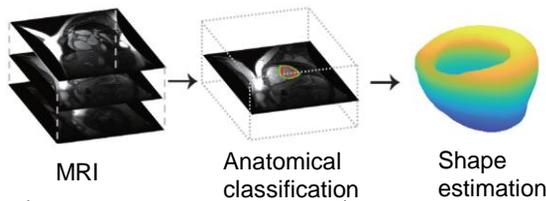


#### Abstract

Cardiovascular disease is one of the leading causes of both morbidity and mortality all over the world. **Early diagnosis and treatment planning are demanded** for the wide variety of etiologies and pathophysiologies. In the last decades, intensive research in the field of computational biology has demonstrated the potential ability of three-dimensional (3D) cardiac computational models to give us a clue to perform early diagnosis or to have high affinity with machine learning for treatment planning. We introduces some **physical laws into a Gaussian process for a statistical 3D cardiac computational model**. The heart shape must be ruled by some physical laws, which should be an important clue for the statistical shape estimation. For demonstration, we apply our model into the pipeline that estimates the heart shape from cardiovascular magnetic resonance (CMR) imaging, by combining it with the deep neural networks-based anatomical segmentation of CMR imaging.

#### Heart shape estimation

- Cardiac modeling from magnetic resonance imaging (MRI)



Deep learning for classification

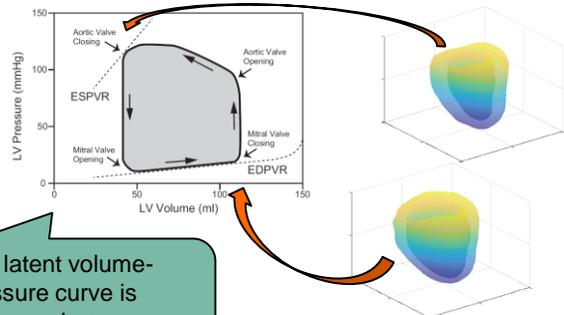
Statistical shape modeling for regression

State-of-the-art deep nets [2]

**Our contribution:** Gaussian process (GP) with physical laws for the heart shape [1]

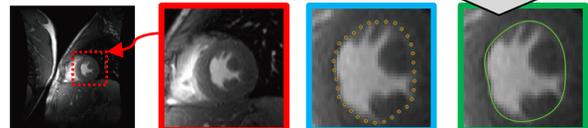
#### Regression with physical laws

- The Frank-Starling law is introduced into a Gaussian process-based statistical shape model.



The latent volume-pressure curve is expressed as a hidden Markov model.

Our method can obtain the similar shape to that handles by experts.



From left to right. **First:** MRI. **Second:** Zoom-in. **Third:** The endocardium manually handled by experts. **Fourth:** Predictive endocardium.

#### Difficulty

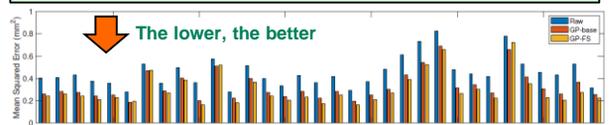
- It is not easy to obtain training datasets for the heart shape, which is typically handled by experts.

➔ We introduce physical law into unsupervised learning.

- It is difficult to estimate details of the heart shape, since MRI provides only statistical information locally averaging over time and space.

➔ We extend the static model into a time-varying statistical shape model.

#### Goal: shape prediction comparable to experts



Mean squared error comparison between baseline methods and our model.

For 29 out of 33 subjects, the mean squared error is improved by around 9%.

■ Raw: Regression without GP fitting.  
 ■ GP-base: GP without physical laws.  
 ■ GP-FS: GP with the Frank-Starling law.

#### References

- M. Nakano, R. Shibue, K. Kashino, S. Tsukada, H. Tomoike, "Gaussian process with physical laws for 3D cardiac modeling," under review.
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