Bridge health condition assessment using instrumented moving vehicles

Zhenkun Li
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Zhenkun Li

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Abstract

Recently, there has been a growing interest in the indirect method of utilizing instrumented vehicles for bridge health monitoring. This approach only necessitates a few sensors mounted on vehicles instead of bridges, making it cost-effective, user-friendly, and easy to maintain. This thesis investigates the extraction of bridge frequencies and damage detection through numerical simulations and laboratory experiments. **Firstly**, to identify the bridge's frequencies from the vehicle's accelerations, a practical 3D vehicle model is developed in place of the frequently used quarter-car or half-car models. To filter out the vehicle's dynamic information, newly formulated equations are used to compute the vehicle's contact-point response. The influence of road roughness is eliminated by employing residual contact-point response of the vehicle’s front and rear wheels. The effectiveness of the proposed method is confirmed by the results of numerical simulations considering various influencing factors. To improve the sensitivity of indirectly identified bridge frequencies to local damage, another parked truck is employed at different positions on the bridge for elaborate model updating and damage identification. Numerical simulation results indicate that the damage can be detected, localized, and quantified while several impacting factors are included. **Secondly**, using support vector machine models, this thesis shows that both low- and high-frequency responses from the instrumented vehicle contain the bridge's dynamic information and can therefore be employed for damage detection. Mel-frequency cepstral coefficients (MFCCs), originally derived from acoustic recognition, are extracted from the vehicle's accelerations as damage-sensitive features. The viability of MFCCs for damage detection has been confirmed through laboratory experiments with a model truck and a U-shaped beam. In addition, to address the challenge of obtaining damaged labels in practical engineering, this thesis introduces the assumption accuracy method. Instead of labeled data, it aims to determine the bridge's health states using accuracy values of binary classifications. Two laboratory beams and vehicles with two different weights have been used to validate the proposed method. Results show that when MFCCs are applied as a dimension reduction technique, the accuracy remains around 0.5 for a healthy bridge and approaches 1.0 once the bridge is damaged. **Finally**, in this thesis, bridge damage detection is accomplished in a real-time manner using the responses from an instrumented vehicle. This demonstrates that the passing vehicle’s short-time vibrations can be employed to assess the bridge’s health condition. By implementing the proposed damage indicator using the deep auto-encoder, the bridge's damage information can be automatically identified. A novel index called identified damage ratio (IDR) is proposed as an indicator for quantifying damage severity. Laboratory experiments show that as damage severity increases, the IDR initially rises significantly and then gradually approaches 100%.

Keywords structural health monitoring, vehicle-bridge interaction, indirect method, damage detection, machine learning
Preface

Pursuing academia requires life-long efforts. It is often the final day that brings back memories of many experiences encountered throughout the years. If asked to pinpoint the most joyous moment, it would undoubtedly be when I was accepted into the doctoral program. I feel fortunate to have had the opportunity to discover, delve into, and comprehend the unknown during my doctoral studies. Life is a mix of hardships, challenges, and opportunities. I have genuinely cherished my time as a doctoral researcher, and I am deeply grateful to my funders, the university, researchers, and staff members. It is their contributions that have made this journey both possible and enjoyable.

I would like to express my profound gratitude to Professor Weiwei Lin for his invaluable guidance during my doctoral studies. Throughout the years, he has motivated my research with weekly discussions, astute insights, and essential feedback on my experiments, paper writing, and in-depth problem analysis. His unwavering commitment to teaching, learning, and research has inspired me to persevere in my doctoral journey, which I believe will serve as a priceless asset for the rest of my academic career.

I am deeply grateful to the pre-examiners, Professor Maria Giuseppina Limongelli and Dr. Donya Haji-ollahi, for their invaluable feedback on my doctoral thesis. I would also like to extend my appreciation to Professor Maria Giuseppina Limongelli, who will personally attend and serve as the opponent for my public dissertation defense.

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I also want to express my final gratitude to my family and friends for your continuous encouragement over the years. Your selfless support has always been my motivation to aim high and keep going in my research.

Lastly, I want to thank myself for not giving up on the hardest days.

Espoo, August 23, 2023,

Zhenkun Li
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This thesis consists of an overview and of the following publications which are referred to in the text by their Roman numerals.


Author’s Contribution

Publication I: “Bridge Frequency Scanning Using the Contact-Point Response of an Instrumented 3D Vehicle: Theory and Numerical Simulation”

Zhenkun Li conducted the literature review, accomplished simulations, analyzed the results, and wrote the manuscript. Weiwei Lin and Youqi Zhang supervised the research and provided important suggestions on the manuscript and review comments.

Publication II: “Indirect damage detection for bridges using sensing and temporarily parked vehicles”

Zhenkun Li conducted the literature review, proposed the idea, accomplished simulations, analyzed the results, and wrote the manuscript. Yifu Lan provided essential feedback and review comments. Weiwei Lin supervised the research and offered important comments on the manuscript and revisions.

Publication III: “Drive-by bridge damage detection using Mel-frequency cepstral coefficients and support vector machine”

Zhenkun Li conducted the literature review, proposed the idea, planned and conducted the experiments, analyzed the results, and wrote the manuscript. Weiwei Lin and Youqi Zhang supervised the research and provided important suggestions on the manuscript and review comments.
Publication IV: “Investigation of Frequency-Domain Dimension Reduction for A^2M-Based Bridge Damage Detection Using Accelerations of Moving Vehicles”

Zhenkun Li conducted the literature review, proposed the idea, planned and conducted the experiments, analyzed the results, and wrote the manuscript. Yifu Lan provided significant feedback and review comments. Weiwei Lin supervised the research and offered essential comments on the manuscript and revisions.

Publication V: “Real-time drive-by bridge damage detection using deep auto-encoder”

Zhenkun Li conducted the literature review, proposed the idea, planned and conducted the experiments, analyzed the results, and wrote the manuscript. Weiwei Lin and Youqi Zhang supervised the research and provided important suggestions on the manuscript and review comments.
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Abbreviations

3D  Three dimensional
AE  Auto-encoder
AI  Artificial intelligence
A²M Assumption accuracy method
ANN Artificial neural networks
BPF Band-pass filter
CNN Convolutional neural network
CP Contact-point
CSB Continuously supported beam
CV Cross-validation
DAE Deep auto-encoder
DCT Discrete cosine transform
DI Damage indicator
DL Deep learning
DOF Degree of freedom
DRT Dimension reduction technique
DS Damage scenario
DSF Damage-sensitive feature
EEMD Ensemble empirical modal decomposition
EMD Empirical mode decomposition
Abbreviations

FE  Finite element
FFT  Fast Fourier transform
IDR  Identified damage ratio
IMF  Intrinsic mode function
KKT  Karush-Kuhn-Tucker
MAC  Modal assurance criterion
MAE  Mean absolute error
MAF  Moving average filter
MFCC  Mel-frequency cepstral coefficient
ML  Machine learning
OMA  Operational modal analysis
PCA  Principal component analysis
PSD  Power spectral density
PT  Parked truck
RBF  Radial basis function
RNN  Recurrent neural network
SHM  Structural health monitoring
SSA  Singular spectrum analysis
SSB  Simply supported beam
SSI  Stochastic subspace identification
STFT  Short-time Fourier transform
SV  Sensing vehicle
SVM  Support vector machine
TFR  Time-frequency representation
VBI  Vehicle-bridge interaction
VMD  Variational mode decomposition
VSM  Vehicle scanning method
Symbols

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<th>Description</th>
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<td>$C_b$</td>
<td>Bridge’s damping matrix</td>
</tr>
<tr>
<td>$c_{si}$</td>
<td>$i$-th suspension’s damping value</td>
</tr>
<tr>
<td>$c_{ti}$</td>
<td>$i$-th wheel’s damping value</td>
</tr>
<tr>
<td>$e$</td>
<td>Sensor installation error</td>
</tr>
<tr>
<td>$E_b$</td>
<td>Young’s modulus of the bridge</td>
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<td>$E_n$</td>
<td>Environmental noise level</td>
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<tr>
<td>$f_{bi}$</td>
<td>Bridge’s $i$-th frequency</td>
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<tr>
<td>$f_{vi}$</td>
<td>3D Vehicle’s $i$-th frequency</td>
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<td>$f_{s\nu i}$</td>
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<td>$I_b$</td>
<td>Moment of inertia of the bridge’s cross-section</td>
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<td>$I_v$</td>
<td>Moment of inertia of the SV’s body</td>
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<td>$I_{v\theta}$</td>
<td>Pitching moment of inertia of the 3D vehicle body</td>
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<td>$I_{v\phi}$</td>
<td>Rocking moment of inertia of the 3D vehicle body</td>
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<td>$K_b$</td>
<td>Bridge’s stiffness matrix</td>
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<td>$k_s$</td>
<td>Threshold for determining the bridge’s health state</td>
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<tr>
<td>$k_{si}$</td>
<td>$i$-th suspension’s stiffness</td>
</tr>
<tr>
<td>$k_{ti}$</td>
<td>$i$-th wheel’s tire stiffness</td>
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Symbols

\( l_b \) \hspace{5mm} \text{Length of the bridge}
\( \overline{m} \) \hspace{5mm} \text{Mass per unit length of the bridge}
\( M_b \) \hspace{5mm} \text{Bridge's mass matrix}
\( M^j_i \) \hspace{5mm} \text{\( j \)-th MFCC of the \( i \)-th frame}
\( m_{ti} \) \hspace{5mm} \text{\( i \)-th wheel's mass of the vehicle}
\( m_v \) \hspace{5mm} \text{Vehicle body mass}
\( \Delta n_s \) \hspace{5mm} \text{The interval of spatial frequency}
\( n_{s,0} \) \hspace{5mm} \text{Reference spatial frequency (= 0.1 cycles/m)}
\( n_{s,i} \) \hspace{5mm} \text{\( i \)-th spatial frequency}
\( p_{b,N} \) \hspace{5mm} \text{Nodal excitation to the bridge}
\( \Delta t \) \hspace{5mm} \text{Sampling time interval}
\( \Delta t_g \) \hspace{5mm} \text{Time lag of the SV's two wheels}
\( u_{bi} \) \hspace{5mm} \text{The bridge's deflection at \( i \)-th contact point}
\( u_{ci} \) \hspace{5mm} \text{\( i \)-th wheel's contact point displacement}
\( v \) \hspace{5mm} \text{Vehicle's speed}
\( x \) \hspace{5mm} \text{Distance to the bridge's left end}
\( x_i \) \hspace{5mm} \text{Training samples}
\( y_i \) \hspace{5mm} \text{Training labels}
\( z_b \) \hspace{5mm} \text{Bridge's nodal displacement}
\( z_r \) \hspace{5mm} \text{Road roughness}
\( z_{ti} \) \hspace{5mm} \text{\( i \)-th wheel's bounce}
\( z_v \) \hspace{5mm} \text{Vehicle body bounce}

Greek letters

\( \eta_i \) \hspace{5mm} \text{Ratio of \( i \)-th tire's stiffness and damping}
\( \theta_i \) \hspace{5mm} \text{Random phase angle used to generate road roughness}
\( \theta_v \) \hspace{5mm} \text{Vehicle body pitching}
\( \mu \) \hspace{5mm} \text{Damage factor}
\( \xi_i \) \hspace{5mm} \text{Bridge’s \( i \)-th order damping ratio}
\( \sigma_s \) \hspace{5mm} \text{Standard deviation of the signal \( s \)}
\( \varphi_v \) \hspace{5mm} \text{Vehicle body rocking}
1. Introduction

1.1 Background

The last century has witnessed a significant increase in the construction of bridge structures. In many countries, a large portion of these built bridges have been in service for nearly or more than their original design life (50-100 years). For example, in Europe, a large part of existing bridges were constructed after 1945. Bridges designed according to previous codes may experience significant challenges due to the current increase in traffic loads. The safety of those bridges has been a growing concern recently due to aging and deterioration issues [1, 2]. In Finland, according to the Finnish Transport Infrastructure Agency, approximately 7,000 out of 15,160 bridges are expected to require renovation by 2020, and around 5% of them are in poor condition [3]. A similar statistical trend has also been observed in the United States and Japan, with approximately 42% and 39% of bridges, respectively, having been in service for more than half a century [4, 5]. Bridge health assessment and maintenance has become a concern and hot topic over the last two decades due to the gradual deterioration of civil infrastructures over time [6–10]. Structural health monitoring (SHM), as a matured and important branch for the maintenance of infrastructures, offers fundamental techniques for monitoring bridge structures [11–14]. These techniques include sensor deployment, data acquisition and management, damage detection, safety analysis, etc. Among all modules, damage detection is the core task and includes four levels: (1) establish that damage is present, (2) establish the location, (3) quantify the severity, and (4) predict the remaining service life [15].

Traditionally, bridge damage detection heavily relies on visual inspection approaches. It requires experienced engineers to perform comprehensive examinations on the target bridge [16]. However, to meet the demands of modern society, bridge structures are becoming increasingly huge and complex. Moreover, relying solely on human vision limits the detection of
surface defects in the bridge. However, structural flaws like inner cracks and corrosion are frequently encountered in engineering. The increasing number of deteriorated bridges has highlighted the limitations of visual inspection, such as time-consuming, dangerous, labor-costly, etc., which prompted scientific researchers to explore new ways to monitor the bridges [17]. One of the popular ways of bridge health monitoring is to extract the bridge’s dynamic information from its vibrations [18–20]. Modal parameters, including natural frequencies, modal shapes, and damping ratios, can be significant indices for monitoring the condition of the bridge. Modal information is valuable in model updating for both existing and newly constructed bridges. That is to build the precise finite element (FE) model, which mimics the real structure in engineering for purposes such as structural design, maintenance, and residual life prediction. Furthermore, it provides ways to identify damage to the bridge, including stiffness loss, settlement in supports, and aging problems such as material deterioration [21–23]. Conventionally, to obtain the modal parameters of the bridge, different sensors are required to be installed on the bridge to collect its vibration data. Typical on-site measurements include ambient excitation tests, forced vibration tests, impact tests, and so on. In the last several decades, huge amounts of studies have been reported along this line. Since it needs the sensors installed on the surface or inside of the bridge directly, this approach is referred to as the direct method. Notwithstanding, the direct method typically requires a large number of sensors deployed on the bridge to form a sensing network collecting a continuous data stream, which makes it costly and laborious to apply in engineering applications. Also, many sensors are typically required to be installed during the construction period. For bridges that are under operation, traffic pauses may be required when performing the vibration tests [24]. The other drawback of such a sensing network is that one system is only suitable for one bridge, and it cannot be transferred to another one without modification [25]. Due to the above reasons, typically, only the long-span or crucial bridges are prioritized to equip such a sensing system. Looking at bridges around the world, only a small portion of them have been adequately monitored. Short-span bridges and footbridges, which play essential roles in people’s daily lives, are generally not on that list. However, the failure of such bridges can pose significant threats to the life and property of human beings.

In light of these challenges, Yang et al. introduced the indirect method in 2004 [26], which is also known as the vehicle scanning method (VSM) [27] or drive-by method. In this study, a sprung mass was utilized to simulate the passing vehicle, and the bridge was modeled as a simply supported beam. It provided the fundamental theory that the bridge’s frequency could be identified from the vehicle’s responses. Later in 2005, Lin and Yang [28] employed a tractor-trailer system on the Da-Wu-Lun bridge in
Taiwan. The field test showed that the bridge’s dynamic information was included in the vehicle’s vibrations. These two pioneering studies provided the foundation to identify the bridge’s modal parameters and damage detection for subsequent investigations. In the last two decades, the idea of identifying bridge modal parameters using instrumented vehicles has been investigated by numerical simulations, laboratory experiments, and field tests in many means [15, 25, 29–36]. One salient advantage of the indirect method is that it only needs one or several accelerometers installed on the vehicle rather than a huge number of sensors on the bridge. Therefore, it is more economical and easier to operate compared to the direct method. Moreover, as the sensors are attached to the vehicle, it is convenient to check, maintain, and repair them once faults are noticed. Due to the advantages, the concept of indirect structural health monitoring (iSHM) was later proposed in Europe [37, 38]. The development of the iSHM system can also contribute to the formation of a crowdsourcing platform [39]. The research presented in this work is developed in the background of investigation of the indirect method, including bridge modal parameter identification and damage detection.

1.2 Motivation and objectives

Despite the increasing number of studies in bridge damage detection using the response of vehicles, practical engineering applications of the indirect method can still be challenging. The instrumented vehicle can be regarded as both the exciter and signal receiver when it passes the bridge. During this process, the bridge will vibrate, and its dynamic information can be transferred to the vehicle where the sensors are installed. However, it is typically difficult to identify the bridge’s frequency directly from the vehicle’s vibrations. Since the vibration data are collected from the vehicle rather than the bridge, the vehicle frequencies will generally be dominant in the frequency domain rather than the bridge’s frequencies. If there is no prior knowledge about the vehicle, such as the vehicle’s frequencies, it can be hard to recognize the bridge’s frequencies in the frequency spectrum of the vehicle’s accelerations. Even though several studies have investigated the vehicular parameters, removing the vehicle’s information from the accelerations is still challenging. The second factor that can influence the process of identifying the bridge’s frequency from the vehicle’s responses is related to road roughness. Poor road roughness will cause a stronger vehicle-bridge interaction (VBI) response, meaning that the vehicle and bridge will vibrate more dramatically, which is conducive to transferring more information about the bridge to the vehicle. However, during the above VBI process, the information on road roughness will also be shifted to the vehicle, making the bridge’s frequency overshadowed in the frequency
domain. Therefore, the achievement of identifying frequencies of the bridge or damage detection using instrumented vehicles requires addressing the above two key influence factors. Further, even though many researchers have investigated the identification of bridge frequencies from the vehicle responses, few studies are accomplished for the damage detection purpose utilizing the indirectly identified frequencies.

Apart from the influence of vehicle frequencies and road roughness, there are more factors in practical engineering that can affect the indirect method, e.g., environmental noises, vehicle speed, and sensor positions. Furthermore, it has been reported that the frequency is not quite sensitive to local damage [40]. Thus, new damage-sensitive features (DSFs) are anticipated for identifying low-level damage to the bridge. With the development of computer science [41], machine learning (ML) and deep learning (DL) techniques have been identified as powerful tools to extract features from data [42]. In the field of SHM, these techniques have been verified as state-of-the-art ways of accessing the health status of structures [19, 43, 44]. By employing the ML and DL techniques, the monitoring process can be automated, which not only helps to reduce labor costs but also enhances the accuracy of monitoring results. To the best knowledge of the author, few studies have focused on the automatic monitoring of the bridge’s health condition with instrumented vehicles.

The objective of this thesis firstly lies in the use of vibrations of normal vehicles to identify the natural frequencies of the bridge. It aims to overcome two key challenges in the existing literature: the removal of vehicle information in its vibrations and the influence of road roughness. Furthermore, this thesis aims to explore detecting bridge damage using the responses of vehicles, and this process will be accomplished in an automatic manner by employing data-driven methods. The bridge health monitoring procedures are supposed to be antinoise, vehicle parameter insensitive, and sensible to minor damage to the bridge. To achieve this, the thesis tries to develop more realistic vehicle models and minimize the influence of the vehicle’s self-information and road roughness on the vibrations using contact-point (CP) responses instead of traditional accelerations. By doing so, the dynamic characteristics of the bridge will be highlighted and more easily identifiable. Furthermore, to increase the sensitivity of bridge frequencies to its local damage and enhance the amount of available modal information for model updating, a temporarily parked truck (PT) is employed at different positions when a sensing vehicle (SV) is utilized to identify the bridge’s frequencies indirectly. Finally, this thesis will explore various ML and DL techniques to create an automated and reliable system for bridge inspection using instrumented vehicles. Popular classifiers will be explored to check the health conditions of the bridge and differentiate various damage cases using vehicle responses. To improve computational efficiency and minimize the impact of external factors such
as environmental noises, various dimension reduction techniques (DRTs) will be examined. The tools used tend to eliminate useless information in the vehicle’s vibrations and reserve damage-sensitive ones, making the extracted features more sensitive to local damage. New indicators will be proposed to check the health condition of the bridge and provide references to its damage severity.

1.3 Contributions

The main contribution of this thesis is the development of practical methods for identifying bridge frequencies and detecting bridge damage using instrumented vehicles. The proposed approaches consider influences such as road roughness, environmental noises, sensor installation errors, the vehicle’s speed and weight, and different beam bridges. The proposed ideas are validated by numerical simulations and laboratory experiments, providing valuable insights for researchers exploring the indirect method.

In Publication I, a more accurate 3D vehicle model with seven degrees of freedom (DOFs) is developed. Compared to existing vehicle models, such as quarter-car and half-car models, the 3D model can better describe the vehicle’s dynamic characteristics. Further, the CP response between the vehicle and the bridge is derived from its accelerations. The derived response is vehicle frequency-free and thus will not be influenced by the properties of the vehicle itself. Then, the influence of road roughness is eliminated by employing the residual CP response between the front and rear wheels. To make the proposed method more practical, the sensor installation positions are also considered when calculating the CP response from the vehicle’s accelerations. Other factors, such as environmental noises and bridge damping ratios, are also analyzed to provide researchers with recommendations for employing or designing the instrumented vehicle.

A novel damage detection method utilizing two vehicles: an SV and a temporarily PT, is proposed in Publication II. The feasibility of employing indirectly identified frequencies for damage detection, localization, and quantification is investigated. The PT is employed on different positions of the bridge as a physical modification to improve the sensitivity of the bridge frequency to local damage and increase the amount of modal information about the bridge. During the damage detection process, the SV is regarded as the exciter and signal receiver simultaneously for bridge frequency identification. Further, to enhance the robustness of the model updating, a new objective function based on the modal assurance criterion (MAC) is proposed to improve the sparsity of damage factors, leading to better damage detection results compared to conventional methods that rely on relative error-based functions.

Typically, the bridge’s first three order frequencies are within the range
of 0-100 Hz [9, 45]. Thus, current studies generally investigate the low-
frequency responses of the passing vehicle and try to identify the bridge’s 
information from the vehicle’s responses. Publication III not only analyzes 
the low-frequency responses of the vehicle but also explores the high-
frequency components. It shows that the damage-sensitive frequency 
responses are densely distributed in the low-frequency range but sparsely 
disseminated in the high-frequency range. To address the challenge of 
working with frequency responses in a high-dimensional space, this study 
employs the MFCCs, a concept in acoustic recognition for extracting voice 
features, to extract key features of the original frequency responses. This 
research introduces a novel concept that the high-frequency response of the 
vehicle also needs to be analyzed in addition to the low-frequency response 
when detecting bridge damage using vibrations of instrumented vehicles.

Nonetheless, in practical engineering, it is typically difficult to obtain 
signals from cases of damaged bridges to train an ML model. Also, damage 
to a bridge can take various forms and is difficult to predict. Requiring 
labels for the training process refers to the supervised learning method. 
In response to such a dilemma related to training labels, Publication IV 
seeks a novel way to determine the health condition of the bridge using 
vehicle vibrations. Based on the logic that when the bridge is damaged, 
the collected vibrations from the vehicle will change as well, the research 
employs classification accuracy as the threshold to determine the bridge’s 
health condition. It was found that when the bridge is damaged, the 
accuracy can reach a high value (near 1.0 in this study). Rather, if the 
bridge remains healthy, the accuracy values will be around 0.5 when 
MFCCs are utilized as a DRT.

This thesis is then extended to the unsupervised learning method dis-

cussed in Publication V, which typically does not rely on labeled data. 
Deep auto-encoder (DAE) is characterized by learning features of the input 
signal by reconstructing it. In the context of the indirect method, the DAE 
is trained to learn features when the vehicle passes a healthy bridge. Then, 
damage indicators (DIs) are extracted to monitor the bridge’s health con-
dition. By utilizing a short-time Fourier transform (STFT) and frequency 
response below 100 Hz, the DIs can be identified in real time. Finally, the 
DI values when the vehicle passes the bridge can be collected together, 
and the identified damage ratio (IDR) gives references for determining the 
damage severity of the bridge. The research offers a real-time approach 
for the indirect method, which can be beneficial for monitoring relatively 
long bridges.

The articles referenced within this thesis exhibit a profound interconnec-
tion. The back-calculation of CP responses from the vehicle’s accelerations 
is investigated in Publication I, which serves as a theoretical foundation 
for Publication II to identify bridge frequencies from vehicle responses. 
Furthermore, to address the challenge that bridge frequencies may lack
Introduction

sensitivity to local damage, Publication II introduces a PT at different positions on the bridge to increase the amount of modal information regarding the bridge and its frequency sensitivity to local damage. However, compared to numerical simulations, applications of some existing methods in engineering are typically characterized by stochastic influencing factors, which can hinder the extraction of bridge information from the vehicle. To tackle this, Publication III employs ML techniques to detect bridge damage information from vehicle responses. However, the application of supervised methods often faces challenges in practical engineering applications due to the difficulty of obtaining damaged cases. To surmount this, a new method called A²M is developed in Publication IV, which utilizes damage classification accuracy as the criterion for determining bridge health conditions. Further, utilizing the DAE, a well-known unsupervised data-driven method, Publication V makes the bridge health monitoring in a real-time manner. The thesis is developed through a progression from numerical simulations to laboratory experiments and from theoretical concepts to practical applications, as evidenced by the content covered in the five articles.

1.4 Structure of the thesis

The structure of this thesis and the conducted research are illustrated in Figure 1.1. The thesis is organized into five main chapters. Following this introductory chapter, Chapter 2 provides an overview of the current state-of-the-art developments in bridge inspection using vehicle responses. The discussion covers the studies related to bridge frequency identification and data-driven bridge health monitoring using vehicle responses. Chapter 3 introduces basic materials and methods utilized in this thesis, including the built vehicle models, algorithms, methodology, and two validation methods: numerical simulations and laboratory experiments. Specifically, simulations incorporate external factors such as road roughness and environmental noises, while experiments introduce the vehicle and bridge models used in the research. Chapter 4 presents the simulation and experimental results and provides detailed discussions of the proposed methods. Finally, Chapter 5 concludes the thesis and discusses future work.
Figure 1.1. Thesis structure.
2. State-of-the-art on bridge inspection using vehicle responses

This chapter presents an overview of the latest advancements in the field of bridge inspection using vehicle responses. It covers topics such as the identification of bridge frequencies from vehicle accelerations and the use of data-driven methods in bridge health monitoring.

2.1 Bridge frequency identification techniques

For the bridge inspection using instrumented moving vehicles, the initial focus for scholars is on the identification of bridge frequencies based on responses obtained from vehicles. After the groundbreaking research [26], which investigated the bridge’s fundamental frequency identification from the vehicle’s accelerations, the researchers were soon attracted by the advantage of the indirect method. This includes high efficiency, economical nature, and operation-friendly characteristics. However, in this study, the VBI system did not consider the effects of road roughness, which was later confirmed as a key inverse factor influencing the identification of the bridge’s dynamic information from the vehicle’s responses. Also, since the accelerations are collected by the sensors installed on the vehicle, the vehicle’s self-information will be dominant in the vehicle’s responses rather than the bridge’s. Thus, to monitor the bridge’s health condition using vehicle responses, researchers have proposed various approaches to highlight the bridge’s dynamic characteristics.

After conducting the initial research using the sprung-mass model, the idea was further explored through various simulation models [46, 47], laboratory experiments [48, 49], and field tests [50–58], wherein the fast Fourier transform (FFT) was employed on the vehicle’s accelerations. These studies have confirmed the presence of dynamic information of the bridge in the vibrations of passing vehicles, which provided a sound foundation for later exploration. Initially, time-domain signal decomposition techniques were explored. In 2009, Yang and Chang proposed enhancing the probability of identifying the bridge’s frequency using empirical mode de-
composition (EMD) techniques [59]. The EMD method, first introduced by Huang et al. [60], was designed to handle non-stationary and non-linear data and could decompose the signal into several intrinsic mode functions (IMFs). The FFT could then be performed on each of the IMFs to identify the bridge’s frequencies of higher modes individually. OBrien et al. [61] later employed the same technique to identify the vehicle speed pseudo-frequency. Combining the expectation maximization algorithm [62], Eshkevari et al. [63] found the ensemble empirical modal decomposition (EEMD) approach an effective tool for bridge modal identification. The results showed that the EEMD method could deconvolute the drive-by signals without prior information about the vehicle. By comparing EMD and EEMD, Zhu and Malekjafarian [64] noted that the use of EEMD was helpful in overcoming the mode mixing problem in the vehicle’s responses. EEMD, combined with the Hilbert-Huang transform, was further utilized for identifying frequencies of railway bridges [65]. Apart from EMD and its advanced versions, other techniques such as blind modal identification with singular spectrum analysis [66], complete ensemble empirical mode decomposition with adaptive noise [67], and successive variational mode decomposition (VMD) [68] were found to be effective for vehicular signal decomposition as well. The bridge frequency identification process was automated by Abuodeh and Redmond by employing the peaking picking technique and VMD [69]. The proposed approach was verified by different vehicles and varying bridges. Considering road roughness, 69.2% success in identifying bridge frequencies for four vehicle classes was achieved. Preprocessing time-domain signals greatly improves the probability of successfully identifying the bridge frequencies using instrumented vehicles.

Data processing, especially decomposition in the time domain, is intuitive and can be a powerful tool to differentiate the frequencies of the vehicle and the bridge. However, prior knowledge of the vehicle’s dynamic properties is typically required so that the researcher can identify the bridge’s frequencies after the signal decomposition. Scholars then turned their attention toward methods utilizing operational modal analysis (OMA). In 2016, Yang and Chen [70] proposed to tailor the stochastic subspace identification (SSI). They applied it to the identification of bridge frequency from a test vehicle, which helped to suppress the vehicle’s own frequencies. To improve the existing methods, Li et al. [71] proposed a new approach that employed two instrumented vehicles, with one serving as a fixed reference sensor and the other one considered as a moving sensor, to estimate the bridge frequency using reference-based SSI. It was found that the bridge’s frequencies could be highlighted in the stabilization diagram. In 2021, Jin et al. [72] presented the short-time SSI method to estimate the bridge’s frequency using traversing vehicle vibrations. For the elimination of road roughness, two traverses of the same vehicle at different speeds were employed. However, the method was merely feasible.
when the temporal variation of the VBI system could be ignored, and this became more pronounced for high-speed vehicles. To solve this problem, the multivariable output error state space algorithm was adopted by Jin et al. [73] in the following year, and a half-car model was utilized. Results showed that the proposed method was effective for identifying the frequencies of a 3-span bridge, even under conditions of high speeds and significant road roughness. Moreover, other OMA methods, such as peak picking and frequency domain decomposition, were also proved effective for identifying frequencies of the vehicle and bridge [74]. Among OMA techniques, frequency domain decomposition was found to be more efficient than the traditional FFT method in revealing the bridge's frequencies [75]. Nonetheless, despite the proposed methods being able to somewhat suppress the vehicle's frequencies, it remains challenging to identify the bridge frequencies without prior knowledge of the vehicle. Eliminating the influence of vehicle self-information becomes a key task in the indirect bridge modal parameter identification.

At the same time, researchers have observed that the parameters of the VBI system could be of great importance in identifying the bridge’s frequency [76]. This suggests that selecting a suitable vehicle, rather than a normal one, can be crucial for identifying the frequency of a certain bridge. In the reference [76], the authors found that the initial vehicle/bridge acceleration amplitude ratios were the most important factor influencing the extraction of bridge frequency, and the initial acceleration amplitude ratios smaller than three were recommended. Although adjusting such a parameter for a certain VBI system is challenging, the study provides a theoretical basis for further investigations. In 2017, Yang and Lee [77] carefully analyzed the damping effects of the vehicle on indirect frequency identification using the sprung-mass model. They found that higher vehicle damping tended to suppress the vehicle frequency and could suppress the effect of road roughness. In 2021, Shi and Uddin [78] systematically analyzed the identification of bridge frequency using a sprung-mass model. Several findings were listed here: (1) high damping of the bridge could prevent information transmission to the vehicle, making the extraction process harder, but high vehicle damping did not influence that much; (2) the vehicle frequency denoted an important parameter and was recommended to be higher than the interested bridge frequencies; (3) high vehicle speed increased the amplitude of its accelerations and could intensify the camel hump phenomenon. Similar effects could also be observed even though the bridge was not simply supported [79]. Even if the vehicle mass did not attenuate the bridge's frequency spectrum, as it was moving mass (contacted by tires) over the bridge, heavy vehicles might cause incorrect frequency identification of the bridge [80]. It could be understood that the VBI model is actually a dynamic system. Yang et al. [81] derived the time-varying VBI frequencies using the sprung-mass model. It indicated that the vehicle's
State-of-the-art on bridge inspection using vehicle responses

performance was different from a moving mass [82]. When it is passing the bridge, the bridge’s fundamental frequency will be increased, and the vehicle’s frequency will be decreased. The phenomenon was also observed in the laboratory experiments [83–87] and field tests [88–90]. Thus, when the objective is to extract the bridge’s frequency, the vehicle’s mass cannot be selected as too large. Furthermore, selecting the appropriate speed is of great importance. Higher speed can induce stronger VBI responses but will decrease the passing time, leading to poor frequency resolution. Even though the low-resolution problem of FFT can be partially overcome by employing wavelet analysis [91], low speeds are necessary to collect sufficient data and attenuate the vibration of the vehicle [92]. As for the parameter of tires, in the field test conducted by Yang et al. [93] using a hand-drawn cart, it was found that PU wheels were more suitable for the extraction of bridge frequency compared to inflatable and rubber wheels. Also, a heavier test cart could make smaller responses of it, making higher visibility of bridge frequencies in the vehicle’s frequency spectrum. The analysis of the VBI system provides essential concepts for designing a test vehicle to scan the bridge’s frequencies and offers prospective ideas for future studies on the indirect method.

As the objective is to weaken the influence of the vehicle, one can discover that if the vehicle frequencies were filtered out, the bridge’s frequencies could be highlighted [94]. The singular spectrum analysis (SSA) with a band-pass filter (BPF) was demonstrated effective when the vehicle’s frequency was smaller or larger than the bridge frequencies of interest. The combination of VMD and a BPF could be a preferable way to indirectly identify the bridge’s first few frequencies [95]. Also, the VMD demonstrates greater efficiency and sophistication than the EMD in identifying the initial frequencies of the bridge from the vehicle’s responses, as fewer decompositions are required while essentially eliminating the occurrence of mode-mixing. In 2022, Yang and Wang [96] proposed to employ a tuned elliptic filter combined with the advanced moving internal node element method [97]. Illustrative examples, including the consideration of bridge damping and road roughness, verified the proposed method in identifying the bridge’s frequencies. However, the methods associated with filters also necessitate the target band-pass range to filter out the vehicle’s frequencies, making the identification process more challenging in practical engineering. Since the vehicle’s parameters are difficult to measure accurately, Shirzad-Ghaleroudkhani and Gül [98] proposed to design an inverse filter by employing the spectrum of the vehicle’s vibrations when it was off the bridge. Then, the same vehicle would be utilized to move on the target bridge, and the filter was employed to suppress the vehicular frequencies. The proposed technique was then improved by the same authors to tackle the limitations of constant speed and similar surface roughness level requirements in field tests [99]. As readers may observe, if there
are multiple vehicles passing the same bridge, the signals collected by these vehicles can include their own and bridge information, in which the shared part in the accelerations is related to the bridge rather than the vehicle. Based on this theory, in 2017, Nagayama et al. [100] used the cross-spectral density function to extract the bridge frequency from the common vibration components of two commercial vehicles on the Tsukige bridge. Numerical simulation and field test results confirmed the proposed strategy for identifying the bridge’s fundamental frequency. In 2020, Shirzad-Ghaleroudkhani and Gül [101] proposed to identify the bridge's frequency using runs of vehicles with different properties. The key idea here was that when vehicles with various characteristics pass the bridge, the common features of the vehicle’s frequency spectrum would be related to the bridge. Experiments showed that the proposed method could identify minor differences between two bridges with close fundamental frequency, which provided the potential for damage detection using smartphones on vehicles. In 2022, Lu et al. [102] proposed bridge frequency identification from multiple moving-vehicle dynamics using the cross-spectrum method. Since the cross-covariance function for the monitoring data with different frequencies equals zero, the influence from the road roughness can be eliminated from the cross-spectrum. Based on the idea that the bridge’s information was the common vibration component, sensors were installed by Lan et al. [103] at different positions of the vehicle. A clear peak that occurred in the cross-spectrum was utilized to identify the bridge’s frequencies.

Apart from the vehicle frequencies, road roughness can be another essential factor influencing the identification of bridge frequency from the instrumented vehicles [104, 105]. Poor road roughness can strengthen VBI responses but also make the bridge frequencies less visible in the vehicle’s responses. For building the model of road roughness, Chang et al. [106] proposed that the contact between the road roughness and the vehicle should be regarded as a disk model instead of a point model because the point model was unrealistic for wheels, as they were of finite size and could not touch the bottom of valleys. The disk model was later employed by Corbally and Malekjafarian [107] and modified by Xu et al. [108] to account for the wheel size effect such that the generated road roughness could be directly used for the point model. The effects of wheel size were also analyzed by Yang and Cao [109] using the two-mass vehicle model. Results showed that the radius of wheel $R = 0.3$ m could be conducive to bridge frequency identification. The generation of road roughness in numerical simulations typically refers to ISO 8608 [110], which will be introduced in detail in Section 3.3.3. To suppress the inverse influence of road roughness, it was initially found in 2010 that its effects could be partially overcome by amplifying the bridge’s vibrations using ongoing traffic or increasing the vehicle’s traversing speed [111]. However, ongoing
traffic is not always available, and the high speed can sharply decrease the frequency resolution of the vehicle’s responses [112, 113]. A more effective way for weakening the inverse effects of road roughness is to employ two or several connected vehicles [114]. Typically, if the two connected vehicles move in a straight line, the same road roughness will be experienced by them. The classical strategy is to subtract the spectrum of the rear vehicle from the first one. Then, the contribution from the road roughness could be largely removed [115]. A similar approach had also been employed in the time domain instead of the frequency domain [116]. The residual responses of the two connected sprung-mass vehicle models (trailers) could then be employed to identify the bridge’s frequencies. Results showed that the residual responses of two trailers were more effective for bridge frequency extraction since the effects of road roughness were largely eliminated. The idea was later verified effective by laboratory experiments by Kim et al. [117] at Kyoto University and numerical simulations using properties of an actual field bridge [118]. The two connected two-axle vehicles (2-DOF half-car model) or utilizing residual responses of adjacent railway vehicles were also verified effective in eliminating the influence of track irregularity [119, 120]. The strategy was employed by many studies for the identification of bridge frequencies and further damage detection of bridges. Still, the method may be subject to a strict requirement in synchronizing the responses of the two vehicles in the time domain [121, 122]. Also, connecting several identical vehicles in engineering applications can be difficult to operate [123]. New and more practical approaches are imperative to tackle the influence of road profiles.

In the above analysis, it can be concluded that for identifying the bridge’s frequencies from the vehicle’s responses, two obstacles must be overcome: (1) the interference of the vehicle’s self-dynamic information and (2) the negative effects of the road roughness. For the first one related to the vehicle information, the concept of CP response was proposed by Yang et al. [124] in 2017 when a sprung-mass model was utilized. The CP response denotes the interaction between the vehicle and the bridge. When the vehicle passes the bridge, the CP response can typically include two resources: the bridge’s vibrations and the road roughness. It is not related to the vehicle itself and is free from vehicle frequencies. The numerical study shows that the CP response can outperform the original accelerations of the vehicle in identifying the bridge’s frequencies, especially for the higher modes. For the calculation of the CP response, researchers have investigated many approaches, which were introduced below.

Typically, the CP response can be back-calculated from the vehicle’s accelerations. Still, the calculation may vary for different vehicular models and the number of sensors, e.g., CP response calculation for the sprung-mass model with one sensor [124], the 2-DOF quarter-car model with two sensors [107], the 2-DOF half-car model with two sensors [125], and the 4-
DOF half-car model with two sensors [126, 127]. Other methods were also developed by researchers. For example, in 2020, Nayek and Narasimhan [128] tried to extract the CP response of a quarter-car model using only one sensor installed on the vehicle body. The deduction depended on the knowledge of the multi-DOF vehicle dynamics using a Gaussian process latent force model-based joint input-state estimation approach. In 2022, Li et al. [129] proposed to utilize dual Kalman filters to obtain the input forces of two successive vehicles accurately using vehicle responses and to identify the CP response. Then, the residual CP response was employed by auto SSA to identify the bridge’s frequencies. In 2023, Feng et al. [130] derived the transfer functions to obtain the CP response instead of traditional complex differential equations. Also, the number of vehicle parameters is another factor influencing the calculation process, among which the most essential one is the consideration of tire damping because it transfers the equation into a problem of solving first-order linear differential equations. In addition to the CP response, an alternative way is to calculate the contact force, which can also work well for bridge information identification because it is unrelated to the vehicle dynamic modes. Wang et al. [131] proposed to estimate the tire force using the vehicle’s body responses only. A Kalman filter with augmented tire forces in the system state vector was employed. Field tests verified the effectiveness of the tire force estimation. Liu et al. [132] established and calibrated a tire pressure model, which was used for the calculation of the relative displacement of the axle and contact point (RD of A-CP). Then the RD of A-CP was employed to obtain the rear tire’s CP displacement. The effects of road roughness could be removed by two runs of the vehicle. The field test verified that the bridge’s fundamental frequency could be clearly identified. Wang et al. [133] proposed to identify the bridge’s fundamental frequency using a particle filter approach to estimate the excitation at the front and rear tires of a commercial vehicle. The effects of road roughness were mitigated by subtracting the estimated excitation of the rear tire from that of the front tire. Results showed that the bridge’s natural frequency was estimated within an error of 3.2%.

The CP response can be superior to the original vehicle accelerations. In 2021, Xu et al. [134] derived to back-calculate CP responses using a damped sprung-mass model. It is found that the damping of the single-axle test vehicle would not influence much on the CP response. In 2022, the indirect bridge frequency process was automated by Yang et al. [135], in which K-means, a well-known unsupervised learning algorithm, was used to cluster peak frequencies of the CP’s principal components based on the singular spectrum. Based on the dual-beam model simulating the track-bridge system subjected to a moving test vehicle, the concept of CP response was extended to identify the dual frequencies that relate to the track and bridge components [136]. The CP response can be further investigated with time-domain or frequency-domain signal processing techniques.
as introduced before. For example, the extreme-point symmetric mode decomposition could be employed to obtain IMFs serving for extracting the bridge frequency using the CP response of a vehicle [137]. Moreover, the capability of the VMD-BPF technique could be significantly enhanced when the CP response rather than the original accelerations were utilized [95]. Nonetheless, as the CP response contains information about the road roughness and the bridge’s vibrations, the road roughness can overshadow the bridge’s responses because, generally, the scale of the bridge’s vibrations is considerably smaller than that of the road roughness. There are the following ways that can help to eliminate the effects of road roughness in the CP response.

Firstly, since the road roughness will only present its influence when the vehicle runs on the bridge, the transmissibility of the bridge’s vibration will not be affected by it when the vehicle is parked on the bridge; instead, only the vehicle’s information remains [138]. As a trade-off between moving and stationary vehicles, Yang et al. [139] introduced a non-moving period for the indirect method using the single-axle test vehicle. It was noticed that when the vehicle was resting on the bridge, the torsional modes of the bridge could also be identified from the vehicle’s CP response. The idea was later extended to consider the rocking effects of the single-axle test vehicle [140]. The idea was also developed when the vehicle was purely parked on the bridge (no running period) for bridge frequency identification [141, 142]. By this strategy, the frequencies identified from the parked vehicle’s CP response could match very well with that from the bridge. Furthermore, if the test vehicle’s frequency was designed far away from the bridge’s frequencies of interest and the non-moving state could help remove the effects of road roughness, the designed vehicle could be understood as frequency-free for identifying the bridge’s frequencies [143]. Based on this idea, vehicles with adjustable frequencies could have the potential to monitor the bridge’s frequencies [144, 145]. Moreover, it was found that the higher vehicle frequency was conducive to the information transmissibility from the bridge to the vehicle [146], making the bridge’s frequencies outstanding in the vehicle’s frequency spectrum. Temporarily park time or purely stationary vehicle can help weaken the influence of road roughness and highlight the bridge’s frequencies in the vehicle’s CP spectrum. However, it may need more time to collect the vibration data, and the monitoring efficiency can be lowered compared to continuously running vehicles.

Additionally, as it can be understood that the critical problem related to identifying the bridge’s frequencies is the small scale of its vibrations, an appropriate way to enhance the probability of the bridge modal identification is to intensify the vibration of the bridge, making it highlighted compared to the road roughness [147]. Then, when the CP response is utilized, the bridge’s frequencies can be better extracted. One advantage
of the indirect method is that it requires no traffic pause. Therefore, the ongoing traffic load can be regarded as external energy input to the bridge to make it vibrate greater [148–150]. Nonetheless, the ongoing traffic may not always be available. An alternative approach is the use of active excitation. On the one hand, the active excitation can be applied to the vehicle, and the energy is transferred to the bridge by the vehicle. For example, in 2012, Zhang et al. [151] employed a harmonic exciter on the vehicle (named as tap-scan method [152]). Experiments showed that the bridge's vibrations could be amplified, and its frequencies could be clearly identified from the vehicle's accelerations. In 2021, Yang et al. [153] proposed the installation of an amplifier on the vehicle, which suggested the amplifier's frequency be slightly higher than the target bridge frequency. Results indicated that the first two frequencies of the bridge could be identified despite the occurrence of road roughness and bridge damping. In 2022, Yang [154] explored the use of an amplifier in the three-mass vehicle model. With the extra DOF provided by the amplifier, the vehicle's responses were amplified and thus could be potential for identifying the bridge’s frequency using the vehicle’s responses. On the other hand, active excitation can be exerted on the bridge directly. Typically approaches involve a shaker on the bridge, e.g., references [155, 156]. In 2023, the dual amplifier was explored by Xu et al. [157], and it was found that the bridge amplifier performs better than the amplifier on the vehicle in extracting bridge frequencies. To increase the force the vehicle applies, employing cogwheels [158, 159] or modified wheels [160, 161] can be a new way to increase the bridge's vibration amplitudes and therefore suppress the influence of road roughness.

Thirdly, because the CP response contains information about road roughness and bridge vibrations, researchers attempted to eliminate the influence of road roughness using the residual CP response of two runs of different vehicles. Zhan et al. [162] proposed a double-pass double-vehicle technique to remove the influence of road roughness. Typically, two vehicles with different parameters (e.g., mass) were employed to pass the bridge with the same road roughness. After their CP response was identified from the accelerations, the residual CP response of the two vehicles would be utilized to identify the bridge's frequencies. Simulation results showed that the bridge’s frequencies could be well identified with different road roughness classes. A similar idea was employed by Zhan et al. [163] for damage detection purposes and was later verified by Liu et al. [132] in a field test with different road conditions. In 2023, González et al. [164] proposed separating the vehicle, road, and bridge information from drive-by accelerations using the same vehicle at different speeds. By normalizing amplitudes (using $v^4$) of the quarter-car model’s CP response in the spatial frequency domain, the authors found that the influence of road roughness could be eliminated by subtracting power spectral densities (PSDs) of the
estimated CP response of the vehicle at two speeds (real and imaginary parts were subtracted separately).

Last but not least, as a similar approach using vehicle accelerations, another technique to eliminate the inverse influence of road roughness is to utilize the residual CP response of two connected vehicles. The idea was firstly explored by using two single-axle test vehicles [165, 166] for identifying the frequencies of a simply supported bridge. Based on the good performance of CP responses, the idea was theoretically extended to the possibility of scanning the torsional modes of a thin-walled box girder bridge using CP responses of two connected identical single-axle test vehicles [167] and two two-wheel test vehicles [168]. As in practical engineering, cars or trucks generally have two or more axles. To circumvent the difficulty encountered in practical engineering using two connected vehicles, using one vehicle’s one-pass vibrations will be more efficient. In 2022, Jian et al. [24] proposed identifying the bridge’s frequency using a 3D vehicle. In this study, the wheels’ equations of motion were first transferred into the frequency domain, then the frequency responses of the front and rear axles were subtracted with a time lag to eliminate the adverse effect of road roughness. The idea of utilizing residual CP response was also investigated when a single vehicle is employed. In 2022, Yang et al. [125] tried to identify the bridge’s frequencies using a single 2-DOF two-axle vehicle’s residual CP response. Results indicated that the bridge’s modal information could be extracted very well with the occurrence of road roughness, environmental noise, and bridges with different spans. In 2022, He and Yang [123] investigated the applications of CP response of a two-axle vehicle in the frequency domain. The first several frequencies of the bridge were successfully extracted under different conditions.

As discussed above, the identification of bridge frequencies from instrumented vehicles’ accelerations can be challenging. The current techniques can partially overcome the negative influence factors, such as vehicle frequencies, road roughness, environmental noises, etc. However, in engineering applications, the vehicle is quite complex. Practical models and solutions for identifying the bridge’s frequencies using vehicle responses deserve further investigation.

2.2 Bridge damage detection with data-driven methods

Typical damage in bridges includes changes in supports [169], cracks [170, 171], tension loss in cables [172], prestress loss [173, 174], etc. In the previous section, it was demonstrated that the passing vehicle’s accelerations could capture the frequency information of the bridge. However, after signal processing, critical dynamic information related to the bridge, especially in the high-frequency range, may be weakened or even elimi-
nated, despite the extraction of modal parameters from the vehicle's responses. The employment of raw collected signals or simple transformation techniques can offer new perspectives on bridge damage detection using instrumented vehicles. With the development of devices, algorithms, and computer capability, novel techniques were reformed to suit the indirect method for identifying the bridge's damage. For instance, the damage index of the bridge can be estimated directly from the data, eliminating the need for identifying bridge modes.

Following the development of computer science [175, 176], some artificial intelligence (AI) techniques, including ML and DL approaches, have flourished in the bridge health monitoring fields. Some new methods, such as convolutional neural network (CNN) [177], recurrent neural network (RNN) [178], and transformer models [179] have been universally employed and developed. AI techniques are typically involved in automatic feature extraction without manual intervention and thus can be time-efficient and accurate. However, currently, few studies have investigated indirect bridge health monitoring using vehicular responses and ML/DL techniques. Souza et al. [180] reviewed some existing applications of ML techniques in indirect bridge inspection. The following introduces explorations about data-driven bridge health monitoring using instrumented vehicles.

In general, ML/DL techniques can be classified into two groups: (1) supervised learning and (2) unsupervised learning. Supervised learning typically requires labeled data, while the latter can learn from the data itself to identify critical features inside.

For the indirect method using responses of instrumented vehicles, the supervised/semi-supervised learning methods were first explored by the researchers. In 2014, Lederman et al. [181] tried to classify the damage severity or damage positions using the vehicle's accelerations. The bridge's damage was simulated by different mass sizes and positions on the bridge. Results showed that by combining PCA, the damage severity and position could be well predicted by kernel regression. Chen et al. [182] extended the classification framework to a semi-supervised manner, which employed the adaptive graph filter to classify unlabeled and unseen signals and for indirect bridge health monitoring. In the same year, Cerda et al. [183] utilized support vector machine (SVM) models to classify different damage conditions of a laboratory bridge using the vehicle’s accelerations. When four levels of severity were considered, the classification accuracy using frequency features was good or even better than that of the bridge’s responses. Also, it showed that the high speed of the vehicle might decrease the classification accuracy. Malekjafarian et al. [184] utilized artificial neural networks (ANN) in 2019 to detect damage in bridges through vehicle accelerations. The study established two models: (1) the first model used vehicle positions and speeds as input features and labeled the acceleration;
(2) the second model used frequencies and speeds as input features and labeled the vehicle’s frequency responses accordingly. During the training stage, the vibration data of a healthy bridge was used, and errors between predicted signals and true signals were calculated as DIs. The results showed that both the severity and the damage of the bridge could be detected. Corbally and Malekjafarian [185] extended the neural network models by incorporating the influence of temperature changes in identifying cracks in the deck and possible changes in supports. Even though high vehicle speed and poor road roughness were considered, the CP response improved the ability to monitor the behavior of the bridge. Mei et al. [45] utilized MFCCs for the first time in indirect bridge health monitoring in 2019. They proposed a modified transformation method between Hertz and Mel scales specifically for bridge engineering. By applying MFCCs and PCA, they extracted and compared the statistical characteristics of transformed features from numerous vehicles, allowing for the detection of bridge damage and potential severity prediction. Additionally, Mei and Gül [186] used Kullback-Leibler divergence to quantify the distribution of extracted DSFs by MFCCs in different vehicle runs. Both numerical simulations and laboratory experiments confirmed the proposed method’s effectiveness in detecting damage and extracting useful information about its severity. It’s worth noting that the proposed idea was efficient when using smartphones to accelerate the process of smart cities [187]. Souza et al. [188] later adopted the framework proposed by Mei et al. to explore the application of MFCCs for monitoring high-speed railway bridges. Locke et al. [189] trained a CNN in 2019 to classify different levels of bridge damage severity, taking into account environmental temperature, vehicle speeds, and weights during the training process. The results showed that damage severity classification with good accuracy (over 80%) could be achieved by utilizing only low-frequency (3-10 Hz) response peaks. In 2020, Liu et al. [190] proposed that all frequency-domain responses of the vehicle were informative and required analysis for damage detection. The authors utilized a stacked auto-encoder model to reduce the input dimensions, and the low-dimension hidden state in the bottleneck was used to feed a semi-supervised model with a few labeled data. The test results demonstrated the ability to detect a near 0.1% mass increase (additional mass was used to simulate the bridge damage). Mokalled et al. [191] presented a Bayesian estimation technique in 2022 that combined information from a numerical model with field data from a real bridge to detect and classify bridge damage. The study indicated that the proposed technique could accurately detect the presence, location, and severity of damage in many cases. However, the method was sensitive to the level of measurement noise and vehicle velocity. In 2022, Cheema et al. [192] proposed to utilize Uniform Manifold Approximation and Projection as a DRT, and then the Hierarchical Density-Based Spatial Clustering of Applications with Noise
method was employed to identify the number of clusters. It was indicated that the proposed data pipeline could reliably differentiate multiple conditions of a bridge from one another using the vehicle’s vibration data when the laboratory VBI system was used. Pre-trained models could accelerate the convergence of training. Hajializadeh [193, 194] proposed a transfer learning-based framework for drive-by bridge monitoring in 2022. The pre-trained CNN model GoogLeNet was used to transfer weights, and raw train-borne accelerations were utilized as DSFs. Remarkable accuracy was achieved when testing with 30% of the dataset, including healthy and damaged cases. The same author [195] extended the work in the following year by combining two-dimensional CNNs to classify different damage scenarios under various speeds, rail irregularities, and environmental noises. In this study, the input to train the neural network model was the cross-correlation of accelerations from the first and second bogie. Numerical simulations consisting of 2100 runs verified the ability of the trained model to predict damage severity and locations. In 2023, Lan et al. [196] proposed an optimized AdaBoost-linear SVM to classify the bridge in different health states using the vehicle’s raw accelerations. Compared to existing algorithms, the proposed method can improve the accuracy by 5% to 16.7%. Abdu and co-authors [197] utilized a gradient boost regressor to forecast the pier settlement of a bridge in the same year. The authors employed train accelerations in their prediction model. Their simulation, which employed a CRH380A high-speed train, indicated that more than 70% of the forecasted error was less than 0.5 mm, and the highest error recorded was 1.5 mm.

While supervised methods can achieve good performance, acquiring labeled data in practical engineering can be challenging. For a specific bridge, possible damage patterns can be infinite, and training models based on precise models still require further investigation [198]. Instead, unsupervised learning is developed on the data itself without requiring labeled data, which has the potential to extract DSFs from the vehicle’s responses. In 2021, Sarwar and Cantero [199] utilized a DAE to extract mean absolute error (MAE) values from the vehicle’s time-domain accelerations as damage indicators. Results showed that damage could be identified, and its severity could be estimated from the distribution of reconstruction errors. In 2022, Liu et al. [200] employed the Hierarchical Multi-task Unsupervised Domain approach to transfer the damage diagnosis model learned from one bridge to a new bridge without requiring any labels from the new bridge. The framework jointly optimized hierarchical feature extractors, damage predictors, and domain classifiers in an adversarial way to extract features that were both task-informative and domain-invariant. Experiments on three vehicles passing over two bridges demonstrated that the framework outperformed baseline methods and had a smaller prediction variance. The approach achieved an average accuracy of 95%
for damage detection, 93% for damage localization, and an MAE of 0.172 kg for damage quantification, simulated by different additional masses. In 2023, Calderon Hurtado et al. [201] explored the use of an adversarial auto-encoder to monitor the bridge’s health condition using the vehicle’s accelerations. The adversarial auto-encoder model included two parts: the encoder-decoder model and the discriminator. The encoder encoded the input into a latent space, which was then used by the decoder to reconstruct the input. The discriminator was trained to estimate the probability of each sample belonging to the defined prior distribution. The proposed approach accomplished damage detection and severity assessments, outperforming PCA, traditional auto-encoder, and DAE.

Even though existing studies have universally explored the identification of bridge frequencies from vehicle responses, one may notice that the vehicle is typically simplified to quarter- or half-car models. However, real-world engineering applications demand a more sophisticated prototype. This thesis proposes a 3D vehicle model for bridge frequency identification using CP responses. Nevertheless, certain limitations of the frequency-based damage detection approaches can be observed. For example, frequency alteration is typically not observable for small-scale local damage, and it can be easily masked by environmental noises. Further, accurately capturing the bridge’s frequencies can be challenging because of varying traffic and environmental conditions. In this thesis, the insensitivity of bridge frequencies is partially subdued by introducing another heavy PT. Furthermore, for data-driven approaches in the indirect method, current research typically utilizes low-frequency responses of the vehicle. This thesis extensively explores vehicle responses in the high-frequency ranges. Subsequently, the A²M is proposed to overcome the difficulty in acquiring damage cases in engineering, and DAE is employed for monitoring bridge health conditions in a real-time manner.
3. Materials and methods

This chapter provides an overview of the materials and methods used in this thesis. It includes a detailed explanation of the CP response derived from the 3D vehicle model for extracting bridge frequencies, essential algorithms and concepts employed, and two validation approaches: numerical simulations and laboratory experiments.

3.1 Modal-based methods

3.1.1 Frequency identification using the CP response of the 3D instrumented vehicle

From Section 2.1, it can be seen that in current studies, the vehicles are generally simplified as quarter- or half-car models. Using simplified models can provide researchers with novel insights to design and derive new theories for identifying the bridge’s frequencies from the vehicle’s responses or possible damage detection purposes. However, in practical engineering, the vehicle is in a 3D space. When the proposed method is applied in engineering, a sophisticated model is expected to provide more feasible solutions, for example, where to install sensors. For this purpose, in this thesis, a more complicated 3D vehicle model is utilized. For the first time, the state-of-the-art CP response is derived from the 3D vehicle. The fundamental theory is introduced below.

The FE model of the VBI system in this thesis is built in MATLAB [202]. The vehicle model owns seven DOFs. Compared with existing models, it can provide a more practical way of identifying bridge frequencies from vehicular responses. The salient advantage of the used model is that the rocking and pitching effects of the vehicle can be considered at the same time, which is unavoidable in engineering applications. The 3D vehicle model is shown in Figure 3.1. Here, the vehicle’s seven DOFs are highlighted by arrows. They are: body bounce $z_v$, body rocking $\phi_v$, body
pitching $\theta_v$ and four wheels’ bounces $z_{t1}, z_{t2}, z_{t3}$, and $z_{t4}$. The displacements of four contact points between tires and road surface are represented by $u_{c1}, u_{c2}, u_{c3}, u_{c4}$. For the vehicle body, its mass is $m_v$, and the rocking and pitching moments of inertia are $I_{v\phi}$ and $I_{v\theta}$, respectively. The gravity center position is determined by perpendicular distances to the vehicle's edges represented by $a_1, a_2, b_1, b_2$. The masses of four wheels are $m_{t1}, m_{t2}, m_{t3}, m_{t4}$. The contact of wheels and road is accomplished by tires with the stiffness of $k_{s1}, k_{s2}, k_{s3}, k_{s4}$ and damping of $c_{t1}, c_{t2}, c_{t3}, c_{t4}$. The vehicle body and four wheels are connected by four independent suspension systems, and their stiffness and damping are denoted by $k_s1, k_s2, k_s3, k_s4$ and $c_s1, c_s2, c_s3, c_s4$. The vehicle’s speed is denoted as $v$. It is assumed that the vehicle runs at a constant speed when passing the bridge. The vehicle’s dynamic equilibrium equations can be represented by Eqs. (3.1a-3.1g),

\begin{align}
& m_v \ddot{z}_v + c_{s1}(\dot{z}_v - \dot{z}_{t1} - b_1 \dot{\phi}_v + a_1 \dot{\theta}_v) + c_{s2}(\dot{z}_v - \dot{z}_{t2} + b_2 \dot{\phi}_v + a_1 \dot{\theta}_v) + c_{s3}(\dot{z}_v - \dot{z}_{t3} - b_1 \dot{\phi}_v - a_2 \dot{\theta}_v) + c_{s4}(\dot{z}_v - \dot{z}_{t4} + b_2 \dot{\phi}_v - a_2 \dot{\theta}_v) = 0 \tag{3.1a} \\
& I_{v\phi} \ddot{\phi}_v - b_1 c_{s1}(\dot{z}_v - \dot{z}_{t1} - b_1 \dot{\phi}_v + a_1 \dot{\theta}_v) + b_2 c_{s2}(\dot{z}_v - \dot{z}_{t2} + b_2 \dot{\phi}_v + a_1 \dot{\theta}_v) - b_1 \\
& c_{s3}(\dot{z}_v - \dot{z}_{t3} - b_1 \dot{\phi}_v - a_2 \dot{\theta}_v) + b_2 c_{s4}(\dot{z}_v - \dot{z}_{t4} + b_2 \dot{\phi}_v - a_2 \dot{\theta}_v) - b_1 k_{s1}(z_v - z_{t1}) \\
& - b_1 k_{s2}(z_v - z_{t2} + b_2 \dot{\phi}_v + a_1 \dot{\theta}_v) - b_1 k_{s3}(z_v - z_{t3} - b_1 \dot{\phi}_v) \\
& - a_2 \dot{\theta}_v) + b_2 k_{s4}(z_v - z_{t4} + b_2 \dot{\phi}_v - a_2 \dot{\theta}_v) = 0 \tag{3.1b} \\
& I_{v\theta} \ddot{\theta}_v + a_1 c_{s1}(\dot{z}_v - \dot{z}_{t1} - b_1 \dot{\phi}_v + a_1 \dot{\theta}_v) + a_1 c_{s2}(\dot{z}_v - \dot{z}_{t2} + b_2 \dot{\phi}_v + a_1 \dot{\theta}_v) - a_2 \\
& c_{s3}(\dot{z}_v - \dot{z}_{t3} - b_1 \dot{\phi}_v - a_2 \dot{\theta}_v) - a_2 c_{s4}(\dot{z}_v - \dot{z}_{t4} + b_2 \dot{\phi}_v - a_2 \dot{\theta}_v) + a_1 k_{s1}(z_v - z_{t1}) \\
& - b_1 \dot{\phi}_v + a_1 \dot{\theta}_v) + a_1 k_{s2}(z_v - z_{t2} + b_2 \dot{\phi}_v + a_1 \dot{\theta}_v) - a_2 k_{s3}(z_v - z_{t3} - b_1 \dot{\phi}_v) \\
& - a_2 \dot{\theta}_v) - a_2 k_{s4}(z_v - z_{t4} + b_2 \dot{\phi}_v - a_2 \dot{\theta}_v) = 0 \tag{3.1c}
\end{align}

**Figure 3.1.** 3D model of a two-axle vehicle.
where $u_{ci} = u_{bi} + z_{ri}$, $u_{ci} = \dot{u}_{bi} + \dot{z}_{ri}$, $i = 1, 2, 3, 4$. $u_{bi}$ is the bridge’s deflection at the contact point of $i$-th wheel. $z_{ri}$ is the road profile. Initially, the bridge’s deflection $u_{bi}$ and velocity $\dot{u}_{bi}$ are assumed as zero. It means that at this stage, the force applied to the vehicle is generated totally by the road roughness. $\dot{z}_{ri}$ can be obtained by $\ddot{z}_{ri} = vz_{ri}'$, in which ($) represents the derivative to $x$. $x$ is the distance of the contact point to the bridge’s left end. Eq. (3.1) can be solved by Newmark-$\beta$ integration method with $\beta = 0.25$ and $\gamma = 0.5$ for unconditional stability [203].

By taking the second derivative of Eqs. (3.1d)-(3.1g), and rearranging items about $\ddot{u}_{ci}$, Eqs. (3.2) and (3.3) can be obtained,
where, \( k_{s1}, c_{s1}, k_{t1}, c_{t1}, m_{t1}, i = 1, 2, 3, 4 \). and \( m_v, I_{v\phi}, I_{v\theta} \) can be measured and updated by on-site tests. \( \ddot{z}_v, \dot{\varphi}_v, \dot{\theta}_v \) and \( \ddot{z}_{ti} \) are accelerations collected in the experiment. \( a_1, a_2 \) and \( b_1, b_2 \) are constant parameters of the vehicle.

In Eq. (3.3), the first-order derivative of the accelerations can be approximately calculated by first-order finite difference formulas, and the second-order of them can be obtained with second-order central formulas as shown in Eq. (3.4),

\[
\frac{d\ddot{z}_{ti}}{dt} = \frac{\ddot{z}_{ti}(j) - \ddot{z}_{ti}(j-1)}{\Delta t}, \quad \frac{d\ddot{z}_v}{dt} = \frac{\ddot{z}_v(j) - \ddot{z}_v(j-1)}{\Delta t}, \quad \frac{d\dot{\varphi}_v}{dt} = \frac{\dot{\varphi}_v(j) - \dot{\varphi}_v(j-1)}{\Delta t}, \quad \frac{d\dot{\theta}_v}{dt} = \frac{\dot{\theta}_v(j) - \dot{\theta}_v(j-1)}{\Delta t},
\]

\begin{align*}
\frac{d^2\ddot{z}_{ti}}{dt^2} &= \frac{\ddot{z}_{ti}(j+1) - 2\ddot{z}_{ti}(j) + \ddot{z}_{ti}(j-1)}{(\Delta t)^2}, \quad i = 1, 2, 3, 4. \tag{3.4}
\end{align*}

where \( j \) means the \( j \)-th sampling point, and \( \Delta t \) is the sampling time interval which can be calculated by \( 1/f_s \), where \( f_s \) is the sampling frequency.

Related to the installation of the sensors, wheel accelerometer positions can refer to \( S_5 \sim S_8 \) in the reference [204]. However, in practical engineering, it is often difficult to locate the gravity center of the vehicle body. Installing sensors exactly on the vehicle’s gravity center is challenging. In this thesis, it is assumed that the translational accelerometer and angular sensors of the vehicle body are installed in a position with errors from the gravity center, as shown in Figure 3.2.

**Figure 3.2.** Vehicle body sensor installation with errors.

Under this condition, when the vehicle’s body sensors are installed on the star point in Figure 3.2, the constants of the vehicle will be changed accordingly, which can be represented by Eq. (3.5),

\[
\tilde{a}_1 = a_1 - e_2; \tilde{a}_2 = a_2 + e_2; \tilde{b}_1 = b_1 + e_1; \tilde{b}_2 = b_2 - e_1 \tag{3.5}
\]

where \( \tilde{a}_1, \tilde{a}_2, \tilde{b}_1, \tilde{b}_2 \) are new constants for the vehicle body when the sensor is not put on the gravity center exactly. \( a_1, a_2, b_1, b_2 \) are the original constants for locating the gravity center.

As the vehicle’s body is assumed to be rigid, when the angular sensors are not on the gravity center, the collected angular accelerometers \( \dot{\varphi}_v \) and \( \dot{\theta}_v \) will not change. However, the vertical accelerations of the vehicle body
will be different. The updated vehicular body accelerations can be denoted by Eq. (3.6),

\[ \ddot{z}_v = \ddot{z}_v + e_1 \ddot{\phi}_v + e_2 \ddot{\theta}_v; \ddot{\phi}_v = \ddot{\phi}_v; \ddot{\theta}_v = \ddot{\theta}_v \]  

(3.6)

where \( z_v \) is the acceleration of the vehicle body’s gravity center, which cannot be directly measured in practice. \( \ddot{z}_v, \ddot{\phi}_v \) and \( \ddot{\theta}_v \) are the accelerations measured on the new sensor position.

By replacing \( z_v, a_1, a_2, b_1, b_2 \) by \( \ddot{z}_v, \ddot{a}_1, \ddot{a}_2, \ddot{b}_1, \ddot{b}_2 \) in Eq. (3.3), it can be found that values of \( Q_i(t) \) will not be changed, and the influence of errors on sensor position has been eliminated. Since \( Q_i(t) \) is not changed and Eq. (3.2) is just related to \( k_{ti}, c_{ti} \) and \( Q_i(t) \), the sensor position will not influence the calculation of the CP response. Therefore, it can be seen that the body translation sensor’s position will not influence the results of calculated CP responses as long as \( \ddot{a}_1, \ddot{a}_2, \ddot{b}_1, \ddot{b}_2 \) are carefully measured to locate the sensor’s position on the vehicle body.

By solving the first-order linear differential equations in Eq. (3.2) and assuming that the CP response starts at zero at \( t = 0 \), Eq. (3.7) can be obtained for four wheels.

\[ \ddot{u}_{ci}(t) = k_{ti} \frac{c_{ti}}{c_{ti}} e^{-\frac{k_{ti}}{c_{ti}} t} \left[ \int_0^t Q_i(\tau) e^{\frac{k_{ti}}{c_{ti}} \tau} d\tau \right], i = 1, 2, 3, 4. \]  

(3.7)

Due to the discrete nature of the collected accelerations in practical engineering, the integration term in Eq. (3.7) cannot be obtained directly. To overcome this, one can transform the integration into numerical summation with respect to time, resulting in the solution being presented in a discrete form as shown in Eq. (3.8),

\[ \ddot{u}_{ci}(t) = k_{ti} \frac{c_{ti}}{c_{ti}} \sum_{j=1}^{\lceil t/\Delta t \rceil} (Q_i|_j) e^{\frac{k_{ti}}{c_{ti}} (j\Delta t - t)} \Delta t, i = 1, 2, 3, 4; j = 1, 2, \ldots \]  

(3.8)

where \( \Delta t \) represents the sampling time interval, as previously stated. The variable \( j \) denotes the \( j \)-th sampling point of accelerations, while \( Q_i|_j \) is calculated at this point using Eq. (3.3). For the purpose of this study, the simplest rectangular numerical integration method is employed. However, one can improve the precision of numerical integration by using methods such as Midpoint, Trapezoid, or Simpson’s rule.

### 3.1.2 Damage detection with the SV and PT

**Indirect bridge frequency identification**

Previous studies have examined the identification of bridge frequencies through the analysis of vibrations from instrumented vehicles. However, there has been limited research exploring the utilization of indirectly identified frequencies for damage detection. In this section, an approach is
developed to detect, localize, and quantify local damage in a bridge using an SV and a PT. To simplify the calculation process, half-car models are employed to simulate the SV and PT, while a simply supported bridge is utilized, as shown in Figure 3.3.

![Figure 3.3. SV, PT, and bridge models.](image)

The SV is assumed to travel at a constant speed \( v \) to identify the frequencies of the bridge indirectly. It is simulated using a two-axle vehicle model with four DOFs: body bounce (\( z_{sv} \)), body rotation (\( \theta_{sv} \)), front wheel bounce (\( z_{t1} \)), and rear wheel bounce (\( z_{t2} \)). The SV’s body has a mass of \( m_v \) and a moment of inertia of \( I_v \), while the front wheel has a mass of \( m_{t1} \) and the rear wheel has a mass of \( m_{t2} \). The stiffness and damping values of the SV’s front and rear suspension systems are represented by \( k_{s1}, c_{s1} \) and \( k_{s2}, c_{s2} \), respectively. Similarly, the tire’s stiffness and damping values are denoted as \( k_{t1}, c_{t1} \) for the front wheel and \( k_{t2}, c_{t2} \) for the rear wheel. The center of gravity of the SV’s body is located by \( a_1 \) and \( a_2 \), with the axle distance denoted as \( a = a_1 + a_2 \). To account for the difficulty in precisely determining the center of gravity of a vehicle body, it is assumed that the accelerometer is installed at the position with an error of \( e \) from the center of gravity. Both the vehicle’s body and wheels are considered rigid objects, meaning they do not deform under the influence of external forces. Based on the proposed SV model, the dynamic equilibrium equations are shown in Eq. (3.9),

\[
M_{sv}\ddot{z}_{sv}(t) + C_{sv}\dot{z}_{sv}(t) + K_{sv}z_{sv}(t) = f_{cv}
\]

where \( M_{sv}, C_{sv}, \) and \( K_{sv} \) are the SV’s mass, damping, and stiffness matrices, as represented in Eqs. (3.10)-(3.12). \( \ddot{z}_{sv}(t), \dot{z}_{sv}(t), \) and \( z_{sv}(t) \) are its accelerations, velocities, and displacements at all four DOFs, as shown in Eq. (3.13). Vibrations of the SV will change with time \( t \) when it passes the bridge. \( f_{cv} \) means the external excitation input into the SV. The displacements at contact points of the SV are represented by \( u_{c1} \) and \( u_{c2} \), and the
SV’s input excitation can be calculated by Eq. (3.14).

\[
M_{sv} = \begin{bmatrix}
    m_v & 0 & 0 \\
    0 & I_v & 0 \\
    0 & 0 & m_{t1} \\
    0 & 0 & m_{t2}
\end{bmatrix}
\]  
(3.10)

\[
C_{sv} = \begin{bmatrix}
    c_{s1} + c_{s2} & a_1 c_{s1} - a_2 c_{s2} & -c_{s1} & -c_{s2} \\
    a_1 c_{s1} - a_2 c_{s2} & a_1^2 c_{s1} + a_2^2 c_{s2} & -a_1 c_{s1} & a_2 c_{s2} \\
    -c_{s1} & a_2 c_{s2} & c_{s1} + c_{t1} & 0 \\
    -c_{s2} & a_2 c_{s2} & 0 & c_{s2} + c_{t2}
\end{bmatrix}
\]  
(3.11)

\[
K_{sv} = \begin{bmatrix}
    k_{s1} + k_{s2} & a_1 k_{s1} - a_2 k_{s2} & -k_{s1} & -k_{s2} \\
    a_1 k_{s1} - a_2 k_{s2} & a_1^2 k_{s1} + a_2^2 k_{s2} & -a_1 k_{s1} & a_2 k_{s2} \\
    -k_{s1} & a_1 k_{s1} & k_{s1} + k_{t1} & 0 \\
    -k_{s2} & a_2 k_{s2} & 0 & k_{s2} + k_{t2}
\end{bmatrix}
\]  
(3.12)

\[
z_{sv} = [z_{sv}, \theta_{sv}, z_{t1}, z_{t2}]^T
\]  
(3.13)

\[
f_{cv} = [0, 0, k_{t1} u_{c1} + c_{t1} \dot{u}_{c1}, k_{t2} u_{c2} + c_{t2} \dot{u}_{c2}]^T
\]  
(3.14)

A similar two-axle model is utilized for the temporarily parked truck, and its properties are illustrated in Figure 3.3. The truck is positioned at different locations on the bridge to gather a comprehensive set of acquired modal information about the bridge and the sensitivity of its frequencies to local damage. In general, heavy trucks are characterized by significantly higher stiffness and damping values for their wheels and suspensions compared to regular cars. It has been observed that when the stiffness is sufficiently high, the mass of the truck \(M_{pt}^j = \overline{m}_v + \overline{m}_{t1} + \overline{m}_{t2}\) can be divided into two parts [205], as indicated in Eq. (3.15),

\[
M_{pt,1}^j = \overline{m}_v \times \overline{a}_2 / (\overline{a}_1 + \overline{a}_2) + \overline{m}_{t1}
\]  
\[
M_{pt,2}^j = \overline{m}_v \times \overline{a}_1 / (\overline{a}_1 + \overline{a}_2) + \overline{m}_{t2}
\]  
(3.15)

where \(M_{pt,1}^j\) means the mass added to the position where the truck’s front axle is on, and \(M_{pt,2}^j\) is the mass added to the rear axle’s position. \(j\) is utilized to present the position of the PT’s rear axle on the bridge.

To indirectly identify the bridge’s frequencies from the SV’s vibrations, the residual CP response of its two wheels is back-calculated, which is introduced as follows. When the SV passes the bridge, its dynamic equilibrium equations related to its wheels can be represented by Eqs. (3.16a) and (3.16b).

\[
m_{t1} \ddot{z}_{t1} - c_{s1}(\dot{z}_{sv} - \dot{z}_{t1} + a_1 \dot{\theta}_{sv}) - k_{s1}(z_{sv} - z_{t1} + a_1 \theta_{sv}) + c_{t1}(\dot{z}_{t1} - \dot{u}_{c1}) + k_{t1}(z_{t1} - u_{c1}) = 0
\]  
(3.16a)
where $u_{c1}$ and $u_{c2}$ are the CP displacements of the front and rear wheels. Similarly to Section 3.1.1, by taking the second-order derivative of the above two equations and putting items related to CP responses to the left side, we can obtain Eqs. (3.17)-(3.19).

\[
\ddot{u}_{ci} + \frac{c_{ti}}{k_{ti}} \frac{du_{ci}}{dt} = \Psi_i(t), i = 1, 2. \tag{3.17}
\]

\[
\Psi_1(t) = \frac{m_{t1} \dot{z}_{t1}}{k_{t1}} - \frac{c_{s1}}{k_{t1}} \left( \frac{d\dot{z}_{sv}}{dt} - \frac{d\dot{z}_{t1}}{dt} + a_1 \frac{d\dot{\theta}_{sv}}{dt} \right) - \frac{k_{s1}}{k_{t1}} \left( \dot{z}_{sv} - \dot{z}_{t1} + a_1 \dot{\theta}_{sv} \right) \tag{3.18}
\]

\[
\Psi_2(t) = \frac{m_{t2} \dot{z}_{t2}}{k_{t2}} - \frac{c_{s2}}{k_{t2}} \left( \frac{d\dot{z}_{sv}}{dt} - \frac{d\dot{z}_{t2}}{dt} - a_2 \frac{d\dot{\theta}_{sv}}{dt} \right) - \frac{k_{s2}}{k_{t2}} \left( \dot{z}_{sv} - \dot{z}_{t2} - a_2 \dot{\theta}_{sv} \right) \tag{3.19}
\]

As Eq. (3.17) is a first-order linear differential equation, its solution can be represented by Eq. (3.20) when the accelerations are collected in the discrete format in practical engineering.

\[
\dot{u}_{ci}(t) = \begin{cases} 
\Psi_i(t), i = 1, 2, & \text{if } c_{ti} = 0 \\
\eta_i (\sum_{s=1}^{t/\Delta t} \Psi_i(s\Delta t - t) \Delta t), i, s = 1, 2, \ldots & \text{if } c_{ti} \neq 0 
\end{cases} \tag{3.20}
\]

Here, $\eta_i = k_{ti}/c_{ti}, i = 1, 2,$ is defined as the ratio of the stiffness and damping of the SV's tires. $\Delta t$ represents the sampling time interval, and $s$ denotes the $s$-th sampling point of the SV's accelerations. By utilizing Eq. (3.20), the CP responses of the SV's front and rear wheels can be obtained. Similar to Section 3.1.1, it is determined that the sensor installation error $e$ on the SV can be eliminated when calculating $\Psi_1(t)$ and $\Psi_2(t)$. Additionally, to eliminate the influence of road roughness, the residual CP response is computed by subtracting the CP response of the rear wheel from that of the front wheel with a time lag of $\Delta t_g$. The time lag can be calculated as $\Delta t_g = (a_1 + a_2)/v$. Typically, the stiffness-damping ratio is generally the same for the front and rear tires, denoted as $\eta = \eta_1 = \eta_2$. Therefore, the calculation of the residual CP response can be expressed using Eq. (3.21). Furthermore, the FFT will be utilized to transform the time-domain residual CP response into the frequency domain, enabling manual identification of the bridge's frequencies. For simplicity, the residual CP responses are
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denoted as $\ddot{u}_c^1 - \ddot{u}_c^2$, and the function arguments are omitted for clarity.

$$\ddot{u}_c^1(t) - \ddot{u}_c^2(t + \Delta t_g) =$$

$$\begin{cases} 
\Psi_1(t) - \Psi_2(t + \Delta t_g) & \text{if } c_{ti} = 0 \\
\eta \Delta t \left( \sum_{s=1}^{s' \Delta t} \Psi_1 s \exp\left( \eta(s \Delta t - t) \right) - \Psi_2 s \exp(\eta(s + \frac{s' \Delta t}{\Delta t})\Delta t - t) \right) & \text{if } c_{ti} \neq 0 
\end{cases}$$

(3.21)

**Damage simulation**

In the simulation, the damage to the bridge is accomplished by stiffness reduction as represented by damage factors $\mathbf{\mu} = [\mu_1, \mu_2, \cdots, \mu_N]$, where $\mu_j$ denotes the ratio of the stiffness after damaging the $j$-th substructure to the original stiffness. In this context, the term “substructure” specifically alludes to the substructure method commonly employed in model updating [206, 207], rather than referencing the bridge’s components as typically used in the field of bridge engineering. For instance, $\mu_2 = 0.8$ indicates a 20% reduction in the stiffness of the second substructure. If $K_j$ is used as the extended stiffness matrix of the $j$-th substructure in the global coordinate system, the stiffness matrix of the potentially damaged bridge can be expressed as Eq. (3.22).

$$K_b^d(\mathbf{\mu}) = \sum_{j=1}^{N_s} \mu_j K_j$$

(3.22)

**Temporarily parked truck**

(1) Frequency vector formation when the PT is at different locations

The selected PT should have sufficient mass to induce changes in the natural frequencies of the bridge, thereby effectively altering its mass characteristics. By parking the PT at $N_s - 1$ different locations (substructures) on the bridge, the bridge’s natural frequencies, with the presence of the PT, will correspondingly change. When the PT’s rear axle is positioned at the $j$-th location, the SV indirectly identifies the first $K$ order frequencies of the bridge as $f_b^j = [f_{b1}^j, f_{b2}^j, \cdots, f_{bK}^j]^T$, as illustrated in Figure 3.4. Consequently, we can obtain $(N_s - 1) \times K$ frequency data points for the bridge by incorporating the PT. All the identified frequencies can be combined to form a frequency vector, as illustrated in Eq. (3.23).

$$f_b = [f_b^1, f_b^2, \cdots, f_b^{N_s-1}]^T$$

(3.23)

(2) Determination of the truck’s mass

In addition to increasing the number of utilized modes, the PT is designed to enhance the sensitivity of the bridge’s natural frequencies to local damage. The relative sensitivity of the $k$-th natural frequency with respect to
the damage factor of the $l$-th substructure, when the mass $(M_{pt,i}^j, i = 1,2)$ is positioned at the $j$-th location, can be calculated using Eq. (3.24),

$$ R_{kj}(\mu, M_{pt,i}^j) = \frac{\partial f_{b,kj}(\mu, M_{pt,i}^j)}{\partial \mu} = \frac{\psi_{b,kj}^T(\mu, M_{pt,i}^j)K_j\psi_{b,kj}(\mu, M_{pt,i}^j)}{2f_{b,kj}(\mu, M_{pt,i}^j)} $$

(3.24)

where $\psi_{b,kj}$ represents the modal shape vector, and $K_j$ denotes the extended stiffness matrix of the $l$-th substructure. In practical applications, $M_{pt,i}^j$ may vary at different locations to enhance the relative sensitivity of various substructures. However, adjusting the mass of the PT during the assessment is challenging. Therefore, in this study, it is assumed a constant mass value for the PT. As a result, the proposed method only requires moving the PT along the bridge to different locations. By utilizing Eq. (3.24), the sensitivity of the mass to each substructure of the undamaged bridge can be determined, enabling the selection of the proper mass of the PT.

**Objective functions**

The proposed method requires building and updating the FE model of the bridge. Once the PT is parked at a specific location, the bridge’s mass matrix needs to be modified to incorporate the PT’s effects. Let $M_{b,j}$ denote the bridge’s mass matrix when the PT’s rear axle is positioned at the $j$-th location. By performing eigenvalue decomposition of the structural stiffness matrix $K_j^d(\mu)$ and the mass matrix $M_{b,j}$ of the bridge FE model, the frequency vector $f_b(\mu)$ of the bridge can be obtained. Eq. (3.25) demonstrates a conventional approach for minimizing the relative error between the frequencies of the FE model and the experimental bridge, represented by the objective function $L_1$, where $\| \cdot \|$ denotes the Euclidean norm. The $L_1$ function has been utilized in several existing studies [208–210].

$$ L_1(\mu) = \| f_b(\mu) - f_b \|_2^2 $$

(3.25)
In this thesis, a new objective function $L_2$ is proposed, which integrates the MAC values between the frequency vectors, as shown in Eqs. (3.26) and (3.27),

$$L_2(\mu) = 1 - \text{MAC}(f_b(\mu), f_b) + \lambda \|1 - \mu\|_1$$  \hspace{1cm} (3.26)  

$$\text{MAC}(f_b(\mu), f_b) = \frac{|f^T_b(\mu) f_b|^2}{(f^T_b(\mu) f_b)(f^T_b f_b)}$$  \hspace{1cm} (3.27)  

where the term $\lambda \|1 - \mu\|_1$ means the $l_1$-norm of $1 - \mu$, which can promote the sparsity of the identified damage, and it is beneficial to locate the position of possible damage in the bridge [211–213].

### 3.2 Data-driven approaches

#### 3.2.1 Support vector machine (SVM)

SVM is a popular classification algorithm that has been widely utilized in the health monitoring of structures [214–216]. It has strong theoretical foundations and excellent classification capability. The fundamental concept behind SVM is to maximize the margin between two classes using a hyperplane, as illustrated in Figure 3.5.

![Basic principles of SVM](image)

**Figure 3.5.** Basic principles of SVM.

If the datasets own $m$ samples presented by $(x_i, y_i), i = 1, 2, 3, ..., m; y_i \in \{1, -1\}$, the optimal hyperplane will be

$$w \cdot x_i + b = 0$$  \hspace{1cm} (3.28)  

where the weights are denoted by $w$, the data points lying on the optimal hyperplane are represented by $x_i$, and the bias is denoted by $b$. The maximum margin is obtained by finding the maximum value of $d$, as illustrated in Figure 3.5. To achieve this, the objective function Eq. (3.29)
needs to be minimized.

\[ f(w) = \frac{2}{d^2} = \frac{\|w\|^2}{2}, \quad (3.29) \]

\[ s.t. \quad y_i(w \cdot x_i + b) \geq 1, i = 1, 2, 3, ..., m \]

In order to minimize Eq. (3.29), its dual problem is considered. The standard Lagrange multiplier method, introduced in Eq. (3.30), is a proven approach for solving this optimization problem. This method consists of two parts: the original problem and the inequality constraint. By introducing the Lagrange dual function (Eq. (3.31)), which only contains \( \alpha_i \), and ensuring that the original Lagrange function satisfies the Karush-Kuhn-Tucker (KKT) optimality conditions, the optimization problem can be solved. It has been found that all support vectors satisfy the KKT optimality conditions. The values of \( w, b \), and the linear decision function can be obtained as shown in Eqs. (3.32) and (3.33).

\[ L(w, b, \alpha) = \frac{1}{2} \|w\|^2 - \sum_{i=1}^{m} \alpha_i (y_i (w \cdot x_i + b) - 1), \quad (\alpha_i \geq 0) \quad (3.30) \]

\[ L_d = \sum_{i=1}^{m} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{m} \alpha_i \alpha_j y_i y_j x_i \cdot x_j \quad (3.31) \]

\[ w = \sum_{i=1}^{m} \alpha_i y_i x_i; b = y_i - w \cdot x_i \quad (3.32) \]

\[ f(x_{test}) = \text{sign}(w \cdot x_{test} + b) = \text{sign}(\sum_{i=1}^{m} \alpha_i y_i x_i \cdot x_{test} + b) \quad (3.33) \]

where \( x_{test} \) means any test samples, and \( \text{sign}(\cdot) \) is the sign function. When the input is greater than 0, it returns 1; otherwise, it returns -1.

In cases where the data cannot be perfectly separated by a linear hyperplane, the margin must be adjusted. To optimize the original constraint conditions, the penalty parameter \( C \) and the slack variable \( \zeta_i \) are introduced. The updated constraint can be seen in Eq. (3.34).

\[ f(w, \zeta_i) = \frac{\|w\|^2}{2} + C \sum_{i=1}^{m} \zeta_i, \quad (3.34) \]

\[ s.t. \quad w \cdot x_i + b \geq 1 - \zeta_i; \zeta_i \geq 0, i = 1, 2, 3, ..., m. \]

where the parameter \( C \) is used to regulate the degree of penalization in the objective function. When \( C \) takes a large value, SVM enforces a strict constraint on the classification errors, resulting in a smaller margin (hard margin). Conversely, when \( C \) is small, some classification errors are allowed, leading to a larger margin (soft margin).

Nonlinear classification problems require mapping the data from the original space \( x \) to a higher-dimensional space \( \Phi(x) \), where \( \Phi \) represents
the mapping function. The decision function for such problems can be seen in Eq. (3.35). However, the mapping function is often unknown, and even if it is known, computing \( \Phi(x_i) \cdot \Phi(x_{test}) \) can be computationally intensive. To address this issue, SVM employs kernel functions \( K \), which are introduced in Eq. (3.35). Table 3.1 lists commonly used kernel functions in SVM. The hyperparameters \( C, \gamma, r, \) and \( d \) must be set before applying SVM.

\[
f(x_{test}) = \text{sign} \left( \sum_{i=1}^{m} \alpha_i y_i \Phi(x_i) \cdot \Phi(x_{test}) + b \right)
\]

(3.35)

<table>
<thead>
<tr>
<th>Kernel</th>
<th>Expressive formulas</th>
<th>Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear</td>
<td>( K(x,y) = x^T y = x \cdot y )</td>
<td>( C )</td>
</tr>
<tr>
<td>Polynomial</td>
<td>( K(x,y) = (\gamma(x \cdot y) + r)^d )</td>
<td>( C, \gamma, r, d )</td>
</tr>
<tr>
<td>Sigmoid kernel function</td>
<td>( K(x,y) = \tanh(\gamma(x \cdot y) + r) )</td>
<td>( C, \gamma )</td>
</tr>
<tr>
<td>Radial basis function (RBF)</td>
<td>( K(x,y) = e^{-\gamma |x-y|^2} )</td>
<td>( C, \gamma )</td>
</tr>
</tbody>
</table>

This study utilizes the Scikit-learn package [217] to implement the SVM algorithm. The package offers various application programming interfaces for selecting different parameters, including the kernel function, penalty parameter, and other hyperparameters.

### 3.2.2 Mel-frequency cepstral coefficients (MFCCs)

Originally used for acoustic recognition to extract voice features, MFCCs have proven to be effective in SHM, such as pipeline anomaly detection [218], bridge deck monitoring [219], and bolt looseness detection [220], among others. MFCCs provide distinct advantages over Hertz-scale responses: (1) emphasizing low-frequency ranges while retaining high-frequency information, as opposed to Hertz-scale responses treating all frequencies uniformly; and (2) extracting information from diverse frequency ranges, in contrast to Hertz-scale spectra that predominantly emphasize amplitudes. Initially, MFCCs were designed to mimic the linear nature of the human auditory system under 1 kHz, which becomes logarithmic over 1 kHz [221]. The original mutual transformation between Hertz and Mel frequency scales can be seen in Eq. (3.36),

\[
f_m = 2595 \log_{10}(1 + f_h/700)
\]

(3.36)

where \( f_m \) and \( f_h \) represent Mel-scale and Hertz-scale frequencies, respectively. However, due to differences between the auditory system of humans
and the requirements for bridge health monitoring, the equation was modified in reference [45], resulting in the form presented in Eq. (3.37). Figure 3.6 illustrates the relationship between Hertz- and Mel-scale frequencies.

\[ f_m = 5\ln(1 + f_h/5) \]  

\[ (3.37) \]

**Figure 3.6.** Relationship between Hertz and Mel frequency scale below 800 Hz.

To extract MFCCs from the original vehicular accelerations, the following five steps are involved: (1) Data preprocessing; (2) FFT; (3) Mel Filterbank; (4) Logarithm; and (5) Discrete Cosine Transform (DCT).

**Data preprocessing and FFT**  As the focus is on the bridge’s dynamic information present in the vehicle’s vibrations, only signals captured when the vehicle is on the bridge will be utilized. Therefore, the first step involves isolating the signals captured when both of the vehicle’s axles are on the bridge. The collected accelerations are then divided into \( N \) frames, with \( N = 1 \) indicating all signals are projected onto the Mel scale. However, when \( N > 1 \), the entire signal is divided into \( N \) frames, and the accelerations within each frame are transformed into the frequency domain using FFT. The energy of signals is computed by calculating the square of the frequency-domain responses. To tackle the spectrum leakage issue, the
Hann window is applied to the signal in each frame. Figure 3.7 illustrates the first two steps involved in extracting MFCCs.

**Mel Filter bank, Logarithm, and DCT** Once each energy spectrum is obtained, it is convolved with Mel filterbanks. The selection of filterbanks is crucial, as it determines the number of MFCCs extracted. Additionally, one can choose between even or uneven filterbanks. When using even filter banks, frequency responses are treated equally (similar to the Hertz scale). On the other hand, uneven filterbanks are denser in low-frequency ranges and sparser in high-frequency ranges. For instance, dividing 0-800 Hz in Hertz scale into 15 filter banks evenly or unevenly (using Eq.(3.37)) can be seen in Figure 3.8. Finally, a logarithm and a DCT are applied to each bank to obtain the final MFCCs.

![Filterbank Amplitudes](image)

**Figure 3.8.** Illustration of even and uneven filterbanks.

![MFCC Extraction](image)

**Figure 3.9.** Extraction of MFCCs: steps 3, 4 and 5.

The above five steps can be represented in Eq. (3.38)

\[
M^j_i = D(\ln(Mel(|\mathcal{F}(s_i)|^2) + \epsilon)), i = 1, 2, 3, \ldots, N; j = 1, 2, 3, \ldots, P
\]  

(3.38)

where \( M^j_i \) represents the \( j \)-th MFCC of the \( i \)-th frame. The constant \( \epsilon \) is necessary for acoustic recognition, particularly when the value in \( \ln(\cdot) \) can be negative. However, since the energy spectrum of passing vehicle signals always has values greater than zero, \( \epsilon \) is not needed in this work, i.e., \( \epsilon = 0 \) in Eq. (3.38). Here, \( s_i \) represents the \( i \)-th acceleration signal after dividing the entire signal into \( N \) frames. \( \mathcal{F} \) denotes FFT, while \( Mel \) represents multiplication of Hertz-scale energy with each Mel filterbank.
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*D* refers to DCT, with DCT-II [222] being adopted here as presented in Eq. (3.39), where \( x \) and \( X \) mean values before and after DCT, respectively. \( x = [x_1, x_2, ..., x_P] \) and \( X = [X_1, X_2, ..., X_P] \) have the same dimensions.

\[
X_k = \sum_{p=0}^{P-1} x_{p+1} \cos \left[ \frac{\pi}{P} \left( p + \frac{1}{2} \right) (k - 1) \right], \quad k = 1, ..., P \tag{3.39}
\]

### 3.2.3 Assumption accuracy method (A²M)

In modern research utilizing machine learning algorithms, supervised learning approaches are widely used. Generally, supervised algorithms necessitate labeled data, which can be challenging to obtain, especially when considering the various damage patterns that bridges can experience in practical engineering. Therefore, it is crucial to explore ways to detect the damaged state of a bridge without labeled damage data to enable the application of machine learning algorithms.

This section presents the fundamental concept of monitoring the health state of a bridge using the proposed assumption accuracy method, as illustrated in Figure 3.10. The procedure involves five steps: (1) original acceleration collection, (2) transform signals into the frequency domain, (3) latent representation, (4) binary classification, and (5) damage detection by A²M.

#### Figure 3.10. Schematic workflow of the A²M.

**Data collection and FFT**  As depicted in Figure 3.10, the proposed method relies on establishing a baseline when the bridge is in a healthy state, such as at time \( T_0 \). At this point, vehicles must traverse the bridge numerous times to obtain an adequate amount of vehicle data (say, dataset 0). It
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is essential to collect as many external factors that may affect damage detection as possible in the initial dataset. Then, after several months or years, at $T_i$, the same vehicle is used to gather vibration data from the bridge once again. In this method, it is assumed that the influencing factors will not change significantly during the monitoring period. As a result, the only change in the VBI system after $T_i$ when dataset $i$ is obtained is the bridge’s damage. After dataset $i$ is collected, the acceleration data from both dataset 0 and dataset $i$ are transformed into the frequency domain to determine the classification accuracy.

**Latent representation, binary classification, and damage detection**  
At $T_i$ when the signals of runs are collected. Actually, the bridge’s damage condition is unknown. To seek this, it is labeled as “assumed damage”. This means that all runs at $T_i$ are labeled differently from runs at $T_0$. For instance, runs from a healthy bridge are labeled as “class 0”, while runs from the assumed damaged bridge are labeled as “class 1”. A classifier can be trained based on these two datasets, and after dividing them into training sets and validation sets, the classification accuracy can be calculated and used as a damage detection index.

However, using the original frequency responses of all runs can be computationally expensive, and unrelated factors such as environmental noises can also affect the classification accuracy if all frequency responses are utilized. In this work, several DRTs are explored to reduce the dimensions of the original frequency responses and, at the same time, reduce the impact of noises. Ultimately, the classification accuracy is checked to determine the bridge’s health state. If the bridge is damaged, the classification accuracy is expected to be high (close to 1.0). Instead, if the bridge remains in good condition, the accuracy will be low (near 0.5), as no bridge damage information can be detected from the vehicle’s vibrations. In other words, the $A^2M$ attempts to make the occurrence of bridge damage the only change during the monitoring periods. This is based on the theory that the bridge’s dynamic information is contained in the vehicle’s responses. Once damage occurs, it will trigger a high accuracy of the binary classification. Conversely, low accuracy implies that the bridge remains in good condition and runs at this moment can be added to dataset 0 for future usage.

When implementing the proposed $A^2M$, the following considerations should be taken into account: (1) During the initial phase, when the bridge is in a healthy state, it is necessary to collect sufficient data by running the vehicle over the bridge multiple times. These runs should include as many influence factors as possible, such as different environmental noises, driving traces, and vehicle speeds. (2) To prevent data imbalance issues during binary classification, the number of samples in classes 0 and 1 should be nearly equal. (3) To calculate classification accuracy, it is recommended to use $k$-folder cross-validation (CV) instead of a one-time validation. In the $k$-folder CV process, the entire dataset (including dataset
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0 and dataset \( i \) is randomly divided into \( k \) sections. This \( k \)-folder CV process should be executed multiple times to avoid occasional high or low accuracy. (4) The classifier must not be too strong, as strong classifiers can identify minor differences between two datasets, even if the bridge remains in a healthy state. The differences detected by these classifiers may be irrelevant to damage and simply represent noisy features. Studies have shown that in high-dimensional space, the vehicle’s frequency responses are linearly separable [183]. Therefore, it is recommended to use linear classifiers such as SVM with a linear kernel and weak classifiers such as Naive Bayes, k-Nearest Neighbors, and Decision Trees without boosting techniques.

3.2.4 Deep auto-encoder (DAE)

Auto-encoder (AE) is an unsupervised method used to extract features from original signals. It does not require any labels, making it a more practical approach for use in real-world engineering applications. The conventional auto-encoder is composed of an encoder and a decoder, and it consists of a single hidden layer, which can be expressed using Eqs. (3.40) and (3.41),

\[
\mathbf{h} = f(\mathbf{W}s + \mathbf{b}) \tag{3.40}
\]

\[
\hat{s} = g\left(\mathbf{W}^*\mathbf{h} + \mathbf{b}^*\right) \tag{3.41}
\]

where \( s \) is the input vector, and \( \hat{s} \) is the output vector. \( \mathbf{h} \) is the hidden state of inputs. \( f \) and \( g \) are the activation functions for the encoder and decoder, respectively. \( \mathbf{W} \) and \( \mathbf{W}^* \) are weight matrices for encoder and decoder, and \( \mathbf{b} \) and \( \mathbf{b}^* \) are bias vectors for the hidden layer and output layer respectively. The target of the auto-encoder is to optimize \( \mathbf{W}, \mathbf{W}^*, \mathbf{b} \) and \( \mathbf{b}^* \) to minimize the difference between inputs and outputs.

Since the auto-encoder is designed to reconstruct inputs using information from the hidden layer, this layer is where the most critical information is stored, while unrelated or insignificant information is discarded. This makes it an effective method for reducing input dimensions. However, due to the loss of information in the hidden layer, the auto-encoder cannot fully reconstruct the inputs. Therefore, the error between inputs and outputs can be used as a loss function to train the auto-encoder.

However, the auto-encoder has limited capability of addressing high-dimensional inputs because it only has one hidden layer, and the trainable parameters in the neural networks are quite insufficient. Learning features from high-dimensional inputs becomes challenging for such a simple neural network. The DAE with more hidden layers can enhance its ability to extract key features from inputs by increasing the number of trainable parameters. This helps the DAE to represent complex inputs by very compressive data (namely, key features). The DAE has been shown in Figure
3.11. However, as the number of hidden layers increases, the auto-encoder may encounter overfitting problems. This means that the auto-encoder learns from some noisy information, and the trained model cannot be applied to other samples. The number of hidden layers is a hyperparameter that must be determined before training the DAE.

![Diagram of the deep auto-encoder model](image)

Figure 3.11. Illustration of the deep auto-encoder model.

For a DAE model, given an unlabeled dataset $S = [s_1, s_2, \ldots, s_N]$ and the reconstructed dataset $\hat{S} = [\hat{s}_1, \hat{s}_2, \ldots, \hat{s}_N]$, the loss function can be represented by Eqs. (3.42) and (3.43),

$$L(\theta; S, \hat{S}) = \frac{1}{N} \sum_{i=1}^{N} (\|s_i - \hat{s}_i\|^2) + \Omega(\theta)$$ (3.42)

$$[W_l, b_l, W^*_l, b^*_l] = \arg\min_{W_l, b_l, W^*_l, b^*_l} L(\theta; S, \hat{S}), \quad l = 0, 1, \ldots, L$$ (3.43)

where $\theta$ represents all parameters in the DAE network, including weight matrices $W_l, W^*_l$ and bias vectors $b_l, b^*_l$; here, the subscript $l$ denotes the parameters for the $l$-th hidden layer and there are $L$ hidden layers in total. The regularization term $\Omega(\theta)$ is applied to the weights to prevent overfitting problems.

In order to minimize the loss function, all parameters are updated in the opposite direction of the gradient of the loss function, denoted as $\nabla_\theta L(\theta)$. When the computer cannot address all inputs at the same time, a mini-batch approach is commonly used in the training process. This has been shown to improve training efficiency and accelerate convergence [223].

In this thesis, the DAE is utilized to extract features of the vehicle’s vibration data when passing a healthy bridge. The goal of the DAE is to minimize errors when reconstructing the input. Notably, compared to previous auto-encoder studies, the vehicle’s frequency responses are utilized as input features to feed the DAE model. This is because acceler-
ations often contain high-frequency components induced by noise, which can negatively affect damage detection results [224].

For damage detection, the DI can be represented by the square error between a frame’s original frequency responses $s$ and its reconstructed frequency responses $\hat{s}$ using a trained DAE, as shown in Eq. (3.44).

$$\text{DI} = \| s - \hat{s} \|^2$$  (3.44)

For each frame, there will be a single DI value. For the vehicle’s one run (it passes the bridge once), the DIs can be computed in real time. The DAE model is specifically trained on frequency responses collected from the vehicle traversing an undamaged bridge, enabling it to reconstruct “healthy” frequency responses with remarkable accuracy. However, when the vehicle crosses a damaged bridge, the vehicle’s frequency responses will become abnormal for the trained DAE. This enables the DAE to automatically distinguish between healthy and damaged bridge conditions. When the bridge is in good condition, the DI values will be relatively low. Conversely, if the bridge is damaged, the trained DAE will not recognize the frequency responses as “healthy”, so DI values will be relatively high. Therefore, DI values can be utilized to determine the health conditions of the bridge.

### 3.3 Numerical simulations

#### 3.3.1 3D vehicle and bridge models

For the verification of bridge frequency identification from the vehicle’s responses, a 3D vehicle and a simply supported beam in numerical simulations are employed in this thesis. The vehicle and bridge’s parameters can be found in Table 3.2. All symbols are the same as introduced in Section 3.1.1. The sampling time interval for both the vehicle and the bridge is set as $0.001 \text{ s (} f_s = 1000 \text{ Hz})$. The vehicle and the bridge are assumed motionless at the beginning (zero displacements, zero velocity, and zero acceleration), and the contact responses for four wheels are set as zeros when $t = 0$. This thesis employs the uncoupled model to simulate the interaction between the vehicle and the bridge [225]. This assumption is based on the theory that the mass of the vehicle is small, and the passage of it will not significantly induce changes in the bridge’s frequencies.

The vehicle’s frequencies are denoted by $f_{v1} \sim f_{v7}$ in Table 3.2. Tire damping of the vehicle is from the reference [24], and other parameters are collected from a full-car model in the reference [226]. The vehicle’s axle distance and width are 2.87 m and 1.45 m, respectively. Due to the uneven weights of the vehicle, the gravity center is not in the geometrical center.
of the vehicle body but is eccentrically located. Namely, \(a_1, a_2, b_1, b_2\) are mutually different. Since the influence of sensor installation errors can be eliminated, as proved in Section 3.1.1, here it is assumed that the vehicle body sensors are installed on its gravity center.

For the bridge, a simply supported Euler-Bernoulli beam is utilized. The bridge’s dynamic equilibrium equations can be represented as Eq. (3.45),

\[
M_b \{\ddot{z}_b\} + C_b \{\dot{z}_b\} + K_b \{z_b\} = p_{b,N}
\]

where \(M_b, C_b,\) and \(K_b\) are the bridge’s mass, damping, and stiffness matrices. \(\dot{z}_b, \ddot{z}_b,\) and \(z_b\) are the bridge’s acceleration, velocity, and deflection vector, respectively. \(p_{b,N}\) is the nodal load for the bridge. The bridge’s damping matrix is simulated by the Rayleigh damping assumption, and it can be calculated by Eq. (3.46),

\[
C_b = a_0 M_b + b_0 K_b
\]

where \(a_0\) and \(b_0\) can be obtained when two random damping ratios are determined in advance. Because it is always difficult to acquire detailed information regarding the relationship between the frequency and damping, typically, it is assumed that two identical damping ratios of the two control frequencies (e.g., first and second-order damping ratios \(\xi = \xi_1 = \xi_2\) [189]). Then, the coefficients \(a_0\) and \(b_0\) can be calculated by Eq. (3.47),

\[
[a_0, b_0] = 2\xi/(f_{b1} + f_{b2}) [f_{b1} f_{b2}, 1]
\]

In this work, a 25 m bridge with ten finite elements is employed, and its parameters are adopted from the reference [148] and can be found in Table 3.2. The FE model of the bridge is shown in Figure 3.12.

---

**Table 3.2. Parameters of the 3D vehicle and bridge.**

<table>
<thead>
<tr>
<th>VBI</th>
<th>Parameters</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(m_v)</td>
<td>1085 kg</td>
<td></td>
</tr>
<tr>
<td>(I_{v\phi})</td>
<td>1100 kg (\cdot) m²</td>
<td></td>
</tr>
<tr>
<td>(I_{v\theta})</td>
<td>820 kg (\cdot) m²</td>
<td></td>
</tr>
<tr>
<td>(m_1, m_2, m_3, m_4)</td>
<td>40, 40, 40, 40 kg</td>
<td></td>
</tr>
<tr>
<td>(c_{s1}, c_{s2}, c_{s3}, c_{s4})</td>
<td>(2 \times 10^3, 2 \times 10^3, 2 \times 10^3, 2 \times 10^3) N(\cdot)s/m</td>
<td></td>
</tr>
<tr>
<td>(c_{t1}, c_{t2}, c_{t3}, c_{t4})</td>
<td>(430, 430, 430, 430) N(\cdot)s/m</td>
<td></td>
</tr>
<tr>
<td>(k_{s1}, k_{s2}, k_{s3}, k_{s4})</td>
<td>(1 \times 10^4, 1 \times 10^4, 1 \times 10^4, 1 \times 10^4) N/m</td>
<td></td>
</tr>
<tr>
<td>(k_{t1}, k_{t2}, k_{t3}, k_{t4})</td>
<td>(1.5 \times 10^5, 1.5 \times 10^5, 1.5 \times 10^5, 1.5 \times 10^5) N/m</td>
<td></td>
</tr>
<tr>
<td>(a_1, a_2, b_1, b_2)</td>
<td>1.4, 1.47, 0.7, 0.75 m</td>
<td></td>
</tr>
<tr>
<td>Speed (v)</td>
<td>5.0 m/s (18 km/h)</td>
<td></td>
</tr>
<tr>
<td>Vehicle frequencies</td>
<td>(f_{v1} \sim f_{v7})</td>
<td>0.673, 0.935, 1.551, 10.066, 10.067, 10.069, 10.074 Hz</td>
</tr>
<tr>
<td>Bridge</td>
<td>Length (l_b)</td>
<td>25 m</td>
</tr>
<tr>
<td>Bridge</td>
<td>Young’s modulus (E_b)</td>
<td>27.5 GPa</td>
</tr>
<tr>
<td>Bridge</td>
<td>Moment of inertia (I_b)</td>
<td>0.2 m⁴</td>
</tr>
<tr>
<td>Bridge</td>
<td>Mass per unit length (\bar{m}_b)</td>
<td>2400 kg/m</td>
</tr>
<tr>
<td>Bridge frequencies</td>
<td>(f_{b1} \sim f_{b3})</td>
<td>3.805, 15.220, 34.260 Hz</td>
</tr>
</tbody>
</table>
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\[ l_b = 25 \text{ m} \]

\[ \lambda = 2.5 \text{ m} \]

Figure 3.12. Simply supported bridge model.

3.3.2 SV, PT, and bridge models

The parameters of the employed SV are illustrated in Table 3.3, which are adopted from the reference [226]. The damping values of suspensions and tires are referred to the sensing vehicle in reference [24].

Table 3.3. Parameters of the SV.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Symbol</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Body mass</td>
<td>( m_v )</td>
<td>542.5 kg</td>
</tr>
<tr>
<td>Body moment of inertia</td>
<td>( I_v )</td>
<td>550.0 kg m(^2)</td>
</tr>
<tr>
<td>Wheel mass</td>
<td>( m_{t1}, m_{t2} )</td>
<td>40.0 kg</td>
</tr>
<tr>
<td>Suspension stiffness</td>
<td>( k_{s1}, k_{s2} )</td>
<td>10000, 10000 N/m</td>
</tr>
<tr>
<td>Suspension damping</td>
<td>( c_{s1}, c_{s2} )</td>
<td>2000, 2000 N s/m</td>
</tr>
<tr>
<td>Tire stiffness</td>
<td>( k_{t1}, k_{t2} )</td>
<td>150000, 150000 N/m</td>
</tr>
<tr>
<td>Tire damping</td>
<td>( c_{t1}, c_{t2} )</td>
<td>430, 430 N s/m</td>
</tr>
<tr>
<td>Constants</td>
<td>( a_1, a_2 )</td>
<td>1.4, 1.47 m</td>
</tr>
<tr>
<td>Speed</td>
<td>( v )</td>
<td>5.0 m/s (18 km/h)</td>
</tr>
<tr>
<td>Frequencies</td>
<td>( f_{sv1}, f_{sv2}, f_{sv3}, f_{sv4} )</td>
<td>0.9348, 1.3335, 10.0699, 10.0718 Hz</td>
</tr>
</tbody>
</table>

The parameters of the bridge are obtained from the reference [227]. The bridge has a length of \( l_b = 30 \) m, a mass per unit length of \( \bar{m}_b = 6000 \) kg/m, and a bending stiffness of \( E_b I_b = 2.5 \times 10^{10} \) N/m\(^2\). For the damping model, the Rayleigh damping assumption (as shown in Eq. (3.46)) is employed, with the first two damping ratios set to \( \xi = \xi_1 = \xi_2 = 0.02 \). The FE model of the bridge is shown in Figure 3.13, consisting of six substructures, each consisting of two finite elements. By employing the FE model of the undamaged bridge (i.e., \( \mu = [1,1,1,1,1,1] \)) without the PT, the bridge’s first three natural frequencies can be calculated as: \( f_{b1} = 3.5627 \) Hz, \( f_{b2} = 14.2513 \) Hz, and \( f_{b3} = 32.0721 \) Hz. It is worth noting that the mass ratio between the SV and the bridge is only \( (542.5 + 40 + 40)/6000/30 = 0.35\% \). Therefore, the mass of the SV passing over the bridge is negligible, and it does not significantly impact the bridge’s frequencies.

3.3.3 Road roughness

Road roughness is a significant factor that affects the vehicle’s vibration data and can interfere with the bridge’s frequencies. In this work, the road profile is generated based on ISO 8608 [110], which follows the PSD
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function. ISO 8608 includes eight classes of road roughness labeled A-H (from the best to poorest). The PSD function used to generate road roughness is represented by Eq. (3.48),

$$G_d(n_{s,i}) = G_d(n_{s,0}) \left( \frac{n_{s,i}}{n_{s,0}} \right)^{-w}$$  \hspace{1cm} (3.48)

where $n_{s,0}$ is the reference spatial frequency taken as 0.1 cycle/m, $n_{s,i}$ represents the spatial frequency taken as numbers ranging from 0.01 to 10 $m^{-1}$ with an interval of 0.01 $m^{-1}$, and $w$ is the fit exponent, which is usually set as 2. The roughness coefficient $G_d(n_{s,0})$ is determined by the road roughness class, as shown in Table 3.4. Once $G_d(n_{s,i})$ is determined, the road roughness can be generated by a normal zero-mean, real-valued stationary Gaussian process, as shown in Eq. (3.49),

$$z_r(x) = \sum_{i=1}^{N} \sqrt{2G_d(n_{s,i}) \Delta n_s \cos(2\pi n_{s,i}x + \theta_i)}$$  \hspace{1cm} (3.49)

where $z_r(x)$ represents the generated road profile, while $N$ denotes the number of generated harmonic waves, corresponding to the length of the spatial frequency vector, $n_s = \{n_{s,i}\}$. Here, $n_{s,i}$ is the $i$-th spatial frequency. The interval of spatial frequency, $\Delta n_s$, is set at 0.01 cycle/m. Additionally, $\theta_i$ denotes the random phase angle, which is randomly sampled from a uniform distribution in the range $[0, 2\pi]$.

### 3.3.4 Environmental noises

When using sensors to collect a vehicle’s vibrations, it is inevitable that environmental noises will also be captured. The impact of these noises on
the signals can typically be replicated using Eq. (3.50) [148, 213],

\[ s_n = s + E_n \cdot \sigma_s \cdot \text{randn}(N_s) \]  

(3.50)

where \( s_n \) represents the signals with added noises, while \( s \) denotes the noise-free recorded accelerations. \( E_n \) represents the noise level, and \( \sigma_s \) represents the standard deviation of the signal \( s \). The function \( \text{randn}(N_s) \) generates \( N_s \) random numbers following a standard normal distribution.

In this thesis, the impact of noises of varying levels will be examined and analyzed for their effect on identifying the frequencies of bridges.

### 3.4 Laboratory experiments

#### 3.4.1 Vehicle model

This thesis also employs laboratory experiments as another method. The experiments consist of a model truck with varying weights and speeds, a simply supported steel beam, and a two-span continuous beam, which are elaborated on below.

To simulate the vehicle in practical engineering, a Tamiya model truck (see Figure 3.14a) is employed. The model is scaled down from a real truck with a scale ratio of 1:14 and can be operated on the bridge through a remote control unit (see Figure 3.14b). Its dimensions are 570 mm in length, 200 mm in width, and 260 mm in height. The truck comes equipped with an independent suspension system, connection shift, rubber tires, and other features, as shown in Figure 3.15. For the experiment, two Brüel & Kjær 4371 acceleration sensors are installed on the truck’s front and rear axles to gather its vibration data. The sampling frequency used is 10 kHz. The truck is powered by a Tamiya Ni-MH 7.2 V–3000 mAh battery and can be driven by a 540-brushed electric motor. It is worth noting that the engine’s noise can significantly impact the acceleration readings, as is often the case in practical engineering scenarios.

In order to ensure that a truck travels in a straight line when passing over a bridge, two guide cables are employed, as illustrated in Figure 3.14a. This is done to simulate practical driving conditions. Since the cables pass through two pipes that are attached to the truck, they have minimal impact on the truck’s vertical vibration. It is important to note that the cables are not tightly stretched, which can cause the truck’s path to vary while passing over the bridge.

The original mass of the truck, referred to as the normal vehicle (v0), is 4.305 kg. In order to enhance the accuracy of damage detection and increase the amplitude of the bridge’s vibrations [66, 228], an additional mass of 5.157 kg is added to the truck’s trunk, creating the heavy vehicle.
(v5). Following the addition of the extra mass, the front axle of the truck weighs 4.315 kg, while the rear axle weighs 5.147 kg.

The vehicle’s speed during the experiment may vary due to the battery’s capability, which has been noted to affect drive-by damage detection [229]. To ensure experimental fidelity, the truck is set to run at a constant speed when passing the beam. To achieve the highest speed, a wooden acceleration runway is utilized to propel the truck from a stationary state, and a deceleration runway is placed at the beam’s end to slow it down. The truck’s speeds are not identical for each laboratory test run. Analysis shows that the vehicle’s speeds are distributed between 0.72 and 1.05 m/s.

Regarding the dynamic characteristics of the vehicle model mentioned above, a free vibration test was conducted with an accelerometer attached to the rear axle. The results indicated that the bouncing frequency of the rear axle is 19.531 Hz. In comparison, a real car tested in reference [230] exhibited a rear axle frequency of 15.075 Hz. The scaled vehicle not...
only scales the dimensions of a real car but also preserves its dynamic characteristics.

### 3.4.2 Bridge models

There are two bridge models utilized in the laboratory experiments: simply supported beam (SSB) and continuously supported beam (CSB), as shown in Figure 3.16.

![Figure 3.16. Two beams utilized in the experiments.](image)

For the simply supported bridge model, an I-shaped beam (HEA 400) is employed. There are also sensors attached at the bottom of the beam for analysis and comparison to the drive-by bridge damage detection results. The material of the beam is Q355 with a tested average Young's modulus of 199.0 GPa. The support length at each end of the beam is 0.2 m, and its span length is 4.0 m. Its mass is 550 kg. The deployment of the beam and vehicle can be found in Figure 3.17. By a free vibration experiment in the laboratory, as shown in this figure, the SSB model’s first two frequencies are 35.280 and 110.631 Hz.

![Figure 3.17. Simply supported bridge model in the experiment.](image)

Another one employed in the experiments is the continuously supported beam (UPE 300). The length of the beam is 6.0 m with three hinge supports at 0.15, 3.0, and 5.85 m, respectively. The beam’s mass is weighted as 248.64 kg. Similarly to the simply supported beam, sensors are attached to its bottom, as indicated by the direct method. Its deployment is represented in Figure 3.18. By a free vibration experiment in the laboratory, as shown in the figure, the CSB model’s first three frequencies are determined as
30.748, 42.528, and 98.033 Hz.

\[ \approx v_{3.8} m_{0.15} m_{1.9} m_{0.15} m \]

**Figure 3.18.** Continuous bridge model in the experiment.

It is noteworthy that in existing research involving numerical simulations or laboratory experiments, the ratio of vehicle mass to bridge mass is usually below 5% [24, 81, 231]. In the planned experiments, the maximum ratio of vehicle mass to bridge mass is 3.8% when employing the heavy vehicle and the CSB models. This ratio is deemed satisfactory for simulating a realistic VBI system.

### 3.4.3 Bridge damage scenarios

Theoretically, once bridge damage occurs, its local stiffness will decrease. Simulating damage in numerical simulations is relatively straightforward by reducing the stiffness of some finite elements. However, in experiments, once a beam is damaged, it is difficult to restore it to a healthy state. To simulate bridge damage, one practical approach is to add extra mass to the structure, given that the bridge’s natural frequencies are linked to its mass and stiffness matrices [45, 232, 233]. In this thesis, different masses are added to the bridge span(s) to simulate its global damage. It is worth noting that employing such a method cannot realistically validate the scenarios when the real damage occurs in practical engineering applications, particularly when considering a mass variation on the bridge and temperature changes over the monitoring period. However, in laboratory experiments, it can still be a good way to verify the capability of proposed methods to detect frequency variation. The degree of such stimulative damage can be represented by the ratio of the added mass with respect to the bridge’s mass. An example of adding 5 kg mass to the midpoint of the CSB model’s span is shown in Figure 3.19. Different damage scenarios will be discussed in Section 4.2.
Figure 3.19. Adding 5 kg extra mass to the mid-span of the CSB model.
4. Results and discussions

Based on the previously introduced materials and methods, this chapter presents results and discussions on numerical simulations and laboratory experiments in this thesis. The results of bridge frequency extraction using the 3D vehicle and damage identification with the SV and PT are provided when several influential factors, such as environmental noises and bridge damping, are considered. Furthermore, the chapter presents results from using data-driven methods for bridge damage detection through vehicle responses, followed by discussions on practical applications.

4.1 Bridge frequency identification and modal-based damage detection

4.1.1 Bridge frequency identification with the instrumented 3D vehicle

In this section, the A-class road roughness with $G_d(n_{s,0}) = 4 \times 10^{-6} \text{m}^3$ is utilized. The road roughness generated for the left and right wheels of the vehicle is represented by the black line in Figure 4.1.

Figure 4.1. Generated road roughness for the 3D vehicle.
Results and discussions

As noted by Yang et al. [125], an important consideration when using generated road profiles is that a vehicle’s wheel does not encounter zigzag road roughness point by point. Instead, there is a contact area between the tire and the bridge. A common approach to account for this effect is to use a smoothed road profile. In this study, the contact length between the vehicle’s tire and the bridge is assumed to be 0.04 m. This translates to using a moving average filter (MAF) with a window size of 8 sampling points \((0.04/5/0.001 = 8)\) to smooth the original road roughness. In the case of the 3D vehicle, wheels 1 and 3 experience the same road roughness, and so do wheels 2 and 4. The smoothed road roughness using an MAF is represented by the red dashed line in Figure 4.1.

To better represent the deduction results of the CP response, the bridge damping is temporarily ignored here and will be discussed in Section Consideration of different bridge damping ratios. Figure 4.2 displays the simulation results for the acceleration of the vehicle. Figure 4.3 shows the frequency spectrum of the vehicle’s accelerations. It can be seen that the vehicle’s accelerations are quite complex. The amplitudes of the bridge frequencies have been overshadowed by the vehicle frequencies in the frequency-domain responses, making it difficult to accurately identify the bridge frequencies. Hence, mitigating the influence of vehicle frequencies and road roughness is a demanding task.

![Figure 4.2. Simulated accelerations of the 3D vehicle.](image)

Figure 4.4a displays the computed CP response of wheel 2, as determined by Eq. (3.8). In order to assess the accuracy of the back-calculated CP responses, the MAE has been computed using Eq. (4.1). Here, \(\hat{y}_t\) denotes the calculated CP responses, while \(y_t\) represents the ground truth. The resulting MAE value is 0.797 m/s\(^2\). It is worth noting that the CP response scale ranges from -10 to 10 m/s\(^2\), and as such, these errors will not result in significant deviations when identifying bridge frequencies using the computed CP responses.

\[
\text{MAE} = \frac{1}{N} \sum_{t=1}^{N} (|\hat{y}_t - y_t|), \tag{4.1}
\]
Results and discussions

Figure 4.3. Normalized frequency spectrum of vehicle’s accelerations.

Figure 4.4b displays the frequency spectrum of wheel 2’s CP response. Despite the precise calculation of CP responses, the frequencies of the bridge remain unidentified. This is due to the dominance of peaks in the frequency domain generated by road roughness, which occurs randomly. It can be understood that the frequencies of the bridge are masked by the road roughness in the frequency domain of an individual wheel’s accelerations or CP responses.

Figure 4.4. CP response of wheel 2 and its normalized frequency spectrum.

In order to address the issue caused by road roughness, residual CP responses can be utilized. This study differs from reference [165], which requires two connected vehicles, as it only uses a single 3D vehicle passing over the bridge. As shown in Section 3.1.1, it has been demonstrated that the frequencies of the vehicle can be removed by employing CP responses. If the influence of road roughness can be eliminated, the frequencies of the bridge can be extracted more accurately. Since wheels on the same side of the vehicle experience the same road roughness with a time lag (assuming the vehicle travels in a straight line), their CP responses will be partially similar when they pass the same point of road roughness. The CP responses comprise two components: the acceleration caused by road roughness and the deflection of the bridge. The only difference between the CP responses of two wheels when they pass the same position on the
bridge is the component caused by the bridge’s deflection. By subtracting the CP responses of the rear wheels (wheels 3 and 4) from those of the front wheels (wheels 1 and 2) at the same position on the bridge, the effects of road roughness can be eliminated.

Figure 4.5. Normalized frequency spectrum of the residual CP response.

Figure 4.5 illustrates the frequencies of the bridge identified through the residual CP responses of wheels 1, 3 and 2, 4. The residual CP response amplitudes calculated using Eq. (3.8) match the actual amplitudes closely, indicating that the CP response calculation has a high level of precision. Furthermore, it is clear that the first three frequencies of the bridge can be identified without the influence of the vehicle’s frequencies by utilizing the residual responses of either the left wheels (1, 3) or the right wheels (2, 4).

Consideration of different noise levels

In this section, different levels of environmental noise are considered in the process of identifying the bridge’s frequencies using the residual CP response of wheels 1 and 3. The parameters used in this section are identical to those in Section 3.3.1. An example of adding 5% noise to the acceleration of wheel 2 is demonstrated in Figure 4.6a. Subsequently, by utilizing Eq. (3.8), the CP responses of wheel 2 can be obtained, as illustrated in Figure 4.6b. It is apparent that the presence of noise significantly affects the accuracy of the calculated CP responses, resulting in poor matching with the actual CP responses. The results of identifying the frequencies of the bridge under various noise levels are presented in Figure 4.7.

Based on Figure 4.7, it is clear that when the noise level is low (e.g., 1% noise), even though the calculated CP responses cannot accurately match ground truth, the first three frequencies of the bridge are still distinguishable. As the noise level rises, represented by 3% noise, the third bridge frequency becomes partly obscured by the noise peaks. Also, compared with Figure 4.5a when no noise is introduced, identification of the bridge’s first two frequencies is also influenced. At 5% and 7% noise levels, the third frequency is entirely submerged by the noise. However, these adverse noise effects are limited to high-frequency ranges (above 20
Results and discussions

From the above analysis, it can be observed that environmental noises have a negative impact on extracting the bridge’s frequencies from CP responses. The primary reason for this is the unpredictable nature of environmental noises, which cannot be eliminated by the residual CP response. Nevertheless, in real-world engineering scenarios, noises typically only have effects on high-frequency ranges, while bridge frequencies exist in lower ranges. Hence, the identification of lower bridge frequencies using the proposed method will not be influenced. To decrease the influence of environmental noises on the manual identification of bridge frequencies,
a low-pass filter can be utilized to remove noisy peaks in high-frequency ranges and highlight the low frequencies of the bridge.

**Consideration of different bridge damping ratios**

As discussed in Section 3.3.1, the bridge’s damping ratio is simulated by Rayleigh damping, which involves determining two-order damping ratios. This section employs two scenarios, namely $\xi_1 = \xi_2 = 1\%$ and $\xi_1 = \xi_2 = 2\%$, to calculate the damping matrix of the bridge denoted by $C_b$. The parameters used in this analysis are identical to those presented in Section 3.3.1. The bridge frequency identification results are shown in Figure 4.8, where the residual CP response of wheels 1 and 3 is utilized.

From Figure 4.8, it can be seen that when the damping ratio is relatively low, the first three frequencies of the bridge can be accurately identified. However, as the damping ratios increase to 2%, the peaks surrounding the bridge’s frequencies become more complex. Peaks at both the second and third frequencies are suppressed. Therefore, it can be concluded in this section that bridges with high damping can adversely impact the transmission of their dynamic properties to vehicles. Additionally, when a bridge exhibits high damping, its vibrations are also restrained, leading to less bridge-related information in the CP responses.

### 4.1.2 Indirect bridge damage detection with the SV and PT

**Indirect bridge frequency identification using CP responses**

To simulate the practical case in engineering applications, several influencing factors, including road roughness, environmental noise, and ongoing traffic, are considered in the damage detection process.

The road roughness is generated by Eqs. (3.48) and (3.49) with $G_d(n_{x,0}) = 4 \times 10^{-6}$ m$^3$. Similarly to Section 4.1.1, an MAF is utilized to smooth the generated road roughness. Figure 4.9 shows the original and smoothed road roughness. The generated road roughness length is 35.47 m.
Results and discussions

Figure 4.9. Generated road roughness for the SV.

In addition to the SV, four additional vehicles (V1-V4) are considered as part of the ongoing traffic, each sharing the same parameters as the SV. However, it is important to note that the ongoing traffic may consist of vehicles with different parameters and speeds, as mentioned in reference [148]. The SV is assumed to enter the bridge at 0 seconds. The entering time and speed of each vehicle are provided in Table 4.1.

Table 4.1. Ongoing traffic.

<table>
<thead>
<tr>
<th>Ongoing traffic</th>
<th>SV</th>
<th>V1</th>
<th>V2</th>
<th>V3</th>
<th>V4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Entry time (s)</td>
<td>0</td>
<td>0.860</td>
<td>-4.214</td>
<td>1.980</td>
<td>-3.004</td>
</tr>
</tbody>
</table>

According to Eq. (3.50), 5% environmental noise is added to the SV’s accelerations [148]. The indirect bridge frequency identification results in absence of the PT are shown in Figure 4.10. It can be seen that the first two bridge frequencies can be identified in the frequency domain despite there being influence factors, but the third one has been completely submerged.

Figure 4.10. Indirect bridge frequency identification results using the SV.

**Determination of the truck’s mass**

The first step in utilizing a PT is to determine its mass value, denoted as $M_{pt}$. The PT is introduced to enhance the number of modes considered and increase the sensitivity of the bridge’s frequencies to local damage. In this section, the PT’s mass is determined through sensitivity analysis. Figure 4.11 illustrates the relative sensitivity with respect to the mass $M_{pt,i}$.
when it is positioned on different substructures. As the simply supported bridge is structurally symmetric, the relative sensitivity values of the first and sixth substructures are identical, as are those of other symmetric substructures.

![Figure 4.11](image-url) Relative sensitivity with respect to mass on substructures.

In the case of substructure 1, it can be observed that the sensitivity of \( f_{b1} \) to the PT's mass is relatively low (around zero). However, as the mass value increases, the sensitivity of \( f_{b2} \) and \( f_{b3} \) becomes more pronounced. When the mass reaches approximately 60 tons, the sensitivity of \( f_{b3} \) reaches its peak. Therefore, a mass value of 60 tons is deemed suitable for the first substructure.

Regarding the second substructure, a similar trend can be noticed. The sensitivity of \( f_{b1} \) remains relatively unchanged with increasing PT mass. However, the sensitivity of \( f_{b2} \) and \( f_{b3} \) decreases as the mass value increases, particularly when the mass exceeds 15 tons for \( f_{b2} \). To preserve the higher sensitivity of the second substructure, the mass value should be kept below 15 tons.

For the third substructure, it can be observed that the PT's mass has little effect on \( f_{b1} \) and \( f_{b2} \). Even for \( f_{b3} \), although there is an increase in sensitivity, the increment is not significant. Additionally, when considering the PT's mass, it is essential to account for the weight restrictions imposed on trucks using the bridge. In this thesis, a 25-ton truck is employed with the following parameters: \( \alpha_1 = 2.6 \text{ m}, \alpha_2 = 2.4 \text{ m}, m_{t1} = 1000 \text{ kg}, \) and \( m_{t2} = 1500 \text{ kg} \).

**Damage detection**

This thesis examines three damage scenarios in this section, including single minor damage, single large damage, and multiple damages. Additionally, the local damage occurs in different locations. All damage scenarios are listed below:

- **Scenario 1**: single minor damage, \( \mu = [1, 0.8, 1, 1, 1, 1] \);
- **Scenario 2**: single large damage, \( \mu = [1, 1, 1, 0.3, 1, 1] \);
- **Scenario 3**: multiple damages, \( \mu = [1, 1, 0.5, 1, 0.8, 1] \).

For various scenarios, when the PT's rear axle is parked on positions from 1 to 5, the indirect frequency identification results are provided in Table 4.2.
Table 4.2. Identified frequencies by the SV when the PT is on different positions (Hz).

<table>
<thead>
<tr>
<th>PT's position</th>
<th>$j = 1$</th>
<th>$j = 2$</th>
<th>$j = 3$</th>
<th>$j = 4$</th>
<th>$j = 5$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scenario 1</td>
<td>$f_{b1}^j$</td>
<td>3.3264</td>
<td>3.1433</td>
<td>3.1128</td>
<td>3.1738</td>
</tr>
<tr>
<td></td>
<td>$f_{b2}^j$</td>
<td>12.7563</td>
<td>12.7563</td>
<td>13.3057</td>
<td>12.8784</td>
</tr>
<tr>
<td>Scenario 2</td>
<td>$f_{b1}^j$</td>
<td>2.7466</td>
<td>2.5024</td>
<td>2.4109</td>
<td>2.4719</td>
</tr>
<tr>
<td></td>
<td>$f_{b2}^j$</td>
<td>12.1155</td>
<td>12.1155</td>
<td>12.7563</td>
<td>12.7563</td>
</tr>
<tr>
<td>Scenario 3</td>
<td>$f_{b1}^j$</td>
<td>2.9297</td>
<td>2.8076</td>
<td>2.7771</td>
<td>2.8076</td>
</tr>
<tr>
<td></td>
<td>$f_{b2}^j$</td>
<td>12.3291</td>
<td>12.2681</td>
<td>12.7563</td>
<td>12.0850</td>
</tr>
</tbody>
</table>

It is evident that the presence of the PT on the bridge leads to a decrease in the bridge’s natural frequencies. Moreover, the extent of frequency reduction varies depending on the PT’s location. The degrees of reduction for $f_{b1}, f_{b2},$ and $f_{b3}$ are not uniform across different locations. These changes in frequencies due to the additional mass offer valuable insights into the extent of bridge damage.

The next step involves conducting damage detection using the indirectly obtained frequency values. An additional challenge in this process is the construction of an accurate numerical model for the bridge, which is often difficult in practical engineering. To account for this, the assumption that there are errors associated with the construction of the FE model is introduced. The parameters used in the FE model of the bridge are as follows: $\hat{L} = 30.5\text{ m}, \hat{E}_b \hat{I}_b = 2.375 \times 10^{10}\text{ N/m}^2,$ and $\hat{m} = 5800\text{ kg/m}^3,$ which represent the errors in building the FE model of the bridge. By considering these model errors and utilizing Eqs. (3.25) and (3.26), the optimized damage factors $\mu$ are presented in Figure 4.12.

![Figure 4.12](image-url)

Figure 4.12. Damage identification results for different scenarios.

From Figure 4.12, it can be observed that when dealing with minor damage and considering the most influential factors, Eq. (3.25) is unable to accurately determine the location and severity of the damage. Instead, it assumes that all substructures are intact. However, it is still capable of identifying a single large damage, as seen in scenario 2. On the other hand, when multiple damage locations and varying degrees of damage are present, Eq. (3.25) tends to prioritize the detection of large damage (substructure 3 in scenario 3) while overlooking minor damage (substructure 5 in scenario 3). To address this limitation, Eq. (3.26) is employed. By utiliz-
ing the MAC-based objective function, all damage locations and degrees can be accurately identified with acceptable precision, which validates the effectiveness of the proposed strategy that incorporates the use of an SV and PT.

4.2 Data-driven bridge damage detection

4.2.1 Bridge damage detection using MFCCs and SVM

In this section, the objective is to detect the bridge's damage automatically based on the vibrations of passing vehicles. The analysis is on the basis of the laboratory experiment utilizing normal and heavy vehicles and the CSB bridge model as introduced in Section 3.4. For the damage, the mass is added by two hooks to the CSB model's two spans at the same time. All damage cases can be found in Table 4.3.

<table>
<thead>
<tr>
<th>Cases</th>
<th>Added mass</th>
<th>Damage degree</th>
<th>Heavy vehicle runs</th>
<th>Normal vehicle runs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 0</td>
<td>0 kg</td>
<td>0.00%</td>
<td>506</td>
<td>565</td>
</tr>
<tr>
<td>Case 1</td>
<td>5 kg</td>
<td>5.63%</td>
<td>49</td>
<td>56</td>
</tr>
<tr>
<td>Case 2</td>
<td>10 kg</td>
<td>9.65%</td>
<td>50</td>
<td>57</td>
</tr>
<tr>
<td>Case 3</td>
<td>15 kg</td>
<td>13.67%</td>
<td>42</td>
<td>56</td>
</tr>
<tr>
<td>Case 4</td>
<td>20 kg</td>
<td>17.70%</td>
<td>51</td>
<td>57</td>
</tr>
<tr>
<td>Case 5</td>
<td>25 kg</td>
<td>21.72%</td>
<td>51</td>
<td>56</td>
</tr>
<tr>
<td>Case 6</td>
<td>30 kg</td>
<td>25.74%</td>
<td>47</td>
<td>57</td>
</tr>
</tbody>
</table>

In this work, both low- and high-frequency vehicle responses were utilized to assess the health of a bridge. Since the frequency spectrum is symmetrical, only half of the spectrum (0-5000 Hz with a sampling frequency of 10 kHz) was chosen for analysis. The frequency resolution was artificially set to 0.0763 Hz by padding zeros to the end of the time-domain signals. A total of 65537 frequency response points were obtained, and all of these points were used as features to train SVM models. To compare the effect of choosing different frequency ranges, all hyperparameters of the SVM models were initially set as constant values: $C = 1.0$, $\gamma = 0.01$, $r = 0.0$, and $d = 3$. The analysis begins with the use of a heavy vehicle, with 50 runs from case 0 and all runs from case 2 being examined. To obtain testing accuracy values, a 5-fold CV strategy is employed.

SVM using frequency responses
Prior to utilizing the frequency responses, the StandardScaler from the Scikit-learn package is utilized to make data for one feature have a mean
value of 0 and a standard deviation of 1 [234]. While MinMaxScaler is another famous tool to normalize features, it is very sensitive to outliers. Consequently, StandardScaler is selected in this thesis. The testing accuracy achieved using the vehicle’s responses in increasing frequency ranges is shown in Figure 4.13.

![Figure 4.13. Accuracy using frequency responses in increasing ranges.](image)

As shown in Figure 4.13, increasing the selected frequency range (from 0-0.0763 Hz to 0-1500 Hz) leads to higher test accuracy for SVM models that utilize Linear and Sigmoid kernels. Conversely, when Polynomial and RBF kernels are employed, the test accuracy is comparatively lower due to the high sensitivity of these kernels to their hyperparameters. Furthermore, utilizing frequency responses within the 0-300 Hz range yields better accuracy with the Linear kernel compared to solely using responses within the 0-60 Hz range. As the employed frequency range continues to expand to 0-750 Hz, the test accuracy stabilizes at around 1.0 (accuracy values beyond 0-1500 Hz are not plotted as the accuracy values become stable). The fundamental reason for the above phenomenon is that the bridge’s higher-frequency information can also be transferred to the vehicle instead of only low-frequency vibration information. Therefore, the inclusion of high-frequency responses of the vehicle can contribute to the increase in damage detection accuracy of SVM models.

In order to investigate the distribution of bridge damage information in the high-frequency range, only the newly added short-range frequency responses are used here for classification. The frequency interval of 7.63 Hz is selected, which includes 100 frequency response points ranging from 0-7.63 Hz, 7.63-15.26 Hz, 15.26-22.89 Hz, and so on. The classifier used for this investigation is the Linear SVM model. The classification results, obtained through ten random selections from case 0 (in total 506 runs), are shown in Figure 4.14.

From Figure 4.14, one can notice that the maximum accuracy drops to 0.91, as compared to Figure 4.13, due to the utilization of only a few
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Figure 4.14. Accuracy using short-range frequency responses.

frequency responses for classification. If the bridge damage information exists within the selected frequency interval, the classification accuracy can reach relatively high values (peaks). It can be found that damage features are relatively dense in the range of 0-750 Hz. Besides, damage features are also distributed around 1300 Hz (obvious peaks) and 2400 Hz (weak peaks). Beyond this range, the accuracy drops to approximately 0.5, indicating that the SVM model cannot identify the bridge’s damage information. Hence, this study indicates that the bridge’s damage features are densely distributed in the low-frequency range. In the high-frequency range, the bridge’s damage features are sparsely disseminated, but they can still contribute to damage detection.

SVM using MFCCs

As demonstrated in the previous section, utilizing the vehicle’s frequency responses is an effective method for distinguishing between healthy and damaged cases. However, as the frequency range used as input to the SVM model increases, the number of features also increases. For instance, selecting frequency responses within the 0-1000 Hz range yields 13109 features. Although this can improve test accuracy, training the SVM becomes computationally expensive. The following sections will discuss the use of MFCCs to detect damage using the instrumented vehicle’s responses.

Selection of the number of filterbanks  To calculate MFCCs, the first step involves selecting an appropriate number of filterbanks. In this thesis, a range of 3-100 filterbanks is used for analysis. Similarly, case 2 in Table 4.3 is employed as the damaged bridge, and all time-domain responses of the vehicle are considered a single frame ($N = 1$ in Eq. (3.38)). The hyperparameter $C$ is shared among all four kernels and set to 1.0. The grid-search strategy is utilized to determine the optimal values of the other hyperparameters: $\gamma$, $r$, and $d$. Additionally, both evenly and unevenly distributed filterbanks, as described in Section 3.2.2, are employed and compared.
Figure 4.15 displays the accuracy scores achieved using different kernels and numbers of MFCCs.

![Accuracy plots](image)

*(a) Even filterbanks (b) Uneven filterbanks*

**Figure 4.15.** Accuracy using an increasing number of filterbanks.

From Figure 4.15, one can see that when the number of evenly distributed banks is deficient, MFCCs cannot capture damage information in the frequency-domain responses. When the number increases to near 40, the accuracy becomes relatively stable. If better results are required, the number is expected to be more than 60. In comparison, if Mel filterbanks are unevenly distributed, similarly, a small number of the filter banks is not very effective for damage classification. However, when the number increases to 20, the classification performance using all four kernels can reach good results. Using the uneven ones can save half the number of filter banks used in damage detection.

The main reason for the above phenomenon is that the latter concentrates on low-frequency responses but does not ignore the high-frequency range, while the evenly distributed filter banks treat all frequency ranges equally. Thus, more banks are needed to capture damage features in both low- and high-frequency ranges. Compared to evenly distributed Mel filter banks, MFCCs utilizing the uneven ones are computationally efficient since fewer features will be input into the SVM model and will be employed in this thesis for later analysis. To maintain high accuracy, 61 filter banks that perform well on all kernel functions are utilized.

**Selection of kernel function** To select the best kernel, the performance of four kernels using one frame for all cases is shown in Table 4.4. The grid-search strategy is used for Polynomial, RBF, and Sigmoid kernels to find the best test accuracy.

It can be seen from Table 4.4 that the test accuracy can attain a minimum of 0.916 with various kernels. Among all kernels, the Polynomial kernel achieves the highest accuracy, followed by the Linear kernel. Nonetheless, Table 3.1 demonstrates that the Polynomial kernel involves four hyperparameters, making it time-consuming to determine the optimal values, particularly using grid-search when $d > 3$. Consequently, this thesis selects the Linear kernel.
Table 4.4. Accuracy using different time frames and different kernels.

<table>
<thead>
<tr>
<th>Cases</th>
<th>Linear</th>
<th>Polynomial</th>
<th>RBF</th>
<th>Sigmoid</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case1</td>
<td>0.948</td>
<td>0.983</td>
<td>0.937</td>
<td>0.916</td>
</tr>
<tr>
<td>Case2</td>
<td>0.975</td>
<td>0.989</td>
<td>0.978</td>
<td>0.955</td>
</tr>
<tr>
<td>Case3</td>
<td>0.989</td>
<td>0.991</td>
<td>0.985</td>
<td>0.977</td>
</tr>
<tr>
<td>Case4</td>
<td>0.992</td>
<td>0.993</td>
<td>0.989</td>
<td>0.982</td>
</tr>
<tr>
<td>Case5</td>
<td>0.999</td>
<td>1.000</td>
<td>0.998</td>
<td>0.995</td>
</tr>
<tr>
<td>Case6</td>
<td>0.994</td>
<td>0.995</td>
<td>0.973</td>
<td>0.984</td>
</tr>
</tbody>
</table>

MFCCs considering time frame If $N = 1$, all time-domain responses are treated as a single frame, and the application of Eq. (3.38) yields $P$ MFCCs. On the other hand, if $N > 1$, the time-domain responses are partitioned into $N$ frames, resulting in $N \times P$ MFCCs when a vehicle traverses the bridge once. In this study, six frames are analyzed, yielding $61 \times 6 = 366$ MFCCs as input features. Since the vehicle’s passage time varies, the time-domain responses are divided into six frames on average. For each frame, the same process is employed to extract MFCCs and feed the SVM. The damage detection results are presented in Table 4.4. One can see that when different kernels are employed for different cases, dividing the original signals in the time domain into six frames makes the damage detection accuracy better than just regarding all vibration data as one frame in most scenarios, especially for case 1 when the damage degree is relatively low. Therefore, six frames are employed in the later discussion.

Damage severity prediction
To provide appropriate maintenance work, it is also important to detect the extent of damage (or damage degrees). For this reason, the damage severity prediction is investigated in this section. As shown in Table 4.3, all cases are labeled as classes 0-6. For case 0, 50 random samples out of all 506 samples are used to avoid the sample imbalance problem. Therefore, there are 340 samples and 366 features in total.

In the process of training and testing an SVM model, 50% of samples are used to train, and the rest are utilized for testing. The confusion matrix, a generally utilized summary matrix of prediction results on a classification problem, is used in this work to evaluate the trained SVM model’s perfor-
Figure 4.16. Comparison between true and predicted labels using heavy and normal vehicles.

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In previous discussions, the heavy vehicle (v5) presented in Table 4.3 was used. To investigate the impact of car weight, the vehicle without extra weights (v0) was employed. The resulting confusion matrix is displayed in Figure 4.16b. It can be observed that the number of incorrect predictions increases when using the normal vehicle. However, the misclassifications are still situated around the diagonal, suggesting that a significant portion of damaged cases can still be accurately identified by the SVM model. After a 5-fold CV, the overall test accuracy for the normal vehicle was 0.791. Therefore, it is recommended to employ heavy vehicles in practical engineering to enhance the accuracy of bridge damage detection.

4.2.2 Bridge damage detection using \( A^2M \) and dimension reduction techniques

In this section, two bridge models (SSB and CSB) and two vehicle models (v0 and v5) are employed. Since the bridge’s damage is not predictable in
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practice, it is assumed that the damage occurs in different positions with varying severity. In the experiment, this variety is simulated by adding different masses to several positions. Damage cases used in this section are listed in Table 4.5.

**Table 4.5. Bridge with damage of different severity and locations.**

<table>
<thead>
<tr>
<th>VBI model</th>
<th>Scenario 1: SSB+v0</th>
<th>Runs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Runs on healthy bridge</td>
<td>Case s00(^1) (healthy)</td>
<td>568</td>
</tr>
<tr>
<td></td>
<td>Case s01 (0.3L(^3): 15 kg, 0.6L: 4 kg)</td>
<td>66</td>
</tr>
<tr>
<td>Runs on damaged bridge</td>
<td>Case s02 (0.4L: 20 kg)</td>
<td>79</td>
</tr>
<tr>
<td></td>
<td>Case s03 (0.5L: 2 kg)</td>
<td>66</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>VBI model</th>
<th>Scenario 2: SSB+v5</th>
<th>Runs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Runs on healthy bridge</td>
<td>Case s50 (healthy)</td>
<td>562</td>
</tr>
<tr>
<td></td>
<td>Case s51 (0.3L: 15 kg, 0.6L: 4 kg)</td>
<td>66</td>
</tr>
<tr>
<td>Runs on damaged bridge</td>
<td>Case s02 (0.4L: 20 kg)</td>
<td>66</td>
</tr>
<tr>
<td></td>
<td>Case s03 (0.5L: 2 kg)</td>
<td>67</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>VBI model</th>
<th>Scenario 3: CSB+v0</th>
<th>Runs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Runs on healthy bridge</td>
<td>Case c00 (healthy)</td>
<td>565</td>
</tr>
<tr>
<td></td>
<td>Case c01 (0.3LL(^4): 10 kg, 0.3RL: 20 kg)</td>
<td>56</td>
</tr>
<tr>
<td>Runs on damaged bridge</td>
<td>Case c02 (0.3RL(^4): 30 kg)</td>
<td>58</td>
</tr>
<tr>
<td></td>
<td>Case c03 (0.5LL: 5 kg)</td>
<td>56</td>
</tr>
<tr>
<td></td>
<td>Case c04 (0.5LL: 10 kg, 0.5RL: 20 kg)</td>
<td>58</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>VBI model</th>
<th>Scenario 4: CSB+v5</th>
<th>Runs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Runs on healthy bridge</td>
<td>Case c50 (healthy)</td>
<td>506</td>
</tr>
<tr>
<td></td>
<td>Case c51(^2) (0.3LL: 10 kg, 0.3RL: 20 kg)</td>
<td>51</td>
</tr>
<tr>
<td>Runs on damaged bridge</td>
<td>Case c52 (0.3RL: 30 kg)</td>
<td>48</td>
</tr>
<tr>
<td></td>
<td>Case c53 (0.5LL: 5 kg)</td>
<td>51</td>
</tr>
<tr>
<td></td>
<td>Case c54 (0.5LL: 10 kg, 0.5RL: 20 kg)</td>
<td>50</td>
</tr>
</tbody>
</table>

\(^1\) Case s00: s → SSB, 0 → v0, 0 → healthy case
\(^2\) Case c51: c → CSB, 5 → v5, 1 → damage case 1
\(^3\) L: the span of SSB, 0.3L: the mass is attached to the position of 1/3 span
\(^4\) LL: CSB’s left span, RL: CSB’s right span; 0.3LL: the mass is attached to the position of 1/3 CSB’s left span.

To combine the models of beams and vehicles, there are four scenarios in total, as shown below. For the bridge in damage conditions, all damage cases are combined as “damaged”. For the binary classification of SC1 vs. SC2 (or CC1 vs. CC2), a half number of runs from the “healthy” scenario is regarded as “assumed damaged” to train the classifier, and 5-fold CV accuracy could be obtained. Similarly, for SC1 vs. SC3 (or CC1 vs. CC3), the same number of runs from “healthy” runs will be selected for the binary classification with “damaged” runs. The classifier is selected as logistic regression [235].

- Scenario 1: SC1 vs. SC2 (the bridge remains healthy), and SC1 vs.
SC3 (the bridge is damaged).

- Scenario 2: SC1 vs. SC2 (the bridge remains healthy), and SC1 vs. SC3 (the bridge is damaged).

- Scenario 3: CC1 vs. CC2 (the bridge remains healthy), and CC1 vs. CC3 (the bridge is damaged).

- Scenario 4: CC1 vs. CC2 (the bridge remains healthy), and CC1 vs. CC3 (the bridge is damaged).

When the raw frequency responses of the vehicle are utilized, the accuracy values are shown in Figure 4.17. Clear divergence can be observed when the bridge keeps healthy (SC1 vs. SC2 or CC1 vs. CC2), and it is damaged (SC1 vs. SC3 or CC1 vs. CC3) with all combinations of vehicles and beams. To determine the threshold for damage detection for general cases in engineering, the 5% and 95% quantiles are calculated for all scenarios are shown in Table 4.6. To select a good threshold $k_s$, it is expected that when the bridge is healthy, 95% accuracy values are less than $k_s$, and when the bridge is damaged, 95% accuracy values are greater than $k_s$. It can be seen from Table 4.6 that $k_s = 0.84$ satisfies both the SSB and CSB models.

![Figure 4.17. Classification accuracy with different frequency ranges.](image)

Nonetheless, the above study employing raw frequency responses is in a space with a high dimension. For example, when frequency responses
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Table 4.6. Determination of the accuracy threshold using raw frequency responses.

<table>
<thead>
<tr>
<th>VBI model</th>
<th>Scenario 1: SSB+v0</th>
<th>Scenario 2: SSB+v5</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>SC1 vs SC2</td>
<td>SC1 vs SC3</td>
</tr>
<tr>
<td>Quantile</td>
<td>5%</td>
<td>95%</td>
</tr>
<tr>
<td>Accuracy</td>
<td>0.55</td>
<td><strong>0.64</strong></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>VBI model</th>
<th>Scenario 3: CSB+v0</th>
<th>Scenario 4: CSB+v5</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CC1 vs CC2</td>
<td>CC1 vs CC3</td>
</tr>
<tr>
<td>Quantile</td>
<td>5%</td>
<td>95%</td>
</tr>
<tr>
<td>Accuracy</td>
<td>0.74</td>
<td><strong>0.83</strong></td>
</tr>
</tbody>
</table>

between 0 and 500 Hz are selected, the classification accuracy becomes steady. However, employing frequency responses in the range of 0-500 Hz results in 6553 features, which poses a challenge for the classifier and necessitates more CPU resources for calculating the classification results. Thus, before using the proposed method in engineering, it is necessary to find ways to reduce the input dimensions of the classifier. Using latent representations of the original input has two advantages: (1) the DRTs can reduce the dimension of the input for training; (2) the DRTs can normally eliminate unimportant information and keep essential features in the latent space.

Damage detection using PCA

One of the most popular DRTs is the PCA [236], which maps \( n \)-dimension data into \( k \) principal components while maintaining important information. Correlated variables can be eliminated by PCA, making representations clear and independent for decision-making.

After utilizing the PCA as a DRT to reduce the vehicle’s frequency responses to 1-200 latent representations, the resulting classification accuracy values are presented in Figures 4.18a (4) and 4.18b (4). It can be seen that when the bridge is in good condition, the accuracy values are below 0.8. However, following bridge damage, the accuracy values increase significantly. Furthermore, when a heavy vehicle is employed, accuracy values are higher for damaged bridges. Results using raw frequency responses present similar results. After conducting the CV process ten times, the joint distribution of accuracy values is plotted in Figures 4.18a (1) and 4.18b (1). The marginal distribution of accuracy values is depicted in Figures 4.18a (2) and (3), 4.18b (2) and (3). When the bridge is healthy, it can be seen that the accuracy values are relatively low (SC1 vs. SC2 or CC1 vs. CC2). However, when there is true bridge damage (SC1 vs. SC3 or CC1 vs. CC3), the distribution of accuracy values becomes thinner, and the accuracy values get very high. To determine the threshold, quantiles
are calculated in Table 4.7. It can be seen that the predetermined \( k_s = 0.84 \) can be used to determine the bridge’s healthy condition.

Figure 4.18. Classification accuracy using PCA.

Table 4.7. Quantiles of accuracy values using PCA.

<table>
<thead>
<tr>
<th>VBI model</th>
<th>Scenario 1: SSB+v0</th>
<th>Scenario 2: SSB+v5</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>SC1 vs SC2</td>
<td>SC1 vs SC3</td>
</tr>
<tr>
<td>Quantile</td>
<td>5% 95%</td>
<td>5% 95%</td>
</tr>
<tr>
<td>Accuracy</td>
<td>0.52 0.61 0.89</td>
<td>0.56 0.69 0.91</td>
</tr>
</tbody>
</table>

Table 4.8 can be obtained.

Damage detection using MFCCs

The results of damage detection using MFCCs as a DRT are presented in Figure 4.19. Observing Figures 4.19a (4) and 4.19b (4), it can be concluded that accuracy values are around 0.5 when the bridge is in a healthy condition. However, after the bridge is damaged, the SSB model shows that different vehicle weights can cause a divergence in accuracy values. Nevertheless, both scenarios can achieve high accuracy levels (>0.84). Similarly, for the CSB model, when the vehicle weight is relatively low, the accuracy is slightly lower than when the heavy vehicle is utilized. Moreover, the accuracy distribution graphs (Figures 4.19a (3) and 4.19b (3)) indicate that when the bridge is healthy, regardless of the vehicle weights, accuracy values are intensively distributed between 0.4 and 0.6, which indicates a healthy state of the bridge. By computing quantiles for all the scenarios, Table 4.8 can be obtained.

From Table 4.8, it can be seen that when the bridge is in a healthy...
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(a) Using the SSB model  
(b) Using the CSB model

Figure 4.19. Classification accuracy using MFCCs.

Table 4.8. Quantiles of accuracy values using MFCCs.

<table>
<thead>
<tr>
<th>VBI model</th>
<th>Scenario 1: SSB+v0</th>
<th>Scenario 2: SSB+v5</th>
</tr>
</thead>
<tbody>
<tr>
<td>SC1 vs SC2</td>
<td>SC1 vs SC3</td>
<td>SC1 vs SC2</td>
</tr>
<tr>
<td>Quantile</td>
<td>5%</td>
<td>95%</td>
</tr>
<tr>
<td>Accuracy</td>
<td>0.46</td>
<td><strong>0.54</strong></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>VBI model</th>
<th>Scenario 3: CSB+v0</th>
<th>Scenario 4: CSB+v5</th>
</tr>
</thead>
<tbody>
<tr>
<td>CC1 vs CC2</td>
<td>CC1 vs CC3</td>
<td>CC1 vs CC2</td>
</tr>
<tr>
<td>Quantile</td>
<td>5%</td>
<td>95%</td>
</tr>
<tr>
<td>Accuracy</td>
<td>0.45</td>
<td><strong>0.54</strong></td>
</tr>
</tbody>
</table>

state, 95% of the accuracy values in all four scenarios are below 0.54, which is acceptable with a threshold of \( k_s = 0.84 \). After damage occurs, the accuracy significantly increases in all scenarios, with 95% of the values greater than the threshold. Moreover, when a heavy vehicle is used, the accuracy further increases, reaching 0.98 for both the SSB and CSB models (compared to 0.89 and 0.91, respectively, with a light vehicle). The accuracy difference between a healthy and damaged bridge is more prominent in this case. Therefore, similar to the analysis when raw frequency responses are used, it is recommended to use a heavier vehicle (approximately 5% of the bridge’s mass) when applying the proposed method in practical engineering.

4.2.3 Real-time bridge damage detection using DAE

In this section, the CSB model and the heavy vehicle model are utilized for real-time bridge damage detection verification. To better represent results, cases using the heavy vehicle in Table 4.3 are named DSs 0-6 in Table 4.9. DS 0 denotes that the bridge is healthy. Similarly to Section 4.2.1, the damage is simulated by mass added by two hooks to the CSB
model’s two spans, and the damage degree is represented by the mass ratio of additional mass to the beam.

Table 4.9. Damage scenarios used for real-time bridge damage detection.

<table>
<thead>
<tr>
<th>Damage scenarios</th>
<th>DS 0</th>
<th>DS 1</th>
<th>DS 2</th>
<th>DS 3</th>
<th>DS 4</th>
<th>DS 5</th>
<th>DS 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Truck runs</td>
<td>506</td>
<td>49</td>
<td>50</td>
<td>42</td>
<td>51</td>
<td>51</td>
<td>47</td>
</tr>
<tr>
<td>Added mass</td>
<td>0 kg</td>
<td>5 kg</td>
<td>10 kg</td>
<td>15 kg</td>
<td>20 kg</td>
<td>25 kg</td>
<td>30 kg</td>
</tr>
<tr>
<td>Damage degree</td>
<td>0.00%</td>
<td>5.63%</td>
<td>9.65%</td>
<td>13.67%</td>
<td>17.70%</td>
<td>21.72%</td>
<td>25.74%</td>
</tr>
</tbody>
</table>

Real-time frequency responses analysis

Before applying the DAE to achieve real-time bridge damage detection using the vehicle’s accelerations, one can look closer at the time-frequency representations (TFRs) of the vehicle and the bridge. With a non-overlapping time of 0.01 s, the TFRs of the accelerations of the vehicle and bridge using STFT are shown in Figure 4.20.

One can see from Figure 4.20 that when the indirect method is employed, the vehicle’s rear axle frequency (19.531 Hz) is the most outstanding. However, the bridge’s fundamental frequency (30.748 Hz) is very weak in the TFR, which is difficult to employ as an index for damage detection. Instead, if the acceleration of the bridge is used, the bridge’s fundamental frequency can be captured (see Figure 4.20: DS 0: direct). Furthermore, it can be found that the vehicle’s frequency can be faintly identified in the bridge’s responses. By analysis of the bridge’s vibrations, for DSs 1-6, the beam’s fundamental frequency becomes 28.571, 27.551, 26.326, 25.306, 24.286, and 23.674 Hz after the corresponding mass is attached. However, these frequency values are overshadowed by environmental noises and vehicle frequencies in the vehicle’s TFR. Therefore, feature extraction techniques are required to identify the DSFs from the vehicle’s responses. The following sections will introduce the damage detection method using DAE.
Results and discussions

Automatic damage detection
As the first three frequencies of the bridge are relatively low, the proposed method employed frequency responses within 0-100 Hz as the input for training the DAE model. After fine-tuning, the following hyperparameters can be employed when training the DAE model for bridge damage detection, as shown in Table 4.10. For training the DAE model using “healthy” runs, 90% of 1-400 runs in DS 0 are used for training, and the rest is for validation. The final 401-506 runs are for testing. Utilizing the hyperparameters in Table 4.10, the training, validation, and testing loss are shown in Figure 4.21. It is clear that after training, the DAE model can construct data of “healthy” runs with a low loss.

Table 4.10. Hyperparameter of the DAE.

<table>
<thead>
<tr>
<th>Hyperparameter</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Neurons in layers</td>
<td>(1310)→(512)→(256)→(128)→(256)→(512)→(1310)</td>
</tr>
<tr>
<td>Activation</td>
<td>LeakyReLU</td>
</tr>
<tr>
<td>Optimizer</td>
<td>Adam</td>
</tr>
<tr>
<td>Learning rate</td>
<td>$1 \times 10^{-5}$</td>
</tr>
<tr>
<td>Batch size</td>
<td>128</td>
</tr>
<tr>
<td>Regularization: $l_2$ penalty</td>
<td>$1 \times 10^{-5}$</td>
</tr>
<tr>
<td>Epochs</td>
<td>1200</td>
</tr>
</tbody>
</table>

Figure 4.21. Training, validation and testing loss for the intact bridge.

For DSs 1-6, utilizing the trained DAE model, the original and reconstructed frequency responses of one frame are shown in Figure 4.22. It can be seen that with the increase of damage degree, the DAE tends not to reconstruct the input very well. Especially for DSs 5 and 6, some details of the frequency spectrum have been lost in reconstruction. Therefore, the DI calculated by Eq. (3.44) can be utilized to determine the bridge’s health conditions automatically.
Results and discussions

![Graphs showing frequency responses for DSs 1-6.](image)

Figure 4.22. Reconstruction of DSs 1-6’s frequency responses.

**Real-time damage detection using vehicle responses**

The last section has discussed the training processing and damage detection for a frame. To achieve real-time bridge monitoring, when the vehicle passes the bridge, the trained DAE model can be used for real-time generated frames. Figure 4.23 has plotted the real-time damage detection results for one run and multiple runs when the vehicle passes a healthy bridge (DS 0: 401-506 runs) and damaged bridges (DSs 1-6).

It can be seen that when the bridge is intact (DS 0: 401-506 runs), the extracted DIs are near zero, which indicates that the DAE can reconstruct the frequency responses well and the bridge is in a healthy state. Additionally, one can find that when the vehicle is close to the bridge’s ends, the DIs can become high, and the same phenomenon can be observed in DSs 1-6. Thus, the proposed method can easily misidentify the bridge’s health condition near the supports, which matches the results of the reference [171]. The threshold to determine the bridge’s health condition must consider the poor performance near ends. Figure 4.24 has shown the sorting results of all DIs of DS 0: 401-506 runs. It can be seen that the first $4e^4$ DIs may not be influenced by the bridge ends. This thesis employed the $4e^4$-th DI value as the threshold identifying the bridge’s health condition, which is $7.815e^{-4}$.

Figure 4.23a shows one run in all DSs. The threshold is employed to
Results and discussions

Figure 4.23. Real-time damage detection results.

(a) Real-time DI for one run

(b) Real-time DI for DSs 0-6

detect the bridge’s condition when the vehicle passes the bridge. It can be seen that when the bridge is not damaged (DS 0: 1 run), it can be identified as healthy most time (green points). In comparison, when the bridge is damaged, the bridge is detected as damaged most time (red points). Also, one can notice that when the damage severity is low (e.g., DSs 1 and 2), sometimes the bridge can be mistakenly identified as healthy (see DS 1: 5.43-5.50 s, 5.78-5.83 s, 5.88-5.89 s, 5.49-6.21 s, and DS 2: 3.21-3.24 s, 3.31-3.34 s). Nonetheless, after the damage severity becomes high, mistakes are rarely observed (see one run of DSs 3, 4, 5, and 6).

The real-time damage detection results of all runs in DS 1-6 are shown
Results and discussions

Figure 4.24. Sorting DIs of DS 0: 401-506 runs in ascending order.

in Figure 4.23b. It can be seen that when the bridge is damaged, the DIs become greater compared to DS 0. The scales of DIs for DS 1-6 are roughly [0, 0.05], [0, 0.1], [0,0.3], [0, 0.1], and [0, 0.5]. It can be found that the value of DIs does not have a positive linear correlation relationship with damage severity. Thus, the value of DIs may not be suitable for determining the severity of the damage. In this thesis, a new index named IDR is proposed to estimate the damage severity of the bridge, as denoted by Eq. (4.2),

\[
IDR = \frac{N_d}{N} \times 100\%
\]

where \(N_d\) represents the total moments when the bridge is detected as damaged, while \(N\) signifies all the frames for a specific DS. For instance, for DS 1, there are 49 runs and 26,828 frames in total. Among these, the bridge is identified as damaged at 19,205 moments. Consequently, the IDR is calculated as 19,205/26,828, which equals 71.58%. Upon examining the damage indicators for DSs 2-6, the respective IDRs are 80.29%, 82.42%, 92.87%, 97.54%, and 97.62%. This demonstrates that as damage severity increases, the IDR will be enhanced, too. In other words, the trained DAE can more easily detect severe damage with fewer errors. It is essential to note that when the bridge sustains significant damage, the trained DAE can identify its damaged state in real time with high accuracy (greater than 90%), which is indicative of a high IDR. At this point, if the damage degree continues to increase, the rate of IDR growth will decelerate (e.g., only a 0.08% increase between DSs 5 and 6) and eventually approach 100%. By summarizing all IDRs for DS 1–6, the overall damage detection accuracy of the proposed method is 86.2%.
5. Conclusions and future work

5.1 Concluding remarks

This thesis explores approaches for identifying the bridge’s information using instrumented vehicles, including the deduction of CP responses from a 3D vehicle’s accelerations and damage identification using extracted bridge frequencies from an SV when the PT is in different positions. Further, several distinguishing features, such as MFCCs and reconstruction errors of the DAE, are extracted from the vehicle’s vibrations via several data-driven methods. Several key findings are summarized below:

Simulation results indicate that the proposed equations for calculating the CP response from an instrumented 3D vehicle are effective and suitable for the scenario when sensor installation errors are considered. In the CP response, the vehicle’s dynamic information has been eliminated. To mitigate the effects of road roughness, the residual CP response between the front and rear wheels is employed. The results indicate that bridge frequencies become dominant in the frequency domain and can be clearly identified when using the residual CP response. Analysis of other influential factors shows that environmental noise can have a negative impact on the identification of bridge frequencies, but this is only the case in the high-frequency range (>20 Hz in this thesis). Additionally, high damping of the bridge can restrain the transmission of its dynamic information to the vehicle and thus can inversely influence the identification of the bridge’s frequencies.

To address the challenge that the bridge’s frequencies are not sensitive to local damage, this thesis introduces a PT on sequential positions of the bridge, which can increase the amount of modal information for bridge model updating at the same time. In addition, a novel MAC-based objective function that performs more robustly than the traditional relative error-based one is also included. Several influencing factors, including road roughness, bridge damping, environmental noises, ongoing traffic, and FE
model errors, are considered in the process of damage detection. The numerical simulation results indicate that the proposed MAC-based objective function can detect the bridge's damage position and degree robustly with acceptable precision.

Another key contribution of the thesis is that it explores the vehicle's high-frequency responses. Using SVM models on the frequency responses of the vehicle, it is discovered that the bridge’s damage information is not only contained in the low-frequency responses of the vehicle but also in the high-frequency components, which can contribute to the detection of bridge damage. Further, it is found that the damage features are densely distributed in the low-frequency ranges while sparsely disseminated in the high-frequency ranges. To improve the efficiency of damage detection, MFCCs are extracted from the vehicle’s responses, which makes damaged cases linearly separable from healthy cases. Results indicate that Linear SVM models combined with MFCCs using uneven filterbanks can achieve fast damage detection with high accuracy. Moreover, it is tested that heavy vehicles are conducive to obtaining better damage detection results.

To overcome the challenge of obtaining damage examples in practical engineering, this thesis proposes using classification accuracy to determine the health conditions of the bridge. The newly obtained runs of vehicles are assumed as damaged to do a binary classification with healthy runs (baseline). Results show that the threshold $k_s = 0.84$ is suitable for the determination of the bridge’s health condition. To reduce the dimensions of input, PCA and MFCCs are employed and tested to be effective when the proposed threshold is utilized. When employing MFCCs, the test accuracy values are distributed around 0.5 when the bridge is healthy, while they become high (near 1.0 in this study) when the bridge is damaged.

Finally, bridge health monitoring is achieved in real time using the responses of an instrumented vehicle. It is verified that the short-time vibration data from the passing vehicle can be utilized to evaluate the bridge’s health condition. Compared to existing methods, which require the vehicle to pass over the bridge, the proposed method using short-time accelerations is more efficient. By employing the proposed DI, the bridge’s damage information can be automatically identified without extracting modal parameters. When six different damage scenarios are explored, relatively high accuracy can be achieved (86.2% in this study), though the trained DAE model may misreport the health condition of the bridge near the support. Furthermore, in the laboratory tests, it is noticed that the value of DIs may not be suitable for determining the damage severity. Instead, the proposed IDR can be utilized as a reference for detecting the bridge’s damage severity. With the increase in damage severity, the IDR increases remarkably at first and then gradually approaches 100%.
5.2 Suggestions for future work

It should be noted that while this thesis has made several significant findings, the effectiveness of the proposed approaches may be influenced by various factors in practical engineering. These topics are quite interesting and important to investigate but have not been covered within the scope of this thesis. The author suggests that researchers interested in this method explore these topics in future work.

- For the extraction of bridge frequencies from vehicle responses, more influential factors in practical engineering, such as vehicle engine influence, vehicular model updating errors, winds, and earthquakes, have not been extensively investigated for the proposed methods in this thesis and deserve further studies in the future.

- Natural frequencies of the bridge are important indices for bridge inspection. However, the VBI system is time-varying, and the bridge's frequency identified from the vehicle indirectly or from the bridge directly can vary with time, which has not been considered in this thesis.

- The data-driven methods employed in this thesis have assumed that the same vehicle with fixed parameters can be utilized for bridge health condition monitoring. However, the use of one vehicle serving for years over the designed period of the bridge is challenging. Future work could encompass addressing potential inaccuracies in identifying vehicular parameters and incorporating long-time bridge inspection.

- The influence of road roughness can still be a main inverse factor overshadowing the bridge's information in the vehicle’s responses. In the experiments, relatively smooth road roughness was tested. Further investigation should include the effects of poorer road roughness, different traces when the vehicle passes the bridge several times, and accounting for slightly curved driving scenarios in engineering applications.

- The identification of bridge modal parameters is typically based on simple vehicle or bridge models. However, in engineering applications, the VBI system exists in a 3D space. Extending current methods to spatial modes using sophisticated vehicular models is demanding in future studies.

- Another key influence factor is the speed of the passing vehicle. Currently, this study assumes that the vehicle(s) transverse the bridge at a constant speed. However, even for an experienced driver, it can be challenging to keep the speed unchanged, especially when the
bridge’s spans become long. Future studies can consider slightly changed speeds when the vehicle passes the bridge.

- Using laboratory experiments can be an excellent way to verify proposed approaches. However, in practical engineering, there exist more complex scenarios and influence factors, such as real-world engine effects, complicated vehicular systems, different bridge types, etc. Field tests are required to demonstrate the effectiveness of the proposed bridge frequency identification and data-driven methods.

- In present investigations, most damage scenarios are simulated by FE models, additional mass, or incisions in laboratory experiments. The patterns of real damage in practical bridges deserve further exploration.

- Temperature effects are essential for bridge health monitoring. Future work can include the effects of temperatures on bridge modal parameter identification and damage detection using the responses of vehicles.

- The future work can also include the identification of different damage patterns, such as corrosion, fatigue cracks, tension loss in cables, etc., with the help of other state-of-the-art techniques.
References


