Identifying Patterns and Relationships within Noisy Acoustic Data Sets

Krithika Balakrishnan, Eyal Bar-Kochba, and Alexander S. Iwaskiw

ABSTRACT

Acoustic emissions analysis can provide key information for monitoring the structural integrity of a system, such as the behavior of bone under various loading conditions and other complex biomechanical applications. However, when analyzing acoustic emissions data from complex systems, including systems that experience high-rate (10^3 s^{-1}) loading, complex bending modes, unique shape effects, and multiple failure mechanisms, it is difficult to extract meaningful information and relationships because of an abundance of confounding factors. This article presents a methodology developed at the Johns Hopkins Applied Physics Laboratory (APL) for understanding fracture and characterizing acoustic signatures with distinct failure modes, leveraging techniques such as independent component analysis, self-organizing maps, and K-means clustering algorithms.

INTRODUCTION

Acoustic emissions (AE) techniques rely on monitoring the stress waves generated by rapid, local redistributions of stress concentrations that correlate to various damage mechanisms, as shown in Figure 1. As a result, AE data can be used to monitor the structural integrity of systems, and this technique is useful because of its high sensitivity and real-time monitoring capability.[1] The AE analysis technique has been widely used to monitor the structural health of concrete in civil engineering applications, specifically for crack detection and corrosion monitoring.[2,3] It has also been used to investigate deformation behaviors in steels, including dislocation movement and yielding in austenitic stainless steel.[4] In more recent years, AE monitoring has expanded into composite materials and has been used to determine failure mechanisms in carbon/epoxy composites,[5] analyze the primary frequency content in failure modes of glass/polypropylene composites,[6] and characterize bone fracture in vertebrae and long bone.[7] Although there are a variety of tools to leverage for AE analysis, there remain many challenges to extracting meaningful information from complex systems. Especially for composite materials and multiple-material systems, such as biomechanical systems, pinpointing fracture timing and determining fracture properties is difficult because of nonhomogeneous material properties that give rise to more intricate wave propagation features.[7,8]

In composite studies, AE analysis depends on signals recorded during tensile tests at various orientations to give rise to distinct failure modes, which are then classified according to (1) a single parameter (e.g., amplitude or frequency), (2) several parameters using pattern

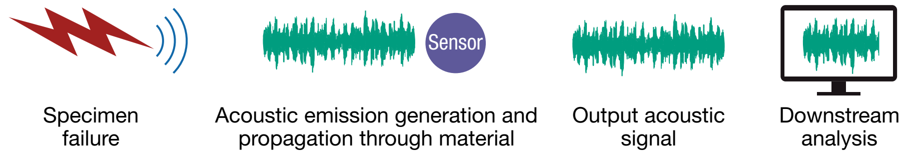

Figure 1. Acoustic signal path. Acoustic signals travel from the source through some propagation medium. Signals are then picked up by the acoustic sensor, and the resulting waveform can be analyzed.

recognition, or (3) the extensional and flexural mode content.[8] However, not all systems are amenable to a simplified component setup to discern distinct damage mechanisms. For instance, biomechanical modeling of complex trauma is needed to improve mitigation and protection strategies (e.g., seat belts, body armor, and bike helmets). Of particular interest is the phenomena of nonpenetrating ballistic-induced trauma, termed behind-armor blunt trauma (BABT). With armor standards depending on the severity of a relatively unknown and complex phenomena, biomechanical characterization and advanced mechanical models are needed.

To develop robust biomechanical models for BABT, the entire system under study needs to be tested and validated to enable understanding of failure as it relates to injury and disease. In these scenarios, the experimental setup may be noisy, and the resulting acoustic signals corresponding to material failure may be weak. This results in a major practical limitation of the AE technique, which is the presence of sources of AE other than the failure of interest. Current work in using pattern recognition techniques such as supervised and unsupervised learning algorithms as well as statistical approaches on time estimation of the received signal is attempting to address these challenges.[8,9] Although AE has been verified in the laboratory on small-scale components, practical applications using AE analysis for realistic, complex systems are limited. Therefore, an analysis pipeline that can move AE from a qualitative technique to practical utility in the investigation of complex systems is necessary.

The analysis pipeline proposed in this research leverages well-understood methodologies in signal processing to create a new combined processing flow to uncover failure in complex systems. While each individual step—for example, deconvolution during preprocessing, independent component analysis (ICA), and self-organizing maps (SOMs)—has been used in previous AE analysis, the strength in combining these methods is gained from the ability to discern underlying patterns in a limited acoustic data set to correlate the burst events back to distinct sources in the system. This pipeline can be leveraged for a variety of applications where noninvasive acoustic monitoring can provide important insights into the underlying failure mechanisms of the material.

EXPERIMENTAL SETUP

BABT is the nonpenetrating injury resulting from rapid deformation of armor covering the body.[10] To shed light on future armor systems, understanding the underlying mechanism of BABT loading and building a knowledge base of injuries and mitigation strategies is crucial. In the absence of validated computational models, it is important to conduct experiments to elucidate the relationship between BABT loading and injury. A recent study conducted by APL characterized the relationships among BABT loading, armor performance, and human injury outcomes by using experimental results from 14 instrumented postmortem human subject (PMHS) experiments. To verify the fidelity of the PMHS as a mechanical surrogate, each specimen was instrumented with various sensors, including strain gauges, pressure transducers, and AE sensors. This instrumentation allows for robust characterization of the PMHS biomechanical response to BABT loading. Ultimately, data collected from this testing can be used to validate a computational model, better explain the biological surrogate as a mechanical system, and better design injury mitigations or armor.

The biological specimen was placed on a custom mounting rig and positioned upright, supported by a seat, and strapped to the fixture. As shown in Figure 2, the impact location of the specimen is in the middle of the sternum, between the third and fourth rib levels. Each specimen was fitted with custom armor plates and subjected to a ballistic impact centered on the armor, resulting in a nonpenetrating ballistic event (i.e., the round did not fully penetrate the armor) striking the specimen causing BABT.

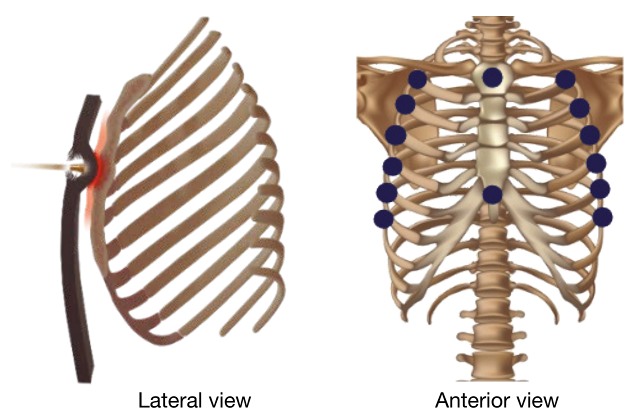

Figure 2. Experimental setup and BABT loading description. The lateral view shows a graphical depiction of armor backface impacting the sternum, causing BABT injuries. The anterior view highlights the AE sensor installation locations on the lateral ribs and sternum.

Each armor and specimen was shot once. Typical ballistic events induce material strains on the order of 10^3 s^{-1} (see Carr, Horsfall, and Malbon[10]). To achieve several representative loading rates, the ballistic tests were conducted across a range of striking velocities, or the velocity of the round when striking armor. Multiple fractures of the sternum and ribs were observed, along with lacerations and abrasions of the skin at the impact. To capture information from these fractures, 14 Nano30 miniature AE sensors[11] were installed in each biological specimen, with 2 sensors on the sternum and 12 sensors on both the left and right sides of lateral ribs 2–7. Individual sensors were adhered to bone using cyanoacrylate after the periosteum had been cleared. The Nano30 sensor was chosen for its ability to capture the high-frequency response (125–750 kHz) of bone fracture for the application. AE sensor data were collected using a PicoScope 5000 high-rate data acquisition system at a 4.8-MHz sampling rate to capture higher frequencies of interest.

Because of the abundance of stress wave propagation in the specimen in each test—including the initial projectile impact on the armor, armor deformation, potential bone fractures, soft tissue damage, and general system vibration—analyzing the data set to isolate bone fracture signals and failure mechanisms is a challenge. There is also redundancy in the signals captured by each sensor. However, understanding the underlying failure mode in the material is important to developing a better model of BABT loading and complex injury. Therefore, to assess whether the acoustic signature associated with distinct fracture events and transient stress waves could be characterized from the noisy data set, a new analysis pipeline is required to parse the experimental results.

ANALYSIS METHODOLOGY

Preprocessing

The first step in the processing pipeline, as shown in Figure 3, is preprocessing the raw, measured signal to enable downstream analysis. For generic fracture studies, frequencies between 20 kHz and 1.5 MHz are of practical use, because at higher frequencies, the signal is too weak and attenuation is large, and at lower frequencies, extraneous noise dominates the system.[12] Published data suggest that for bone fracture cases, the frequency bandwidth of interest can be narrowed down even further to between 50 and 400 kHz.

Figure 4 highlights the range of interest, as evidenced in existing literature. Previous experimental data suggest that fracture of vertebral bodies can lie between 76.5 and 292 kHz[7,13,14] and long bone fractures between 100 and 200 kHz.[7] Therefore, a band-pass filter applied between 50 and 300 kHz can capture the range of interest for rib

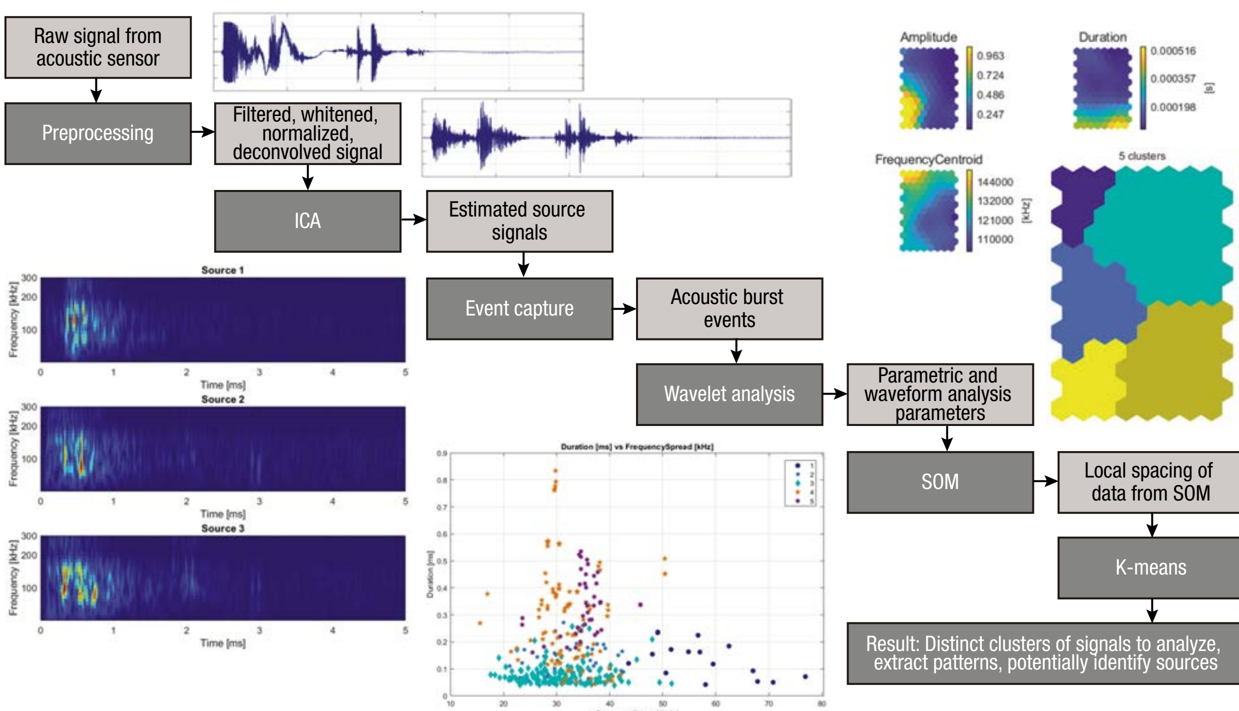

Figure 3. Analysis methodology flowchart. The analysis flow begins with preprocessing the received signal followed by ICA to isolate source signals. Parametric analysis of the burst signal via event capture in the signal provides key parameters such as amplitude and duration of the burst signal. The burst events are studied through wavelet analysis, which provides the time-frequency representation to understand the data. Finally, unsupervised learning techniques, including SOMs and k-means clustering algorithms, are used for pattern recognition characterizing fracture events.

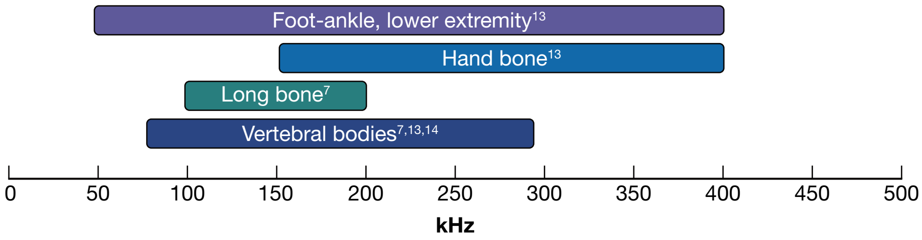

Figure 4. Previously published characteristic fracture frequencies for bones. In previous research, bone fracture frequency has been studied in isolated tensile tests with acoustic monitoring. Those results are summarized here, and it is apparent that most studies have found bone fracture frequencies between 50 and 400 kHz.

and sternum fractures while truncating the resonance response of the sensor, which is reported at 300 kHz.

The measured AE signals are directly affected by the frequency characteristics of the sensor, where certain frequencies are accentuated.[15] To mitigate the influence of the nonconstant frequency characteristics, regularized Tikhonov deconvolution[16] was applied based on the manufacturer-provided sensitivity. After deconvolution, the data were then whitened—a technique used to make the data behave statistically like white noise, which is useful for downstream ICA—and normalized for comparison across data sets.[17]

Independent Component Analysis

In this system, multiple source events originate from both rib and sternum fractures to transient stress wave propagation. There are also multiple receivers (i.e., 14 AE sensors). Therefore, separating the sources out of redundant, mixed received signals becomes a nontrivial challenge. This type of problem is commonly referred to as the "cocktail party problem," where a number of people are talking simultaneously in a room at a cocktail party, and a listener is trying to follow one of the discussions.[18] To address this problem, ICA attempts to decompose a multivariate signal into independent non-Gaussian signals and it can derive an approximation of the source signal from a mixed response.[17] An overview of the technique is shown in Figure 5. If we know the types of injury observations after testing, such as the presence of sternum and rib fractures, we can use ICA to estimate the source signal for each failure mode. In this system, sources will be generalized as stemming from (1) rib fracture, (2) sternum fracture, and (3) transient stress wave propagation.

Because of the complexity in this test, there is not enough detail to distinguish between multiple rib fractures in the same specimen. However, it is hypothesized that general rib fracture can be separated from sternum fracture because of the distinct material properties in the rib and the sternum. In this study, distinguishing between failure modes is the primary goal—future experimentation and analysis of known sensor and fracture localization and wave propagation dynamics are needed to estimate signal time of arrival and discern between multiple events of the same failure type. Another important note here is that ICA can provide distinct results each time it is run because of the nature of the estimation process. As a result, batch studies are beneficial to identify the underlying dominant mode.

Event Capture

Parametric analysis is also useful for characterizing AE, and this is dependent on finding "burst" events. Robust, accurate event capture is essential for properly identifying and characterizing AE that correspond to different stress waves. Event capture in this analysis was achieved through setting two thresholds and windowing through the data. One threshold was set via z-score

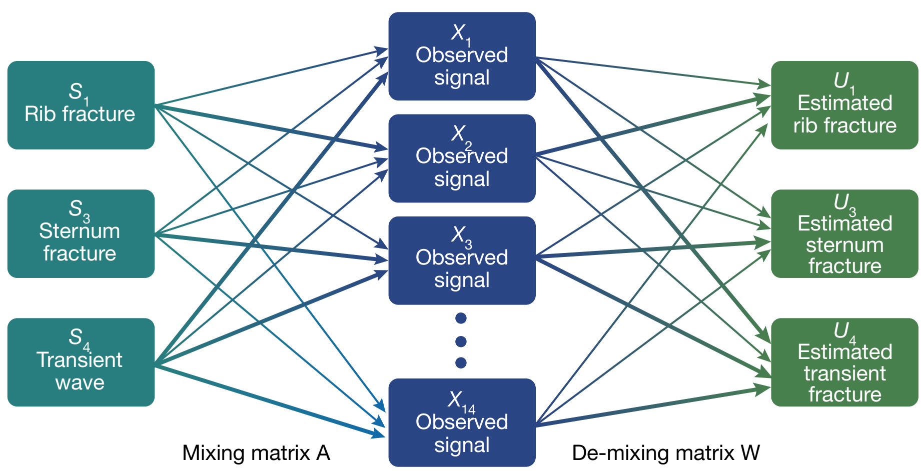

Figure 5. ICA for blind source separation. In each test, there are up to three independent sources stemming from rib fracture, sternum fracture, and transient stress wave propagation. These signals are mixed and received by the array of 14 AE sensors. ICA can be used for blind source separation by estimating the mixing matrix from the received signals and taking its inverse, thus recovering the original source signals.

normalization of spectral energy greater than 0.05, which will capture events with the highest energy, and another threshold looks at a signal-to-noise ratio greater than 10 dB to capture events out of background noise. Windowing through the signal data at 2-ms intervals is important to capture some moderate-energy events originating from sources that are physically distant from the sensor.

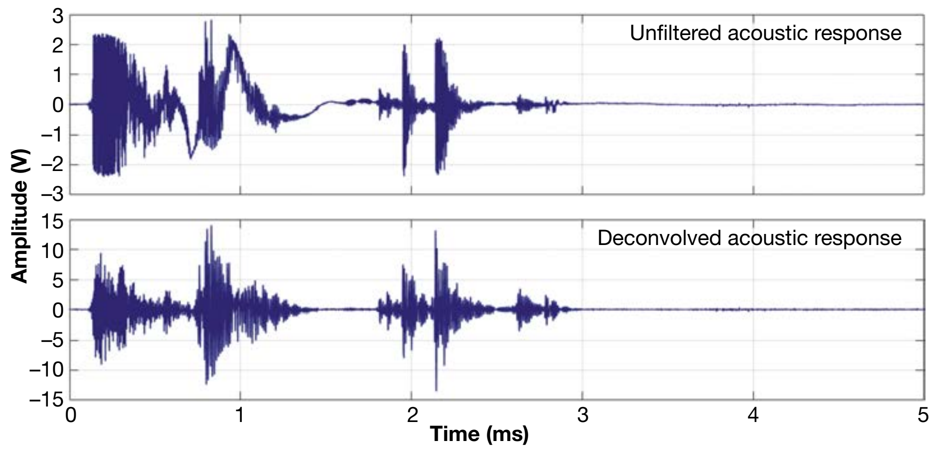

Figure 6. Significance of deconvolution. During the preprocessing step, deconvolution of the sensor sensitivity is an integral component to recover important burst events and their parameters.

Wavelet Analysis

Because of the rich signal content in the frequency domain, a continuous wavelet transform was applied to convert the time-series signal into a time-frequency representation. From the many methods to perform this transformation (e.g., short-term Fourier transforms), a wavelet transform was chosen because of its ability to localize frequency transients and nonstationary signals,[19] characteristics that are present in this AE data set. Selecting the appropriate mother wavelet function is dependent on the properties of that wavelet and its similarity to the original signal. For this analysis, an analytic Morlet (Gabor) wavelet was used, which has equal variance in time and frequency.[20]

Self-Organizing Maps

SOMs are artificial neural networks trained via unsupervised learning techniques to produce a low-dimensional discretized representation of the data set, called a map.[21] This technique has been used in previous acoustic analysis to differentiate between failure modes in composites.[8] The real power of an SOM is its ability to elucidate underlying relationships in the acoustic events, across various sensors and across tests, to show whether there are differences between fracture versus nonfracture events, sternum fracture versus rib fracture events, and transient stress wave versus fracture stress wave propagation. The following parameters of the selected burst events were fed into the SOM: amplitude, rise time, duration, frequency centroid, and frequency spread, along with the next three dominant frequency tones.

K-means Clustering Algorithm

K-means clustering is another type of unsupervised learning that is used to group data points based on feature similarity.[22] SOM's local representation of the data provides some information on macro-clusters and feature relationships, and using K-means afterward can reduce the number of clusters to identify the ideal grouping configuration.[23] To find the most appropriate groupings, a series of batch studies was run on the resulting SOM data.

Statistical Analysis

The resulting groupings from the K-means clustering algorithm are fed into a multivariate analysis of

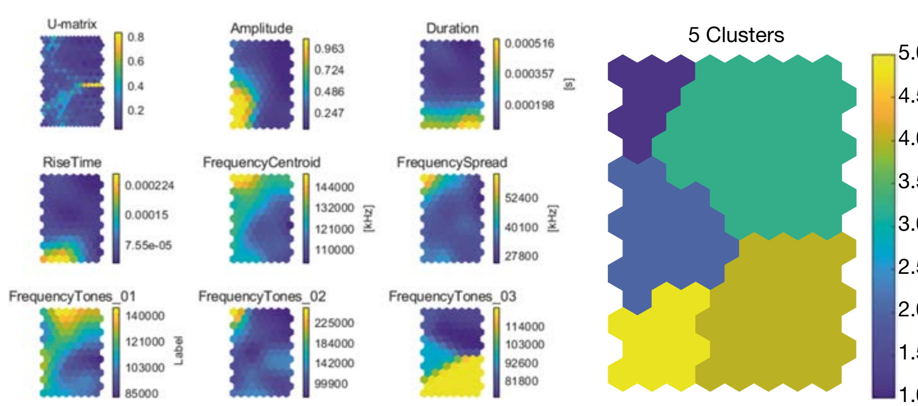

Figure 7. Partitions for final clustering groups. The five clustering groups, as determined from the k-means algorithm, are overlaid here with a snippet of the SOM data to highlight how the groupings aligned. From the SOM, the local organization of the data reveals interesting information about how each burst event compared across the various attributes. This presents all the burst events (415 independent events) across all sensors, in all tests.

variance (MANOVA) analysis, which is useful to test whether the independent groupings have a statistically significant amount of variance. Through this method, underlying patterns in the data set can be leveraged to understand how independent acoustic events correlate to distinct sources and damage mechanisms.

RESULTS AND DISCUSSION

With 14 AE sensors placed in each of the 14 PMHS tests, there were 196 streams of data to process. These raw signals were fed through the preprocessing flow, and the importance of the deconvolution step is shown in Figure 6. To obtain a more accurate understanding of the source signal, Tikhonov deconvolution of the sensor sensitivity from the signal data is necessary—otherwise, the acoustic burst parameters that are correlated to different failure modes would be captured incorrectly.

The results from preprocessing, ICA, event capture, and waveform analysis provide a set of acoustic parameters that describe burst events, in terms of the amplitude, rise time, duration, frequency spread, frequency centroid, and frequency tones. This information is fed through to an SOM+K-means algorithm implementation to achieve the final clustering groups, as shown in Figure 7.

Because of the nature of signal approximation from ICA, and the K-means clustering algorithm implementation, which can estimate different groupings for the same SOM, batch studies are needed to understand the dominant distribution from the data. To assess the distribution of final clustering groups from the pipeline, a set of batch results is shown in Figure 8.

In one ideal scenario, with three signals from the post-ICA analysis that has been fed through the SOM and clustering algorithms, there should be three resulting clusters. However, given the possibility for extraneous vibrations and stress wave propagation in the system through nonhomogeneous materials, getting the precise resolution for each source wave may not be possible with the limited experimental data.

However, even with this limited data set, getting five resulting clusters from three source signals is an important step toward understanding how various attributes of the burst event might be distinct based on the source. It could be that the characteristics of burst events may form subcategories, correlating to different failure mechanisms for the same or different sources. Additional data are needed to dig through this information and validate the resulting clustering groups.

This analysis pipeline provided a way to parse the received signal information to estimate the source signal

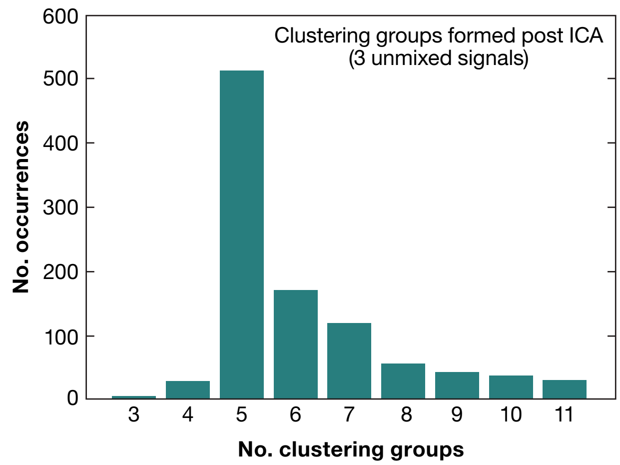

Figure 8. Quality-control batch results. There were 1,000 runs to assess the distribution of final clustering groups. For each run, the results from the SOM were fed into a k-means clustering algorithm that determined the optimal clustering based on several k-means partitions. The best of these for each run were selected based on a sum of squared errors. These results demonstrate that the dominant mode was five clustering groups generated from the input SOM data.

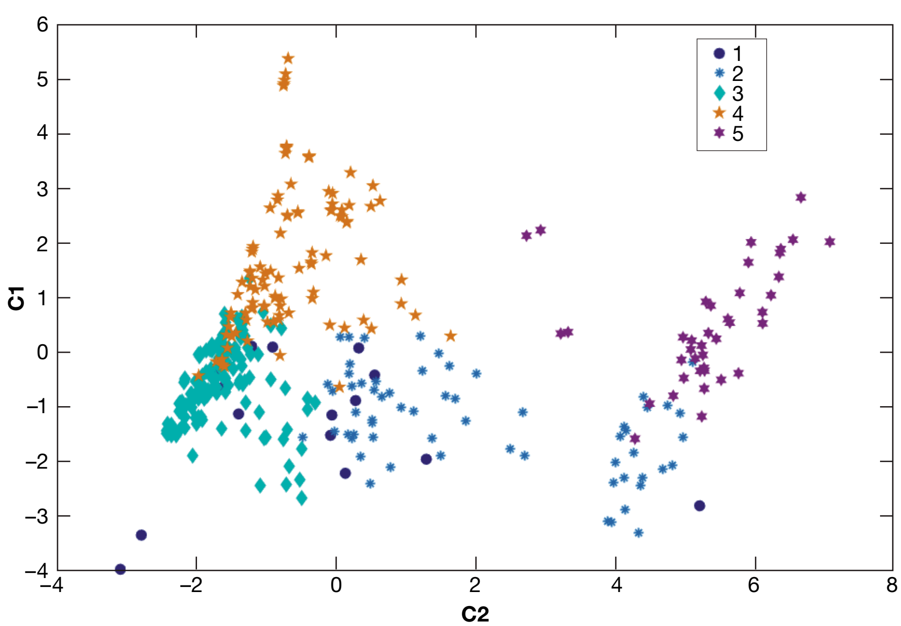

Figure 9. MANOVA results. The grouped scatter plot is shown against the first two canonical variables to show the separation between the groups. The dimension of the group means was four, and the *p*-values were all less than 1e-6, so the groupings are significant.

and create groupings based on underlying patterns in the data set. When looking at the clustering groups, an initial test for significance was conducted using MANOVA, as shown in Figure 9.

Previous data indicated the importance of frequency to determine the underlying damage mechanism, and distinct material failures have different fracture frequencies.[17,19] Therefore, looking at the frequency centroids and frequency spreads for the various groups is prudent to characterize a burst event with a particular source damage mechanism. From Figure 10, it is apparent that the frequency centroids are similar across most groups, except for group 1, which has much larger frequency centroids and spreads on average. Additionally, while there is overlap in the frequency centroid and frequency spread of groups 3 and 4, the frequency centroid for group 3 is on average higher than it is for group 4. This information, coupled with other acoustic parameter information, can inform hypotheses about the correlation of these groups to a given source. Since ribs and sternum are similar, but distinct, materials, one hypothesis is that groups 3 and 4 can correlate to either rib or sternum fractures.

Understanding the amplitudes of the burst events provides more insight into the groupings, and Figure 11 shows a slice of those data. The amplitude of a burst event is correlated to the energy level in the traveling acoustic wave and highlights that there are some higher-energy bursts than others. For instance, one potential hypothesis stems from the fact that the energy transmitted from the projectile hitting the specimen is higher than the energy released during bone fracture.

Interestingly, the resulting data show that cluster groups 2 and 5 have higher amplitudes on average than

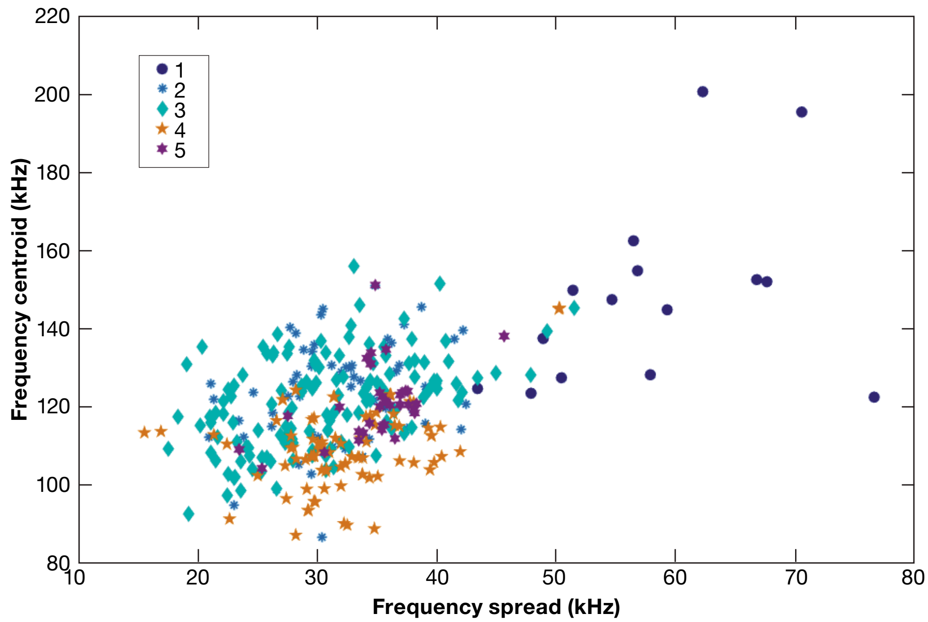

Figure 10. Clusters sliced by frequency spread vs. frequency centroid. While groups have similar frequency spreads and frequency centroids, events from group 1 have much larger frequency spreads and centroids. The frequency spreads for groups 3 and 4 are quite similar, but their frequency centroid ranges are not completely overlapping, with group 3 having some high-frequency centroids captured when compared with group 4.

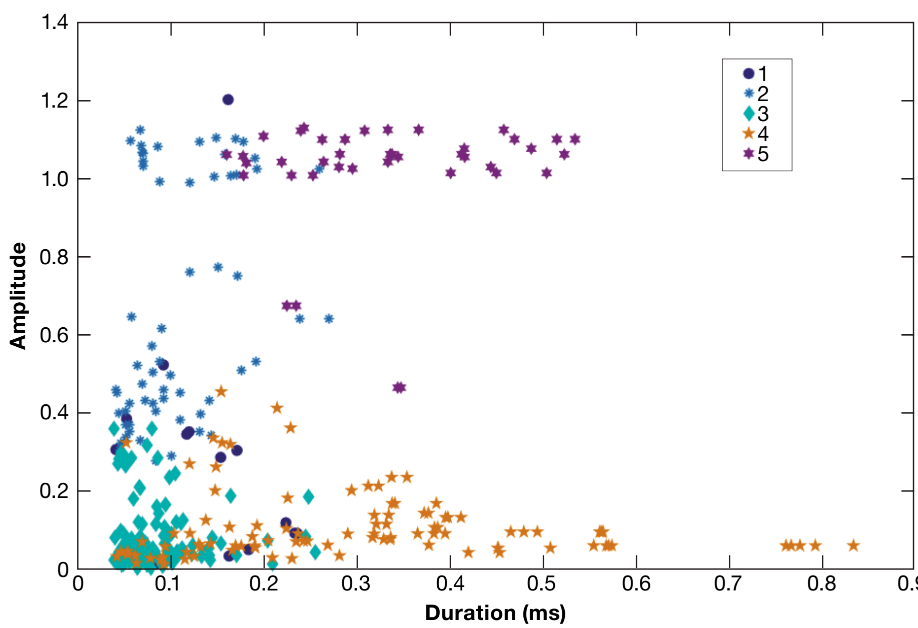

Figure 11. Clusters sliced by duration vs. amplitude. Events from groups 2 and 5 have large normalized amplitudes, and events from groups 1, 2, and 3 have short durations. Most events from group 3 have very small amplitudes, though not all. Events from group 4 have small amplitudes and durations that cover the entire range from 0 to 0.9 ms.

Table 1. Mean values for attributes selected for analysis

Group	Arrival (ms)	Amplitude	Duration (ms)	Rise Time (ms)	Frequency Centroid (kHz)	Frequency Spread (kHz)	Frequency Tones 01 (kHz)
1	2.11	0.27	0.13	0.06	147.40	57.80	121.19
2	0.52	0.67	0.11	0.04	123.59	31.87	115.06
3	3.67	0.08	0.08	0.03	121.98	30.66	118.52
4	2.25	0.11	0.29	0.08	109.89	32.02	93.52
5	0.25	1.02	0.33	0.17	122.00	35.05	110.36

This table summarizes some of the features of a characteristic acoustic burst from each group. This information can be used to understand which burst events correspond to specific source signals. Note the difference between groups 1, 3, and 4 and groups 2 and 5 in terms of arrival times and amplitudes. Group 1 has the highest frequency centroid and largest frequency spread when compared with the rest of groupings, while group 4 has the lowest frequency centroid.

cluster groups 1, 3, and 4—this could serve as a separation point between events that originate from transient stress wave propagation versus bone fracture.

Further slices of the data, across rise times and frequency tones, reveal more details about the relationship between acoustic parameters and the final organization. Using this pipeline, even from a complex, noisy experimental setup, hypothesized relationships between acoustic parameters and failure mechanisms can be drawn. Table 1 summarizes key parameters across the observed clustering groups.

From a deeper look into the data as a function of the clustering groups and various attributes, a preliminary understanding can be developed for the correlation of one group to a particular source signal. Earlier onset times and high-normalized amplitudes could correlate to the high-energy, initial stress wave resulting from the initial ballistic impact. Next, as the stress concentrations from this impact propagate through the skeletal system, bones would fracture. Because of the location of the sternum in relation to the energy transfer path in BABT loading, the sternum likely fractures before there are any rib fractures. The current framework for BABT loading in the rib cage includes transient stress wave propagation through the rib cage in phase A, local tensile and compressive loading in phase B leading to fracture, and bulk engagement of the torso in phase C, which can also lead to fracture. Figure 12 demonstrates how the acoustic data fit into this understanding.

Additionally, some prior research indicates that material elastic modulus affects the AE signal frequency,[24] and this information can be used to distinguish between sternum and rib fracture events. Using these groupings and the stated hypotheses to derive insights in the AE properties corresponding to the various source events can help create labeled data sets to better validate injury prediction models and drive future analysis that can even pinpoint fracture timing.

BABT is a complex phenomenon that is still not fully understood—decoupling each part of the problem to verify and validate biomechanical models is difficult because of the presence of superimposed failure. The data collected from the APL study provide insight into BABT loading and its correlation to human injury, but the data alone are not sufficient to deepen existing understanding.

Processing and analyzing the resulting experimental data in a consistent, clear, and robust methodology to

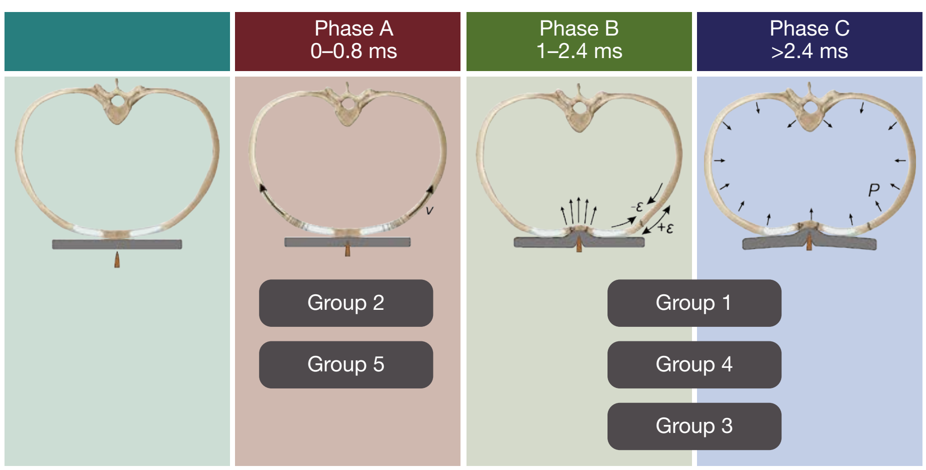

Figure 12. Preliminary understanding of acoustic groups within the BABT loading framework. An axial view of the sternum, rib cage, and spine is shown at various stages of skeletal loading due to BABT. This is aligned with the acoustic groups that were determined using the analysis pipeline. Groups 2 and 5 are hypothesized to correlate to the transient stress wave propagation prevalent in phase A of BABT loading, while groups 1, 4, and 3 are hypothesized to live between phase B and phase C. This information is also supported by the arrival times presented for the clustering groups and their correlation with the current understanding of the phase durations for BABT.

best capture the root damage mechanisms is crucial. Without applying adequate preprocessing, for instance forgoing the deconvolution as shown in Figure 6, the resulting conclusions from the data would not reflect an accurate understanding of the acoustic parameters for the source event. Without analyzing the acoustic bursts in the time-frequency domain, key insights into burst frequencies and frequency spreads would not be known. ICA is important in this pipeline because of the need to understand the source itself, and without that step, the signals would remain mixed. Without unsupervised learning such as SOM and K-means clustering, identifying patterns in the data set would be very difficult. The strength of the unsupervised pattern recognition techniques also depends on the quality of the data set that is fed in, and therefore, the application and refinement of robust signal processing techniques in achieving the parametric and waveform acoustic parameters is integral to developing a more comprehensive result.

While the proposed analysis methodology paves the way for key insights from limited acoustic data sets, it is not without limitations. Sensor installation and location introduce variance. The installation process is difficult, and the amount of contact between the sensor and the bone at the installation location, as well as the sensor's contact with other tissue and potentially even the armor backface, can affect the results. The sensor location with respect to the impact location and the variation of the sensor installation locations across the tests also need to be further investigated. Further analysis into the sensor locations and the resulting emissions could provide an opportunity to understand propagation dynamics. While all PMHS were within the normal bone mineral density range, specifically –1 to +2.2 standard deviations around normal, this and other anthropometric variations could influence fracture susceptibility and the resulting AE.

Currently, there is insufficient resolution in the signal data to discern between multiple rib fracture events on the same or adjacent ribs in the same experimental test. Additionally, this method does not pinpoint the time of bone fracture or material failure; it simply identifies which bursts may correlate to energy released in that process. Further work is needed to understand the bone fracture process, and more data can provide insight into the crack initiation and growth process in this type of complex loading scenario. The noise from the experimental setup, as well as some of the estimations in the signal processing pipeline, introduces additional uncertainty and error—therefore, more data are needed to validate the clustering groups found in this initial data set to specifically correlate them back to fracture types and sources.

Further work in this area is also needed to enable understanding of the mechanical basis for the differences in these attributes across groups. Fundamentally, the material properties should drive the way stress waves propagate, and better understanding of composites such as bone can drive further work in predictive analysis or labeling data sets to improve methods for monitoring failure. Other separation models such as a nonnegative matrix or tensor factorization, as well as other unsupervised learning and clustering techniques including hidden Markov, hierarchical, and paraclique methods, can also be used to iterate on this analysis.

CONCLUSION

AE analysis provides continuous, passive monitoring of the structural integrity in systems. Although it has been used extensively in various fields, there are limitations in the practical applications of AE to detect structural changes in systems that experience a large amount of acoustic and electrical background noise, contain nonhomogeneous materials, and experience multiple superimposed failures. In these systems, it becomes difficult to isolate AE sources and correlate them back to distinct failure mechanisms.

For biomechanical systems modeling BABT loading, AE analysis can be a very powerful tool aiding our understanding of human injury by informing and validating injury risk and prediction models. To effectively utilize AE data from a complex system, robust data processing techniques are required. The analysis pipeline proposed in this research uses existing methodologies in a combined pipeline to reveal relationships between acoustic parameters and underlying damage mechanisms in the system. While individual steps in the analysis are well established, this pipeline uses the benefits across these various techniques to understand complex loading phenomenon and material failures. Initially applied to a biomechanical model, this methodology has uncovered new information about the acoustic parameters for transient stress wave propagation, sternum fracture, and rib fracture in BABT loading. Correlating acoustic bursts correctly with fracture events could allow for real-time monitoring of injury during future experimentation. Well-labeled acoustic data sets for fracture initiation and propagation, along with wave propagation models, can also aid predictive capabilities, such as predicting injury timing from BABT and predicting which bones may be prone to future injury upon repeated loading. Additionally, AE data paired with strain and acceleration data can yield further insight into the system. This can be applied beyond BABT loading scenarios to other complex human biomechanics loading models as well, where AE data can be used to augment various experimental and computational models.

Looking ahead, there is a need for future work to validate the proposed groups and acoustic parameters relating to distinct failure modes. Component-level testing to isolate the AE sources, as well as experiments that can provide direct access to other imaging or sensing modalities that could confirm the AE source, would contribute to better understanding the relationship between AE and fracture initiation and propagation to failure.

Within the biomechanics field, this analysis can be used to create better failure modeling and validation for finite element analysis injury prediction models. Additionally, understanding the failure characteristics in complex high-rate/high-energy injuries would contribute to better understanding failure tolerances. Beyond biomechanics, this analysis pipeline can be leveraged to understand damage mechanisms in complex systems and move the use of acoustic parameters to more application spaces. It can also be used to further an understanding of material properties and mechanics to develop relationships on how material structure affects AE signal parameters, and even aid in the fabrication of new heterogeneous materials.

REFERENCES

[1] M. A. Hamstad, "A review: Acoustic emission, a tool for composite-materials studies," *Exp. Mechanics*, vol. 26, pp. 7–13, 1986, https://doi.org/10.1007/BF02319949.

[2] K. Ohno and M. Ohtsu, "Crack classification in concrete based on acoustic emission," *Construction Building Mater.*, vol. 24, no. 12, pp. 2339–2346, 2010, https://doi.org/10.1016/j.conbuildmat.2010.05.004.

[3] A. Zaki, H. K. Chai, D. G. Aggelis, and N. Alver, "Non-destructive evaluation for corrosion monitoring in concrete: A review and capability of acoustic emission technique," *Sensors*, vol. 15, no. 8, pp. 19069–19101, 2015, https://doi.org/10.3390/s150819069.

[4] Z. Han, H. Luo, and H. Wang, "Effects of strain rate and notch on acoustic emission during the tensile deformation of a discontinuous yielding material," *Mater. Sci. Eng. A*, vol. 528, nos. 13–14, pp. 4372-4380, 2011, https://doi.org/10.1016/j.msea.2011.02.042.

[5] P. J. de Groot, P. A. M. Wijnen, and R. B. F. Janssen, "Real-time frequency determination of acoustic emission for different fracture mechanisms in carbon/epoxy composites," *Composites Sci. Technol.*, vol. 55, no. 4, pp. 405–412, 1995, https://doi.org/10.1016/0266-3538(95)00121-2.

[6] C. R. Ramirez-Jimenez, N. Papadakis, N. Reynolds, T. H. Gan, P. Purnell, and M. Pharaoh, "Identification of failure modes in glass/polypropylene composites by means of the primary frequency content of the acoustic emission event," *Composites Sci. Technol.*, vol. 64, no. 12, pp. 1819–1827, 2004, https://doi.org/10.1016/j.compscitech.2004.01.008.

[7] B. D. Goodwin, F. A. Pintar, and N. Yoganandan, "Acoustic emission signatures during failure of vertebra and long bone," *Ann. Biomed. Eng.*, vol. 45, no. 6, pp. 1520–1533, 2017, https://doi.org/10.1007/s10439-017-1818-4.

[8] R. Gutkin, C. J. Green, S. Vangrattanachai, S. T. Pinho, P. Robinson, and P. T. Curtis, "On acoustic emission for failure investigation in CFRP: Pattern recognition and peak frequency analysis," *Mech. Syst. Signal Proc.*, vol. 25, no. 4, pp. 1393–1407, 2011, https://doi.org/10.1016/j.ymssp.2010.11.014.

[9] M. J. Eaton, R. Pullin, and K. M. Holford, "Towards improved damage location using acoustic emission," *Proc. Inst. Mech. Eng. C: J. Mech. Eng. Sci.*, vol. 226, no. 9, pp. 2141–2153, 2012, https://doi.org/10.1177/0954406212449582.

[10] D. J. Carr, I. Horsfall, and C. Malbon, "Is behind armour blunt trauma a real threat to users of body armour? A systematic review," *BMJ Mil. Health*, vol. 162, no. 1, pp. 8–11, 2016, https://doi.org/10.1136/jramc-2013-000161.

[11] MISRAS Group, "Nano30 Sensor," Product Data Sheet, Physical Acoustics Corporation, https://www.physicalacoustics.com/content/literature/sensors/Model_Nano30.pdf.

[12] I. C. Visconti and R. Teti, "Acoustic emission from composite materials," in *3rd Nat. Conf. Composite Mater.*, Italy, 1978.

[13] M. W. J. Arun, N. Yoganandan, B. D. Stemper, and F. A. Pintar, "A methodology to condition distorted acoustic emission signals to identify fracture timing from human cadaver spine impact tests," *J. Mech. Behav. Biomed. Mater.*, vol. 40, pp. 156–160, 2014, https://doi.org/10.1016/j.jmbbm.2014.08.023.

[14] C. Van Toen, J. Street, T. R. Oxland, and P. A. Cripton, "Acoustic emission signals can discriminate between compressive bone fractures and tensile ligament injuries in the spine during dynamic loading," *J. Biomechanics*, vol. 45, no. 9, pp. 1643–1649, 2012, https://doi.org/10.1016/j.jbiomech.2012.03.025.

[15] K. Ono, "Frequency dependence of receiving sensitivity of ultrasonic transducers and acoustic emission sensors," *Sensors*, vol. 18, no. 11, art. 3861, 2018, https://doi.org/10.3390/s18113861.

[16] A. N. Tikhonov and V. Y. Arsenin, *Solutions of Ill-Posed Problems*, New York: Winston, 1977.

[17] A. Hyvärinen and E. Oja, "Independent component analysis: Algorithms and applications," *Neural Netw.*, vol. 13, nos. 4–5, pp. 411–430, 2000, https://doi.org/10.1016/S0893-6080(00)00026-5.

[18] C. E. Cherry, "Some experiments on the recognition of speech, with one and with two ears," *J. Acoust. Soc. Amer.*, vol. 25, no. 5, pp. 975–979, 1953, https://doi.org/10.1121/1.1907229.

[19] A. Borghetti, S. Corsi, C. A. Nucci, M. Paolone, L. Peretto, and R. Tinarelli, "On the use of continuous wavelet transform for fault location in distribution power networks," *Int. J. Elect. Power Energy Syst.*, vol. 28, no. 9, pp. 608–617, 2005, https://doi.org/10.1016/j.ijepes.2006.03.001.

[20] C. Heil and D. Walnut, "Gabor and wavelet expansions," in *Recent Advances in Fourier Analysis and Its Applications*, NATO ASI Series (Series C: Mathematical and Physical Sciences), vol. 315, J. S. Byrnes and J. L. Byrnes, Eds., Dordrecht: Springer, 1990, pp. 441–454, https://doi.org/10.1007/978-94-009-0665-5_25.

[21] U. Asan and S. Ercan, "An introduction to self-organizing maps," in *Computational Intelligence Systems in Industrial Engineering. Atlantis Computational Intelligence Systems*, vol. 6, C. Kahraman, Ed., Atlantis Press: Paris, 2012, pp. 295–315, https://doi.org/10.2991/978-94-91216-77-0_14.

[22] J. MacQueen, "Some methods for classification and analysis of multivariate observations," in *Proc. 5th Berkeley Symp. Math. Stat. Probab. 1*, 1967, pp. 281–297.

[23] B. Brentan, G. Meirelles, E. Luvizotto Jr., and J. Izquierdo, "Hybrid SOM+k-means clustering to improve planning, operation and management in water distribution systems," *Environ. Model. Softw.*, vol. 106, pp. 77–88, 2018, https://doi.org/10.1016/j.envsoft.2018.02.013.

[24] Z. Wang, J. Ning, and H. Ren, "Frequency characteristics of the released stress wave by propagating cracks in brittle materials," *Theor. Appl. Fracture Mech.*, vol. 96, pp. 72–82, 2018, https://doi.org/10.1016/j.tafmec.2018.04.004.

Krithika Balakrishnan, Research and Exploratory Development Department, Johns Hopkins University Applied Physics Laboratory, Laurel, MD

Krithika Balakrishnan is an engineer in APL's Research and Exploratory Development Department (REDD), previously as a Discovery Program staff member and currently as a member of the Mechanical Engineering Systems Analysis and Design Group. She has a BS in mechanical engineering and a BS in cellular and molecular biology, both from the University of Michigan. Krithika has worked on a variety of programs across multiple technical areas, leveraging her experience in data analysis, signal processing, computational modeling, test engineering, and guidance and control systems. Her email address is krithika.balakrishnan@jhuapl.edu.

Eyal Bar-Kochba, Research and Exploratory Development Department, Johns Hopkins University Applied Physics Laboratory, Laurel, MD

Eyal Bar-Kochba is a chief scientist and project manager in APL's Research and Exploratory Development Department. He has a BS in electrical engineering from State University of New York at Stony Brook and an MS and a PhD in engineering from Brown University. Eyal's background is in solid mechanics, but recently he has been working on data analytics primarily related to biomechanics and human performance, with applications including modeling injury risk to humans due to blast, ballistic, or blunt trauma; image processing and algorithm development for noninvasive brain–computer interfaces; data processing and machine learning for human motion capture and wearables data; and algorithm development for full-field material deformations. His email address is eyal.bar-kochba@jhuapl.edu.

Alexander S. Iwaskiw, Research and Exploratory Development Department, Johns Hopkins University Applied Physics Laboratory, Laurel, MD

Alexander S. Iwaskiw is a biomechanical engineer, section supervisor, and project manager in APL's Research and Exploratory Development Department. He has a BS in biomedical engineering from Bucknell University and an MS in mechanical engineering from Johns Hopkins University. Alex leads large multidisciplinary teams developing injury mitigation strategies in a variety of military applications. He has expertise in multiple technical areas, including high-rate sensors, biological tissue preparation, medical image processing, object-oriented software development, high-rate material characterization, and data analysis. His email address is alexander.iwaskiw@jhuapl.edu.