Proceedings of The ASME 2024 Conference on Smart Materials, Adaptive Structures and Intelligent Systems
SMASIS2024
September 9-11, 2024, Atlanta, GA, USA

SMASIS2024-111009

REAL-TIME SHOCK EVENT CLASSIFICATION FROM UNIVARIATE STRUCTURAL RESPONSE MEASUREMENTS

Zhymir Thompson
Department of
Mechanical Engineering
University of South Carolina
Columbia, South Carolina 29208
Email: zhymir@email.sc.edu

Gurcan Comert
Department of
Engineering and Computer Science
Benedict College
Columbia, South Carolina 29204
Email: gurcan.comert@benedict.edu

Devon Goshorn
Department of
Mechanical Engineering
University of South Carolina
Columbia, South Carolina 29208
Email: goshorna@email.sc.edu

Joud N. Satme
Department of
Mechanical Engineering
University of South Carolina
Columbia, South Carolina 29208
Email: jsatme@email.sc.edu

Austin R.J. Downey
Department of
Mechanical Engineering
Department of Civil and
Environmental Engineering
University of South Carolina
Columbia, South Carolina 29208
Email: austindowney@sc.edu

Jason D. Bakos
Department of
Computer Science and Engineering
University of South Carolina
Columbia, South Carolina 29208
Email: jbakos@cse.sc.edu

ABSTRACT

To enable real-time control of next-generation active structures during shock events, there is a need to identify the start of a shock event within microseconds of its initiation. The delayed classification of a shock event may cause damage to the system that could have been prevented with assumed next-generation active control mechanisms. Addressing the challenge of ultra-low latency shock event classification requires utilizing prior information on normal behaviors (i.e., the system under vibrational loading) to identify abnormalities that can be classified as features of a shock event. The purpose of changepoint shock classification is to automatically recognize when a structure of interest behaves differently than expected in some measurable way. In this work, we analyze two different methods for shock classification using changepoint methodologies. We study the use of adaptive cumulative summation and expectation maximization algorithms in this work. Each method presents advantages and disadvantages for different scenarios. This study aims to derive features (streams of time series data) for the changepoint algorithms and revise the changepoint models to be used in real-time robust shock event detection. In this work, a printed circuit board under continuous vibrations before, during, and after a shock event is used to investigate the proposed methodologies. The printed circuit board is monitored with an accelerometer that is used to monitor both the vibrational and shock state of the system. The vibrational response of the system consists of accelerations up to 20 $\mathrm{m/s^2}$, while the shock event consists of loadings up to 2,000 $\mathrm{m/s^2}$. This work showed that the CUSUM algorithm is fairly effective at identifying the shock state in data but generates many false positives during normal behavior times, with no false positives post-shock, indicating accurate shock state detection despite early errors. In contrast, the Expectation Maximization (EM) algorithm shows improved performance by correctly predicting no shock in the initial phase and accurately identifying

the onset of the shock state. It occasionally misclassifies shocked points as normal due to its change point identification process. Compared to CUSUM, EM has fewer false positives before the shock and similar performance during and after the shock event. Future research efforts will focus on developing online versions of these algorithms, which can identify system states with a minimum number of errors. The limitations of the system and its robustness to noise are discussed.

INTRODUCTION

Buildings and vehicles are examples of structures that are expected to undergo stress regularly. These structures encounter both static, consistent stress and sudden inconsistent stress throughout their lifetimes, and are expected to respond appropriately to mitigate damage. Static stress could be the weight of the structure itself, or some force applied consistently to the structure. Inconsistent stress could be an earthquake, a sudden impact, or a strong gust of wind. High-rate dynamic events are an extreme of the second type of stress described. High-rate dynamic events are such where high force (> 100gn) is applied to a structure in a short time-frame (< 100 ms) [1]. All of these types of stress are usually expected to occur at some point, but it is not definitively known when exactly that time will come.

Structures can be designed to respond to both of these types of stress. Mitigation strategies can generally be split into passive and active damage mitigation. Passive damage mitigation involves designing a structure that is capable of responding to stress without processing data to make a decision. Active damage mitigation relies on a device to make a decision given some input and execute a specific behavior to respond. Passive damage mitigation tends to be more common, and structures are designed with their expected wear in mind. For example, cars incorporate crumple zones in the front and rear to reduce impact from head-on collisions. Buildings are designed with a strong foundation and numerous support points to improve their integrity. Shock events, sudden impacts that disturb and excite the normal modes of a structure [2], are inconsistent, dynamic events. Since shock events excite the preexisting modes of a structure, an active mitigation strategy would first need to be able to identify abnormal behavior compared to expected behaviors. Further, to respond to and reduce the impact of these unexpected shock events effectively, one would need to classify and respond to the event in real-time.

Real-time identification of aberrant behavior requires both a fast algorithm and suitable hardware. There are several methods for detecting these changes. However, not all of these methods are fast enough to be used in real-time identification. Similarly, not all of these methods are suitable for use on an edge device. If a method requires too much memory such that it cannot reasonably fit on an edge device, it is unlikely to be capable of performing under real-time performance constraints.

Changepoint detection algorithms are an existing collection of methods for detecting abnormal behavior in a sequence of observations [3]. Changepoint detection algorithms are divided into offline and online algorithms. Offline algorithms typically take a sequence of observations and an expected number of changepoints as input. They then compute the optimal changepoints to divide the data. Online changepoint detection algorithms normally utilize statistics and prior knowledge about the expected data to decide if some given observation deviates enough from what is expected to constitute labeling as abnormal. Offline algorithms work best when the number of changepoints is known. They tend to be more accurate, but they also tend to be significantly slower as a tradeoff. Online algorithms tend to be less accurate, but in exchange, they are faster. A selection of online methods for the detection of changepoints are described. Specifically, the pros and cons of the Cumulative Summation (CUSUM) and Expectation Maximization (EM) algorithms are weighed.

METHODOLOGY

This section explains the experimental setup and machine learning model developed for this work

Experimental setup

A custom dataset was developed for this work that seeks to mimic an electronic system under continuous excitation that experiences a shock event. To expand, the developed dataset mimics an electronic system on a car driving down the road (i.e. continuous vibrations) where it then encounters a pothole (impact). The experimental system is shown in Figure 1 where the electronics package is mounted on the table of a Lansmont Model P30 shock test system. A DC motor in a 3D-printed housing drives a click wheel that is connected to the mount holding the printed circuit board (PCB) using a short carbon steel beam. Then, by exciting the PCB with the click-wheel actuator and subjecting it to shock loading using the drop table, the setup generates a continuous forced vibration before, after, and during a shock event. An accelerometer (model 352A92 manufactured by PCB Piezotronics) was used to record acceleration at a rate of 1 MS/s. This dataset has been made available through a public repository [4].

Figure 2 displays the acceleration data for the dataset along with overlays for different sections of interest. The leftmost overlay shows the normal oscillations of the circuit board. The acceleration is normally around 10 $\mathrm{m/s^2}$ occasionally increasing to at most 20 $\mathrm{m/s^2}$. These oscillations last for about 45 microseconds before the disruption to the system. The disruption occurs about 45 microseconds into the experiment run. The acceleration spikes and the system is considered to be in a state of shock. The acceleration spikes to over 2,000 $\mathrm{m/s^2}$ before slowly dropping down to pre-shock levels. The spikes are consistent and decrease

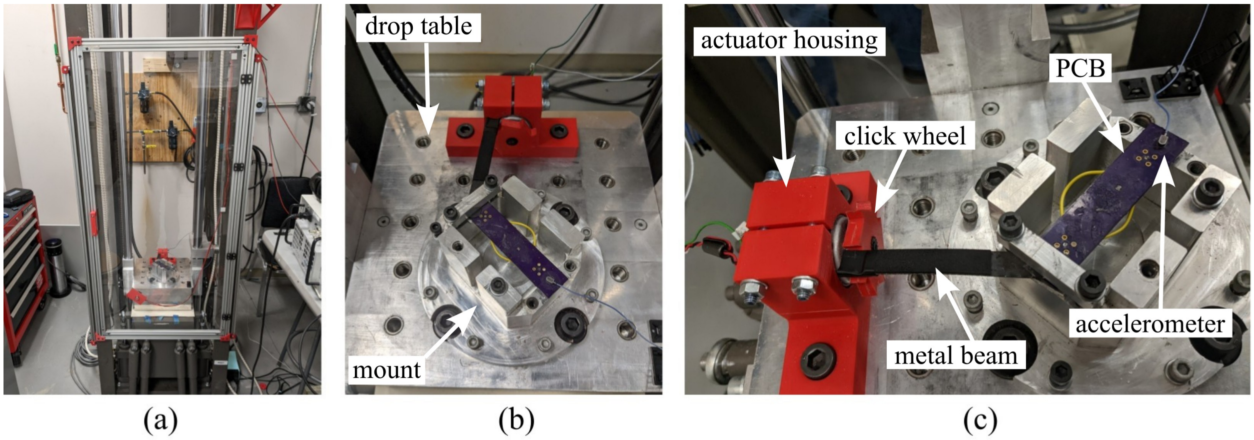

FIGURE 1. Image of the test, showing: (a) the shock test system, (b) the front view of the test setup on the drop table, and (c) the side view of the test setup on the drop table.

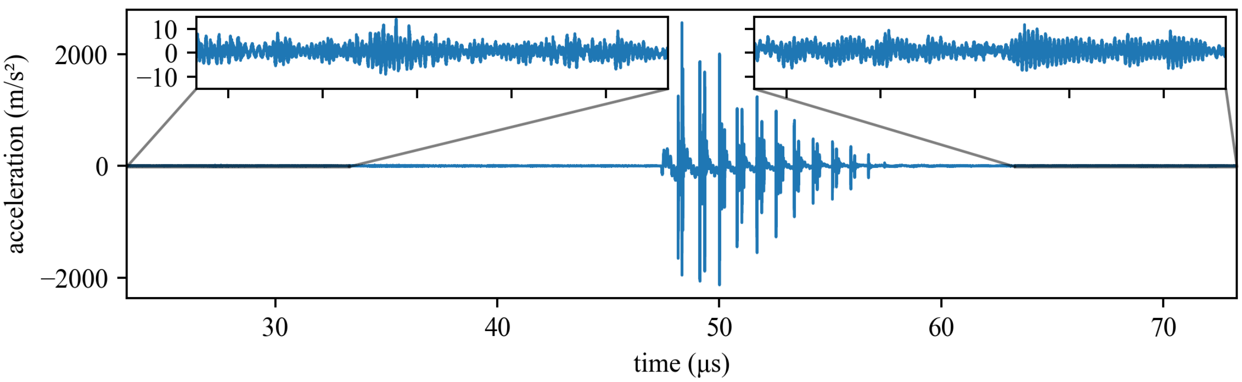

FIGURE 2. A plot of the accelerometer data. Overlays are included to zoom in on sections of the data before and after the shock event.

to a base level. The rightmost overlay shows the aftermath of the shock event. The signal has returned to acceleration values reminiscent of those before the shock was introduced.

The difference between normal and abnormal acceleration is expressed in Figure 2. The peak acceleration at shock is two orders of magnitude higher than the peak acceleration before the shock. A change in dynamics occurred between 45 microseconds and 58 microseconds. The point at which the change began is more difficult to determine. The change occurred before the first peak, but visually that specific point is nearly impossible to determine. This task becomes even more difficult in the moment. A sudden increase in acceleration could be the start of a shock or accountable error. It is also difficult to determine at what point the system is no longer in a state of shock. By 60 microseconds the effects of the shock had dissipated. The effects could have worn off at 57 microseconds or 59 microseconds. The exact point at which a shift to normal behavior occurred is difficult if not impossible to pinpoint.

Figure 3 shows the power spectrum for different sections of time in the example signal. (a) and (c) have similar power spectra while (b) differs noticeably. This is further evidence that the effects of the shock had mostly dissipated by the end of the experiment. This difference also hints at what one would expect a sufficient shock classification model to infer.

Model Development

Two methods are demonstrated in this work. Here we briefly explain the methods and their pros and cons.

Adaptive cumulative summation is an online method for detecting potentially abnormal events for a given sequential process [5]. The adaptive Algorithm 1 compares the means of the previous and current events to determine if the current event is likely to be a change.

The direct usefulness of the CUSUM algorithm lies in quality control, where the mean process level is monitored by the CUSUM chart or algorithm. In this study, CUSUM is used to monitor the state while detecting changes. The method assumes

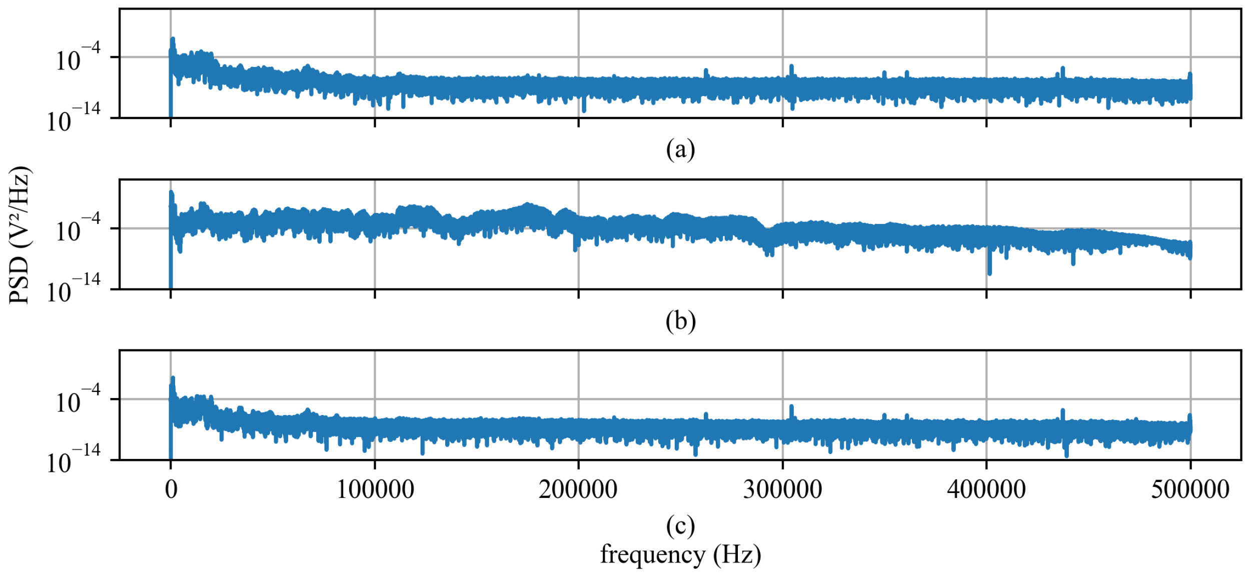

FIGURE 3. Power spectrum for the data in Figure 2. (a) is the spectrum for the time period before the shock, (b) is for the time period containing the shock evenet, and (c) for after the shock.

an identically independently distributed variable Y_i having known (μ_1, σ^2), and μ_2, a new process mean of the variable Y_i which is estimated after observing a possible shift. Following CUSUM parameters are selected: $K = \delta\sigma/2$, $H = 5\sigma$, and $\delta = 1$.

Algorithm 1 CUSUM for detecting changes in series of N observations

Require: Choose parameters, $\mu = \overline{Y}_{1:20}$, $\sigma = \sqrt{S^2_{Y_{1:20}}}$, $K = \delta\sigma/2$, $\delta = 1$, $\alpha = 0.025$

Choose parameters, H is set to 5σ
for $Y_i \ni i \in 1:N$ **do**
  $C_i^+ = \max\{0, C_{i-1}^+ + \frac{\alpha D_i}{\sigma^2}[Y_i - D_i - \alpha D_i/2]\}$
  $C_i^- = \max\{0, C_{i-1}^- - \frac{\alpha D_i}{\sigma^2}[Y_i + D_i + \alpha D_i/2]\}$
  $D_i = \overline{\mu}_{i-1} - \mu_i$
  $\overline{\mu}_i = \alpha\overline{\mu}_{i-1} - (1-\alpha)Y_i$
  if $C_i^+ > H$ or $C_i^- > H$ **then** Y_i is a change of state, set: $C_i^+ = C_i^- = 0$
  end if
end for

The adaptive algorithm is used for processes having other than zero means, and it has a single weight parameter (α) [6]. In Algorithm 1, $D_i = (\bar{\mu}_i - \mu_1)$ and $\bar{\mu}_i = \alpha\bar{\mu}_{i-1} + (1-\alpha)Y_i$ at time step i. For fewer false positive detections, we have considered $H = 5\sigma$. The C_i^+ and C_i^- represent the positive deviations (values above the target) and negative deviations (values below the target), respectively. In this study, we do not assume the normal mean and standard deviations to be known. We calculate them from a few normal values as $\mu = \bar{Y}_{1:20}$, $\sigma = \sqrt{S^2_{Y_{1:20}}}$.

Algorithm 2 EM for detecting two mixtures in series of N observations

Require: Two classes of observations $X_{1:100} = [X_{1:70} \sim N(\overline{Y}_{1:70}, S^2_{Y_{1:70}}), X_{71:100} \sim N(100, 20^2), Y_i]$

Initialize parameters, $\Theta = (\mu_1, \mu_2, \sigma_1, \sigma_2, \pi)$ (alternatively from $X_{1:100}$)
for $Y_i \ni i \in 1:N$ **do**
  for $j \in 1:11$ **do**
    $p(Y_i \sim N(\hat{\mu}_2, \hat{\sigma}_2^2)) = \hat{\pi}\phi(Y_i|\hat{\mu}_2, \hat{\sigma}_2^2)[\hat{\pi}\phi(Y_i|\hat{\mu}_2, \hat{\sigma}_2^2) + (1-\hat{\pi})\phi(Y_i|\hat{\mu}_1, \hat{\sigma}_1^2)]$
  end for
  $\hat{\mu}_1 = \frac{\sum_{i=1}^N (1 - p(Y_i \sim N(\hat{\mu}_2, \hat{\sigma}_2^2))Y_i)}{\sum_{i=1}^N (1 - p(Y_i \sim N(\hat{\mu}_2, \hat{\sigma}_2^2)))}$
  $\hat{\mu}_2 = \frac{\sum_{i=1}^N p(Y_i \sim N(\hat{\mu}_2, \hat{\sigma}_2^2))Y_i}{\sum_{i=1}^N p(Y_i \sim N(\hat{\mu}_2, \hat{\sigma}_2^2))}$
  $\hat{\sigma}_1^2 = \frac{\sum_{i=1}^N (1 - p(Y_i \sim N(\hat{\mu}_2, \hat{\sigma}_2^2))(Y_i - \hat{\mu}_1)^2)}{\sum_{i=1}^N (1 - p(Y_i \sim N(\hat{\mu}_2, \hat{\sigma}_2^2)))}$
  $\hat{\sigma}_2^2 = \frac{\sum_{i=1}^N p(Y_i \sim N(\hat{\mu}_2, \hat{\sigma}_2^2))(Y_i - \hat{\mu}_2)^2}{\sum_{i=1}^N p(Y_i \sim N(\hat{\mu}_2, \hat{\sigma}_2^2))}$
  $\hat{\pi} = \frac{\sum_{i=1}^N p(Y_i \sim N(\hat{\mu}_2, \hat{\sigma}_2^2))Y_i}{N}$
  if $p(Y_i \sim N(\hat{\mu}_2, \hat{\sigma}_2^2)) > 0.01$ **then** Y_i is a change of state
  end if
end for

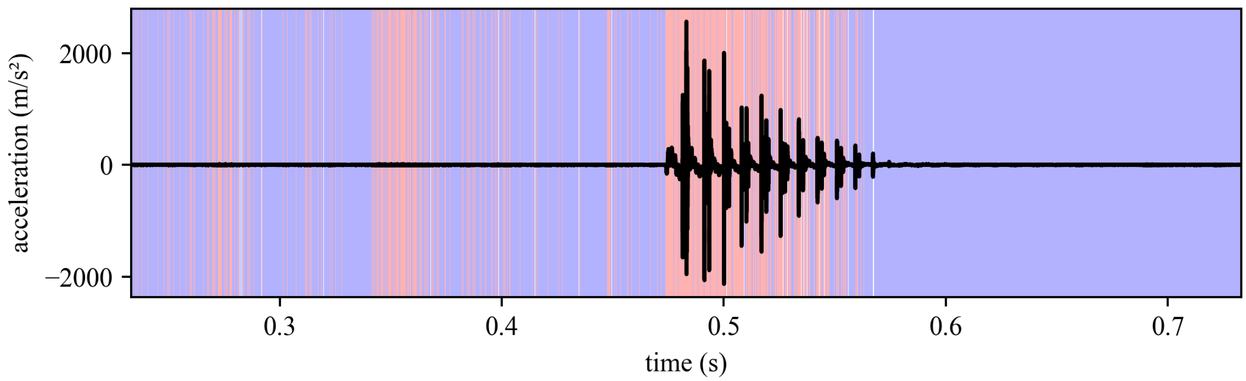

FIGURE 4. A plot of the shock states estimated by the CUSUM algorithm. Blue shading indicates the algorithm predicted the system was not in a state of shock. Red shading indicates the algorithms predicted the system was in a state of shock.

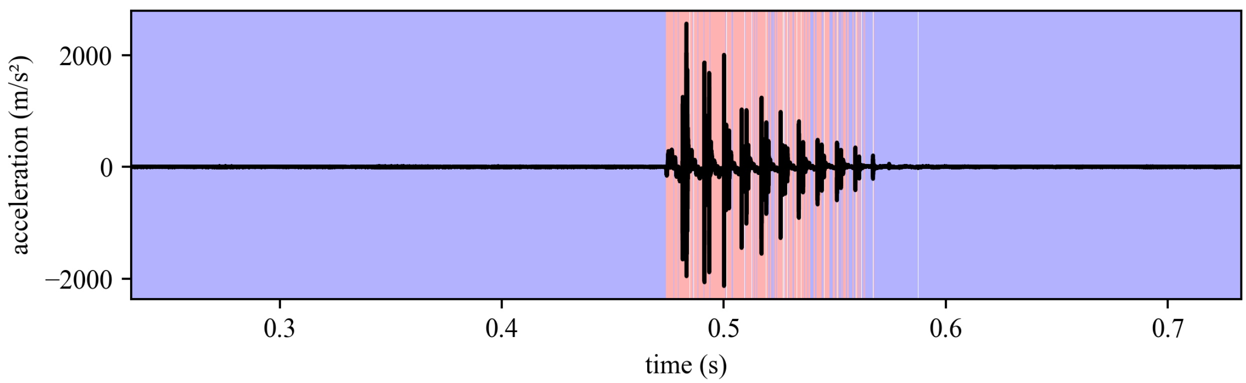

FIGURE 5. A plot of the shock states estimated by the expectation-maximization algorithm. Blue shading indicates the algorithm predicted the system was not in a state of shock. Red shading indicates the algorithms predicted the system was in a state of shock.

Gaussian mixtures classify input data as one of some number of groups [7,8]. Each event is compared to the prior statistics for previously classified events, and that information is used to classify the current event. We use the expectation maximization (EM) algorithm to calculate and update the prior information. The EM algorithm calculates the probability of an unknown event belonging to one of two groups given the prior information and samples from the groups. The algorithm goes back and forth between calculating these probabilities and updating the statistics data used to calculate them for some number of iterations. Finally, the Algorithm 2 computes the probability of an event being a change from a normal state with some percentage of certainty.

First, a list of sample data is generated to initialize normal and abnormal distributions. In this study, first hundred $(N-1)$ values of the data to generate 70 vibration data $X_{1:70} \sim N(\bar{Y}_{1:70},\ S^2_{\bar{Y}_{1:70}})$ and three significantly different values to represent possible unknown shocks, for instance $X_{71:100} \sim N(100, 20^2)$. Then, the new observation Y_i is estimated to belong to one of the states. We can initialize using a small no-shock sample data $X_{1:70}$ or by the expert opinion of no-shock/shock values. Parameters are initialized for (i) Gaussian no-shock observations and (ii) shock mean, variance, and proportion, denoted as $\Theta = (\mu_1,\ \mu_2,\ \sigma_1,\ \sigma_2,\ \pi)$. Then, until convergence, we calculate responsibilities for $N = 1, \ldots, 101$, where the last value X_{101} is Y_i, and the probability of shock is calculated $p(Y_i \sim N(\hat{\mu}_2, \hat{\sigma}^2_2)$.

Results

Figure 4 shows the plot of the states predicted using the CUSUM algorithm. The algorithm achieves a fair performance in identifying the shock state of the data. There are a multitude of false positives in the normal behavior time frame of the data. This is especially interesting since there are no false positives after the shock event. Despite the initial false positives, the model correctly identifies when the model entered a state of shock.

Figure 5 shows the inferred state of the data given by the EM algorithm. The algorithm correctly predicted that no shock occurred in the first 45 microseconds of the experiment. Further, the algorithm identifies the beginning of the shock state. There are points throughout the shock state that the algorithm determined were not shocked despite surrounding observations being shocked. This is due to the process that the algorithm uses to identify change points. The points identified as not being shocked have statistics that more closely match normal observations than abnormal observations. Despite this, the overall area of the shock is correctly classified. Compared to CUSUM, expectation-maximization had fewer false positives in the pre-shock observations and performed similarly during and after the shock event.

CONCLUSION

This work compared two online changepoint detection algorithms. The CUSUM algorithm performed well but had many false positives before the shock event occurred. By contrast, the EM algorithm had no false positives before the shock event. Both identified the start of the shock event, and both identified the majority of the shock event correctly with some false negatives throughout. Overall, the EM algorithm performs better, but it is much slower than the CUSUM algorithm. Future work will involve optimizing these algorithms to be viable in real-time environments. This work will involve making the existing algorithms more accurate and robust to noise in the input data.

ACKNOWLEDGMENT

This work is supported by the National Science Foundation (NSF) grant numbers 1937535, 1956071, 2234921, and 2237696. This material is also partially supported by the Air Force Office of Scientific Research (AFOSR) through award no. FA9550-21-1-0083. Any opinions, findings, conclusions, or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation or the United States Air Force.

REFERENCES

[1] Dodson, J., Downey, A., Laflamme, S., Todd, M. D., Moura, A. G., Wang, Y., Mao, Z., Avitabile, P., and Blasch, E., 2021. *High-Rate Structural Health Monitoring and Prognostics: An Overview*. Springer International Publishing, Oct., pp. 213–217.

[2] Field, J., Walley, S., Proud, W., Goldrein, H., and Siviour, C., 2004. "Review of experimental techniques for high rate deformation and shock studies". *International Journal of Impact Engineering,* ***30***(7), Aug., pp. 725–775.

[3] Aminikhanghahi, S., and Cook, D. J., 2016. "A survey of methods for time series change point detection". *Knowledge and Information Systems,* ***51***(2), Sept., pp. 339–367.

[4] Goshorn, D., Satme, J., and Downey, A., 2019. Dataset-7-forced-vibration-and-shock. https://github.com/High-Rate-SHM-Working-Group/Dataset-7-forced-vibration-and-shock, Oct.

[5] Montgomery, D. C., 2009. *Introduction to statistical quality control*. John Wiley & Sons (New York).

[6] Siris, V. A., and Papagalou, F., 2006. "Application of anomaly detection algorithms for detecting syn flooding attacks". *Computer communications,* ***29***(9), pp. 1433–1442.

[7] Dempster, A. P., Laird, N. M., and Rubin, D. B., 1977. "Maximum likelihood from incomplete data via the EM algorithm". *Journal of Royal Statistics Society, Series B,* ***39***, pp. 1–37.

[8] Hastie, T., Tibshirani, R., and Friedman, J., 2009. *The Elements Statistical Learning: Data Mining, Inference, and Prediction*, 2 ed. Springer.