

Motivation

We propose to estimate rule-based myocardial fiber model (RBM) parameters from DT-MRI, with the goal of personalizing the fiber architecture for cardiac simulations. The RBM is based on a space-dependent angle distribution on the heart surface and then extended to the whole domain through an harmonic lifting of the fiber vectors. For the angles estimation we use a static Unscented Kalman Filter (UKF). We also show the effect of different fiber distributions on cardiac contraction simulations.

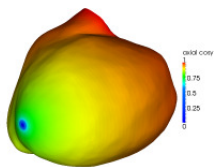
Rule-based fiber model

The construction of the spatially variant fiber model includes the following parts:

- Lifting operation (L) of surface parameter $g(\mathbf{x})$:

$$\begin{aligned} \Delta f(x) &= 0, & \text{for } x \in \Omega \\ f(x) &= g(x), & \text{for } x \in \Gamma \subset \partial\Omega \\ \partial_{n_\Omega} f &= 0, & \text{for } x \in \partial\Omega \setminus \Gamma \end{aligned}$$

- Construction of axial and circumferential coordinate system



Local axial coordinate system, created by solving (L), given Dirichlet boundary conditions (heart apex: 0, heart base: 1).

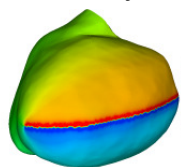
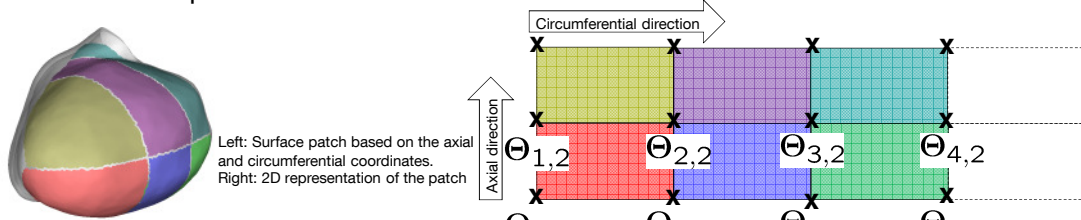


Figure shows local circumferential coordinate system, created by solving (L), given -1/1 Dirichlet condition at a given long-axis line at the left ventricular free wall.

- Bilinear interpolation of Θ in axial and circumferential direction



Left: Surface patch based on the axial and circumferential coordinates. Right: 2D representation of the patch

- Rule-based fiber algorithm, inspired from [1]: For given long-axis \mathbf{l} evaluate:

I. For surface S_i do:

For every node $\mathbf{x}_j \in S_i$ do:

1. Evaluate the local pseudonormal $\mathbf{n}(\mathbf{x}_j)$, circumferential direction

$$\mathbf{c}(\mathbf{x}_j) = \text{cross}(\lambda_j \mathbf{n}(\mathbf{x}_j), \mathbf{l}) \text{ with } \lambda_j = \begin{cases} +1, & \text{for } \mathbf{x}_j \in \text{epicardium} \\ -1, & \text{for } \mathbf{x}_j \in \text{endocardium} \end{cases}$$

2. Compute the interpolation of angle $\Theta_{i,j}$: $\delta(\mathbf{x}_j) = \Theta(\text{cir}(\mathbf{x}_j), \text{axi}(\mathbf{x}_j))$

3. Generate the surface fibers:

$$\tilde{\mathbf{g}}(\mathbf{x}_j) = \cos(\delta(\mathbf{x}_j)) \mathbf{c}(\mathbf{x}_j) + \sin(\delta(\mathbf{x}_j)) \frac{\text{cross}(\mathbf{n}(\mathbf{x}_j), \mathbf{c}(\mathbf{x}_j))}{\|\text{cross}(\mathbf{n}(\mathbf{x}_j), \mathbf{c}(\mathbf{x}_j))\|}$$

$$\mathbf{g} = \frac{\tilde{\mathbf{g}}}{\|\tilde{\mathbf{g}}\|}$$

II. Solve the harmonic lifting (L) with $g(\mathbf{x})$

Unscented Kalman Filter

We aim to minimize the following functional:

$$J(\Theta) = \|\mathbf{f}_m - \mathbf{f}(\Theta)\|_{W^{-1}}^2 + \|\Theta - \Theta_-\|_{P^{-1}}^2$$

with

- noisy fiber measurements \mathbf{f}_m from DTMRI measurements
- rule-base algorithm \mathbf{f} with variables Θ
- a priori estimate Θ_- , $\mathbf{W} = \gamma \mathbf{Id}$, $\mathbf{P} = (\text{std}_0)^2 \mathbf{Id}$, γ , std_0 positive scalars
- norms $\|\cdot\|_{W^{-1}}$ and $\|\cdot\|_{P^{-1}}$ for weighting the terms

For solving this least squared problem for Θ we apply the reduced order unscented Kalman filter (ROUKF)[2] in a static manner:

- simplex sigma points $\mathbf{I}_k^{(i)}$, $1 \leq i \leq k+1$, recursively calculated via

$$\begin{aligned} \mathbf{I}_1^{(*)} &= \left[-\frac{1}{\sqrt{2\alpha}}, \frac{1}{\sqrt{2\alpha}} \right], \quad \alpha = \frac{1}{k+1} \\ \mathbf{I}_d^{(*)} &= \begin{bmatrix} 0 \\ \vdots \\ 0 \\ \frac{1}{\sqrt{\alpha d(d+1)}} \dots \frac{1}{\sqrt{\alpha d(d+1)}} \frac{-d}{\sqrt{\alpha d(d+1)}} \end{bmatrix}, \quad 2 \leq d \leq k \end{aligned}$$

- Innovation for each particle:

$$\begin{aligned} \mathbf{C} &= \sqrt{\mathbf{P}}, \text{ meaning Cholesky decomposition} \\ \Theta^{(i)} &= \Theta_- + \mathbf{C} \mathbf{I}_k^{(i)}, \quad 1 \leq i \leq k+1, \quad [\Theta^{(*)}] = [\Theta^{(1)} \dots \Theta^{(k+1)}] \\ \Gamma^{(i)} &= \mathbf{f}_m - \mathbf{f}(\Theta^{(i)}), \quad 1 \leq i \leq k+1, \quad [\Gamma^{(*)}] = [\Gamma^{(1)} \dots \Gamma^{(k+1)}] \end{aligned}$$

- Estimation

$$\begin{aligned} \mathbf{L}^\Theta &= \alpha [\Theta^{(*)}] [\mathbf{I}_k^{(*)}]^T \\ \mathbf{L}^\Gamma &= \alpha [\Gamma^{(*)}] [\mathbf{I}_k^{(*)}]^T \\ \mathbf{U} &= \alpha [\mathbf{I}_k^{(*)}] [\mathbf{I}_k^{(*)}]^T + (\mathbf{L}^\Gamma)^T \mathbf{W}^{-1} \mathbf{L}^\Gamma \\ \Theta_{cor} &= \Theta_- - \mathbf{L}^\Theta \mathbf{U}^{-1} (\mathbf{L}^\Gamma)^T \mathbf{W}^{-1} \alpha \sum_i^{k+1} \Gamma^{(i)} \\ \mathbf{P}_{cor} &= \mathbf{L}^\Theta \mathbf{U}^{-1} (\mathbf{L}^\Theta)^T \end{aligned}$$

Results

The tools described above are now used to estimate a smooth fiber organization from 3D ex-vivo DT-MRI* data. For the ROUKF we use the a priori values $\Theta_- = 60^\circ$, $\text{std}_0 = 10.0$, $\gamma = 1.0$, and 144 degrees-of-freedom for the surface angles distribution, on a 1.7M tetrahedra mesh**.

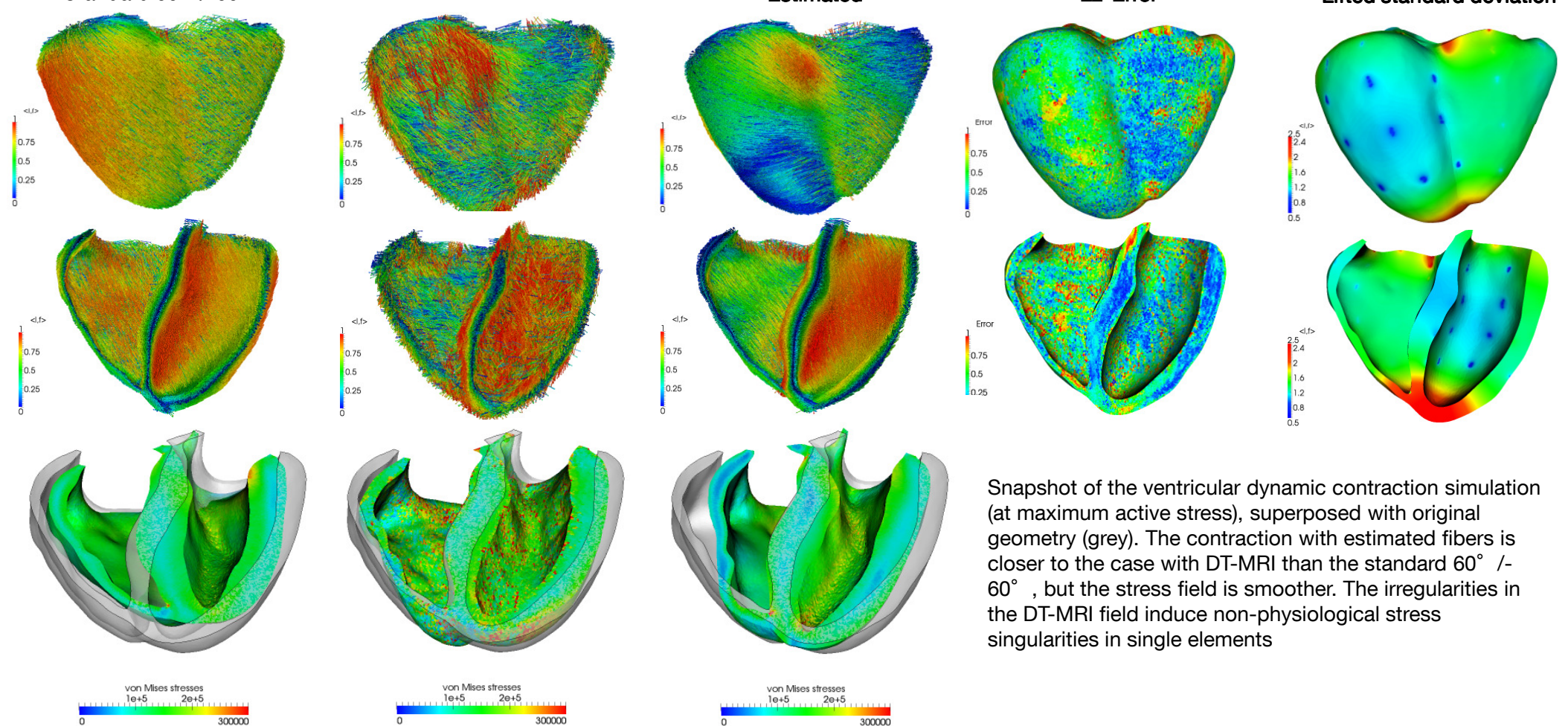
Standard $60^\circ / -60^\circ$

DT-MRI

Estimated

L2-Error

Lifted standard deviation



Acknowledgements. This work was supported by the Institute for Advanced Study (TU München) and one of its fellow Prof. Michael Ortiz (Caltech)

[1] Wong, J., Kuhl, E.: Generating fibre orientation maps in human heart models using poisson interpolation.

Computer Methods in Biomechanics and Biomedical Engineering (2012) 1{10 PMID: 23210529.

[2] Moireau, P., Chapelle, D.: Reduced-order Unscented Kalman Filtering with application to parameter identification in large-dimensional systems.

COCV 17 (2011) 380{405 doi:10.1051/cocv/2010006.

*DTMRI data Openly available on http://gforge.icm.jhu.edu/gf/project/dtmri_data_sets/; **Geometry created from in-vivo CT - imaging (courtesy of Klinikum Rechts der Isar)