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Introduction

Vehicle scanning method (VSM), originally known as the indirect method for bridge measurement, is an efficient method for bridge health monitoring that utilizes mainly the responses collected by the moving test vehicles. This method offers the advantage of mobility, efficiency, and cost-effectiveness as it requires only one or a few vibration sensors mounted on the test vehicle, eliminating the need for deployment of numerous sensors on the bridge. Since its initial proposal by Yang et al. (2004a), the VSM has gained intensive attention from researchers worldwide. Over the past two decades, significant progress has been made in various aspects of the VSM, including the identification of bridge frequencies, mode shapes, damping ratios, damages, and surface roughness, as well as applications to railways. To provide researchers and engineers with a better understanding of the up-to-date research on the VSM, a state-of-the-art review of the related research conducted worldwide was compiled by Xu et al. (2025), which forms the basis of this chapter.

1.1 Background

Bridges serve as crucial transportation links for connecting two regions that are separated by rivers, valleys, or other physical barriers. They are pivotal to the economic growth via the enhancement of local transportation and the fostering of regional development. The health status of bridges in service is always of great concern, as they may deteriorate due to aging, overloading, scouring, and natural disasters, such as earthquakes, floods, mudslides, and windstorms. Ensuring the health and integrity of the bridge is of paramount importance to safeguard the daily bridge users while maintaining the local commercial activities. In this regard, structural health monitoring (SHM) of bridges has been intended as a technique for promptly detecting the hidden damages and potential risk on a bridge.

The conventional monitoring method for bridge monitoring, known as the *direct method*, involves the installation of a vast amount of vibration sensors on the bridge to generate vibration data for further analysis and assessment (Doebling et al. 1998; Carden and Fanning 2004; Yan et al. 2007; Fan and Qiao 2011; Hou and Xia 2021; Das and Roy 2022). However, the direct method, including the vibration sensors and data logger, is typically customized for specific bridges. It has been criticized for the high setup and maintenance costs. Besides, the continuously generated tremendous volume of data is difficult to digest efficiently. Moreover, the lifespan of electronic devices, such as sensors and data acquisition system, installed on bridges may not exceed that of the bridge to be monitored. For the reasons stated, the direct

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method has mainly been applied to locationally important bridges or to those of peculiar structural shapes. With the growing number of short- and mid-span bridges constructed worldwide, there is an urgent need to develop an economical and efficient health monitoring method that can be easily and widely put into practice.

To address the limitations of the direct method, Yang et al. (2004a) first proposed the utilization of an instrumented moving vehicle to extract bridge frequencies. Subsequently, this concept was validated through a field test, demonstrating the successful extraction of frequencies of a simple girder bridge from the vehicle response (Lin and Yang 2005). To distinguish it from the conventional direct method, this method was originally referred to as the *indirect method*, since no data need to be collected from the bridge. Some researchers also labeled it as the drive-by method. However, to more precisely convey the meaning of the technique implied, this method was subsequently renamed as the *vehicle scanning method* for bridges (Yang et al. 2020b). Since the VSM requires only a small number of vibration sensors to be mounted on the scanning vehicle, it offers advantages in terms of equipment maintenance and updates. Moreover, as the vehicle can access any point (or lane) of the bridge along its path of scanning, it offers significant benefits for identifying both the overall and local vibration property of the bridge. Such an advantage will be manifested in high-density mode shape identification and damage localization for the bridge. Compared with the direct method, the VSM is featured by its mobility, economy, and efficiency, all attributed to the fact that it requires only a small number of vibration sensors to be mounted on the scanning vehicle.

In the beginning of research for the technique, focus was primarily placed on scanning the first few frequencies of the bridge by theoretical or experimental means (Yang et al. 2004a, 2013b, 2020f; Lin and Yang 2005; McGetrick et al. 2009; Siringoringo and Fujino 2012). Subsequently, the technique was extended to the identification of other properties of the bridge, such as mode shapes (Yang et al. 2014, 2024a; Malekjafarian and OBrien 2014; Xu et al. 2024b), damping ratios (González et al. 2012; Keenahan et al. 2014; Yang et al. 2019b, 2024d; Xu et al. 2024a), damage detection (Bu et al. 2006; Zhang et al. 2012), and surface roughness reconstruction (González et al. 2008; Yang et al. 2020a), as well as for applications to railways (Caprioli et al. 2007; Weston et al. 2007a; Quirke et al. 2017b; Yang et al. 2020d). With the rapid development of incoming technologies, e.g., Internet of Things (IoT) systems, big data technologies, and cloud computing, the practicality of the VSM for bridge health monitoring is anticipated to be greatly enhanced.

Since the advent of the VSM, it has drawn increasing interest from researchers worldwide and demonstrated its capability and potential for bridge health monitoring. Due to the rapid development of the technique, review articles on the various aspects of progress have been published from time to time. For instance, Malekjafarian et al. (2015) conducted a review of the works up to 2015 on the indirect method for bridge monitoring. Zhu and Law (2015) presented a review up to 2015 on the SHM based on the vehicle–bridge interaction (VBI) and discussed the challenges for practical implementation. Yang and Yang (2018) conducted a state-of-the-art review up to 2017 on modal identification and damage detection using the moving test vehicles. Shokravi et al. (2020) presented a review up to 2020 focusing on vehicle-assisted techniques, highlighting the advancements in VBI, mobile sensor networks, and test vehicle classification. Yang et al. (2020c) conducted a state-of-the-art review on the vehicle-based methods for detecting various properties of highway bridges and railway tracks. Wang et al. (2022b) conducted a review on the advances in research related to VSM for bridges. In addition, Malekjafarian et al. (2022a) reviewed the mobile sensing of bridges using moving vehicles up to 2022, discussing the progress to date, challenges, and future trends. Singh et al. (2023) surveyed the most recent developments of VSM from 2017 to 2022 and articulate future research directions in their review paper.

To provide a solid research background for this book, it is imperative to conduct a comprehensive systematic review of the advancements over the past two decades (i.e., 2004–2024). In this chapter, the referenced papers will be initially classified based on the nature of their methods. Subsequently, within each category, the papers will primarily be cited and commented in chronological order according to their years of publication. This classification approach employed by the authors is well organized, which facilitates a comprehensive understanding of the developmental history of the VSM while providing a valuable roadmap for researchers to conduct VSM-related investigations.

This chapter begins by providing an overview of the fundamental concept of utilizing a moving test vehicle to extract the dynamic properties of bridges, including frequencies, damping ratios, and mode shapes. Then, a concise summary of the research conducted by Yang and coworkers is provided. Subsequently, the works conducted by researchers worldwide are classified into five primary categories: bridge modal parameter identification, bridge damage identification, pavement roughness identification, VSM for railway tracks and bridges, and the application of smartphone-based IoT systems in VSM. Finally, conclusions and recommendations are given in the concluding section.

1.2 Basic Concept of the VSM for Bridges

In this section, the basic concept of the VSM for extracting bridge modal parameters (i.e., frequencies, mode shapes, and damping ratios) will be briefly described.

1.2.1 Bridge Frequency Identification

As shown in Fig. 1.1 (Yang et al. 2004a), the analysis model adopted is a simply supported beam subjected to a test vehicle moving at speed v. The vehicle is modeled as a single degree-of-freedom (DOF) sprung mass m_v supported by a spring-dashpot unit (with stiffness k_v and damping coefficient c_v), which can be easily realized as a single-axle test vehicle in field applications (Yang et al. 2020f; Xu et al. 2021). The bridge considered is a uniform Bernoulli–Euler beam of span length L, flexural stiffness EI, and per-unit-length mass m.

When the test vehicle traverses the beam, its gravitational and inertial forces in the vertical direction will be transmitted to the bridge through the contact point (CP), resulting in vibration on the bridge. This

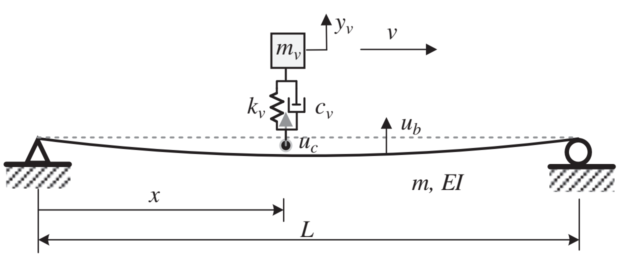

Figure 1.1 A single-DOF test vehicle traveling over a beam.

vibration, in turn, will be transmitted back to the test vehicle due to the interaction between the vehicle and the bridge. Naturally, the vertical vibration response of the test vehicle incorporates components of bridge vibration. Leveraging this principle, the dynamic characteristics of the bridge can be analyzed by installing sensors on the test vehicle and recording its response while crossing the bridge. Previously, accelerometer-type sensors have been frequently used for this purpose in practice.

By employing the fast Fourier transform (FFT) or time–frequency tools (such as short-time Fourier transform (STFT) or wavelet transform (WT)) to analyze the vehicle response, bridge frequencies can be identified from the vehicle's acceleration spectrum. In general, the vehicle response is obtained from the vibration sensors installed on the vehicle's body or axle. From experience, we know that the vehicle spectra may be dominated by the frequencies of the test vehicle itself, making the bridge frequencies not so visible or hidden in the spectra. To remedy this problem, it is suggested that the vehicle–bridge contact response be used, to substitute for the vehicle response, in extracting the bridge properties. The contact response cannot be directly measured, but can be calculated from the vehicle's responses by using the contact response formula given by Yang et al. (2018a) and Xu et al. (2021). A comparison of the spectral results for the contact spectrum with the vehicle spectrum shows that due to elimination of the vehicle frequencies, the bridge frequencies, including those of the higher modes, have been made more visible and can be easily extracted from the contact response (Yang et al. 2018a; Xu et al. 2021).

1.2.2 Bridge Mode Shape Identification

In some of the previous studies, it was found that bridge frequencies may not be so sensitive to occurrence of damages. For the reason stated, bridge mode shapes and their derivatives have been largely used for damage identification. The mode shapes possess a notable characteristic: they can capture local information about the bridge and are sensitive to local damages. However, it was known that physically capturing the mode shapes of a bridge using the vibration sensors deployed on the bridge is typically costly and laborious. The selection of measurement points must be meticulous to ensure no desired modes are missed. From this perspective, the use of the VSM is advantageous. Using the VSM, there is no need to select specific measurement points since the entire length of the bridge will be scanned by the test vehicle. As the vehicle can access any point (or lane) of the bridge along its travel path, it can produce data for identifying both the overall and local vibration information of the bridge. Generally speaking, the VSM is more suitable for high-density mode shape identification and damage localization for the bridge.

Before a mode shape can be identified for the bridge, it is necessary to identify the associated frequency. In this regard, the modal component response for the specific frequency of the bridge of concern can be singled out from the vehicle or contact response by the bandpass filter or mode decomposition techniques. Then, one can proceed to recover the instantaneous amplitude from the extracted modal component response, using techniques such as Hilbert transform (HT)-based techniques (Yang et al. 2014), STFT (Malekjafarian and OBrien 2014), WT (Jian et al. 2020; Xu et al. 2023a, 2023c), and the like. Subsequently, by transforming the instantaneous amplitude from the time domain to the spatial domain, the mode shape of the bridge of concern can be obtained. However, the mode shape recovered by the above procedure is given in absolute value. The final mode shape should be adjusted based on engineer's judgment and experience.

In the process of mode shape identification, another issue to be addressed is that the mode shapes obtained tend to be distorted by bridge damping. To remove the distortion effect of bridge damping on mode shape recovery, three methods can be used according to the authors' knowledge. The first method is to identify the bridge damping ratio first and then using the damping ratio to correct the identified bridge mode shapes. Although this method is straightforward, it is not covered in this book due to the complexity of the process and difficulty in obtaining an accurate damping ratio. The second method uses a moving vehicle to capture the global modal response of the bridge, when crossing the bridge, and a stationary vehicle to offer a reference response at a fixed location of the bridge for removing the damping effect (Yang et al. 2024a). The third method utilizes the spatial correlation between the front and rear CPs of a two-axle test vehicle to establish the global modal response of the bridge along its span length at different instants as the vehicle traverses the bridge (Xu et al. 2024b). By utilizing the spatial correlation between the front and rear contact responses, a recursive formula for removing the damping distortion effect is established for the instantaneous amplitude of the component response of the bridge. Both the second and third methods do not require prior knowledge of bridge damping ratios, for which the details will be given in Chapters 10 and 11.

1.2.3 Bridge Damping Ratio Identification

Compared with frequency and mode shape of the bridge, the damping ratio is another important property that has not received equal attention previously. The key to identifying the damping ratio is to obtain the decay response from the modal component response of the bridge. However, since the vehicle's position changes during its movement over the bridge, to acquire the decay response is not as straightforward. To this end, the correlation between the front and rear wheels of a two-axle test vehicle can be utilized in determining the bridge damping ratio.

For identification of the damping ratio for the mode of the bridge of concern, the associated bridge frequency should be first made available. Similar to Section 1.2.2, the instantaneous amplitude of the specific modal component response of the bridge can be identified by techniques such as the HT, STFT, and WT techniques. For the front and rear wheels acting at the *same location*, but at *different instants* (due to their time lag between the two wheels), the instantaneous amplitude of the specific modal component response of the bridge identified by the rear wheel is smaller than that by the front wheel due to the damping decay effect (Xu et al. 2024a). By utilizing the decay responses between the front and rear wheels caused by time lag, the damping ratio of the bridge can be derived. More details on this part will be given in Chapters 8 and 9.

1.3 Brief on the Works Conducted by Yang and Coworkers

Starting from the 1990s, the term "vehicle–bridge interaction" was advocated by Yang and coworkers to emphasize the equal importance of both the vehicle and bridge vibrations in studying the bridge dynamic problems, unlike most previous studies (Yang and Lin 1995; Yang et al. 1995, 2004b; Yang and Yau 1997; Yau et al. 1999). The relationship between the bridge and the vehicle can be likened to a "mother–child system." The behavior of test vehicle (i.e., the child), which has a relatively small mass, is primarily dominated by the dynamic behavior of the bridge (i.e., the mother). Deeply rooted on this, Yang et al. (2004a) proposed the VSM, originally known as the indirect method, to extract the bridge frequencies from a scanning test vehicle for the first time. In the past two decades, substantial progress has been made in various aspects of the VSM by Yang's research group alone. This section is divided into six parts, namely, vehicle and bridge models used and their vibration mechanisms, enhanced methods for bridge frequency identification, bridge mode shape identification, bridge damping ratio identification, and bridge damage identification.

1.3.1 Vehicle and Bridge Models Used and Their Vibration Mechanisms

To illustrate the feasibility of using a moving test vehicle to extract the bridge frequencies in the first study by Yang et al. (2004a), only the first mode of vibration of a simply supported Bernoulli–Euler beam was considered in the investigation. Subsequently, the feasibility of the method to extract bridge frequencies was verified by a field test by Lin and Yang (2005). The test vehicle used is a self-made single-axle (two-wheel) cart fitted with a seismometer of the acceleration type, designed to mimic the theoretical single-DOF system used. The field test in Lin and Yang (2005) confirmed the effectiveness of the method in extracting bridge frequencies from the spectral response of the test vehicle.

1.3.1.1 Vehicle Models

In 2005, a more general theory that incorporates the effect of multi-modes of vibration of the bridge was presented for extracting the bridge frequencies from the moving vehicle response by Yang and Lin (2005). This study revealed that the desired vehicle response is governed by the driving frequencies, vehicle frequency, and shifted bridge frequencies. Furthermore, the effect of vehicle damping was studied by Xu et al. (2021), as it is a factor that cannot be totally ignored in the design of test vehicles. In this study, the transmissibility between the vehicle and bridge responses was investigated, which is useful to the design and selection of parameters for a test vehicle.

To assess the effects of the key dynamic parameters of the vehicle–bridge system on the response of the test vehicle, a parametric study was conducted (Yang and Chang 2009a), aimed at enhancing the frequency identification of the bridge from the vehicle response. In the order of decreasing importance, it was demonstrated that the successful identification of bridge frequencies depends on the following factors: initial vehicle/bridge acceleration amplitude ratios, speed parameters, and bridge/vehicle frequency ratios.

Previously, the wheel of vehicles was often simplified as a "point" in mathematical formulation for convenience, neglecting the size effect of the wheel. However, the point model is unrealistic from a physics standpoint, since a real wheel of finite radius can never touch the bottom of sharp valleys prescribed by some roughness formulas. Such a problem can be resolved by treating the wheel as a rigid disk of finite radius (Chang et al. 2011). By employing the disk model for the wheels, some unrealistic high-frequency oscillations that occur in point model will be filtered out. However, adopting the disk model can significantly increase the complexity of the VBI analysis compared with the use of the point model. To overcome this issue, Xu et al. (2023d) proposed a refined roughness formula, a substitute version for the power spectral density (PSD) function of ISO 8608 (1995), by including directly the effect of wheel size in generation of the pavement roughness, such that the point model can still be used, but with no unrealistic high-frequency components. Numerical study has demonstrated that the roughness generated by the refined formula can properly reflect the effect of selected wheel size.

If a moving vehicle is to be used as a tool of measuring bridge frequencies, the frequencies of the vehicle and bridge may vary as the test vehicle moves over the bridge. Taking into consideration the coupling effect between the vehicle and bridge, Yang et al. (2013c) presented a closed-form solution for the variation of instantaneous frequencies of the VBI system under the moving loads. It was found that the variation is particularly significant for scenarios where the vehicle/bridge mass ratio is non-negligible or when the vehicle and bridge approach the resonance condition.

In field studies conducted by our research group, it was found that utilizing a single-DOF system for the test vehicle is insufficient to explain all the involved vehicle frequencies. One reason for this is that the two wheels of the test vehicle may encounter different roughness profiles during its passage over the bridge, which may result in the rocking motion induced on the vehicle. To account for both the rocking and vertical motions of a single-axle vehicle, the theoretical framework for the one-axle but two-DOF vehicle system has been established to account for the effect of the two wheels by Yang et al. (2022g).

The suspension system is another factor that deserves further consideration. To address this issue, the two-mass vehicle model was employed for the single-axle test vehicle. To fully unveil the vibration responses in analytical form, closed-form solutions have been derived for the body, wheel, and contact responses of the vehicle by Xu et al. (2022).

As was stated above, the test vehicle primarily used is a single-axle or single-DOF system, which is mathematically elegant, but cannot stand by itself in practice. Attempts have been made to employ a two-axle vehicle. By modeling a two-axle asymmetric vehicle as a two-DOF system, the theoretical framework for the dynamic response of a moving vehicle over a bridge was presented by Yang et al. (2019c). The derived closed-form solution enables the interpretation of the coupled vertical and rotational responses of the moving vehicle inversely excited by the bridge through the two CPs. The vehicle's frequency response functions (FRFs) were analyzed to study phenomena such as coupling, uncoupling, beat, resonance, and cancellation. Furthermore, Xu et al. (2023a) took into account the suspension effect of the two-axle vehicle by modeling it as a four-DOF system.

To enhance the practicality of the vehicle model, a three-dimensional (3D) two-axle four-wheel vehicle model was also constructed to extract the bridge modal parameters from the responses of the test vehicle (Yang et al. 2025b). Since the two axles model provides some spatial correlation between the front and rear wheels, the merit of using the two-axle test vehicle to identify bridge frequencies, mode shapes, and damping ratios has been extensively explored in a number of studies (Xu et al. 2023a, 2024a, 2024b).

1.3.1.2 Bridge's Models and Properties

The VSM technique primarily relies on the interaction between the moving test vehicle and the bridge. The presence of pavement surface roughness becomes troublesome as it may add noisy vibrations to both the responses of the moving vehicle and the bridge via their CP, which moves along with the test vehicle. Essentially, the vibration transmitted from the bridge to the test vehicle comprises two components: the vehicle-induced vibration and roughness-induced vibration (Chang et al. 2010; Yang et al. 2012a). Due to the drastic difference in weight between the moving vehicle and the bridge, the bridge vibration (induced by test vehicle) transmitted to the moving vehicle may be smaller than the roughness-induced vibration. In addition, the spatial distribution of pavement roughness is highly random. To assess the effect of pavement roughness on identification of bridge frequencies, an approximate theory in closed form has been presented (Yang et al. 2012a). It was found that pavement roughness may excite the vehicle vibration to a level higher than the bridge vibration (induced by test vehicle), resulting in bridge frequencies being overshadowed by roughness frequencies in the vehicle spectrum.

Yang et al. (2019a) conducted a study on the modal coupling mechanism of a single-span footbridge, which comprises a suspended beam (bridge deck), two suspension cables (via hangers), and two wind guys (via wind ties). In the study, a virtual eccentrically moving vehicle was employed to scan the dynamic coupling characteristics and coupled frequencies of the slender suspension footbridge. This approach provided a perspective for physically interpreting the dominant modes involved in flexural–torsional coupling, which is essential to understanding the complicated vibration behavior of footbridges.

Thin-walled box girders are widely utilized in highway and railway bridges, which are featured by the existence of plenty of vertical (flexural) and torsional–flexural frequencies. Yang et al. (2021a) presented a theoretical framework for scanning the flexural and torsional–flexural vibrations of thin-walled beams by test vehicles. However, it is difficult to distinguish the vertical frequencies from the torsional–flexural frequencies of thin-walled girders from the vehicle spectra without having idea about the geometric shape of each mode. In the study by Xu et al. (2023b), the kinematic hypothesis of rigid cross sections is employed for separating the vertical and torsional–flexural frequencies from the rocking motion of a single-axle vehicle, without prior knowledge of the geometric mode shape. Subsequently, the effect of damping on torsional–flexural frequencies of monosymmetric thin-walled beams was investigated (Yang et al. 2024c). Moreover, to simultaneously scan frequencies, damping ratios, and mode shapes of thin-walled girder bridges, a complete theory by using a four-wheel test vehicle was established by Yang et al. (2025b). It should be noted that this theoretical framework can be extended and applied to other beam-type bridges.

In previous analytical and numerical studies, bridges are mostly modeled as simply supported beams. In practice, elastic bearings are commonly inserted on the top of bridge piers to mitigate seismic forces upwardly transmitted from the ground. Moreover, the stiffness of the bearings may deteriorate and become unequal over time due to factors such as aging and overloading. Following their early studies on elastically supported beams (Yau et al. 2001), Yang et al. (2022e) made a further effort to scan frequencies of elastically supported bridges with unequal bearings by a moving test vehicle. In this study, a round-trip technique was proposed to detect the varying behaviors of bridges supported by mechanically asymmetric bearings by letting the test vehicle move in both the forward and backward directions. The results demonstrated that the round-trip technique enables the weak end to be easily identified from its much amplified response. In addition, it was found that more bridge frequencies of higher orders can be identified by letting the test vehicle move from the weak end.

In cities with complex topography or limited land availability, curved bridges have gained popularity for use as structures for interchanges. Based on their early studies on curved beams (Yang and Kuo 1986; Yang et al. 2001), Yang et al. (2023c, 2025a) conducted the first-ever scanning of the vertical and radial (lateral) frequencies of a horizontally curved beam from the vertical and lateral motions of a single-axle test vehicle. When a vehicle traverses a circular curve, it experiences the centrifugal force in the radial direction, in addition to the vertical gravity load. Consequently, the tire/wheel assembly of the single-axle test vehicle may undergo lateral motion as well as the vertical motion. To enable the scanning of both vertical and radial frequencies of the curved beam, the single-axle test vehicle (with a single mass) was innovatively modeled as an orthogonal two-DOF system, with one DOF for the vertical motion and the other for the lateral motion.

1.3.2 Enhanced Methods for Bridge Frequency Identification

1.3.2.1 Software-Based Approaches

To extract bridge frequencies of higher modes, the empirical mode decomposition (EMD) was first introduced to process the vehicle response for generating the intrinsic mode functions (IMFs) (Yang and Chang 2009b). A notable feature of the EMD technique is that the sifting process enhances the visibility of higher mode frequencies. It has been demonstrated that by utilizing the IMFs derived from the vehicle response, instead of relying solely on the original data, successful extraction of bridge frequencies of higher orders can be achieved. Furthermore, the extreme-point symmetric mode decomposition (ESMD) (Yang et al. 2020e) and variational mode decomposition (VMD) (Yang et al. 2021e) were also adopted to process the data collected from a passing vehicle. The superiority of the ESMD and VMD techniques was verified by numerical and experimental studies.

Aimed at mitigating the disturbing effect of surface roughness of the bridge, the residual response of two connected vehicles was first employed, instead of the vehicle response (Yang et al. 2012b). By subtracting the spectral response of the following vehicle from that of the leading vehicle, a residual spectrum that is free of the effect of roughness can be obtained. Based on such an idea, the residual contact acceleration of two connected vehicles was also used to extract the first several torsional–flexural frequencies of the thin-walled beam (Yang et al. 2021a). In addition, the concept of two-connected vehicles was further expanded to detect the bridge surface roughness (Yang et al. 2020a). This was achieved by utilizing the correlation between the dynamic deflections of the two vehicle–bridge CPs, based on the displacement influence lines. The ability to filter out the pavement roughness can enhance the performance of the VSM in identification of the bridge modal parameters and damages.

To enhance the visibility of bridge frequencies, the bandpass filter (BPF), singular spectrum analysis (SSA), and SSA–BPF techniques were attempted (Yang et al. 2013a). Among these, the SSA–BPF technique was proved to be most effective for extracting the bridge frequencies. To address the issue of subjective judgment in peak-picking for bridge frequencies, Yang et al. (2022a) proposed a technique that combines SSA and K-means clustering to automatically extract the bridge frequencies from the responses of the moving test vehicle.

To enhance the detectability of bridge frequencies, a customized version of the stochastic subspace identification (SSI) technique was developed for identifying the bridge frequencies from a moving test vehicle (Yang and Chen 2016). This modified approach takes into account the time-variant, coupled, and noisy nature of the VBI system. The results revealed that the proposed SSI approach exhibited remarkable effectiveness in accurately identifying bridge frequencies below 20 Hz, surpassing the conventional methods in this regard.

As far as the vehicle response is concerned, a disturbing fact is the potential dominance of the vehicle frequency peak in the vehicle's spectrum, which tends to obscure the identification of bridge frequencies, especially in the presence of pavement roughness. To resolve this problem, Yang et al. (2018a) proposed utilizing the response of the vehicle's CP with the bridge as a better parameter for scanning the bridge properties. However, the CP response cannot be directly measured for the test vehicle moving over the bridge, but can be calculated by a backward procedure from the vehicle response. Previous field tests have demonstrated the effectiveness of the calculated contact response in extracting bridge frequencies (Yang et al. 2020f). To enhance the accuracy of the back-calculated contact responses, Xu et al. (2021) refined the contact response algorithm defined by Yang et al. (2018a) by incorporating the effect of vehicle damping.

As an extension, to eliminate the masking effect of the vehicle's vertical and rocking frequencies, Yang et al. (2022g) proposed a formula for calculating the contact responses for the two wheels, from the responses measured by sensors mounted on the two wheels. Subsequently, Xu et al. (2022) derived a more general formula for the contact response that considers the vehicle's suspension effect. For two-axle test vehicles, the contact responses were derived for front and rear axles, taking into account both the vertical and rotational (linking) motions of the vehicle (Yang et al. 2022f; Xu et al. 2023a). For multi-DOF moving vehicles, the nodal distribution method and enhanced integration algorithm were utilized to compute the multi-contact responses from the vehicle responses (Shi et al. 2023). Generally speaking, the contact response formula presented in Xu et al. (2021) in integral form is considered exemplary, since it can be extended and applied to various vehicle models.

To accurately identify closely spaced modes of the bridge, the idea of using multi-sensors fitted on the test vehicle was proposed by Yang et al. (2023a). Correspondingly, a procedure combining the WT and singular value decomposition (SVD) technique was developed for accurate identification of closely spaced modes. Such a hybrid time–frequency method was successfully implemented in a field test of a three-span girder bridge in Xiamen, China.

1.3.2.2 Hardware-Based Approaches

In addition to the aforementioned data processing methods, hardware-based approaches can also be employed to improve the overall effectiveness of the VSM. Undoubtedly, a test vehicle is the core tool of the application. Previously, a self-made two-wheel trailer was utilized to simulate the single-DOF system employed in the early-stage theoretical investigations (Lin and Yang 2005). The trailer was towed by a four-wheel tractor to traverse the bridge. The connection between the tractor and the trailer allowed free rotation in all directions, ensuring no transfer of undesired moments between the trailer and tractor. The test results showcased the successful extraction of the first bridge frequency from the vehicle response using the tractor–trailer setup.

Another experimental investigation is on a hand-drawn cart designed for measuring bridge frequencies (Yang et al. 2013b). This study was primarily focused on the elastic properties of cart wheels/tires and the reliability of the extracted bridge frequencies. Three types of wheels/tires, including inflatable wheels, rubber wheels, and polyurethane (PU) wheels, were evaluated for their performance in identifying bridge frequencies. It was concluded that PU wheels exhibited the best performance in extracting bridge frequencies.

To enhance the stability and maneuverability of the test vehicle during its movement, careful design considerations were implemented. Specifically, the test vehicle was designed to ensure that the center of gravity of the vehicle structure remains at a point below the axle for the sake of stability (Yang et al. 2020f). Additional metal plates can be strategically and evenly placed on the two sides of the axle near the wheels to increase the vehicle's weight, thereby enhancing the vehicle stability at higher speeds. Furthermore, solid rubber tires were employed to increase the vehicle's stiffness and its frequency ω_v. It is worth noting that when $\sqrt{2}\omega_v$ exceeds the natural frequency of the bridge $\omega_{b,n}$, the motion of the bridge transmitted to the test vehicle can be favorably amplified (Xu et al. 2021).

To eliminate the negative effects of pavement roughness and vehicle's frequency on bridge frequency identification, a frequency-free movable test vehicle was first tested in a stationary state (Yang et al. 2022d). The test vehicle was calibrated for a benchmarked bridge and subsequently successfully applied to the measurement of a three-span girder bridge. The results demonstrated the effectiveness of the frequency-free test vehicle in accurately detecting the frequencies, mode shapes, and damping ratios of the bridge.

To enhance the effectiveness of the VSM, Yang et al. (2021d) proposed utilizing a vibration amplifier mounted on the test vehicle to amplify the vehicle response transmitted from the bridge. The amplifier can be adaptively adjusted to target and detect the bridge frequency of concern, and thus the bridge frequency can be better identified from the amplifier than from the vehicle response. Subsequently, Xu et al. (2023e) proposed the use of dual-function amplifiers to enhance the overall capability of the scanning test vehicle. One amplifier serves as a tuned mass damper (TMD) to suppress the vehicle's own frequency, while the other to amplify the bridge frequency of interest. In the study, closed-form solutions for the dynamic responses of the amplifier–vehicle–bridge system were derived, and the dynamic amplification factors (DAFs) of the amplifier and vehicle were theoretically presented for assessing the transmissibility of the response from the bridge to the vehicle and then the amplifier of interest.

The effectiveness of the VSM is greatly influenced by the relative amplitudes of the vibration (induced by sources other than roughness) and the part by roughness on the bridge. To this end, a shaker was added to the bridge to enhance the non-roughness bridge vibration to alleviate the pollution from roughness (Yang et al. 2022c). The shaker's DAF formula provided a simple and convenient approach to facilitate vehicle scanning of frequencies for rough or stiff bridges, including those of higher modes.

1.3.3 Bridge Mode Shape Identification

Previously, bridge mode shapes and their derivatives have been extensively employed for bridge damage identification. One notable feature of the mode shapes is their ability to capture local information about the bridge and their sensitivity to local damages. In the work conducted by Yang et al. (2014), the HT technique was first employed to construct bridge mode shapes.

Subsequently, Yang et al. (2018a) derived approximate closed-form solutions for mode shapes from the contact responses using the HT technique. Through comprehensive numerical simulations, it was demonstrated that the contact response outperforms the vehicle response in extracting the mode shapes of the bridge, especially those of the higher orders, under various conditions. Furthermore, the VMD-HT technique was proposed to recover mode shapes from the contact responses of a two-axle test vehicle (Yang et al. 2022f; Liu et al. 2024). In the study, the VMD was applied to processing the contact response for obtaining the bridge component responses, which were then further processed by the HT to yield the bridge mode shapes. The results showed that the proposed procedure is not only effective for single-span bridges but also for multi-span bridges. In addition, it was shown that the residue calculated as the difference of the front and rear axles' responses can effectively mitigate the adverse effect of surface roughness on identification of the modal properties of the bridge.

In constructing the bridge mode shapes, time–frequency analysis techniques have garnered significant attention, with the WT being the most commonly used method. The WT allows the transformation of time domain responses into the time–frequency domain, thereby providing valuable information encompassing both time and frequency. Xu et al. (2023a) conducted a theoretical investigation on the utilization of WT to construct bridge mode shapes from the contact responses back-calculated from a two-axle test vehicle considering the suspension effect. For thin-walled girders, Xu et al. (2023c) used the hypothesis of kinematically rigid cross sections to separate and detect the vertical and torsional mode shapes of thin-walled girders from the rocking motion of a single-axle vehicle. This approach eliminates the need to visually identify the flexural or torsional types of each bridge mode shape, making it easy to identify the mode shapes of various types. Subsequently, Yang et al. (2023d) proposed a method to recover the vertical and radial mode shapes of a horizontally curved bridge using the VMD and synchrosqueezed WT (SWT) using the contact responses generated by a single-axle test vehicle. The VMD technique was employed to process the vertical and radial contact responses, yielding the component responses. The SWT was then applied to generating the mode shapes. The results demonstrated the successful recovery of the vertical and radial mode shapes of the curved bridge using the combined VMD-SWT technique for various factors.

To address the shifting and shrinking effects caused by bridge damping on mode shapes, a three-step mode shape correction method (MSCM) was proposed by Yang et al. (2023b). In this study, the zero-phase filtering technique was employed to extract the component response from the vehicle response for elimination of the edge effect. Subsequently, a trial-and-error approach was presented to objectively calculate the bridge damping ratio. The feasibility of the proposed method was verified through theoretical studies and field experiments.

Recovering bridge mode shapes using the response of a moving test vehicle has gained significant interest. However, the mode shapes obtained tend to be distorted by bridge damping.

To remove the distortion effect of bridge damping on mode shape recovery, Yang et al. (2024a) proposed a normalized formula by utilizing the responses of a moving and a stationary vehicle, which does not require prior knowledge of bridge damping ratios. Specifically, the moving test vehicle was used to scan the global modal response of the bridge as it moves along the bridge span, while the stationary vehicle was used to generate a reference response at a fixed location on the bridge for removing the damping effect. By using the instantaneous amplitudes of the component response extracted through the HT or WT, a recursive formula was established by Xu et al. (2024b) considering the spatial correlation between the front and rear CPs of a two-axle scanning vehicle. By letting the response of the front CP be the target signal and that of the rear CP be the moving reference signal, one can obtain the mode shapes by using the amplitude ratio of two adjacent modal points for the front and rear wheels acting at the same instant, but at different locations.

1.3.4 Bridge Damping Ratio Identification

In comparison with bridge frequency and mode shape, the damping ratio, another crucial property of bridges, has not received equivalent attention in previous studies. To extract the bridge damping ratio, Yang et al. (2019b) presented a theoretical framework utilizing a two-axle moving test vehicle equipped with uniformly spaced accelerometers and laser sensors. The laser sensors were used to measure the relative displacements of the scanning points on the beam from the vehicle body. To mitigate the influence of road roughness, the residual response was obtained as the difference between the responses of two consecutive scanning points. By utilizing the decay responses between the scanning points caused by time lag, the damping ratio of the beam was derived in closed form by the HT.

Subsequently, Yang et al. (2021c) used the VMD and random-decrement technique (RDT) to extract the first few damping ratios of the beam. In the study, the mono-component was obtained by the VMD technique from the contact response. Subsequently, the decay response for each mode was generated by the RDT technique and used to determine the damping ratio.

Bridge damping can affect the contact responses, as well as the mode shape extracted from the contact responses. With the modal components extracted by the HT (Yang et al. 2024d) or WT (Xu et al. 2024a), Yang et al. derived a formula for determining the bridge damping ratio using the correlation between the front and rear CPs of a two-axle test vehicle. The theoretical analysis and numerical simulations demonstrated the robustness of the formula against various levels of vehicle and bridge damping, which works not only for single-span bridges but also for other beam-like structures. Furthermore, a unified theory was presented by Yang et al. (2024b) for identifying the vertical and radial damping ratios of a horizontal curved bridge by the correlation between two connected scanning vehicles using the VMD-SWT. The unified theory allows for the identification of vertical and radial damping ratios of curved bridges in a form similar to straight bridges (Xu et al. 2024a).

1.3.5 Bridge Damage Identification

Damage identification plays a crucial role in the operation and maintenance of bridges. To detect bridge damages, Yau et al. (2017) employed the wavelength characteristic as a useful indicator for detecting and evaluating the severity of slope discontinuity in beams. In this study, the slope discontinuity of a beam was represented by an internal hinge restrained by elastic springs, and the wavelength of the beam was indirectly calculated from the vertical response of the test vehicle as it traveled over the beam. The findings demonstrated that the proposed wavelength-based technique is a promising approach for detecting the damages in girder-type bridges.

The instantaneous amplitude squared (IAS) of the driving component extracted from the contact response was employed by Zhang et al. (2018) as a damage index to detect the bridge damages. The IAS algorithm for damage detection, based on the component analysis and HT, was theoretically investigated in the study. The results revealed that the IAS is sensitive to damages, even in cases of small damages, multi-damages, or in the presence of measurement noise and road roughness. Moreover, the IAS index does not require a baseline measurement, eliminating the need for bridge measurements prior to the occurrence of damages.

Subsequently, Yang and He (2022) presented the uniform translational response (UTR) for localizing the damages in plate-type bridges. Using the first few flexural mode shapes scanned from the contact responses, the UTR curvatures can be computed for the left and right wheels of a single-axle test vehicle. Based on the correlation between the two UTR curvatures generated, the location of each damage can be identified for the plate. Numerical study demonstrated the effectiveness of the method in estimating the longitudinal locations and lateral extents of the damages in plate structures.

1.3.6 Extension of VSM to Railway Tracks

The application and research of the VSM are not restricted to highway bridges, but also to rails, since the basic principle of the scanning method is the same for both highway bridges and railway tracks. Yang et al. (2020d) proposed a technique for detecting the track modulus from the response of a moving test vehicle. By employing the mechanical model of a simple beam resting on an elastic foundation under a moving sprung mass, closed-form solutions were derived for the moving vehicle and bridge, by which the theoretical feasibility for detecting the track modulus was verified.

Subsequently, a technique was proposed for retrieving track–bridge frequencies and track modulus by modeling the track–bridge system as a dual-beam model (Yang et al. 2021b). Closed-form solutions were derived for the responses of the vehicle and its CP with the track, which were further elaborated to determine the dual frequencies associated with the track and bridge components. In the study, the track modulus was identified as the first “plus” frequency of the dual-beam system by a simple formula.

To detect the damages in railway tracks, the damage index IAS proposed by Zhang et al. (2018) was adopted to detect the stiffness loss in railway tracks with elastic foundation (Yang et al. 2020b) and track–bridge systems (Yang et al. 2022b; Shi et al. 2023). By applying the HT to the driving components extracted from the contact accelerations, the IAS was calculated for detecting the stiffness loss in the railway tracks. The effectiveness of the method was validated through numerical simulations, and the sensitivity of the IAS in detecting the stiffness loss in railway tracks with elastic foundation and track–bridge systems was investigated for factors such as damage severity, multi-damages, vehicle speed, track unevenness, and measurement noise.

1.4 Bridge Modal Parameter Identification by Researchers Worldwide

The modal parameters of a bridge, i.e., frequencies, mode shapes, and damping ratios, are the key vibration characteristics that are of concern at all times. Since the first proposal of the VSM, the efficient detection of bridge modal parameters has attracted considerable attention from global researchers. This section will be divided into three parts to review each of these aspects of interest.

1.4.1 Bridge Frequency Identification

Frequency identification of bridges is a fundamental task in the VSM, and it has been extensively studied since its inception. This section will review the vehicle and bridge models used and their mechanism of vibration, the time-varying characteristics of the vehicle–bridge system, and enhanced methods for frequency identification.

1.4.1.1 Vehicle and Bridge Models Used and Their Mechanism of Vibration

McGetrick et al. (2009) numerically investigated the feasibility of using a two-mass vehicle model to monitor the bridge frequencies. The accuracy of the method was found to be higher at lower speeds and on smoother pavement surfaces. The analysis revealed that the magnitude of peaks in the PSD of vehicle accelerations decreased as the bridge damping increased, and this decrease was more discernible for smoother road profiles.

Siringoringo and Fujino (2012) estimated the frequencies of bridges using the response of an instrumented two-axle light commercial vehicle by both analytical and experimental means. Results indicated that the first frequency of the bridge can be extracted from the vehicle's acceleration spectrum. In addition, it was observed that the dynamic response of the vehicle was primarily influenced by bouncing and pitching motions at the entrance/exit, i.e., expansion joint of the bridge, which is an issue to be overcome.

Kim et al. (2014) investigated the feasibility of utilizing an instrumented vehicle to detect the natural frequency and changes in structural damping of a model bridge through a scaled laboratory moving vehicle experiment. Additionally, Kim et al. (2017) conducted laboratory experiments to validate the practical viability of three drive-by methods: (1) bridge frequency extraction using the Fourier spectrum of the vehicle; (2) damage detection through changes in the vehicle's spectral distribution pattern; and (3) identification of roadway surface profiles.

Urushadze and Yau (2017) conducted a preliminary experimental study to assess the feasibility of detecting the fundamental frequency of a bridge through the dynamic response of a vehicle traversing the bridge. Both analytical and experimental investigations revealed that the bridge frequency is present in the vehicle acceleration spectrum and can be well extracted.

The test vehicle plays a crucial role in the process of extracting bridge responses, and a sophisticated vehicle model can enhance the resolution of bridge frequencies. In this regard, J.P. Yang et al. conducted theoretical investigations on the effectiveness of various test vehicle models for the VSM. First, they examined the impact of vehicle damping on bridge frequency identification using a lumped sprung mass model (Yang and Lee 2018). The findings revealed that higher vehicle damping tends to suppress the vehicle frequency, thereby enhancing the visibility of bridge frequencies. Subsequently, a two-mass vehicle model incorporating the unsprung mass was employed to form a two-DOF vehicle model (Yang and Chen 2018; Yang and Cao 2020). Furthermore, a two-axle rigid-mass vehicle model was used to account for the pitching effect of the car body, incorporating both the vertical and rotational DOFs (Yang and Sun 2020). By considering the first modal vibration of the beam, a theoretical formulation of the two-axle three-mass vehicle model was established (Yang 2021). As an extension of this model, the amplifier–vehicle–bridge system was formulated, aimed at enhancing the vehicle vibration through the addition of an amplifier (Yang 2022; Yang and Wang 2024). To mitigate the negative impact of pavement roughness on bridge frequency identification, the residual response of two-axle vehicle (He and Yang 2022) or three-connected vehicles (He et al. 2023a) was used.

In practice, various types of bridges exist in theoretical formulations. Yang and Wang (2019) investigated the dynamic response and stability of an inclined beam under a moving concentrated vertical load, considering the effect of the compressive axial force component in the bending stiffness matrix formulation of the beam. Additionally, for inclined Euler beams subjected to a moving mass and moving follower force, the governing equation and boundary conditions were derived using the extended Hamilton's principle (Yang et al. 2020). To enhance computational efficiency, they proposed an advanced moving internal node element (MINE) method for the dynamic analysis of VBI systems (Yang et al. 2021). This method introduces a moving internal node within the standard beam element, eliminating the need to interpolate dynamic responses at the CP between the moving vehicle and the beams. It has been demonstrated to be effective and efficient for VBI analysis. Furthermore, to address the disk effect of vehicle's wheels, Yang et al. (2023) proposed a new convolution method. Since the convolution is conducted within the spatial domain, the proposed method enables direct application of the disk model to any existing pavement roughness with various spectral compositions.

Sitton et al. (2020b) established closed-form solutions for the vibration of both the bridge and the vehicle as the vehicle traverses a two-span continuous bridge, and provided a method for extracting the bridge frequency from the vehicle response. The accuracy of the closed-form solutions was validated by numerical simulations and by comparison with existing ones. The results demonstrated that the bridge frequencies identified from the vehicle appeared as two peaks, with one peak shifted below and the other above the original bridge frequency. Subsequently, Luo et al. (2024) presented an indirect frequency identification method for continuous girder bridges. They derived an analytical solution for an equal-span continuous beam subjected to a moving vehicle. The findings indicated the importance of selecting an appropriate frequency for the trailer to prevent resonance between the vehicle and the bridge, thereby achieving improved performance.

In most previous numerical studies of the VBI problems, the bridge was often simplified as a uniform beam for the sake of simplicity. Yang and Wu (2021) proposed a nonuniform VBI model to broaden its applicability. The nonuniform bridge consists of beam elements with constant width but varying depths. It was found that, unlike the uniform VBI system, the optimized location for sensor installation is at the front of the vehicle body in the presence of both damping in the vehicle and the bridge.

Shi and Uddin (2021b) presented mathematical models for various non-simply supported boundary conditions, including both ends fixed, fixed simply supported, and one end fixed and the other end free (cantilever) boundary conditions. The closed-form solutions were derived under the assumption that the magnitude of vehicle acceleration is significantly lower than the gravitational acceleration constant. The parametric study revealed that a higher vehicle frequency is preferable in terms of vehicle response, since it may attenuate the bridge frequencies that exceed the vehicle frequency.

Shi and Uddin (2021a) derived closed-form solutions for the vehicle–bridge system, considering the damping effect of both the vehicle and bridge and assuming that the vehicle acceleration is significantly lower than the gravitational acceleration. This study indicated that bridges with high damping may negatively affect the transmission of their dynamic properties to the test vehicle. However, the damping of the vehicle has little effect on the extraction of bridge frequencies. Furthermore, an improved theoretical model was investigated for the dynamic interaction between a single-axle vehicle and a bridge, considering the influence of contact patch size and motor-induced vehicle excitation (Shi et al. 2024).

Alamdari et al. (2021) conducted numerical and experimental investigations to assess the feasibility of the VSM for bridges, and proposed a novel index for quantifying the performance of the transmission between the bridge and the vehicle. It was verified that a vehicle with a higher sensitivity index is capable of scanning more bridge-related information, thereby enhancing the identification of bridge frequencies. Experimental results confirmed the successful identification of the first three vibration modes of the bridge from the test vehicle moving at constant and slow speed, with the aid of ongoing excitation on the bridge.

Jian et al. (2022) conducted a 3D simulation of the VBI system to identify the bridge frequencies from the vertical acceleration of a full-car model's wheels. Li et al. (2023c) utilized the contact responses of a 3D vehicle to extract bridge frequencies. To make the bridge frequencies outstanding in the frequency domain, residual wheel responses (Jian et al. 2022) or contact responses (Li et al. 2023c) were employed to mitigate the adverse effects of pavement roughness.

Liu et al. (2023a) developed a two-stage framework for extracting bridge frequencies by utilizing the vehicle tire pressure. Initially, a tire pressure model was established and calibrated to facilitate the calculation of the relative displacement between the axle and CP based on tire pressure variations. Subsequently, the calibrated tire pressure model was used to identify the bridge frequencies. To eliminate the roughness effect, the residual displacement was used. The feasibility of the framework was examined through numerical, experimental, and field tests.

Zhang et al. (2023) developed a method that combines moving and nonmoving vehicles to extract bridge frequencies. It was found that the nonmoving vehicle enhances the visibility of the bridge vibration in the dynamic response of the moving vehicle. Hashlamon and Nikbakht (2023) conducted theoretical and numerical investigations to extract bridge frequencies from the response of a stationary vehicle in the presence of another moving vehicle. The results demonstrated that the stationary vehicle exhibits higher visibility of bridge frequencies.

Zhu and Shi (2024) proposed a split-type two-axle vehicle model for bridge indirect measurement, and an analytical solution for the response of the VBI system was derived. The study examined the regularity of the vehicle FRF and validated the analytical solution by numerical analysis.

Li et al. (2024b) proposed a method to identify the frequencies of footbridges by utilizing the vibrations of a scooter. The residual contact response was used to eliminate the scooter's self-frequencies and roughness. The effects of environmental noise, footbridge damping, and tire damping were examined to verify the effectiveness of the method.

Jin et al. (2024) focused on the vehicle suspension tuning for bridge-friendliness. They found that variations of the bridge frequency during the vehicle passage are small when the tuned suspensions are used. This finding may have implications in future research in bridge frequency identification using a moving vehicle.

Shokravi et al. (2024) proposed combining the potentiality of connected and autonomous vehicles (CAVs) into the VSM by introducing In-Fleet SHM. Each In-Fleet CAV can automatically collect the vehicle's persistent and temporal data by the embedded sensors and transmit them to edge computing systems for analysis. In-Fleet monitoring has an expanded spatial and temporal coverage, enabling continuous near real-time monitoring of highway bridges of the transportation network.

1.4.1.2 Time-Varying Characteristics of the Vehicle–Bridge System

The presence of a parked vehicle on a bridge may induce variations in the vehicle and bridge frequencies (Yang et al. 2013c). Chang et al. (2014) conducted theoretical and experimental investigations to examine the variability in bridge frequency resulting from a parked vehicle. They emphasized the importance of considering this effect particularly in cases with near vehicle–bridge resonance or for significant vehicle/bridge mass ratios. Additionally, they proposed an analytical formula for estimating the range of variability.

Cantero et al. (2017) conducted an experimental study to investigate the variations of frequencies and modes of the vehicle–bridge system. The results demonstrated that the modal properties of both the vehicle and the bridge do change with varying vehicle position. Furthermore, Cantero et al. (2019) explored the variation of bridge frequencies during a vehicle passage in a laboratory experiment. The results confirmed that the coupling effect is influenced not only by the added mass but also by the mechanical properties of the traversing vehicles.

Li et al. (2020b) utilized the synchroextracting transform (SET) to extract the time-varying characteristics of bridges subjected to vehicle passage. From the time–frequency representation (TRF) of the responses, the instantaneous frequency (IF) of mono-components associated with vehicle and bridge frequencies can be extracted. Numerical investigations, laboratory experiments, and field tests were conducted to validate the proposed approach. The results demonstrated that the time-varying characteristics serve as reliable indicators for assessing the bridge condition. Subsequently, Li et al. (2021) utilized the improved empirical WT (EWT) along with ridge detection of signals in TFR to estimate the instantaneous frequencies of the bridge. Numerical and experimental studies demonstrated the feasibility and effectiveness of the proposed method on the IF estimation.

Zhang and Tan (2021) developed a semi-analytical approach to address the dynamic response of a VBI system, considering the effect of heavy vehicle inertia and the corresponding variations of instantaneous frequencies of both the vehicle and bridge. Frequency modulation technique was employed to generate dynamic responses that encompassed time-varying instantaneous frequencies. The generated responses exhibited good agreement with numerical simulations and previously published laboratory measurements.

Zhang et al. (2021) proposed an IF identification technique based on the modified S-transform reassignment. Subsequently, Yang et al. (2022) employed a filtered iterative reference-driven S-transform technique to identify the time-varying characteristics of a VBI system. Numerical and laboratory studies demonstrated the successful extraction of the VBI system's instantaneous frequencies from the spectrograms generated by the filtered iterative reference-driven S-transform. Importantly, this approach exhibited diminished interference compared with other vehicle response-based time–frequency analysis methods.

Jin et al. (2022) applied the multivariable output error state space (MOESP) algorithm to estimate bridge frequencies from the dynamic response of a vehicle traversing the target bridge in two passes. To eliminate the time-variation effect of the VBI system, the SVD-based pseudo-inverse algorithm was employed prior to implementation of the MOESP method. Numerical experiments demonstrated the successful identification of structural frequencies of the bridge using the proposed approach, even under conditions of high vehicle speeds and pavement roughness.

Tan et al. (2023) employed the second-order synchrosqueezing transform to investigate the time-varying characteristics of frequencies in the VBI system. Numerical simulations and laboratory experiments revealed that both the frequencies of vehicle and bridge are time-varying.

Yang et al. (2023) derived an analytical solution based on a moving mass-beam system to account for frequency variation, and a numerical model with detailed implementation was developed for practical applications. Subsequently, He et al. (2023b) presented a formulation to estimate scale factors by using the vehicle-induced changes in bridge frequencies. The scale factors for mass-normalized mode shapes were derived to eliminate the need to handle randomly scaled mode shapes obtained from output-only modal tests. This approach enables efficient estimation of scale factors without the need to construct a finite element model. Furthermore, Yang et al. (2024) formulated semi-analytical solutions for a system involving a moving mass on a square plate. The numerical findings indicated that the frequency variation of a plate-type bridge can reach up to 30% for the first three modes. Notably, the acceleration responses of the plate-type bridge demonstrated a unique phenomenon of wave propagation, which is not commonly observed in beam-type bridges.

1.4.1.3 Enhanced Methods for Bridge Frequency Identification

Li et al. (2014) employed the generalized pattern search algorithm (GPSA) to optimize the identification of bridge parameters. It was verified that the first bridge frequency and stiffness can be indirectly extracted from the responses of a passing vehicle. The study emphasized that the GPSA algorithm has potential in SHM and the VSM is tractive for civil engineering.

Kong et al. (2016) employed a specialized test vehicle system consisting of a tractor and two following trailers to eliminate the effects of driving frequencies and road roughness. The residual responses were obtained by subtracting the responses of one trailer from the other. Subsequently, the FFT and STFT were used to extract the bridge frequencies and mode shapes from the residual responses. Furthermore, field test was conducted to verify the efficacy of the technique (Kong et al. 2017).

Tan et al. (2017) employed the WT technique to extract the bridge frequencies from the dynamic responses of a passing vehicle. The approach was further extended to identify frequency changes resulting from structural damage. To mitigate the influence of roughness, the signals from the front and rear axles were subtracted.

Nagayama et al. (2017) employed the cross-spectral density function to identify the bridge frequencies from the common vibration components of the responses of two test vehicles. Numerical simulations confirmed the feasibility of the method for extracting bridge frequencies. Additionally, an experimental study featuring synchronized sensing of the two vehicles revealed successful identification of the first bridge frequency under various speed combinations. The road roughness-relevant vehicle dynamics are strongly correlated with the traveling speed. To overcome the adverse effect of road roughness, Lu et al. (2023) determined the desired bridge frequency by analyzing the cross-power spectra of vehicle dynamics at different moving speeds. The efficacy of the proposed method for bridge frequency identification was evaluated through numerical simulations and laboratory experiments. Lan et al. (2023c) determined bridge frequencies from multiple sensors on an ordinary vehicle by observing a distinct peak in the cross spectrum. The method was validated by an experimental study using a steel beam and a scale truck model.

Wang et al. (2018) used the same bridge as in Nagayama et al. (2017) to validate the particle filter approach for estimating the fundamental frequency of a bridge from the responses of an ordinary vehicle. The particle filter method was employed to estimate the excitation inputs to the vehicle, specifically the displacement inputs at the front and rear tire locations. To eliminate the roughness effect, the estimated displacement inputs at the front and rear tires were subtracted. Field measurements were conducted, demonstrating successful and accurate extraction of the bridge's fundamental frequency at various driving speeds.

Zhu and Malekjafarian (2019) employed the ensemble EMD (EEMD) and EMD to decompose the signals measured from the moving vehicle for bridge frequency extraction. This study numerically demonstrated that employing the EEMD improves the results compared with the EMD, since the EEMD can overcome the mode mixing problem. Furthermore, Singh and Sadhu (2023) used the robust EMD (REMD) to decompose the contact response of the test vehicle. The proposed method was verified by numerical and full-scale experimental studies.

Li et al. (2019a) used the SSA technique to decompose the single-channel measured vehicular response into a multichannel dataset. Subsequently, the bridge frequencies were extracted through blind modal identification. Numerical results demonstrated the effectiveness and robustness of the method in extracting bridge frequencies from the test vehicle, even in the presence of class B roughness. Furthermore, a laboratory test was conducted to validate the method using one- and two-axle vehicles.

Tan and Uddin (2020) employed the HT to enhance the identification of the bridge frequency from a passing vehicle due to its superior ability to handle frequency resolution. The proposed method demonstrated robustness against variations in vehicle velocity and signal noise.

Contact response has garnered significant attention as an effective means of identifying bridge modal parameters. Nayek and Narasimhan (2020) extracted bridge frequencies from the contact acceleration of a two-DOF vehicle. Corbally and Malekjafarian (2021) conducted a study on utilizing the response of the CP between the tire and the bridge for extracting bridge frequency. Both numerical simulation and laboratory tests (Corbally and Malekjafarian 2023) were conducted to validate the effectiveness of the contact response in detecting the fundamental frequency of the bridge. In the case of simulated damage scenarios, the contact responses exhibited higher sensitivity in detecting changes in bridge frequency compared with the directly measured signals. Yin et al. (2023) used the contact responses of a two-axle vehicle (Xu et al. 2023a) to extract bridge frequencies. The result showed that extracting bridge frequencies through the contact response is better than that of the wheel response.

Jin et al. (2021) developed a short-time SSI (ST-SSI) framework to estimate bridge frequencies using the dynamic response of a test vehicle. By incorporating the dimensionless parameters, the ST-SSI was successfully applied in analysis in spite of the time-varying characteristics of the VBI system. The results demonstrated that the approach can effectively identify the first two bridge frequencies even at higher test-vehicle speeds (e.g., 10 and 20 m/s).

Singh and Sadhu (2022b) investigated the feasibility of using the wavelet packet transform (WPT) to extract modal responses and identify bridge frequency components by analyzing the wavelet packet coefficients. In addition, a hybrid time–frequency method was proposed to extract the bridge modal frequencies from the resulting WPT coefficients using SET (Singh and Sadhu 2022a). The effectiveness of these methods was validated through numerical simulations as well as a laboratory experiment.

Locke et al. (2022) conducted experimental investigations on the applicability of operational modal analysis (OMA) techniques to the VSM for identifying the modal properties of a 9.14 m bridge span.

The results highlighted the importance of constructing histograms using frequencies identified from multiple tests to consistently determine the bridge frequencies. Additionally, the study revealed a trade-off between the mass of the vehicle and the speed at which bridge frequencies can be accurately identified. This trade-off also affects the occupation time of the vehicle on the bridge and the resolution of bridge frequencies.

The presence of surface roughness on bridges poses a challenge to vehicle-response-based bridge identification methods, as it significantly affects the vehicle response and renders many of these methods ineffective. Li et al. (2022b) introduced a three-step framework for extracting bridge vibration components from the vehicle responses. They include (1) calculating the contact responses using the input forces estimated by a dual Kalman filter (DKF) and vehicle parameters; (2) obtaining the residual contact response through subtraction; and (3) decomposing the residual contact response using the auto SSA technique to extract the bridge dynamic component. Numerical and experimental studies confirmed the effectiveness of the proposed method in improving the drive-by bridge modal identification, even in the presence of road surface roughness.

To measure bridge frequencies, an autonomous system was devised by Cheng et al. (2022) for data collection and transmission, integrating the indirect monitoring method, graphical user interface, and wireless data transmission technology. To assess the safety of a target bridge, post-disaster data are compared with the original frequencies stored in the database. The system underwent testing on several full-scale bridges under typical daily traffic conditions, by which the practicality is demonstrated.

Abuodeh and Redmond (2023) proposed a framework called the autonomous peak-picking VMD (APPVMD), which combines a variety of signal processing techniques and heuristic models, to autonomously extract bridge frequencies from instrumented vehicles. This framework does not rely on prior information or model-informed training. Numerical studies demonstrated that the algorithm is a promising autonomous technique for accurately extracting bridge frequencies from vehicle data.

Lan et al. (2023a) proposed a coherence-prominent peak identification (PPI) algorithm, based on the Bayesian framework, to extract bridge frequencies from city buses. The method was validated through numerical studies and field tests using city buses. The results demonstrated the effectiveness of the method in mitigating the effects of road roughness, environmental noise, and vehicle parameter variations, thereby accurately identifying the bridge frequencies.

Quan et al. (2024) proposed two different subspace-based methods, i.e., an improved ST-SSI method and an improved MOESP method, for identifying bridge frequencies. Their findings confirmed that incorporating random vehicle flows facilitates frequency identification of bridges.

1.4.2 Bridge Mode Shape Identification

In previous studies, bridge mode shapes and their derivatives have been extensively employed for bridge damage identification. One notable characteristic of mode shapes is their ability to capture local information about the bridge, making them sensitive to local damages. Therefore, the accurate extraction of mode shapes holds great significance for application of the VSM. For mode shape identification, commonly used techniques include HT-based techniques (Yang et al. 2014), as well as time–frequency techniques such as STFT (Malekjafarian and OBrien 2014) and WT (Jian et al. 2020; Xu et al. 2023c) techniques, among others.

1.4.2.1 HT-Based Techniques

Malekjafarian and OBrien (2017) employed a truck–trailer system equipped with an actuator at a frequency close to one of the bridge frequencies to construct the mode shapes using the HT technique (Yang et al. 2014). The study demonstrated that external excitation proves advantageous in enhancing the energy of the bridge response at critical frequencies. In addition, a rescaling process was implemented to construct the bridge mode shapes using the response amplitudes measured from two consecutive axles, which yields high resolution and accuracy.

Qi and Au (2017) utilized a suitable filter to extract the bridge component response corresponding to each natural frequency. Then, the HT technique was applied to constructing the bridge mode shapes. To stimulate the bridge responses, an additional impact excitation was applied to the vehicle. The results demonstrated that the supplementary impact excitation improved the accuracy of the mode shape identification by mitigating the adverse effects of measurement noise and roughness.

The roughness may greatly pollute the vehicle response and render the VSM ineffective. Zhan et al. (2020) proposed a method that estimates the surface profile of a bridge using the double-pass double-vehicle technique. Based on the normalized contact response obtained, the frequencies and mode shapes of the bridge can be extracted through spectral analysis and the HT technique. The effectiveness of the method was numerically validated for a three-span continuous bridge.

To improve the VSM for modal identification, an appropriately tuned elliptic filter was employed instead of the conventional bandpass filter by Yang and Wang (2022b). Then, the HT technique was employed to calculate the analytical signal from the narrowband signal. To enhance the computational efficiency of the VSM model, the MINE method was used in the study.

Zhou et al. (2023) employed the HT technique and a two-peak spectrum idealized filter function to extract bridge mode shapes from the responses of a two-axle vehicle. The laboratory tests yielded successful identification of bridge frequencies and mode shapes from the accelerations of a passing two-axle vehicle using the proposed setup.

Zhang et al. (2023) conducted an experimental study to construct bridge mode shapes by a moving vehicle with the aid of a stationary shaker to excite the steady-state-forced vibration of the bridge. By extracting the vehicle acceleration envelope using the HT technique, accurate mode shapes can be obtained. In the study, the first five mode shapes of the bridge model and the first six mode shapes of the field bridge were successfully extracted by the moving test vehicle.

Zhang et al. (2023) proposed a procedure for identification of spatial mode shapes of T-girder bridges. The bridge spatial mode shapes were determined from the bridge-related components of a vehicle traveling at various transverse positions on the bridge by the HT technique. The results demonstrated the high accuracy and efficiency of the method in identifying the spatial mode shapes of T-girder bridges.

Liu et al. (2023) employed the VMD-BPF to decompose the virtual (residual) contact responses and then used the HT technique to extract the bridge mode shapes. To address the impact of vehicle length on mode shape identification, a mode shape splicing method was proposed. Numerical simulation showed that the virtual contact responses can effectively be used for mode shape extraction.

1.4.2.2 Time–Frequency Techniques

Malekjafarian and OBrien (2014) utilized the short time–frequency domain decomposition (STFDD) technique to reconstruct bridge mode shapes from the dynamic response of the test vehicle. The effectiveness of the method was investigated through various numerical simulations. The adverse effect of pavement roughness on mode shape reconstruction can be mitigated by employing external excitations or utilizing the residual acceleration response.

Kong et al. (2016) employed the STFT to extract the bridge mode shapes from a tractor–trailer system, consisting of one tractor and two instrumented trailers. Furthermore, they used different time–frequency analysis methods such as the STFT, Wigner-Ville distribution (WVD), and CWT to construct the bridge mode shapes (Kong et al. 2024). A laboratory test was conducted to verify the performance of the proposed methods.

To identify spatially dense modes of vibration, Marulanda et al. (2017) presented a method for ambient vibration-based mode shape identification utilizing one mobile sensor and one stationary sensor. By examining the correlation between the time–frequency distributions of the two output responses, the mode shapes can be obtained. The experimental study showed the effectiveness of the method in identifying dense mode shapes using a significantly reduced number of sensors and data compared with existing modal identification techniques.

Jian et al. (2020) presented a method for identifying bridge mode shapes using the dynamic responses obtained from a tractor–trailer system, composed of one tractor and three instrumented trailers. Bridge mode shapes were identified by wavelet analysis using the subtracted accelerations of adjacent trailers. Furthermore, a wavelet denoising algorithm was implemented to enhance identification accuracy in the presence of measurement noise. The results showed that the method achieved satisfactory resolution, accuracy, and robustness in identifying bridge modal frequencies and mode shapes.

To obtain high-resolution absolute values of operational mode shapes, the crowdsourced modal identification using continuous wavelet (CMICW) method was proposed by Eshkevari et al. (2022b). The method can gradually amplify the bridge's dynamical signatures and reduces noise in the spatiotemporal map. Experimental testing was conducted to validate the performance of the CMICW method, which successfully identified the frequencies and absolute values of the operational mode shapes of a bridge with high resolution.

1.4.2.3 Other Mode Shape Identification Methods

He et al. (2018b) proposed a mass-normalized mode shape identification method for beam structures. The relationship between changes in bridge frequencies caused by a parked vehicle was utilized to construct the mode shapes by using the frequencies measured on a two-axle vehicle parked at different positions on the bridge. Numerical and experimental studies illustrated that the method can accurately obtain mode shapes with high spatial resolution. Zhang et al. (2019b) also utilized the relationship between the changes in bridge frequencies caused by a moving lumped mass to construct mode shapes. They employed a modified time–frequency analysis technique based on the weighted polynomial chirplet transform to estimate the non-stationary instantaneous frequencies of the bridge. Subsequently, a new sampling algorithm based on accumulative measured energy was used to reconstruct the mode shapes. The method was validated through numerical simulations and laboratory-scale experiments, demonstrating its effectiveness in extracting mode shapes, even at high traveling speeds.

Nayek et al. (2018) proposed an input–output mode shape identification method that utilizes a single actuator and a roving sensor. The proposed identification strategy involves conducting a series of tests using either (1) a fixed sensor and a roving actuator, (2) a roving sensor and a fixed actuator, or (3) a pair of roving sensor and actuator, which may or may not always be collocated. The roving actuator or sensor sequentially excites or measures different locations on the deck, forming the suite of tests. The performance of the proposed approach was evaluated through numerical simulation and laboratory test.

Li et al. (2019b) proposed a method to estimate the mode shapes by one stationary vehicle and one moving vehicle. In the study, the reference-based SSI method was employed to estimate the local mode shape values for each signal segment, and a rescaling technique was applied to these local mode shape values to construct the global mode shapes. The numerical simulations and experimental tests demonstrated that the proposed method can accurately estimate the bridge modal parameters.

Mei et al. (2021) presented a method for mode shape recovery that involves mapping the data collected from moving measurement points to virtual fixed points, resulting in the generation of a sparse matrix. To complete the sparse matrix, a soft-imputing technique was employed. The mode shapes of the bridge were then extracted using the SVD. Experimental results demonstrated the effectiveness of the method in identifying bridge mode shapes. Furthermore, to calculate the responses at the virtual fixed nodes on the bridge, a moving-window signal prediction method based on autoregressive with exogenous time-series models was also proposed (Talebi-Kalaleh and Mei 2023). By integrating the results of the SVD on the predicted displacement responses and frequency domain decomposition (FDD) on the predicted acceleration responses, the mode shapes and frequencies can be identified.

Demirlioglu et al. (2023) evaluated the effectiveness of the VSM in estimating the mode shapes of bridges supported on elastic foundations. Three methods, namely, the reference-based SSI method, elliptic filter method, and half-car method, were employed to obtain the mode shapes using the data collected by the test vehicle. Furthermore, the VMD-HT technique was used to extract the mode shapes from a moving and a stationary vehicle (Demirlioglu and Erduran 2024). The effectiveness of the method was validated through numerical studies conducted on three bridges with different boundary conditions.

Peng et al. (2023b) presented a mobile crowdsensing framework for identifying dense spatial-resolution bridge mode shapes using the vehicle responses. The proposed method for mode shape identification was formulated as a physical-informed optimization problem with two objective function terms. The feasibility and advantages of the model were evaluated by numerical simulations and experimental studies.

1.4.3 Bridge Damping Ratio Identification

Previously, bridge damping has not received equal attention compared with frequency and mode shape. The damping ratio is a highly sensitive parameter that is always challenging to measurement. On the other hand, previous studies have indicated that structural damage can lead to notable variations in damping, highlighting the significance of structural damping as a sensitive indicator of damage (Kawiecki 2001; Curadelli et al. 2008).

According to McGetrick et al. (2009), as the bridge damping increases, the magnitude of peaks in the PSD of vehicle accelerations decreases. This decrease was particularly noticeable for smoother road profiles. Furthermore, González et al. (2012) extended the VSM to the identification of bridge damping. A six-step algorithm was proposed and evaluated for its accuracy against various parameters, such as bridge span, vehicle speed, road roughness, vehicle's initial vibration, signal noise, modeling error, and frequency matching between the vehicle and bridge.

Keenahan et al. (2014) proposed the use of a truck–trailer system to detect variations in bridge damping. Subtraction of the front and rear axle accelerations was adopted to remove the effect of roughness.

The findings revealed that by subtracting the axle accelerations of the trailer from each other, it is possible to detect bridge frequencies and the changes in damping.

In the field of SHM, it is common to encounter datasets that contain missing observations. To address this issue, Matarazzo and Pakzad (2016) introduced the structural identification using the expectation maximization (STRIDE) as a statistical tool for handling missing data. Subsequently, they used the STRIDEX algorithm for the stochastic truncated physical model (TPM) (2018) to estimate the frequencies, mode shapes, and damping ratios from dynamic sensor network (DSN) data. The performance of the STRIDEX algorithm was demonstrated through simulations and experimental measurements obtained from two mobile sensor cars. The results showed that a mobile sensor can provide over 120 times more mode shape points compared with a fixed sensor. Furthermore, Eshkevari et al. (2020a) employed the extended STRIDEX algorithm to identify the operational natural frequencies, mode shapes, and damping ratios of bridges. In the study, the vehicle suspension effect was removed by the vehicle transfer function or EEMD technique, and the roughness-induced vibrations were identified by the second-order blind identification (SOBI) method. In addition, Eshkevari et al. (2020b) used the matrix completion method for modal identification. This approach completes the full matrix in spatial and temporal domains using the data collected from a large number of mobile sensors by alternating least-square. Then, system identification techniques such as the principal component analysis (PCA) and structured optimization analysis were utilized to identify the frequencies, mode shapes, and damping ratios. The results demonstrated the effectiveness of the method in accurately extracting modal properties from sparse DSN data.

Since the bridge damping may shift the bridge mode shape, Tan et al. (2019) employed a series of assumed damping ratios to adjust the instantaneous amplitude identified by the HT technique. The bridge mode shape was determined by selecting the instantaneous amplitude with the highest modal assurance criterion (MAC) value, which corresponded to the identified damping ratio. Laboratory experiments provided further evidence to support the effectiveness of the algorithm.

Zhang (2022) developed a theoretical framework that enables the simultaneous identification of the fundamental frequencies, mode shapes, and damping ratios of a bridge using a passing vehicle–trailers system. By obtaining the amplitude spectrum of the measured vehicle residual response, the frequencies and damping ratios were evaluated by curve fitting. The mode shapes were reconstructed by dividing the Fourier transform of one residual contact response at the natural frequency by another without time lag. The feasibility of such an approach was demonstrated numerically.

Li et al. (2022a) utilized the successive VMD (SVMD) to estimate the modal parameters of a bridge from the dynamic responses of a passing test vehicle. Once the bridge-related dynamic components were extracted through the decomposition process, modal frequencies and damping ratios were estimated using the natural excitation technique and fitting method based on the RDT. The feasibility of the method was validated through an *in-situ* experimental test on a cable-stayed bridge. In addition, He et al. (2023a) employed the VMD and RDT to scan damping ratios from the free-decay components extracted from the two residual contact responses of three-connected moving vehicles.

1.5 Bridge Damage Identification by Researchers Worldwide

Inspired by the idea of Yang et al. (2024a), Bu et al. (2006) proposed a method to detect the damage of a bridge utilizing the dynamic response of passing vehicles. Damage identification is widely recognized as one of the primary objectives of the VSM. This section categorizes damage identification methods into the following: modal parameter-based methods, signal processing-based methods, machine learning (ML)-based methods, and other methods.

1.5.1 Modal Parameter-Based Methods

1.5.1.1 Natural Frequency-Based Methods

He and Ren (2018) proposed a damage detection method for bridges based on the variation of frequencies induced by a parked vehicle. The method used a FEM updating technique to detect damage based on measured frequencies obtained from the vehicle parked at different locations. Numerical and experimental studies were conducted to verify the feasibility of the method. Furthermore, Cao et al. (2021) proposed a damage location index that utilized the frequency change rate of the VBI system obtained by parking the vehicle at different locations before and after damage. The relationship between the frequency-parameter change rate and damage severity was utilized for estimating the severity of the damage.

Mei et al. (2019) conducted damage detection using the data collected from sensors installed on several passing vehicles. The damage was identified by comparing the distributions of transformed features extracted from Mel-frequency cepstral coefficients (MFCCs) and PCA. Numerical and experimental results demonstrated that the method can detect not only the presence of damage, but also its severity.

Li et al. (2023a) presented an approach for localizing and quantifying bridge damages using a sensing vehicle and a temporarily parked truck. The sensing vehicle was used to identify the bridge frequencies, and the addition of the temporarily parked truck at different locations allowed for the collection of additional modal information about the bridge, thereby enhancing the sensitivity to local damage. A MAC-based objective function that utilizes the identified frequencies was used to enhance the robustness of damage detection.

For damage localization and quantification, González et al. (2023) compared the estimated PSD of the bridge component of the contact response with PSDs obtained from a reference database. Roughness effect was removed by subtracting contact responses at different speeds in the spatial domain.

1.5.1.2 Mode Shape-Based Methods

Zhang et al. (2012) proposed a method for approximate extraction of mode shape squares (MOSS) of plate and beam structures using the acceleration data of a passing vehicle equipped with tapping devices. In the study, a damage index was proposed based on the difference between the damaged and intact MOSS curve. Furthermore, a local damage detection algorithm called the global filtering method was established by Zhang et al. (2013) based on the curvature of the operating deflection shape extracted from a passing vehicle. The feasibility of these methods was confirmed by both numerical simulation and laboratory test.

Oshima et al. (2014) employed the estimated mode shapes to identify the bridge damages such as immobilization of rotational support and decrease in beam stiffness at the center point. The numerical simulation showed that the approach is able to recognize the bridge state with severe damage, but has low robustness against noise.

OBrien and Malekjafarian (2016) proposed an algorithm for bridge damage detection utilizing mode shapes estimated by the modified STFDD from a passing vehicle. The detection of damage presence and location was achieved using a damage index based on the MOSS. The study demonstrated that the algorithm can successfully detect the damage presence and location with acceptable accuracy, particularly when the vehicle was moving at a very slow speed.

Mode shape curvature change has been regarded as a promising damage localization index. He et al. (2018a) localized damages in beam structures without the need for reference data by utilizing mode shapes extracted from a moving vehicle. They formulated an index based on the regional mode shape curvature (RMSC) before and after localized damage. Numerical studies demonstrated the superior noise resistance of the RMSC-based damage localization index compared with conventionally used indices. Furthermore, they explored the relationship between damage extents and RMSC changes for damage quantification (He et al. 2019). Numerical and experimental studies were conducted to validate the effectiveness of the proposed method.

Tan et al. (2020b) employed a MOSS-based method for detecting bridge damages, including local damage resulting from a bridge strike and global damage arising from foundation scour. The mode shape can be extracted by using the HT technique. Laboratory experiments were conducted to validate the mode shape extraction and bridge damage detection processes for both cases of local and global damages.

Yang et al. (2020, 2022) presented a method to estimate the dynamic characteristics of the fundamental mode and evaluate the element stiffness of a girder bridge using a passing tractor with two identical trailers. To remove the adverse effects of road surface roughness, the residual acceleration of the two trailers was utilized. Subsequently, the HT (Yang et al. 2020) or STFT (Yang et al. 2022) was employed to reconstruct the fundamental mode shape. Furthermore, the element stiffness of the bridge was evaluated using the reconstructed fundamental mode shape. Also, two stationary vehicles were adopted to construct bridge mode shapes by the SVD and therefore evaluate the element stiffness based on the identified fundamental mode shape (Yang et al. 2023). The methods were verified numerically and field tested on the Li–Zi–Wan bridge.

Zhan et al. (2021) proposed a double-pass mass-addition method for identifying bridge mode shapes and detecting potential damage. Experimental validation confirmed the effectiveness of the method in identifying bridge damages, even in the presence of road surface roughness.

Yang and Wang (2022a) used the appropriately designed elliptic filter and HT technique to extract mode shapes of damaged bridges. Unlike existing VSM techniques, the method does not require the use of a damage index to identify damage locations in bridges. The presence of kinks observed in the mode shapes facilitated the identification of damage locations.

Corbally and Malekjafarian (2022b) proposed the operating deflection shape ratio (ODSR) for bridges, computed from the accelerations of two consecutive axles of a passing vehicle. Unlike the derived bridge mode shapes, the ODSRs are unique dimensionless values, being sensitive to damages. Numerical studies and laboratory experiments confirmed that the ODSR can be calculated from in-vehicle vibration measurements and utilized to detect changes in the structural behavior of the bridge.

Zhang et al. (2022) proposed a damage detecting method for hinge joints in hollow slab bridges based on the curvature mode shape extracted from moving vehicle responses. The study involved a stationary excitation vehicle equipped with a shaker to stimulate the bridge, while another vehicle traversing the driving path and collecting acceleration data for mode shape extraction. Such a technique was used to detect the deck damage of box girder bridges with the moving vehicle traversing along the specially predetermined path (Zhang et al. 2024). Numerical analysis was conducted to validate the effectiveness of the method.

1.5.2 Signal Processing-Based Methods

Li and Au (2014) proposed a multistage damage detection method by using the modal strain energy-based method and genetic algorithm (GA). The modal strain energy-based method estimated the damage location by using a damage indicator from the frequencies obtained from vehicle responses in both the intact and damaged states of the bridge. Subsequently, the identification problem was transformed into a global optimization problem, which was solved by the GA. To enhance the technique for identifying damage in girder bridges with rough surfaces, a guided GA-based method was employed to search for the global optimal value (Li and Au 2015). The method was numerically demonstrated to be effective for identifying the location of damages.

To detect and localize damages of a bridge, wavelet-based damage detection methods have been often used. Hester and González (2017) conducted a theoretical examination of the merits and potential limitations of the VSM for identifying localized stiffness loss in a bridge. They utilized a more elaborate 2D wavelet analysis, examining wavelet coefficients in the time–frequency domain, to detect damage. The study demonstrated that the mother wavelets with shapes closer to the damage component produced the best results. Tan et al. (2020a) examined the utilization of continuous WT (CWT) combined with Shannon entropy to infer the locations and extents of bridge damages. The wavelet entropy at different scales was measured, and the wavelet function corresponding to the scale with the lowest entropy exhibited the highest sensitivity to damages. The WT was applied by Zhang et al. (2022) to detect scour damage. It was found that the wavelet energy increases as the scour damage level increases. Furthermore, Lei et al. (2024) employed the WT technique to identify the location of the bridge damage based on the singularities extracted from the residual contact deflection response. The contact deflection response can be calculated by the generalized Kalman filter under unknown input (GKF-UI) conditions. The effectiveness of the method was demonstrated numerically.

OBrien et al. (2017a) employed the EMD technique to decompose the signal measured from a passing vehicle into its principal components. Then, the IMFs associated with the vehicle speed component were used to detect damages by comparing the signals between healthy and damaged structures. Kildashti et al. (2020) used the difference between the IMFs decomposed by the EMD technique to detect the cable damages using the VSM. Numerical investigations demonstrated that by considering specific vehicle parameters, the vibration response of the vehicle can be used to detect not only the presence of the damage in the bridge, but also the location and severity of the damage.

Krishnanunni and Rao (2021) developed a signal processing approach based on integrating the Tikhonov regularization with signal averaging technique. They demonstrated that by incorporating multiple runs of the vehicle, the method can effectively quantify the structural damage. The capability of the approach in detecting both the magnitude and location of the damage was demonstrated numerically.

Mokalled et al. (2022) utilized a Bayesian estimation technique to perform multilevel damage classification without requiring baseline or labeled data. Furthermore, they proposed a method to map the crack ratios identified on the simplified model to the physical levels of damage. The study demonstrated that the VSM is capable of effectively utilizing noisy experimental data to reliably detect, locate, and quantify small levels of crack damage along the entire length of a bridge. In addition, OBrien et al. (2024b) utilized a Bayesian approach to estimate the roughness profile and detect bridge damage by analyzing the accelerations recorded from a fleet of passing vehicles. The method can accurately quantify the damage level of a bearing and infer additional bridge properties related to bearing damage.

1.5.3 Machine Learning-Based Methods

In recent years, the advancement of computational technology and data science has made ML and particularly deep learning (DL) algorithms more accessible and widely employed in vibration-based structural damage detection. These algorithms have been developed and effectively applied in the field of the VSM.

Chen et al. (2014) presented a multi-resolution classification framework with semi-supervised learning (SSL) on graphs for bridge health monitoring. The framework employed adaptive graph filtering to facilitate semi-supervised classification, allowing for the classification of unlabeled and unseen signals, while correcting mislabeled signals. The method's effectiveness was validated using a dataset comprising 6,240 acceleration signals generated by a lab-scale bridge–vehicle dynamic system.

Liu et al. (2019) presented a semi-supervised algorithm for damage localization and quantification using multitask learning. This approach preserves the nonlinear characteristics of the VBI system and mitigates the propagation of significant uncertainties in damage location estimation. Furthermore, Liu et al. (2020) employed various dimensionality reduction techniques to extract representative features from the vibration response of vehicles and subsequently proposed an unsupervised damage severity comparison model and a semi-supervised damage severity estimation model for the indirect monitoring of bridges. Applying a supervised learning model trained on one bridge directly to new bridges may lead to reduced accuracy due to variations in the data distributions among different bridges. Therefore, Liu et al. (2021) proposed the hierarchical multitask unsupervised domain (HierMUD) adaptation framework, which enables the transfer of a damage diagnosis model learned from one bridge to a new bridge without the need for any labels from the new bridge. The effectiveness of the framework was evaluated using experimental data collected from two bridges and three vehicles. The findings offered compelling evidence to support the applicability of the VSM for bridges.

Malekjafarian et al. (2019) proposed a two-stage ML approach for bridge damage detection. In the first stage, an artificial neural network (ANN) was trained using the vehicle responses obtained during multiple passes over a structurally sound bridge. In the second stage, a damage indicator was defined based on a Gaussian process that detects variations in the distribution of prediction errors. Numerical studies demonstrated the successful detection of damage, even at low levels, in the presence of road roughness profiles and measurement noise. Furthermore, Corbally and Malekjafarian (2022a) trained the ANN to recognize the influence of temperature effects on bridges. Simulation results demonstrated that the algorithm can successfully identify damage while effectively mitigating the impact of temperature variations. Then, Corbally and Malekjafarian (2024a) developed a DL framework for bridge condition monitoring by a passing vehicle. This approach enables the identification of the presence, type, location, and severity of bridge damage without requiring premeasured training data. Furthermore, Corbally and Malekjafarian (2024b) utilized the ML techniques to leverage the effect of vehicle speed and ODSR as an alternative damage-sensitive feature. Through laboratory experiments, the study demonstrated the method's capability to detect mid-span cracking and seized bearings.

Locke et al. (2020) developed a finite element model for a simply supported bridge, incorporating environmental and operational effects as well as different levels of structural damage. The multilayer convolutional neural network (CNN) was used to analyze the extracted data, and a robust relationship between observations and bridge health was established. The results of the multi-class study showed the CNN's effectiveness in detecting bridge damage amid various real-world noise signals.

Sarwar and Cantero (2021) utilized vertical accelerations of a fleet of vehicles passing over a healthy bridge to train a deep autoencoder model (DAE) for extracting bridge damage sensitive features. They showed that when considering the distribution or results from multiple vehicle-crossing events, the trained DAE exhibits sensitivity to damage by revealing errors in signal reconstruction. Furthermore, they proposed a probabilistic deep neural network based method (2023) to investigate and quantify the influence of different sensor information combinations. Such a technique was capable of estimating the uncertainty of its predictions under varying operational and environmental conditions. The effectiveness of these methods was evaluated in two case studies involving five-axle trucks crossing a simply supported beam and a multi-span continuous bridge.

Cheema et al. (2022) presented a data-driven approach by integrating a nonlinear dimensionality-reduction technique using uniform manifold approximation and projection (UMAP) together with a nonparametric clustering technique using hierarchical density-based spatial clustering of applications with noise (HDBSCAN). Furthermore, Calderon Hurtado et al. (2023) proposed an unsupervised learning framework utilizing an adversarial autoencoder for damage detection utilizing only the measured responses from a vehicle passing. The framework utilized the reconstruction error estimated by the proposed model as a damage detection index. Then, they presented an approach that utilizes computer vision-based unsupervised learning methods for the detection and quantification of damage on simply supported bridges Hurtado et al. (2024). The performances of two state-of-the-art unsupervised generative ML methods, namely, the convolutional variational autoencoders (CVAE) and convolutional adversarial autoencoders (CAAE), were compared for the task of damage assessment. The damage index was defined based on the measured error between the original and reconstructed images. In another study, Alamdari (2024) formulated the problem of bridge health monitoring as an unsupervised semantic segmentation task. The objective was to detect unexpected irregularities in the time-series data collected by the test vehicle, thereby identifying the onset of structural damage. The study showed the potential of the method as a cost-effective and robust tool for bridge health monitoring.

Li et al. (2023d) employed both low- and high-frequency responses of a passing vehicle to detect damages in bridges. They utilized MFCCs and support vector machine (SVM) for classifying damage severity. A laboratory experiment showed that high-frequency responses contain much information about the bridge's condition, and the use of MFCCs improved computational efficiency in the detection process. Subsequently, they proposed a damaged-label-free, ML-based, indirect bridge-health monitoring method named assumption accuracy method (Li et al. 2023b). To enhance the efficiency and precision of damage detection, the PCA and MFCCs were explored to space the vehicle's frequency responses into low-dimension spaces for classification. They found that MFCCs were more sensitive to detect bridge damage. Then, Li et al. (2023e) presented an unsupervised DAE to automatically detect the bridge's damage in real time. The potential of this approach was investigated using a laboratory U-shaped beam and a model truck equipped with two accelerometers.

Lan et al. (2023d) utilized a data-driven approach based on optimized AdaBoost-linear SVM to indicate bridge damage using only raw vibration signals obtained from a passing vehicle. Furthermore, they proposed a novel time-domain signal processing algorithm for the raw vehicle acceleration data of data-driven drive-by inspection methods, which can improve the accuracy and efficiency of ML models in the vehicle-based damage detection (Lan et al. 2023b). Then, Lan et al. (2024) proposed an automatic physics-guided diagnosis framework for bridge health monitoring utilizing only raw vehicle accelerations. The framework is based on physical insights and statistical methods, in which typical ML operations are not performed. The methods were validated using a dataset obtained from laboratory experiments, in which a steel beam and a scale truck model with an engine were employed.

Yin et al. (2024) trained a long short-term memory (LSTM) network to predict the contact response. A damage indicator, Euclidean distance damage index (EDDI), based on the difference between the actual and predicted contact responses was proposed. The results demonstrated the efficacy of EDDI in discerning between the damaged and healthy states of the bridge.

1.5.4 Other Methods

To enhance the results of damage identification, hardware measures have also been implemented. Xiang et al. (2010) developed an active tap-scan method for damage detection, capable of extracting bridge damage from the acceleration data obtained from a passing vehicle equipped with a shaker. Furthermore, they proposed a passive tap-scan approach, utilizing an automated vehicle with specially designed tire treads to scan the bridge (Hu et al. 2020). Instead of employing a shaker, the tapping force is generated passively by coordinating the vehicle velocity with the periodic pattern of the tire tread. Experimental results validated the theoretical analysis and addressed critical factors contributing to the success of the method. Furthermore, they utilized the passive tap-scan technique to detect stiffness transitions in beam structures (Hu et al. 2023). The practical effectiveness of this damage detection method was demonstrated through a field test conducted on an actual bridge.

OBrien and Keenahan (2015) designed and developed a traffic speed deflectometer (TSD) for measuring pavement deflections, which can also be utilized for bridge damage detection. They proposed an adapted cross-entropy optimization algorithm to determine the apparent profile, and the time-shifted difference in the apparent profile was employed as the damage indicator. The TSD model was further enhanced to incorporate a vehicle equipped with five displacement sensors (Keenahan and OBrien 2018). The time-shifted kurtosis was introduced as a damage indicator. Furthermore, OBrien et al. (2023, 2024a) proposed a bridge damage indicator based on the moving reference influence function (MRIF) obtained from apparent profile difference to detect bridge bearing damage using accelerations collected from a instrumented vehicle fleet. The results demonstrated the accurate estimation of the bridge roughness profile and successful identification of bridge bearing damage using the MRIF.

Kong et al. (2015) employed the transmissibility between a simple beam and a single-DOF vehicle to establish damage indicators for bridge assessment. The transmissibility of the vehicle responses was measured using either a reference vehicle and a moving vehicle or two moving vehicles at a fixed distance. Numerical study was conducted to verify the method.

Zhu et al. (2018) estimated the local anomalies of a structure by analyzing the VBI force using the Newton's iterative method based on the homotopy continuation method. The numerical results demonstrated the high sensitivity of the interaction force along the vehicle's travel path in detecting local damages in the bridge. Then, they presented a two-step method for the bridge damage identification (Li et al. 2020a). In the first step, the pavement roughness was estimated from the dynamic responses of a passing vehicle using the DKF. In the second step, bridge damage was identified through interaction force sensitivity analysis with the Tikhonov regularization. Experimental investigations demonstrated that the proposed method can effectively and reliably identify the interaction force and bridge surface roughness. Furthermore, numerical simulations confirmed that the proposed strategy was efficient and accurate, enabling a rapid evaluation of bridge conditions.

Kumar et al. (2021) investigated the feasibility of utilizing the dynamic tire pressure for bridge health monitoring by establishing a relationship between the variation in VBI force and the changes in dynamic tire pressure. The study initially estimated tire model parameters using the Bayesian inference. Subsequently, the tire model was employed to reconstruct the changes in VBI force based on the measured tire pressure, which is indicative of bridge damage. Numerical experiments showed the method's potential for damage identification, even in the presence of measurement noise and other uncertainties.

Aloisio et al. (2021) presented an indirect procedure for estimating the bending stiffness of simply supported girders using an instrumented vehicle. The vehicle incorporates a swinging pendulum equipped with a laser sensor. The displacement response of the pendulum provides an estimation of the bending stiffness for each bridge span by optimizing the correlation function between the recorded displacement of the pendulum and that generated through numerical simulation. The feasibility of the procedure was evaluated on a set of real-case bridges.

1.6 Pavement Roughness Identification by Researchers Worldwide

Roughness plays a crucial role in driving comfort. For the VSM, identifying roughness and eliminating its negative effects is an important task. Since the surface roughness for bridges is generally different from that for roads and this book is focused exclusively on *bridges*, no attention will be paid to the *road* surface roughness identification methods (Imine et al. 2006; Nguyen et al. 2019; Yu et al. 2022; Fares and Zayed 2023). Consequently, this section is devoted mainly to the research progress on pavement roughness identification for bridges. It should be noted that road surface roughness identification methods cannot be directly applied to bridges due to involvement of the VBI effect. Only studies that considered the VBI effect in roughness identification will be reviewed herein.

Wang et al. (2017) estimated the bridge roughness using the responses from a sensor-equipped probe car (modeled as the four-DOF half-car system) considering the VBI based on a particle filter. The accuracy of the method was verified against the roughness measured by a portable profiler in a field test.

Zhan and Au (2019) estimated the roughness profile by conducting multiple runs of a vehicle along the bridge with varying added masses. The study examined three vehicle models, i.e., the spring-mass model, spring-damper-mass model, and half-vehicle model. The feasibility and effectiveness of the method were evaluated by numerical simulations that included both a simply supported bridge and a continuous bridge.

Shereena and Rao (2020) investigated the simultaneous identification of road roughness and vehicle parameters considering the VBI effect. The identification process involved coupling an unbiased minimum variance estimator with an optimization scheme. The technique was demonstrated to be successful in estimating the vehicle parameters, roughness profile, and vehicle responses simultaneously.

He and Yang (2021) proposed a computational framework, based on the DKF-UI algorithm, for simultaneously estimating the state of the VBI system and pavement profile of a bridge using the dynamic responses of a moving vehicle. The study revealed that the VBI effect on estimating pavement profile can be ignored for a relatively light vehicle or a stiff bridge.

Feng et al. (2023) investigated the utilization of axle accelerations from a standard two-axle vehicle traversing a bridge to quantify the rotational stiffness of the supports and the height of pavement roughness. They obtained the road profile by calculating the difference between the displacement of the bridge under each axle and the displacement of the CP. The study showed a high level of agreement between the true and estimated road profiles for the bridge.

1.7 Vehicle Scanning Method for Railway Tracks and Bridges

In addition to its application in highway bridges, the VSM has gained significant traction in railway systems, covering a wide range of applications such as track geometry estimation, dynamic parameter identification for railway tracks and bridges, and track defect detection.

1.7.1 Track Geometry Estimation

Weston et al. (2007a) presented the theory and practical results of employing a bogie-mounted pitch-rate gyro to acquire the mean vertical alignment. Trial results from the Tyne and Wear Metro vehicles and a Class 175 mainline vehicle demonstrated effective monitoring of vertical irregularities. Furthermore, either bogie lateral acceleration or yaw rate can also be utilized to estimate the mean lateral track irregularity (Weston et al. 2007b).

Tsunashima et al. (2008) and Mori et al. (2010) proposed a probe-vehicle system that utilizes vertical and lateral accelerations of a car body to estimate rail irregularities. A roll angle of the car body, calculated using a rate gyroscope, was used to differentiate between irregularity of the line and that of the track level. Experimental results demonstrated the effective estimation of rail irregularity and rail corrugation conditions. Furthermore, by applying the Kalman filtering (KF) to estimate track irregularity from car-body motions, accurate estimations of vertical track irregularity were achieved (Tsunashima et al. 2014; Odashima et al. 2017).

Wei et al. (2016) employed the acceleration sensors on the bogie and the car body to estimate track irregularities. Four acceleration sensors were installed on each bogie to measure short- and middle-term wavelength irregularities, and four sensors were placed on the car body to measure moderate and long wavelength irregularities. The track alignments were then obtained by double integrating the signals preprocessed by a DC filter and a low-pass filter. Field tests were conducted on Shanghai Metro Line 1 to demonstrate the effectiveness of the method.

OBrien et al. (2016) utilized the cross-entropy optimization technique to determine the elevation profile of a railway track. The concept was numerically validated using a two-dimensional quarter-car dynamic model. Subsequently, a field test was conducted to assess the applicability of the method and to explore additional measures required to enhance the method's robustness against noisy field measurements (OBrien et al. 2017b). To this end, an Irish Rail intercity train was equipped with instrumentation for a duration of one month to test a novel optimization-based method for inferring the longitudinal profile of the railway track.

Three different model-based techniques were proposed by De Rosa et al. (2019) to estimate lateral and cross-level track irregularities from the vehicle response. The techniques included one in frequency domain and two in time domain. The results indicated that the linear observation model was well suited for identifying lateral alignment and cross-level track irregularities. Furthermore, both the frequency domain method and the approach based on the KF demonstrated accurate results, even in the presence of high levels of measurement noise.

Xiao et al. (2020) proposed a KF-based algorithm for real-time identification of track irregularities in railway bridges, considering the VBI effect. A state space model was established to represent the time-dependent VBI system subjected to unknown track irregularity excitations. The KF algorithm was utilized to optimally estimate the state vector of the VBI system and to identify the track irregularities. Subsequently, to enhance the convergence of estimation, an extended Kalman filter (EKF) algorithm with an adaptive procedure was proposed (Xiao et al. 2021), for simultaneous identification of the frequencies and track irregularities of the bridge. Furthermore, they proposed a recursive Bayesian Kalman filtering (RBKF) algorithm to quantify the identification uncertainty of the track irregularities and bridge frequencies (Xiao et al. 2022). Two numerical examples were presented to validate the accuracy of the algorithms.

Niu et al. (2020) proposed an approach to assess the track irregularity by using the transfer function from the measured carriage-body acceleration. The autoregressive with exogenous input model and state space model, respectively, were constructed using the system identification techniques to establish the transfer relationship between the track irregularity and carriage-body acceleration. The correlation value between the predicted and measured carriage-body acceleration demonstrated that both models can effectively capture the transfer characteristics between the track irregularity and carriage-body acceleration.

Muñoz et al. (2021) proposed a simple measuring system, combining a dynamic model-based KF estimator, for continuous monitoring of track geometry and estimation of lateral alignment on in-service vehicles. Furthermore, Muñoz et al. (2022) enhanced the procedure by the KF technique to measure both lateral and vertical track irregularities from different sensors mounted on a dedicated vehicle. The effectiveness of the method was experimentally validated in a 1:10 scaled track facility at the University of Seville.

Hao et al. (2023) proposed the attention mechanism CNN-gated recurrent unit (AM-CNN-GRU) model for track geometry estimation from the vehicle-body acceleration. The model was trained and tested using the inspection data obtained from comprehensive inspection trains on three major high-speed railways in China. The effectiveness of the model was evaluated for different models, high-speed lines, sub-rail infrastructures, and speeds.

Guo et al. (2023) proposed a method for identifying the vertical and lateral track irregularities by utilizing a system-based attitude calculation and a model-based unknown input observer estimator from the dynamic responses obtained by distributed multi-sensors installed on both the vehicle and bogie. The experimental results showed a reasonable agreement between the results obtained from the track inspection vehicles and the identified irregularity profiles.

Stoura et al. (2023) proposed a method that combines reduced-order vehicle models with a model-based Bayesian inference approach to estimate roughness profiles. The dynamic interaction between the trains and tracks was considered. To enhance the inference, a prior updating of the vehicle model parameters was employed using an unscented Kalman filter (UKF) and available measurements from a diagnostic vehicle. The results demonstrated that the method can accurately estimate the rail roughness profiles while achieving computational efficiency.

Carrigan and Talbot (2023) proposed a method for estimating rail roughness PSD using axle-box accelerations. The method utilized a transfer function in frequency domain that takes into account variations in track support stiffness and the vibration coupling between wheels. The effectiveness of the method was demonstrated by simulated and measured data.

Data-driven methods can effectively handle concatenation of multidimensional signals and complex rail irregularities. However, they can be sensitive to uncertainties. To address this issue, Zhuang et al. (2023) proposed a DL framework that incorporates heterogeneous factors at each link in its ensemble strategy. The performance of the method was quantitatively evaluated by considering various on-site rail-surface conditions. The results showed the prediction errors of 4.7% and 6.5% and classifier accuracies of 98.4% and 93.7% for irregularities and defect severities, respectively.

Cai et al. (2023) proposed a Bayesian-optimized improved bidirectional LSTM (BO-BiLSTM) neural network model for point estimation of irregularities. The model utilized the vehicle's vertical and lateral acceleration as input and demonstrated an estimation error approximately 50% lower than that of conventional recurrent neural networks. They suggested developing lightweight neural network models to save the calculation time and estimating the short-wave irregularity of the turnout area using the axle box acceleration (ABA) data to improve accuracy in the future.

Zhang et al. (2024) found that onboard microelectromechanical system (MEMS) accelerometers, especially those installed on the bogie, provide the best balance between proximity to the source and insensitivity to impulsive noise when estimating the track condition parameters. The study indicated that two bogie MEMS accelerometers with vertical and lateral measurement axes are effective for estimating the geographical distributions of vertical and horizontal alignment.

Pires et al. (2024) proposed a data-driven approach to estimate geometric track irregularities from instrumented railway vehicle. ML models were trained and used to find the nonlinear mapping between the data collected by the instrumented railway vehicle and track irregularities.

1.7.2 Identification of Dynamic Parameters of Railway Tracks and Bridges

Quirke et al. (2017b) proposed a method for the detection of track stiffness variation through an analysis of vehicle accelerations. The cross-entropy optimization technique was used to determine the track stiffness profile that generates a vehicle response closely matching the measured vertical accelerations of a railway carriage bogie. Numerical studies successfully demonstrated the effectiveness of the method in estimating local variations in track stiffness. This idea was subsequently extended to damage detection for railway bridges, which involves apparent profiles sensed by the passing vehicle (Quirke et al. 2017a).

Matsuoka et al. (2021) developed a drive-by system to detect resonant bridges from the data measured by high-speed railway vehicles. The resonance detection index (RDI) was defined as the difference between the track irregularities measured by the first and last vehicles. The index was utilized to emphasize the component that is excited by the vehicle length, thereby proposing a method for detecting resonant bridges. Subsequently, based on the distinct peaks of track irregularities observed at the first and last vehicles, a method was developed to estimate bridge deflection (Matsuoka and Tanaka 2023). The maximum deflections of five bridges, estimated using the track irregularity data, exhibit a strong agreement with the separately conducted on-site deflection measurements.

Zhan et al. (2021a) proposed a method for identifying the modal frequencies of railway bridges using the dynamic responses of two-axle vehicles. They improved the time-domain subtraction method (TSM) for two connected two-axle vehicles to mitigate the impact of track irregularities on bridge frequency identification. Furthermore, they proposed a method to identify bridge frequencies from high-speed railway vehicles by combining the responses of multiple vehicles (Zhan et al. 2021b). The residual vehicle responses were obtained and combined to eliminate additional driving frequencies and to prevent interference on bridge frequency identification. The method was validated through numerical simulations.

Malekjafarian et al. (2022b) utilized an EEMD-based Hilbert–Huang transform (HHT) technique to monitor the natural frequencies of the Malahide viaduct bridge in northern Dublin. The frequencies obtained from drive-by measurements were compared with those from direct measurements, confirming the efficacy of indirect approaches.

Erduran et al. (2023) presented a method for extracting bridge frequencies from vibrations measured by train-mounted sensors. The CWT was employed to differentiate the bridge frequencies from other peaks present in the Fourier spectrum of the accelerations of train bogies. The effectiveness of the method was demonstrated by numerical studies.

1.7.3 Track Defect Detection

Caprioli et al. (2007) conducted a comparison between the WT and conventional Fourier analysis for estimating the track status using the acceleration signals from a train bogie. They aimed to find a balance between complex mathematical techniques, such as wavelet packet analysis, which may be challenging for engineers to comprehend. The case study demonstrated that the WT is a promising technique that yields satisfactory results for fault detection in rails from the ABAs. Subsequently, Bocciolone et al. (2007) conducted a feasibility study on a reliable diagnostic tool aimed at obtaining the rail status via the axle-box accelerations, with a primary focus on the problem of short-pitch corrugation. This study investigated the optimal measurement points and the influence of the train's substructure and traveling conditions on the recorded vibration levels. This study primarily concentrated on the measurement problem, deferring the theoretical aspects to a future study.

Molodova et al. (2011) utilized the ABA measurements to evaluate various short track defects, such as squats, poor welds, insulated joints, and corrugation. By establishing a quantitative relationship between the ABA and track defects through finite element modeling, they were able to detect the locations and severity of defects in the track and rail profile. Additionally, they employed the WT to analyze ABA data for squat detection (Molodova et al. 2014). To make the early detection of squats become feasible, three improvements were proposed by Li et al. (2015). In another study, Molodova et al. (2016) derived the frequency characteristics of the ABA to detect insulated rail joints (IRJs). They evaluated a set of real-life IRJs under different conditions on two tracks in the Netherlands, achieving an 84% detection rate for IRJs.

Chen et al. (2014) employed the EMD to analyze the characteristic frequency distribution of the ABA induced by defects and utilized the HHT to examine the time–frequency changes in the signal. Their findings demonstrated the effective localization of rail defects and the detection of short wave irregularities within a certain degree.

Cantero and Basu (2015) proposed a WT-based automatic assessment method for detecting local track defects in weaker sections, utilizing the vertical accelerations recorded from a moving train. The method enables the selection of suitable thresholds for different segments of the infrastructure. Peaks exceeding the threshold indicate a high concentration of energy resulting from an isolated irregularity due to a deteriorating or damaged track section. Monte Carlo simulation was conducted to validate the method for various irregularities and vehicle properties.

Wang et al. (2017) proposed an approach based on frequency shift to identify damaged supports, including loose or missing fasteners and damaged ballast. The study revealed a significant drop in natural frequencies when the auxiliary mass is removed over the damaged support. However, the approach presented by Wang et al. (2017) is static in nature, where the train or auxiliary mass remained stationary at one position before moving to the next position for subsequent measurements. To extend their previous work, Zhang et al. (2019a) extended the method by utilizing the dynamic responses of a passing train. The method was demonstrated to be effective for detection of damaged supports, as validated numerically and experimentally.

Lederman et al. (2017a) conducted track inspection using the vibration data collected from an operational passenger train. Four features, i.e., temporal frequency, spatial frequency, spatial domain, and signal energy, on simulated data were tested. It was found that signal energy was the most effective feature for detecting both track changes and tamping changes. Furthermore, a sparse approach for analyzing the vibration data obtained from an operational train was proposed for track monitoring (Lederman et al. 2017b). Then, a data fusion approach for enabling data-driven rail-infrastructure monitoring using multiple in-service trains was presented (Lederman et al. 2017c). The objective was to develop a method to combine extracted features from multiple passes over the tracks from various sensors on different trains. An adaptive Kalman filter was introduced to overcome challenges faced in this regard. The performance of the method demonstrated that data fusion aids in detecting track changes and can serve as a crucial component in a data processing pipeline for network-level track monitoring using in-service trains.

The use of vehicle responses in track geometry assessment enables the identification of critical defects, while enhancing the maintenance operations. Kraft et al. (2018) proposed a vehicle response-based assessment method for track geometry using multi-body simulation. Defects were detected by the exceedances of track geometry and vehicle response parameters.

A track-vehicle scale model was built by Rapp et al. (2019) to generate continuous acceleration data for various types of short-wavelength failures. Five methods were investigated with automated failure analysis for the detection of local irregularity. These methods included analyzing typical amplitude ranges, performing frequency analysis using windowed spectral acceleration density, utilizing cross-correlation, applying wavelet analysis, and employing failure detection based on the classification of peaks by amplitude and wavelength. All of these methods successfully detected the local irregularity at the correct position.

Tsunashima and Hirose (2020) employed the HHT to identify the track faults from car-body acceleration. Numerical study and field test demonstrated that the HHT offers excellent time–frequency resolution and that IMFs provides detailed information about track faults.

Bai et al. (2020) proposed a model for data-driven bias correction and defect diagnosis using in-service vehicle acceleration measurements. The model consists of two sub-models: the bias correction sub-model, which aims to eliminate false positive track vibration defects detected by track quality instruments, and the defect diagnosis sub-model, which is designed to diagnose the causes of severe vertical and lateral cabin vibrations (i.e., track vibration defects). The model was validated using the actual measurement data obtained from the Lanxin Railway.

Zhan et al. (2023) proposed an indirect bridge frequency identification and damage detection method based on the virtual contact responses of railway vehicles moving over the bridge. The method utilized the spectral entropy of the TRF to quantify time–frequency changes, which serves as a damage index for localizing the bridge damage. Furthermore, they proposed a damage detection method for high-speed railway bridges using response-based sensitivity analysis of high-speed trains (Wang et al. 2024). To address the critical issue of limited response data recorded by high-speed vehicles moving over the bridge, they merged the responses of multiple vehicles. Then, a damage indicator was established by evaluating the change in interaction force before and after damage occurrence when a vehicle passed through a pier (Wang et al. 2024). The DKF was utilized to estimate the interaction forces between vehicle bogies and wheel sets based on the dynamic responses of the passing vehicles. Numerical studies were conducted to validate the effectiveness of the proposed methods.

A deep CNN was constructed, optimized, trained, and tested for automatic damage detection using the acceleration signals collected from an instrumented train by Hajializadeh (2023). The hyperparameters of the algorithm were optimized using the Bayesian optimization techniques. The accuracy of the algorithm was experimentally evaluated for four distinct damage scenarios (comprising different locations and intensities) and three traveling speeds.

Shi et al. (2024) proposed an on-board damage detection method for heavy-haul railway bridges utilizing bogie accelerations, which allows for accurate damage localization and quantification. The sensitivity of bogie vertical accelerations to damage was analyzed, leading to the development of a sensitivity equation for the coupled system. Results indicated that the method outperforms the conventional ones in terms of damage localization and quantification.

Ghiasi et al. (2024) proposed an AI-based approach for identifying track geometrical defects using a dedicated measuring high-speed train. The algorithm defined anomalies as relative changes to the historical behavior. A comprehensive dataset from field measurements of a Société Nationale des Chemins de Fer Français (SNCF) Réseau IRIS320 high speed train was used to implement the proposed approach.

1.8 Application of Smartphone-Based IoT System in VSM

A smart city refers to a city development model that utilizes information technology and communication technology to improve urban operations and provide resident services. It involves integrating and leveraging technologies such as big data, the IoT, and artificial intelligence to achieve intelligence and efficient operation in various aspects of urban infrastructure, transportation, public services, etc. With the emergence of the concept of smart city, there has been a growing interest in the application of smartphones, which are widely used mobile devices, in health monitoring (Sony et al. 2019; Yu et al. 2022; Sarmadi et al. 2023). Building upon this concept, the utilization of vehicle-mounted smartphones for bridge health monitoring has rapidly evolved.

McGetrick et al. (2017) compared the performance of smartphone sensors with wired accelerometers, a data acquisition system, and a Leica GS14 smart antenna. In terms of cost, the smartphone system was found to be approximately 100 times less expensive than the alternative specialized equipment. It was found that there are qualitative limitations when applying existing drive-by monitoring algorithms to crowdsourced acceleration data. Factors such as consistent sampling rates, sensor type, and position and orientation need to be further investigated.

Matarazzo et al. (2018) showed that mobile sensor networks were well suited for routine monitoring of bridge vibrations. In an application conducted on the Harvard Bridge in Boston, it was observed that acceleration data collected using smartphones in moving vehicles consistently revealed significant indicators of the bridge's first three frequencies. Notably, the precision of the results improved when data from multiple smartphone datasets were combined. In a subsequent study (Matarazzo et al. 2022), they developed an analytical method that effectively extracted modal properties from the data collected by smartphone on vehicles. The method was applied successfully to partially controlled crowdsourced data collected on a long-span suspension bridge in the United States and a short-span highway bridge in Italy. Further analysis indicated that incorporating crowdsourced data into a maintenance plan for a new bridge can extend its service life by over 14 years, representing a 30% increase, without incurring additional costs.

Mei and Gül (2019) presented a framework for monitoring a population of bridges utilizing smartphones in a large fleet of moving vehicles. For this, they developed a damage detection method based on MFCCs and Kullback–Leibler divergence. Subsequent analytical and experimental results (Shirzad-Ghaleroudkhani et al. 2020) showed that by analyzing vibration data recorded using a smartphone on a vehicle crossing a bridge, it is possible to detect the fundamental frequency as well as potentially higher mode frequencies of the bridge. Given that severe damage to a bridge would significantly impact its fundamental frequency, this study demonstrated the potential for identifying such damage through a suitable crowdsensing framework that collects data from a substantial number of smartphones on various vehicles traversing the bridge. Furthermore, three applications of smartphones and in-vehicle cameras for bridge and road health monitoring were presented (Mei et al. 2020). The study showed that the crowdsensing-based monitoring framework holds promise as a high-level prescreening tool, capable of monitoring various components of the transportation infrastructure system with lower costs and improved efficiency.

Shirzad-Ghaleroudkhani and Gül (2020) employed the inverse filtering technique to extract bridge features from acceleration signals recorded on passing vehicles using smartphones. The inverse filter was designed based on the vibration spectrum data from the vehicle and was used to remove car-related frequencies. Subsequently, an improved inverse filtering method was proposed (Shirzad-Ghaleroudkhani and Gül 2021), taking into account the effect of vehicle speed and surface roughness. The successful application of this approach to two full-scale bridges showcased its potential for future bridge monitoring endeavors. Furthermore, they presented an indirect bridge monitoring method that utilizes Mel-frequency cepstral analysis of inverse-filtered vehicle acceleration signals collected via smartphones (Shirzad-Ghaleroudkhani and Gül 2024). They used an abnormality index to detect changes in frequency spectrum patterns, serving as an indicator of the bridge structure's health condition. The laboratory experiments demonstrated the effectiveness of the method in detecting bridge damage through drive-by monitoring.

Sitton et al. (2020a) presented four post-processing strategies for estimating bridge frequencies from smartphone data. These techniques utilized the discrete Fourier transform (DFT) and multiple signal classification (MUSIC) algorithms to extract the fundamental bridge frequency by using single-vehicle and crowdsourced post-processing techniques. Furthermore, Sitton et al. (2024) employed the bridge frequency changes detected by smartphones in passing vehicles, along with a point cloud method, to identify critical damage scenarios and estimate the remaining life of bridges. They employed a crowdsourced Welch method to average spectra, effectively reducing the impact of noise and transient events. Numerical and experimental studies demonstrated the accurate estimation of bridge frequencies and the characterization of changes in bridge frequency caused by various damage scenarios.

Quqa et al. (2022) conducted studied the feasibility of utilizing drive-in smartphone data gathered by citizens operating micromobility light vehicles (e.g., bicycles and kick scooters) to extract dynamic characteristics of urban bridges, including natural frequencies and modal amplitudes. The outcomes from a real footbridge located in Bologna, Italy, indicated that while individual datasets collected by each vehicle may exhibit significant noise, a crowdsensing-based approach has the potential to offer features that can be utilized for monitoring urban infrastructures on a territorial scale.

Di Matteo et al. (2022) tested the feasibility of using a passing vehicle to estimate the natural frequencies of a bridge by field test. The results obtained from the smartphone were compared with those from the conventional piezoelectric accelerometer. The comparison demonstrated that even this low-cost and widely used technique can yield accurate results.

Meng et al. (2023) developed a smartphone application that allows for the monitoring of interior vibrations and noise in trains, as well as the real-time evaluation of human comfort levels. The system utilized a smartphone as an IoT sensing device, an Internet connection gateway, and an edge-computing device.

Liu et al. (2023b) proposed a smartphone-based method to identify bridge frequencies by utilizing the contact response of a four-DOF vehicle model. To facilitate practical applications, this method was integrated into a self-developed smartphone APP, enabling seamless data acquisition and timely identification of bridge frequencies. Numerical and experimental studies were conducted to validate the effectiveness of the method.

Peng et al. (2023a) developed an IoT sensing system that integrates a triaxial MEMS accelerometer, temperature sensor, global positioning system (GPS), and 4G module on Raspberry Pi 4 Model B. The sensor node can be mounted on a moving vehicle to collect the triaxial acceleration responses, temperature, and GPS information. The results verified that the developed IoT sensing system can successfully identify the first frequency of a full-scale footbridge.

1.9 Conclusions and Recommendations for Future Work

In this chapter, the research on the VSM for bridges from 2004 to 2024 has been reviewed. Since the initial proposal of the VSM in 2004, it has gained significant momentum from researchers worldwide. The VSM offers advantages in terms of mobility, efficiency, and economy for bridge health monitoring, as it requires only one or few vibration sensors to be mounted on the test vehicle, but none on the bridge. Over the past two decades, substantial progress has been made in various facets of the VSM, encompassing the identification of bridge frequencies, mode shapes, damping ratios, damages, and roughness, along with its application to railways. Based on the review of related literature and the authors' expertise, the following conclusions and recommendations for future work are made.

1.9.1 Conclusions

1) The mechanism of identification of the VSM for bridge parameters is well unveiled in previous studies. The VSM has been demonstrated to be applicable to various types of bridges, including simply supported bridges, multi-span bridges, curved bridges, thin-walled bridges, and bridges with various support conditions. Simultaneously, various vehicle models, including single-axle and two-axle vehicles, have been effectively utilized. Moreover, past research has advanced from 2D to 3D models, substantially strengthening the applicability of the VMS method.
2) The methods for identifying bridge modal parameters, including frequencies, mode shapes, and damping ratios, have been well established. Significant theoretical research and experimental

validation have been conducted, particularly on bridge frequencies and mode shapes, leading to some consensus. Although research on identifying damping ratios is relatively limited, significant progress has been made for reliable methods of identification. The establishment of theoretical frameworks for bridge modal parameter identification based on the VSM has laid the foundation for bridge health monitoring.

3) The use of VSM to detect bridge damages has been demonstrated by numerous numerical and laboratory experiments. Primary methods in this regard include those relying on bridge modal parameters and data processing techniques. Recently, ML technologies have advanced rapidly for bridge damage detection. Numerous studies on damage detection have been published, aiming to identify and quantify the damages to bridge structures. However, the intricate nature of actual bridge structures and the variability in environmental conditions may pose unforeseen challenges when attempting to generalize a damage detection method for practical applications. Therefore, further research is needed to advance the techniques of practical bridge damage identification.
4) Bridge vibrations collected by the vehicle are affected by vehicle's own frequencies. Various signal processing methods, including the contact response algorithms, filtering techniques, and modal decomposition techniques (such as EMD- and VMD-based methods), have been proposed and utilized to mitigate this adverse effect.
5) Pavement roughness is another factor that may downgrade the quality of the scanning technique. Previously, progress has been made in assessing the roughness level based on vibration responses of the test vehicle considering the VBI effect. To mitigate the adverse effects of roughness, recourse was taken to hardware approaches (e.g., introducing random traffic or an additional shaker) and software approaches (e.g., residual response analysis, filtering techniques, noise reduction, blind source separation, or ML).
6) Axle-box or bogie accelerations have been utilized to assess geometrical properties of railways, including track irregularities, light squats, and ride comfort. By integrating various data processing techniques and equipment, effective methods have been developed for identifying track modulus and for detecting potential track defects.
7) With the development of IoT technology, recent studies have utilized modern devices such as smartphones, vehicle networks, and cloud server to enhance the VSM technique. This kind of applications in bridge health monitoring shows promise and may become effective tools for future bridge management.

1.9.2 Challenges and Recommendations

While the VSM for highway bridges and railway bridges has been widespread and under intensive research, it remains an intriguing area challenging to engineers and researchers for implementation. Several suggested future directions are outlined as follows:

1) Structural detection is inevitably affected by uncertainty factors such as surface roughness, measurement noise, environmental changes, and non-perfect test vehicles. These factors may change the bridge vibration characteristics or pollute the collected data, thus hindering the identification of bridge modal parameters or damage identification. Further research is needed to develop effective methods for mitigating all these adverse effects.

2) Bridges, as large-scale structures, exhibit complexity in materials, structural forms, and geological supports, subjected to weathering and ageing. Small damages in a bridge may not result in detectable changes in vibration characteristics. Therefore, further research is needed to develop effective VSM-based damage identification methods for bridges.
3) In the past, validation of the VSM has often been conducted by laboratory experiments, as lab model tests are easier to design and implement. For the VSM to gain full trust and acceptance by agencies on bridge maintenance, further field tests are necessary.
4) Unlike highway bridges where the vehicle/bridge mass ratio is negligible, railway trains are typically heavy relative to the tracks. The time-varying nature of the railway track needs to be considered, as it may relate to the structural health status. Besides, railway trains are generally complex, requiring the development of effective signal denoising techniques that can reveal their intrinsic structural characteristics. The vibration frequencies of tracks are significantly higher than those of highway bridges, suggesting the need to develop sensitive damage indicators for the damage detection of railway tracks and components. The spatiotemporal synchronization of signals collected by trains at high operating speeds remains a challenge as well, for which in-depth and continuous research should be conducted.
5) With the rapid development of electric vehicles, intelligent driving technologies have been proposed, which may revolutionize the transportation systems. These vehicles are equipped with various sensors such as cameras, lidars, and ultrasonic sensors. It is likely that onboard devices may be combined with the IoT, advanced communication technology, big data technology, and cloud computing, to create a new era for bridge monitoring. By deeply integrating these technologies, the efficiency, accuracy, and intelligence of the VSM will be significantly enhanced, providing strong support for the safe operation of transportation systems.
6) The artificial intelligence provides new avenues for bridge health monitoring. From the phenomenal aspects, ML offers a distinct advantage in extracting essential features from multiple datasets and self-refining through continuous learning from incoming new data. Existing research has demonstrated the potential use of ML and DL techniques for SHM, particularly in enhancing the accuracy and efficiency of damage detection. These studies offer new perspectives for extending the range of the VSM in bridge health monitoring. However, they are based mostly on laboratory or numerical data for training, as real structural damage data are scarce, posing a challenge that needs to be addressed.
7) Structural detection requires interdisciplinary integration, involving mechanics and mathematical analysis, vehicle engineering, sensor technology, communication technology, signal processing technique, and more. Successful damage identification methods necessitate close collaboration across various disciplines.