

# ADAPT in SC: Utilizing Change Point Detection for Structural Dynamic Response Classification

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## Abstract

❖ Change point detection methods offer the ability to classify the dynamic response of structures subjected to shock and vibration events.

❖ Grounded in the premise that structural systems undergoing continuous vibrations exhibit distinct behavioral shifts when encountering shock events, this study introduces a framework for leveraging change point detection algorithms to analyze time series data from vibrational sensors.

❖ The study outlines the process of implementing various change point detection algorithms, including both parametric and non-parametric methods, to identify critical transitions within vibration data.

## Forced Vibration and Shock Data

A dataset (<https://github.com/High-Rate-SHM-Working-Group/Dataset-7-forced-vibration-and-shock>) that looks at PCBs under continuous vibration before undergoing a shock event.

This dataset contains the measured acceleration data for an electronics unit under continuous vibration before undergoing a shock test. Figure 1 presents the experimental test configuration where the package is mounted on a Lansmont Model P30 shock test system designed to generate a continuous forced vibration before, after, and during a shock event [here](#). The accelerometer is a PCB Piezotronics 352A92 measured at 1 MS/s.

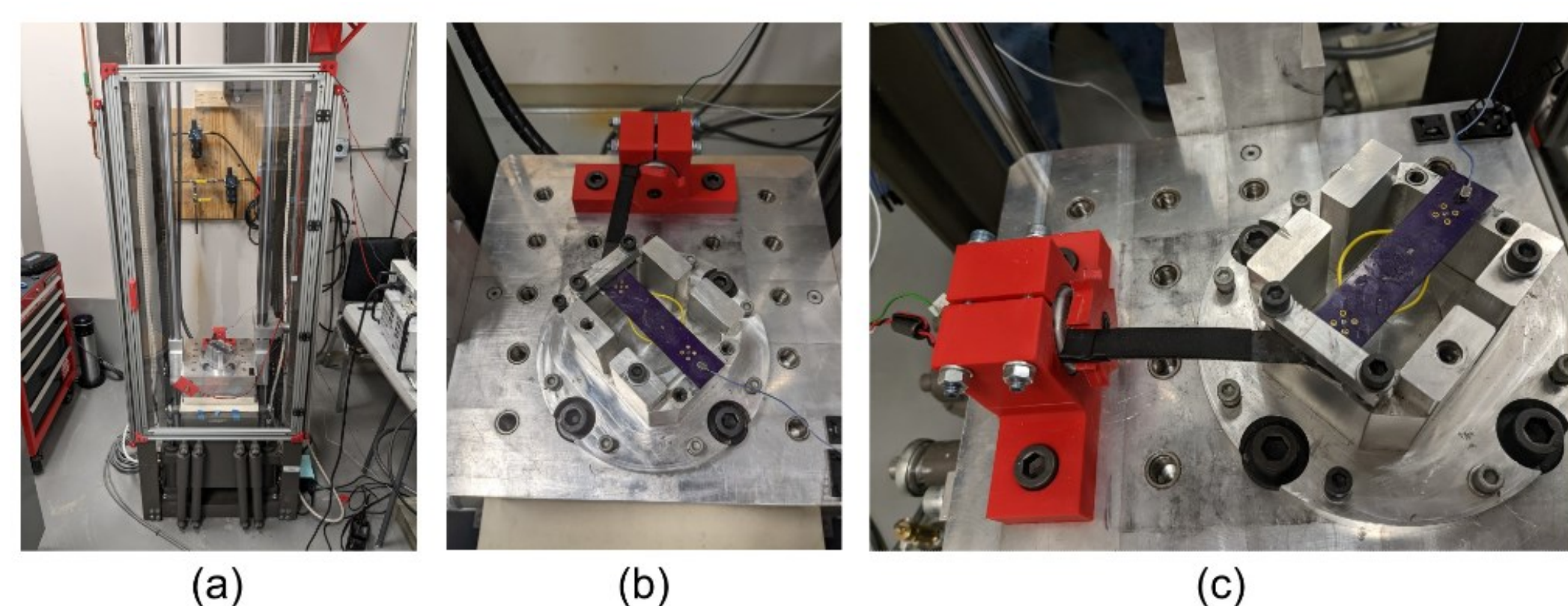


Figure 1: Image of the test, showing: (a) the shock test system, (b) the front view of the test setup on the drop table, and (c) the side view of the test setup on the drop table. (click the image to view a video of the test on YouTube).

## Methodology

Machine learning detection methods were used. Hyperparameters were determined using a training dataset. Unseen datasets were used for testing. Methods used:

K-Means, Gaussian Mixtures, Elliptic Envelope, Isolation Forests, Local Outlier Factor

## Results

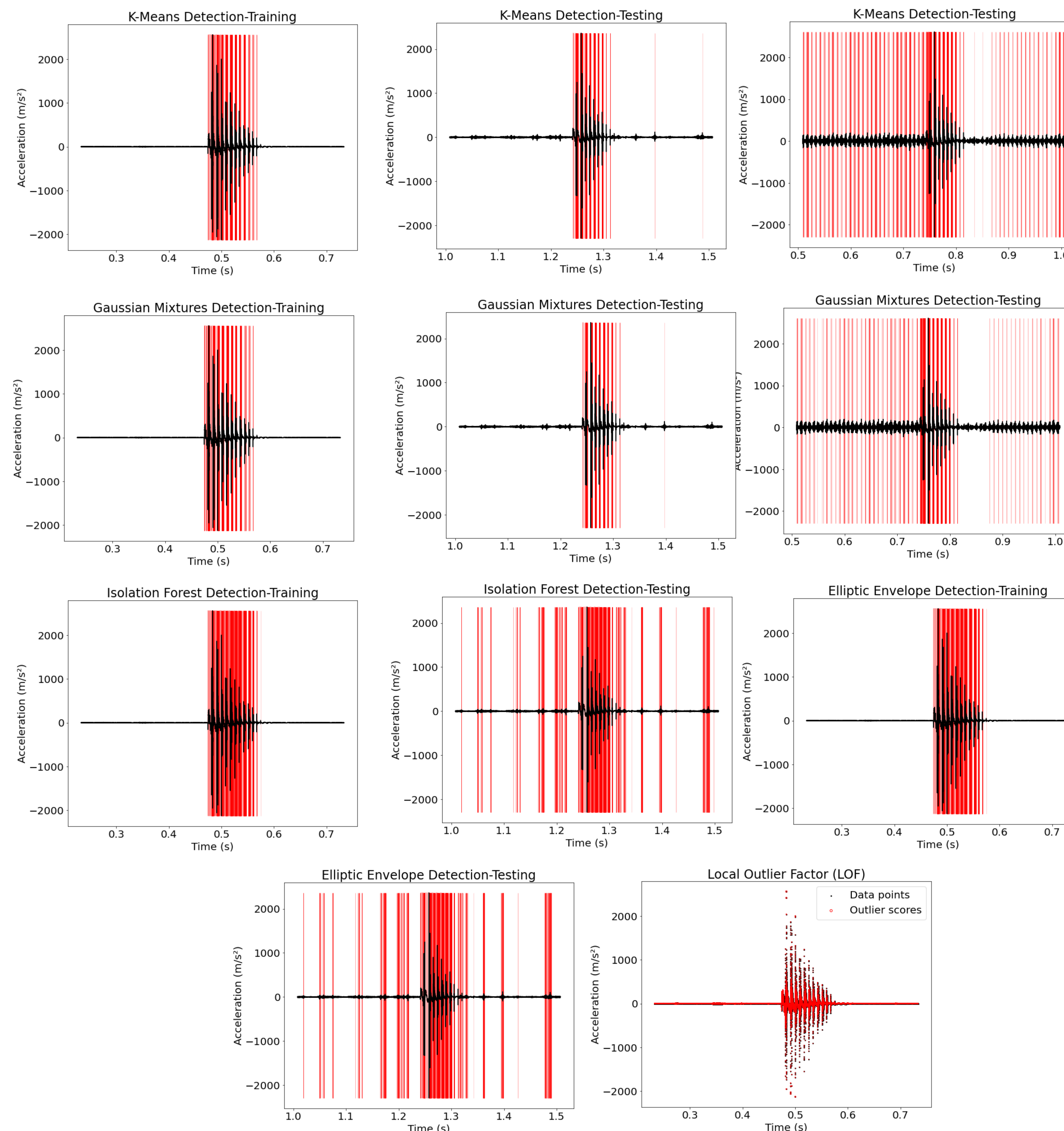


Figure 2: Performance of the models used for detecting vibration and shock states

## Conclusions and Future Work

❖ This approach is predicated on the hypothesis that significant changes in the data's statistical properties—such as mean, variance, and frequency—can effectively signal the onset and cessation of shock states, thus providing a clear demarcation of structural response phases.

❖ The effectiveness of these algorithms is evaluated through a series of experiments involving both simulated and real-world structures subjected to controlled impact tests. Future directions are suggested for integrating change point detection with other analytical techniques to enhance the predictive capabilities of structural health monitoring frameworks.

❖ We trained machine learning models to detect vibration and shock states for high-rate data.

❖ ML-based models are promising in detecting the states.

❖ Computational times are  
 ❖ K-Means < Elliptic Envelope < Gaussian Mixtures < Local Outlier Factor

❖ Rolling windows framework will be set up for the models.

❖ Computational times will be tracked if the methods can be used in real-time.

## Acknowledgments

- ❖ This research was supported by
  - ❖ Tier I UTC C2M2, Clemson lead
  - ❖ National UTC TraCR, Clemson lead
  - ❖ Department of Energy Minority Serving Institutions Partnership (MSIPP)-SRNL TOA 0000525174 CN1.
  - ❖ FMCSA, FM-MHP-0678-22-01-00
  - ❖ NASA ULI (University of South Carolina-Lead),
  - ❖ NSF Grants Nos. 1954532, 2131080, 2200457, 2234920, and 2305470.
  - ❖ ADAPT in SC, NSF OIA-2242812
  - ❖ MSEIP II Cyber Grants: P120A190061, P120A210048

## References

1. Devon Goshorn, Joud Satme, and Austin Downey. Dataset-7-forced-vibration-and-shock, October 2019. URL: <https://github.com/High-Rate-SHM-Working-Group/Dataset-7-forced-vibration-and-shock>
2. Pedregosa, Fabian, Gaël Varoquaux, Alexandre Gramfort, Vincent Michel, Bertrand Thirion, Olivier Grisel, Mathieu Blondel et al. "Scikit-learn: Machine learning in Python." The Journal of machine Learning research 12 (2011): 2825-2830.