

Haptic Modeling of Inhomogeneous Viscoelastic Objects



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Introduction

- This work provides a new approach for modeling of inhomogeneous viscoelastic deformable objects.
- Employs the principles of feature-based learning and perceptual adaptive sampling mechanisms to reduce the dataset.
- A single random forest-fractional derivative (RF-FD) based data-driven model is trained on the reduced dataset.
- The existing clustering based solution in the literature where one model is trained for each cluster.
- Results demonstrate that the proposed approach provides a better prediction accuracy in estimating the responses on inhomogeneous objects as compared to the existing solution in the literature.

Data Collection

- Data is collected using a force-feedback device and a load cell, recording position-force measurements with an inverted cosine force control signal.
- Three physical mockups made of soft silicone (Ecoflex 0010 from SmoothOn Inc.) are used for the experiments, referred to as Object O₁, Object O₂ and Object O₃.
- For each object, data is collected from 200 randomly selected contact locations within a 60 mm by 50 mm modeling area that exhibits a high level of inhomogeneity.

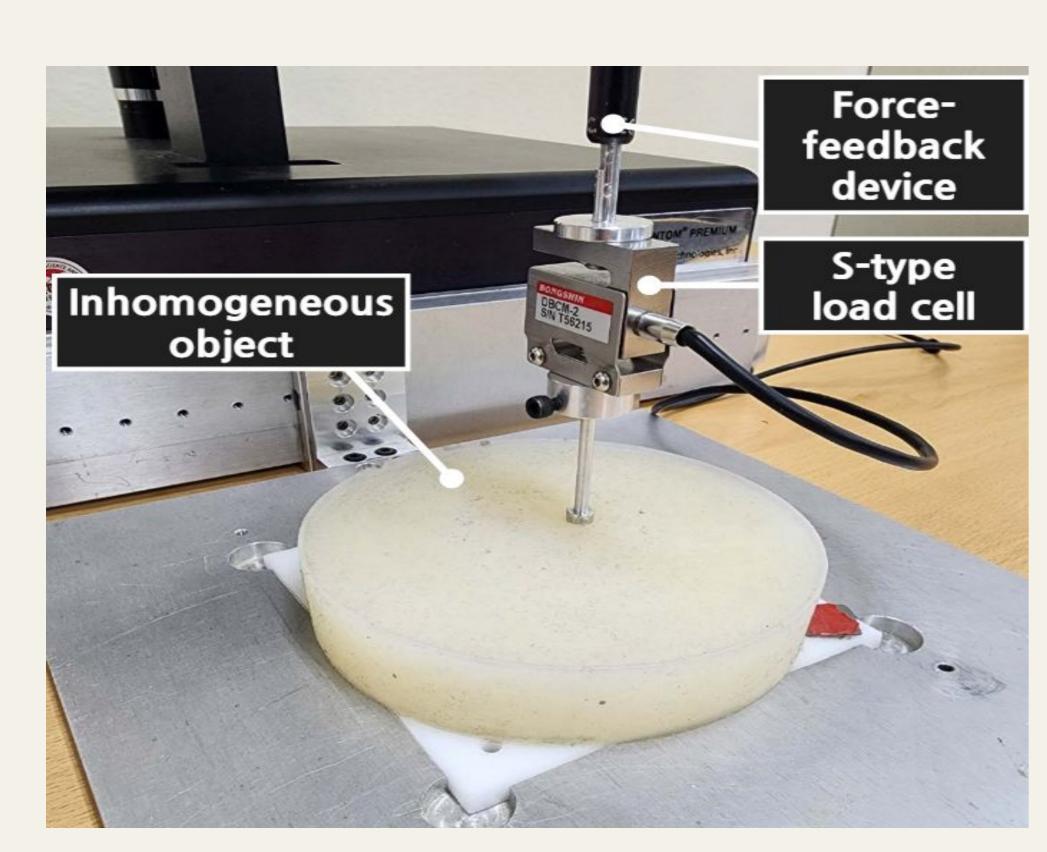
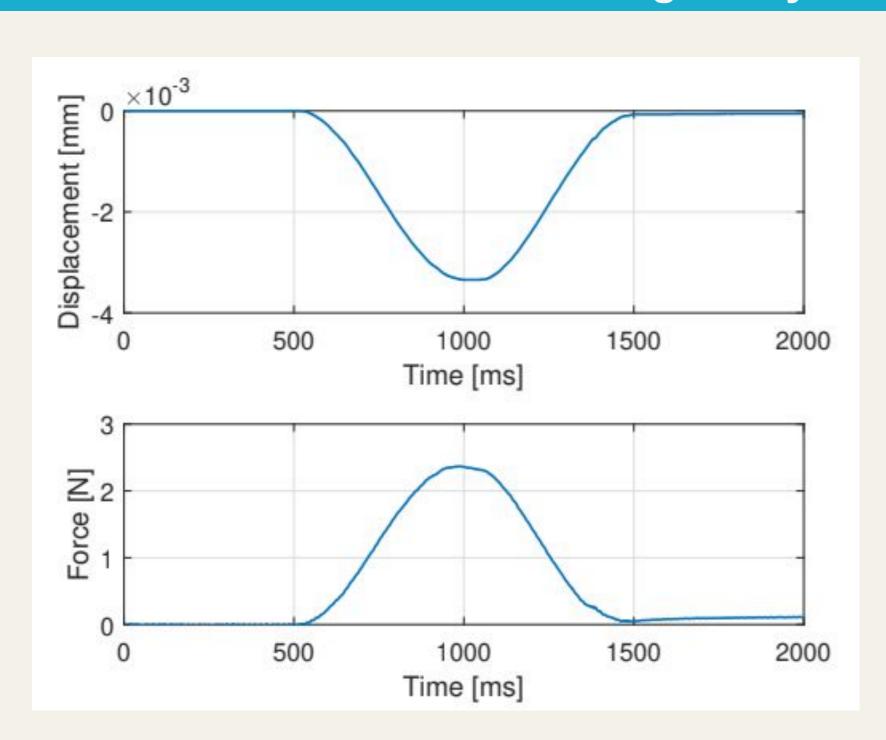
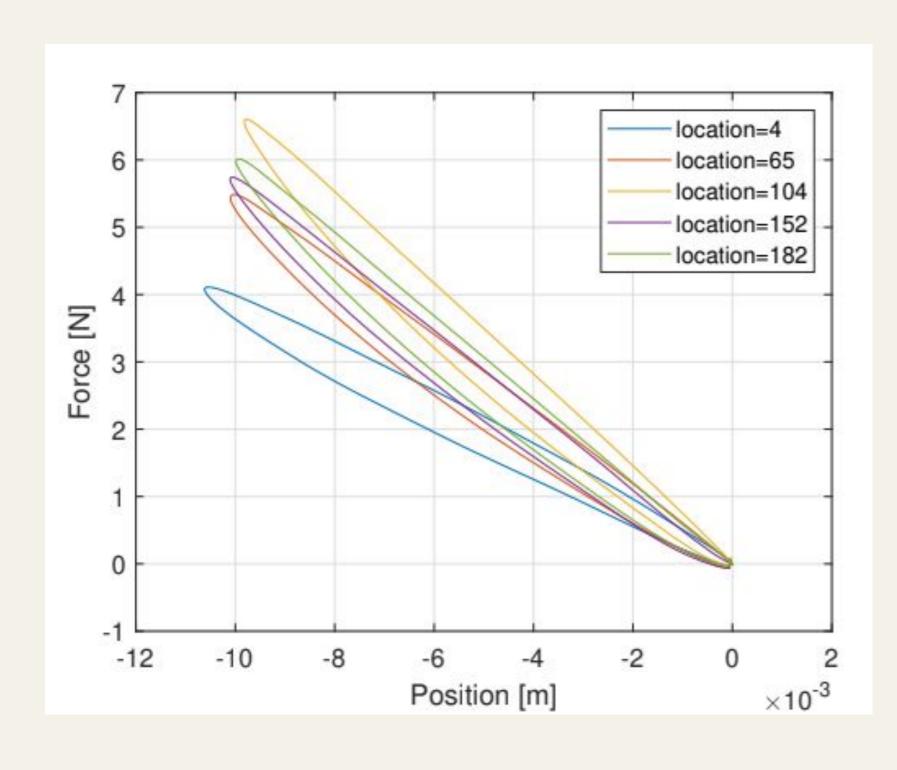


Illustration of inhomogeneity

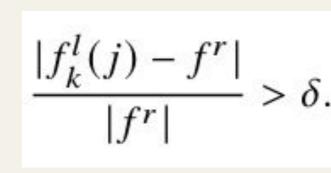


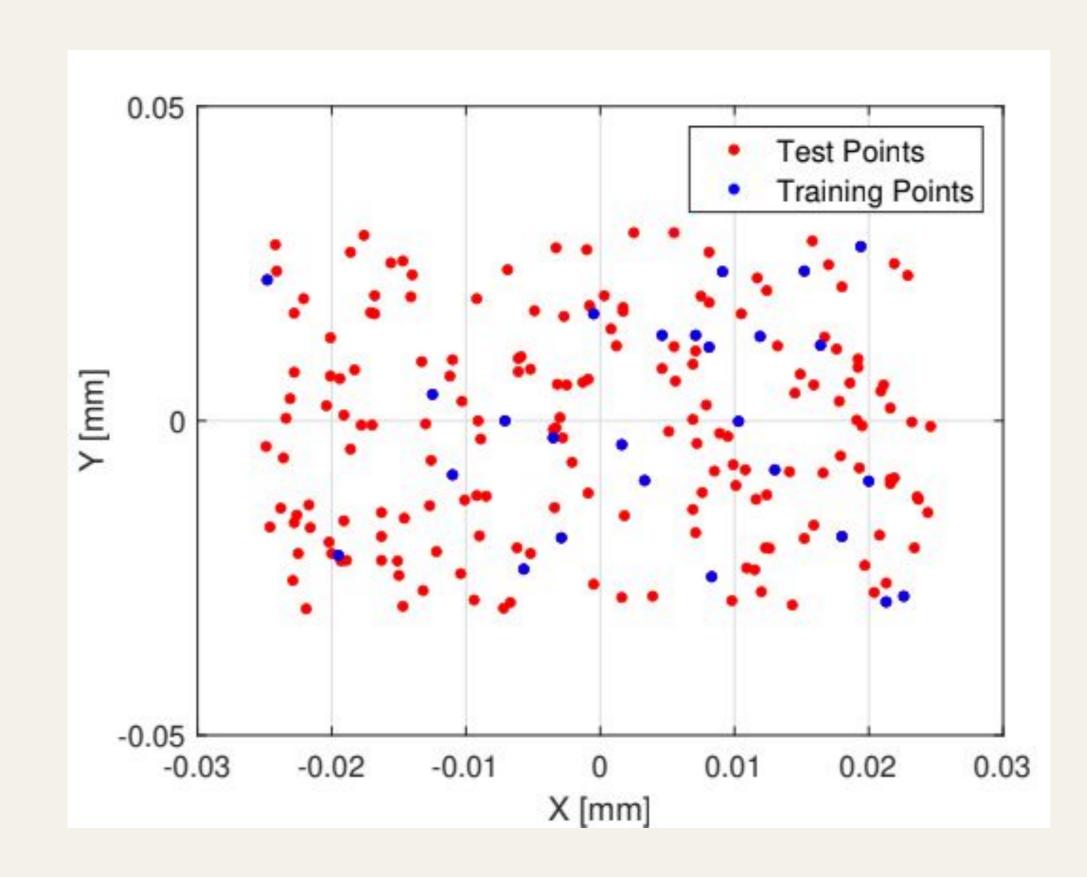


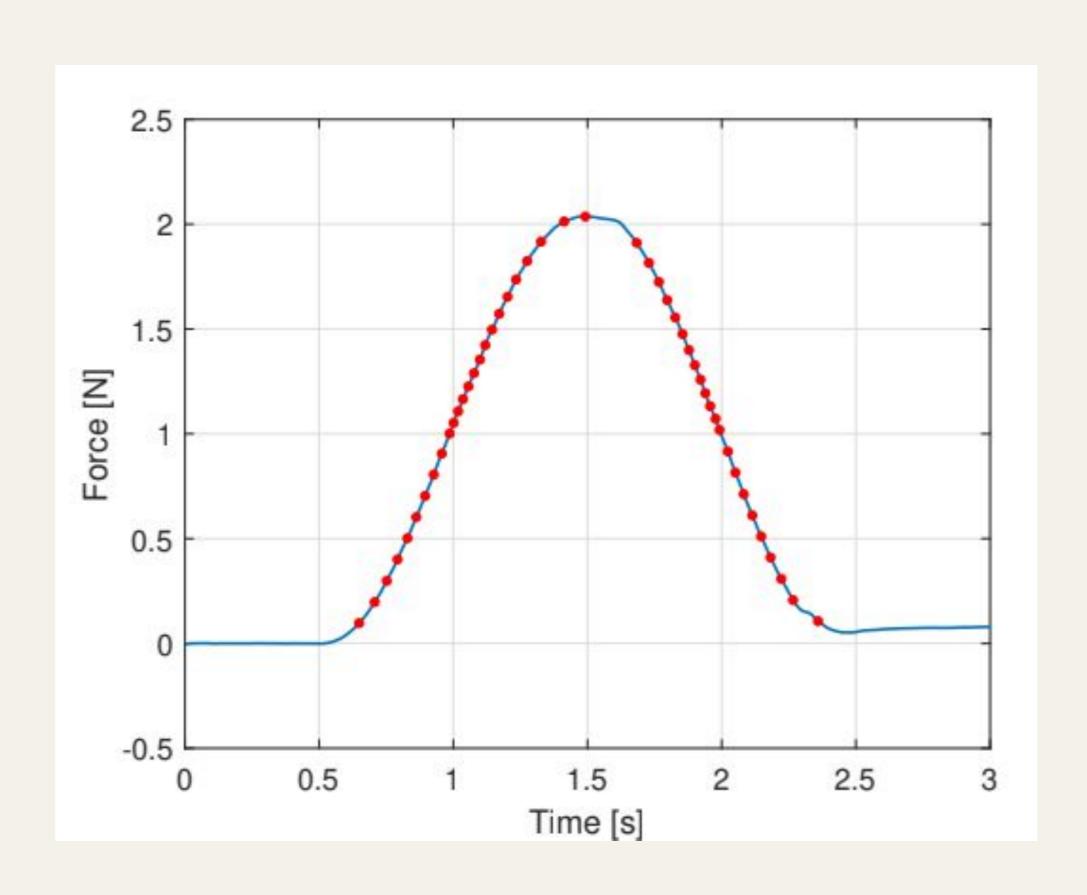
Feature-based Learning and Perceptual Sampling

Feature-based Learning for Location Selection $f^l \approx c_{0,l} + \sum_{n=1}^N \left[c'_{n,l} \cos(n\omega t) + \mathrm{j} \ c''_{n,l} \sin(n\omega t) \right]$

Perceptual Sampling for Significant Sample Selection:







Haptic Modeling: RF-FD

- A RF-FD (Random Forest with Fractional Derivatives)
 data-driven model is used to learn a non-parametric mapping
 function between input (position) and output (force) samples.
- The model's input features include fractional derivatives (FDs) of position information and the X-Y position of the contact location. Ten orders of FDs are used, ranging from 0.05 to 0.50.

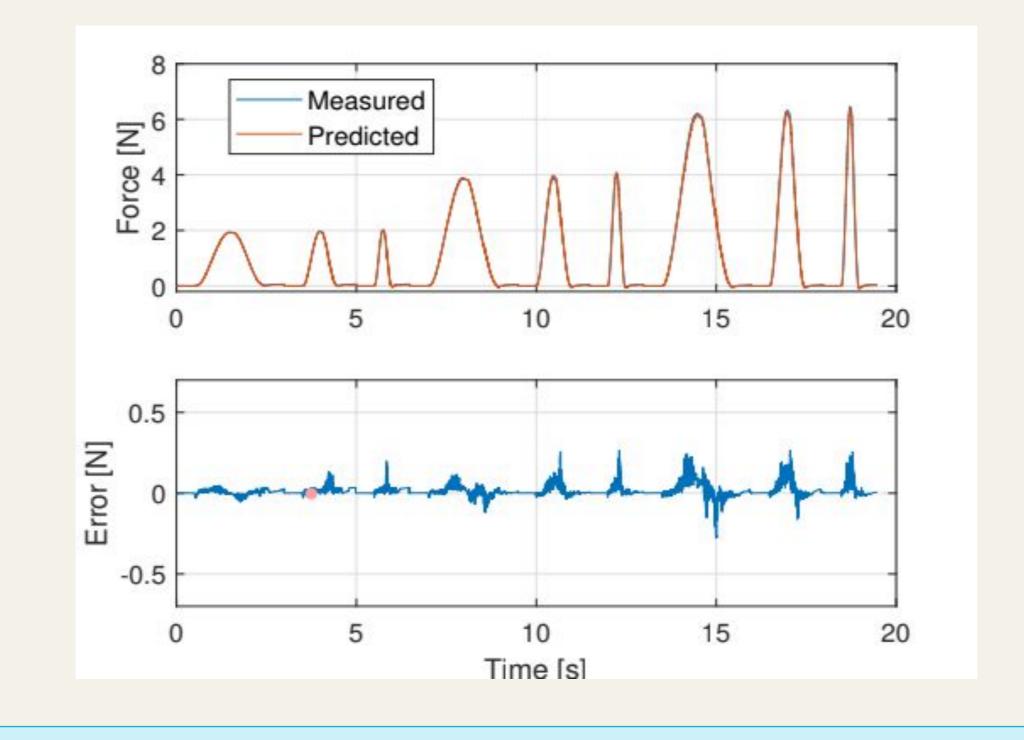
$$I[n] = (X, Y, D^{r_1}d[n], D^{r_2}d[n], \cdots, D^{r_{10}}d[n])$$

$$\mathbf{I}_k = \{I[i] | I \in \mathbb{R}^{12}, i \in S_k\}$$

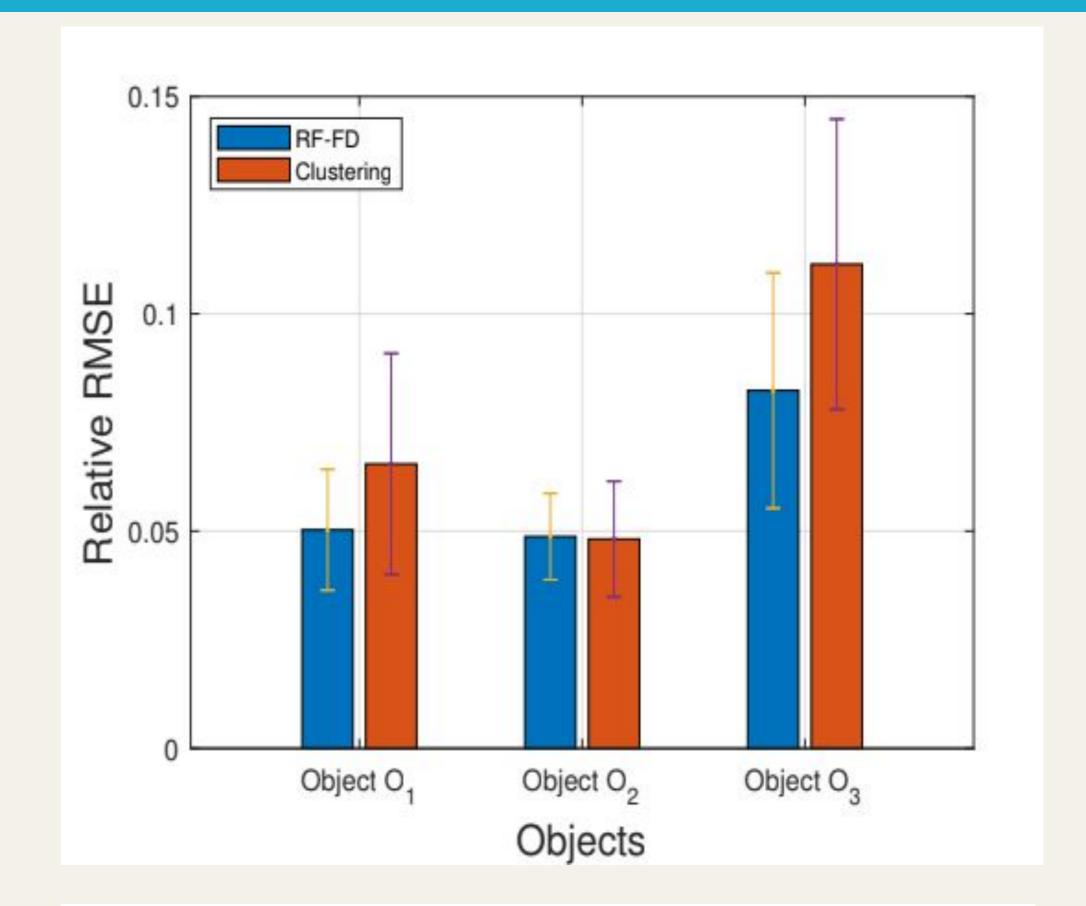
$$\mathbf{f}_k = \{f_k[i] | f_k \in \mathbb{R}, i \in S_k\}$$

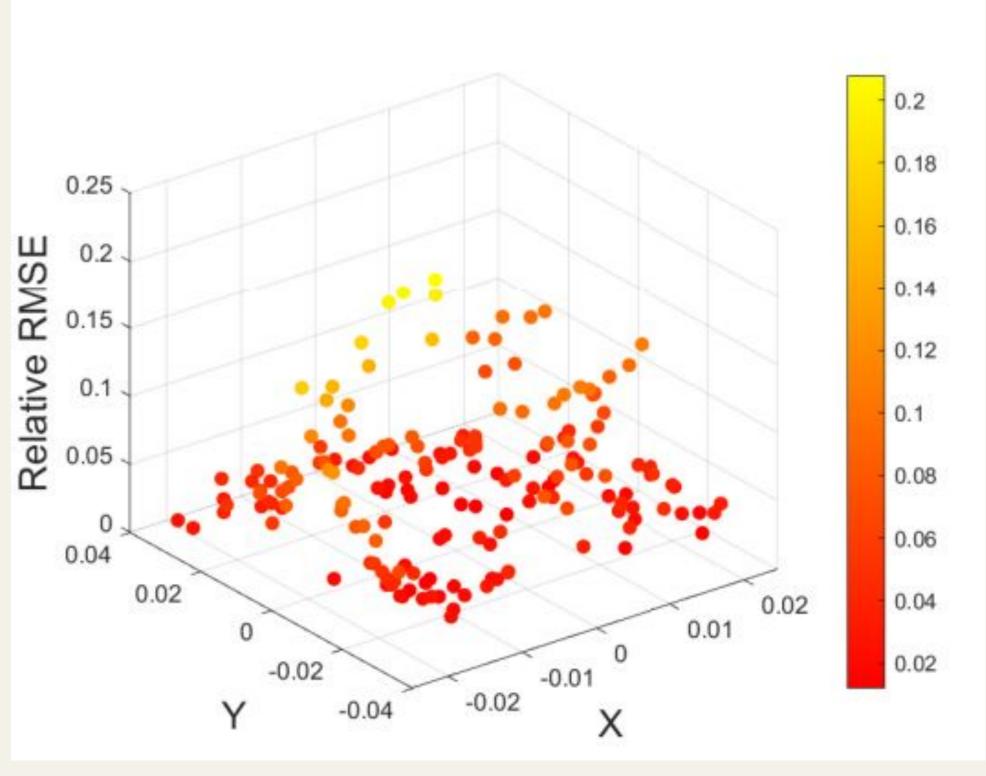
$$\mathbf{I}_g = {\{\mathbf{I}_k | \mathbf{I}_k \in \mathbb{R}^{12 \times \bar{T}_k}, k = 1, 2, \cdots, T_r\}}$$

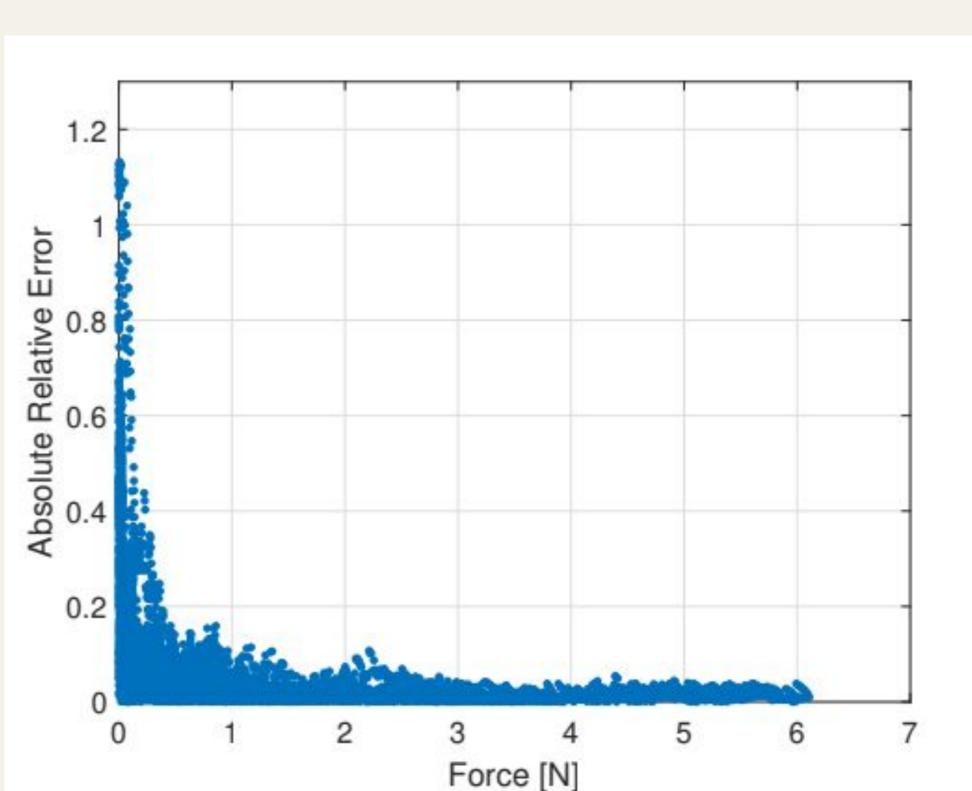
$$\mathbf{f}_g = \{\mathbf{f}_k | \mathbf{f}_k \in \mathbb{R}^{1 \times \bar{T}_k}, k = 1, 2, \cdots, T_r\}$$



Results







Conclusion

- The approach required to train just one RF-FD based data-driven model on the reduced dataset for modeling an inhomogeneous deformable object.
- Single trained model predicts interactions at unknown locations of the objects with good accuracy.
- Requires a much lesser number of trained models as compared to the existing clustering based solution.
- Provides better prediction accuracy in terms of the RMSE and maximum error..

Acknowledgement

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