Estimating Rail Neutral Temperature using Local Resonance and Probabilistic Machine Learning

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ABSTRACT

The continuous welded rail (CWR) has been widely used in modern railways due to their support to high transport speed while requiring less maintenance compared with jointed track. However, CWR is susceptible to internal stress because of restrained free thermal expansion and contraction in its axial direction. During summer, the excessive heat on the rail will cause expansion of the rail, but it is constrained, leading to a huge axial force. If the axial force is excessively large, thermal buckling could be triggered depending on track conditions. In fact, the sense and magnitude of the built-up rail axial stress depend on the rail temperature relative to the set rail neutral temperature (RNT). Estimating RNT without taking baseline measurements has been a long-standing challenge for the railway engineering community. In this study, we present the most recent advancement in RNT estimation using intrinsic local resonances in rails. This study demonstrates that frequencies of these local resonances, including zero-group velocity and cutoff frequency resonances whose energy are trapped locally close to the load zone, are insensitive to the presence of rail supports and sensitive to rail temperature and axial loads, which has great potential for RNT estimation. The data collection system can consistently extract rail local resonances from a fully instrumented revenue-service site, where strain gauges and thermocouples were attached and calibrated during the track construction and can supply the ground truth of RNT and rail thermal forces. Probabilistic machine learning algorithms are developed to predict RNT of the revenue-service site using rail temperature and frequencies of rail local resonances, both of which are directly measurable. The performance of the proposed machine learning framework is evaluated by comparing the predictions with the ground truth.

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INTRODUCTION

The continuous welded rail (CWR) has been widely used in modern railways due to their support to high transport speed while requiring less maintenance compared with jointed track. However, CWR is susceptible to internal stress because of restrained free thermal expansion and contraction in its axial direction. During summer, the excessive heat on the rail will cause expansion of the rail, but it is constrained, leading to a huge axial force. If the compressive axial force is excessively large, rail thermal buckling would be triggered. In winter, the axial fore will turn into tensile force and may cause tensile fracture of the rail. In both scenarios, a great loss of properties and lives will be expected if no in-time measures are taken before the pull-apart or buckling of rail happens. For a constrained rail, the change of temperature ΔT would induce thermal stress of $-E\alpha\Delta T$, where E is the elastic modulus of rail track, and α is the rail coefficient of thermal expansion. Since rail thermal stress management is critical thermal buckling prevention, the railway industry has adopted the concept of rail neutral temperature (RNT), which is the stress-free temperature. The RNT evolves after initial construction resulting from several factors including the interaction of a rail with the ambient environment and supporting track structure (fasteners, seats, ties and ballast) and disturbances by maintenance activities. Consequently, monitoring RNT is both crucial and challenging for rail maintenance. Researchers and practitioners have explored different measurement techniques to evaluate the in-situ RNT of CWR. A comprehensive literature review on the non-destructive evaluation methods for rail thermal stress and neutral temperature measurement can be found in [1].

The research team recently reported the existence of local resonances, associated with the zero-group velocity and cutoff frequency points, in free and continuous welded rails [2-4], and we demonstrated that these local resonances can be used for RNT measurement with a reasonable accuracy leveraging artificial neural networks (ANN) [5]. However, the absence of prediction variances in ANN greatly undermines its applicability. This is especially true in the practical engineering world, where people care more about the uncertainties of the prediction instead of a point estimation. Fortunately, the probabilistic machine learning is a useful tool to address this challenge. In this study, we illustrate the effectiveness of probabilistic machine learning models for RNT prediction based on rail local resonances. Specifically, the Gaussian process is a widely used probabilistic machine learning tool for structural health monitoring and nondestructive testing and evaluation. It is a stochastic process which characterizes a finite collection of random variables through a multivariate Gaussian distribution. With its mean and covariance function derived, a Gaussian process could be fully defined.

FIELD DATA COLLECTION

Our field data collection was conducted on the FrontRunner track operated by Utah Transit Authority, close to Vineyard, UT in Utah, as shown in Figure 1. The ground truth of the RNT was obtained by the strain gauge-thermocouple monitoring system, which was installed and calibrated during the track construction in November 2021. The system can continuously monitor, stream, and store the longitudinal rail force, rail temperature, rail neutral temperature data with an interval of 5 minutes, which enables us to monitor the seasonal evolution of RNT. In this study, we used the RNT measurements from the system as the ground truth. The rail local resonance measurements were collected via multiple site visits. The test setup includes a handheld thermocouple to monitor the rail temperature at the neutral axis of the rail web, piezoelectric patches for broadband excitation, broadband acoustic emission sensors attached to the rail head and web to collect rail dynamic responses, as shown in Figure 1. Only the local resonance frequencies of interest were used to predict the RNTs in this work, and a typical local resonance spectrum is shown in Figure 2. The horizontal axis represents the resonance frequency of interests. The resonant frequencies of interest include 30 kHz, 40 kHz, 61 kHz, 67 kHz, 97 kHz, 94 kHz, which have been identified as local resonances associated with ZGV or cutoff frequency points in the dispersion curves of the 115RE rail. Meanwhile, to balance accuracy and computational efficiency, only three most important frequencies, 67 kHz, 61 kHz, 97 kHz are considered. Therefore, the input vector has four dimensions (three resonant frequencies and the rail temperature). The total number of the original data samples is 275. To expand the data set, the original dataset was augmented by drawing samples from one standard deviation from the mean. In total, the number of the augmented data points increased to 1,604. The ratio of training data to testing data is set at 6:4.

Figure 1. Field data collection setup.

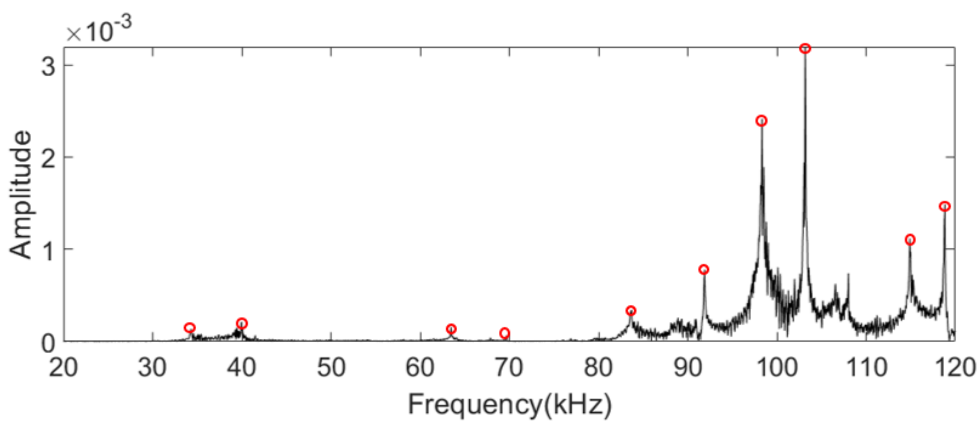


Figure 2. Typical amplitude spectrum of CWR collected from the field site. Red circles indicate the peaks of local resonances.

PROBABILISTIC MACHINE LEARNING

A Gaussian process is a stochastic process, capable of handling nonlinear problems, where any finite number of random variables observe Gaussian distribution [6, 7]. It has its mean function $m(\mathrm{x})$ and covariance function $k(\mathrm{x}, \mathrm{x}^T)$ defined as Gaussian kernel in this work,

$$f(\mathrm{x}) \sim GP(m(\mathrm{x}), k(\mathrm{x}, \mathrm{x}^T)) \quad (1)$$

Let the input of the training dataset be $\{\mathrm{x}_i, \mathrm{y}_i\}(i = 1, 2, 3, \ldots, N)$, the training input matrix be X, and the testing input matrix be X_*, $\{\mathrm{x}_{j*}, j = 1, 2, 3, \ldots, M\}$. The noise of the output in the training dataset is assumed to have a Gaussian noise as

$$\mathrm{y}_i = f(\mathrm{x}_i) + \epsilon, \; \epsilon \sim N(0, \sigma_n^2) \quad (2)$$

The joint distribution of combining the training dataset and testing dataset is assumed to be

$$\begin{bmatrix} \mathrm{y} \\ f_* \end{bmatrix} \sim N\left(0, \begin{bmatrix} K(X,X) + \sigma_n^2 I & K(X, X_*) \\ K(X_*, X) & K(X_*, X_*) \end{bmatrix}\right) \quad (3)$$

Using the complete square trick for Gaussian distribution and considering matrix manipulation, the posterior could be written as

$$f_* | X, \mathrm{y}, X_* \sim N(K(X_*, X)[K(X,X) + \sigma_n^2 I]^{-1}\mathrm{y}, K(X_*, X_*) - K(X_*, X)[K(X,X) + \sigma_n^2 I]^{-1} K(X, X_*)) \quad (4)$$

The hyper-parameters of the model included the necessary parameters from kernel function. They are optimized through maximizing the evidence function, which is given as

$$\mathrm{y} | X \sim N(0, K(X,X) + \sigma_n^2 I) \quad (5)$$

The hyper-parameters of the model are put into a vector in form of

$$\theta = [k_\theta, \sigma_n^2]^T \quad (6)$$

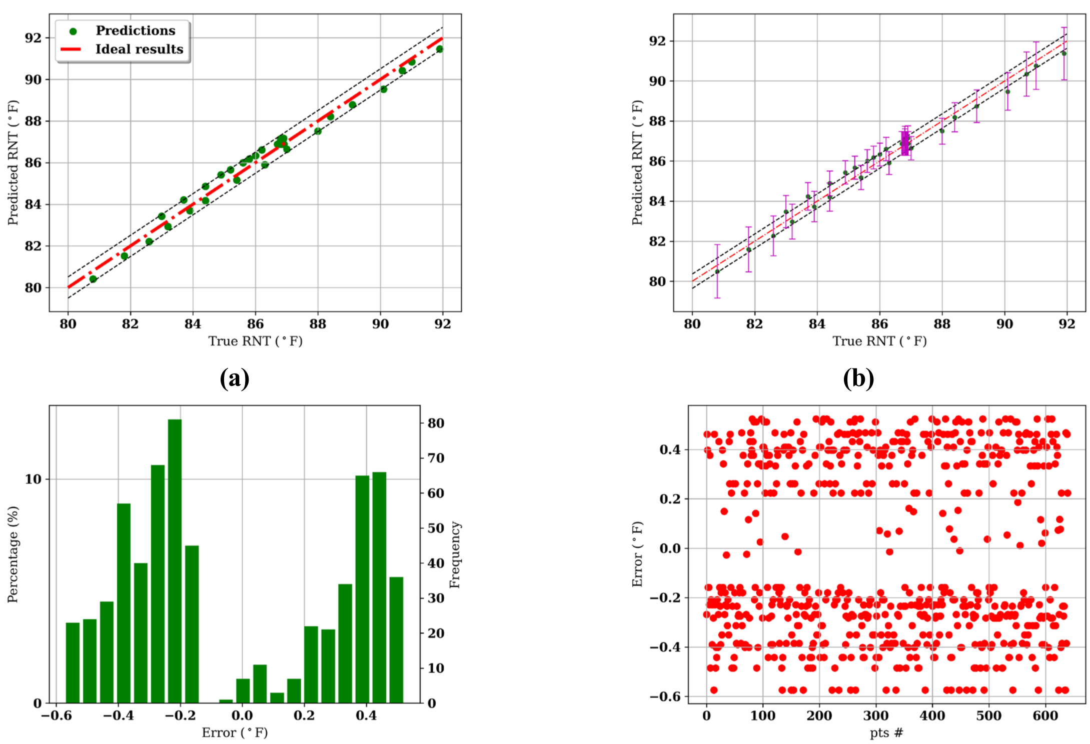
k_θ is the free parameter vector from the selected kernel function; σ_n^2 is the noise term and it needs to be larger than 0. Through maximizing the evidence function, the hyper-parameters of the Gaussian process model could be completely determined. The negative log evidence or log likelihood could be written into

$$-\log p(\mathrm{y}|X, \theta) = \frac{N}{2}\log(2\pi) + \frac{1}{2}\log|K(X,X) + \sigma_n^2 I| + \frac{1}{2}\mathrm{y}^{\mathrm{T}}[K(X,X) + \sigma_n^2 I]^{-1} \quad (7)$$

Although gradient descendent methods could be used to minimize the negative loglikelihood, the negative loglikelihood itself is non-convex and the results by gradient descendent method are often the local minimums. Instead, this work considers the basinhopping-based SLSQP method, where multiple searches are carried out to find the optimal hyper-parameters globally.

RESULTS

The prediction results are shown in Figure 3. Clearly, the prediction results are compact and very close to the ground truths, with the root mean squared error being at 0.36 °F, which is shown in Figure 3(a). The error bar of the predictions, i.e., the square root of the prediction variance is shown in Figure 3(b) as the magenta I-shaped symbol. The black dashed lines are one root mean square error δ_{rmse} away from the ideal results. Obviously, all the predictions are well bound by the black dashed line. Meanwhile, the frequency of the errors of the predictions are shown in Figure 3(c), which were achieved through histogram of the RNT predictions subtracting to its ground truths. The errors are located in [-0.6 °F, 0.5 °F]. The error distribution is presented in Figure 3(d). The errors are symmetrically distributed between the two sides of 0. All the predictions are located in a reasonable range, demonstrating the effectiveness of using GPR for rail neutral temperature predictions. The prediction variance in Figure 3(b) shows that the advantage of GPR over common machine learning algorithms. Therefore, it is recommended to use GPR for RNT prediction when prediction variances are needed.



(c) **(d)**

Figure 3. RNT prediction results (a) RNT predictions. (b) RNT predictions with variance. (c) Error frequency distributions. (d) Error distributions.

CONCLUSIONS

This work explored a probabilistic machine learning model, the Gaussian process, for the prediction of rail neutral temperature, which is critical for rail thermal stress management and buckling prevention. The Gaussian kernel were adopted. With seven features, six of which are resonance frequencies and the other one is rail temperature, the Gaussian process can support a satisfactory RNT predictions with small root mean squared errors based on field-collected data. Future research shall focus on uncertainty quantification for RNT predictions.

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