Assessment of Rail Track Condition Using Novel Nondestructive Evaluation Technologies

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William W. Hay Railroad Engineering Seminar
February 5, 2021
My research work focuses on sensing, testing and imaging for infrastructure materials and structures.

We must consider complex material characteristics, large size and limited access to engineer the next generation of cost effective and accurate health monitoring technologies for effective forensics and rehabilitation ensuring sustainable infrastructure.
In situ characterization of concrete rail tie condition using air-coupled ultrasonic measurements

Mr. Sai Evani and Dr. Agustin Spalvier
Monitoring (concrete) rail tie condition is important

Defective rail ties fail to provide required support to the rails, resulting in development of additional bending stresses in the rail and alteration of track geometry, both of which increase the risk of derailment.

Condition assessment of rail ties is typically performed by an experienced technician through visual inspection.

This process is time consuming and inefficient in cases where the defect does not manifest visibly on the surface, or when deterioration occurs in inaccessible locations, such as the rail seat area.

Conceptual vision of contactless scanning approach for effective rail tie inspection
Our approach for monitoring tie condition: air-coupled ultrasonic surface wave inspection

Surface waves scatter when they encounter inclusions in the rail tie e.g. cracks, delaminations, and other damage. Fully air-coupled sensors transmit and receive mechanical waves propagating along the free surface of a rail tie without physical coupling.

Air-coupled testing configuration: transducer sender and MEMS array receivers
Ultrasonic scan data were collected from each end of concrete rail ties

A scanning frame placed on top of the rail controlled the position of the sensors, where the transmitted position was fixed at the tie center and the receiver array scanned across the shoulder portion of the tie to form a scan line.
Data were collected from a set of concrete rail ties with varying visual (ground truth) condition: healthy, transverse cracking, longitudinal cracking, RSD, corrosion.

Data from 81 healthy and 93 damaged scan lines were collected.
Signal data were analyzed in both time and frequency domains to extract information about propagating and backscattered wave fields.

- **Time signal**: Coherent pulse.
- **Time-space domain**: Stacked signals over space.
- **Frequency-wavenumber domain**: 2-dimensional Fourier transform (over time and space). Color bar shows normalized amplitude.
Speed and energy characteristics can be extracted from t-x domain data

A robust wavefront fitting algorithm identifies the first four wavefronts, fit a straight line and consider the average as wave speed. Wave energy is calculated by integrating the amplitude of the time signal. Both wave speed and wave energy are expected to decrease in the presence of damage.
Speed and energy characteristics can also be extracted from f-k domain data.

The peak amplitude within the f-k domain serves as a central point for this: the magnitude of the peak amplitude provides energy while speed is provided by $2\pi f_{\text{peak}} / k_{\text{peak}}$.

**f-k scan from a healthy rail tie**

- Frequency ($f$): 49.6 kHz
- Wave-number ($k$): 115.8 rad/m
- Speed (f-k): 2691 m/s

**f-k scan from a damaged rail tie**

- Frequency ($f$): 49.6 kHz
- Wave-number ($k$): 145.4 rad/m
- Speed (f-k): 2143 m/s
How to analyze the various data? Machine learning!

• We have four signal parameters collected across 174 scan lines (81 healthy and 93 damaged)

• The whole data set was distributed randomly into a training set (50-healthy and 50-damaged) and a test set (31-healthy and 43-damaged)

• The training set is used to estimate a threshold boundary between healthy and damaged conditions (a “decision space”) using the support vector machine (SVM) algorithm. The test set is used to evaluate accuracy of the decision space.

• The SVM algorithm computes a hyperplane by maximizing the distance between proposed decision boundary and training data points near the decision boundary (called support vectors) such that most of the data points in the training set are correctly classified (i.e., the predicted label is same as the ground truth label)
Example two-dimensional decision spaces computer from the training data

We can also create a four-dimensional decision space using all the extracted parameters.
### Performance of four-dimensional decision space

#### Performance on training set

<table>
<thead>
<tr>
<th>Predicted condition</th>
<th>True condition</th>
<th>Damaged</th>
<th>Healthy</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Damaged</td>
<td>Damaged</td>
<td>40 (True positive)</td>
<td>10 (False negative)</td>
<td>80</td>
</tr>
<tr>
<td>Healthy</td>
<td>12 (False positive)</td>
<td>38 (True negative)</td>
<td>76</td>
<td></td>
</tr>
</tbody>
</table>

#### Performance on test set

<table>
<thead>
<tr>
<th>Predicted condition</th>
<th>True condition</th>
<th>Damaged</th>
<th>Healthy</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Damaged</td>
<td>Damaged</td>
<td>34 (True positive)</td>
<td>9 (False negative)</td>
<td>79</td>
</tr>
<tr>
<td>Healthy</td>
<td>5 (False positive)</td>
<td>26 (True negative)</td>
<td>84</td>
<td></td>
</tr>
</tbody>
</table>

Prediction accuracy with test set is about 80%
Summary

- Air coupled sensors provide high quality signal data while using a platform that provides practical *in situ* implementation.

- Four signal parameters, extracted from t-x and f-k domains, demonstrate sensitivity to the presence of damage in concrete rail ties; each of these parameters showed global reduction in value in the presence of damage.

- Machine learning algorithms help us sort out a very complicated data set and draw conclusions from it. The four-dimensional decision space provided predictions with highest accuracy (80%) among all the decision spaces considered in this study.
In situ estimation of rail stress using nondestructive vibration measurements

Dr. Xuan Zhu, Mr. Chi-Luen Huang, Mr. Marcus Dersch, and Mr. Sangmin Lee
Monitoring longitudinal rail stress in continuously welded rail is important

Rail track thermal buckling is a long-standing safety issue for continuously welded rail structures (CWRs), usually caused by excessive longitudinal stress developed by extreme temperatures.

Effective *rail neutral temperature* (RNT) management is essential to track buckling prevention. There is a demand from the industry for *in-situ* rail stress/RNT measurement to facilitate maintenance decision making.

Rail buckling event caused by restrained thermal expansion

Derailment in Northbrook, IL caused by rail buckling (2012)
Our approach for monitoring longitudinal rail stress: contactless vibration measurements

Acoustic measurements of rail vibration provide a rich data set that contains information about the temperature and stress state of the rail, but also contains disruptions from other influences. We believe that a machine learning approach can extract useful information about rail stress from the complex acoustic data set.
Contactless test configuration using microphones

Microphone: Effective frequency response with $\pm 2$dB ranging from 4 to 70000 Hz

- 5 locations across a cross-section for impacting and receiving
- 25 combinations of impacting and receiving
- “E-A” configuration illustrated here
FEM vibration simulation showing vibration mode shapes and frequencies

Fixed supporting condition
Field tests on in-service rail

- BNSF main line near Streator, IL
- Instrumented with temperature and strain sensors before rail cut
- Multiple data collection visits during the period from early August 2019 to June 2020
- Two testing locations: East and West (each at 2m from the cut)
- Different support conditions: Tie spacing, rail anchor, spike tightness
Detail about sensors and stress and temperature data acquisition

Welding strain gauges in full-bridge configuration

Additional strain gauges for train detecting
Example rail condition data from the east test location throughout the day of Aug. 5, 2019

*Rail neutral temperature (RNT) is the rail temperature at which zero axial stress is present in the rail.*
Field tests on in-service rail

Contactless microphone provides high quality, reliable vibration data

The instrumented rail system provides continuously streaming, high quality stress, temperature, and RNT data
Multiple vibration resonance frequency values across a broad range of frequencies are affected by temperature-induced stress in the rail -- this provides a rich data set for us to use.

<table>
<thead>
<tr>
<th>Frequency (Hz)</th>
<th>Insensitive</th>
<th>Sensitive</th>
<th>More sensitive</th>
</tr>
</thead>
<tbody>
<tr>
<td>3.25 k</td>
<td>~3.8 kHz</td>
<td>~37 kHz</td>
<td>~76.5 kHz</td>
</tr>
<tr>
<td>4.25 k</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>36.5 k</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>37.5 k</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>76 k</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>77 k</td>
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</tbody>
</table>
We need help extracting meaningful signal features from the entire spectrum: we use non-negative matrix factorization (NMF)
NMF looks for patterns and consistency in rich data sets, identifies them and groups them.
Stress and temperature prediction using AI using selected features as input values

Input

- differential frequencies with top sensitivity to strain and temperature
- Inputs labeled by strain and temperature

Supervised learning with feed-forward neural network (FNN)

Output

- stress and temperature and RNT

The neural network will be trained using field data from the east location

The neural network performance will be evaluated using data from the west location
Summary

- Air coupled acoustic sensing allows us to collect lots of meaningful data, with potential to be implemented on a moving test platform.

- Vibrational resonance data show correlation with temperature induced stress.

- Machine learning algorithms help us sort out a very complicated data set and draw conclusions from it.
Acknowledgments

- The work reported here represents important contributions from a number of collaborators: Dr. Xuan Zhu, Mr. Chi-Luen Huang, Mr. Marcus Dersch, Mr. Sai Evani, Dr. Agustin Spalvier and Mr. Sangmin Lee, access to the rail test site provided by BNSF railways, and overall assistance from RailTEC.

- The work was made possible through support from the US National Academies (Rail safety IDEA) and the American Association of Railroads (Tech Scan).