Semi-Annual 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
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Reporting Period: ***04/01/2019 – 09/30/2019***
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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 phase of the project, we focus primarily on modeling the testbed structure and formulating physics-informed inverse identification algorithms. We have formulated the first-principle based piezoelectric impedance modeling. Experimental results match very well with the numerical model. We have developed the preliminary framework of Bayesian inference inverse identification algorithm to facilitate the identification of fault location and severity. This framework can provide fault identification with probability. Additionally, we have communicated with ConnDOT on the proposed work and preliminary results.

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

In the previous phase of the project (10/31/2018 – 03/31/2019), we perform preliminary investigation on sensing mechanism development. 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. In the current phase of the project (04/01/2019 – 09/30/2019), we first construct a testbed structure and formulated a baseline model. The testbed structure is integrated with piezoelectric transducer. Representative fault conditions are introduced to produce simulated data for fault detection and identification. We then 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.

Describe any accomplishments achieved under the project goals…

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

$$\mathbf{M}_{(e)}\ddot{\boldsymbol{\delta}}_{(e)} + \mathbf{C}_{(e)}\dot{\boldsymbol{\delta}}_{(e)} + \mathbf{K}_{(e)}\boldsymbol{\delta}_{(e)} + \mathbf{k}_{12(e)}Q = \mathbf{F}_{(e)} \quad (1)$$

$$\mathbf{k}_{12(e)}^{T}\boldsymbol{\delta}_{(e)} + k_{22}Q = V \quad (2)$$

When applying Bayesian theorem for structural model updating, the hypothesis $\boldsymbol{\theta}$ is interpreted as the vector of parameters that need to be identified. $\mathbf{Y}$ 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

$$p(\boldsymbol{\theta} \mid \mathbf{Y}, M) = \frac{p(\mathbf{Y} \mid \boldsymbol{\theta}, M)\, p(\boldsymbol{\theta} \mid M)}{\int p(\mathbf{Y} \mid \boldsymbol{\theta}, M)\, p(\boldsymbol{\theta} \mid M)\, d\boldsymbol{\theta}} \quad (3)$$

The prior distribution $p(\boldsymbol{\theta} \mid M)$ expresses the initial knowledge of concerned parameters, e.g., stiffness, mass, damage location. The posterior distribution $p(\boldsymbol{\theta} \mid \mathbf{Y}, M)$ 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.

$$p(\mathbf{Y} \mid \boldsymbol{\theta}) = \frac{1}{\sqrt{(2\pi)^k \, |\Sigma|}} e^{-\frac{(\mathbf{Y}-\mathbf{Y}(\boldsymbol{\theta}))^T \Sigma^{-1} (\mathbf{Y}-\mathbf{Y}(\boldsymbol{\theta}))}{2}} \quad (4)$$

where $\mathbf{Y}$ is a measured admittance vector, having length k, and $\mathbf{Y}(\boldsymbol{\theta})$ 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.

We let the stiffness matrix of the structure with fault be represented as $\mathbf{K}_d$ where the subscript 'd' refers to the damaged state, which is then expressed as

$$\mathbf{K}_d = \sum_{j=1}^{m} \mathbf{K}_{sj}(1 - D_j) \quad (5)$$

In Equation (5), $\mathbf{K}_{sj}$ is the stiffness sub-matrix of the *j*-th segment ($j=1,\cdots,m$) under the healthy condition, D_j is the fault index that indicates the percentage change of its stiffness due to fault occurrence, and the summation sign refers to the direct summation operation involved in finite element formulation. For the *j*-th segment, if D_j is identified to be a non-zero value based on the inverse analysis to be presented, we can conclude that fault occurs at the *j*-th segment with severity level D_j. Our objective is to identify D_j ($j=1,\cdots,m$) by using the admittance change measurements. Hereafter we introduce the following notation of fault index vector,

$$\mathbf{D}=[D_1,\cdots,D_m]^T \tag{6}$$

As pointed out in literature, the piezoelectric impedance/admittance-based damage detection is omnidirectional in nature, because physically the transducer can excite local oscillations in all directions and at the same time sense those oscillations. This is manifested in the transducer-structure interaction relation (shown in Equations (1) and (2)) as well as in the admittance expression. We can observe from these equations that the fault occurrence in any structural elements/segments may cause admittance change. Here we want to fully unleash this advantage of the impedance/admittance-based approach by providing an effective inverse identification algorithm.

From Equations (1) and (2), we can develop mathematically the relation between admittance change and the change of structural property. Structural fault to be identified is generally insignificant in size, so Taylor series expansion can be adopted. The admittance of the system with fault can be expressed as

$$Y_d(\mathbf{D})\approx Y(\mathbf{D}=\mathbf{0})+\sum_{j=1}^{m}\frac{\partial Y}{\partial D_j}\Big|_{\mathbf{D}=\mathbf{0}} D_j \tag{7}$$

which then yields

$$\Delta Y(\omega)=Y_d-Y(\mathbf{D}=\mathbf{0})=\sum_{j=1}^{m}[\omega i(k_c-\mathbf{K}_{12}^T\mathbf{Z}_s^{-1}\mathbf{K}_{12})^{-2}\mathbf{K}_{12}^T\mathbf{Z}_s^{-1}\mathbf{K}_{sj}\mathbf{Z}_s^{-1}\mathbf{K}_{12}]D_j \tag{9}$$

where $\mathbf{Z}_s$ denotes the dynamic stiffness of the structure, i.e.,

$$\mathbf{Z}_s=\mathbf{K}-\omega^2\mathbf{M}+i\omega\mathbf{C} \tag{10}$$

Equation (9) is valid for impedance change acquired at one specific excitation frequency point. Assuming the admittance change information at a total of *n* frequency points is available and grouping together all the relations between the admittance change and the fault index vector, we have the following matrix form expression

$$\Delta\mathbf{Y}=\begin{bmatrix}\Delta Y(\omega_1)\\ \vdots \\ \Delta Y(\omega_n)\end{bmatrix}=\mathbf{S}_{n\times m}\mathbf{D} \tag{11}$$

where $\Delta\mathbf{Y}$ is an *n*-dimensional vector containing admittance changes at ω_j ($j=1,\cdots,n$), **D** is the *m*-dimensional fault index vector, and $\mathbf{S}_{n\times m}$ is the sensitivity matrix. Theoretically, under each set of admittance change $\Delta\mathbf{Y}$, one can find the fault index vector **D** through matrix inversion of Equation (11). In reality, however, *n*, the number of admittance measurement frequency points, is usually smaller than *m*, the number of segments in the finite element model. Indeed, structural fault effect is mostly reflected around the peaks of the admittance curves that correspond to the structural resonances. Only a relatively small number of frequency points around those peaks can yield satisfying signal-to-noise ratio in admittance measurements. The number of segments, on the other hand, usually is large because of the large number of finite elements involved in the numerical model of high-frequency admittance analysis. As such, the inverse problem is under-determined.

In this research, instead of matrix inversion, we exploit the matrix relation shown in Equation (11) to develop a pre-screening scheme that can reduce the computational cost necessary for identifying the location and severity of fault. Here in this research we assume single fault occurrence. Then,

$$\Delta\mathbf{Y}=D_k\mathbf{s}_k \tag{12}$$

where $\mathbf{s}_k$ denotes the *k*-th column of the sensitivity matrix $\mathbf{S}_{n\times m}$. In other words, when the *k*-th structural segment has fault, the admittance change vector must be linearly dependent to the *k*-th column of the sensitivity matrix, and the ratio of these two vectors is equal to the fault severity level. This gives rise to the idea of performing a pre-screening of possible fault scenario (i.e., location and severity) by using $\mathbf{S}_{n\times m}$ and $\Delta\mathbf{Y}$ directly without resorting to matrix inversion, which is summarized as follows.

1) We start from treating each segment as potential fault location candidate, and compute an *estimated* fault index for the *k*-th segment that is defined as

$$D_k^{\text{est}} = \text{mean}\left(\frac{\Delta Y(\omega_j)}{s_{jk}}\right) \qquad (k = 1,\cdots,m) \tag{13}$$

If for a certain *k*, D_k^{est} is greater than 1 or less than 0, we can conclude that fault cannot occur at this *k*-th segment (since an actual fault index cannot be greater than 1 or less than 0).

2) We then analyze the similarity of the remaining columns of the sensitivity matrix with respect to the admittance change vector, and define a similarity index as

$$SI_k = \arcsin\left(\frac{\mathbf{s}_k^T \Delta\mathbf{Y}}{|\mathbf{s}_k|\cdot|\Delta\mathbf{Y}|} - 1\right) \tag{14}$$

where SI_k represents the directionality or similarity of the two vectors. If $\mathbf{s}_k$ is linearly dependent on $\Delta\mathbf{Y}$, i.e., the directionality SI_k is equal to 0. Larger difference in these two vectors leads to larger value of directionality SI_k.

We define a *relative* similarity function for the *k*-th column vector of the sensitivity matrix with respect to the admittance change vector as

$$P_k = \frac{e^{-|SI_k|}}{\sum_{j=1}^{m} e^{-|SI_j|}} \tag{15}$$

The numerator reflects the similarity corresponding to the *k*-th column vector, while the denominator reflects the summation of the similarities. Equation (15) then represents a relative comparison of the vector similarities. We can rank P_k in the descending order, and larger P_k value indicates higher likelihood of fault occurring at the *k*-th segment. In practice, one can choose a threshold value based on the distribution of P_k values, which will further reduce the candidate locations of fault occurrence.

Table 1 Similarity prediction

Segment #	Similarity	Fault severity
110	0.097	0.01590
35	0.095	0.01635
46	0.089	0.01286
185	0.087	0.01534
151	0.077	0.00363
173	0.069	0.02920
196	0.062	0.01333
65	0.061	0.01207
215	0.059	0.04800
121	0.050	0.01334
207	0.045	0.01216
140	0.035	0.02446
98	0.030	0.02951
14	0.025	0.02062
57	0.023	0.01259

We carry out experiment to examine the prescreening procedure followed by Bayesian inference. A 0.6 g mass is attached onto the plate at location corresponding to the 110th segment in the model, which causes the same resonant frequency change as that due to a 1.6% local stiffness loss. The admittances are measured around the 14th and 20th resonant frequencies. The measured admittance changes are used as input to the pre-screening procedure to provide preliminary estimations of fault location candidates and severity levels (Table 1). We compute the sensitivity matrix entries using Equation (11). The pre-screening indicates that the 110th segment has the highest similarity index. There are several other segments that have high similarity indices as well. The segments with the top 10 similarity index values are chosen as the location candidates for the following Bayesian inference. Meanwhile, a total of 13 fault severity levels for each fault location candidate are taken into account, which are centered around the corresponding estimated fault index values with interval being 0.001%. The measured directionality y_m is the directionality between the experimental measured admittance and the admittance prediction for the heathy structure. The variance is again assumed to be 1×10^{-6}. Figure 11 shows the Bayesian inference results. Clearly, the probability of the actual fault parameter, i.e., severity level 5 at the 110th segment, is much higher than the other fault parameter. In other words, our approach predicts that a fault with severity 1.589% occurs at the 110th segment. This is very close to the actual fault condition. This case study validates the proposed method for fault identification.

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

This project has involved ono graduate student, Yixin Yao, to carry out the numerical and experimental investigations. Starting in August, an additional graduate student, Yang Zhang, has joined this effort, who will focus on improving the fault identification and prognosis algorithms. 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

In this phase of research, research results have been disseminated in the following occasions:

- Dr. Kai Zhou, a postdoctoral researcher working with Dr. Jiong Tang, attended the TIDC 1st Annual Conference At University of Maine, Orono, ME, June 6-7, 2019.
- A tele-con with Conn DOT engineers was carried out on June 28, 2019, in which project scope and preliminary results were shared.
- Discussion with academia and industry on fault diagnosis and prognosis was conducted in ASME IDETC-CIE 2019 held in Anaheim, California (Aug 18-21, 2019). Dr. Jiong Tang is the conference general chair.

Participants and Collaborators:

Participants: Dr. Jiong Tang, PI, project lead; Yixin Yao, graduate student, research assistant; Yang Zhang, 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 further improvement of fault identification algorithm with more comprehensive case studies.