ISSN: 1813-4890

A Separation Method of Temperature Effect in Bridge Deflection Monitoring Based on Wavelet and SSA-VMD.

Ming Gao, Xin Bai

Chongqing Jiaotong University, China

Abstract

A method for isolating temperature effects in bridge deflection data is proposed, utilizing Wavelet Transform (WT), Variational Mode Decomposition (VMD), and Shape Matching (SM). The original data undergoes high-frequency filtering with WT, followed by VMD decomposition of low-frequency signals into explicit AM-FM components. The SM algorithm is then employed for shape-based signal recognition. VMD and SM complement each other, addressing issues of signal shape and data differences. Practical experiments demonstrate a high correlation coefficient (0.99) at cross-section measuring points, affirming the method's effectiveness in separating temperature effects.

Keywords

Deflection Monitoring; SM; temperature effect; VMD; Wavelet.

1. Introduction

Deflection is one of the key parameters for diagnosing damage and evaluating the health of bridge structures, and it can reflect the comprehensive performance of the bridge structure intuitively and effectively. However, in practical deflection monitoring of bridges, various complex response signals, such as temperature effects, often exist in deflection data due to multiple factors, which makes it difficult to evaluate the safety of bridge structures. Separating the temperature effect can more intuitively obtain the high-frequency signals caused by loading and other effects, making it more convenient to achieve bridge health diagnosis and providing more reliable evidence for bridge health diagnosis. Therefore, accurately separating the temperature effect from deflection data has become a research hotspot in the field of bridge deflection monitoring.

Existing research on deflection separation mainly focuses on finite element method and signal processing. Xiaoyonggang[1] et al. obtained the relationship between deflection and temperature by using finite element software to calculate the deflection under fitted temperature field. Yang Hongyin[2] et al. obtained the basic characteristics of temperature, strain and deflection through feature analysis, and separated the deflection changes caused by temperature effect and external load in the high-frequency and low-frequency bands of original monitoring data. Xiong Xin[3] simplified the two-dimensional temperature distribution pattern by thermal analysis model, and concluded that the large temperature gradient significantly increased the compressive stress of lower chord at the pier on the sunny side and the deflection of the edge span. Chen Ruizhe[4] calculated the features of multiple measurement data using environmental temperature, bridge moving load and bridge deflection, and fused them. They identified abnormal deflection through a random forest classification model and achieved 88% recognition accuracy. Yang Deng[5] transformed the original vehicle load monitoring data into time-continuous vehicle influence coefficients (VIC) based on the deflection influence line (DIL) concept. They established a correlation model between VIC input, environmental temperature data input, and deflection data output using a gated recurrent unit (GRU) neural network. The model can predict deflection with good separation effect. Yang Shu-ren[6] analyzed the strain response of bridge under vehicle load based on bridge strain influence line theory, and proposed a bridge damage identification and evaluation method based on strain ratio. They identified the damage of test section according to the change of strain ratio distribution, and proposed a rapid damage identification method under closed and open traffic conditions. Rong Pang[7] established a feature extraction and analysis method for multiple heterogeneous bridge state sensing data, and proposed a dynamic evaluation model of bridge technology based on the fusion of multiple heterogeneous data sources. However, in practical engineering, the environment where the bridge is located is complex, and there are various environmental effects that are mutually coupled. Therefore, accurate results cannot be obtained through finite element analysis. With the development of engineering signal processing technology, scholars have begun to study the separation of bridge detection data from the perspective of signal processing. Liang Zongbao[8] proposed a wavelet multiscale analysis method, which statistically regressed deflection and temperature data to accurately obtain the relationship between the two and extract their regression equation. Based on this relationship, the temperature effect can be extracted under known temperature. Huang Qiao[9] used the wavelet multiscale analysis method to reconstruct the deflection signal on two time scales (daily and yearly cycles) and achieved the separation of temperature effect. Li Huicheng[10] analyzed that the seasonal temperature difference is the main factor affecting the long-term vertical deformation of prestressed concrete cable-stayed bridge main girder by establishing a health monitoring system for remote control and operation. Tan Dongmei[[11]-12] successively applied empirical mode decomposition and empirical wavelet transform to temperature effect separation, and the correlation coefficients of the components separated by the methods were all above 0.9. Yang Jian[13] proposed a new method based on singular value decomposition to extract temperature effect signals from bridge deformation signals, and the correlation coefficient between the extracted temperature deformation value and the source signal reached 0.99. Huang Huijuan[14] combined whale optimization algorithm and variational mode decomposition to construct an adaptive data feature decomposition method, which was verified to be effective.Zhu Ying[15] et al. constructed a uniformly distributed temperature field using bounding box algorithm and hidden surface removal algorithm. The experimental results showed that there was a significant difference between the main beam linear calculation results and the overall temperature rising and falling model when considering the non-uniform temperature field caused by sunshine. Ying Chen[16] et al. applied the data fusion of multiple factors to the safety evaluation of cable-stayed bridges using numerical simulation and data fusion methods. However, there were significant numerical differences between the main component and the other components in the separation of deflection data, which was difficult to eliminate effectively in subsequent operations, and thus still had a certain impact on practical separation.

This article proposes a method for separating temperature effects in bridge deflection monitoring based on wavelet transform and VMD-SM. The method first uses wavelet transform to filter the high-frequency signals in the original deflection data, and then uses variational mode decomposition to decompose the low-frequency signals into a series of explicit amplitude-frequency-modulated signals. Finally, a shape-based matching method is used to match the separated signals to separate the temperature effects in the deflection signal. Compared with traditional methods, this method has greatly improved in separation effect and accuracy, and has good application prospects for separating temperature effects in bridge deflection monitoring.

2. Theoretical Framework

2.1. Wavelet transform

The wavelet transform (WT) inherits and develops the idea of localizing short-time Fourier transform, while overcoming the drawbacks of fixed window size across frequencies. It can provide a "time-frequency" window that changes with frequency, making it an ideal tool for signal time-frequency analysis and processing.

The title for any contribution should be short and meaningful (a maximum of two lines). A subtitle may be added. The authors' first and family names (for a maximum of four authors) should be stated above the title, beginning with the main author, but without academic titles or qualifications. If additional authors were involved, then the four main authors should be named above the title, and all other authors may be listed at the end of the contribution.

$$WT(\alpha, \tau) = \frac{1}{\sqrt{\alpha}} \int_{-\infty}^{\infty} f(t) * \varphi(\frac{t-\tau}{\alpha}) dt \tag{1}$$

As shown in equation 1, the basic principle of wavelet transform is to use a wavelet function as a basic unit for scaling (α) and shifting (τ) transformations to simulate signal values, decomposing the signal values into multiple signals of different scales and multiple levels.

2.2. Variational mode decomposition(VMD)

The Empirical Mode Decomposition (EMD) can decompose complex nonlinear and non-stationary signals into a linear combination of Intrinsic Mode Functions (IMFs) [17] The basic idea is to locally process the signal, and through a series of iterations, decompose the signal into IMFs. Each iteration extracts one intrinsic mode function (IMF) vibration mode from the signal[18] and removes it from the original signal. Then, the remaining signal is iteratively processed until no more IMF can be extracted. However, EMD has limitations in sensitivity to noise and sampling. These limitations can only be partially addressed by further mathematical attempts on this decomposition problem, such as synchronized compression, empirical wavelet, or recursive variational decomposition.

To address these limitations, K. Dragomiretskiy and D. Zosso proposed a method called Variational Mode Decomposition (VMD) [19], which is similar to Empirical Mode Decomposition (EMD) in decomposing non-stationary signals into a set of intrinsic mode functions. However, unlike EMD, VMD utilizes an optimization model to determine the intrinsic mode functions, allowing for better control of the accuracy and smoothness of the decomposition results. It has been shown to have better performance in decomposing signals with high-frequency noise and low signal-to-noise ratios. The formula of this method is as follows:

First of all, the problem of changing points. Suppose the original signal F is decomposed into a kit, ensuring that the decomposition sequence is a limited bandwidth component with a central frequency. At the same time The same as the original signal is equal, the corresponding constraint change expression is to express

$$\min_{\{\mu_k\}\{\omega_k\}} \left\{ \sum_k \left\| \partial_t \left[(\delta(t) + j / \pi t) * \mu_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \right\} \tag{2}$$

$$s.t. \sum_{k=1}^{K} \mu_k = f \tag{3}$$

Among them, K is the number of modals (positive integer) that requires stages, and u_k and ω_k correspond to the K -mode component and central frequency after the decomposition. δ(t)is the Dirac function and * is a convolution operator.

Then find the solution (1), introduce the lagrange multiplication operator λ, transform the constraint change problem into a non -binding change problem.

$$L(\{u_k\},\{\omega_k\},\lambda)=\alpha\sum_k\left\|\partial_t\left[(\delta(t)+j/\pi t)*u_k(t)\right]e^{-j\omega_k t}\right\|_2^2+\left\|f(t)-\sum_k u_k(t)\right\|_2^2+\left\langle\lambda(t),f(t)-\sum_k u_k(t)\right\rangle \quad (4)$$

Among them, α is a secondary punishment factors, and the role is to reduce the interference of Gaussian noise. Using the alternate direction of the ADMM (ADMM) iteration algorithm combined with Parseval/Plancherl, Fourier's equidistance transformation, optimize the various modal components and central frequency, and search for the saddling point of the lagRange function. The expression of B and λ is as follows:

$$\mu_k^{n+1}(\omega) \leftarrow \frac{f(\omega)-\sum_{i\neq k}\mu_i(\omega)+\lambda(\omega)/2}{1+2\alpha(\omega-\omega_k)^2} \quad (5)$$

$$\omega_k^{n+1} \leftarrow \frac{\int_0^\infty \omega\left|\hat{u}_k^{n+1}(\omega)\right|^2 d\omega}{\int_0^\infty \left|\hat{u}_k^{n+1}(\omega)^2 d\omega\right|} \quad (6)$$

$$\hat{\lambda}^{n+1}(\omega)\leftarrow\hat{\lambda}^n(\omega)+\gamma\left(\hat{f}(\omega)-\sum_k\hat{u}_k^{n+1}(\omega)\right) \quad (7)$$

Among them, γ is noise tolerance to meet the preservation requirements of signal decomposition, and $\hat{u}_k^{n+1}(\omega)$, $\hat{u}_i(\omega)$, $\hat{u}_i(\omega)$ and $\hat{\lambda}(\omega)$ correspond to the Fourier transformation of $\hat{u}_k^{n+1}(t)$, $\hat{u}(t)$, $\hat{f}(t)$ and $\hat{\lambda}(t)$ respectively.

2.3. Introduction to Sparrow Search Algorithm.(SSA)

The Sparrow Search Algorithm (SSA) was proposed by Xue and Shen in 2020 (Jiankai Xue 2020), which mainly simulates the foraging and anti-predator behavior of a sparrow flock. In a natural state, individuals monitor each other, and followers in a bird flock typically compete for food resources of high food capture rates in order to improve their own predation rates. While foraging, all individuals remain vigilant of the surrounding environment to prevent the arrival of predators. To complete foraging, sparrow individuals are usually divided into discoverers and joiners, and each sparrow individual's position represents a possible solution, with the solution process consisting of discoverer updates, follower updates, and danger warnings. The main rules that the algorithm needs to follow are as follows:

1) Discoverers generally have higher energy reserves and are responsible for searching for areas with abundant food in the entire population, providing areas and directions for all joiners to forage. 2) Once a sparrow discovers a predator, the individual begins to make chirping sounds as an alert signal. When the alarm value is greater than the safety value, the discoverer will lead the joiners to other safe areas to forage.

3) The identities of discoverers and joiners are dynamic. As long as a better food source can be found, every sparrow can become a discoverer, but the proportion of discoverers and joiners in the entire population remains the same.

4) The lower the energy of a joiner, the poorer its foraging location in the entire population. Some hungry joiners are more likely to fly elsewhere to forage and gain more energy.

5) During foraging, joiners can always search for discoverers that provide the best food and then obtain food from the best food or forage around the discoverer. At the same time, some joiners may constantly monitor discoverers in order to compete for food resources and improve their own predation rates.

6) When danger is perceived, the sparrows on the edge of the flock will quickly move to a safe area to obtain a better position, while the sparrows in the middle of the flock will move randomly to approach other sparrows.

2.3.1. Discoverer Update

In the Sparrow Search Algorithm, discoverers with better fitness values are given priority in searching for food during the search process. In addition, since discoverers are responsible for searching for food for the entire sparrow population and providing directions for all joiners to forage, they can obtain a larger foraging search range than joiners. According to Rules (1) and (2), the position update for the discoverer during each iteration is described as follows:

$$X_{i,j}^{t+1} = \begin{cases} X_{i,j}^{t} \cdot \exp\left(-\dfrac{i}{\alpha \cdot iter_{\max}}\right) & if \ R_2 < ST \\ X_{i,j}^{t} + Q \cdot L & if \ R_2 \geq ST \end{cases} \tag{8}$$

Here, t represents the current iteration number, j = 1, 2, 3, ..., d. itemmax is a constant representing the maximum number of iterations. Xij represents the position information of the i-th sparrow in the j-th dimension. α ∈(0, 1] is a random number. R2 (R2 ∈[0, 1]) and ST (ST ∈ [0.5, 1]) represent the warning value and safety value, respectively. Q is a random number that follows a normal distribution. L represents a 1x d matrix where each element in the matrix is 1. When R2 < ST, it means that there are no predators in the foraging environment, and discoverers can perform extensive search operations. If R2 ≥ ST, it means that some sparrows in the flock have found predators and alerted other sparrows in the flock. At this time, all sparrows need to quickly fly to other safe places to forage.

2.3.2. Joiner Update

For joiners, they need to follow Rules (4) and (5). As described earlier, during the foraging process, some joiners constantly monitor the discoverers. Once they notice that a discoverer has found better food, they will immediately leave their current location to compete for food. If they win, they can immediately obtain the food of the discoverer, otherwise they need to continue to follow Rule (5). The position update for joiners is described as follows:

$$X_{i,j}^{t+1} = \begin{cases} Q \cdot \exp\left(\dfrac{X_{worst} - X_{i,j}^{t}}{i^2}\right) & if \ i > n/2 \\ X_p^{t+1} + \left|X_{i,j}^{t} - X_p^{t+1}\right| \cdot A^{+} \cdot L & otherwise \end{cases} \tag{9}$$

Where Xp is the currently discovered optimal position, and Xworst represents the current worst global position. A represents a 1x d matrix where each element is randomly assigned a value of 1 or -1, and A += AT (AAT)-1. When i > n / 2, it means that the i-th joiner with lower fitness value did not obtain food and is in a very hungry state, so it needs to fly elsewhere to forage and gain more energy.

2.3.3. Danger Warning

When danger is perceived, the sparrows on the edge of the flock will quickly move to a safe area to obtain a better position. These sparrows' initial positions are randomly generated in the population, and according to Rule (6), their mathematical representation is as follows:

$$X_{i,j}^{t+1} = \begin{cases} X_{best}^{t} \cdot \beta \left|X_{i,j}^{t} - X_{best}^{t}\right| & if \ f_i > f_g \\ X_{i,j}^{t} + K \cdot \left(\dfrac{\left|X_{i,j}^{t} - X_{worst}^{t}\right|}{(f_i - f_w) + \varepsilon}\right) & if \ f_i = f_g \end{cases} \tag{10}$$

This paragraph appears to describe a swarm intelligence algorithm that uses sparrows as a metaphor for the behavior of the individuals in a population. Among the variables mentioned,

ISSN: 1813-4890

Xbest represents the current global optimal position, while beta is a control parameter for the step size that is a random number drawn from a normal distribution. K is another random number ranging between -1 and 1, and fi represents the fitness value of an individual sparrow in the population. fg and fw respectively represent the current global best and worst fitness values. Epsilon is a small constant used to prevent division by zero. When fi > fg, the sparrow is at the edge of the population and is vulnerable to predators. Xbest represents the safest position that the individual can move towards. When fi = fg, the sparrow is aware of the danger and needs to move closer to other individuals to minimize the risk of predation. K represents the direction of the sparrow's movement and is also a control parameter for the step size.

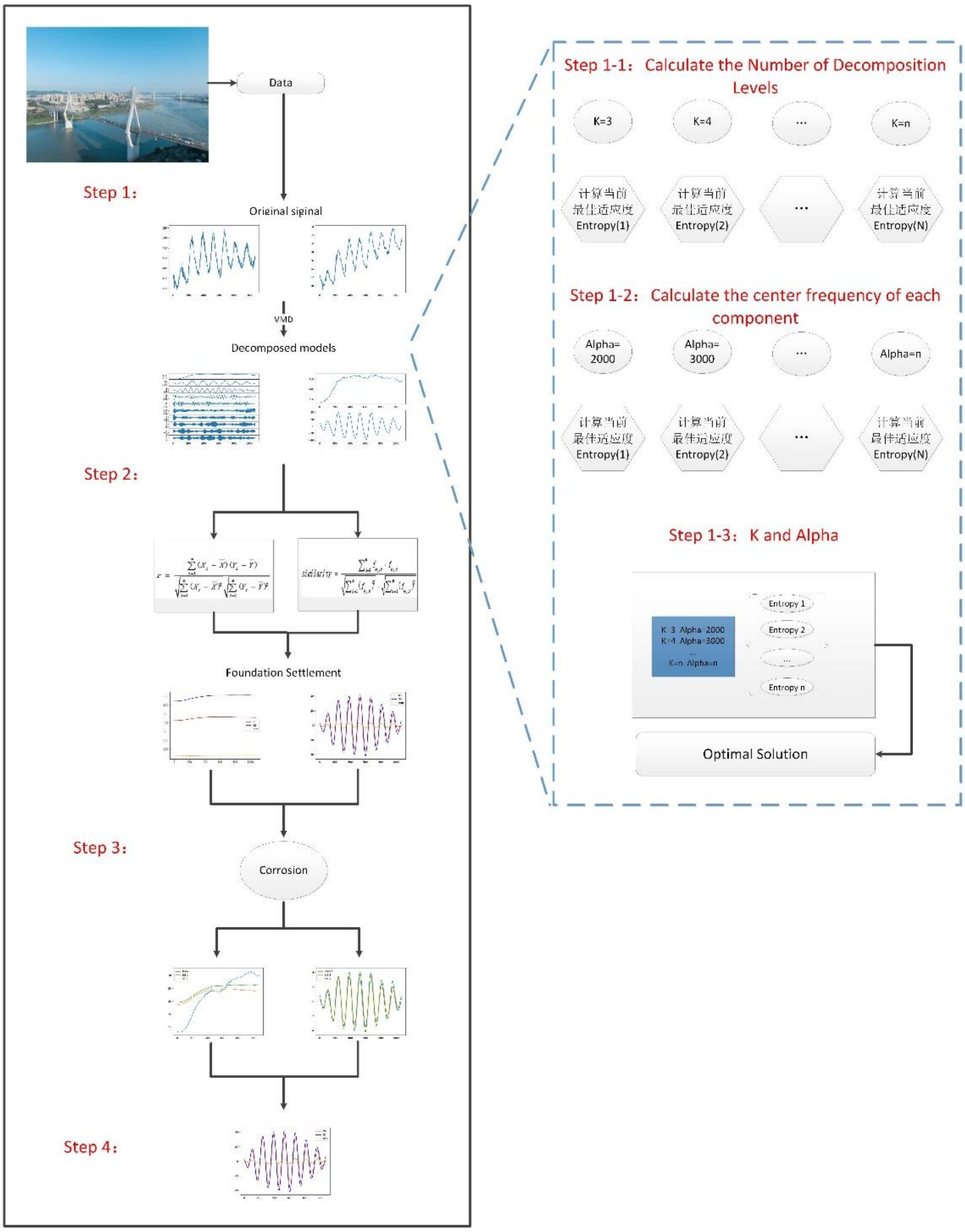

Fig1.SSA-VMD

2.4. SSA-VMD algorithm

VMD, with robust noise resistance, can separate two closely related sub-sequences and is more suitable for non-stationary time series, reducing complexity, especially for highly non-stationary sequences. However, the choice of the signal decomposition number (K) and the central frequency (Alpha) for each component in VMD requires manual selection. These parameters impact the effectiveness of the VMD method, and their optimal combination is not guaranteed. SSA, as a novel optimization algorithm, exhibits excellent performance in simple problems, characterized by fast computation, rapid convergence, and ease of implementation, offering high search accuracy and robustness. Therefore, this study optimizes VMD's parameter selection using SSA to achieve adaptive determination of the number of VMD components. Additionally, due to numerical differences in the expression of various effects in bridge deflection data, the final separated signals may exhibit significant discrepancies with the original data. To address this issue, this study incorporates a morphological erosion method, inspired by image morphology, to alter signal shapes while preserving data characteristics, reducing the impact of signal amplitude on the desired outcome. The integration of SSA and VMD with the erosion operator not only achieves effective deflection data separation but also reduces errors introduced by data magnitude, significantly improving the accuracy of temperature effect separation. The implementation process of this method is outlined as follows.

3. Separation of measured bridge deflection signals.

Considering that the deflection effect caused by temperature is highly similar to the temperature waveform in the signal waveform, two groups of deflection data and temperature data at the same section of Masangxi Bridge were selected for the experiment in this paper. The waveforms of the three signals are shown in Figure 2 below:

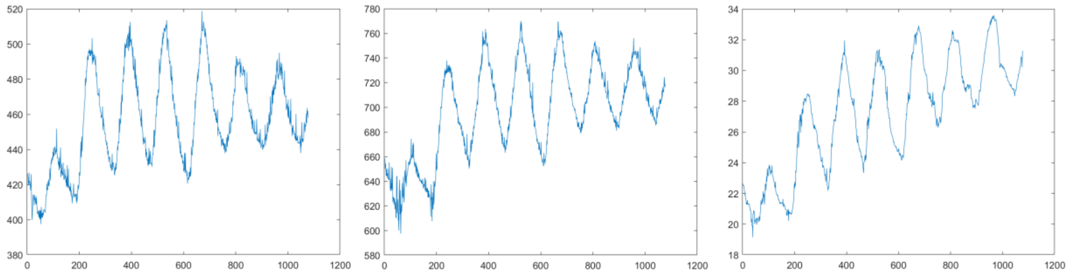

Fig2.Visualization of raw data

3.1. Processing of measured deflection signals

The measured deflection signal can be considered as mainly composed of deflection caused by environmental noise and vehicle loads, daily temperature difference effect, annual temperature difference effect, and long-term deflection[20]. The deflection caused by environmental noise and vehicle loads is distributed in the high-frequency part of the signal, which is significantly different from the frequency of other signals. In this paper, the original data is filtered by wavelet transform to remove high-frequency signals. The filtered deflection curve is shown in the following figure 3.

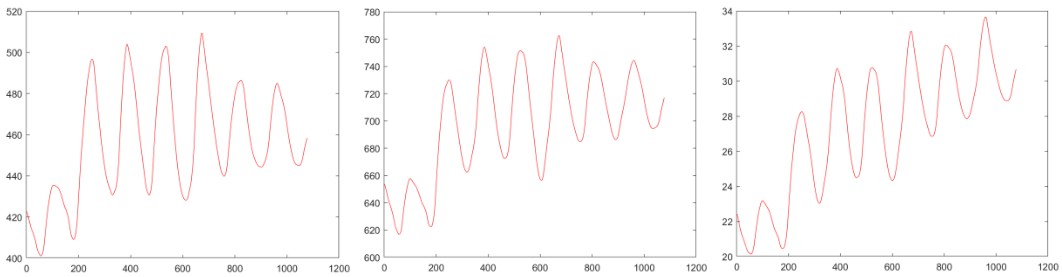

Fig3.Low-frequency data visualization.

After filtering out the high-frequency signals caused by vehicle load effects and environmental noise through wavelet transform, the remaining deformation can be considered to be composed of the effects of daily temperature difference, annual temperature difference, and long-term deflection. However, since the time span of the sampling is much smaller than the period of annual temperature difference and long-term deflection, the collected signal cannot fully represent the complete changing patterns of annual temperature difference and long-term deflection. Therefore, only the separation of daily temperature difference effect is considered.

3.2. Temperature effect separation and result analysis

The filtered signal was separated using the VMD-SM method. First, the deflection signal was decomposed into six components, and the temperature signal was decomposed into two components. The separation results are shown in the following figure 4:

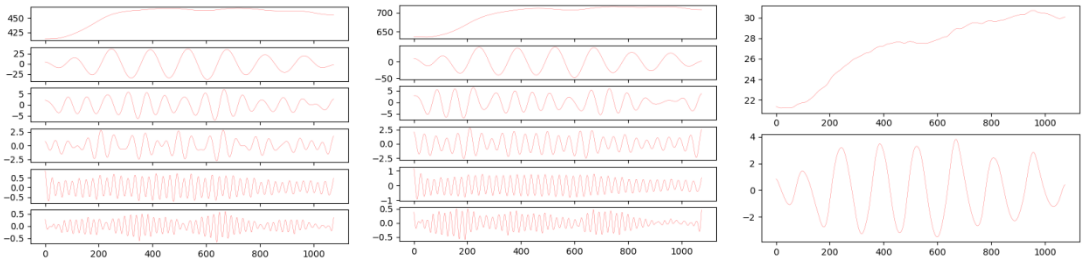

Fig4.Visualization of data after VMD decomposition.

The degree of shape similarity between the obtained separation results is shown in the following table:

Tab1.Similarity Table between N5 Component and Temperature Component of DeflectionSignal

	1	2	3	4	5	6
1	0.99875046	0.01510201	0.04964089	0.05424271	0.05838127	0.05883446
2	0.0047675	0.99736159	0.502981	0.43867543	0.34497906	0.34153776

Tab2.Similarity Table between S5 Component and Temperature Component of Deflection Signal.

	1	2	3	4	5	6
1	0.99884988	0.0154846	0.05015661	0.05571156	0.05849882	0.05876228
2	0.0052462	0.99847332	0.47291623	0.40145122	0.34357438	0.3457947

After removing the long-term effects, the waveform comparison of the extracted high-similarity signals is shown below:

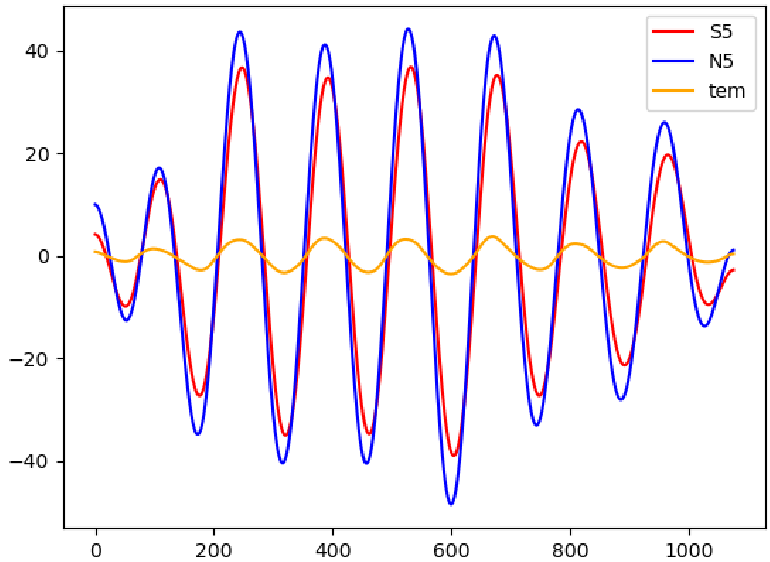

Fig5.Visualizing Separated Data

The waveforms of the separated signals indicate that the deformation caused by temperature effects during the separation process is highly similar to the actual temperature changes, and the temperature effects separated from the data at the same cross-section exhibit high similarity in both waveform and numerical value. Therefore, this method can achieve accurate deformation separation while ignoring the numerical differences in practical applications, and can be used for practical temperature effect separation.

4. Conclusion

1.The successful use of VMD in decomposing the original signal provides reliable input data for morphology-based component identification methods, while SM solves the problem of VMD's inability to handle numerical differences. The advantages of the two methods complement each other.

2.The results of signal separation from actual measurements show that the separated values have extremely high similarity to the temperature waveform in terms of waveform morphology comparison, and the similarity of the separated signals from the same section is also very high, proving the accuracy of the method.

3.The method proposed in this paper greatly reduces the influence of numerical values on signal separation while being able to handle blind source signals, and has high versatility.

4.The influence of wind loads, annual temperature differences, and other factors was not considered in the separation of deflection signals, and should be included in future research, requiring further study.

References

[1] Xiao Yonggang, Peng Jiang. Analysis of the temperature effect on the main beam during the construction of cable-stayed bridge. Highway and Automotive Transport, 2022, No. 213 (06): 91-94.DOI:10.20035/j.issn.1671-2668.2022.06.021.

[2] Yang Hongyin, Zhang Aixin, Zhang Wei, et al. Correlation analysis of bridge operation monitoring data and temperature effect removal. Science Technology and Engineering, 2022, 22(17): 7142-7147.

[3] Xiong, X., & Li, J. (2022). Two-dimensional temperature field distribution and effect of steel-concrete composite beams. In Proceedings of the 2022 World Transport Convention (WTC2022) (Bridge Engineering and Tunnel Engineering) (pp. 7). People's Communications Press Co., Ltd. ,2022:7.DOI:10.26914/c.cnkihy.2022.018965

[4] CHEN Ruizhe, TU Wei, LI Qingquan, GU Yu, ZUO Xiaoqing, GAO Wenwu. The method of bridge deflection outlier detection by fusing multi-sourced surveying data. Bulletin of Surveying and Mapping, 2022, 0(9): 105-110 .DOI:10.13474/j.cnki.11-2246.2022.0272.

[5] Deng, Yang, Hanwen Ju, Wenqiang Zhai, Ai-qun Li and You-liang Ding. "Correlation model of deflection, vehicle load, and temperature for in-service bridge using deep learning and structural health monitoring." Structural Control and Health Monitoring 29 (2022): n. pag.

[6] Shuren Y ,Song D . Bridge Damage Identification and Assessment Method Based on Strain Ratio. Journal of Highway and Transportation Research and Development (English Edition),2021,15(1). DOI: 10.1061/JHTRCQ.0000764

[7] Rong P ,Yan Y ,Peng Z , et al. Dynamic Evaluation Technology of Bridge Based on Multi-source Heterogeneous Data Fusion. IOP Conference Series: Earth and Environmental Science,2021,638(1). DOI 10.1088/1755-1315/638/1/012064

[8] Liáng Zōngbǎo. Research on Bridge Structural Safety Evaluation Based on Statistical Analysis of Monitoring Information. Chongqing: Chongqing University, 2006. DOI:10.7666/d.y1023111.

[9] Huang Qiao, Zhao Danyang, Ren Yuan, et al. Multi-timescale analysis of the deflection of cable-stayed bridges under temperature load. Journal of Harbin Institute of Technology, 2020, 52(03): 18-25+32.

[10] Li Huicheng, Lin Yunda, Wang Bingjian. Influence of temperature on the deflection of prestressed concrete cable-stayed bridge girder and its long-term monitoring research. Highway Traffic Technology (Applied Technology Edition), 2019, 15(09): 197-198.

[11] Tan Dongmei, Yao Huan, Wu Hao, et al. Separation of temperature effects on monitoring deflection of cable-stayed bridges based on EWT-FastICA. Vibration. Testing and Diagnosis, 2022, 42(05): 980-987+1038-1039. .DOI:10.16450/j.cnki.issn.1004-6801.2022.05.021

[12] Tan Dongmei, Yao Huan, Wu Hao, et al. Separation of temperature effects in bridge deflection monitoring based on EEMD-JADE[J].Journal of Civil and Environmental Engineering(Chinese and English) ,2020,42(03):90-99.

[13] Yang Jian, Liu Xiaping, Yang Hong, et al. A new method for extracting temperature effects in bridge deformation[J]. Journal of Guangzhou University (Natural Science Edition), 2013, 12(03): 38-44.

[14] Huang Huijuan, Yan Quansheng. Processing method for monitoring deflection data of bridges based on WOA-VMD[J]. Science and Technology Innovation, 2022(31): 118-121.

[15] Zhu Ying, Guo Hui, Sun Daqi, Shuang Miao. Fine analysis of the spatio-temporal non-uniform temperature field and its effects on a railway steel truss girder suspension bridge under sunshine[J/OL]. Engineering Mechanics: 1-13 [2023-03-27].

[16] Ying Chen, Jiuhong Zhang, Yanfeng Li , and Jialong Li.Analysis of Bridge Health Detection Based on Data Fusion.Advances in Civil Engineering 2022(30):1-11. DOI:10.1155/2022/6893160

[17] Li Heng. Optimization theory and method in empirical mode decomposition [D]. Xi'an: Xidian University, 2017.

[18] Guo Yina. Research on single-channel linear mixed signal blind source separation algorithm [M]. Beijing: Electronics Industry Press, 2016.

[19] K. Dragomiretskiy and D. Zosso, "Variational Mode Decomposition," in IEEE Transactions on Signal Processing, vol. 62, no. 3, pp. 531-544, Feb.1, 2014.doi: 10.1109/TSP.2013.2288675.

[20] Bai Caihong,Xu Suyun,Tang Jingyi,Zhang Yuxi,Yang Jiahui,Hu Kaifeng. A 'shape-orientated' algorithm employing an adapted Marr wavelet and shape matching index improves the performance of continuous wavelet transform for chromatographic peak detection and quantification[J]. Journal of Chromatography A,2022,1673. DOI: 10.1016/j.chroma.2022.463086

[21] Chen Guoliang, Lin Xungen, Yue Qing, et al. Long-term deflection separation and prediction of bridges based on time series analysis. Journal of Tongji University(Natural Science), 2016, 44(6).