<u>Bi-Monthly Progress Report</u>:
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
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Reporting Period: *06/1/2019 – 07/31/2019*
Date: *07/31/2019*

<u>Overview:</u>

Provide overview and summary of activities performed during previous two months….

Piezoelectric impedance sensing has shown promising aspects in structural health monitoring, owing to its high-frequency active interrogation feature. With harmonic excitation, it is possible to carry out inverse analysis to facilitate the real-time identification of fault location and size. On one hand, the finite element analysis can provide an accurate method to predict the structural dynamic analysis. On the other hand, however, the damage identification based on the inverse analysis is challenging because of high computational cost and the usually under-determined nature of the problem. That is, the number of unknowns is generally very large so a usual matrix inversion may not lead to meaningful results. The Bayesian inference approach has shown certain advantages. Essentially, it allows fault identification through repeated forward analysis, thereby avoiding matrix inversion of an under-determined problem. Moreover, this approach allows the computation of any type of statistics of the model parameters to be identified. The intent of this phase of the research is to develop a feasible and robust algorithm to conduct damage localization and identification based on piezoelectric impedance/admittance information.

Provide context as to how these activities are helping achieve the overarching goal of the project…

The research activities conducted during this period encompasses the formulation and execution of fault identification built upon Bayesian inference. A testbed structure integrated with piezoelectric transducer is analyzed. Representative fault conditions are introduced to produce simulated data for fault detection and identification. The data is 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.

Describe any accomplishments achieved under the project goals…

Here we consider a structural testbed integrated with piezoelectric transducer. The coupled structure-transducer equations can be derived as

$$\mathbf{M}_{(e)}\ddot{\boldsymbol{\delta}}_{(e)} + \mathbf{C}_{(e)}\dot{\boldsymbol{\delta}}_{(e)} + \mathbf{K}_{(e)}\boldsymbol{\delta}_{(e)} + \mathbf{k}_{12(e)}Q = \mathbf{F}_{(e)} \tag{5}$$

$$L\ddot{Q} + R\dot{Q} + \mathbf{k}_{12(e)}^{T}\boldsymbol{\delta}_{(e)} + k_{22}Q = V \tag{7}$$

When applying Bayesian theorem for structural model updating, the hypothesis $\boldsymbol{\theta}$ is interpreted as the vector of parameters that need to be identified. $\mathbf{D}$ denotes the measured signature, which in this study is the electrical admittance of piezoelectric transducer. M denotes modeling assumptions, reflecting the existing experience and knowledge. We then have

$$p(\boldsymbol{\theta} \mid \mathbf{D}, M) = \frac{p(\mathbf{D} \mid \boldsymbol{\theta}, M)\, p(\boldsymbol{\theta} \mid M)}{\int p(\mathbf{D} \mid \boldsymbol{\theta}, M)\, p(\boldsymbol{\theta} \mid M)\, d\boldsymbol{\theta}} \tag{8}$$

The prior distribution $p(\boldsymbol{\theta} \mid M)$ expresses the initial knowledge of concerned parameters, e.g., stiffness, mass, damage location. The posterior distribution $p(\boldsymbol{\theta} \mid \mathbf{D}, M)$ indicates the updated knowledge of the parameters $\boldsymbol{\theta}$ conditional on the prior knowledge and measured admittance information. Considering that uncertainties exist in real measurement, here we define the likelihood function as a multivariate normal distribution to conduct the screen of model output over $\boldsymbol{\theta}$ space.

$$p(\mathbf{D} \mid \boldsymbol{\theta}) = \frac{1}{\sqrt{(2\pi)^k |\Sigma|}} e^{-\frac{(\mathbf{D}-\mathbf{D}(\boldsymbol{\theta}))^T \Sigma^{-1} (\mathbf{D}-\mathbf{D}(\boldsymbol{\theta}))}{2}} \tag{9}$$

where $\mathbf{D}$ is a measured admittance vector, having length k, and $\mathbf{D}(\boldsymbol{\theta})$ is the model output parameterized by $\boldsymbol{\theta}$. Σ is the covariance matrix of $\mathbf{D}$. Under this framework, the damage status of the structure monitored can be eventually identified.

Here we intend to localize and identify small-size damage in a plate structure. The host structure is an aluminum square plate ($0.5m \times 0.5m \times 0.005m$) with attached piezoelectric circuitry. The plate is clamped at its two ends. The corresponding finite element model divides the plate into ($100 \times 100 \times 1$) elements. The piezoelectric transducer is a square one with length 0.0025m, which covers 25 (5×5) plate elements. The numerical result first demonstrates the piezoelectric admittance of the healthy plate without the inductance (baseline). Then, the inductance is added and its value is adjusted to 3.6662 H, in order to generate desired resonant effects. The circuitry with inductance can be emulated with a one DOF spring-mass system. We assume damage occurs in a single element with 40% Young's modulus reduction, and the damaged element is located in certain position.

As no prior knowledge of possible damage severity (reduction of element Young's modulus) and location is known, we choose bivariate uniform distribution as the prior distribution. The number of samples parameterized from such distribution are equal to the product of the possible damage severity candidates and damage location candidates. In real situation, the damage severity candidates are continuously sampled within certain range and damage can probably occurs in each element of plate, which yields an extremely large number samples based on prior distribution. Due to the essence of Bayesian inference, the repeated evaluation of the likelihood function corresponding to such samples using pure Monte Carlo simulation is computationally prohibitive since each evaluation of likelihood function depends on the harmonic analysis with multiple excitation frequency components, which is already costly. For the purpose of illustrating the effectiveness of proposed methodology, here we only consider a small region of plate where damage is likely to occur (including 100 elements). Moreover, the possible damage severity candidates are reduced to a vector [40% 60% 80%]. The interested frequencies range from 1060Hz to 1140Hz, generating uniformly distributed 50 frequency components. Although the damage severity does not continuously vary, we can use meta-modeling technique such as Gaussian process to interpolate and predict the posterior probabilities under unobserved damage severity candidates in the future study. Taking uncertainties into account, the 0.5% admittance measurement standard deviation is introduced to establish the likelihood function. Furthermore, in this case study, we demonstrate the results with respect to the different inductance values ($L_1 = 3.6662$ and $L_2 = 3.5662$), aiming at facilitating the identification process and further providing the adaptive inductance tuning guideline for practical experimental manipulation.

Table 1. Comparison summary of identification results –10 most possible scenarios

L_1			L_2			L_1 and L_2		
Element index	Severity	Probability	Element index	Severity	Probability	Element index	Severity	Probability
20	40%	4.1689	20	40%	3.0737	20	40%	7.0342
19	40%	4.1247	19	40%	3.0654	19	40%	6.9407
18	40%	4.0459	18	40%	3.0519	18	40%	6.7782
17	40%	3.9598	17	40%	3.0239	17	40%	6.5730
10	40%	3.8210	16	40%	2.9336	16	40%	6.1270
16	40%	3.8047	10	40%	2.8719	10	40%	6.0238
29	40%	3.7965	29	40%	2.8371	29	40%	5.9127
28	40%	3.7368	35	60%	2.8291	28	40%	5.7939
30	40%	3.7286	28	40%	2.8245	30	40%	5.7248
5	40%	3.6304	34	60%	2.8012	6	40%	5.5170

Note: actual damage scenario- element index: 20; severity: 40%;

Comprehensive analyses are carried out. Summarized in Table 1 are the identification results. One can observe that the Bayesian inference approach can indeed identify both the location and severity of damage, i.e., the actual damage scenario is confirmed by the Bayesian inference as having the largest probability. This confirms the validity of the approach.

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

This project currently involves on graduate student, Yixin Yao, to carry out the numerical and experimental investigations. This provides 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

In this phase of research, communication with Conn DOT has been established. A tele-con with Conn DOT engineers was carried out on June 28, 2019, in which project scope and preliminary results were shared.

Participants and Collaborators:

Participants: Dr. Jiong Tang, PI, project lead; Yixin Yao, graduate student, research assistant.
Collaborator: Jan Kocur, Sperry Rail Service, providing technical assessment and industry insights.

Changes: N/A

Planned Activities:

The next phase of the research will focus on improving the fault identification algorithm by removing the a priori assumption on possible damage location and severity.