Stochastic Correction of Boundary Conditions during Liver Surgery

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***Abstract*—Boundary conditions play essential role in forming the predictive capacity of the biomechanical model of liver, which is used to facilitate the intra-operative navigation during surgery operation. However, these conditions are presented mainly by ligaments, and the properties of them cant be measured reliably. Therefore, the idea is to propose the data assimilation approach where the deformation of the liver tissue is used to estimate the organ attachments. The behavior of liver can be recorded on stereo camera, ultrasound, or some other modality, but, due to observational errors, there is a high amount of uncertainty in the system. One possible option is to model boundary conditions as stochastic values and to use the reduced-order unscented Kalman filter for their estimation. This filter obtains the result as iterative process based on computation of the weighted average between observed data and the physically-based model that simulates behavior of liver. Based on an approach previously proposed in [1], this work is focused on estimation of the modified boundary conditions, which happens when ligaments are cut during surgery process. This estimation incorporates changes in liver shape movement under various manipulations. The method is evaluated using synthetic data in two scenarios: the deformation of parallelepiped mesh under single direction straight forward deformation and the deformation of liver model under more complex movements.**

1. Introduction

Nowadays, the augmented reality plays an important role in navigation in laparoscopic surgery. However, cameras and other modalities provide surgeons only with limitied visibility of the area of interest. So information about other structures such as tumors, blood vessels, and unobserved part of organs can increase surgical accuracy and reduce the time of the operation. In our work, a finite element model is used to describe the behavior of organs. This model is obtained by reconstruction from pre-operative images. During the operation, the information is updated using data provided by a laparoscopic camera or an ultrasound device.

Beside the properties of the object, the boundary conditions (BCs) also have a significant impact on the simulated behavior and thus, they essentially affect the accuracy of the model. Unfortunately, in the case of liver, they are mainly given by ligaments, which cannot be observed directly in the images, provided by medical systems. Therefore, the main idea is to estimate them based on shape movement of the liver model, when performing various manipulations.

Unfortunately, the papers dealing with the estimation of BC are not numerous. In [2], to estimate surface loads corresponding to BCs, the authors solve an optimization problem that minimize energy between the rest and deformed shape of an organ. In [3] a statistical atlas is used to transfer the positions of attachments to the actual geometry of the object. In [4] the authors describe a database of liver deformations obtained from medical data. They use unknown properties and BC values, which they add to the system as additional unknown parameters. But all this methods generally estimate fixed boundary conditions and dont take into account the possibility of their modification.

In [5] the authors construct and work with so called compliance boundary conditions. Recently, authors validated this method, using several different scenarios [6]. In their approach, boundary conditions are defined as an additional compliance matrix, the values of which are computed based on stiffness of object material and difference in movement between internal object positions and boundary ones. Unfortunately, to use this approach the positions of the whole part of the object under consideration should be known. But in case, when observation are obtained through laparoscopic camera, only several dozens of features on the liver could be detected. These features are usually located on the visible part of the liver, so almost no information about boundary positions are given. Moreover, in this approach the amount of parameters that can be estimated is very dependent on the amount of given data. Thus, tracking only a few information, the compliance BC couldn't provide us with a lot of useful data.

A possible solution is to use the reduced-order unscented Kalman filtering (ROUKF) approach [7], to which the work [1] is already dedicated. The filtering method, which estimates BC, use features that can be tracked on medical images. The main idea, described there is to split the whole set of features onto two parts. First set is related to so called *"control points"* that describe liver deformation in space. The second set contains *"observation points"*, which are used as groundtruth data to compute the correction for unknown values. Nevertheless, the estimation is performed only for initial values. Unlike that work, this paper shows that BC can be also detected after their modification during intervention process. This is helpful when behavior of liver model is changed under various manipulations because of cutting some ligaments or stitching.

2. Method description

The finite element (FE) method has been selected to simulate the elastic behavior of the object. A co-rotational formulation of linear elasticity is employed and the model is discretized using linear tetrahedral elements [8]. To extract the rigid motion from the whole deformation a QR decomposition is performed. The force in each finite element is connected with displacement according to equation:

$$f = R^T K R u = R^T E^T D E(Rx - x_0) \tag{1}$$

where matrix R contains the rigid rotation of the element, x_0 is the initial position, x is the current position, matrix D describes material stress-strain relation, matrix E includes the properties of element that connect displacement and strain values, and K is the stiffness matrix. The more detailed description on construction of the matrices E and D is given in [9]. The force for the whole object is obtained by assembling the forces for the all tetrahedral elements.

To compute the dynamics of an object, an implicit Euler method is used [10]. The time is integrated by solving the second-order differential equation:

$$M\ddot{u} + B\dot{u} + R^T K R u = f \tag{2}$$

where M is mass matrix, $\ddot{u}$ and $\dot{u}$ are acceleration and velocity, and B is damping matrix that is approximated by two damping constants:

$$B = \alpha K + \beta M \tag{3}$$

The model of object is fixed in space with several elastic springs, which represent BCs at specific locations, as presented in Fig. 1. These springs connect specific points of the model with the original positions that don't change. To deform the object, it is attached by another elastic spring to a solid object (SO), position of which can be specified in space. The stiffness of this spring is fixed and quite high, allowing the object to deform according to the position of SO, ignoring its internal elastic properties.

The experiments are splitted into two parts. The first part is used to generate synthetic data that describe object shape deformation and position in space. During this process, the model is deformed according to a position of SO, using implicit Euler method. At some moment the emulation of cutting of some ligaments is performed. Here, the stiffness of one of boundary springs is set to a value close to zero. Then deformation continues up to the some final state. During the simulation, some selected points on the object surface, which present specific elements are stored. In Fig. 1 they are marked as small spheres. The location of the SO is stored as well. This data is used in the second part of the experiments.

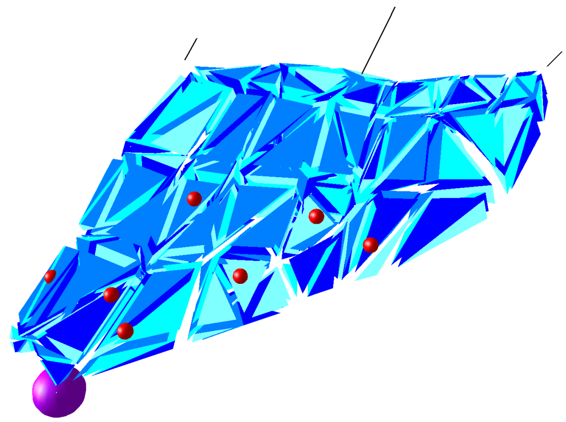

Figure 1. Liver model scene overview. Black strips - elastic springs that simulate BC, violet sphere - SO or *"control point"*, which forms deformation of the object, red points - detected features or *"observation points"* that describe liver's real shape

The second part is dedicated to estimation of the BC based on filtering process. The ROUKF [7] is used for the estimations. In this process elasticity of each boundary spring is presented as stochastic parameter with Gaussian distribution, as required by filter. The stored data is used as known information to estimate the values of stochastic parameters. In this case the location of SO is used as control feature to describe the object deformation. And values of specific elements, which present observation features, are used by filter as some known data for parameters estimation. For detailed description of the algorithm related to filtering process, see the paper [2]. During the process, the same implicit Euler method is used to deform the object. As a result, the final values of estimated parameters are compared with the stiffness values that were set to springs when synthetic data have been generated.

3. Experiments and results

To estimate the results computed by the proposed approach, two scenarios have been implemented. The first scenario deals with a parallelepiped, whereas the second one is dedicated to the deformation of a liver model, where the trajectory of the SO is created by a haptic device.

3.1. Parallelepiped deformation

The parallelepiped was created with Gmsh software. The object represensts a tetrahedron mesh with sizes (30 $\times$ 15 $\times$ 3 cm). Youngs modulus is set to 5 kPa and Poisson ratio equals 0.45. To emulate boundary conditions three springs with different stiffness (150, 200, 300 N/m) have been selected. All of them are attached to the model from the same side: two are connected to the object at two corners and the third one is in the middle of the face (Fig. 2). During the deformation the stiffness of the last spring is set to zero.

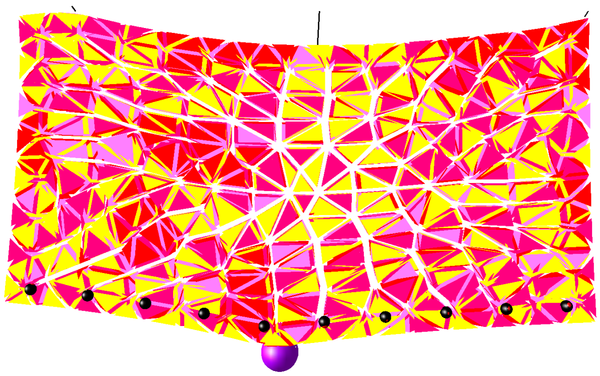

Figure 2. Parallelepiped model scene. Black strips - elastic springs that simulate BC, violet sphere - SO or *"control point"*, which forms deformation of the object, black points - detected features or *"observation points"* that describe object's real shape

The SO which exerts model movement is attached to the opposite face. It moves in single direction and with constant velocity, during the whole process.

The results show that filtering estimation quickly detects the change of boundary conditions in the system and is able to estimate the updated values during several hundreds of iterations, as presented in Fig. 3. Although the average difference between original stiffness and estimated stiffness before correction (2 N/m) is less than one after correction (6 N/m).

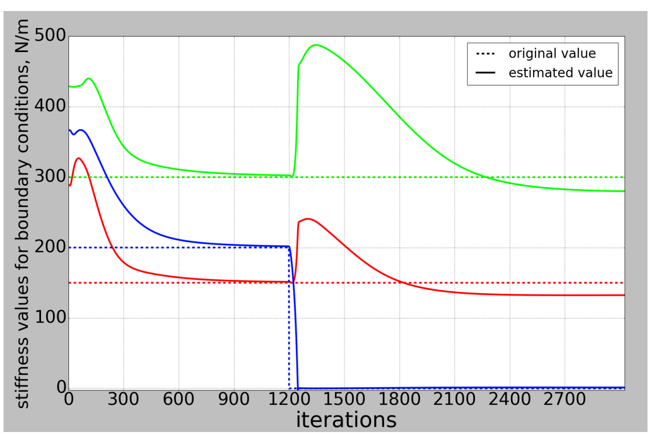

Figure 3. Estimated stiffness values for springs that simulate parallelepiped BC

3.2. Liver deformation

For the second scenario the simple liver model have been taken. It was discretized with 596 tetrahedra and to simulate mechanical behavior the same Youngs modulus and Poisson ratio have been selected, as given on Fig. 1. Three springs emulate boundary conditions for liver model. The elastic springs have been created close to each other. Also during the simulation process, in order to emulate cutting, the stiffness of the average spring has been set to a value close to zero.

In any case, compared with the parallelepiped object, liver model has more complex shape. Apart from that, instead of straight movement in one direction, a bit complex movement for the SO has been done. To set the location for the SO, an Omni haptic device is used. The SO is strictly attached to its position. The haptic device is manipulated by hand, which allows to specify the position in space more directly.

According to results, the ROUKF is able to detect the modification in this case as well, see Fig. 4. The main difference compared with previous scenario is that it takes approximately 3 times more iterations for the filter to estimate the changed values. Also, the final estimation is less precise. The average difference before correction is 3 N/m, which is close to the error from previous scenario; however, the average difference after correction is 12 N/m.

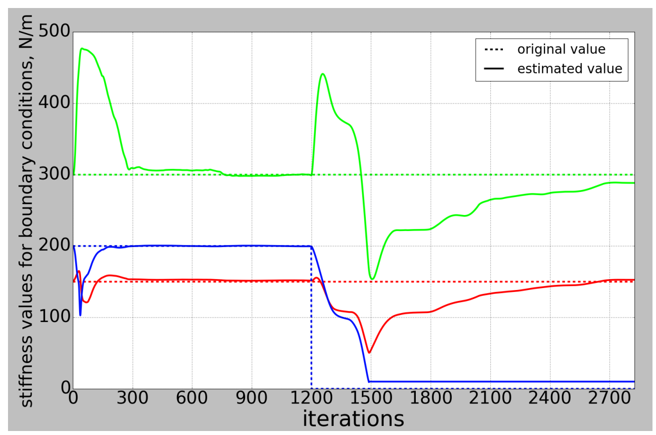

Figure 4. Estimated stiffness values for springs that simulate liver BC

The error between average difference before and after correction in the second case is bigger that in the first one. This is due to the fact that in the second case the deformation is more complicated, which makes it more difficult for ROUKF to estimate the correct stiffness values, and it requires more information to correct them for the same level of precision.

As a result of these experiments, it is worth to say that filtering approach can be used not only to estimate the initial parameters for boundary conditions, but also to correct them in time. This correction can be done for objects with various shapes, and the deformation doesn't need to be necessarily simple and straightforward.

4. Conclusion

In this paper, the Kalman filter algorithm has been employed for correction of values of boundary conditions. The method was tested using data obtained from parallelepiped and simple model of liver movements. The estimation have been verified using synthetic data. The results show that filtering approach quickly reacts to changes of BC and is able to estimate the modified parameters.

One important moment is the fact that any data assimilation using Kalman filtering approach is a stochastic process, and thus the filtering system relies completely neither on the estimated values, nor on the observed information. So, if the data shows that model undergoes some untypical deformations, the filter will start to modify the estimated parameters, which in given experiments depict BC, until the new equilibrium point will be achieved. Therefore, using Kalman filtering approach, it is possible to track the changes of mechanical system and estimate the parameters that corresponds to its new behavior.

Nowadays, one of the modern solution that is also used to estimate parameters for various systems is Particle filtering method [11]. The main idea behind this approach is iteratively performing two steps. During the first step, the system undergoes resampling, in which the new elements around the best found approximations are generated. And, the second step is dedicated to the finding of the new approximations, where the best appropriate elements go through the modeling process. To find the best estimation, the difference between simulated observations and real ones is computed. The minimum of the difference shows the best option.

Particle filters have a number of advantages like independence on the type of the model and motion, simple parallelization, and easiness of implementation [11], [12].

On the other hand, particle filters have also drawbacks that make them quite unsuitable to use for given scenario [12], [13]. First of all, they are non-deterministic, which makes really hard to understand whether the problem with such amount of unknowns is solved. Secondly, particle filters require generating of a lot of particles: and the more the amount of unknowns in the system, the much more particles have to be generated to cover the whole space. This problem is also known as *particle deprivation problem*. For example, for system with 10 unknowns, if for every unknown 10 particles could cover all relevant regions, then 10^{10} particles are required to cover the whole space. Handling this amount of particles require high-performing clusters. There is no such equipment in operating room, so the computation requires time. However, during operation surgeons have to be provided with relevant data about organ deformation; therefore, real-time computations is the crucial moment here. And finally, in the case of unscented filter the dynamic behavior of the variance could be used as some sort of ”detector” to tell us the possibility of convergence and the uniqueness of solution. In the case of particle filter, because of resampling, there is no such ”detector”. Therefore, it is quite hard to analyze it. As a result, particle filters could be used confidently only for problems with small amount of unknown parameters.

In future research we plan to perform tests using data obtained from laparoscopic camera during operation procedure and to improve the modeling of boundary conditions, by incorporating the constitutive law of ligaments that surround the liver. We are also going to do further researches in ligaments modeling to find out whether the noise of the constructed model has a Gaussian nature.

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