35th Annual International Conference of the IEEE EMBS
Osaka, Japan, 3 - 7 July, 2013

Navigation System with Real-time Finite Element Analysis for Minimally Invasive Surgery

Ken'ichi Morooka[1], Yousuke Nakasuka[1], Ryo Kurazume[1] Xian Chen[2],
Tsutomu Hasegawa[1], Makoto Hashizume[4]

Abstract— **This paper presents a navigation system for minimally invasive surgery, especially laparoscopic surgery in which operates in abdomen. Conventional navigation systems show virtual images by superimposing models of target tissues on real endoscopic images. Since soft tissues within the abdomen are deformed during the surgery, the navigation system needs to provide surgeons reliable information by deforming the models according to their biomechanical behavior. However, conventional navigation systems don't consider the tissue deformation during the surgery. We have been developing a new real-time FEM-based simulation for deforming a soft tissue model by using neural network[1]. The network is called the neuroFEM. The incorporation of the neuroFEM into the navigation leads to improve the accuracy of the navigation system. In this paper, we propose a new navigation system with a framework of the neuroFEM.**

I. Introduction

A minimally invasive surgery is a surgical technique which is smaller invasive than traditional open surgery. Such benefit leads that recovery time and return to normal activities is shorter for patients. Owing to this reason, minimally invasive surgery contributes to the improvement of patients' quality of life. On the contrary, minimally invasive surgery requires surgeons special surgical skills compared with open surgery. For example, surgeons need to estimate the internal structures of the patient body through endoscopic images. Such special surgical skills sometimes impose mental load on the surgeons. Recently, some kinds of systems for supporting minimally invasive surgeons have been developed. Basically, the support system uses the volumetric models of target tissues. Using recent advanced techniques for computational anatomy, the models are automatically generated by preoperative medical images of a patient. Therefore, the support system is one application of computational anatomy.

One support system for minimally invasive surgeons is a navigation system [2], [3], [4], [5] for endoscopic surgery. The navigation shows virtual images by superimposing the models into real endoscopic images. The models contain the internal information of the tissues such as the presence of blood vessels and tumors which exist in the tissues. Such information can never be obtained from the endoscopic images. The use of the virtual images enables surgeons to approach the tissues or tumors safely and accurately. In this paper, we focus on laparoscopic surgery in which operates in abdomen.

Most of the conventional navigation systems have dealt with bone and nerves in the ontological surgery. Since these shapes have not changed during the surgery, the conventional navigation systems display the model shape generated in the preoperation phase. In laparoscopic surgery, when a contact occurs between surgical instruments and tissues, the tissues are deformed according to their biomechanical behavior. Naturally, the navigation system must display realistic model deformation to provide suitable virtual images. However, the conventional navigation systems don't consider the deformation.

To achieve this, the navigation system needs the function of estimating the deformation of the target tissue. Methods have been proposed for simulating the behavior of soft tissues [6], [7]. Among these methods, the finite element method (FEM) is a well-known technique for accurately modeling the behaviors of continuous objects. On the contrary, the FEM-based simulation of tissue deformation is very time-consuming. In the case of soft tissues with nonlinear behaviors, the problem becomes more serious because the simulation is very complex.

This paper proposes a new navigation system for laparoscopic surgery by using our techniques of real-time FEM analysis. We have been developing a real-time FEM-based simulation for deforming a soft tissue model by using neural networks [1]. Our simulator, called the neuroFEM, can achieve real-time nonlinear FEM simulation of deforming the model with acceptable accuracy compared with the original nonlinear FE analysis. Using the neuroFEM, our navigation system can provide the suitable virtual images considering the tissue deformation.

II. Navigation system with neuroFEM

Our navigation system consists of main three components (Fig. 1). A stereo endoscope acquires stereo images during the surgery. Using the stereo images, 3-dimensional imaging systems provide visual information regarding spatial depth. This information helps surgeons to easily estimate the 3D structure of a patient and the relative position of the anatomic structure. The neuroFEM estimates the deformation of soft tissue models based on the information extracted from given stereo images. The output of the neuroFEM is a volume model, which contains the 3D positions of nodes and their connect. In the another workstation, a commercial software

[1]K. Morooka, Y. Nakasuka, R. Kurazume and T. Hasegawa are with Faculty of Information Science and Electrical Engineering, Kyushu University, Fukuoka, Japan `morooka at ait.kyushu-u.ac.jp`

[2]X. Chen is with Faculty of Engineering, Yamaguchi University Yamaguchi, Japan

[3]M. Hashizume is with Faculty of Medical Sciences, Kyushu University, Fukuoka, Japan

978-1-4577-0216-7/13/$26.00 ©2013 IEEE

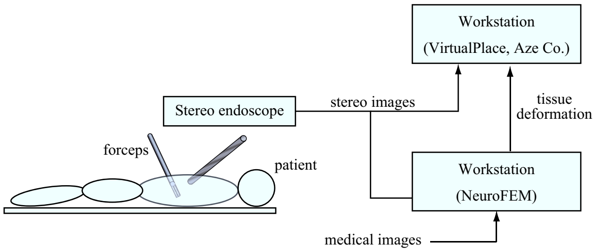


Fig. 1. Overview of our navigation system.

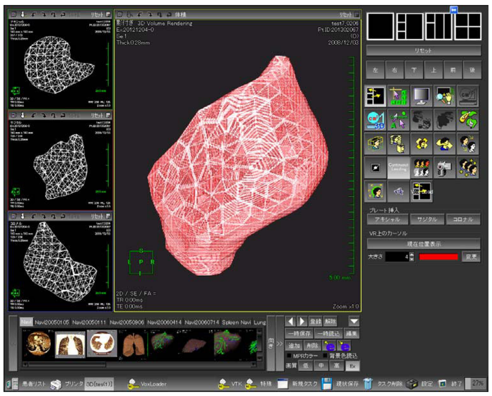


Fig. 2. Example of virtual images of our navigation system.

for medical image processing, the Virtual Place (AZE Co.), is used to display the virtual images by fusing the deformed model into the stereo images. We develop a new plugin in order that the Virtual Place keeps on reading the current model deformation. In addition, the model is converted to a sequence of DICOM images by the method in [8]. Fig. 2 shows the example of the virtual images provided by our system.

A. NeuroFEM

To construct the neuroFEM, a training data is a pair of an external force and the corresponding deformation mode, which is the model deformed by the force. An original FE analysis is applied to calculate the deformation modes. By changing the force parameters, many training data are generated, and collected in a training dataset. Using the training dataset, the neuroFEM learns the relationship between external force acting on a target tissue and the corresponding deformation pattern of the tissue. Given an arbitrary force as input data, the neuroFEM outputs the corresponding deformed model.

The computational time of the nonlinear FEM analysis increases exponentially according to the number of the nodes included in the model. On the contrary, the runtime of the neuroFEM depends not on the data size of the model but on the total number of the neurons included in the network. Also, the computations of the neuroFEM are the linear combination of simple nonlinear functions. Owing to the less expensive computations, the neuroFEM requires few computation for the simulation compared with the original nonlinear FEM analysis.

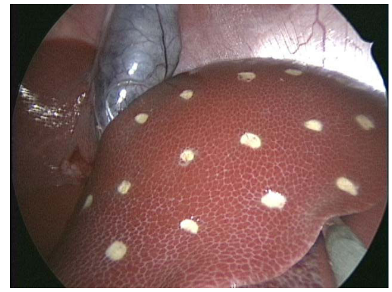


Fig. 3. Example of surface markers generated by cauterizing the tissue surface.

Many possible deformation patterns are needed to train the network with acceptable accuracy. Especially, several soft tissues change gross alterations in size and shape. In the case of such tissues, the number of their deformation patterns increases exponentially. The use of the large dataset may make it impossible to train one neural network. Even though the training of the network is terminated, the accuracy of the trained network is not enough to estimate the deformation in the surgical simulator.

Our solution for this problem is to partition the large dataset into some sub-datasets [9]. In our method, k-means++ [10] is employed to partition the dataset. Compared with the original k-means, which is one of a well-known clustering algorithm, k-means++ automatically determines the initial centroids of the clusters based on the data distribution. Each sub-dataset is used to train one network. As a result, our simulator is constructed by combining the multiple trained networks.

The dataset division allows us to decrease of the training data used in the training of one network. Moreover, we have proposed a method for the training data from each sub-dataset while providing sufficient data to cover the target problem [11]. At the same time, redundant data are removed from the dataset based on the similarity between training data. The selection leads to both speed up the training process and improve the training accuracy[12].

III. Extension of NeuroFEM for Navigation

As stated in section II-A, the external force is employed as the input of the neuroFEM. However, in the real surgery, it is difficult to measure the accurate parameters of the external force caused by the forceps. Therefore, another information is needed as the input of the neuroFEM. One component of our navigation system is a stereo endoscope which acquires stereo images during the surgery. Using the stereo images, the visible tissue surface from the camera is estimated by a conventional stereo matching method. Therefore, the neuroFEM is extended to estimate the deformation of the whole tissue by using the partial shape of the tissue surface.

A. Estimation of tissue deformation by using stereo endoscope

To recover the surface using stereo images captured simultaneously, the system needs to find the closest possible matching points between the images. One approach to the stereo correspondence problem is to establish the correspondence by matching geometric and/or appearance features extracted from the images. However, tissues has uniform appearance and simple shape with less geometric features. Stereo correspondence fails in the presence of the uniform appearance.

To solve the problem, the markers on the tissue surface are used to predict the deformation by the neuroFEM. Fig. 3 shows the example of possible markers generated by cauterizing the tissue surface. The markers are extracted from the images by basis image processing techniques. The size of each marker is about 5 [mm], and expert surgeons say that this damage by the cauterization is not problem for the patient. However, we will develop the markers with less invasion. Since the correspondence between the markers in the stereo images can be found easily and accurately, the 3D positions of the markers can be calculated. Therefore, the vector composed of the marker positions is used as the input data of the neuroFEM.

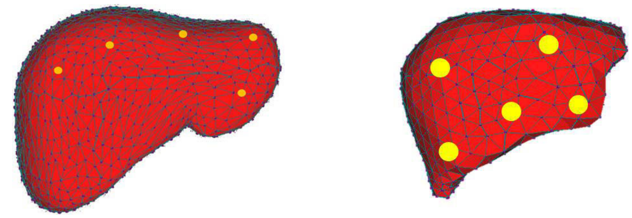
Here, we must consider the following two problems for using surface markers. When the markers are chosen from only a specific small area, the patterns of the marker positions are similar to each other even though the deformation modes have different shapes. In this case, the network may be trained incorrectly so that one input data corresponds to several kinds of the output. Considering the variation of the input data, the markers are selected from the whole tissue surface.

The determination of the number of the markers is important for the estimation accuracy of the neuroFEM. While the use of many markers may provide useful information for the tissue surface reconstruction, the stereo correspondence becomes complex. Therefore, the determination of the correspondences between the markers is very time-consuming. To make matter worse, the wrong correspondences may be determined, resulting in the reconstruction of unnatural surface. Therefore, a minimum number of markers is desirable to estimate the tissue deformation in real-time. Although, there are several reports for marker localization [13], few researches focus on the first requirement. Therefore, we automatically determine optimal marker locations for the navigation using the neuroFEM.

B. Optimal marker selection for the neuroFEM

For each vertex on the surface of the tissue model, the maximum displacement of the vertex is calculated by using all the training data. All vertices are sorted in descending order of their maximum displacements, and collected in a list. Using the list, the markers is selected by the following steps:

1) Set a parameter k to $k = 1$.
2) Select the first vertex in the list as the k-th marker $\boldsymbol{p}_k$, and remove it from the list.
3) $k \leftarrow k + 1$
4) Set a loop parameter t to $t = 1$.



(a) (b)

Fig. 4. Surface markers selected by (a) our marker determination method and (b) the random selection method.

5) If t-th vertex $\boldsymbol{v}_t$ is satisfied with

$$\|\boldsymbol{v}_t - \boldsymbol{p}_n\| > \theta \quad (1 \leq n \leq k) \tag{1}$$

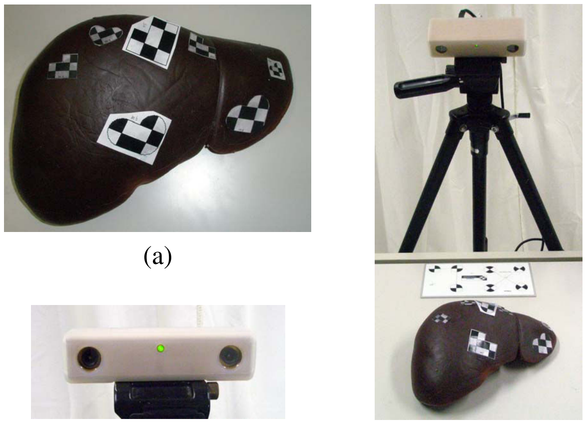
for all the selected markers, choose the vertex and go to step 6, Otherwise, $t \leftarrow t + 1$ and go to step 5.

6) Regard the chosen vertex as the k-th marker and removed it from the list.
7) If k is the maximum marker number K, terminate the algorithm. Otherwise, go to step 3.

IV. EXPERIMENTAL RESULT

To verify the applicability of the proposed method, we made some experiments for estimating tissue deformation by using surface markers. In this experiment, a liver model is used composed of 4,804 nodes and 15,616 tetrahedral elements. The fixed nodes of the models are selected considering their anatomical space restrictions and the advices of surgical experts. The model is created by the commercially available softwares (CDAJ-Modeler CFD, CD-adapco JAPAN Co., LTD.) while its deformation modes are generated by the FEM analysis software ("Marc" produced by MSC.Software Co.). The number of hidden layers and number of neurons in each hidden layer are determined thorough preliminary experimental results.

The first experiment is to evaluate the validation of the markers selected by the proposed method described in the section III-B. Five markers are chosen as shown in Fig. 4 (a). Therefore, the input of the neuroFEM is represented by the 15-dimensional vector. To compare with the proposed method, we select randomly five markers from the whole liver surface several times. This method is called the random method. Fig. 4 (b) shows the example of the marker selected by the random method. Neural networks are trained by using the markers selected by the two method. Each network consists of four layers. There are 15 and 24 units in the input and the output layers while each hidden layer has 120 units. 8,793 training data are used in the training process. We evaluate the training accuracy of the obtained neuroFEM. Here, the training error of a neuroFEM is defined by the average vertex distance between the models estimated by the neuroFEM and the nonlinear FEM analysis when an arbitrary external force is given. The average training error of the neuroFEM generated by the proposed method is 1.48×10^{-2} [mm]. In the case of the random method, the minimum error



(a) (b) (c)

Fig. 5. Experimental environment: (a) the phantom of a liver; (b) a stereoscopic vision; (MicronTracker, Claron Technology Inc.); (c) the experimental setup.

is 1.53×10^{-2} [mm]. Compared with the random method, the proposed method can stably construct a neuroFEM with acceptable accuracy.

In the second experiment, instead of using a real liver, the proposed navigation system is applied to estimate the deformation of the phantom of a liver (Kyoto Kagaku, Co. LTD., Japan) (Fig. IV (a)). Fig. IV (c) shows the setup in the second experiment. On the phantom surface, the five markers are put at the locations determined by our method. In the experiment, left lobe of the liver is lifted by the forceps. The motion of the phantom is tracked by a stereoscopic vision (MicronTracker, Claron Technology Inc.) (Fig. IV (b)). The stereoscopic vision outputs the 3D positions of the markers in real-time. When the positions is input to the neuroFEM, the neuroFEM estimates the deformation of the phantom.

Our method is evaluated by using two another test markers. Using the test markers, we calculate the difference between their positions estimated by the neuroFEM and the measured positions by the stereoscopic vision. The experiment using the phantom are repeated five times. In the case of the test markers, the minimum and maximum differences are 15 and 29 [mm], respectively. Such difference is caused by the registration error between the coordinates of the model and the stereoscopic vision before deforming the liver phantom. Practically, the registration error using the test markers is about 13 [mm]. This is because it is difficult to accurately generate or put the markers at the location which the proposed method has determined. Such misalignment of the markers sometimes occurs in the real laparoscopic surgery. Therefore, the process of complementing the misalignment is needed to robustly estimate the deformation by the neuroFEM.

V. Conclusion

We proposed a new framework of the navigation system using the neuroFEM for laparoscopic surgery in which operates in abdomen. In this paper, the neuroFEM is extended to estimate the deformation by using several markers put on the surface of the tissue. Moreover, the determination of the marker locations have been developed to generate the network with acceptable accuracy. Using the proposed method, the neuroFEM estimates the deformation of soft tissues in real-time while keeping the estimation accuracy compared with the original non-linear FE analysis. On the contrary, to construct the navigation system, we need to solve several problems such as the misalignment of the markers. These are our future works.

Acknowledgment

This research is partially supported by Grant-in-Aid for Scientific Research on Innovative Areas, "Computational Anatomy for Computer-aided Diagnosis and Therapy", MEXT, Japan.

References

[1] K. Morooka, X. Chen, R. Kurazume, S. Uchida, K. Hara, Y. Iwashita, and M. Hashizume, "Real-time nonlinear fem with neural network for simulating soft organ model deformation," in *MICCAI (2)*, 2008, pp. 742–749.

[2] K. Konishi, M. Nakamoto, Y. Kakeji, K. Tanoue, H. Kawanaka, S. Yamaguchi, S. Ieiri, Y. Sato, Y. Maehara, S. Tamura, , and M. Hashizume, "A real-time navigation system for laparoscopic surgery based on three-dimensional ultrasound using magneto-optic hybrid tracking configuration," *International Journal of Computer Assisted Radiology and Surgery*, vol. 2, no. 1, pp. 1–10, 2007.

[3] J. Hong, N. Matsumoto, R. Ouchida, S. Komune, , and M. Hashizume, "Medical navigation system for otologic surgery based on hybrid registration and virtual intraoperative computed tomography," *IEEE Transactions on Biomedical Engineering*, vol. 56, no. 2, pp. 426–432, 2009.

[4] N. Matsumoto, J. Hong, M. Hashizume, , and S. Komune, "A minimally invasive registration method using surface template-assisted marker positioning (stamp) for image-guided otologic surgery," *Otolaryngology - Head and Neck Surger*, vol. 140, no. 1, pp. 96–102, 2009.

[5] F. Volonte, F. Pugin, P. Bucher, M. Sugimoto, O. Ratib, and P. Morel, "Augmented reality and image overlay navigation with osirix in laparoscopic and robotic surgery: not only a matter of fashion," *Journal of Hepato-Biliary-Pancreatic Sciences*, vol. 18, no. 4, pp. 506–509, 2011.

[6] C. Basdogan, M. Sedef, M. Harders, , and S. Wesarg, "Vr-based simulators for training in minimally invasive surgery," *IEEE Computer Graphics and Applications*, vol. 27, no. 2, pp. 54–66, 2007.

[7] U. Meier, O. López, C. Monserrat, M. Juan, , and M. Alcaniz, "Real-time deformable models for surgery simulation: a survey," *Computer Methods and Programs in Biomedicine*, vol. 77, no. 3, pp. 183–197, 2005.

[8] T. Tawara and K. Ono, "Fast large scale voxelization using a pedigree," in *The 10th ISGG Conference on Numerical Grid Generation*, 2007.

[9] K. Morooka, T. Taguchi, X. Chen, R. Kurazume, M. Hashizume, and T. Hasegawa, "An efficient construction of real-time fem-based simulator for soft tissue deformation with large dataset," in *CARS2012*, 2012, p. 427.

[10] D. Arthur and S. Vassilvitskii, "k-means++: the advantages of careful seeding," in *the eighteenth annual ACM-SIAM symposium on Discrete algorithms*, 2007, pp. 1027–1035.

[11] K. Morooka, T. Taguchi, X. Chen, R. Kurazume, M. Hashizume, and T. Hasegawa, "A method for constructing real-time fem-based simulator of stomach behavior with large-scale deformation by neural networks," in *SPIE Medical Imaging 2012: Image-Guided Procedures, Robotic Interventions, and Modeling*, 2012, p. 83160J.

[12] P. Sollich and D. Saad, "Learning from queries for maximum information gain in imperfectly learnable problems," in *NIPS*, 1994, pp. 287–294.

[13] B. Dong, Y. Graves, X. Jia, and S. Jiang, "Optimal surface marker locations for tumor motion estimation in lung cancer radiotherapy," *Physics in Medicine and Biology*, vol. 57, no. 24, pp. 8201–8211, 2012.