Evaluation of Different Pathology Generation Strategies for Surgical Training Simulators

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Abstract

During the last few years several surgical training simulators have been proposed. One of the main advantages of these simulators is the ability to provide riskless training on a wide range of different cases in a compressed period of time. Therefore the generation of variable surgical scenes is a crucial component of a simulator. This paper compares three different approaches for the generation of pathologies specifically suited for surgical training simulators. The generated models can be embedded in the healthy organ model to challenge the trainee with a new case in every training.

Key words: Surgical Simulators, Pathologies

1 Introduction

Endoscopic interventions require specific skills, which nowadays are acquired during actual surgery in assistance of experienced physicians. Virtual reality based surgical simulators represent an appealing alternative for future training and education. The enormous computational requirements of these simulators have prevented an earlier development of such systems. More recently, various simulators for different endoscopic procedures like laparoscopy and hysteroscopy have been proposed [2,3]. There is consensus that a surgical training simulator can not only offer a risk-free learning environment, but also allow for training on a much wider range of clinical cases. Nevertheless, previously proposed systems use a single organ model, thus providing the same environment in all trainings. The generation of different surgical scenes has not yet been treated as a specific issue. Our current research aims at a high fidelity hysteroscopy simulator in which both the healthy organ anatomy and the pathologies vary from training to training, thus challenging the trainee in every session with a new case.

The configuration of a surgical scene entails both the selection of a healthy anatomical organ model, which could statistically correspond to a type of patient specified, as well as the incorporation of one or possibly more pathologies into the organ. This paper summarizes and evaluates different strategies for the generation of pathologies specifically suited for surgical training simulators. The main requirement for any such pathology generation strategy is a fully automatic creation of realistic shapes after definition of some parameters by the physician. The input parameters have to be specified in medical terminology and no further interaction with a physician or a simulator expert should be needed after initialization. The generation procedure has to introduce variations and provide the necessary informations for texturing, blood perfusion and biomechanical modeling. Finally, the emerging structures have to be incorporated into the healthy organ models.

Previously reported tumor growth models focused on other features of the tumor gestation process, e.g. the exact cellular interactions or the stability of the growth [1,4]. These features can be neglected in the current application. This is the first time that the generation of pathologies suitable for surgical simulators is analyzed on a broad basis of possible approaches, to the best of our knowledge.

2 Pathology Generation Strategies

The three methods investigated are briefly summarized in the following sections. The pathologies modeled are leiomyomas and polyps protruding to different extents into the uterine cavity, therefore being visible and treatable by hysteroscopy. Both polyps and myomas are benign tumors and a common finding in women in their childbearing years. Their clinical relevance as well as the different properties of these pathologies make them excellent candidates for the evaluation of the different approaches presented.

All myomas start growing inside the myometrium and seem to be squeezed out of the tissue as they grow. Myomas have a much stronger tendency to keep their shape than any of the surrounding tissues, as they are composed of dense fibrotic tissue. Thus, a myoma will be able to grow almost independently from its surroundings by keeping a spherical shape. Polyps, in contrast, originate as focal hyperplasias of the basalis and build elongated structures of soft tissue mass. They are mainly composed of glands, stroma and blood vessels. Both pathology types vary in size ranging from a couple of millimeters to several centimeters, filling the entire uterine cavity.

Cellular Automaton A previously presented cellular automaton is able to model the growth process of leiomyomas [5]. A cellular automaton is intrinsi-

cally stable and offers therefore an appealing way to implement a rule-based system. In a regular, three dimensional lattice, two different cell types (tissue, tumor) and the cavity (empty compartments) interact in every iteration with a local neighborhood. A minimal set of rules was specified, so that intramural and submucosal, both sessile and pedunculated, myomas can be generated. The rules model the generation of new tumor cells, the dissipation of the mass surrounding the tumor and the force acting on the myoma from the tissue. The last rule leads to the slow extrusion of the pathology from the tissue. The growth process is initiated by inserting a tumor seed in at least one compartment within the tissue. The probabilistic application of the rules introduces the variability in the resulting structures. To incorporate the myomas in the organ model, the latter has first to be transformed into the domain of tumor growth by voxelization of the organ's surface. After growth, the resulting structure is transformed back into a surface model. An example of a resulting myoma after 22 iterations using a single tumor seed can be seen in the first image in Figure 1.

Skeleton-Based Design The simplified skeleton-based approach allows for direct specifications of pathologies [6]. Based on a straight-line skeleton axis and the associated width function, a revolution object with a characteristic profile curve is defined. The profile is defined by the control points of a B-spline curve. The dimension of input parameters is further reduced by adjusting the control points based on some anatomical values, e.g. the dimensions of the peduncle. The resulting surface is perturbed at different resolutions to generate variations of the shape. The final model is merged with the surface of the uterus. Therefore the imaginary socket of the pathology is placed at some user selected position inside the uterine cavity. An optimal connection between the two surfaces is found and the socket of the pathology attracted to the uterus to create a smooth transition between the objects.

As no growth process is involved, the model cannot incorporate physiological information. Also no differentiation of healthy and pathological tissue is possible. The second image in Figure 1 illustrates a polyp embedded in the uterine cavity.

Particle System Finally, a particle-based growth model was developed [7]. Different types of particles are introduced (healthy tissue, pathology and surface). Every particle represents a certain amount of tissue and thus requires a corresponding amount of space. This is encoded in the particle by assigning a force profile to each particle. Within a limited range of interaction and depending on the distance between the particles they repulse or attract each other with forces related to their profiles. The surface-particles are interconnected to build a triangulated surface, which represents the endometrium and constitutes an impermeable membrane for all other particles. The connections are modeled by springs, allowing the membrane to stretch and deform as the

pathology grows. The resulting forces in the surface are kept small by subdividing the mesh adaptively and resetting the equilibrium length of the springs after every iteration.

The pathology is initialized by introducing a single particle with an increased proliferative index. This particle is located inside the healthy tissue in case of a myoma whereas it is placed on the surface for a polyp. In every iteration the tumor grows by dividing one tumor particle. All particles adapt to the new situation and apply forces on the surface, which finally leads to a constrained growth. The initial surface of the organ is used as the membrane, so that the growth process is directly performed in the organ's representation. The last image in Figure 1 shows an exemplary polyp after 240 growth iterations.

3 Comparison and Evaluation

The different concepts and algorithms allow for a clear distinction of the field of applications of these methods. Table 1 depicts the basic differences of the presented models.

The particle-based approach is the most accurate of the models under scrutiny in terms of biological processes imitated. The gestation of the tumor is represented by the division of particles and can be related to the proliferative rates of different cells. The framework can easily be extended to introduce malign tumors with competing cell populations and necrotisation. The particles are free to move in a continuous space and no discretization limits the modeling, as opposed to the cellular automaton. The distinction between tumor and healthy tissue in both the cellular automaton and the particle system can be exploited in the simulation to assign different biomechanical properties to each tissue.

The implementation of the particle system is more demanding than the one of the cellular automaton or the skeleton approach. As mentioned, a cellular automaton is intrinsically stable. The skeleton based design has only a few control points of the characteristic curve which have to be kept in certain boundaries for reasonable results. This can easily be enforced by checking the input values given by the user. The particle system instead can easily become unstable, e.g. if too strong force profiles are chosen. In addition, special care is required to prevent particles from penetrating the membrane.

The computational time required on a Linux based PC with a 2.53 GHz Pentium processor scale roughly as follows: about one second for the design of a skeleton-based pathology, around one minute to grow the cellular automaton model and up to several hours for the particles-based growth. The skeleton

Table 1
Main characteristics of the different methods.

Property	Cellular Automaton	Skeleton-Surface	Particles System
Physiology	basic	none	more advanced
Stability	intrinsic	input control	critical
Computational time	minutes	seconds	hours
Interaction	none	possible	none
Integration in organ	complex	simple	obsolete

model has constant complexity $O(k)$. The cellular automaton has $O(nm)$ complexity, with n the number of growing steps and m the size of the volume. The particle system's complexity is $O(nm^x)$, with n being the number of particle divisions, m the number of particles and x a factor between 1 and 2, as most particles have to be tested against each other, even in an optimized implementation.

Physicians might desire more control over the generated structures. The computational time required by the particle approach does not allow for any reasonable interaction during the growth phase. Restarting the process with modified parameters would be far too time consuming. For such situations, the skeleton based pathology design seems to be the best choice. Mass-spring models of this size can be modified at interactive rates, so that the resulting pathology can directly be altered by the user.

A cellular automaton is based on a volumetric data representation while all other models use surface representations. The integration of this model in the healthy anatomy requires at least one transformation of the representation and additional modifications of the surface models, as collisions cannot be handled in a cellular automaton.

4 Conclusion and Future Research

The results obtained with the different methods have all been discussed with experienced gynecologists. They all produce good to excellent results. Yet the implementation of different methods for the generation of pathologies has shown that all of them have specific advantages and disadvantages. As the goal of current research is a high fidelity simulator and computational power continuously increases, we strongly believe that the simulation of the growth process based on particles leads to the most accurate results and is therefore the most promising in the long term.

Validation of the results is an important and demanding task. The visual inspection convinced the experts in all cases. We expect that the final simulation with the incorporation of biomechanical parameters and haptic feedback will

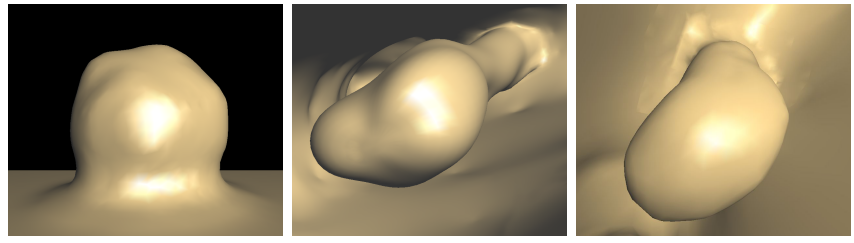

Fig. 1. Results obtained with the different generation strategies. More examples and animations of the growth processes can be found online at `http://www.vision.ee.ethz.ch/~rsierra/cars2003`.

give more insights on the suitability of the different approaches. So far, the particle method can be seen as a benchmark for the other models, as it involves the most biological knowledge.

In the future, the generation of variable anatomical models of the healthy organs will be investigated in order to create a coherent, variable surgical scene.

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References

[1] H. Greenspan. On the Growth and Stability of Cell Cultures and Solid Tumors. *J. theor. Biol.*, 56:229–242, 1976.

[2] K.Montgomery et al. Surgical Simulator for Hysteroscopy: A Case Study of Visualization in Surgical Training. *IEEE Visualization 2001*, 2001.

[3] C. Kuhn. *Modellbildung und Echtzeitsimulation deformierbarer Objekte zur Entwicklung einer interaktiven Trainingsumgebung für Minimal-Invasive Chirurgie.* Forschungszentrum Karlsruhe GmbH, Karlsruhe, 1997.

[4] A. Qi et al. A Cellular Automaton Model of Cancerous Growth. *J. theor. Biol.*, 161:1–12, 1993.

[5] R.Sierra, G.Székely, and M.Bajka. Generation of Pathologies for Surgical Training Simulators. *MICCAI*, Proceedings, Part II:202–210, 2002.

[6] R.Sierra, M.Bajka, and G.Székely. Pathology Design for Surgical Training Simulators. *In Proceedings IS4TM*, 2003.

[7] R.Sierra, M.Bajka, and G.Székely. Pathology Growth Model Based on Particles. *submitted to MICCAI*, 2003.