Motion Estimation and Reconstruction of a Heart Surface by Means of 2D-/3D-Membrane Models

K. Roberts[a], U. D. Hanebeck[a]

[a]*Intelligent Sensor-Actuator-Systems Laboratory, Institute of Computer Science and Engineering, University of Karlsruhe (TH), Germany, {Kathrin.Roberts|Uwe.Hanebeck}@ieee.org*

Abstract. In order to assist surgeons during minimally invasive interventions on the beating heart, it would be helpful to develop a robotic surgery system, which synchronizes the instruments with the heart surface, so that their positions do not change relative to the point of interest (POI). The synchronization of the robotic manipulators requires an estimation of the heart surface motion. In this paper, a model-based motion estimation of the heart surface is presented. The motion of a partition of the heart surface is modelled by means of a thin or thick vibrating membrane in order to represent the epicardial surface or the connected epicard and myocard. The membrane motion is described by means of a system of coupled linear partial differential equations (PDEs), whose 3D-input function is assumed to be known. After spatial discretization of the PDE solution space by the Finite Spectral Element Method, a bank of lumped systems is obtained. A Kalman filter is used to estimate the state of the lumped systems by incorporating noisy measurements of the heart surface. Measurements can be the position or velocity of sonomicrometry-based sensors or of certain landmarks, which are tracked by optical sensors. With the model-based estimation it is possible to reconstruct the entire partition of the heart surface even at non-measurement points and thus at each POI.

Keywords: Motion Synchronization; Heart Surface Model; Model-based Motion Estimation

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1. Introduction

In order to assist surgeons during minimally invasive interventions on the beating heart, it would be helpful to develop a robotic surgery system, which synchronizes the instruments with the beating heart, so that their positions do not change relative to the point of interest (POI). The new alternative could facilitate interventions such as the placing of epimycardial left ventricular electrodes within the cardiac resynchronization therapy or the coronary artery bypass grafting (CABG) for patient with atherosclerosis. Instead of using the traditional heart-lung machine (on pump) during CABG, which leads to several risks like temporal cognitive loss, stroke and kidney complications, in many cases, this procedure can be replaced by an off pump CABG surgery.

Until now, the most used master-slave robotic surgery systems daVinci and ZEUS did not offer an autonomous motion synchronization of the manipulators with the beating heart. The system architecture of a robotic surgery system in order to operate on the beating heart, first introduced in [1], should have two new features. First, in order to give the surgeon the impression that he operates on a motionless heart the image from the intervention area has to be stabilized. During the intervention the manipulators are synchronized with the heart surface based on the estimation of the heart surface motion. Second, for the synchronization, a method for motion prediction of the beating heart at each POI on the organ's surface, based on measurements of heart motion, is required.

Several studies for motion compensation algorithms with respect to the beating heart exist. In order to predict the heart's motion at a POI in one direction, a displacement model with weighted Fourier series is used in [4]. In [1], 2D-motion of a POI is estimated by an autoregressive model based on 2D position measurements from a single camera. In [5] a method for predicting motion of surface points based on their x- and y-trajectories, respiration pressure signal, and ECG signal observed in the past is presented. The features are tracked robustly even with short-time occlusions. A predictive-control approach for filtering the heart motion is presented in [6] and [7]. In [6], a 6 DOF robot is set up, which is synchronized with an oscillating target using visual servoing techniques and a modified generalized predictive controller to learn and predict the organ's motion. The model-based predictive controller described in [7] is based on a motion model containing sonomicrometry measurements of the POI-trajectory out of the past heart beat cycle. In [3] a dense 3D structure recovery for temporal motion tracking of deformable surfaces from stereo image pairs is presented. In this approach a constrained disparity registration is used after an image rectification. In order to generate a still image of a moving surface in [2] a real-time binocular eye tracking of the surgeon is used.

In the above mentioned methods, with exception of [5], the possibility of reconstruction of the heart motion at non-measurement points or occluded points is not discussed. In [8], we have presented a model-based estimator in order to predict and reconstruct a partition of the heart surface even at non-measurement points. The heart surface is modelled as a round vibrating 2D-membrane, whose motion in z-direction is described by a partial differential equation (PDE). The input function of the PDE is assumed periodic and is reconstructed. In this article, our approach from [8] is extended to a rectangular membrane which can move in all three dimensions. The external function is assumed to be known. In particular, the membrane can be either thin to represent the epicardial surface or thick to represent the connected epicard and myocard. In the following, in Section 2 the derivation of the membranes state models and the used state estimator is shortly discussed. In Section 3 simulation results are presented.

2. Method

The elasticity of the heart surface is assumed to be linear. Hence, the motion of the membranes modulating the moving epicardial surface or the connected epicard and myocard are described by the Lamé equations of the form:

$$(\lambda + \mu)\nabla \text{div}\, \underline{u} + \mu \nabla^2 \underline{u} + d\dot{\underline{u}} + \left(\underline{f} - \rho \ddot{\underline{u}}\right) = 0. \qquad 1)\,($$

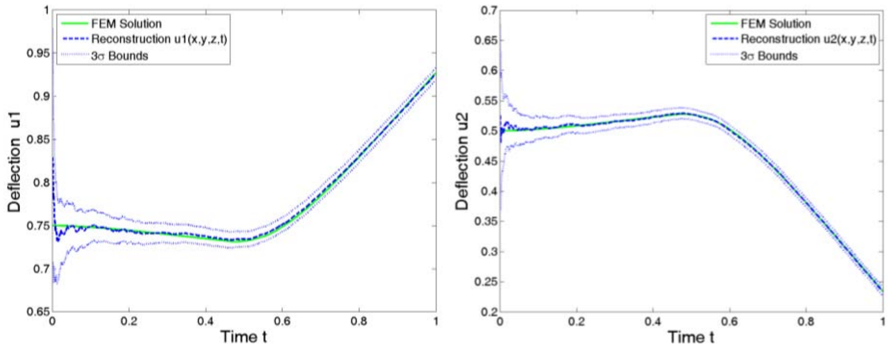
The Lamé equations are a system of coupled PDEs, where the solution function $\underline{u} = (u_1, u_2, u_3)$ describes the displacement of a membrane point (x, y, z) in the three dimensions x, y, and z. The function $\underline{f} = (f_1, f_2, f_3)$ is the external force, which deforms the membrane in all three dimensions. In (1), the parameters λ, μ, and ρ are material parameters and d is the damping term. The thick membrane is described as a cuboid with six Neumann boundary conditions. The Neumann boundary conditions permit free membrane motion in all three directions. In the case of the thin membrane, the variables and derivations in z-dimension in (1) are neglected. As a result, the thin membrane is defined as a rectangle with four Neumann boundary conditions. For spatial discretization of the solution space of each linear PDE equation of the system (1), we use the Spectral Finite Element Method as discussed in [9]. In this paper, we consider only one finite element. Hence, for each direction j the solution u_j is approximated by a finite sum according to

$$u_j(x,y,z,t) = \sum_{i=1}^{N} \varphi_i(x,y,z)\alpha_i(t) \approx \sum_{i=1}^{N} \varphi_i(x,y,z)\alpha_i(t) \quad \text{for } j = 1,2,3. \tag{2}$$

In (2), $\varphi_i(x,y,z)$ are three-dimensional polynomials and $\alpha_i(t)$ are their time dependent weights. As described in [9], the system of PDEs can be transformed to a bank of lumped systems of order two, where the state consists of the α_i and $\dot{\alpha}_i$ for each dimension j. The measurement equation, which maps the state to the position and velocity of a measurement point, is defined similar as in [9]. Then a Kalman Filter is used in order to predict the state, based on the system equation, and to update the state by incorporating noisy measurements.

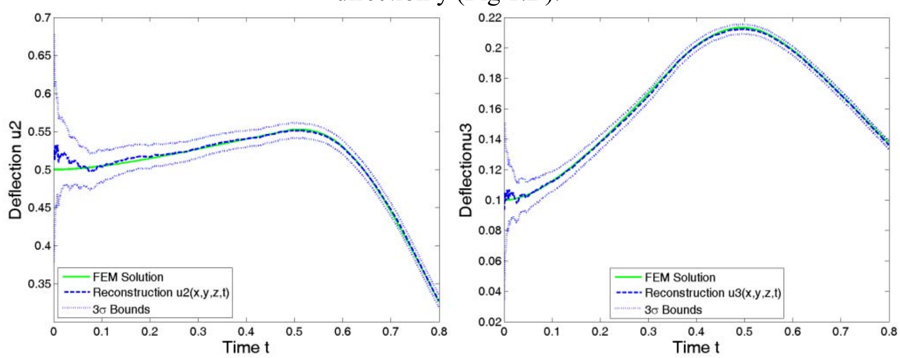
3. Results

With the model-based estimation described in Section 2, it is possible to reconstruct the entire rectangular partition of the heart surface even at non-measurement points. The membrane models are evaluated, while the moving heart surface is represented by a Finite Element solution. The noisy position and velocity measurements are generated, while on the solution of local points Gaussian noise is added. Fig. 1 shows the estimate of the solution *u* for the thin membrane and Fig. 2 for the thick membrane at a non-measurement point. In both cases the external force describes a rotation around the z-axis and a sinus bulge in z-direction. In Fig. 3 reconstruction results for the two membranes over time are presented.



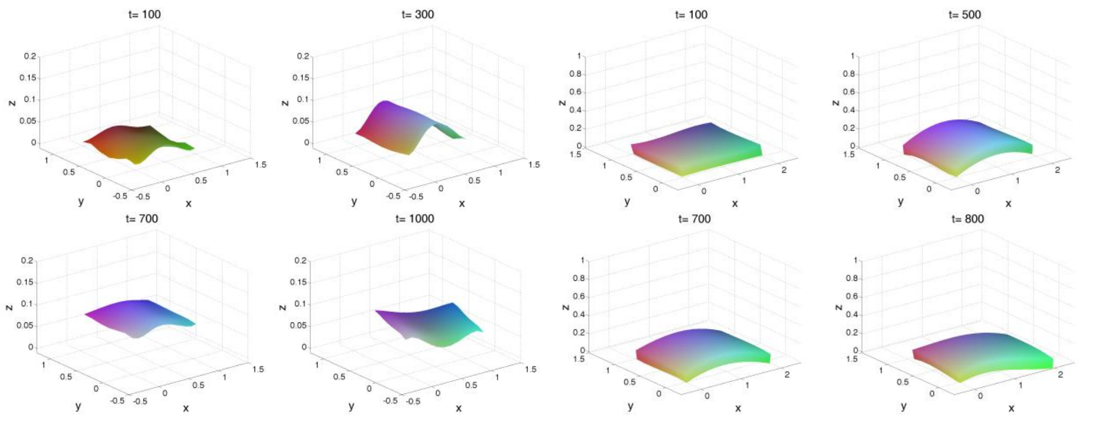
A **B**

Fig. 1. Reconstruction at a non-measurement point for the thick membrane in direction x (Fig. 1A), and in direction y (Fig 1.B).



A **B**

Fig. 2. Reconstruction at a non-measurement point for the thick membrane in direction y (Fig. 2.A), and in direction z (Fig. 2.B)



A **B**

Fig. 3. Reconstruction over time of the thin membrane (Fig. 2A) with 36 measurement points and of the thick membrane (Fig. 2B) with 48 measurement points.

4. Conclusions

The reconstruction results of the simulated heart surface in Section 3 are promising and seem to be applicable. Future work is concerned with adaption to the individual patient heart motion by estimating the model parameter, e.g. the material parameters and to estimate the external force in a training model to predict the distributed heart motion.

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