High-Rate Structural Health Monitoring and Prognostics: An Overview

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ABSTRACT
Structural Health Monitoring (SHM) includes both static and highly dynamic engineering systems. With the advent of real-time sensing, edge-computing, and high-bandwidth computer memory, there is an ability to enable high-rate SHM (HR-SHM). The paper defines the technical area of high-rate structural health monitoring and prognostics and presents the HR-SHM technical grand challenges including: multi timescales of the problem, adequate sensor network and response, real-time assessment, and decision-making with quantified uncertainty and risk. Key issues to address in such challenges include the time duration of the event, time scales of the physics, multiple sources of uncertainty, as well as limited spatiotemporal constraints for hardware execution. The paper defines the high-rate time scale as *1 ms* on the integrated paradigm including data acquisition, assessment execution, and decision-making. The spatial issues include the resolution of the area monitored, the communication distance, and the number of edge sensors. The temporal issue includes the sensor type (e.g., THz) as well as multiple sources of uncertainty. These constraints must be coupled to allow for high-rate implementation that is robust, adaptable, and beneficial to the missions of interest. To address the grand challenge, we propose physics-informed real-time fusion (PIRF) of high-speed dynamic data. Technologies such as machine learning and edge-computing can be further harnessed to enable structural and functional prognostics for high-rate dynamic systems. Quantification of uncertainty, both aleatory and epistemic, is necessary for real-time state estimation to be connected with the confidences to integrate risks into the decision-making.

Keywords: structural health monitoring, high-rate,dynamics; decision-making, uncertainty quantification

INTRODUCTION

Structural Health Monitoring (SHM) includes both static and highly dynamic engineering systems. With the advent of real-time sensing, edge-computing, and high-bandwidth computer memory, there is an ability to enable high-rate SHM (HR-SHM). In May 2020, the Air Force Research Laboratory hosted a workshop "High-Rate Monitoring, Damage Detection, Structural Prognosis, and Reaction." At this workshop, the authors discussed and defined the need for high-rate structural health monitoring and outlined technical challenges and approaches to this area. This paper summarizes the current discussions of the HR-SHM panel discussion at IMAC XXXIX. The panel has three topics: (1) technical areas of HR-SHM and prognostics**,** (2) outline of potential HR-SHM technical grand challenges, and (3) review of proposed technical approaches.

The ability to accurately monitor a structure's functional integrity, remaining life, and react to maximize function and minimize risk is the ultimate goal of SHM and prognostics. The SHM technical community has established numerous methods for monitoring the health of static structures with low-frequency responses with great success [1,2,3,4]. Structures with high-rate dynamics include civil structures exposed to blast, automotive safety systems subjected to collisions, debris strikes to space shuttles, and aerial vehicles [5,6]. These systems have many additional technical challenges to overcome for appropriate monitoring the functional integrity. High-rate dynamics have been previously defined by Hong et.al [7] as:

> "a dynamic response from a high-rate (<100 ms) and high-amplitude (acceleration > 100 g_n) event such as a blast or impact. […] A system subject to high-rate dynamic environments can often experience sudden plastic deformation, and damage can extend to the structure, electronics, and/or sensors […]. The high-rate problem contains many complexities that can be summarized as having:
>
> 1. large uncertainties in the external loads;
> 2. high levels of non-stationarities [in the structure] and heavy disturbances;
> 3. unmodeled dynamics from changes in system configuration."

The complexities of high-rate dynamics drive the need for a specific technical area of HR-SHM and prognostics. The HR-SHM technical area has unique technical grand challenges that need to be addressed due to the short timescales in which data needs to be processed and decisions need to be made.

The paper summarizes the state and outlines the HR-SHM technical grand challenges. The high-rate time scales need to be defined for specific time scales which are intimately related to an integrated paradigm including data acquisition, assessment execution, data fusion, and decision-making [8]. These timescales and computational constraints must be coupled to allow for high-rate implementation that is robust, adaptable, and beneficial to the missions of interest. This grand challenge and possible methods to address these challenges are defined as (1) specifying the time scale, (2) determining the decision needs for performance assessment [9, 10], (3) methods of statistical analysis (e.g., advances in deep learning [11]), (4) correspondence with materials response [12], and (5) effective methods of model correspondence with data collection [13])

DEFINING HIGH-RATE

The timescales of systems and sensor responses are usually fixed while the rate of loading on the structure and timescales requirement for decision-making drives the constraints on the integrated paradigm of data acquisition, algorithm processing, assessment execution, and decision-making.

Understanding the various time scales required for decision-making and the other aspects involved is critical to the design of HR-SHM systems. Table 1 summarizes types and examples of timescales for high-rate monitoring of structures with high-rate dynamics. The timescale set of Table 1 represents the relevant time scales over which data acquisition must occur, algorithms must execute and process, and decisions must be made about the state, prediction, etc.

Table 1 Types and examples of timescales for high-rate monitoring.

Time scales of…	Time Scales	Examples
duration of the event	30 µs – 100 ms	Structural loading - blast, high-speed impact, automotive crash [7]
sensor response	3 µs – 10 us	Accelerometer, strain gage, ect. [14]
different physical behavior regimes	250 µs – 1 sec	Energy propagation, structural resonance
algorithm execution and decision-making	100 µs – 1 ms	Damage detection, uncertainty quantification, state awareness [15]

Approaches to high-rate SHM analysis have to be developed for the long and short timescales, such as foreground (changes fast, < 1 ms) and background (changes slow, > 1 ms). More specifically, three timescale regimes are defined for the time elapsed between event detection to decision-making (i.e. latency), these regimes are:

1. High-Rate – 1 ms
2. Very High-Rate – 100 µs
3. Ultra High-Rate – 1 µs

The goal for the first approaches in developing HR-SHM should target 1 ms timescales from event detection to decision-making. As sensors, algorithms, and hardware improve (such as non-inertial sensors and imaging sensing [16]), systems can work at addressing the decision-making for structures during events with very high-rate dynamics. The ultra high-rate timescale is one that is difficult to reach with existing technologies, and will necessitate advances in hardware, algorithms, data acquisition/transmission, and computing.

TECHNICAL CHALLENGES

The overarching challenge posed by HR-SHM is to determine the condition of a structural system in less than a millisecond, while the structure sustains unknown/unmeasured, high-magnitude, and short-duration impacts. In that short amount of time, there is a challenge on the reliance on scarce sensor data to identify the key aspects of response, detect changes in structural parameters, and subsequently perform structural prognostics for decision-making. This encompasses analysis, computation, and hardware implementation. The algorithms must not only be suitable for high-rate implementation, they must also be robust and continually woven into the program/process of uncertainty quantification; predictions or decisions must be connected to confidences in those actions so that risk profiles of the decision-makers can be integrated. Further, context modeling supports development of efficient measurement processing which supports decision-making at any time scale [17].

There are four grand technical challenges:

- adequate sensing,
- lack of system knowledge,
- high variability in loading, and
- limited resources for algorithm implementation.

The first challenge is ***adequate sensing***, especially high rate sensing, and presents itself in the observability and influence on the system due to the sensing, such as mass loading. Several high-rate applications are associated with weight-sensitive scenarios, and the structure to be monitored may not allow permanent sensor installation. Spatial issues include the resolution of the area monitored, the communication distance, and the number of edge sensors. Temporal issues include the sensor type (e.g., THz, imagery) as well as multiple sources of uncertainty. The corresponding uncertainty brings the technical challenge of signal processing utilizing a network of novel sensors with small dimension, lightweight, survivable, fast dynamic response, and variabale (e.g., low, high) uncertainty. Methods of data fusion, machine learning, and signal processing can support the multiresolution (time, space, and frequency) *sensing awareness* analysis.

The second challenge is the lack of ***physical knowledge*** of the high-rate process, thus requiring a combination of system identification, load estimation, and damage detection (all forms of complex inverse processes). In addition, the poor observability in the sensing procedure, the poor quality of data, and insufficient sampling rate make it difficult to compensate for the lack of physics through only data-driven modeling. One difficulty in enabling *structural awareness* for high-rate structures is learning the state of a structure online during a high-rate dynamic event.

The third challenge is the consistency/repeatability of ***high-rate events***. While the physics is not clear for many high-rate processes, the consistency of high-rate testing/events are normally very low. During high-rate events, a structure will often generate previously unmodeled dynamics due to changes in system configuration or damage. The challenge of *environment awareness* brings very high uncertainties and a tremendous amount of difficulties in predictive modeling, such as damage prognostics.

The fourth challenge is the limited ***computational and power resources*** for the implementation of the real-time algorithms. These limited resources are key factors to what algorithms can be trained, deployed, and executed to enable rapid decision-making on the relevant timescales (~1 ms). The computational technical challenge includes identifying the appropriate algorithm and hardware combinations to be effective on the short timescales. The elements of *energy awareness* correspond to the demands on the processing, network, and system identification.

These key technical challenges are interdependent and technically challenging for high-rate analysis and this list is certainly not complete. It is expected that the technical community will unveil new challenges as they pursue the HR-SHM research area. To-date no approaches exist that address all of the above outlined technical challenges which drives the need for new and collaborative technical approaches overviewed in the next section.

TECHNICAL APPROACHES

To address the first challenge of high-rate sensing, approaches may include non-inertial (including non-contact) and full-field sensing approaches. Non-inertial sensing uses measurement methods that decouples the sensing mechanism from the inertial response of the dynamic structure and sensor package. Using non-contact sensing would enable non-local sensing and potentially sensing faster than the traditional sensors (e.g., accelerometers). Examples to support high-rate sensing are high-speed video motion magnification that has been demonstrated to be more noise robust in revealing invisible system dynamics under the noise floor, and also provide zero-mass-loading system monitoring. Additionally, full-field approaches are key to supplementing spatiotemporal sparse data. The full-field data could be provided with vision-based systems or data fusion of sensor networks and algorithms that infer or map full field data from limited measurement points.

To address the second and third challenges of lack of physics and inconsistency of the data observations, approaches may include developing physics-enhanced machine learning (PEML) models, which integrates the learning model with any known physics. Machine learning using data-based methods alone currently prove very powerful tools for predicting remainable useful life for rotational machinery [18, 19] and prediction of high-rate dynamics [20]. Additional current trends include PINN (physical-informed neural networks), physics-informed machine learning (PIML) [21], and digital twin interpretability [22]. PIML approaches which combine advances in machine learning and physical modeling are typically at temporal rates at the level of desired sensing, but could be adapted for higher temporal rates. For high-rate dynamical analysis, it would require real-time fusion of high-speed dynamic data augmented by model-based data to address the unmodeled and rapidly changing dynamics in the structure. These methods may use a number of model reduction and model-updating approaches to refine this system models both offline and real-time. Additionally the approaches need to use uncertainty quantification (UQ) methods to enable predictions [23, 24] or decisions connected to confidences in those actions so that risk profiles of the decision-makers can be integrated.

The fourth challenge is the implementation of these algorithms on hardware for real-time execution. The hardware is an interdependent challenge with developing algorithms in software to address the second and third technical challenge. Developing the hardware implementation for real-time execution would require cognitive sensing such as that of software defined radios, cognitive radar, and other recent developments in configuring the sensors to measure at various timescales. Since the "cognitive" approaches combine both the hardware and software, they are methods that support the tailored response to the evolving high-rate variations, external disturbances, and sensor measurements.

A critical need for the development of HR-SHM is ***experimental validation*** for the high-rate algorithms. To enable a comparable analysis, data sets from various experimental tests that have different aspects of the high-rate dynamics would be collected and distributed for development of new approaches and testing algorithms. These data sets should be sufficient to cover the considered time scales (and have multiple "goals" that the data owners want to get out of the exercise), should sufficiently span a large range of operational and environmental variability, and should have numerous instances of whatever "failure" mode targets are desired (e.g., structural damage, the operability of electronics, actuators, etc.). Coupled with the data would be the need for appropriate metrics, design of experiments scenarios, and different situations. One existing experimental apparatus available to the authors is DROPBEAR, which provides some aspects of repeatable, controllable non-stationary dynamics, but additional experimental methods are being persued to better capture repeatable experimental data with high-rate dynamics [25].

SUMMARY

This paper defined the technical area of high-rate structural health monitoring (HR-SHM) by specifically adapting SHM mindset to structures with rapid loading and high-rate dynamics. The desired timescales from sensing to decision-making in regards to HR-SHM are starting with 1 ms, with 100 μs being a longer term goal. Four grand technical challenges were outlined: (1) adequate sensing, lack of system knowledge, (2) limited resources for algorithm implementation, (3) high variability in loading, and (4) implementation requirements. These technical challenges are interdependent, multi-faceted, and complex. To start to address the coordination of these challenges, a number of feasible approaches are discussed such as a data set and challenge problem that supports algorithm development . The proposed approaches include physics-informed real-time fusion (PIRF) of high-speed dynamic data coupled with machine learning methods augmented with model information and implemented in edge-computing architectures. These PIRF methods need uncertainty quantification to be present to address multiresolution variability in sensing, response, and analysis to enable risk-based decision-making. Together these approaches can be further harnessed to enable structural and functional prognostics for high-rate dynamic systems.

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