A Two-Stage Blind Source Separation Method for Structural Health Monitoring Signals Integrating Deep Kernel Regression and Wavelet Multiresolution Analysis

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Abstract

In structural health monitoring (SHM) systems, sensor signals are often affected by multiple external load effects that are strongly coupled across different frequency bands, posing significant challenges for accurate signal interpretation. To address this issue, this paper proposes a two-stage blind source separation method aimed at effectively decoupling sensor signals across multiple frequency ranges. In the first stage, a deep kernel regression (DKR) model integrating a long short-term memory (LSTM) network with Gaussian process regression (GPR) is developed. By adaptively learning the complex mapping between time-varying environmental factors and kernel hyperparameters, the model enables accurate prediction and removal of low-frequency temperature-induced strain components. In the second stage, wavelet multiresolution analysis (WMRA) is applied to the residual signal. Through optimized selection of the wavelet basis and key parameters, the mid-frequency quasi-static vehicle-induced response and high-frequency signal components are effectively separated. The proposed method is validated using 227 days of monitoring data collected from a real long-span bridge. The results demonstrate that the proposed approach can progressively extract signal components with clear physical interpretations from the original mixed signals. The separated vehicle-induced responses exhibit smooth curves consistent with mechanical principles, while time-frequency analysis confirms the effective suppression of high-frequency interference. Overall, the proposed method provides an effective tool for fine-grained signal decomposition in structural health monitoring, significantly improving the accuracy and reliability of load effect separation, and shows strong potential for engineering applications.

Keywords –

Structural Health Monitoring, Sensor Signal Processing, Blind Source Separation, Deep Kernel Regression, Wavelet Multiresolution Analysis, Gaussian Process Regression

1 Introduction

For a health monitoring system of a bridge or building structure, sensor measurements contain crucial information about the structural load-bearing condition and constitute one of the most critical components of the monitoring system [1]. However, sensor signals result from the combined action of multiple external loads. For effective condition assessment and damage early warning, it is necessary to precisely decompose sensor data to isolate effects caused by different load types. To better characterize structural response components, the field of structural health monitoring has developed a series of solutions to eliminate or reduce the influence of interfering responses and separate the desired structural response for health state evaluation. Typically, researchers categorize the information in the total structural response of a bridge into three parts: i) high-frequency components dominated by vibration effects; ii) long-term, low-frequency components induced by factors like temperature; and iii) vehicle-induced quasi-static effects, which lie between the two in frequency. To perform refined signal analysis, blind source separation of measured signals is required.

In theory, modern signal processing methods can separate effects caused by temperature variation, vehicle loads, and noise based on their distinct frequency characteristics. For example, previous studies have leveraged temperature-induced strain for bridge condition assessment [2] and developed automatic uncoupling methods to isolate vehicle- and temperature-induced strains [3]. Subsequent signal reconstruction algorithms can then recover the original distributed effects. However, signals in different frequency bands often exhibit substantial frequency disparities, making direct decomposition using a single unified framework challenging. For instance, while high-frequency signals can be decomposed using time-frequency methods, these approaches struggle with low-frequency components like diurnal (24-hour period) temperature-induced effects [4]. To address this issue, the optimal strategy is to design tailored blind source separation algorithms according to the characteristics of each signal component. Therefore, this paper proposes a two-stage sensor signal blind source separation algorithm that integrates deep kernel regression and wavelet transform.

The algorithm first constructs a deep kernel regression-based time-series prediction model to extract the temperature-induced component from the signal [5]. This model employs a sequential feature extraction module and a non-sequential feature fusion module, utilizing multi-source, multi-format historical and real-time data to predict the kernel parameters of a Gaussian Process Regression model. Using these predicted parameters, the model forecasts the low-frequency thermal response. Subsequently, the residual signal is processed using wavelet multiresolution analysis to separate the mid-frequency vehicle-induced response from the remaining high-frequency components. Through this proposed dual-stage signal decomposition approach, efficient sensor signal processing is achieved.

This study presents three principal contributions: (1) a novel two-stage framework that decouples temperature-induced (low-frequency) and vehicle-induced (high-frequency) strain components using Deep Kernel Regression (DKR) and Wavelet Multiresolution Analysis (WMRA), respectively; (2) the DKR model synergistically integrates deep learning adaptability with Gaussian process uncertainty quantification and physical interpretability—overcoming limitations of ARIMA in nonlinear thermal dynamics and LSTM in confidence estimation; and (3) WMRA ensures mathematically rigorous, adaptive time-frequency decomposition robust to mode-mixing artifacts of empirical mode decomposition variants, enabling precise isolation of transient vehicle responses. Collectively, this physics-informed, uncertainty-aware methodology advances structural health monitoring through interpretable, reliable multi-component strain separation.

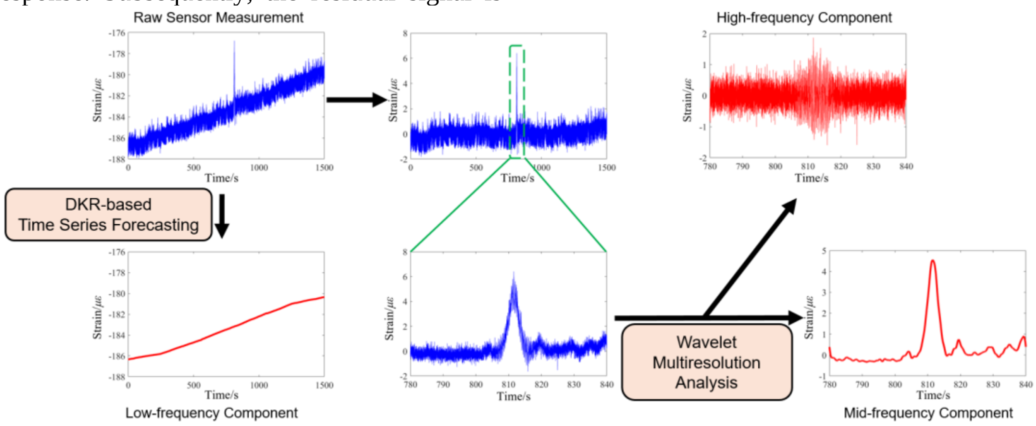

Figure 1. Framework of the two-stage signal decomposition method

2 Data Acquisition and Preprocessing

2.1 Raw Data Collection

The raw data is derived from the health monitoring system of a long-span suspension bridge in Hebei Province, China. The monitoring system installed four strain sensors on the bottom surface at the mid-span and the three-quarter span of the bridge's main span respectively. In addition, a temperature sensor was mounted at the pylon to detect the environmental conditions. Therefore, a total of nine sensors were used for data collection in this task, including eight strain sensors and one temperature sensor, as shown in Figure 2. All sensors had a sampling frequency of 200 Hz, and the final dataset included all available data collected over 227 days from February 22 to October 6, 2022.

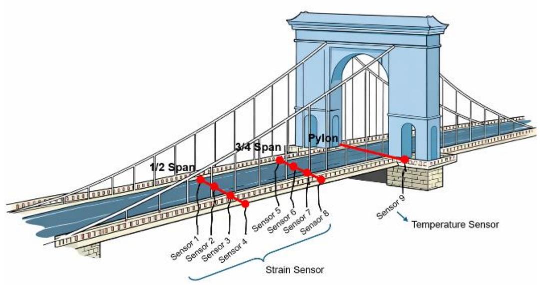

Figure 2. Layout of strain sensors and temperature sensors

2.2 Offline Extraction of Temperature-Induced Strain

Since the low-frequency signal processing in the proposed two-stage method relies on a data-driven approach, data preprocessing is required to construct the dataset for deep kernel regression. The raw strain data contain outliers caused by heavy vehicle loads. To robustly extract temperature-induced strain components, the robust locally weighted scatterplot smoothing (RLOESS) algorithm is adopted [6].

RLOESS minimizes the influence of outliers by iteratively adjusting data point weights. Its core steps include neighborhood selection, weight calculation, weighted quadratic polynomial regression, and smoothed value estimation. Using this method, temperature-induced strain data over the entire 227-day monitoring period were successfully extracted.".

3 Stage I: Deep Kernel Regression Model for Low-Frequency Signal Extraction

To address the challenges of predicting temperature-induced strain in complex structures, a deep kernel regression (DKR) model is proposed. This model integrates a long short-term memory (LSTM) [7] network with Gaussian process regression (GPR) [8], enabling deep learning–based estimation of GPR kernel hyperparameters that vary with environmental conditions. This approach overcomes the limitation of conventional GPR models that rely on fixed kernel parameters, while combining the feature learning capability of deep learning with the interpretability and uncertainty quantification advantages of Bayesian methods. A detailed discussion of this algorithm can be found by Xu and Liu's work [9].

3.1 Gaussian Process Regression-based Time Series Forecasting

Compared to other methods, GPR has three critical advantages: (i) GPR provides a full Bayesian framework that quantifies prediction uncertainty via posterior variance—a non-negotiable requirement in structural health monitoring where safety-critical decisions depend on confidence intervals; (ii) The kernel function explicitly encodes prior physical knowledge (e.g., periodic temperature effects through the Periodic kernel), enhancing model interpretability and alignment with engineering principles; (iii) Unlike black-box models, GPR offers transparent hyperparameter interpretation (e.g., length-scale parameters directly reflect signal smoothness and periodicity), facilitating domain expert validation.

GPR is a non-parametric Bayesian regression method. For an input time series $X = \{x_1, x_2, ..., x_N\}$ and its corresponding temperature-induced component output $Y = \{y_1, y_2, ..., y_N\}$, GPR assumes the target function $f(x)$ follows a Gaussian process prior: $f(x) \sim GP(m(x), k(x, x'))$, where $m(x)$ is the mean function and $k(x, x')$ is the kernel (covariance) function. Given training data (X, y), the posterior distribution of the predicted values f^* at test points X^* remains Gaussian, with mean μ^* and variance Σ^* given by Equations (1) and (2), respectively.

$$\mu^* = K(X^*, X)[K(X, X) + \sigma_n^2 I]^{-1} y \tag{1}$$

$$\Sigma^* = K(X^*, X^*) - K(X^*, X)[K(X, X) + \sigma_n^2 I]^{-1} K(X, X^*) + \sigma_n^2 I \tag{2}$$

To capture the composite characteristics of short-term monotonicity and long-term periodicity in temperature-induced strain data, a combined kernel function is chosen as the product of a Radial Basis Function (RBF) kernel (which is suitable for modeling gradual temperature-induced drift) and a Periodic kernel (which encodes repeating temperature-induced patterns). This combined kernel contains three hyperparameters $\Theta = (\Theta_1, \Theta_2, \Theta_3)$, controlling the function's rate of change, period length, and weight, respectively, as shown in Equation (3):

$$\begin{aligned} K(\Theta_1, \Theta_2, \Theta_3) &= \Psi\left[k_{RBF}(x_i, x_j), k_{Periodic}(x_i, x_j)\right] \\ &= \left[exp\left(-\frac{\|x_i - x_j\|^2}{2\Theta_1^2}\right)\right]^{\Theta_3} \left[\left(-\frac{2\,sin^2\left(\frac{\pi}{p}\|x_i - x_j\|\right)}{\Theta_2^2}\right)\right]^{1-\Theta_3} \end{aligned} \tag{3}$$

As hyperparameters significantly impact prediction results in GPR-based time series tasks, they must be dynamically adjusted based on the data.

3.2 Forecasting Framework

Based on the constructed dataset and environmental variables, a hybrid deep learning–Bayesian regression framework is developed:

1. **Sequential feature extraction:** An LSTM network is used to extract temporal features from historical temperature-induced strain data.
2. **Non-sequential feature fusion:** Fully connected layers integrate LSTM features with key environmental variables, including date, time, and temperature.

3. **Deep kernel regression:** The fused features are used to predict GPR kernel hyperparameters via a deep learning module, followed by real-time temperature-induced strain prediction using the parameterized GPR model.
4. **Model training:** The entire framework is trained by maximizing the marginal likelihood of the training dataset.

The algorithmic framework of this model based on deep kernel regression is shown in Figure 3.

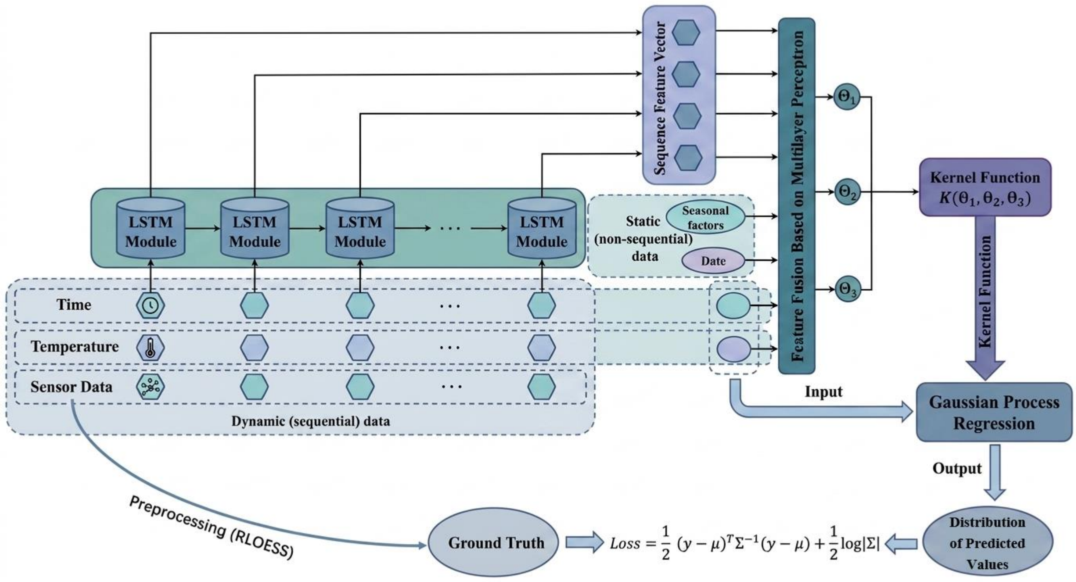

Figure 3. Framework of the deep kernel regression method

3.3 Forecasting Framework

The training objective is to find the optimal hyperparameters Θ_{opt} that maximize the probability of the true strain values under the predictive distribution. The loss function is defined as the negative log marginal likelihood, as shown in Equation (4):

$$\mathcal{L} = \frac{1}{2}(y-\mu)^T\Sigma^{-1}(y-\mu) + \frac{1}{2}\log \mid \Sigma \mid \tag{4}$$

This loss function consists of two terms: the first is a weighted prediction error, and the second relates to prediction uncertainty (determinant of the covariance matrix). Optimising this loss function not only drives predictions closer to true values but also constrains output uncertainty, enhancing model robustness.

4 Stage II: Wavelet Multiresolution Analysis for High-Frequency Signal Separation

After successfully extracting the low-frequency temperature-induced components in Stage I, the residual signal still contains mixed mid- to high-frequency components, primarily consisting of vehicle-induced quasi-static effects and vibration-related noise. To address this, Stage II employs Wavelet Multiresolution Analysis (WMRA) for further signal decomposition [10]. This stage focuses on separating the vehicle-induced quasi-static response (mid-frequency) from high-frequency noise and vibrations. Unlike conventional filtering techniques, WMRA provides localized time-frequency characterization, making it particularly suitable for processing non-stationary signals under varying operational conditions. This section details the theoretical foundations, parameter selection strategies, and implementation procedures of the WMRA-based separation framework.

4.1 Wavelet Transform and Multiresolution Analysis

Following the extraction of low-frequency thermal signals in the first stage, and considering the significant frequency differences between vibration-induced high-frequency effects and vehicle-induced quasi-static responses, this section employs Wavelet Multiresolution Analysis (WMRA) for signal separation. Wavelet transform possesses time-frequency localization capabilities, enabling effective separation of signal components with different frequencies.

Wavelet transform overcomes the lack of temporal locality in Fourier transform. For a function $f(t)$, its continuous wavelet transform is defined as

$$W_f(a,b) = \langle f, \psi_{a,b} \rangle = |a|^{-1/2} \int_R f(t)\psi\left(\frac{t-b}{a}\right) \mathrm{d}t \quad (5)$$

where $\psi_{a,b}(t)$ is the wavelet basis derived from the mother wavelet $\psi(t)$ through scaling factor a and translation factor b. For discrete signals, the discrete wavelet transform is used:

$$\psi_{j,k}(t) = a_0^{-j/2}\psi\left(\frac{t-ka_0^j b_0}{a_0^j}\right) = a_0^{-j/2}\psi\left(a_0^{-j}t - kb_0\right) \quad (6)$$

Multiresolution Analysis (MRA) is central to discrete wavelet transform, approximating the signal space $L^2(R)$ through a series of nested subspaces $\{V_j\}$ that satisfy conditions of monotonicity, approximation, scaling, and translation invariance [11, 12]. The signal can be decomposed layer by layer into low-frequency approximation (A_j) and high-frequency detail (D_j) components, as illustrated in Figure 4.

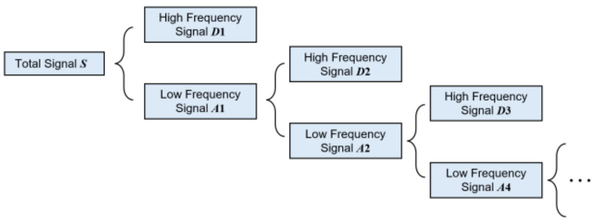

Figure 4. Signal decomposition method based on wavelet multi-resolution analysis

4.2 Selection of Key Parameters

Many wavelet functions exist with differing properties, leading to varied separation results for structural monitoring data. Therefore, targeted analysis of wavelet function characteristics is crucial for selecting an appropriate function. Generally, the following aspects guide the selection of wavelet functions and parameters:

1. **Wavelet Function Selection:** The choice depends on properties such as support length, orthogonality, vanishing moments, and symmetry. Commonly used wavelets include Daubechies (dbN) and Symlets (symN). Selection follows the principle of self-similarity, considers discriminant functions and support length, and balances properties based on signal characteristics.
2. **Decomposition Level Determination:** The number of decomposition levels n is determined by the signal sampling frequency f_n and the upper-frequency limit f_m of the target component to be separated. Too few levels lead to insufficient separation; too many may lose information and increase computational load.
3. **Thresholding:** To eliminate noise and irrelevant high-frequency components, thresholding is applied to the decomposed high-frequency coefficients. Common threshold functions include:

a. Hard Thresholding: Coefficients with absolute values greater than the threshold λ are retained; others are set to zero. This preserves local signal features but may cause reconstruction oscillations.

b. Soft Thresholding: Coefficients with absolute values greater than λ are shrunk towards zero (subtracting λ). This yields smoother reconstructed signals but may blur edge information. Soft thresholding is more widely used in practice.

4.3 Signal Separation and Denoising Procedure

Assuming the observed noisy signal model is $s(t) = f(t) + e(t)$, where $f(t)$ is the effective signal and $e(t)$ is noise (typically assumed to be Gaussian white noise), the objective of wavelet-based signal separation/denoising is to suppress noise while preserving or separating target frequency components (e.g., live load effects). The basic procedure is as follows:

1. **Decomposition:** Select an appropriate wavelet function and decomposition level, and perform discrete wavelet decomposition on signal $s(t)$ to obtain low-frequency approximation coefficients and high-frequency detail coefficients at each level.
2. **Thresholding:** Apply the selected threshold function to the high-frequency detail coefficients to suppress noise and irrelevant high-frequency components.
3. **Reconstruction:** Perform inverse wavelet transform using the processed coefficients (including low-frequency coefficients and thresholded high-frequency coefficients) to reconstruct the separated or denoised signal.

For the bridge monitoring data processing task in this paper, the key wavelet analysis parameters are selected as follows: The Daubechies wavelet (db4) is chosen due to its compact support and orthogonality, which provide good time-frequency localization suitable for analyzing non-stationary strain signals. Its appropriate number of vanishing moments (4) effectively extracts high-frequency transient components while smoothing low-frequency trends, and it offers high computational efficiency.

The decomposition level is determined to be 7. Based on a 200 Hz sampling frequency and signal characteristics, a 7-level decomposition finely divides the frequency bands. Empirical verification shows that 7 levels achieve an optimal balance between separation effectiveness and computational complexity. Soft thresholding is employed because its coefficient shrinkage enables smoother processing, avoiding potential signal discontinuities (Gibbs phenomenon) associated with hard thresholding, making it more suitable for subsequent analysis of slowly varying components.

In summary, for this stage, the algorithm uses the db4 wavelet for 7-level decomposition, applies soft thresholding to detail coefficients D1-D7, and reconstructs the signal to obtain high-frequency vibration signals and mid-frequency vehicle-induced signals. This method effectively separates load effects of different frequencies.

5 Algorithm Training and Testing

5.1 Deep Kernel Regression Model Training and Testing

The processed 227 days of temperature-induced strain data for each strain gauge were segmented into 1093 data sequences of 300-minute length. Data from 8 sensors resulted in a total of 8744 sequences. The dataset was split into training, validation, and test sets with a 70%/15%/15% ratio. Model hyperparameters were optimised based on the trained model's performance on the validation set. After obtaining the optimal model, its performance was evaluated by comparing it with classical algorithms (AR, ARIMA) [13] and deep learning algorithms (RNN [14], GRU [15], LSTM [7]) on the same test set. The prediction results of various methods on the test set are shown in Figure 5.

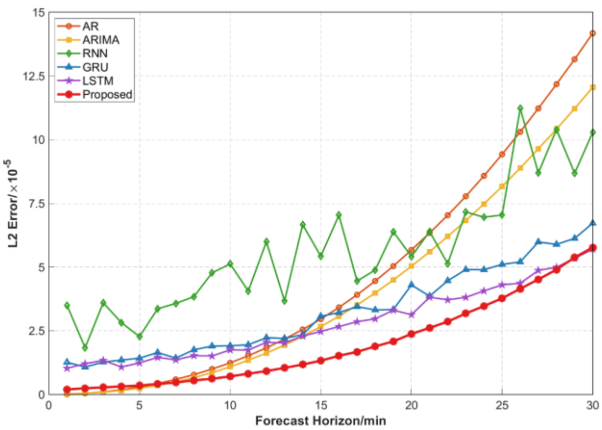

Figure 5. Error over time

Overall, traditional algorithms (AR/ARIMA) exhibited smaller errors and smoother prediction trends in the initial prediction period (approximately the first 5 minutes), aligning with the minor fluctuation characteristics of temperature-induced strain. However, as the prediction horizon increased, errors grew significantly, deviating from true values, indicating their poor adaptability for long-term prediction. Deep learning algorithms (RNN/GRU/LSTM) generally followed the actual trend, but predicted values showed substantial volatility and instability, significantly differing from the actual slowly varying state of temperature-induced strain.

Testing demonstrates that the proposed model maintains the interpretability and output stability of Bayesian methods while achieving superior medium-to-long-term prediction accuracy compared to the benchmark algorithms. Furthermore, the model framework exhibits good extensibility, allowing for the incorporation of additional sensor information to further enhance predictive performance.

5.2 Wavelet Multiresolution Analysis Algorithm Testing

To validate the proposed second-stage signal separation method, a segment of measured strain data was selected for testing. First, the Deep Kernel Regression (DKR) algorithm proposed in Section 3 was applied to extract the low-frequency temperature-induced strain. The original data were then subtracted by this thermal component to obtain strain data with temperature effects removed.

The signal after temperature effect removal still contained noticeable noise and high-frequency vibration induced by vehicle-bridge coupling. To further extract the vehicle-induced quasi-static effect, a 6,000-sample data segment (corresponding to 30s) containing a vehicle crossing event was selected, and wavelet multiresolution analysis was applied for high-frequency separation. After signal reconstruction, the vehicle-induced quasi-static effect was obtained, as shown in Figure 6. The smoothness of the reconstructed signal was significantly improved. The signal shapes from all four sensors were similar, each presenting a unimodal smooth curve consistent with the theoretical bridge influence line. This verifies that the separation method effectively extracts the quasi-static response induced by vehicle loads while suppressing high-frequency noise and vibration.

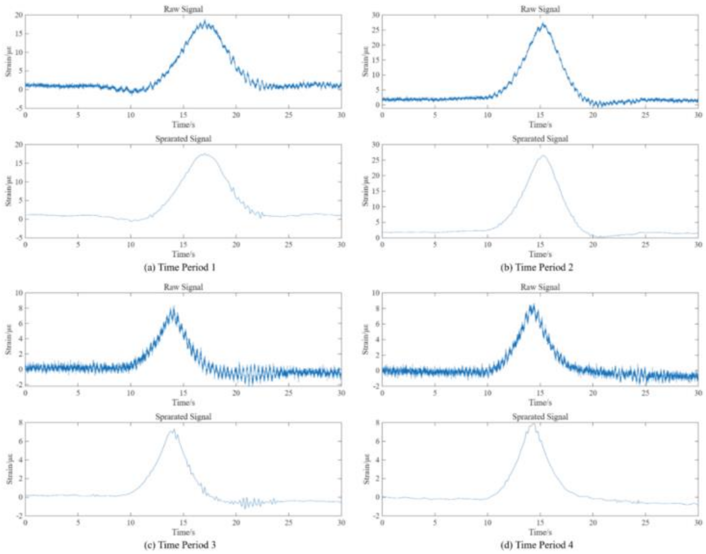

Figure 6. Signal Decomposition Method Based on Wavelet Multi-Resolution Analysis

To further analyse the separation effectiveness, wavelet time-frequency diagrams of the signal before and after high-frequency separation were compared (Figure 7). It can be observed that before separation (Raw), the time-frequency diagram contained numerous scattered energy points in the high-frequency region, primarily originating from sensor noise and vehicle-bridge coupling high-frequency vibrations. After separation (Denoised), the energy distribution of high-frequency components almost completely disappeared, with the time-frequency diagram concentrated in the low-frequency region. Time-frequency analysis indicates that the proposed method effectively filters high-frequency components from the signal and successfully extracts the low-frequency-dominated physical response of vehicle-induced quasi-static effects, validating the effectiveness of the signal separation algorithm. Combining the demarcated algorithm with some existing vehicle perception algorithms enables the refined research on vehicle-bridge correlation [16-19].

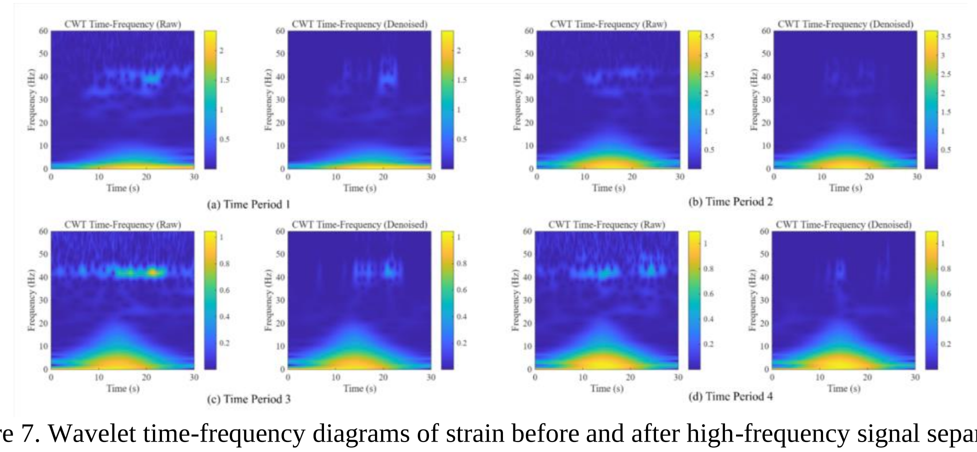

Figure 7. Wavelet time-frequency diagrams of strain before and after high-frequency signal separation

6 Conclusion

This paper addresses the challenge of mixed multi-source signals in bridge health monitoring by proposing an innovative two-stage blind source separation method. Employing a staged processing strategy, it integrates deep kernel regression with wavelet multiresolution analysis, effectively tackling the difficulty traditional methods face in simultaneously handling signal components with large frequency disparities.

In the first stage, we constructed an adaptive model based on deep kernel regression. By fusing the sequential feature extraction capability of LSTM networks with the probabilistic framework advantages of GPR, precise separation of temperature-induced effects was achieved. This model dynamically adjusts kernel parameters based on environmental factors, demonstrating performance superior to traditional methods in medium-to-long-term prediction. In the second stage, we optimized the wavelet multiresolution analysis method, determining parameter configurations suitable for bridge monitoring signals. This method effectively separated vehicle-induced quasi-static effects from high-frequency vibration and noise, reconstructing smooth response curves that align with theoretical expectations.

Experimental validation based on 227 days of measured data demonstrates that the proposed two-stage method can clearly separate three types of physical effect components from complex raw signals: low-frequency thermal trends, mid-frequency vehicle-induced responses, and high-frequency noise. This method provides an approach to decouple components induced by highly random human activities from infrastructure responses [20] and an effective solution for the fine-grained processing of bridge health monitoring data.

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