TIDC Transportation Infrastructure Durability Center AT THE UNIVERSITY OF MAINE

Quarterly Progress Report:
Project Number and Title: 1.6 Progressive fault identification and prognosis of railway tracks based on intelligent inference
Research Area: #1 Transportation infrastructure monitoring and assessment for enhanced life
PI: Jiong Tang, Department of Mechanical Engineering, University of Connecticut
Co-PI(s): N/A
Reporting Period: 10/01/2019 – 12/31/2019
Submission Date: 12/31/2019

Overview:

Summary of activities performed

The goal of this project is to develop highly accurate and robust fault identification and prognosis methods specifically tailored for railway track systems. In this project period, we continue our research on formulating physics-informed inverse identification algorithms. Building upon the framework of pre-screening and Bayesian inference, we explore a new pre-screening approach based on a multi-objective optimization technique to tackle challenge in inverse identification. With damage locations and severities as unknown variables, one of the objective functions is the difference between impedance-based model prediction in the parametric space and the actual measurements. Considering that damage occurrence generally affects only a small number of elements, we choose the sparsity of the unknown variables as another objective function, deliberately, the l0 norm. Subsequently, a multi-objective Dividing RECTangles (DIRECT) algorithm is developed to facilitate the inverse analysis where the sparsity is further emphasized by sigmoid transformation. Our preliminary simulations indicate that this multi-objective optimization technique has great potential to identify possible damage locations.

How these activities are helping achieve the overarching goal of the project

In the previous phases of the project (10/31/2018 – 09/30/2019), we perform preliminary investigation on sensing mechanism development and inverse identification algorithms. Through circuitry integration and tunable resonance, we can greatly enhance the impedance/admittance measurement quality and also enrich the measurement information. This lays down a foundation for the subsequent tunable sensor design and the fault detection/identification algorithmic investigation. Subsequently, we have formulated and executed fault identification built upon Bayesian inference. Simulation data were then used to practice the identification of fault location and severity. The outcome provides a preliminary demonstration of the feasibility of Bayesian inference for fault identification. The activities carried out in this project period can provide pre-screening of damage scenarios that include multi-damage occurrences. This result can then be utilized for probability based Bayesian inference.

Describe any accomplishments achieved under the project goal

The high detection sensitivity of impedance/admittance-based active sensing approach is built upon the high-frequency responses excited and measured. A very large number of finite elements are needed to establish the baseline model for credible prediction of high-frequency responses. As we divide the structure into segments to facilitate damage identification, the structural properties of each segment remains to be identified because each segment is susceptible of fault occurrence, which yields a large number of unknowns. On the other hand, structural faults generally manifest themselves around the peaks of the piezoelectric impedance/admittance curves only, which means the input measurement information is usually limited in practice. Moreover, it is mathematically difficult to select frequency points to ensure the full rank of the sensitivity matrix (that relates fault location/severity with measurement, shown in Equation (8)) even if the number of frequency points is large. Therefore, the inverse identification formulation typically is under-determine. Although one may apply artificial constraints to seek for such as least square solutions, these solutions may not reflect the true fault scenario.

Hereafter, we cast the inverse identification problem into an optimization framework. Let $\Delta\mathbf{Y}$ be the measured admittance change. The prediction of admittance change in the parametric space is denoted as $\Delta\hat{\mathbf{Y}} = \mathbf{S}\hat{\boldsymbol{\alpha}}$. Certainly, we need to minimize the difference between these two, i.e.,

$$\min \left\| \mathbf{S}\hat{\boldsymbol{\alpha}} - \Delta\mathbf{Y} \right\|_2 \tag{1}$$

where $\|\bullet\|_p$ denotes the l_p norm defined as $\|\mathbf{x}\|_p = \left(\sum_i |x_i|^p\right)^{1/p}$. Equation (1) has a large number of local minima given that $\mathbf{S}$ is rank-deficient. It is worth noting that a true damage scenario in practical situation usually affect only a small number of segments. In other words, the damage index vector $\boldsymbol{\alpha}$ is sparse by nature. Here we introduce the sparse regularization by enforcing a sparse constraint on $\hat{\boldsymbol{\alpha}}$. Traditionally, an l_2 regularizer $\|\hat{\boldsymbol{\alpha}}\|_2$ has been used, which, however, is not designed toward sparse solutions. As illustrated in Figure 1, larger p (i.e., subscript of l_p) tends to spread out the error more evenly among variables and return a non-sparse $\hat{\boldsymbol{\alpha}}$ with many nonzero elements. Thus, we are more interested in l_0 or l_1 norm. While l_1 norm is usually used in statistical and signal processing as a convex approximation of non-convex l_0 to improve computational efficiency (Davenport et al, 2011), it introduces a mismatch between the goal of itself and that of l_0 norm. As such, we may fail to recover the maximally sparse solution regardless of the initialization. In damage identification, finding a solution of Equation (1) with the presence of modeling and measurement error cannot be simply solved as a convex optimization problem because it is indeed a multi-modal problem (having multiple local optima). Therefore, the convex approximation of l_0 would not be a necessity. Thus, the second objective function here is chosen as the minimization of the l_0 norm of $\hat{\boldsymbol{\alpha}}$, i.e.,

$$\min \|\hat{\boldsymbol{\alpha}}\|_0 \tag{2}$$

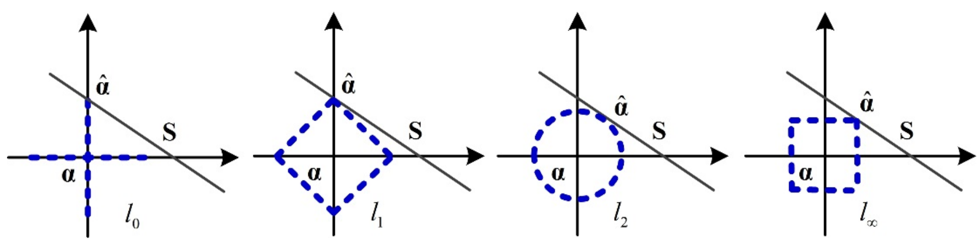

Figure 1. Approximation of point $\boldsymbol{\alpha}$ in $\mathbf{R}^2$ using l_0, l_1, l_2 and l_∞ norm.

One way of handling the two objective functions selected above (Equations (1) and (2)) is to formulate a composite objective function, i.e.,

$$\min \ \|\mathbf{S}\hat{\boldsymbol{\alpha}} - \Delta\mathbf{Y}\|_2 + \lambda\|\hat{\boldsymbol{\alpha}}\|_0 \tag{3}$$

where λ is the weighting factor. The choice of weights is usually ad-hoc since the relative importance of each objective is unknown. A more critical issue is that such a single objective optimization usually gives one single optimum which may or may not fit the true damage scenario at all. Indeed, mathematically, the inverse identification problem is oftentimes under-determined. While we know the damage index vector must be sparse, we generally do not know how sparse it is. In this research, we formulate a multi-objective optimization,

$$\text{Find: } \hat{\boldsymbol{\alpha}} = \{\hat{\alpha}_1, \hat{\alpha}_2, ..., \hat{\alpha}_n\}, \quad \alpha^l \le \hat{\alpha}_j \le \alpha^u, \quad j = 1, 2, ..., n$$
$$\text{Minimize: } f_1 = \|\mathbf{S}\hat{\boldsymbol{\alpha}} - \Delta\mathbf{Y}\|_2 \text{ and } f_2 = \|\hat{\boldsymbol{\alpha}}\|_0 \tag{4}$$

where α^l and α^u are the lower bound and upper bound of the damage index. A fundamental advantage of this multi-objective optimization formulation is that it naturally yields a set of optimal solutions explicitly exhibiting the tradeoff between objectives, i.e., the Pareto front/surface. This fits exactly the under-determined nature of the damage identification problem, and provides identification results that can be used for further inspection and prognosis which is the actual procedure of performing SHM. In this project period, utilizing the baseline simulation model we have established in previous phases, we have been able to successfully extract damage scenarios with multi-damage occurrence using the above-mentioned multi-objective optimization.

Complete the following tables to document the work toward each task and budget (add rows/remove rows as needed)…

Table 1: Task Progress			
Task Number	**Start Date**	**End Date**	**Percent Complete**
Task 1:	09/2018	03/2020	90%
Task 2:	04/2020	03/2021	10%
Task 3:	03/2021	03/2022	10%
Task 4:	04/2022	09/2023	30%

Table 2: Budget Progress		
Entire Project Budget	**Spend Amount**	**Spend Percentage to Date**
$254,000	$62,207.09	24.5% (12/31/2019)

Describe any opportunities for training/professional development that have been provided…

This project has involved one M.S. student, Yixin Yao, who carries out the numerical and experimental investigations, and one Ph.D. student, Yang Zhang, who focuses on improving the fault identification and prognosis algorithms. Starting in fall 2019, 4 undergraduate senior students from UConn Management and Engineering of Manufacturing Program, Alexander Biron, Kelly Quinn, Jason Trieu, and Meghan Palumbo, have been developing an experimental testbed which is partially supported by this project. These involvements provide opportunity for training. The project progress is being communicated with industry collaborator, Sperry Rail Service, which provides another opportunity for training of state-of-the-art knowledge of active materials and advanced signal processing techniques for working professionals.

*Describe any activities involving the dissemination of research results (be sure to include outputs, outcomes, and the ways in which the outcomes/outputs have had an impact during the reporting period. Please use the tables below for any Publications and Presentations in addition to the description of any other technology transfer efforts that took place during the reporting period.)… Use the tables below to complete information about conferences, workshops, publications, etc**. List all other outputs, outcomes, and impacts after the tables** (i.e. patent applications, technologies, techniques, licenses issued, and/or website addresses used to disseminate research findings).*

Table 3: Presentations at Conferences, Workshops, Seminars, and Other Events				
Title	**Event**	**Type**	**Location**	**Date(s)**
Machine Learning With Limited Data	8th International Conference on Through-Life Engineering Services	Conference	Cleveland, OH	Oct 27-29, 2019

Table 4: Publications and Submitted Papers and Reports				
Type	**Title**	**Citation**	**Date**	**Status**
N/A				

Participants and Collaborators:

Table 5: Active Principal Investigators, faculty, administrators, and Management Team Members			
Individual Name	**Email Address**	**Department**	**Role in Research**
Jiong Tang	Jiong.tang@uconn.edu	Mechanical Engineering	PI

Table 6: Student Participants during the reporting period				
Student Name	**Email Address**	**Class**	**Major**	**Role in research**
Yixin Yao		M.S.	Mechanical Engineering	Carry out simulation and experiment
Yang Zhang		Ph.D.	Mechanical Engineering	Carry out inverse identification
Alexander Biron		Senior	MEM	Assist testbed setup
Kelly Quinn		Senior	MEM	Assist testbed setup
Jason Trieu		Senior	MEM	Assist testbed setup
Meghan Palumbo		Senior	MEM	Assist testbed setup

Table 7: Student Graduates			
Student Name	**Role in Research**	**Degree**	**Graduation Date**
N/A			

Table 8: Research Project Collaborators during the reporting period						
Organization	**Location**	**Contribution to the Project**				
		Financial Support	**In-Kind Support**	**Facilities**	**Collaborative Research**	**Personnel Exchanges**
Sperry Rail Service	Shelton, CT		X	X		
Connecticut Manufacturing Simulation Center	Storrs, CT		X	X		

List all other outputs, outcomes, and impacts here (i.e. patent applications, technologies, techniques, licenses issued, and/or website addresses used to disseminate research findings). Please be sure to provide detailed information about each item as with the tables above.
N/A

Have other collaborators or contacts been involved? If so, who and how? (This would include collaborations with others within the lead or partner universities; especially interdepartmental or interdisciplinary collaborations.
N/A

Changes:

Discuss any actual or anticipated problems or delays and actions or plans to resolve them…
N/A

Discuss any changes in approach and the reasons for the change…
N/A

Planned Activities:

The next phase of the research will focus on further improvement of fault identification algorithm with more comprehensive case studies utilizing the enhanced sensory circuitry.