Implementation of Information Entropy in an Industrial Internet of Things Approach for Structural Health Monitoring Applications

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ABSTRACT

Structural Health Monitoring (SHM) involves damage assessment processes that contribute towards overall safety decisions. The need for real-time assessment and decision-making in SHM has long been attempted in various ways via connections between data acquisition and information extraction. In this context, this investigation presents a novel approach to enable real time data streams for SHM. To achieve this goal, an Industrial Internet of Things (IIoT) framework developed is used in conjunction with Nondestructive Evaluation (NDE) datasets for near real-time diagnostics. To demonstrate the performance and results of applying this method, the case of laboratory scale testing of crack initiation is presented in this manuscript. Specifically, compact-tension specimens of an aerospace-grade aluminum alloy were used in accordance with ASTM standards. Acoustic Emission (AE) datasets were acquired and were subsequently used in an in-house built, scalable IIoT system capable of edge, fog, and cloud computing. At the fog layer, a trained model was loaded to classify the signals in real-time. The trained model relies on signal Information Entropy (IE) values as input and outputs to form an indicator of crack initiation. The AE data input is shown as a test-case for any general time-series type data acquired in SHM applications such as accelerometers and vibration sensors. The main innovation of this approach is the fact that a combination of hardware, computing and IE analysis proves to be advantageous to flag the incubation and subsequent initiation of fracture. The IIoT system described can be applied to a variety of SHM applications for continuous type monitoring.

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INTRODUCTION

Structural Health Monitoring (SHM) includes a variety of processes and methods capable of assessing aging and deterioration among other effects of structures. Recent advances in Industrial Internet of Things (IIoT) and big data frameworks have enabled SHM techniques to augment decision-making with data-driven insights [1]. The industry has thus been moving towards predictive maintenance of e.g., bridges, aircrafts, railways etc., targeting automation in maintenance and sustainment operations. Some of the key bottlenecks of evaluating complex systems which motivate research and development of IIoT methods in SHM, include the time scale involved in monitoring structures, the high sensing sampling rates required to assess evolving operational and loading conditions, and the adoption of a variety of non-correlated and non-synchronized sensor networks [2]. These bottlenecks practically result in hindrances both in storage and analysis of SHM data.

Structural performance related data have long been acquired using Non-Destructive Evaluation (NDE) methods and have been used to directly or indirectly infer on the detection of damage, degradation, or deterioration of critical parts or of entire structures [3]. NDE methods and techniques used to detect and evaluate flaws in materials and structures generally do not impair the overall usefulness of the component. All NDE methods involve some form of energy (e.g., heat, acoustic waves, radiation, light, etc.) for inspection purposes. Common NDE methods include optical, radiography, acoustic emission (AE), ultrasonic, electromagnetic and several other approaches [3-5].

The detection of cracks in SHM is of particular importance as it is one of the most common reasons which lead to structural failure. If cracks are detected early and reliably, data-driven maintenance cycles at appropriate stages of damage development are possible of being implemented. In relation to the research presented in this manuscript, various stages of crack initiation and growth have been characterized by AE monitoring [6-8]. Furthermore, AE feature-based machine learning approaches have been introduced to characterize and classify crack detection, mostly though offline [9-11].

In efforts to convert data to knowledge, information theory, introduced by Claude Shannon in 1948, initiated the quantification of digital information. Specifically, Information Entropy (IE) measures the uncertainty or disorder of a phenomenon [12]. Recently, there have been several efforts to integrate IE with data acquired by sensing methods. In the context of this manuscript, it should be noted that connecting IE for AE monitoring in relation to fracture events [8, 13-15] has already shown that the statistical/probabilistic representation of AE signals can reliably detect stages of damage regardless of acquisition parameters. Furthermore, Burud et al. have considered the application of IE for AE analysis in the spectral range instead of the time domain [16]. The results, portray IE as a reliable approach to define damage metrics. However, Chai et al. specifically mention the need for more research in applying related data post-processing in the case of real-time monitoring, e.g. related to the initiation of cracks, to effectively monitor critical damage [8].

To address the aforementioned bottlenecks, probabilistic methods, combined with machine learning and cloud-based computing have enabled the integration of

structural data into diagnostics and prognostics [17-19]. In the author's previous work, their in-house developed IIoT system integrated three distinct layers namely the Edge, Fog, and Cloud to overcome bottlenecks in processing NDE big data within machine learning [19-22]. Within this context, the proposed work in this manuscript leverages an IE approach with a custom-built IIoT system to detect crack incubation and crack initiation. The motivation for this work is in near real-time implementation in applications that include continuous monitoring.

METHODS

Figure 1 portrays an overview of the IIoT framework presented in the author's previous work [19-21, 23]. The developed IIoT architecture is subdivided into two parts: an onsite and a Cloud network both at a macro and testing scale (Figure 1). The onsite network hosts an Edge and Fog layer. The Edge is a compute node closest to the sensing setup. In Figure 1, the Edge layer is composed of AE piezoelectric sensors (Pico) and a PCI-2 data acquisition system (DAQ; all AE equipment was commercially available by MISTRAS Group) and was used to acquire AE signals when testing a compact tension (CT) specimen in a servo hydraulic loading frame. The sensors were bonded to the specimen's surface using hot glue and the received signals were amplified using 2/4/6-AST™ type pre-amplifiers. A threshold of 45 dB was used to minimize the recording of unwanted noise from e.g., the mechanical vibrations introduced by the testing machine. The recorded signals were band-pass filtered in the frequency range of 100 kHz–1 MHz and a sampling rate of 5 MHz was utilized. CT specimens were manufactured form a 4 mm thick Aluminum 2024 Alloy plate in accordance with ASTM E1820 and ASTM E647 [24, 25].

The Fog part of the IIoT system in Figure 1 is a decentralized computing node responsible for data pre-processing within the local Edge network. The testing scale configuration portrays three possible single-board memory computers used by authors for the onsite IIoT system. The onboard device is responsible for pre-processing, aggregating, parsing, and filtering data before the data is sent to the Cloud. The model used to detect crack initiation was trained on the Cloud and was then used real-time at the Fog. Each AE signal was outputted as a separate waveform file and decoded at the Fog layer to apply the model. For an envisioned aerospace application, the Fog would connect with the Cloud layer via satellite communication as shown in Figure 1.
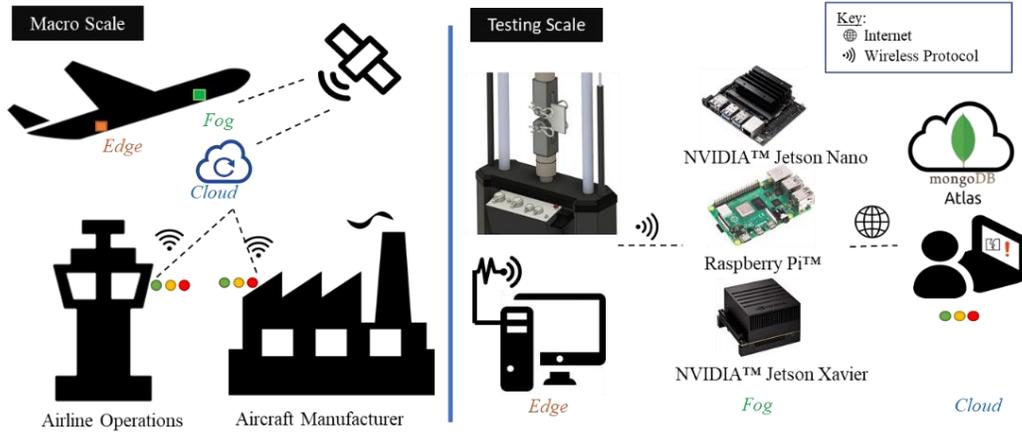
Figure 1. Custom IIoT System developed in this manuscript; envisioned Macro Scale implementation and the actual testing Scale version as presented in this manuscript are shown, including the involved Edge, Fog, and Cloud Layers

The Cloud layer generally involves a network of remote servers over the Internet to store, manage, and visualize data. For the case in this manuscript, the data was structured in a BSON format to create a database hosted on MongoDB Atlas server. A dashboard was also developed to allow the end user to detect when crack initiation occurs. The end user would connect to the Cloud via any wireless protocol or Internet for envisioned future applications of this IIoT setup. The set up is created for the crack initiation use case, however can be expanded for cyclic loading use cases as well.

Information Entropy Model

The model used to detect crack initiation was trained on the Cloud. A probability value associated with each AE signal (waveform) was determined by calculating the relative frequency using a non-parametric distribution (Figure 3). Using the probability mass function, the respective probability values were input to the IE function. The probability values for each bin were then evaluated with IE from 1 to the n, where n is the number of bins (Equation 1). The Interquartile Range (IQR) was calculated from the resulting entropy values, *IE*. The upper bound of the IQR was used to distinguish outliers in the entropy values. The upper bound was calculated via Equation 2 where Q3 represents the 75th percentile. Any signal above the upper bound was thus classified as crack initiation.
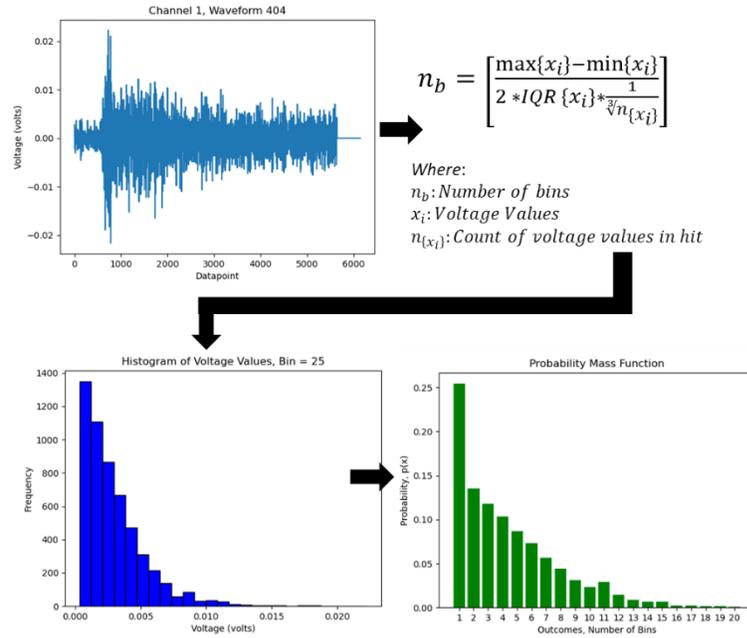
$$n_b = \left\lceil \frac{\max\{x_i\} - \min\{x_i\}}{2 * IQR\{x_i\} * \frac{1}{\sqrt[3]{n_{\{x_i\}}}}} \right\rceil$$

Where:
n_b: *Number of bins*
x_i: *Voltage Values*
$n_{\{x_i\}}$: *Count of voltage values in hit*

Figure 3. AE Signal Probabilistic Representation for Information Entropy

$$IE = -\sum_{i=1}^{n} p(bin_i) * \log_2(p(bin_i)) \quad\quad (1)$$
$$Upper\ Bound = Q3 + (1.5 * IQR) \quad\quad (2)$$

RESULTS

Model Training and Testing

As the specimen underwent monotonic tension load, the DAQ converted mechanical stress waves to electrical signals. The electrical signals were then outputted as a series of voltage vs time values. Using the IE approach, each signal was classified as 'crack initiation' or 'no crack'. The results of the training process portray the crack initiation signals upon the onset of load drop (Figure 3). The crack initiation signals were further verified using two methods. The rate of change of the load curve (Figure 2) shows a large drop upon the onset of crack initiation at 481.26 seconds, in accordance with the procedures described in the ASTM standards.
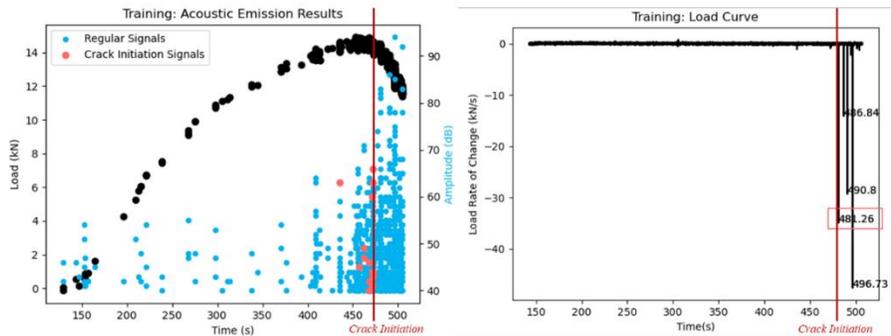

Figure 3. AE Training Results verified with the Load Curve and Rate of Change of Load Curve

Using the afore mentioned upper bound, approximately 31 crack initiation signals were classified before 480.8s, thus indicated crack incubation before the load drop to provide an early indicator of impeding damage. Furthermore, the crack signals labeled in Figure 2 were mapped onto the AE feature space to characterize the signals. Based on Table 1, the top eight features with respect to percent change show a large difference between signal averages for regular (i.e. not crack related) crack initiation signals. This characterization is congruent with previous findings by the authors in which it was found that crack initiation AE signals are of the so-called burst-type as opposed to continuous type which is more characteristic of secondary AE sources and noise.

TABLE I. AE TRAINING RESULTS VERIFIED BY AE FEATURES

	Regular Signal Averages ± Standard Deviation	Crack Initiation Signal Averages ± Standard Deviation	Percent Difference (%)
Absolute Energy (aJ)	1,574.2 ± 9,288	579,510.3 ± 1,327,735	198
Energy (aJ)	7.9 ± 10.9	195.4 ± 206.2	184
Signal Strength (picovolt-sec)	52,285.2 ± 68,364	1,224,171.9 ± 1,288,039	183
Counts	93.2 ± 117.8	383.4 ± 88.6	121
Counts to Peak	15.3 ± 24.2	61.0 ± 74.5	119
Reverberation Frequency (kHz)	103.1 ± 124.5	388.5 ± 87.9	116
Average Frequency (kHz)	110.1 ± 120.3	383.4 ± 88.6	110
Root Mean Square (RMS16) (mV)	0.003 ± 0.005	0.005 ± 0.004	48

There were two tests conducted for this research. The first test, used for training, contained 354 waveforms for Channel 1 and 490 waveforms for Channel 2. The second test, used for testing, contained 464 waveforms for Channel 1 and 12,189 waveforms for Channel 2. For the model analysis, the Channel with the larger number of waveforms was used. To analyze the waveforms a Python environment was configured using Numpy, Scipy, Pandas, among other packages. Numpy and Scipy were used for the numerical analysis while Pandas was used for the data structure to organize the raw data and respective label output.
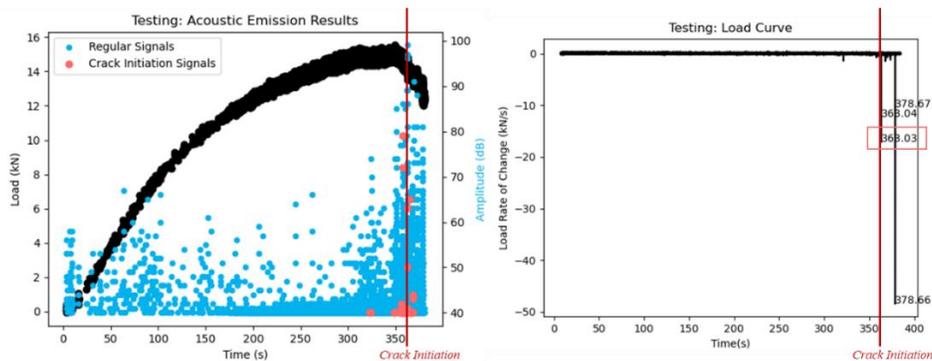

Figure 4. AE Testing Results verified with the Load Curve and Rate of Change of Load Curve

Real-time Implementation

The IE approach is particularly advantageous for real-time analysis as it synthesizes the entire raw waveform into a single metric indicative of signal information. In order to implement this approach real-time, the Fog node could be configured with a Watchdog script which is capable of reading the AE waveforms and calculating the respective IE value per signal. The single IE value per waveform would then be inputted to the trained model. In this use case, the trained model was the Upper Bound calculated from the IQR approach. If the IE value is found above the value, the signal would be labeled as 'crack initiation' otherwise, a regular signal. The Watchdog would further be configured to parse the signal to send the data to the cloud in a BSON structure. Figure 5 shows the data structure for real-time waveforms. The key value of 'Experiment' allows the user to efficiently query the data for model training offline. The database contains two collections namely 'All Data' and 'Preload' which signify the data collected live during the experiment and the data prior to the experiment respectively. This type of data structure further allows complex loading cases such as Fatigue in which larger datasets are generated and now can be streamed to the Cloud real-time with an appropriate data structure.
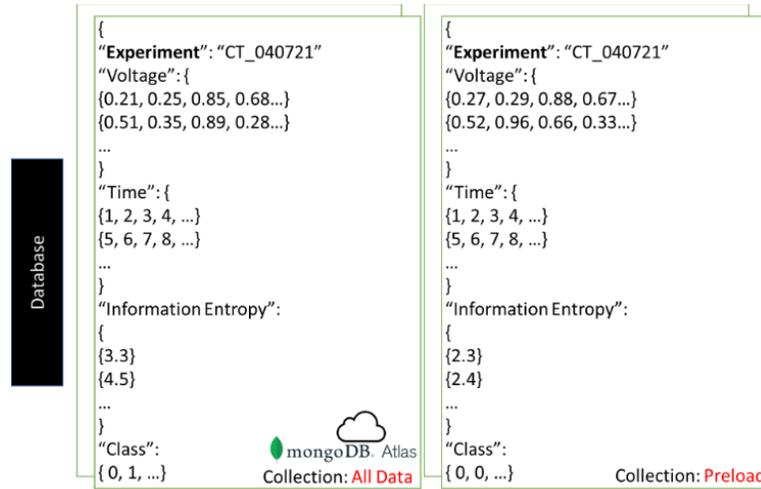

Figure 5. Real-time Cloud Data Structure for Time-Series Sensor Data

In terms of hardware, the Edge would consist for example of the PCI2 system by Physical Acoustics and the Fog Device could be the NVIDIA Jetson Nano based on the authors previous work [21]. For the real-time implementation, a Server Message Block (SMB) and Samba are relevant network protocols that facilitate the sharing of resources between devices in a network. The Windows machine (Edge: PCI2) and NVIDIA device (Fog: Jetson Nano) can be configured with these protocols for a seamless integration of these systems. This interaction between SMB and Samba ensures a consistent sharing mechanism that allows AE file transfer in real-time between hardware. The Cloud could be hosted remotely on Amazon Web Services (AWS) Server with a MongoDB configuration.

CONCLUDING REMARKS

The work presented shows the use of a distributed IIoT system to classify crack incubation and crack initiation in real time. The main advantage of this approach is the ability to leverage raw NDE signals, in this case AE related voltage time series, to classify crack initiation. Alternative methodologies have leveraged feature-based approaches which may not be able to be directly applied to real-world scenarios with varying sensors and data acquisition systems, especially when online monitoring is of importance. Analyzing the raw signals provides a flexible approach to the user to leverage any sensing and acquisition methodology. Future work for this research includes remaining useful life prediction estimations after the identification of crack initiation and applying this system to fatigue and structural-scale experiments.

ACKNOWLEGMENTS

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