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Research Paper

Velocity-based cardiac contractility personalization from images using derivative-free optimization

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ABSTRACT

Model personalization is a key aspect for biophysical models to impact clinical practice, and cardiac contractility personalization from medical images is a major step in this direction. Existing gradient-based optimization approaches show promising results of identifying the maximum contractility from images, but the contraction and relaxation rates are not accounted for. A main reason is the limited choices of objective functions when their gradients are required. For complicated cardiac models, analytical evaluations of gradients are very difficult if not impossible, and finite difference approximations are computationally expensive and may introduce numerical difficulties. By removing such limitations with derivative-free optimization, we found that a velocity-based objective function can properly identify regional maximum contraction stresses, contraction rates, and relaxation rates simultaneously with intact model complexity. Experiments on synthetic data show that the parameters are better identified using the velocity-based objective function than its position-based counterpart, and the proposed framework is insensitive to initial parameters with the adopted derivative-free optimization algorithm. Experiments on clinical data show that the framework can provide personalized contractility parameters which are consistent with the underlying physiologies of the patients and healthy volunteers.

1. Introduction

Cardiac model personalization is a process to obtain a biophysical model which accounts for the subject-specific cardiac physiology, and is usually realized as parameter estimation. Given a generic cardiac model derived from invasive experiments of anatomy, electrophysiology, and cardiac mechanics, the model parameters are estimated from subject-specific *in vivo* measurements such as non-contact endocardial maps and magnetic resonance images (MRI). As simulation of the whole organ has reached a degree of realism which is quantitatively comparable with available cardiac images and signals acquired routinely on patients, model

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personalization gives a potential impact to clinical practice by improving disease diagnosis and therapy planning, such as cardiac resynchronization therapy (Sermesant et al., 2012).

Cardiac mechanics is the interaction among active contraction stresses, passive mechanical properties (stiffness), and boundary conditions exerted by surrounding anatomical structures (Germann and Stanfield, 2005; Glass et al., 1991). Various cardiac electromechanical models have been proposed to describe such an interaction with different physiological plausibilities, complexities, and computational efficiencies (Nash, 1998; Sermesant et al., 2006a; Usyk et al., 2002; Wong et al., 2010b). According to the characteristics of the models, different personalization algorithms have been proposed. In Hu et al. (2003), the homogeneous and transversely isotropic Young's moduli of a piece-wise linear passive mechanical model were estimated with the active contraction using an expectation–maximization (EM) algorithm from tagged MRI. In Liu and Shi (2009), the heterogeneous and isotropic Young's moduli and Poisson's ratios were estimated simultaneously with cardiac deformation using an extended Kalman filter-based EM algorithm from cine and tagged MRI. In Chabiniok et al. (2011), the regional maximum contraction stresses were estimated using reduced-order unscented Kalman filtering (rUKF) from porcine cine MRI. In Wang et al. (2009), homogeneous passive material stiffness of a nonlinear transversely isotropic model was estimated with a sequential quadratic programming (SQP) method from tagged MRI and *ex vivo* DT-MRI of canine hearts. In Xi et al. (2011), the performances of rUKF and SQP for the estimation of stiffness parameters were compared on synthetic data. In Marchesseau et al. (2013), a method based on the unscented transform algorithm was proposed to calibrate the global mechanical parameters of the Bestel–Clément–Sorine electromechanical model (Bestel et al., 2001), followed by the personalization of the regional maximum contraction stresses using rUKF.

In this paper, we concentrate on cardiac contractility personalization. While efforts have been spent on estimating maximum contraction stresses (Hu et al., 2003; Chabiniok et al., 2011; Delingette et al., 2012), the estimations of contraction and relaxation rates have seldom been studied. As these rates are related to clinically important measurements such as the rates of blood pressure (Rushmer et al., 1964; Mason et al., 1971), they are important parameters which should also be estimated. Nevertheless, this is not a trivial task. For example, in our previous work (Delingette et al., 2012), the gradient-based quasi-Newton L-BFGS-B algorithm was utilized to optimize a position-based objective function. Although the utilized adjoint method allows efficient computation of the gradient, it requires the system derivatives of the complicated cardiac electromechanical model. This limits the exploration of the proper objective functions and also the types of parameters to be estimated, as some objective functions are highly nonlinear with respect to the desired parameters. Therefore, only the maximum contraction stresses were estimated in Delingette et al. (2012) even after some model simplifications.

In consequence, we propose the use of derivative-free optimization for cardiac contractility personalization. Without the analytical, numerical, and computational difficulties associated with gradient evaluation, objective functions which may provide better parameter estimation can be investigated with relative ease. By using derivative-free optimization, we propose a velocity-based objective function for simultaneous estimation of regional maximum contraction stresses, rates of contraction, and rates of relaxation. Experiments were performed on synthetic data to show the capability of the framework in identifying regional contractility, and its sensitivity to noise and initial parameters. Experiments on patient and volunteer data also show its clinical relevance.

2. Cardiac electromechanical model

In the computational environment, the personalized cardiac geometry can be represented as points bounded by surfaces. Using numerical methods such as finite element methods (FEM) (Bathe, 1996; Sermesant et al., 2006a) or meshfree methods (Belytschko et al., 1996; Wong et al., 2010b), the dynamics of a cardiac electromechanical model can be given as

$$\mathbf{M}\ddot{\mathbf{U}} + \mathbf{C}\dot{\mathbf{U}} + \mathbf{K}\mathbf{U} = \mathbf{F}_b + \mathbf{F}_c \tag{1}$$

where $\mathbf{M}$, $\mathbf{C}$, and $\mathbf{K}$ are the mass, damping, and stiffness matrices, and $\ddot{\mathbf{U}}$, $\dot{\mathbf{U}}$, and $\mathbf{U}$ are the acceleration, velocity, and displacement vectors. $\mathbf{F}_b$ comprises the displacement and pressure boundary conditions. $\mathbf{F}_c$ is the active contraction force vector derived from electrophysiology and tissue structure. The electromechanical model in Sermesant et al. (2006a) is used in this paper. To facilitate the complicated inverse problem, the stiffness matrix $\mathbf{K}$ describes linear elasticity, though tissue anisotropy is considered. Therefore, the passive mechanical properties are characterized through Young's moduli (E_f, E_{cf}) and Poisson's ratios (ν_f, ν_{cf}) along and across the fibers.

The force vector $\mathbf{F}_b$ comprises the displacement and pressure boundary conditions (Sermesant et al., 2006a). To hold the mesh in place, displacement boundary conditions are applied to the FEM nodes at the fibrous structure around the valves, and also to some FEM nodes at the apex. These boundary conditions are applied through the penalty method (Bathe, 1996), which is equivalent to attaching a FEM node to one end of a spring which has adjustable stiffness (penalty), with the other end of the spring fixed at the original nodal position. To simulate the four cardiac phases, including filling, isovolumetric contraction, ejection, and isovolumetric relaxation, pressures and penalty constraints are applied to the endocardia of the left and right ventricles. For filling, pressures equal to the mean pressures of the atria are applied. For isovolumetric contraction and relaxation, penalty constraints are applied to keep the ventricular volumes constant. For ejection, pressures equal to the mean pressures of the aorta and the pulmonary artery, which are computed using the three-element Windkessel model with the blood volume changes, are applied. The ventricular pressures of the cardiac cycle can be obtained by combining the ventricular pressures of all phases. As the isovolumetric constraints and the Windkessel model depend on the cardiac kinematics and mechanics, different active contraction forces produce different ventricular pressures.

To obtain $\mathbf{F}_c$, the relation between the action potential and the active contraction can be modeled as (Sermesant et al., 2006a)

$$\frac{\partial \sigma_c}{\partial t} + \sigma_c = u\sigma_0 \tag{2}$$