Non-contact intelligent inspection of infrastructure
Research Area: #1 Transportation

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Abstract

In this project, we develop non-contact sensing mechanism for health monitoring as well as the associated machine-learning based technique for decision making. Currently available sensory systems for structural health monitoring are almost all based on transducers that are directly attached to or embedded in structures monitored. As a result, they face with critical barriers, such as extremely high implementation cost in very large scale structures due to the large number of sensors needed and relatively high false alarm rate due to malfunction of sensors themselves. The non-contact nature of the proposed sensing modality will cause paradigm shift: it leads to mobile sensory system that can monitor very large scale structures employing only a small number of sensors, and it allows us to increase considerably the confidence level of structural health monitoring. In this research, concurrent breakthroughs in sensor synthesis and data analysis are pursued. We (a) develop a new non-contact impedance-based sensing mechanism via two-way magneto-mechanical dynamic interaction that is enhanced by adaptive electrical circuitry integration, which facilitates the tunable high-frequency interrogation to disclose structural anomaly; and (b) formulate accurate and robust decision making strategies that that take full advantage of the new machine learning techniques.

Chapter 1: Introduction and Background

1.1 Project Motivation

In this research, we explore a new modality of non-contact active sensing that utilizes magneto-mechanical coupling to facilitate unprecedented, fast inspection of infrastructure components such as railway tracks. We further develop machine learning technique to rapidly process the data to realize decision making and fault classification. These represent paradigm-shifting advancements with respect to the current practice: 1) high-frequency active interrogation is conducted without direct contact between the sensor probe and the underlying structure, thereby significantly expediting the inspection while maintaining high accuracy and robustness; and 2) with the machine learning approach, there is no need to develop complex finite element model of the structure to be inspected, and empirical knowledge can be conveniently incorporated into decision making. While physically different, the magneto-mechanical impedance measured by the new sensor is conceptually similar to piezoelectric impedance. As such, the knowledge acquired from the current phase of research can be applied. As the continuation of the current research based on piezoelectric transducers, we these new concepts to generic testbeds. Meanwhile, the methodology developed can be extended to a variety of infrastructure components such as bridge structures and railway tracks.

1.2 Research, Objectives, and Tasks

The overarching goal of this project is to develop a new and robust damage identification sensory system that can detect damage in large-scale infrastructure components through the concurrent advancements in non-contact sensing and machine learning based decision making. Our specific objectives are

a. Explore new non-contact sensing mechanisms and formulate analysis and design methodologies;
b. Develop novel machine learning algorithms that can conduct fault detection based on measurement signals.

To accomplish these objectives, research activities along two thrust areas are executed, sensor design and damage identification algorithmic investigation. Four tasks are conducted:

Task 1: Development of mathematical model of magneto-mechanical impedance sensor
Task 2: Adaptive sensor synthesis with optimal performance
Task 3: Formulation of neural network for fault detection and classification
Task 4: Robust decision making

1.3 Report Overview

In the subsequent chapters, we present the research methodology and results obtained throughout this research.

Chapter 2 outlines the materials involved in this research. The sensor design and analyses are based upon correlated experimental investigation and analytical studies. Damage detection and sensor anomaly analysis is through machine leaning techniques. The experimental testbeds are summarized.

Chapter 3 presents in detail the research tasks as well as the key data/results. The analytical modeling of sensor-structure interaction is developed. In order to increase the detection sensitivity, advanced mechatronic synthesis is carried out which can effectively amplify the anomaly signature in the impedance measurement acquired by the non-contact sensor. Fault detection based on machine learning technique is then presented for bolt joint loosening that is extremely hard to detect and analyze using conventional techniques. All the results are validated experimentally.

Chapter 4 summarizes the workforce training aspect of the project as well as knowledge dissemination.

Chapter 5 provides the overall conclusion as well as recommendation for future work

Chapter 2: Methodology

2.1 Materials

In terms of physical materials, this project involves non-contact magneto-mechanical transducers used as actuators and sensors concurrently for impedance measurement, advanced circuitry elements, piezoelectric transducers for excitation and sensing, host structures made of aluminum plates, as well as power supply and data acquisition equipment.

In terms of reporting materials, in this final report we provide details of

a) sensor design;
b) analytical investigation of sensor-structure interaction;
c) adaptive non-contact sensing mechanism analysis; and
d) fault detection based on machine learning.

2.2 Test Setup & Process

As shown in Figure 1, we use an electrical coil inserted with a permanent magnet which is further coupled with advanced circuitry elements to form the sensor unit. When excitation current goes through the coil, harmonic magnetic field is generated, inducing eddy currents into the metal nuclear structure. The eddy currents, moreover, can generate the Lorentz force under the permanent magnet effect to induce ultrasonic waves in the structure, leading to local oscillations in the structure. Various failure modes such as stress cracking, fatigue cracking, erosion, or bolt joint loosening will change the local oscillations and essentially change the distribution of the induced eddy currents, which will in turn affect the magnetic flux density through the coil and eventually change the current of the coil, or the structural impedance. By analyzing the change of the impedance information one can detect and identify the cracking or erosion. This impedance measurement is exactly analogous to the piezoelectric impedance sensing. [1,2].
An important innovation is the introduction of tunable resonance. Here we integrate a tunable capacitance. The tunable capacitance and the coil form a resonant circuit for actuation amplification.

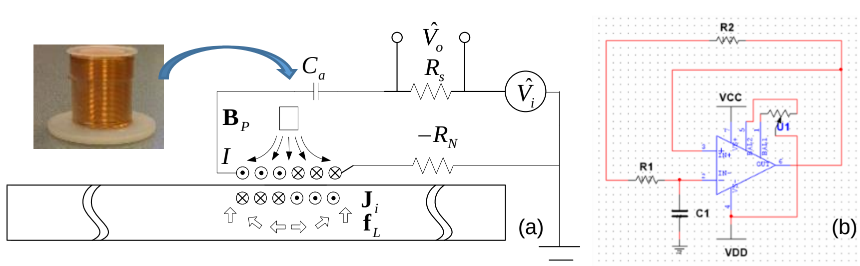

Figure 1. a) Magneto-mechanical sensor with circuitry integration; b) tunable capacitance circuit.

To explore machine learning based fault detection and further explore the possibility of sensor anomaly detection, we construct a testbed as shown in Figure 2. The intention is to detect bolt-joint loosening as well as sensor anomaly occurrence.

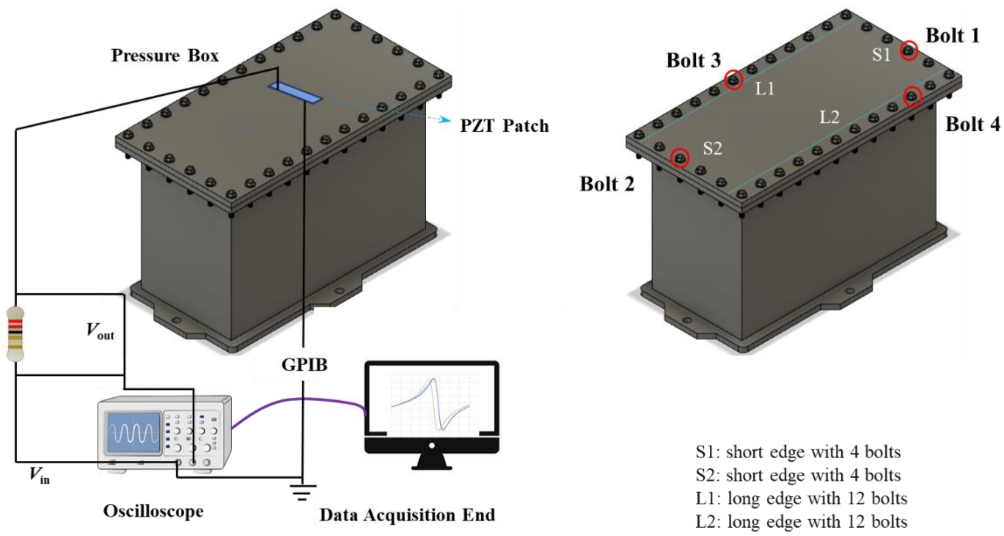

Figure 2. Testbed setup for fault detection of bolt joint loosening.

The details of the analyses and testings are reported in Chapter 3.

Chapter 3: Results and Discussion

3.1 Non-contact sensor analysis and sensitivity enhancement through mechatronic synthesis

The analytical investigation of the non-contact sensor is built upon a one degree-of-freedom (DOF) model to represent the interested mode of the mechanical structure. The dynamic equation of the structure under the effect of the magnetic transducer can be written as

$$m\ddot{q} + c\dot{q} + kq = f_{Lz} \tag{1}$$

Here, m, c and k are the equivalent mass, damping and stiffness, and q is the mechanical displacement. Applying a sinusoidal voltage input to the magnetic transducer induces eddy currents into the electrically conductive surface of the structure. Under the simultaneous effects of the eddy currents flowing in the structural surface and the static magnetic field of the permanent magnet, the Lorentz force is generated, the magnitude of which can be derived as $\hat{f}_{Lz} = k_{M1}\hat{Q}$. Hereafter the hat notation indicates the magnitude. Q is the electrical charge flow. k_{M1} is one of the two parameters characterizing the magneto-mechanical coupling effect. Meanwhile, the transducer dynamics is described by [3]

$$L_M\ddot{Q} + \left(R_M + R_s\right)\dot{Q} + V_M = V_i \tag{2}$$

where L_M and R_M are the coil inductance and resistance, R_s is the resistance (that is usually small) of a resistor serially connected into the circuit to facilitate the measurement of electrical current, V_i is the voltage input. V_M is the voltage output due to the structural dynamic response. When the structure vibrates upon the Lorentz force excitation, the eddy currents in the structural surface are re-distributed, which affect the magnetic field inside the coil. This magnetic field change can induce new voltage in the circuit. One can then derive $\hat{V}_M = k_{M2}\hat{q}$, where k_{M2} is another magneto-mechanical coupling constant. The magneto-mechanical impedance extracted by the magnetic transducer can then be expressed as

$$\hat{Z}_C = \frac{\hat{V}_i}{\hat{I}} = \frac{[-L_M\omega^2 + i\omega(R_M + R_s)](-m\omega^2 + ic\omega + k) - k_{M1}k_{M2}}{i\omega(-m\omega^2 + ic\omega + k)} \tag{3}$$

An enabling idea of this project is to incorporate circuitry elements to the magnetic transducer, which induces dynamic interaction between the sensor and the structure to enhance the coupling and to amplify the damage signature. We connect a capacitor (C_a) and a negative resistance element (R_N) to the magnetic transducer (Figure 1), which, together with the coil inductance and inherent resistance, form a resonant circuit. The electro-magnetic dynamics of the transducer with circuitry integration can then be expressed as

$$L_M\ddot{Q} + \left(R_M + R_s - R_N\right)\dot{Q} + (1/C_a)Q + V_M = V_i \tag{5}$$

Combining Eqs. (1) and (5), we can obtain the magneto-mechanical admittance as

$$\hat{Y}_C = \frac{\hat{I}}{\hat{V}_i} = \frac{i\omega(-m\omega^2 + ic\omega + k)}{[-L_M\omega^2 + i\omega(R_M + R_s - R_N) + 1/C_a](-m\omega^2 + ic\omega + k) - k_{M1}k_{M2}} \tag{6}$$

As can be seen from Eq. (6), the magneto-mechanical admittance includes the information of the structural mass, stiffness, and damping properties. The change of this admittance can be used to infer damage occurrence in the structure. While the impedance and the admittance are inverses of each other, hereafter we focus on the admittance as information carrier for damage detection, because, as shown in Eq. (6) and by the analysis presented below, the admittance measurements can be greatly impacted by circuitry integration.

Indeed, one major change introduced by the circuitry integration is that, in addition to the original structural resonance, a new resonant effect due to circuitry dynamics can be created in the relation of admittance versus frequency. It is well-known that in stationary wave/vibratory motion-based damage detection, the damage-induced change of response is most significant around the resonant peaks. We cam select the capacitance C_a such that the circuitry resonant frequency ($\sqrt{1/LC_a}$) matches the structural resonant frequency ($\sqrt{k/m}$). As we will apply excitation voltage around the structural resonant frequency to detect damage, under such capacitance selection the circuitry resonance may amplify the voltage received by the transducer, thereby amplifying the local vibratory motion. We will use negative resistance R_N to cancel out the coil inherent resistance R_M to further reduce the circuitry impedance [4]. As such, the sensing voltage in the transducer circuitry may also be amplified.

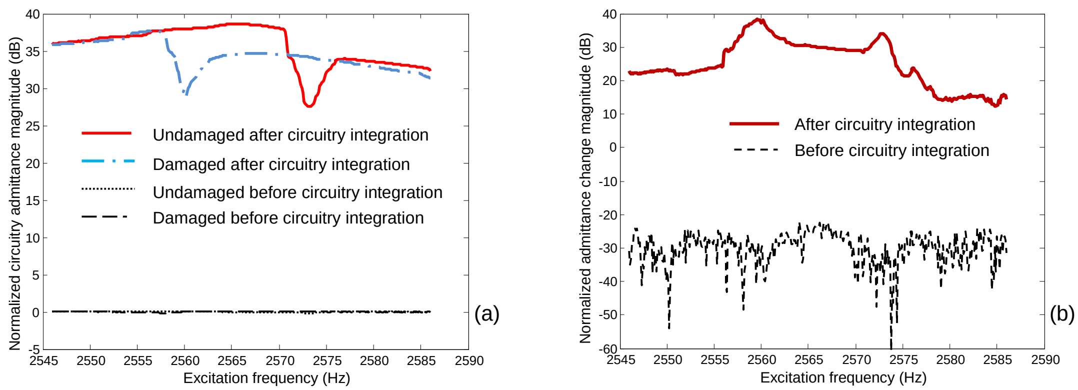

Figure 3 Experimental results of adaptive sensing: a) magneto-mechanical admittance measurements without and with damage, before and after circuitry integration; b) change of magneto-mechanical admittance due to damage, before and after circuitry integration.

We have performed experimental validation. The comparisons of admittance measurement and damage detection results are plotted in Figure 3 (in dB scale). With the circuitry integration, the admittance measurements are greatly amplified (Figure 3a). For the undamaged beam, after the circuitry integration, the peak admittance magnitude measured is increased by about 38 dB, which indicates greatly increased signal-to-noise ratio in measurement. As damage occurs, the magnitude changes and frequency shifts between the resonant peaks of the undamaged and damaged admittance curves become much more significant after circuitry integration. Figure 3b shows the curves of admittance change. With the circuitry integration, the curve of admittance change becomes very clear and smooth. Furthermore, it can be seen that the peak magnitude of admittance change is increased by about 70 dB. That is, the admittance difference (i.e., the damage indicator) is amplified by more than three orders of magnitude, which demonstrates that the new concept of circuitry integration can effectively enhance the magneto-mechanical coupling/interaction around resonances.

3.2 Machine learning based fault detection using impedance measurement

Impedance measurement can be effective in detecting and identifying structural damage based on finite element inverse analysis. Nevertheless, there are damage scenarios in infrastructure systems that are very hard to model using first-principle analysis. For example, bolt fasteners are widely used in various systems due to their affordability, ease of installation, and reliable interchangeability. These fasteners are crucial for maintaining secure, sealed connections in infrastructure, where their performance ensures the structural integrity of pressure vessels. However, bolt loosening remains a significant concern, particularly in environments exposed to vibration, temperature fluctuations, and mechanical stress [5]. Consequently, data-driven approaches, such as machine learning, have become the predominant method in bolt loosening detection, often combined with various sensing techniques. These techniques include acoustic emission (AE), fiber Bragg-grating (FBG) sensors, electrical conductivity, piezoelectric transducers, and vibration-based methods [6].

In these complex systems, data availability is often limited due to the challenges of acquiring comprehensive measurements, making damage detection even more demanding. Additionally, conventional deep learning methods, whether supervised or unsupervised, face several notable challenges in such scenarios. Supervised learning, while powerful, requires large volumes of labeled data, and the labeling process is often time-intensive and impractical for real-world applications. For larger datasets, complex network architectures are typically necessary, further increasing computational costs. Conversely, in small-sample scenarios, these methods often struggle to generalize effectively, as they are highly sensitive to data variability and noise. Addressing noise or variability usually demands additional network design or feature extraction processes, adding complexity and reducing their applicability in real-time or resource-constrained environments.

Alternatively, dictionary learning offers an all-in-one framework for damage detection, addressing many limitations of traditional deep learning methods [7]. It is effective in both large- and small-sample scenarios by representing data as sparse combinations of basis vectors, or atoms, learned directly from raw data. This sparse representation emphasizes key features while suppressing noise, inherently performing denoising during the process. Unlike deep learning, dictionary learning eliminates the need for complex network architectures or extensive labeled datasets, making it computationally efficient and highly interpretable. Diagnosis is achieved by first obtaining a sparse vector for the test dataset using the trained dictionary. Each sub-dictionary is then used to reconstruct the test data, and the reconstruction error is calculated. The sub-dictionary minimizing the reconstruction error identifies the corresponding fault category.

In the processing of engineering signals or engineering data analysis, it is often desirable to represent signals in ways that highlight their underlying structure while minimizing redundancy. One approach that has gained considerable attention is sparse representation, where a signal is expressed as a combination of a few significant components from a larger dictionary. A signal $\mathbf{y} \in \mathbb{R}^m$ can often be represented in a sparse manner using a combination of elements from a predefined dictionary. Mathematically, this can be expressed as [8]:

$$\mathbf{y} = \mathbf{D}\mathbf{x} = \sum_{j=1}^{n} x_j \mathbf{d}_j = \sum_{j \in S} x_j \mathbf{d}_j \tag{7}$$

where, $\mathbf{D} \in \mathbb{R}^{m \times n}$ is a dictionary matrix whose columns $\mathbf{d}_j$ form a set of basis vectors, and $\mathbf{x} \in \mathbb{R}^n$ is a sparse coefficient vector. In general, the dictionary $\mathbf{D}$ is overcomplete, meaning that it contains more basis vectors than the signal's dimensionality (i.e., $m < n$). This allows for flexibility in choosing a sparse set of coefficients, where most of the entries in x_j are zero, and only a few non-zeros elements contribute significantly to the signal. The goal is to choose the dictionary **D** in such a way that the signal can be represented with minimal non-zero coefficients, revealing its sparsity in the chosen domain. Many types of signals, particularly periodic, or structured data like image and audio, have sparse representations when transformed into suitable bases, such as Fourier or wavelet domains. If there is no information available about the signals, then the basis matrices can be obtained via training signals using Dictionary Learning, which will be explained in the next section. The sparse representation is illustrated in Figure 4.

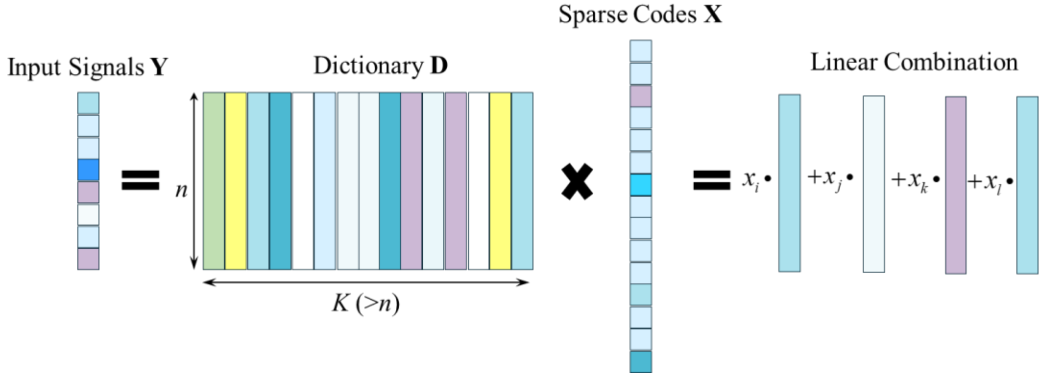

Figure 4. Illustration of sparse representation.

The primary aim of this study is to recover the signal $\mathbf{y} \in \mathbb{R}^m$ using compressive sensing framework, where only a limited set of measurement $\mathbf{z} \in \mathbb{R}^p$ is available. Here, $p << m$. Each measurement vector **z** is a linear projection of the full signal **y** and can be expressed as

$$\mathbf{z} = \boldsymbol{\theta}\mathbf{y} = \boldsymbol{\theta}\mathbf{D}\hat{\mathbf{x}} = \boldsymbol{\varphi}\hat{\mathbf{x}} \tag{8}$$

Here, $\boldsymbol{\varphi} = \boldsymbol{\theta}\mathbf{D}$, and $\boldsymbol{\theta} \in \mathbb{R}^{p\times m}$ represents the measurement matrix, which typically serves as a binary matrix indicating sensor locations. Each row of $\boldsymbol{\theta}$ matrix has a single non-zero element (with a value of 1) corresponding to the sensor's location, while all other entries are zero. Because the number of measurements p is much smaller than the signal length m, reconstructing the original signal **y** from **z** becomes an underdetermined problem. The solution hinges on finding a sparse representation of the measurements z in a subspace of the dictionary D. The task is to find $\hat{\mathbf{x}}$, the sparse representation of **z** in the sub-dictionary of **D** basis, i.e., $\boldsymbol{\varphi}$. $\hat{\mathbf{x}}$ can be obtained accurately by solving optimization problems as follows:

$$\min_{\hat{\mathbf{x}}} \| \mathbf{z} - \boldsymbol{\varphi}\hat{\mathbf{x}} \|_F^2 \quad \text{s.t.} \ \| x_j \|_0 < T \ \ \forall j \tag{9}$$

where, $\|\cdot\|_0$ is the L_0 norm and T is the sparsity level. As with dictionary learning, we use the Orthogonal Matching Pursuit (OMP) algorithm [9] to solve this optimization. Once obtaining $\hat{\mathbf{x}}$ we can reconstruct the full-filed data by solving the forward problem,

$$\hat{\mathbf{y}} = \mathbf{D}\hat{\mathbf{x}} \tag{10}$$

Dictionary learning has found increasing usage in both image processing and machine learning applications. In the realm of image processing, it has demonstrated its effectiveness in tasks such as denoising, edge detection, and image super-resolution. Within machine learning, dictionary learning is applied for feature extraction, improving data compression, and making accurate predictions for missing data. In this research, we adopt the K-SVD (K-singular value decomposition) algorithm [10]to conduct dictionary learning. The K-SVD method addresses the following optimization problem:

$$\min_{\mathbf{D},\mathbf{x}} \| \mathbf{y} - \mathbf{D}\mathbf{x} \|_F^2 \quad \text{s.t.} \quad \| x_j \|_0 \le T \quad \forall j \tag{11}$$

where x_j denotes the *j*-th column of matrix $\mathbf{x}$. The notation $\| \cdot \|_F^2$ represents the squared Frobenius matrix norm of a matrix. Consequently, the goal of K-SVD is to identify both the dictionary **D** and the coefficient matrix **x** that collectively minimize the reconstruction error between the original training data and the reconstructed signals. K-SVD ensures that the number of non-zero entries in each column of **x** does not exceed a given threshold *T*. The optimization problem tackled by K-SVD is non-convex and computationally intensive. To address this, K-SVD divides the problem into two sub-steps: **sparse coding**, where the coefficient **x** is computed to represent the data using a fixed dictionary **D**, and **dictionary update**, where the dictionary **D** is adjusted to better fit the data while keeping the sparse representation intact.

Figure 2 illustrates the experimental setup for detecting bolt loosening on a pressure box. The pressure box consists mainly of two parts: the lid and the rectangular main box. The lid is fastened to the main box using 32 bolts. The entire box is constructed to mimic the building blocks in the terrestrial habitats. Due to harsh environmental conditions such as moonquakes and temperature fluctuations, the bolts may become loosened, leading to unexpected pressure leakage that could threaten the crew in the habitat. Therefore, health monitoring of the bolt joints is necessary. The data acquisition for different fault types is summarized in Table 1.

Table 1. Bolt loosening damage case setup.

Location	Bolt Loosening Level
Bolt 1	Healthy, 40%, 75% and 100%
Bolt 2	Healthy, 40%, 75% and 100%
Bolt 3	Healthy, 40%, 75% and 100%
Bolt 4	Healthy, 40%, 75% and 100%
Total 13 cases	Healthy, Bolt 1 (40%, 75%, 100%), Bolt 2 (40%, 75%, 100%), Bolt 3 (40%, 75%, 100%), Bolt 4 (40%, 75%, 100%)

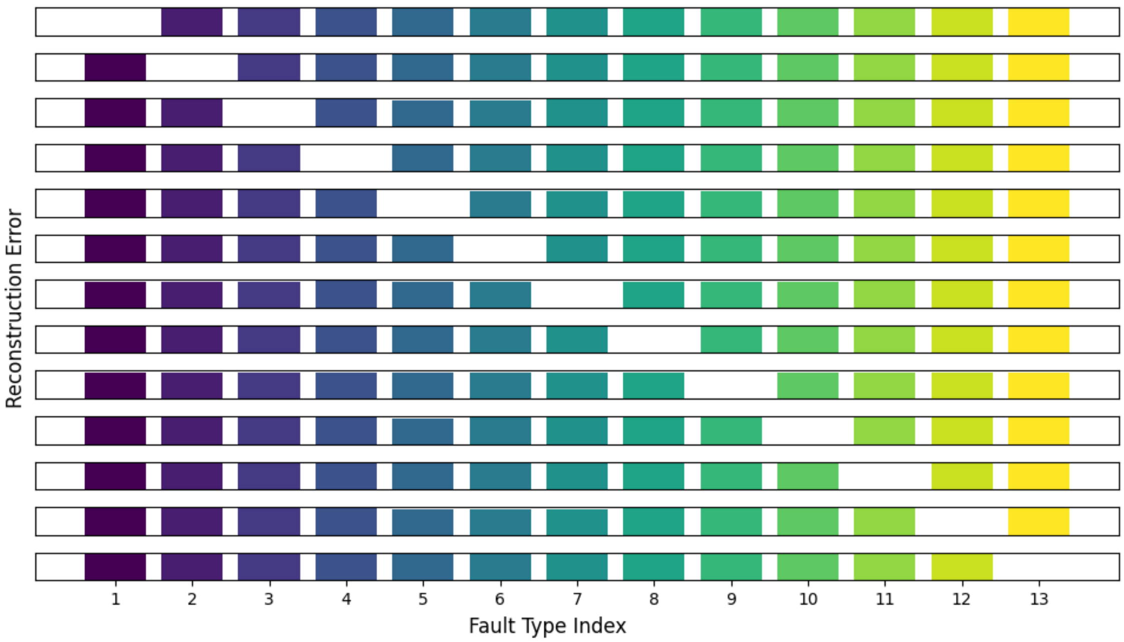

Figure 5. Bolt loosening damage classification on testing datasets.

Figure 5 illustrates the results of the damage detection and classification process. The figure contains 13 subplots corresponding to the 13 cases in Table 1, each corresponding to a specific bolt loosening type. The first subplot represents the healthy state, while every subsequent group of three subplots corresponds to 40%, 75%, and 100% torque loss for bolts 1 to 4. To explain how damage classification and detection are achieved using the reconstruction strategy, we focus on the first and last subplots. The core idea behind reconstruction-based fault detection is that, given a test data sample, we search through all dictionaries and obtain sparse coefficient vectors through sparse coding. We then use these coefficients to reconstruct the test signal. If the test data corresponds to a certain damage type, the dictionary associated with that class will effectively reconstruct the test data. Conversely, dictionaries not associated with the test data's class will produce reconstructions with larger errors. We use the Root Mean Square Error (RMSE) as an error metric, calculated between the reconstructed data and the original test data. A smaller RMSE indicates a better match and suggests that the test data belongs to that particular damage category. For example, in the first subplot, the test data comes from the healthy state. We perform dictionary search and reconstruction using all dictionaries, then compute the RMSE between each reconstructed signal and the test data. Visualization shows that the reconstruction using the first dictionary (healthy state) yields the smallest RMSE, correctly indicating that the test data belongs to the healthy class. In the last subplot, the test data corresponds to the 13th class, which represents the fully loosened state of Bolt 4. We again perform dictionary search and reconstruction, obtaining 13 reconstructed signals. By computing the RMSE between each reconstructed signal and the test data, we find that the 13th reconstructed signal has the smallest RMSE. This result indicates that the test data belongs to the 13th damage category. Similar explanations apply to the damage monitoring of other test data samples. Moreover, the results also suggest strong classification ability, with the reconstruction-based strategy yielding accurate detection and classification of the different damage categories. The RMSE metric consistently shows smaller errors for the correct dictionaries, indicating that the method performs well in identifying the appropriate damage types, which demonstrates classification performance to 100%.

Using the learned dictionary and sparse codes, we can reconstruct the testing data, as shown in Figure 6. The top subplot shows the comparison between the original test data and the reconstructed signals using atom 2 and atom combinations 2, 4, and 7 respectively. The bottom subplot focuses on a specific frequency range (45,000 to 46,000 Hz) for a more detailed comparison. When only atom 2 is used for reconstruction, we can see that the reconstructed data is largely consistent with the original test data. When we use all the atoms with coefficients, namely atoms 2, 4, and 7, we can observe that, as shown in the zoomed-in plot, the reconstruction using three atoms is closer to the actual test data compared to using only atom 2. This indicates that the two atoms (atoms 4 and 7), which seemed like noise, play a certain role in fine-tuning during reconstruction. However, their sparsity is close to zero, meaning the primary contribution still comes from atom 2.

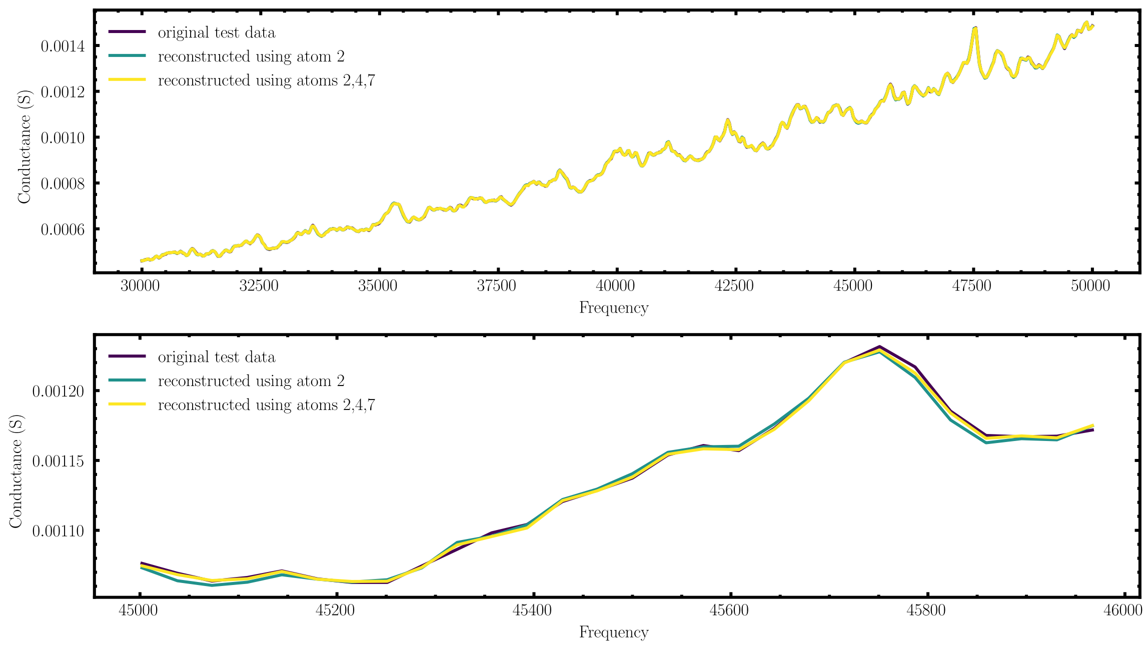

Figure 6. Data reconstruction using different atoms for testing data 1 (healthy state).

When higher reconstruction accuracy is desired, it is expected that all atoms would contribute to the reconstruction. However, we observe from the sparse code that some atoms, which resemble noise, have very small coefficients. This raises the question of whether such atoms affect damage identification, which we aim to verify. Therefore, we remove atoms 4 and 7 and reconstruct using only atom 2, followed by calculating the RMSE and performing damage classification based on the reconstruction error. Similarly, for other test data, only the principal atoms that exhibit the same changes as the training data are used for reconstruction, excluding the contribution of noise-like atoms. The classification results are shown in Figure 14. It is evident that the reconstruction method is still able to accurately classify each category with accuracy of 100%. This result indicates that the contribution of noise-like atoms to damage identification can be ignored, even though they may have a minor tuning effect when participating in data curve reconstruction.

From the above analysis, it can be concluded that dictionary learning first captures the overall trend of the training data. The features are amplified in the dictionary as principal modes.

Furthermore, the dictionary also separates noise from the training data. Comparing the classification results before and after removing the contribution of noise atoms shows that removing noise factors has no effect on damage classification. This method can be applied to other similar fields, such as denoising, image processing, and more.

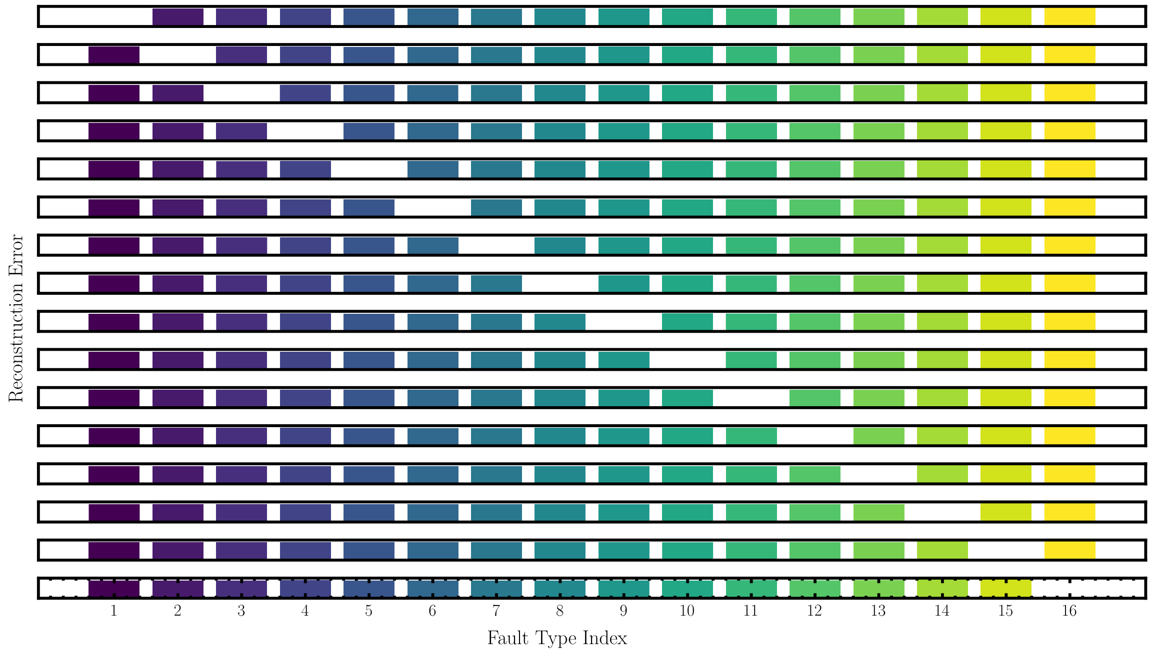

Figure 7. Bolt loosening damage classification on testing datasets without noise-like atoms for reconstruction.

Chapter 4: Education Impact and Knowledge Dissemination

Throughout this project, three graduate students are involved at different stages of research. Yang Zhang and Ting Wang set up the testbed and conducted data acquisition. Yang Zhang and Qianyu Zhou worked on damage identification algorithm. In particular, Yang Zhang led the algorithm development and case demonstration, while Qianyu Zhou provided support. The work is heavily experimental. All these students gained significant amount of experiences on mechatronic synthesis, sensor tuning, machine learning, and decision making for structural fault detection. The research components have been incorporated to their respective Ph.D. dissertations. Yang Zhang and Ting Wang are approaching the end of their Ph.D. studies. Qianyu Zhou is progressing well in his Ph.D. study.

The research findings have been integrated into several undergraduate- and graduate-level classes that the PI has instructed in project years, including ME3220 Mechanical Vibrations, ME 5420 Advanced Mechanical Vibrations, ME 5210 Intelligent Material Systems and Structures, and ME 5895 Structural Dynamics.

The research outcome has been presented systematically in TIDC annual review meetings and poster competitions. The key research findings are being summarized into archival publications.

Chapter 5: Conclusions and Recommendations

The goal of this project is to develop a new and robust damage identification sensory system that can detect damage in large-scale infrastructure components through the concurrent advancements in non-contact sensing and machine learning based decision making. We have successfully accomplished this goal.

Our findings are the following:

- Leveraging magneto-mechanical coupling, there is indeed two-way coupling between the non-contact sensor and the host mechanical structure. Moreover, one can extract magneto-mechanical impedance that is analogous to piezoelectric impedance measurement to facilitate damage identification.
- Circuitry integration with tunable capacitance and negative resistance can effectively amplify the measurement signal-to-noise ratio in magneto-mechanical impedance measurement, yielding a new sensing mechanism.
- Machine learning techniques can be combined with impedance sensing to enable highly sensitive fault detection and classification, especially for scenarios where first-principle based inverse analysis is hard to establish. In particular, dictionary learning for bolt-loosening detection is formulated and thoroughly examined for a benchmark structure.
- Dictionary learning provides an effective way to extract key features from complex impedance signatures, allowing one to represent the underlying patterns with a sparse set of representative atoms. The classification of test data into different damage categories is based on the reconstruction error.
- The interpretability of learned dictionary is provided that the dictionary can capture the trends in the training data while separating out the noise. The noise contribution is negligible in the reconstruction and does not affect the accuracy of damage classification.
- The reconstructed full-field measurement can lead to successful structural fault detection.

The research outcomes lay down a foundation for engineering implementation for infrastructure monitoring. In order to fully unleash the potential of the new technology, we envision the following further advancements:

- More research will need to be done to solidify the non-contact impedance sensing technique, in particular to handle the noise measurement owing to ambient factors. Possible directions including digitalizing the circuitry integration.
- Machine learning offers a tremendous prospect to facilitate data-drive techniques for fault detection and classification without the need of going through first principle modeling. One promising direction is to incorporate modeling into machine learning directly to facilitate physics-informed machine learning for fault detection.

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