - m_{ij})^2/\sigma_{ij}^2\right] \tag{2}$$

where m_{ij}, σ_{ij} are the midpoint and variance of the input fuzzy set, respectively.

3) Defuzzy. The output of the fuzzy system is averaged with weighted factors, that is,

$$y = \sum_{i=1}^{20} w_i(X)^* y_i, \quad w_i(X) = \frac{\prod_{j=1}^{2} A_{ij}(x_j)}{\sum_{i=1}^{20}\left[\prod_{j=1}^{2} A_{ij}(x_j)\right]} \tag{3}$$

where $w_i(X)$ is the standard output contribution from the ith fuzzy rule.

Now, the structure of the fuzzy system has been identified.

4.3 Parameter identification

After the structure identification of the fuzzy system, the premises and number of rules are decided. Then the consequent parameters (p_{ij}) of the system should be estimated and the parameters (m_{ij}, σ_{ij}) of the input MFs are optimized. The ANFIS is a universal approximator that allows a fuzzy inference system to learn by using a back-propagation algorithm based on an input-output data set. Learning is performed in two stages: at first, the antecedent parameters are kept fixed and the information is propagated to the fourth layer, where the consequent parameters are identified by using the minimum least mean squares method, then the consequent parameters are fixed and the error is back-propagated, allowing the antecedent parameters modified by means of a gradient method. The training process is accomplished by using MatLab 6.0[17] (Mathwork Com.), that is, the collected 120 pairs of input-output data are divided into two groups randomly and are used as training and checking separately. After 80 epochs of training, the mean square error is 0.036 for the training group and 0.0804 for the checking group. Fig. 3 (a) shows the input Gaussian MFs after optimisation. Compared with the original ones, they are not separated equally along the input spaces. Fig. 3 (b) shows the established cutting force model.

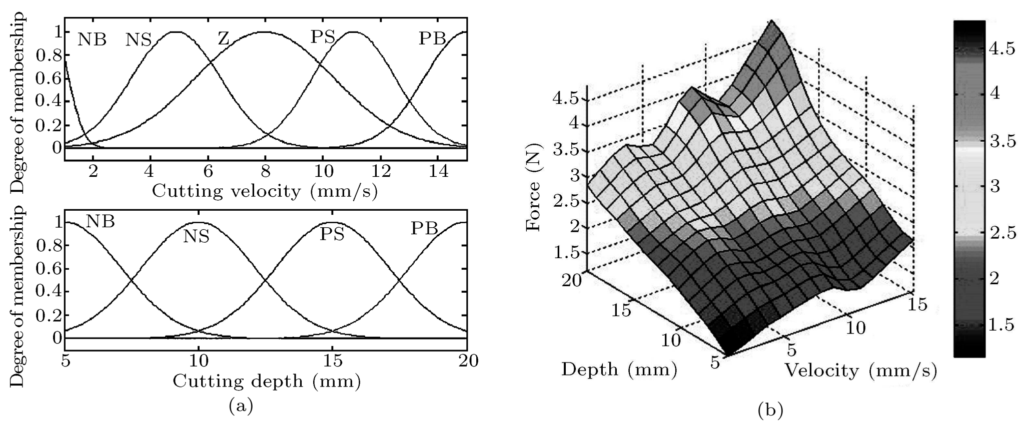


Fig. 3 The membership functions (MF) of the input variables after training (a) and the haptic model (b)

5 Haptic simulations

5.1 Haptic scalpel

The haptic system consists of the following parts: a haptic scalpel and its driver, an A/D card, a 3D motion tracker and a PC (PIII-800, 256M, GeForce III). Fig. 4 shows the compositions and diagrammatic sketch of the haptic system. In order to display the haptic more naturally and realistically, the haptic scalpel is made resemblant to the real scalpel in its shape and usage. Since an operation must be done deliberately, a surgeon′s "hand-feeling"(*e.g.* force feedback) is very important, and any little imprudent action would be the cause of a medical accident. In order to simulate the real operation process more factually, high precision and perfect real-time quality are required for haptic training device. Since surgical scalpel is very sharp, the haptic force from the handle of the scalpel is very small and smooth. The driving force of the haptic scalpel should be continuous without fluctuation and should run in real-time. We choose a step motor, which cooperates with a screw-driven machine, to generate the haptic force. Check [22] for the detailed mechanical design.

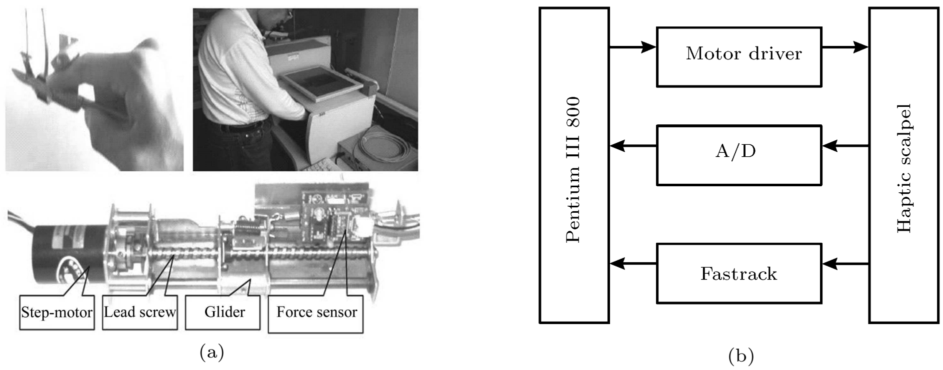


Fig. 4 The haptic system composition (a) and its diagrammatic sketch (b)

5.2 Haptic display

The working process of this system can be better under stood by checking Fig. 4 (b). The position and velocity acquired from the 3D tracking device are firstly filtered as described in Section 4.1 to decrease the dithering effect. Then, the haptic model established above is used to determine the correct force for display. Finally, it is sent to the step motor to drive the haptic device according to the established haptic model. A whole surgical simulating system should provide not only real-time haptic rendering (1 KHz) but also visual rendering (50Hz) and the cooperation of each other. As the visual aspect of surgery is researched much deeply, we are currently concerned with only haptic rendering. In order to examine the effectiveness of the haptic scalpel without the visual feedback, a preliminary experiment is conducted by providing a fixed cutting depth to drive the model. As for selecting the force profiles suitable for cutting simulations, it is observed that the forces differ widely, depending on the controlled variables of tissue type, animal type, and cutting style. We select swine′s livers for simulating straight-line cutting at different depths and velocities. Fig. 5 (a) shows a comparison between the model generated force and measured real cutting force, and Fig. 5 (b) shows the simulated cutting process and the original recorded real cutting process, both at cutting depth of 5mm. It is shown that the haptic model can be effectively used as cutting force prediction and simulation.

6 Conclusions

Firstly, a multi-parameter acquisition system is presented in this paper based on image processing and magnetic tracking method, which is validated from swine′s liver cutting experiment. From the acquired input-output data pairs and based on fuzzy neural network theory, a new haptic model is established for the liver cutting operation. Compared with conventional physical modeling, the calculation of reacting force is independent of the geometry model of the cutting surface, and can be used for real-time surgery cutting simulation. While limited by the number of samples and the interference from cutting acceleration and orientation, the precision of this model needs to be further improved. Finally, a virtual scalpel as the haptic interface is described. Despite the present limitations of the hardware, preliminary experiments have shown that realistic simulations are possible. Simplicity is the main advantage of our haptic device and it could achieve real-time haptic display. Yet, there are limitations to using haptic scalpel to simulate different cutting styles, and more quantitative and qualitative results are needed for a deep comparison by surgeons.

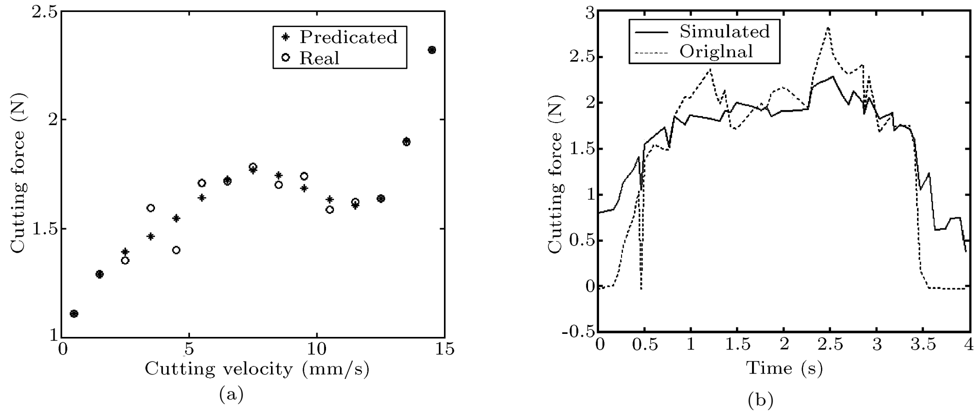


Fig. 5 The comparison between acquired and predicted (a) and simulated and pre-recorded (b) cutting force at depth of 5mm

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