Frequency-Based Rapid Structural Damage Detection Using Embedded Edge Computing on Resource-Constrained Devices

by

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Abstract

Structural Health Monitoring (SHM) is essential for ensuring reliability and longevity of useful structures. Traditional SHM approaches rely on manual or remote data transmission and external processing, which introduce latency and can depend on stable communication links. This work aims to advance SHM by integrating edge-computing techniques for rapid damage detection to enable faster and more autonomous structural assessments in resource-constrained environments. The research spans three key contributions including 1) frequency-based damage detection of civil structures using a sensor package with the addition of an edge processor, 2) additions to the computational efficiency of the edge-computing sensor package in a more resource-constrained environment, and 3) frequency-based damage detection for electronic assemblies with embedded sensors subjected to high-rate dynamic events. The main focus is to enhance structural safety, resilience, and adaptability for structures in critical areas. The first contribution involves drone-deployable vibration sensors and explores the feasibility of edge-computing for autonomous SHM in inaccessible or hazardous environments. The sensors analyze frequency-domain data in real-time to reduce reliance on external data processing. The second contribution constrains the edge-computing abilities of the sensor package to the embedded microcontroller and evaluates the computational efficiency of on-the-edge processing. Lastly, the third contribution demonstrates Fast-Fourier Transform (FFT) analysis for identifying structural damage in printed circuit boards (PCBs) exposed to mechanical shock. This study makes use of embedded sensors to build the foundations of edge-computing for self-diagnosing electronics, also paving the way for active control and damping of

vibrations in electronic assemblies. The findings of this work demonstrate the effectiveness of edge-enabled SHM to enhance rapid structural assessments by reducing response times and enabling decision-making at the data source. These advancements contribute to the broader vision of intelligent monitoring systems that can operate autonomously across diverse structural environments.

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Chapter 1

Introduction

Structural health monitoring (SHM) is a critical method for ensuring safety and longevity of engineered systems, ranging from civil infrastructure exposed to extreme conditions to electronic assemblies in high-rate dynamic environments. Traditional SHM methods rely on external data processing, which is typically performed off-site, creating a workflow that introduces latency in decision-making and requires stable communication links. In scenarios such as real-time damage detection in electronic systems or post-disaster assessments of civil structures, time delays can be detrimental. Additionally, having to rely on centralized computing is impractical in resource-constrained situations where rapid insights are necessary.

Computing SHM data on the edge can significantly reduce response times. By deploying algorithms directly onto embedded devices, structural anomalies can be detected in real-time, eliminating the need for continuous data transmission or off-site processing. This approach is particularly useful in diagnosing issues in electronic assemblies with embedded sensors or civil structures with rapidly deployable sensor packages.

In civil infrastructure monitoring, drones equipped with vibration sensors can be deployed to assess structural integrity following natural and man-made disasters. An example of a civil structure that SHM would be used on is shown in Figure 1.1. While this approach inherently decreases response times especially in cases in which the structure is damaged, the method can be further improved with the use of microcontrollers to make necessary computations on the edge. Integrating Fast Fourier

Transform (FFT) frequency analysis on embedded systems within drone-deployable sensor packages allows for rapid anomaly detection.

Figure 1.1: Example of a pedestrian walking bridge which could be a candidate for SHM.

Similarly, electronics subjected to high-rate environments such as mechanical shock can benefit from rapid detection of structural damage. Frequency-based damage detection using FFT algorithms has been demonstrated as an effective method for monitoring printed circuit board (PCB) health. Implementing an edge-computing approach for FFTs directly on electronic assemblies enables proactive responses to possibly damaging events.

This work focuses on integrating edge-computing for SHM in resource constrained systems to address challenges in computational efficiency, power consumption, and real-time frequency identification. Experimental results from drone-based SHM applications as well as electronic PCB testing in high-rate environments are presented to demonstrate the effectiveness of edge-processing FFTs for damage detection. The findings contribute to the broader vision of autonomous, real-time monitoring systems capable of enhancing the durability and reliability of critical structures.

In these studies, vibration-based damage detection networks and edge-enabled systems were tested. Along the first domain of this work, drone-deployable wireless sensor nodes were developed as shown in Figure 1.2. Vibration sensor packages equipped with an accelerometer and a microcontroller were designed and tested for capability of Fast Fourier Transform (FFT) processing and peak detection computations for modal frequencies. This package was integrated with UAV compatibility for deployment onto physical structures like beams or bridges. Results from the on-device data processing were compared to high-fidelity, off-site analyses and showed low root mean squared error from the two frequency domain calculations.

Figure 1.2: Wireless drone-deployable sensor nodes attached to a pedestrian walking bridge.

In the second domain of this work, damage detection, response, and control of electronic assemblies were investigated. Repeated use of electronics in high-rate environments can lead to catastrophic systems failures as shown in Figure 1.3. PCBs were designed with embedded sensors to investigate the feasibility of damage detection in small electronics subjected to high-rate conditions. A MEMS accelerometer, two strain gauges, and a resistor were mounted on the PCB for continuous data acquisition during testing. The PCBs were then evaluated on high-rate loading using a drop tower to intentionally detach the resistor. The resistor detachment showed an increase in natural frequency, which was expected due to the higher mass that the component adds when attached. The change in frequency was shown to be detectable through the embedded sensors.

Physical structures, such as PCBs, bridges, or even airframes, will degrade over time due to fatigue, impacts, thermal cycling, environmental conditions, or any other scenario that can impact structural integrity. SHM is a data-driven method to clarify the state of a structure where visual or physical inspection methods might fail. From a theoretical perspective, damage in a structure alters its mass, damping, and stiffness, which in turn changes the system's natural frequencies and mode shapes. Tracking these quantities over time provides a way to infer damage in a structure non-invasively. Furthermore, edge-computing creates an opportunity to develop rapid decision-making capabilities. This would push SHM into the domain of real-time feedback and control, where damage detection would trigger a response, such as an alarm, control adjustment, or mission re-routing.

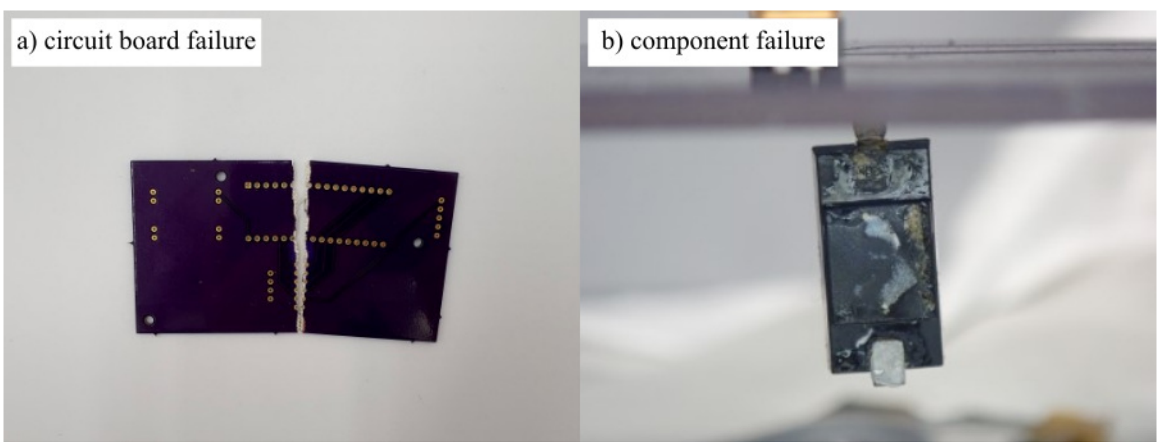

Figure 1.3: Degraded PCBs exhibiting damage shown as a) fully broken printed circuit board and b) failure of an electrical component.

Chapter 2

Frequency-Based Damage Detection using Drone-deployable Sensor Package with Edge Computing

Abstract

For rapid infrastructure assessment following natural and man-made emergencies, the utilization of minimally invasive and cost-effective drone deployable sensor packages has gained significant attention. While compact sensors with wireless data transfer capabilities have demonstrated potential for monitoring structural dynamics of critical infrastructure, such systems typically require data to be processed off-device and often off-site. These additional steps hinder the rapid assessment aspect. A challenge arises when transmission is not feasible due to degraded communication links during natural or man-made emergencies. Moreover, off-site data processing may add unnecessary delays to actions that can be taken by emergency personnel following infrastructure damage. To maximize the usefulness of sensor packages for rapid infrastructure assessment, the integration of edge computing techniques into the sensors themselves to analyze data in real time presents a promising solution. The objective

[1] Ryan Yount, Joud N. Satme, and Austin R.J. Downey. Frequency-based damage detection using drone-deployable sensor package with edge computing. In Conference Proceedings of the Society for Experimental Mechanics Series. Springer Nature Switzerland, August 2024. doi:10.1007/978-3-031-68142-49 Reprinted here with permission of the publisher, 2/25/2025

of this work is to demonstrate edge computing for frequency-based structural health monitoring techniques to showcase the effectiveness of on-device data processing for the rapid assessment of infrastructure. The proposed approach continuously computes the power spectral density of windowed vibration measurements taken from a structure of interest that has the potential to experience further damage, for example, the monitoring of a bridge immediately after a flooding event. This work presents contributions in terms of a methodology, focusing on the hardware implementation of edge computing algorithms. Additionally, a study of the performance and resource utilization of a windowed power spectral density processing algorithm on-device is provided.

2.1 Introduction

The emergence of high mobility, compact sensing nodes has the potential to transform the landscape of SHM and modal analysis. These nodes, designed for deployment on unmanned aerial vehicles (UAVs) or other platforms, provide a unique advantage by combining rapid mobility with minimally invasive data collection, as shown in Figure 2.1. Utilizing unmanned deployment methods for these sensor nodes enhances personnel safety compared to conventional approaches, particularly when dealing with large structures [20]. This flexibility enables the swift deployment of sensors across a structure, facilitating dynamic data acquisition and structural assessment with remarkable efficiency. The integration of electropermanent magnets (EPM) and radio frequency (RF) communication into the sensing nodes proved beneficial to capturing the vibration signatures from remote and challenging-to-reach infrastructures. Edge computing allows for real-time processing of data at the source, which is critical for applications such as SHM. Instead of collecting data from sensors and processing it after a test, a sensor package that can process data locally can provide immediate insights into a system's structural condition. In this paper, we delve into an improvement of a pre-existing UAV-deployable sensing node. Leveraging EPMs and RF communication, this sensing node exhibits prowess in gathering vibration signatures from infrastructures located in difficult-to-reach locations. Positioned as a wireless sensor network (WSN), these sensors reduce the challenge of high installation and maintenance costs associated with traditional wired methods [3]. Deployed via drones, these standalone sensors rapidly access structures using onboard accelerometers to collect data according to a preset schedule or event triggering for subsequent analysis. The comprehensive breakdown of the designed open-source sensing system is available in a publicly accessible repository [24].

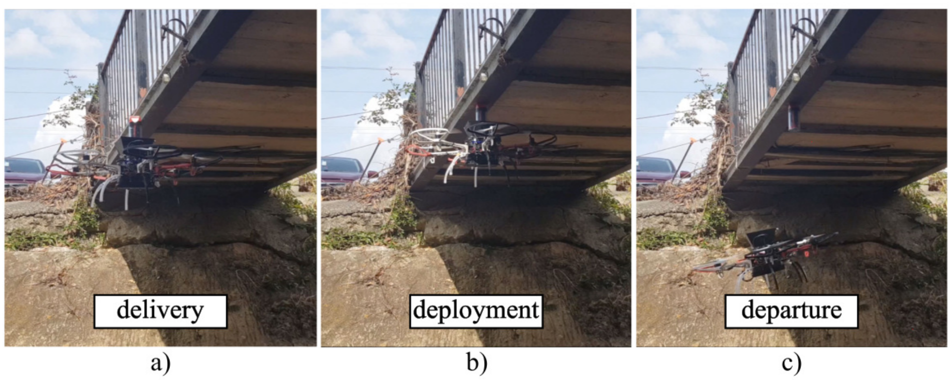

Figure 2.1: Different stages of sensor package UAV deployment with a) delivery b) deployment c) departure.

In this work, the integration of an edge-processing unit into this sensor network is introduced. Enhancements to the sensing system's real-time data analysis aspect is investigated, by leveraging edge-computing, to compute key features of the structure's dynamic response. This proposed procedure promises to further reduce the time affiliated with structural prognostics of the sensing system.

2.2 Sensor design

The sensor package featured in this study represents an embedded system-based device, designed for long-term deployment, and equipped with several subsystems [26].

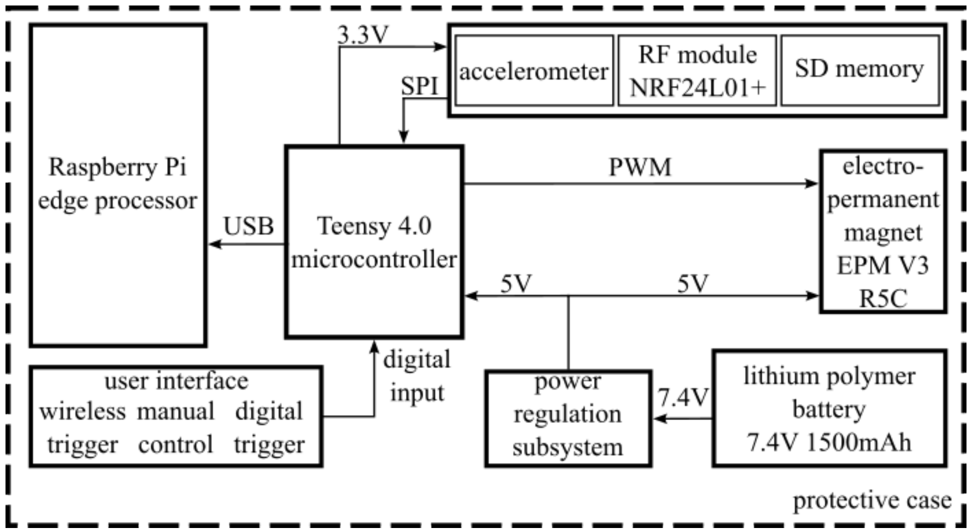

Figure 2.2: Block diagram of the components of the sensor package with the addition of the edge processor.

As shown in Figure 2.2, the processing core is an ARM-Cortex-M7, residing on a Teensy 4.0 microcontroller. To ensure sustained operation, the sensor package is provided with a 1500 mAh 2-cell lithium polymer battery, complemented by a dedicated power management subsystem that regulates voltage distribution to all other subsystems. Central to the sensor package's functionality is a high-performance MEMS accelerometer, the Murata SCA 3300-d01, which operates over the Serial Peripheral Interface (SPI) protocol. For minimally invasive deployments, an EPM V3R5C NicaDrone electropermanent magnet is seamlessly integrated. These magnets, characterized by their low power consumption, require only a brief 5W pulse for state switching. This process is typically only performed twice per deployment. Facilitating wireless communication and command exchange is the Nordic Semiconductors NRF24L01 module, operating at 2.4 GHz via the ShockBurst protocol. This module offers the crucial capability of connecting with multiple sensor nodes simultaneously, which is desirable for effective wireless sensor triggering. To ensure precise data logging and trigger time referencing, the sensor package is equipped with a real-time clock.

Furthermore, data integrity is safeguarded through the incorporation of non-

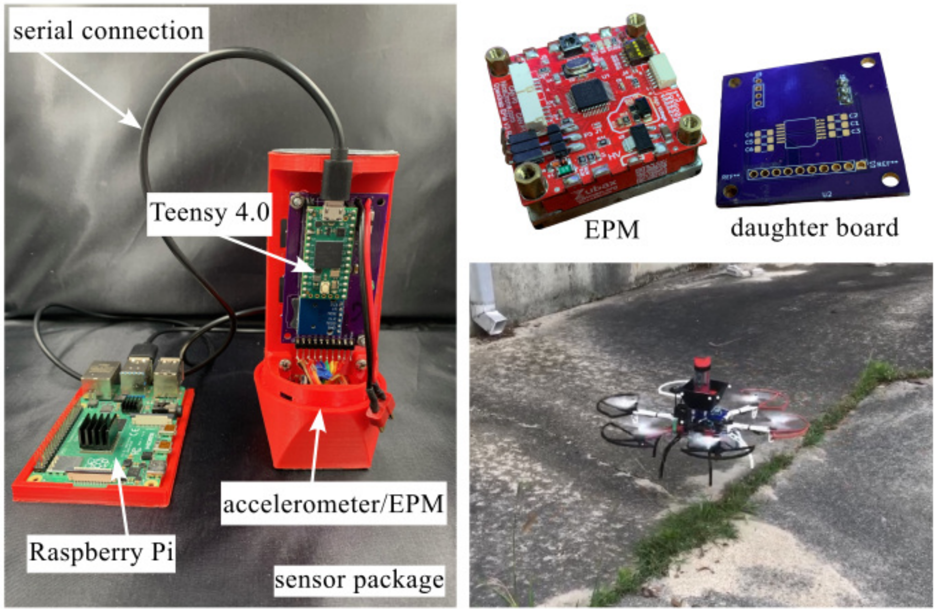

Figure 2.3: Sensor package with key components annotated along with a sensor package set up on a UAV.

volatile memory in the form of an SD card module. This ensures that valuable data is not lost in the event of power fluctuations or shutdowns. The sensor package is protected from the elements by its encapsulation within a protective 3D-printed PLA and PVC frame. This shields the delicate electronics from the harsh environment during field deployments as shown in Figure 2.3. The sensor package's footprint and weight have been optimized to be suited for UAV deployment [4].

2.3 Edge Computing Algorithm

In this section, the key features extracted from time-domain vibration data, along with a test and validation results are presented.

The Fast Fourier Transform (FFT) is a pivotal algorithm for the efficient computation of the Discrete Fourier Transform (DFT) applied to diverse datasets. Its application unveils the frequency components concealed within a time-domain signal. The FFT is often utilized in a spectrum of domains such as audio processing, image analysis, and the field of vibration analysis. This particular algorithm is extremely

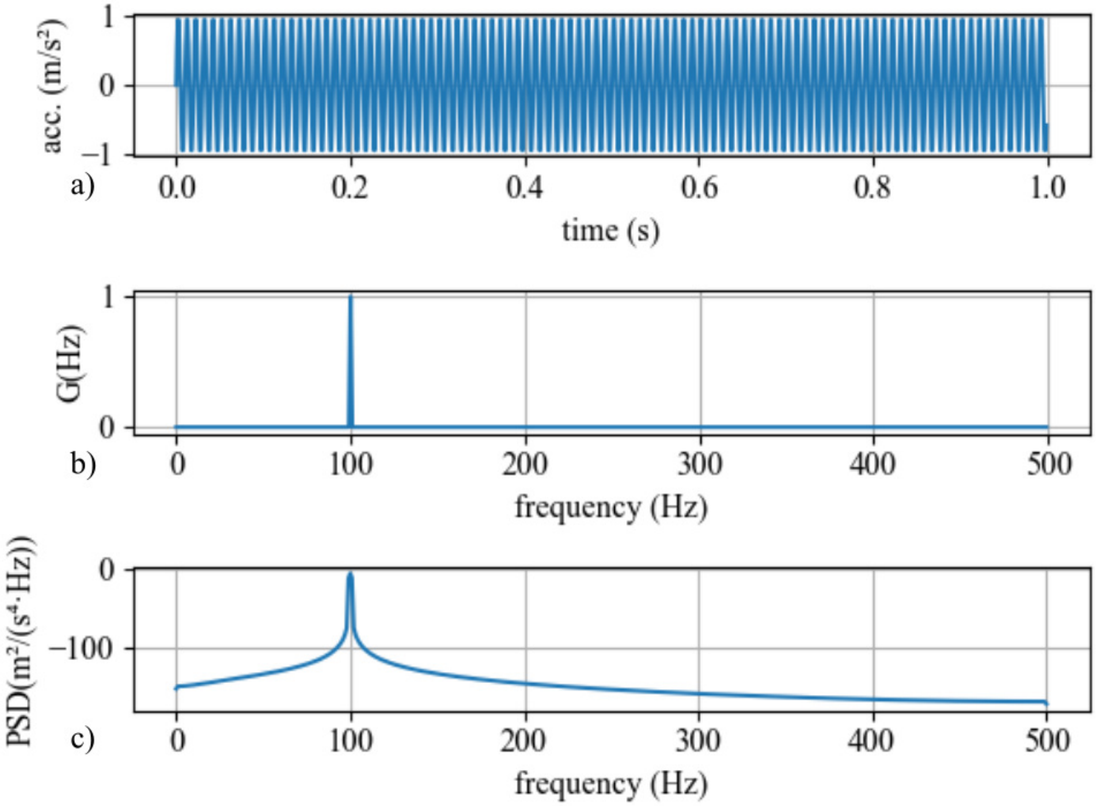

Figure 2.4: Synthetic data of a 100 Hz sinusoidal signal captured by the on-board edge-processor with a) time domain; b) FFT; c) PSD.

important to wireless sensor networks dedicated to structural health monitoring, as the extent of structural damage detectable through a system's dynamics is inversely related to the frequency range of excitation [33]. The FFT operation receives an extensive time-domain acceleration dataset obtained from the sensor nodes. This procedure undergoes a transformation of the data, shifting the signal from the time domain into the frequency domain. The signal is deconstructed into the various magnitudes of the frequency components. In many applications, only the positive frequency components are relevant, prompting the exclusion of the negative frequency bins. Consequently, the x-axis within Figure 2.4 represents the frequency components, while the y-axis showcases the magnitude of each frequency component to offer insight into the signal's dominant frequency components. In parallel, the Power Spectral Density (PSD) is an invaluable metric to elucidate the dispersion of power or energy across distinct frequencies within a signal. It is a key tool in various domains, including noise analysis, signal quality assessment, and vibration analysis, extending its applicability to the realm of wireless sensor networks employed for structural health monitoring. The computation for the PSD necessitates a precedent FFT calculation. Once the frequency components have been determined, the magnitude of the FFT coefficients is squared since the PSD conveys power and power is proportional to the square of the magnitude. Subsequently, the PSD values are normalized by dividing by the total signal length and the square of the sampling frequency. This normalization ensures the values are expressed in units of power per Hertz, providing a foundation for the analysis. To allow for a clearer representation of the power distribution across different frequencies, the values are articulated as decibels per Hertz.

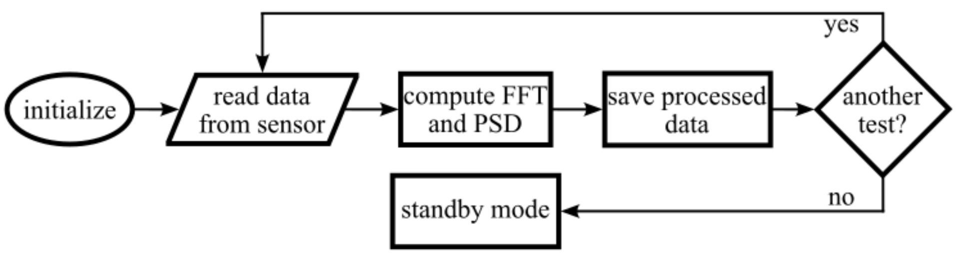

Figure 2.5: Flowchart of the code on the edge processor.

The Python code used on the edge processor is designed to perform a series of data processing and visualization tasks on real-time data received through a serial connection, typically from an external device like a sensor. As presented in Figure 2.5, the code establishes a serial connection between the sensor package's Teensy 4.0 and the edge-processing Raspberry Pi and reads incoming data. It collects pairs of time and acceleration values until the whole dataset is acquired. Once the full dataset is gathered, the FFT is computed to analyze the frequency components. Subsequently, the PSD is calculated to represent the distribution of power with respect to frequency in the system. The time-domain, FFT, and PSD results are then saved onto nonvolatile memory.

2.4 Testing procedure

The primary objective of this experiment is to investigate the power consumption associated with various functions performed by the edge-computing system.

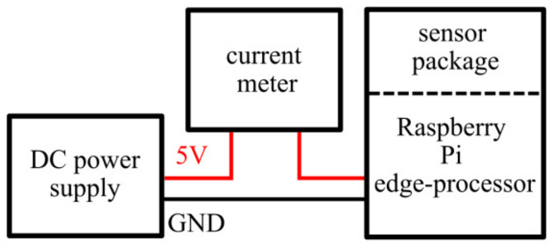

Figure 2.6: Block diagram depicting the power draw experiment with key components annotated.

As represented in Figure 2.6, the experimental setup consists of several components, including a DC power supply, an ammeter in series to measure current, an edge computing platform (Raspberry Pi), a sensor package (Teensy 4.0) with serial communication capabilities, and a data logger to record temporal power consumption. The software code developed for this experiment encompasses four essential tasks: firstly, the initialization of the edge computing platform; secondly, the continuous reading of data from the sensor package through se-rial communication; thirdly, signal processing to generate frequency response and power spectral density information; and lastly, the storage of processed data into memory for analysis. Once the serial data stream is completed, the edge processor transitions into standby mode to conserve energy. This experiment serves as a valuable tool to gain insights into the computational power requirements for extracting crucial features from time-domain data sent serially to the edge computing device, thereby aiding in optimizing energy-efficient edge computing solutions.

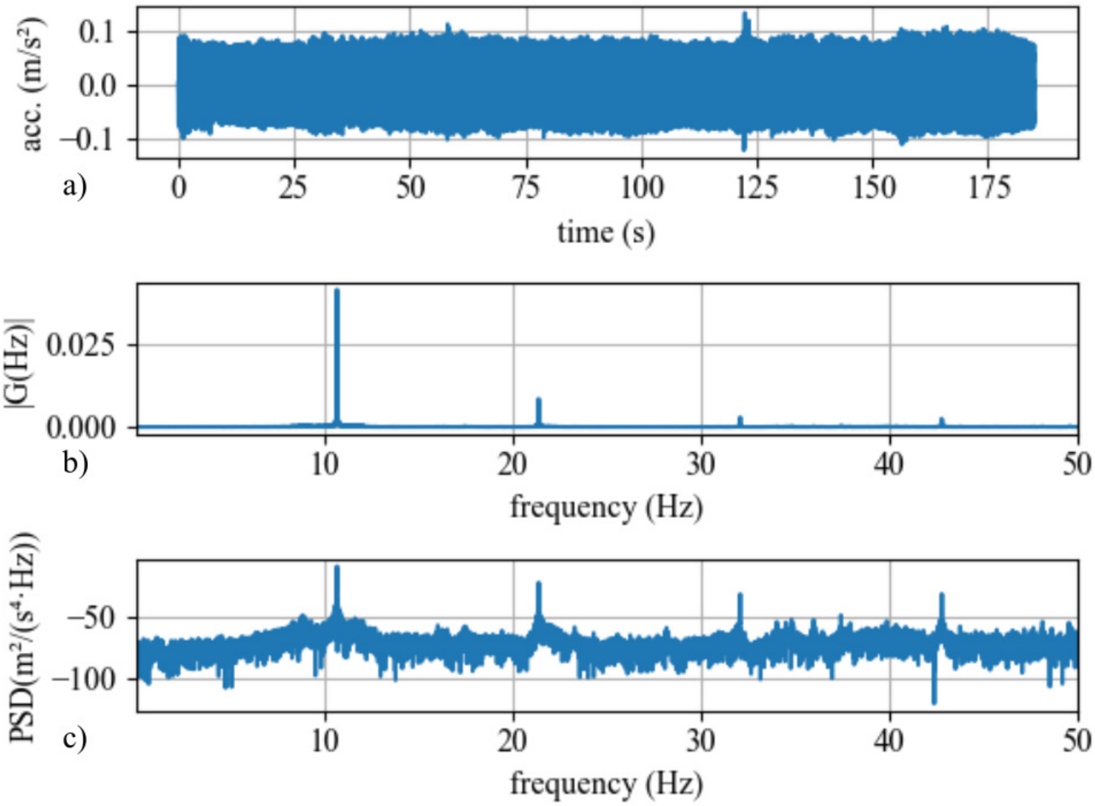

Figure 2.7: Vibration response of data captured by the sensor package deployed on a real structure, with the edge-processor capturing a) time domain; b) FFT; c) PSD of the structure under excitation.

In order to validate the effectiveness of the edge processor, a practical test using real acceleration data obtained from a bridge through the sensor package was conducted. The edge processor was able to analyze this data, providing plots in the form of the time domain, FFT, and PSD as shown in Figure 2.7. This real-world application demonstrated the processor's ability to swiftly process structural data under continuous excitation conditions.

In the power consumption testing of the sensor package with the integrated edge computing processor, several observations were made. The power consumption profile exhibited distinct phases during operation, as shown in Figure 2.8. Upon initializa-

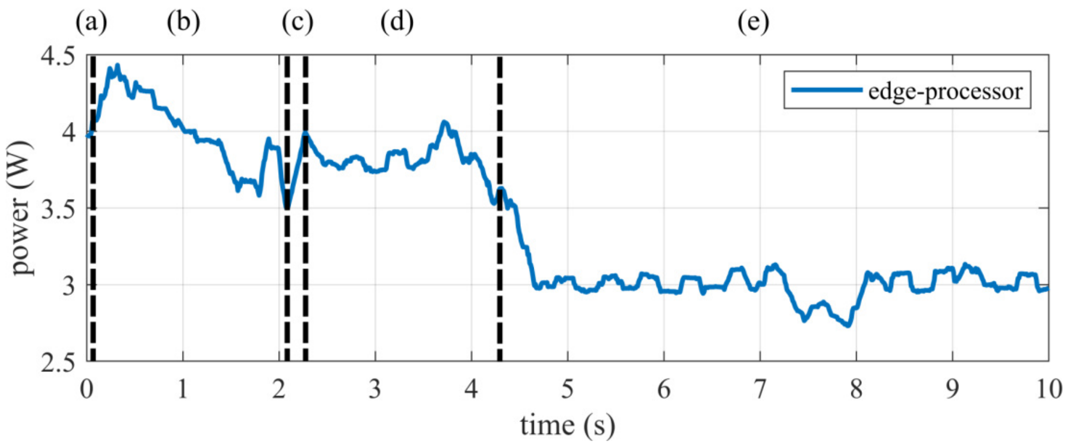

Figure 2.8: Power draw of the edge processor sectioned into: (a) initialization; (b) reading data; (c) computing the FFT and PSD; (d) saving the processed data, and; (e) standby mode.

tion, the system's power usage climbed to approximately 4 watts as the sensor package and edge processor powered up. Subsequently, during data collection, the power draw spiked to around 4.4 watts until gradually decreasing to less than 4 watts. During the data processing phase, where the processor computes the FFT and PSD of the captured data, power consumption increased slightly to roughly 4 watts again. Following data processing, the processor saved the computed data, maintaining a power usage in the range of 3.7 to 4.1 watts. Finally, when the sensor package entered standby mode, awaiting the initiation of the next test, power consumption remained at approximately 3 watts. The results of power consumption testing with the newly integrated edge processor within the sensor package strongly support the viability of edge processing as a favorable alternative to active retrieval of data. Although the power consumption of the edge processing system could be improved, the sensor package can still perform calculations with efficiency that is crucial for real-time structural analysis. Performing these calculations on the edge reduces data transfer delays associated with physical retrieval and processing of captured data from infrastructure.

2.6 Conclusion

In this work, the addition of an edge processor on an embedded system-based high-mobility sensor network is examined. During viability testing, the power consumption results underscore the effectiveness of edge processing in terms of energy efficiency, data accessibility, and reduced processing delays. These advantages showcase edge processing as a valuable alternative to active data retrieval, particularly for applications where resource constraints, remote deployment, and real-time anal-ysis are critical considerations. The system under investigation holds the potential for extensive deployment, offering a means for swift assessment of infrastructure in the aftermath of severe weather events. This deployment can quickly deliver initial insights into the condition of the infrastructure. While the system currently presents a viable solution, there are still avenues for future improvement. Notably, despite the sensor's relatively compact size, the inclusion of the edge processor significantly expands the footprint. Subsequent research will explore the utilization of smaller edge processors to further reduce the size and power consumption of the sensor package. Additionally, future work will delve into employing edge processors across multiple sensor packages within a network. This approach aims to enable rapid computation across an entire structure, rather than relying on a single localized point for processing.

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Chapter 3

Edge Processing for Frequency Identification on Drone-Deployed Structural Health Monitoring Sensor Nodes

Abstract

For rapid civil infrastructure assessment following natural and man-made emergencies, the utilization of minimally invasive and cost-effective drone deployable sensor packages has the potential to become a valuable tool. Although compact sensors with wireless data transfer capabilities have proven effective in monitoring the structural dynamics of infrastructure, these systems require data processing to occur externally, frequently off-site. These extra steps impede the high-speed assessment of a structure's state. Difficulties can arise when the transmission is unfeasible due to degraded communication links during natural or man-made emergencies. Additionally, off-site data processing can add unneeded interruptions to actions that can be taken by emergency personnel after infrastructure damage. To enhance the effectiveness of sensor packages in expediting infrastructure assessment, incorporating real-time data analysis through embedded edge computing techniques emerges as a promising

[1] Ryan Yount, Joud N. Satme, David Wamai, and Austin R. J. Downey. Edge processing for frequency identification on drone-deployed structural health monitoring sensor nodes. In Paul L. Muench, Hoa G. Nguyen, and Robert Diltz, editors, Unmanned Systems Technology XXVI. SPIE, June 2024. doi:10.1117/12.3013712 Reprinted here with permission of the publisher, 2/25/2025

solution. The objective of this work is to demonstrate on-device data processing for frequency-based structural health monitoring techniques using drone-deployable sensors. This approach advances the effectiveness of drone-deployable sensors in rapid infrastructure assessment by mitigating their susceptibility to errors or delays in data communications. The proposed approach computes the frequency components of vibration measurements taken from a structure of interest, for example, the monitoring of a bridge immediately following a damaging event such as a flood. This work presents contributions in terms of outlining a methodology that emphasizes the hardware-based implementation of edge computing algorithms and examines the required on-device performance and resource utilization for structural health monitoring at the edge. The execution time for the sensor's edge computing functions was profiled, resulting in an additional 9.77 seconds per test, an advancement over traditional transmit and analyze methods.

3.1 Introduction

The assessment of the structural health of civil infrastructure in the aftermath of natural disasters and man-made emergencies is a critical area for advancement [22]. Extreme weather conditions and environmental factors often render structures inaccessible or dangerous to inspect and maintain, posing significant risks to human operators. Moreover, accessibility issues can arise under normal circumstances, compounded further by the aftermath of emergencies. Traditionally, structural health monitoring (SHM) has predominantly been performed by on-site work crews, necessitating substantial investments in both time and equipment for a thorough examination of each structure. These conventional approaches typically involve the collection of data, which is then processed off-site, which inherently delays the availability of crucial real-time insights into a structure's dynamic behavior.

The introduction of rapid, minimally invasive, nondestructive testing technologies presents a promising solution for overcoming these limitations. A future aspect of this methodology is the utilization of on-the-edge data processing, which significantly reduces the timeline for obtaining actionable insights into the structural health of infrastructure. The current landscape of drone technology within SHM primarily focuses on leveraging drones equipped with integrated sensors for tasks such as digital image correlation, crack detection, and thermal imaging [23]. These applications, while valuable, do not fully utilize the potential of drones in SHM. By using drones for deploying vibration sensors that can perform on-device data processing, there exists an opportunity to deepen our understanding of structural dynamics under challenging conditions [4, 21].

Current approaches in SHM have seen significant advancements through the integration of UAVs, edge computation, and SHM measurement techniques [17]. UAV-based remote sensing has emerged as a vital approach for bridge condition assessment, offering an efficient, cost-effective, and accessible means to inspect and monitor the structural health of bridges and other infrastructures [10]. The use of UAVs allows for rapid data collection even from areas deemed difficult to access, reducing the need for physical scaffolding and enhancing safety during inspections.

With various approaches to structural health monitoring and numerous technologies currently in use, such as optical and thermal imaging, acoustic emissions, and vibrations, the work by Hassani et al. [12] sets a framework for SHM sensor evaluation. From monitoring various types of civil structures to damage prognosis algorithms, the authors offer a methodology for evaluating cases to assist in the selection of the most suitable sensing technology for a given application. The authors also present a detailed review method for evaluating state-of-the-art sensors and damage detection and prognostics algorithms. Furthermore, Hassani et al. [13] also define optimal sensor placement (OSP) as the placement of sensors that results in the least amount of monitoring cost while meeting predefined performance requirements. This emphasizes the role of aerially deployable wireless sensing systems due to their high mobility while still being a cost-effective solution with similar performance to their wired counterparts.

Edge computation is being increasingly integrated into SHM systems to address the delays in data processing from on-site crews. The use of edge computational devices enables real-time data analysis and decision-making directly at the data acquisition site. This approach reduces the need to travel off-site for real insights into a structure as well as decreasing the need to transmit large amounts of raw data to a centralized server. Despite its potential, the implementation of edge computing in SHM comes with challenges, including the development of robust algorithms capable of operating under the conditions of constrained computational resources available [19].

Vibration-based SHM techniques, utilizing MEMS accelerometers, have become a standard for detecting anomalies and assessing the structural integrity of buildings, bridges, and other critical infrastructure. These techniques rely on analyzing the vibrational characteristics of structures to identify potential damage or changes in structural behavior over time. Advances in MEMS technology have improved the sensitivity and reliability of these sensors, making them more useful for SHM applications [30].

This work presents a methodology for integrating edge computation directly onto drone-deployable sensor packages designed for the vibration monitoring of civil structure [28]. In this preliminary work, the algorithms specifically designed to detect and track changes in the first mode of a vibrating structure are deployed to an edge computing device [36]. By facilitating real-time analysis of vibration data directly on the device, the approach minimizes the delay or potential for lost data caused by data transmission. These advancements can improve emergency personnel's response to infrastructure damage. Drones can be leveraged to access hazardous or hard-to-reach areas. The proposed sensor package, designed to autonomously monitor a structure's first natural frequency, can function independently and alert first responders or technicians to any alterations in the structure's vibrational properties.

The contributions of this work are twofold. First, a previously proposed algorithm [36] for frequency-based damage detection is expanded to include an automated methodology to find the frequency associated with the first mode of the structure. Second, the appropriateness of the edge computing algorithm is demonstrated by deploying the algorithm to the same ARM Cortex-M7 microcontroller that is used on the open-source drone-deployable sensing node designed for SHM. The sensor design and code are available on GitHub [**?**].

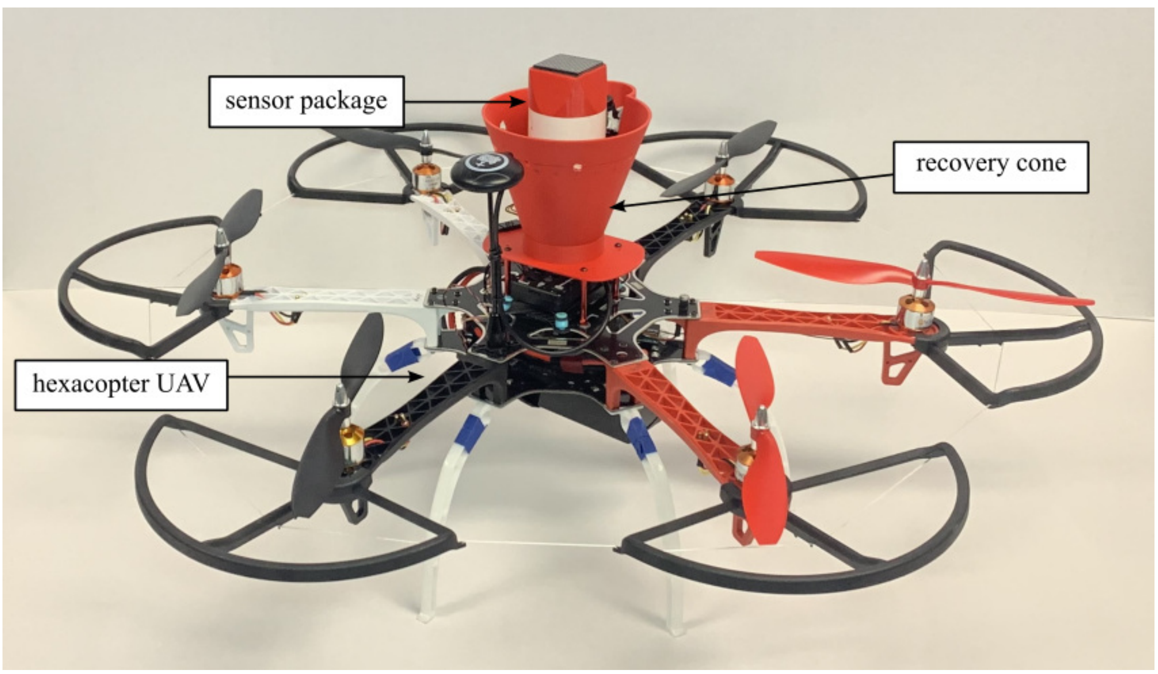

Figure 3.1: Labeled components for a typical drone sensor package deployment.

3.2 Methodology

This section describes the methodology employed to examine and validate the effectiveness of the sensor package for edge computational SHM. The methodology is divided into three subsections, each detailing a component of the study: the hardware specifics of the sensor package, the algorithm installed on the sensor package, and an experimental validation.

The sensor package discussed in this paper is designed for the vibration monitoring of civil structures. For example, Satme et al. reported on a case study that used the sensor packages to perform experimental modal analysis on a pedestrian bridge in use [28]. For rapid assessment, the sensor packages can be deployed by hand or by leveraging UAVs [**?**]. Figure 3.1 illustrates a standard setup for deploying the sensor using a drone, while Figure 3.2 details the step-by-step process of UAV deployment. These sensor packages are considered "smart" in that they can be enhanced with onboard signal conditioning. Satme et al. developed a long short-term memory (LSTM) error-compensating network for the sensor package that demonstrated a 9.3% increase in signal-to-noise ratio ($\mathrm{SNR_{dB}}$) of the collected signals, with the most improvement found at lower frequencies [27]. Hardware and software designs for the sensor packages [24] and deployment systems [25] are open-sourced and freely available.

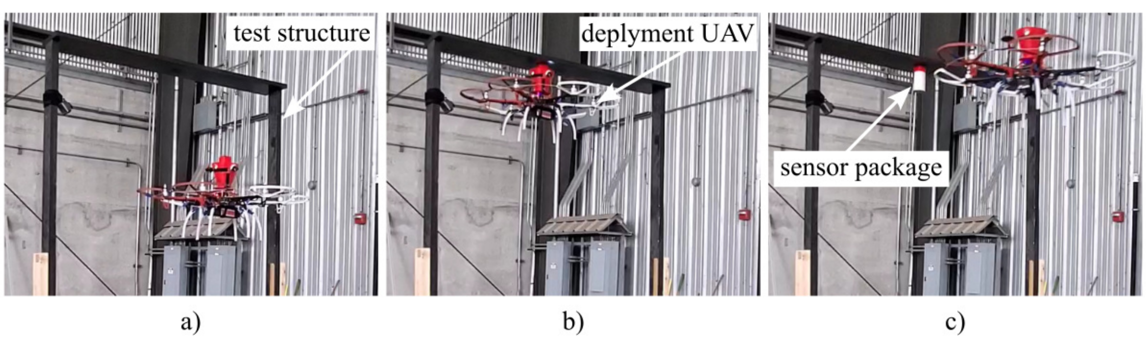

Figure 3.2: Deployment steps for the drone-deployable sensor package showing a) delivery, b) deployment, and c) departure.

The sensor package is shown in Figure 3.3 and is designed as an embedded system-based device for long-term data logging of structural vibrations. The core of this device is an ARM-Cortex-M7 processor housed in a Teensy 4.0 microcontroller. The sensor package receives power from a 1500 mAh 2-cell lithium polymer battery, with a power conditioning and regulating system, ensuring stable power distribution to the various systems on board.

The functionality of the sensor package is provided by a Murata SCA 3300-d01 MEMS accelerometer, which communicates via the Serial Peripheral Interface (SPI) protocol. For deployments with minimal intrusion, the sensor package incorporates an EPM V3R5C NicaDrone electropermanent magnet. This magnetic setup requires a 5W pulse to change states, which is typically done twice during deployment for low power consumption. IO commands and data transmission are handled by a Nordic Semiconductors NRF24L01+ module, which operates at 2.4 GHz using the Shock-Burst protocol. This network enables multi-link communication with several sensor nodes in addition to wireless sensor activation. A real-time clock and a nonvolatile memory module are also incorporated to extend the device memory to conduct computation in addition to ensuring accurate data logging. The package is protected by a 3D-printed PLA frame and a PVC shell to shield against any environmental conditions during field use. The sensor package is designed with a suitable size and weight for UAV deployment.

The methodology implemented on the sensor package includes an application of edge computing for SHM to leverage real-time data acquisition and processing directly on the device. A flow chart containing the basic run sequence of the methodology is shown in Figure 3.4. The methodology starts by initializing the libraries for the components of the sensor package as well as setting up variables and functions for later use. Then, data is collected from the z-axis of the accelerometer with recorded timestamps. Once a full vibration test is completed, the collected data and timestamps are then saved to an SD card in a CSV file format.

After data collection, the file containing the accelerometer data is read and each value is used to perform a Fast Fourier Transform (FFT) analysis. The FFT run on the sensor package is a variant of the Cooley-Tukey FFT algorithm [6]. This

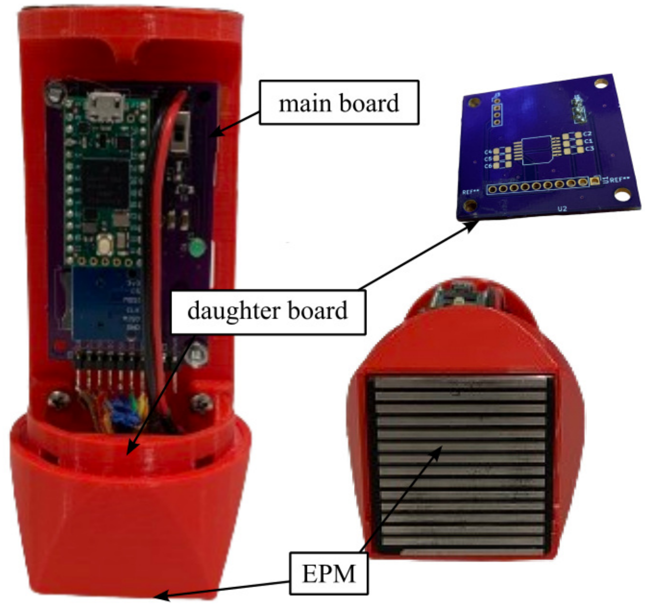

Figure 3.3: The hardware of the sensor package with key components annotated.

algorithm is meant to recursively break down a Discrete Fourier Transform (DFT) with a size that is a power of 2. The dataset is split into two sequences of even-indexed and odd-indexed points. The algorithm then computes the DFTs of these two sequences and combines them back into one sequence to produce the DFT of the original dataset.

The full FFT data is written to a new file on the SD card to provide a record of the frequency magnitudes. A peak detection algorithm is run to identify peak frequencies and their magnitudes, which are saved onto another file on the SD card.

To evaluate the sensor package's performance and the effectiveness of its algorithm, an experimental setup was devised involving a square stock beam positioned with a pinned support and a roller support. The experiment, shown in Figure 3.5, aimed to evaluate the sensor's precision in capturing data under diverse structural scenarios.

Positioned at the midpoint of the beam, the sensor package underwent three tests, each performed to emulate a different structural condition. Following the initial place-

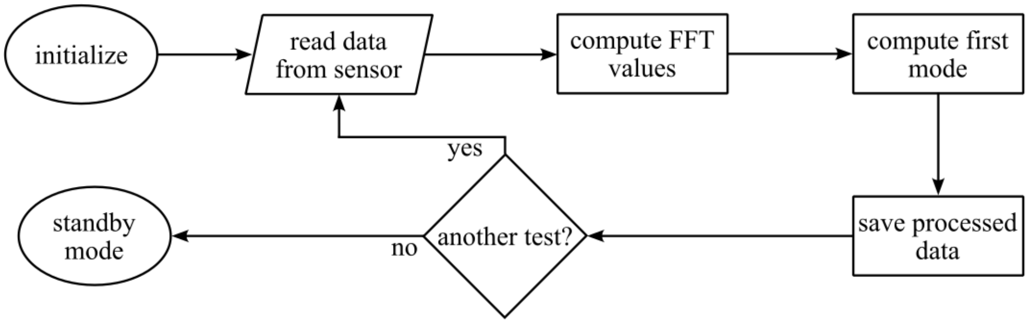

Figure 3.4: Flowchart indicating the sequence of operations deployed on the sensor package for the automated frequency-tracking algorithm.

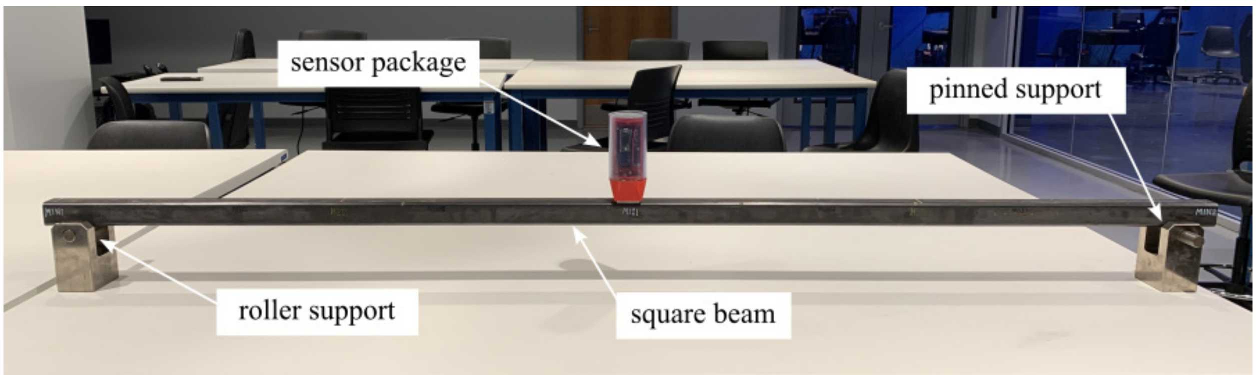

Figure 3.5: Experimental setup of a beam with pinned and roller boundary conditions on each end with key components annotated.

ment, the left roller support was sequentially repositioned closer to the beam's center for subsequent tests. A visualization of the repositioning can be seen in Figure 3.6.

To induce vibrations, a modal impact tool was used, generating an impulse response within the beam, shown in Figure 3.7. The observed impulse response enabled the evaluation of the sensor package's vibration-sensing ability, FFT analysis, and the rapid identification of the beam's first flexural mode through a frequency domain peak detection algorithm.

3.3 Results

This section presents the findings from the analysis of the sensor package's performance, focusing on its algorithm and hardware operation. The sensor's capability to

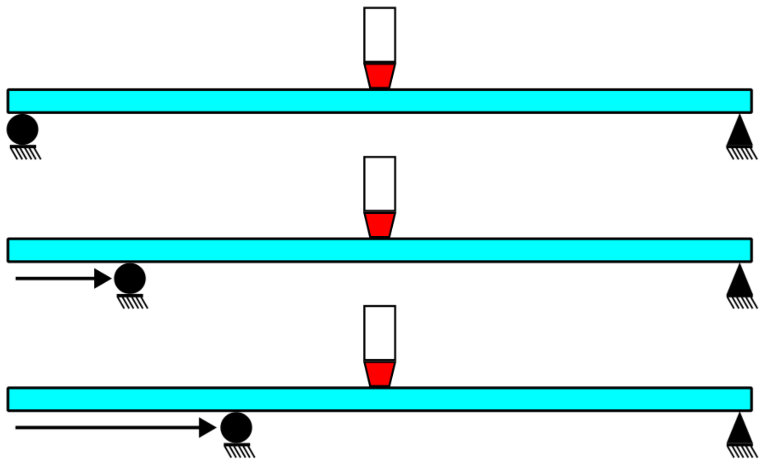

Figure 3.6: Pined-roller beam test setup showing the shifted roller boundary condition to simulate an altered structural state.

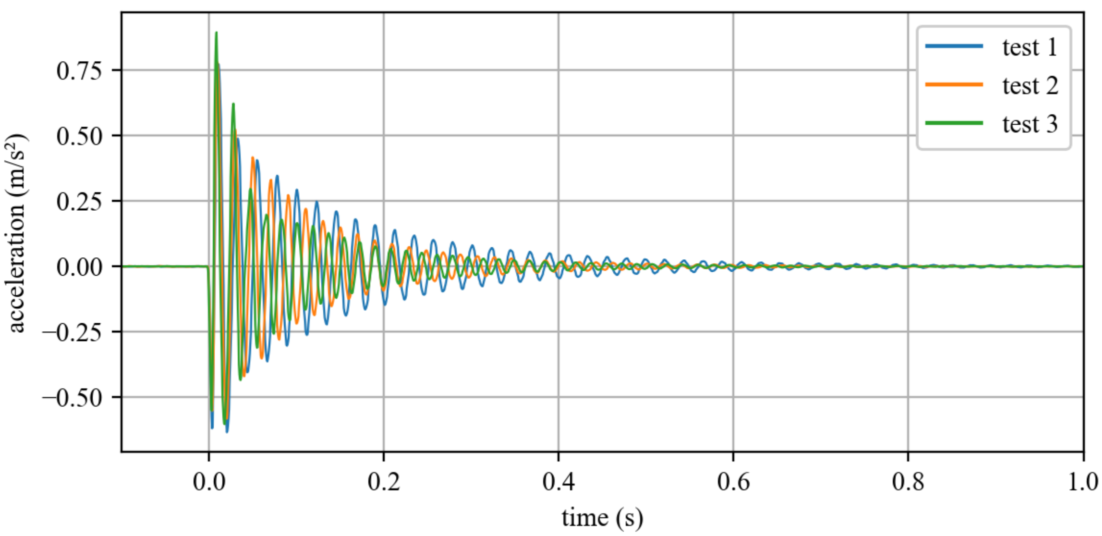

Figure 3.7: Impulse response of three cases of boundary conditions of a beam with roller supports.

process temporal vibration data and identify the first linear modal frequency of structures is examined. Additionally, an investigation into the hardware's computational resource utilization is also reported.

The sensor demonstrated efficiency in processing vibration data from the beam, accurately identifying the system's first flexural modal frequencies. The frequencies identified for the first modes in each successive test were 45.1, 51.0, and 56.0, respectively. These variations in modal frequencies can be directly attributed to the adjustments in the beam's structural configuration for each experiment, evidencing the sensor's sensitivity to changes in structural conditions. To validate the sensor's onboard algorithm's accuracy, its FFT output was compared to an off-edge FFT calculated using the Numpy Library in Python [11] in Figure 3.8. The root mean square error values quantifying the comparison between the onboard and off-edge FFT computations were 0.0032, 0.0028, and 0.0031 in units of the normalized gain for tests 1, 2, and 3 respectively. This indicates a high degree of accuracy across all tests. Note that results here are normalized for the magnitude to account for variations resulting from differences in the Cooley-Tukey FFT algorithms as implemented in the two software packages.

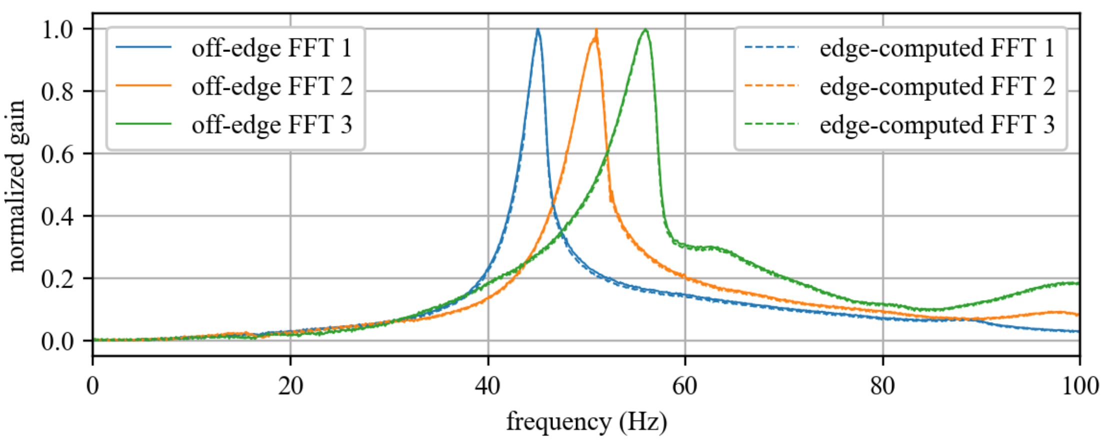

Figure 3.8: FFT comparison showing the offsite FFT alongside the onboard sensor FFT.

A frequency response function (FRF) analysis was conducted to quantitatively measure the similarity between the onboard FFT and the external FFT computation as shown in Figure 3.9. Ideally, a flat FRF, hovering around 1 indicates a perfect correlation between the onsite sensor FFT and the offsite analysis. This would suggest that the sensor's algorithm can match the accuracy of external processing. Although there is a slight deviation between the two FFT analyses, the greatest discrepancy near the modes was approximately 9.4%, seen in test 1 at 46 Hz. This deviation is in an acceptable range, as the magnitude was still enough to recognize what frequency the first mode was located at. The comparison showed a remarkable alignment between the two sets of Fourier transforms.

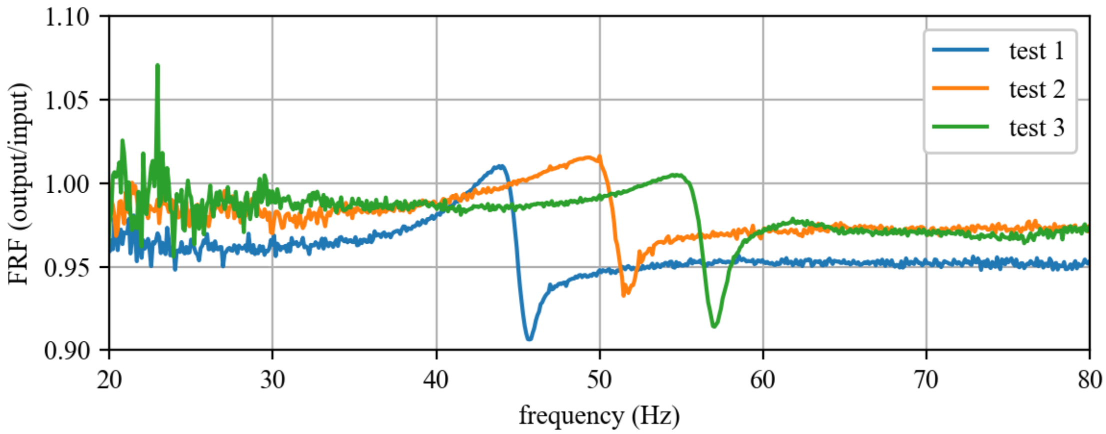

Figure 3.9: FRF comparison showing the difference between the offsite and onboard FFTs.

The Teensy 4.0 Development Board is an ARM Cortex-M7 microcontroller with a 600MHz primary oscillator. The microcontroller is well suited for on-the-edge computing, featuring 2MB of OCM flash, 1MB of RAM, and 8MB of QSPI flash memory. Its modest demand for operational power at 100mA makes it an ideal platform for sensor packages designed for long-term, continuous SHM.

The overall performance of the hardware driving the Fourier analysis and peak-finding algorithms is examined through GNU gprof [9], an open-source profiling software from the GNU's Not Unix software collection. The algorithm itself was written using the Arduino toolchain sourced from the Arduino.h header, allowing access to quality-of-life features such as SD card and Serial communication support. This particular workflow is ideal for ensuring a stable algorithmic implementation capable of running continuously without the need for recalibration or similar intervention. Time efficiency is examined by probing profile data correlating to time, cumulative time, and percent of total time.

Table 3.1: Timing profile describing execution time of processes in the sensor package's algorithm.

process	time (s)	cumulative time (s)	percent of total time (%)
data collection	10.24	10.24	51.07
read sensor	4.43	14.67	22.07
SD card read	0.05	19.54	0.27
SD card write	0.01	19.88	0.07
FFT computation	0.01	19.90	0.07
numeric conversions	0.00	20.01	0.01

A collection of 30 profiling runs was conducted and compiled into a mean aggregate. The configuration of the profiling runs was controlled and consistent, with the sensor package arranged to collect 16384 samples at a 1.6 kHz sampling rate. The data was then processed using the FFT algorithm, which was then followed by a peak-finding algorithm. The sensor package was bench-bound for all runs. This does not affect the quality of the profiling runs. An equal number of floating-point operations occur regardless of data composition or testing environment. The timing profile includes only functions imperative to the algorithm's operation and is shown in Table 3.1.

3.4 Conclusion

The testing and analyses of the sensor package have successfully demonstrated its capability to effectively process and analyze vibration data on the edge. The sensor's detection of flexural modal frequencies under varying structural conditions proves its adaptability to dynamic environments. The congruence between the sensor's onboard FFT analysis and an offsite FFT calculation further validates the accuracy and reliability of the embedded algorithm. The findings from this study underscore the algorithm's ability to be deployed on resource-constrained devices for SHM. Future work will focus on refining the sensor algorithm to read multiple modal frequencies from a structure as well as learning modal frequencies to recognize discrepancies. This study makes contributions in the form of a methodology of edge computing algorithms.

Acknowledgments:

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Chapter 4

Experimental Analysis to Enable Low-Latency Structural Health Monitoring for Electronics in High-Rate Dynamic Environments

Abstract

Electronic assemblies subjected to high-rate dynamic environments offer the potential of increased robustness and resilience to mechanical loading if integrated with active feedback mechanisms that respond when damage is present in the system or alter mission outcomes when appropriate. To enable active structural control of electronic assemblies, the rapid detection of mechanical damage is crucial. This study focuses on monitoring an electronic package under a shock and introduces a method for enhancing the durability of printed circuit boards through onboard frequency-based damage detection. The experimental setup is comprised of printed circuit boards equipped with representative electronic packages enhanced with embedded sensing capabilities, subjected to controlled shock tests using a drop tower system. This study details the data acquisition process, Fast Fourier Transform (FFT) implementation on the electronic assembly, and the algorithmic strategies for peak detection

[1]Ryan Yount, Trotter Roberts, Jacob Dodson, Adriane Moura, and Austin R.J. Downey. Experimental Analysis to Enable Low-Latency Structural Health Monitoring for Electronics in High-Rate Dynamic Environments. Springer Nature Switzerland, 2025 Reprinted here with permission of the publisher, 2/25/2025

and response initiation. The frequency-based damage detection system has the capability to increase the robustness and resilience of systems experiencing shock when combined with a closed-loop control system. In future work, the electronic assembly will be re-designed to autonomously process the resulting vibration data using an FFT computed at the edge to identify a change in the critical frequency components associated with potential damage. This work not only extends the understanding of printed circuit board dynamics under stress but also showcases the practical applications of embedded signal processing to enable enhanced system durability and reliability.

4.1 Introduction

The ability to rapidly detect structural damage in electronic assemblies exposed to high-rate dynamic events is crucial for ensuring reliability and longevity [18]. High-rate dynamic events occur frequently in various contexts, including automotive collisions, and aviation accidents. These high-rate dynamic events, or mechanical shock, are defined as abrupt modifications in force, position, velocity, or acceleration, which induce transient states in the system [7]. Such shocks can lead to rapid and unpredictable responses within the structural integrity of components, making it critical to ensure that systems can recover or adapt in real time. The integration of active feedback mechanisms capable of swiftly detecting and responding to structural damage plays a pivotal role in enhancing the robustness of such systems. These mechanisms employ a network of sensors that continuously monitor the system's state, detecting deviations from normal operation that may indicate damage or failure. Upon detecting an anomaly, the system can immediately implement corrective actions—such as adjusting loads, altering operational parameters, or rerouting energy flows—thereby preventing further damage. This capability not only mitigates potential failures but also optimizes mission outcomes by adding the possibility of adapting system behavior in response to detected damage [31]. By adapting the system's behavior in response to detected damage, these active feedback mechanisms ensure that mission-critical tasks can continue with minimal interruption. Furthermore, this adaptability reduces the need for redundant system designs and manual intervention, thereby increasing operational efficiency and prolonging the system's lifespan [5]. Electronic packages subjected to shock and vibration must endure rigorous testing to validate their durability under real-world conditions. A useful approach to enhancing structural health is onboard frequency-based damage detection [8]. Traditional methods such as accelerometer-based monitoring for Structural Health Monitoring (SHM) have been extensively studied. Accelerometers are commonly used to capture vibration data and analyze modal characteristics of Printed Circuit Boards (PCBs) under varying mechanical loads [1]. Studies aimed at investigating how PCBs respond to mechanical stresses and dynamic forces contribute valuable insights into understanding how to build more robust electronics [14]. By embedding sensors within PCBs and employing signal processing techniques like Fast Fourier Transforms (FFTs) [37], it becomes feasible to monitor vibration signatures of electronic assemblies during and after shock events. The analysis of frequency components allows for the rapid identification of changes indicative of mechanical damage, enabling response mechanisms to mitigate potential failures.

In shock events, the impact can adversely affect the entire system, highlighting the importance of controlled and repeatable testing methodologies. To address this challenge, shock test systems such as drop towers are used, which simulate abrupt mechanical impacts to evaluate how electronic assemblies withstand sudden forces. These systems provide controlled, repeatable environments that replicate the dynamic stresses encountered during deployment. Dynamic analysis techniques have similarly been applied to investigate the behavior of electronic assemblies under mechanical shock loads. For instance, studies have focused on scenarios such as the dynamic analysis of fixed-fixed beams subjected to mechanical shock, revealing critical insights into the structural response and potential failure modes under high-rate loading conditions [29]. Furthermore, the fundamental principles of SHM have been clarified through comprehensive frameworks and theoretical studies. These include the axioms and foundational concepts that underpin effective SHM practices, guiding the development of robust monitoring strategies aimed at enhancing the reliability and longevity of electronic systems [34]. For electronic feedback, resistive circuits have been employed for continuity measurements in electronic assemblies, facilitating real-time assessment of circuit integrity under dynamic conditions [2]. This method is particularly effective in detecting and diagnosing potential faults promptly, thereby enhancing the reliability of electronic systems in high-stress environments.

Advancements in edge computing present promising avenues for real-time data processing in SHM applications. Edge computing architectures enable data analysis closer to the source, which reduces latency [15] and supports timely decision-making based on monitored parameters [32], particularly in smart electronics applications [16]. This capability is particularly advantageous in SHM, where rapid responses to dynamic events are critical for preemptive maintenance and operational efficiency in electronic assemblies.

This study focuses on the development and implementation of a frequency-based damage detection system for electronic assemblies undergoing shock tests using a drop tower setup. The experimental framework involves equipping PCBs with embedded sensors capable of acquiring the necessary vibration data. An FFT algorithm is employed to extract critical frequency components associated with structural integrity, facilitating rapid assessment of damage. Key aspects of this research include a detailed description of the data acquisition process, the implementation of FFTs on the acquired data, and the algorithmic strategies for peak detection and initiation of response actions. The contribution of this work is the advancement our understanding of PCB dynamics under shock-induced mechanical stresses and introducing the application of embedded signal processing for enhancing durability. This study also contributes to the broader field of structural health monitoring in electronic assemblies. While this study focuses on frequency-based damage detection, the next step will involve developing edge computing frameworks to implement these processes in real-time.

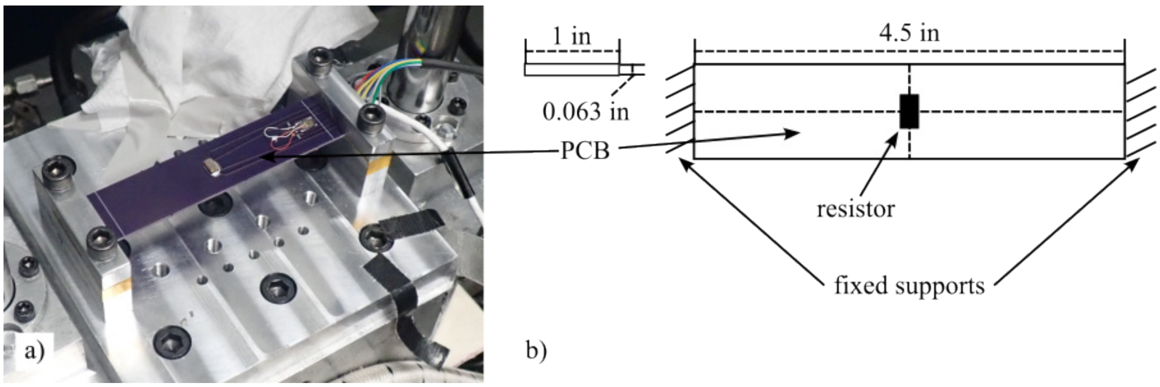

Figure 4.1: a. PCB configured in the test setup b. Geometry and boundary conditions created for simulation of the PCB.

4.2 Methodology

To determine the expected modal frequencies of the PCBs under investigation, vibrational simulations were conducted using finite element analysis software. The geometry and boundary conditions used in the simulation are provided in Figure 4.1. For this experiment, a 5.5 inch PCB was clamped with a pseudo-fixity setup. Since the clamp extended 0.5 inches and was positioned 0.5 inches from the board's edge to provide space for data acquisition wiring, the effective length of the PCB measured from the edge of the clamp to the opposite edge of the board was determined to be 4.5 inches.

The simulations were performed with and without the additional mass attached to the board, aiming to understand the impact of the mass on the board's vibrational characteristics. A frequency analysis was performed to identify the natural frequencies and mode shapes of the PCB as shown in Figure 4.2. The material properties used in the simulations are shown in Table 4.1. This analysis was useful in determining expected outcomes for how the board will respond to mechanical shock and the resulting vibrations.

Table 4.1: Material properties used in the simulations of the PCB

Material	Density (lb/ft^3)	Young's Modulus (psi)	Poisson Ratio
FR4	118.64	2,697,707	0.2

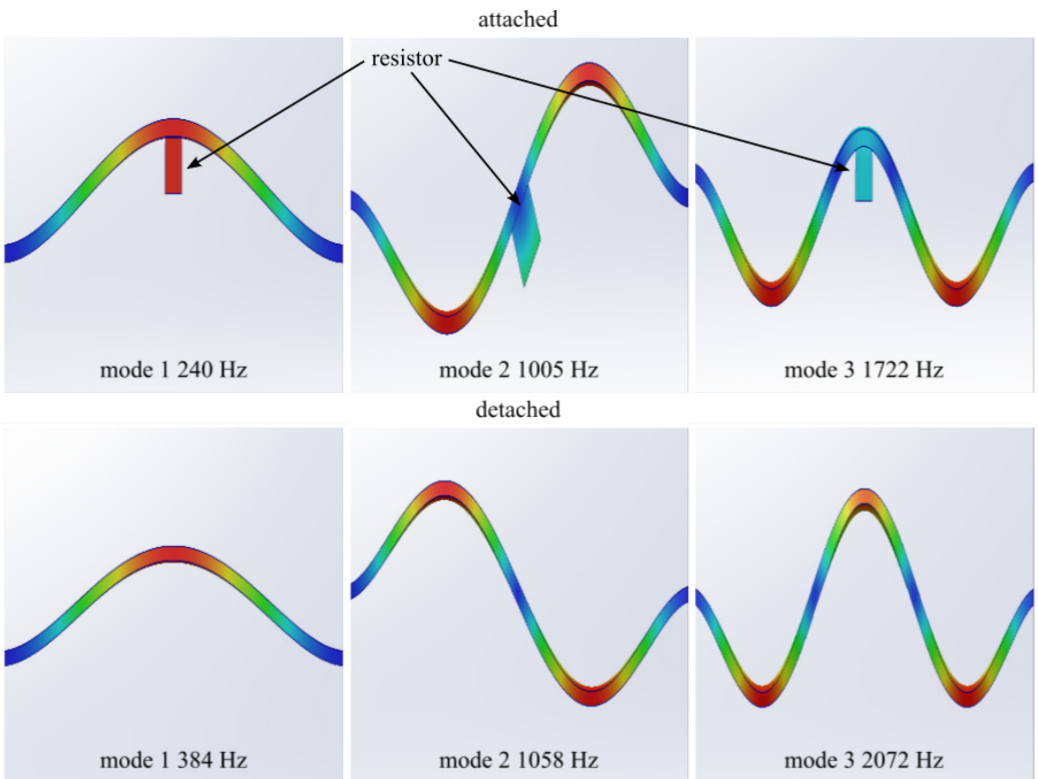

Figure 4.2: Simulation results showcasing the mode shapes and frequencies with and without the mass attached.

Notably, the first mode, which is of primary interest in this study, exhibited significant variation depending on the presence of additional mass. With the resistor connected to the board, mode 1 was found to have a frequency of 240 Hz. After the resistor was removed, the frequency of mode 1 increased to 384 Hz.

To enable the detection of mechanical damage in the PCBs, a frequency-based approach utilizing FFTs is employed [8]. This method leverages the inherent vibration signatures of the assemblies captured by the embedded sensors during shock. The FFT algorithm converts the time-domain vibration signal $x(n)$ into the frequency domain $X(f)$, as shown in Equation 4.1, allowing for the identification of specific frequency components associated with structural integrity. The signal is decomposed into its frequency components using the FFT. Next, the resulting spectrum is normalized by dividing by the number of samples. Lastly, only the positive side of the frequency spectrum is retained, as the FFT output is symmetric for real-valued signals.

$$X(f) = \sum_{n=0}^{N-1} x(n) e^{-j2\pi fn/N} \tag{4.1}$$

where $x(n)$ represents the sampled time-domain signal, N is the number of samples, and f is the frequency.

Algorithmic strategies for peak detection can be implemented on edge computing devices to provide more rapid damage assessment. Such algorithms are designed to analyze FFT-transformed data and identify significant peaks or changes in critical frequency components. As damage occurs, a shift in the modal frequencies is expected. Some strategies include threshold-based peak detection, pattern recognition, and adaptive filtering.

To implement edge computing for rapid damage assessment on the PCBs, several important factors must be considered. A suitable microcontroller capable of handling real-time signal processing tasks should be chosen. This microcontroller must be able to connect to all of the sensors in the system and have a high enough sampling rate to capture the vibration signals of interest. An algorithm to perform and read an FFT on the captured data must be deployed on the microcontroller. Other traits of interest would be a program to trigger a control response such as damping the system when vibrations exceed a threshold and wirelessly transmitting data to an external monitoring system.

While not implemented in this study, the integration of an edge processing device with the damage detection approach enables the implementation of a closed-loop control system. This system would monitor real-time vibration data processed on the edge and could initiate control decisions to mitigate mechanical vibrations when deemed critical. This approach could enhance the resilience of electronic assemblies by actively managing mechanical loads and optimizing performance under dynamic environments. It showcases the potential of edge computing in enhancing system durability through responsive, autonomous control mechanisms.

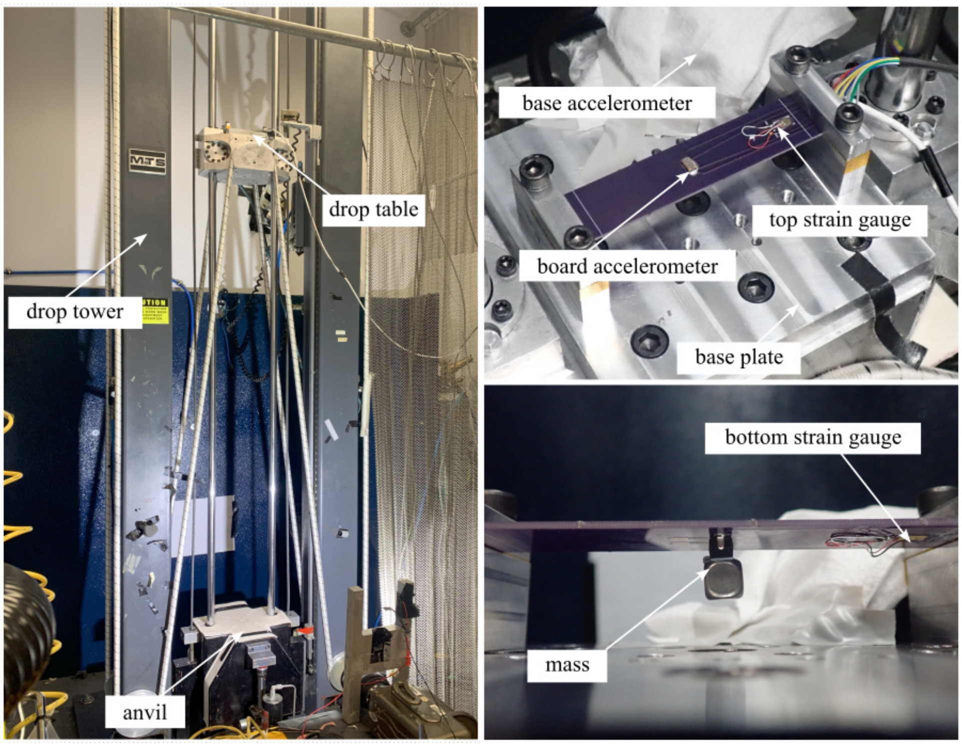

Figure 4.3: Drop tower test setup including the top and bottom of the fixed-fixed PCB.

4.3 Experimental procedure

The experimental setup utilizes a drop tower system to subject electronic packages to controlled shock events. This system, as shown in Figure 4.3, simulates abrupt mechanical impacts to assess the resilience of the assemblies under dynamic conditions. Controlled impacts allow for systematic evaluation of how electronic components respond to sudden forces, which is crucial for understanding their durability in high-rate dynamic environments.

The electronic packages under test were configured as 4.5-inch PCBs clamped as a fixed-fixed beam. Each PCB is equipped with a piezoresistive accelerometer, two strain gauges, and a resistor acting as a mass setup in a resistive circuit. This setup allows for the precise detection of impacts that cause the mass to fall, thereby indicating the onset of structural failure. A close-up example of the PCB before and after detachment is shown in Figure 4.4.

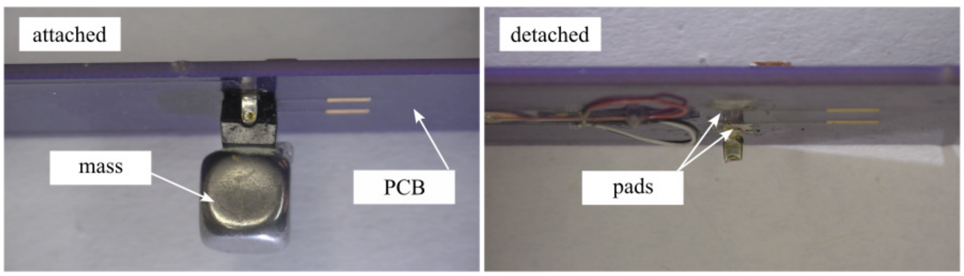

Figure 4.4: Close view of the PCB being tested before and after the mass was detached.

The integration of the shock test system and DAQ facilitated rapid data analysis during testing. The data acquisition process synchronized an accelerometer on the base of the hammer with the sensors on board the PCB for accurate correlation of input and output signals. Additionally, a voltage divider circuit, as shown in Figure 4.5, was used to monitor the integrity of the resistor. The DAQ recorded the output voltage from the circuit, which was 2.5 volts while the resistor was intact and dropped to 0 volts when the resistor detached, providing a reliable time reference for failure events.

The signals were sampled at a rate of 2 million samples per second. While this sampling rate is significantly higher than necessary, it ensured precise data capture and avoided aliasing. A high-speed camera was used in conjunction with the DAQ to visually capture the precise moment of damage initiation on the PCBs, as shown in

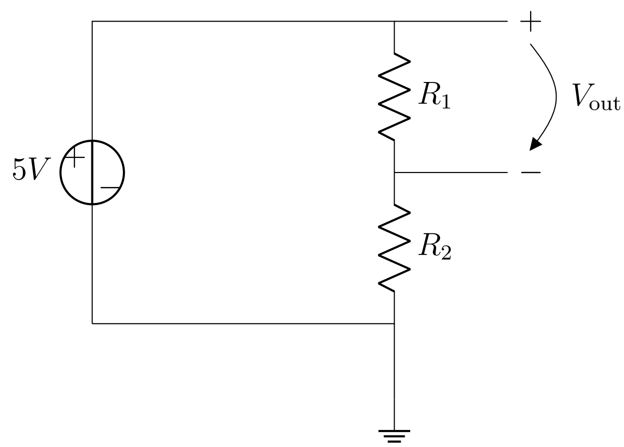

Figure 4.5: Voltage divider circuit used in the experiment to read from the PCB resistor.

Figure 4.6. This visual cue was a supplement of sensor data, enhancing the understanding of failure mechanisms under high-rate conditions.

After each test, the clamps holding the PCBs were torqued to 15 in lbs to standardize test conditions as each clamped end simulated a fixed support. Testing sequences ranged from lower to higher gravity (g) shocks, systematically increasing impact intensity to gather comprehensive data points before observing failure. An example of how the shock propagated throughout the PCB is shown in Figure 4.7.

4.4 Results and Discussion

The experimental data acquired from the shock tests, published in a public repository [35], revealed significant findings regarding the effect of the resistor circuit under stress conditions. Across multiple trials, the provided DC voltage to the resistor circuit stayed relatively constant until a shock occurred where the mass fell. A comparison of time domain signals to assess the behavior of the PCB during the failure test was plotted in Figure 4.8. Some differences are shown during the response, which can be attributed to sequential excitations due to the detached component colliding with the board.

The Fourier analysis conducted on each test indicated pronounced alterations

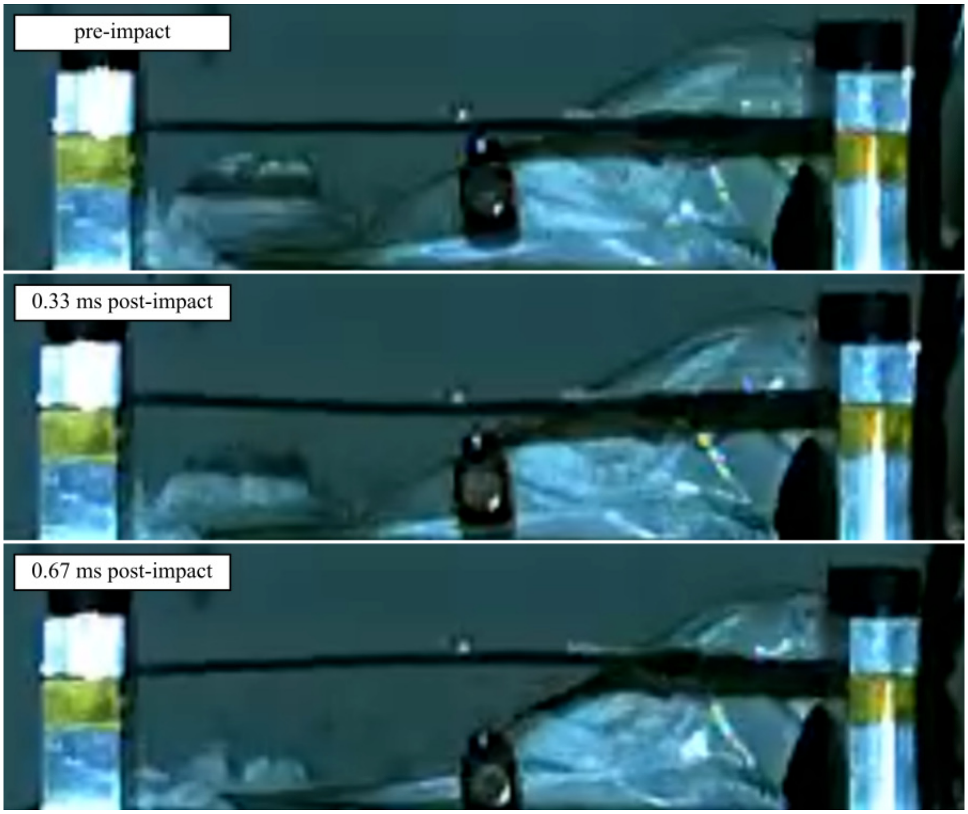

Figure 4.6: Frames from a high-speed camera showing the board during a resistor failure drop.

in the frequency signatures of the boards following the mass detachment, as shown in Figure 4.9. Specifically, when observing the first modal frequency, there was a significant change in line with the change expected from simulations. In Table 2, an analysis of the difference between the frequencies seen in the tested data and the frequencies expected from the simulations is shown.

Condition	Simulated Frequency (Hz)	Tested Frequency (Hz)	Absolute Error (Hz)	Perce
With resistor	240	258	18	
Without resistor	384	354	30	

Table 4.2: Error analysis of the frequencies seen from the simulations and the tested data

This analysis highlights the impact of circuit failure on the electrical signal's spectral content, underscoring the feasibility of rapid damage detection using frequency analysis.

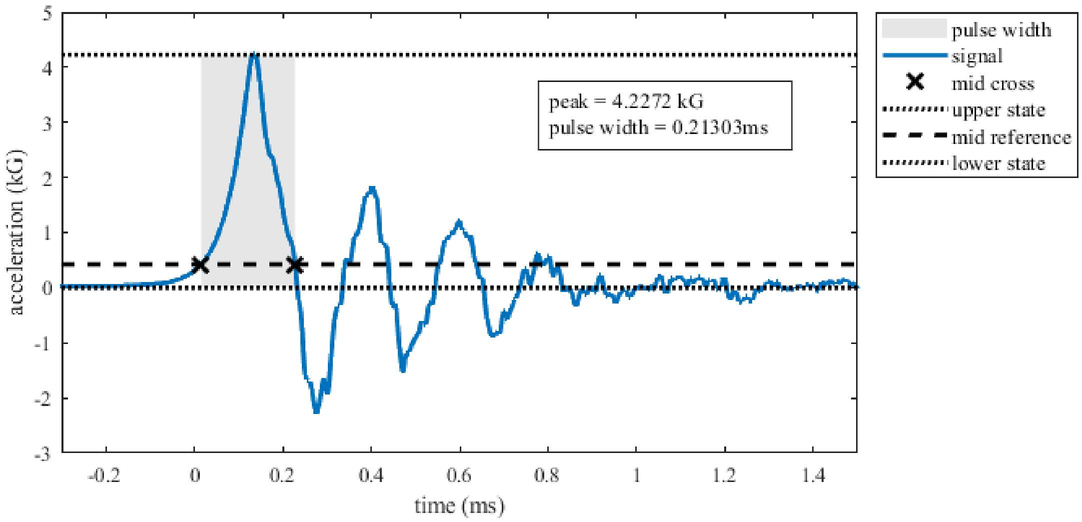

Figure 4.7: Analysis of a time domain signal from the accelerometer on the board during a shock test.

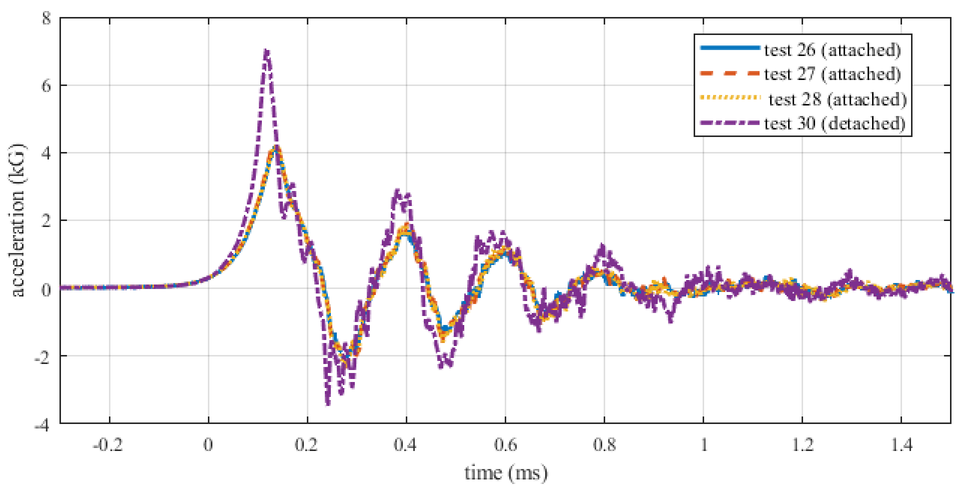

Figure 4.8: Time series representation of shock tests leading up to a final test where the resistor became detached.

4.5 Conclusion

This study demonstrates the effectiveness of frequency-based damage detection using FFTs in identifying mechanical damage in electronic assemblies subjected to high-rate dynamic environments. The notable frequency changes observed upon the occurrence of damage highlight the viability of this method for enhancing SHM in such scenarios.

Integrating edge computing into the damage detection process offers several po-

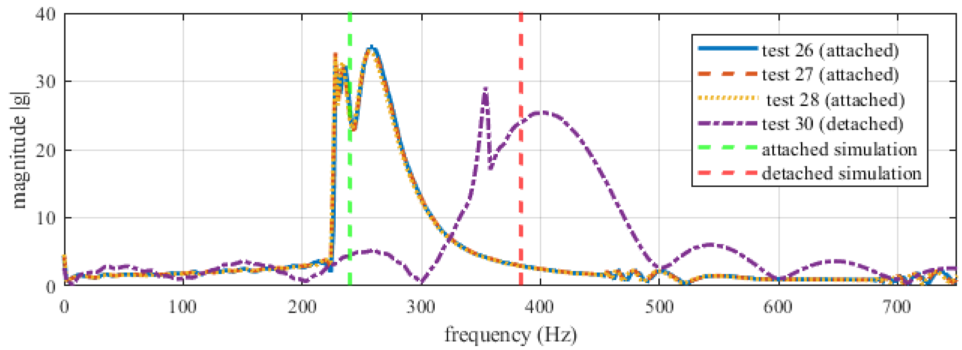

Figure 4.9: Sequential Fourier transforms from shock tests until the resistor becomes detached.

tential benefits. By processing FFT-transformed data locally on edge devices, the system can achieve rapid detection of damage events. This capability reduces latency in decision-making and lays a foundation for implementing responsive control strategies to mitigate mechanical vibrations before they lead to failures.

Future research on this project will include a multi-faceted approach including the implementation of an edge computing device, the optimization of sensor placements, the development of more advanced simulation models, and the integration of these processes with usual packing practices used to mitigate shock.

This paper establishes the foundation for the future development of edge computing architectures, which will enable the autonomous detection of structural changes in real-time. While this work successfully demonstrates frequency-based damage detection, the implementation of closed-loop control using edge devices will be pursued in subsequent studies.

Acknowledgments:

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Chapter 5

Conclusion

This thesis investigated advances made in edge computing for rapid structural health monitoring of civil structures and electronic assemblies. Integrating vibration sensing and frequency-domain analysis onto resource-constrained devices demonstrates the feasibility of real-time structural damage detection in harsh environments. The significance of this work extends to mitigating the potentially catastrophic aftermath of disasters, which becomes important in the rapidly-evolving world climate. The combined body of work spans two main domains: (1) edge-enabled frequency-based SHM for wireless, drone-deployable sensor nodes and (2) shock-based testing and validation of embedded sensors for vibration-based rapid damage detection on electronics. Together, these efforts create a foundation for edge-centric SHM systems which operate autonomously, respond to dynamic loading conditions, and enable data-driven insights in areas where traditional data collection and remote processing are impractical. Our results show that edge devices can accurately detect shifts in modal frequency from structural inconsistencies, with minimal latency and low power consumption.

Future research will build on the autonomous UAV-based deployment of sensor packages by enhancing the real-time object-tracking algorithms and deep learning-based control systems. This includes transferring the deep learning model from external systems to onboard processors and exploring multi-modal sensing strategies such as combining vibration data with visual or acoustic inputs. More extensive field trials on varied infrastructure types will be conducted to validate robustness in uncontrolled environments. The ultimate goal is to enable a closed-loop system where drones not only deploy sensors but also make decisions based on in-flight data analysis.

To further optimize edge-based SHM systems, upcoming work will investigate adaptive sampling and dynamic FFT resolution strategies to balance energy consumption and signal fidelity. A deeper exploration into low-power AI accelerators and task-specific hardware (e.g., FPGAs) could also reduce computational overhead. Integrating self-monitoring of system health and battery levels into the edge node would improve long-term deployment viability, especially in remote or harsh environments.

To develop SHM to a greater extent for electronic assemblies, future work will focus on refining modal frequency tracking under varying boundary conditions and improving sensitivity to microstructural fatigue that may precede catastrophic failure. Active damping or control systems can be integrated with the edge device to initiate real-time response when damage is detected. Additionally, the dataset of shock events and corresponding frequency shifts could be expanded to train machine learning classifiers that differentiate between levels or types of damage in the PCB substrate.

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