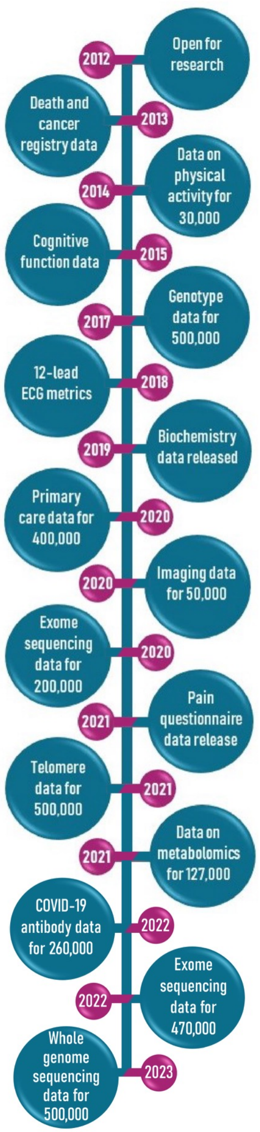
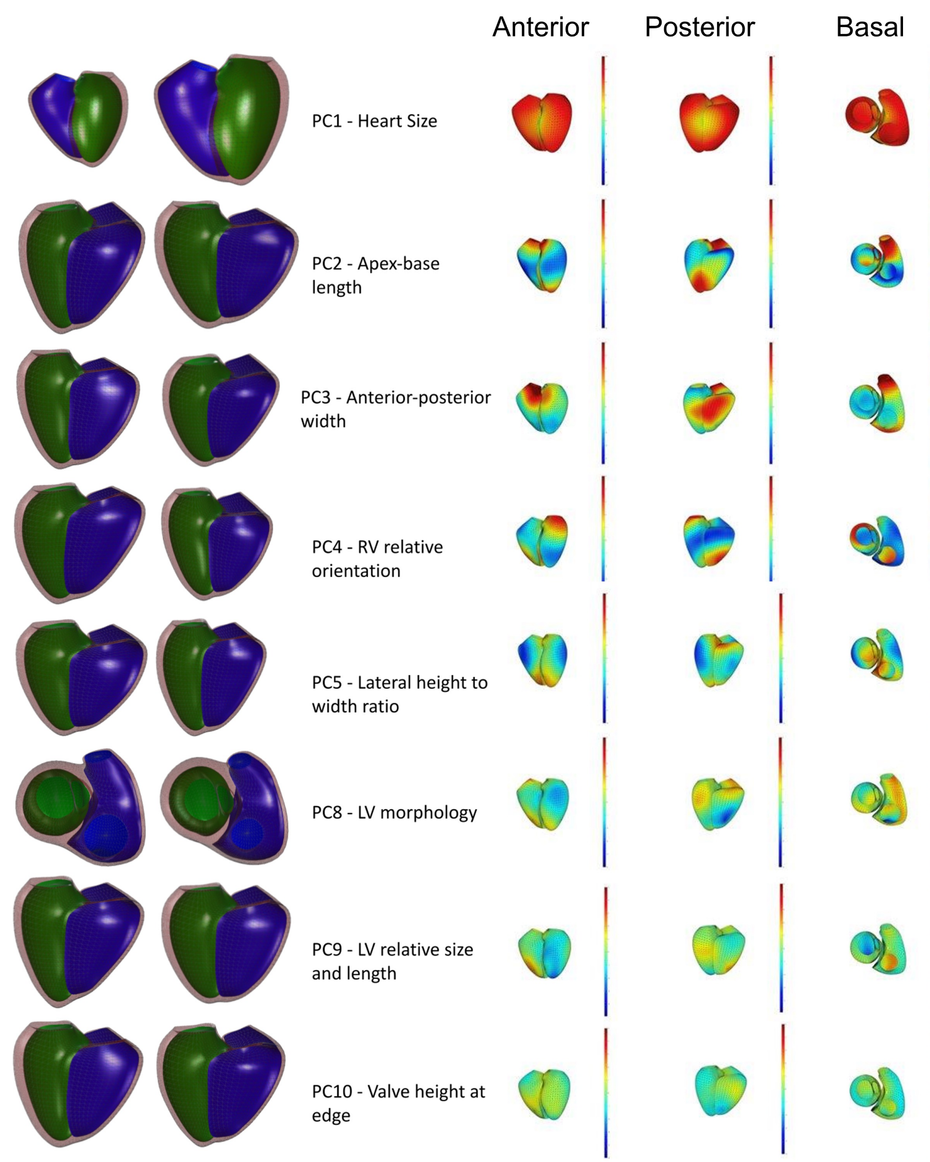
Project Goal



Can we use FE models based on ED/ES biventricular shape modes and hemodynamic measurements from UK Biobank to train a neural network to be (a) a surrogate FE model or (b) and inverse model?



Tools for Ventricular Statistical Shape Modeling

Cardiac Atlas Project

43 followers Auckland, New Zealand http://www.cardiacatlas.org

https://www.cardiacatlas.org/biventricular-modes/

cmrg-lab/
SSA_tutorial

A tutorial with some example code on how to interact with statistical shape atlases.

1 Contributor | 0 Issues | 0 Stars | 0 Forks

https://github.com/cmrg-lab/SSA_tutorial/blob/main/README.md

annaqi13/**sscp25**

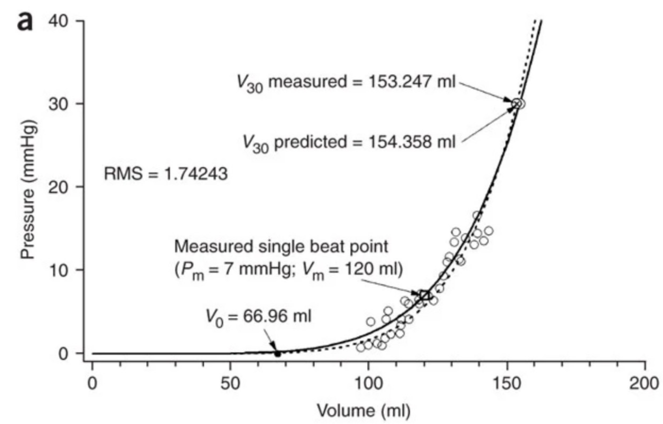
SSCP 25 - Deep Learning for Cardiac Mechanics

https://github.com/annaqi13/sscp25/tree/main

1 Contributor | 0 Issues | 0 Stars | 0 Forks

Data and Tools Available

- UKB ED/ES Atlas, but not the individual subject modes because individual data from UKB participants can only be used on their platform by approved users
- Tools to reconstruct and visualize shapes from atlas modes
- Codes to integrate LV and RV chambers volumes and wall masses from shapes
- Regressions of measured systolic and diastolic arterial blood pressures against ventricular sizes and masses
- Estimates of *unloaded* ventricular shape derived from:
  - Known ED ventricular shape, mass and volumes
  - Estimated ED pressure from published regressions of pulmonary capillary wedge pressures vs. LV ED volume and mass.
  - Published curve fit of EDPVRs when normalized by EDP and EDV by Klotz *et al.* (https://www.nature.com/articles/nprot.2007.270)
  - Correlation of shape modes with ventricular volumes and masses with shape modes to estimate shape with predicted unloaded volume and measured wall mass.

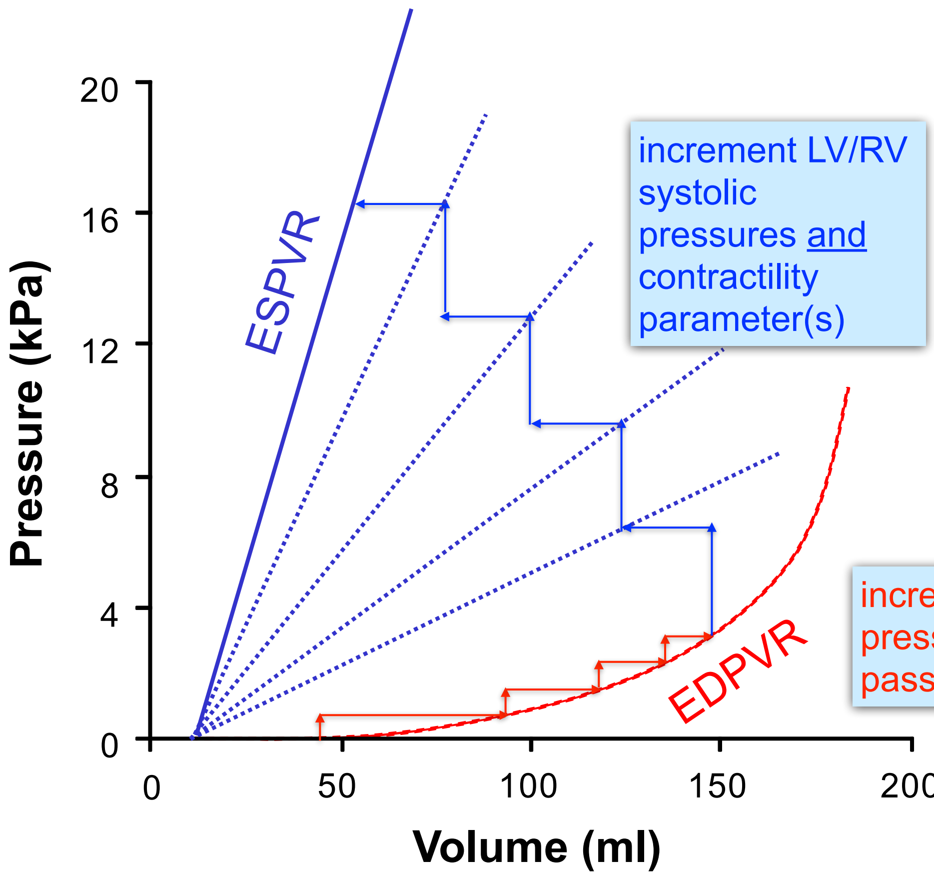


Requirement for a Mechanics Model

- A FE analysis of ventricular mechanics needs:
  - an unloaded reference geometry assumed to have zero stress;
  - a model of the fiber architecture, e.g. fiber angle distribution
  - constitutive law and material parameters (passive and active);
  - boundary conditions – ventricular pressures
- Given these you can predict ED and ES shape
- In general, since cardiac muscle tension development depends on SL, time, shortening velocity and strain history, a biophysically detailed model would need to simulate the entire cardiac cycle and would therefore need to know time varying material properties and boundary conditions, which in turn depend on the ejection and filling of the heart itself.
- However, recall that the whole ventricle behaves remarkably like a time-varying elastance. This means that in practice a model in which active tension only depends on SL (fiber strain) is capable of predicting systolic volumes and deformations independent of the path or history or deformation.
- Therefore, we can make a model that steps directly from the unloaded state to ED passively and from ED to ES

Requirement for a Mechanics Model

Time-varying elastance simulation of ED and ES. Technically, we could think of the solution at every step as a possible ED or ES solution for training the neural network



increment LV/RV systolic pressures and contractility parameter(s)

increment LV/RV diastolic pressures for constant passive material properties

Machine Learning Strategy

- IRL: we do *not* know the material properties or the unloaded shape (even if we do know the ED pressures which often we we have to estimate)
- Typically, estimating these requires computationally expensive patient-specific inverse optimization analysis that could require hundreds of FE solutions to estimate material parameters in one subject.
- But given realistic distributions and combinations of the inputs we could use **forward finite element simulations to train neural networks** in either of 2 ways:
  - **Input layer:** unloaded shape modes, material properties, pressures. **Output layer:** ED/ES **shape modes**. This network is a **"surrogate model"**, or:
  - **Input layer:** ED/ES **shape modes**, pressures. **Output layer:** unloaded shape modes, material properties. This network is an "**inverse model"**.
  - Which approach will converge better is not obvious but the required training data are the same for both.
  - Our hypothesis is that this strategy will be much more feasible, if we train the models with or to learn a modest number of **shape modes** (say 25) than using the large number of degrees of freedom (nodal coordinates) defining the ventricular geometry in the FE models. In other words, the shape atlas is our *latent space*

Practical First Steps

- Familiarize yourself with Anna's workbook for generating points clouds from shape modes corresponding to unloaded shapes and integrating to get volumes and masses
- Use Henrich's scripts to generate unloaded FEniCS meshes from point clouds
- Assign fiber angles (these can be the same for all models)
- Identify a suitable ED and ES constitutive law (Ideally do not assume uniaxial active tension: x-fiber active stress = 0.3x fiber active stress should work better)
- Learn to run an elastic FE model for passive filling to EDP and active contraction to ESP
- Save computed ED and ES shapes and resolve atlas modes
- Identify ranges ED and ES material constants consistent with the expected ranges of ED and ES volumes for known ranges of ED and ES pressures. (This can all be done with a single mean shape model)
- Decide how many constitutive parameters to sample. e.g. A single systolic and diastolic scaling parameter and a hypercube of fixed or random low/med/high values
- Simulate ED and ES solutions in the range of low to high EDP and ESP. Note that this does not require multiple separate simulations just load stepping up to reasonable maximum pressures.
- Hence with one geometry you can generate many solutions for different pressures and material properties
- Repeat for another unloaded geometry