A crowdsensing-based platform for transportation infrastructure monitoring and management in smart cities

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Abstract:

Crowdsensing-based infrastructure monitoring is a rising framework and has the potential to become a high-level monitoring tool and help manage populations of infrastructure systems with reduced cost and increased efficiency in future smart cities. Using this framework, the existing infrastructure system can be pre-screened on a large scale to determine the key infrastructure elements that exhibit abnormal behavior before implementing more detailed on-site monitoring systems or conducting detailed site inspections on individual infrastructure elements. In this framework, a large amount of crowdsensing data, i.e., 'big data', are collected from commercial-grade sensors in mobile personal devices, e.g., smartphones, smart vehicles, and cameras. In order for such crowdsensing-based frameworks to succeed, the crowdsensing data must be efficiently and effectively managed and analyzed to support decision making. In this context, this chapter presents a software platform to analyze and manage the crowdsensing data collected from moving vehicles. The platform includes a database to store the crowdsensing data, algorithms that are integrated for data analysis, and a web-based interactive system for visualization. Three algorithms developed by our group that can process vibration and image data collected from moving vehicles for bridge and road condition assessment are presented in this chapter, which are Mel-frequency cepstral analysis-based method for bridge damage detection, inverse filter-based method bridge frequency identification, and deep learning-based method for road crack detection. In the long-term, we envision that this platform will be open-sourced, and more algorithms that can process other crowdsensing data can be integrated in this platform in the future.

Keywords: Crowdsensing-based platform; Smart cities; Transportation infrastructure; Bridge monitoring; Crack detection.

Overview

Consistent urban development in recent decades has increased challenges facing infrastructure management (White, 2003), demanding new and efficient methods for infrastructure monitoring. Regarding transportation systems, traditional methods required field data collections using pre-installed sensors (Lin et al., 2013; Wenzel, 2009). In these methods, most city monitoring capabilities are concentrated for small, targeted segments of the network. Installation costs, including devices and labor, are substantial when applied to a large metropolitan area. However, with the rise of smart technologies in the forms of smart cars and smartphones, there is an opportunity to collect real-time citizen-sourced data from the whole transportation network. Therefore, there is no need to install extra sensors, leading to a more efficient monitoring framework. Such an approach has been classified as the crowdsensing-based method in the literature.

Crowdsensing-based monitoring approaches for transportation systems have been widely studied in the literature (Mei, Gül, & Shirzad-Ghaleroudkhani, 2020). These studies focused on many aspects, including traffic monitoring (Bhoraskar et al., 2012), road surface monitoring (Sattar et al., 2018), emergency management(Sattar et al., 2018), and bridge monitoring (Matarazzo et al., 2018). Such studies corroborate the fact that citizen-sourced data are valuable sources for the means of monitoring transportation system components. This chapter introduces a platform for road quality and bridge monitoring using crowdsensed data collected from smart cars and smartphones.

Continuous condition monitoring has long been a concern for road asset management. Current practices for road quality monitoring include manual inspection or inspection through professionally instrumented vehicles, which are either inefficient or expensive. In recent years, efforts have been made to develop algorithms for pavement defect detection using deep learning and commercial-grade cameras (Bang et al., 2019; Mei & Gül, 2020; Sawalakhe & Prakash, 2018). Integrating the algorithms with in-vehicle sensors, the road condition of the city can be scanned accurately and quickly by non-professionals.

Bridge monitoring using moving sensors, i.e., indirect bridge monitoring, has recently been a point of interest among researchers (Malekjafarian et al., 2015; Mei et al., 2021). Crowdsensed monitoring of bridges was the direct outcome of such methods, which was addressed in many studies (Matarazzo et al., 2018; Mei & Gül, 2019). The main challenges facing indirect bridge monitoring are vehicle vibrations and road roughness effects. Mixed signals recorded on a vehicle passing over the bridge contain different sources of vibrations. Therefore, detecting bridge features among those sources may not be feasible in all cases. However, recent studies (Shirzad-Ghaleroudkhani & Gül, 2020, 2021) showed that through employing an appropriate filtering process, it is possible to magnify bridge features and suppress other sources in the recorded, mixed signals. As such, crowdsensing-based methodologies could be applied for the means of bridge monitoring using in-vehicle sensors.

The introduced platform in this chapter comprises monitoring two aspects of transportation infrastructure, which are road quality and bridge monitoring. Road quality monitoring through crack detection process is achieved using deep neural networks. Afterwards, bridge monitoring is achieved using two methodologies. First, a damage detection method for bridges using Mel-frequency Cepstrum is presented. Next, inverse filtering methodology to detect bridge frequency is explained. All these methods rely on crowdsensed data and are integrated into a platform to be used in future smart cities.

Platform

In this section, a web-based platform developed for crowdsensing-based monitoring of transportation infrastructure is presented. The platform can be used to manage and visualize the results from crowdsensing-based monitoring to support decision-making. This system is developed in Python based on Django and Leaflet. The results are stored in SQLite database. Three algorithms integrated into this platform are presented. First, the road quality monitoring using crack detection methodology is explained. Afterwards, two methodologies for bridge monitoring and damage detection are explained.

Road quality monitoring

It is known that cost-effective and efficient road quality monitoring technologies are of interest to the infrastructure management authorities. The current version of the platform has integrated a deep learning-based algorithm to detect cracks on the pavement surfaces (Mei, Gül, & Azim, 2020; Mei, Gül, & Shirzad-Ghaleroudkhani, 2020).

In recent years, deep learning has drawn significant attention from researchers in transportation infrastructure management because of its superior performance and full automation in identifying road defects. The deep learning based algorithm integrated into this platform was previously developed by the authors (Mei, Gül, & Shirzad-Ghaleroudkhani, 2020). The overall procedure of the crack detection is presented in Figure 1. It mainly included four steps. First, the original image was split into smaller patches. Then, the deep learning algorithm was applied to the patches. After integrating the crack detection results from the patches, post-processing was introduced to eliminate false positive results. The details of the deep learning algorithm in step 2 are shown in Figure 2. It had an encoder-decoder architecture consisting of convolutional, max pooling, and transposed convolutional layers. Skip connections were introduced to create densely connected layers. In addition, a loss function that considered the connectivity of pixels was used for better training. The model is trained on EdmCrack1000 dataset introduced by the authors. In previous work, the authors have shown that the proposed deep learning algorithm could identify the cracks at pixel level with high accuracy. Different kinds of cracks including alligator cracks, longitudinal and transverse cracks, etc., can be identified successfully using the proposed algorithm. More details about this network can be found in (Mei, Gül, & Azim, 2020).

Synthesizing the crack detection results with GPS data, the road condition can be monitored by crowdsensing using commercial-grade devices like sport cameras. Thus, locations with unfavorable road conditions can easily be identified. In the platform, the image taken at each location can be shown as a dot on the map. A simple indicator called road deterioration index (RDI) is designed as the ratio of the number of crack pixels over the resolution of the image. Different colors are used to represent different severity of the road deterioration in terms of RDI. In general, a higher RDI is corresponding to worse road conditions in terms of identified cracks. When a dot is clicked, the rendered image with cracks highlighted related to that location and the detailed information of the RDI will be presented. A screenshot of the platform for road condition monitoring is presented in Figure 3. All such information integrated in this system can be used to support the decision-making process. For example, from this interactive map, the authorities can know which area they should pay more attention. It should be noted that RDI is an initial effort to relate the crack detection results to the real road condition. Further studies will be conducted to relate such results to more standard indices such as international roughness index (IRI) and Pavement condition index (PCI).

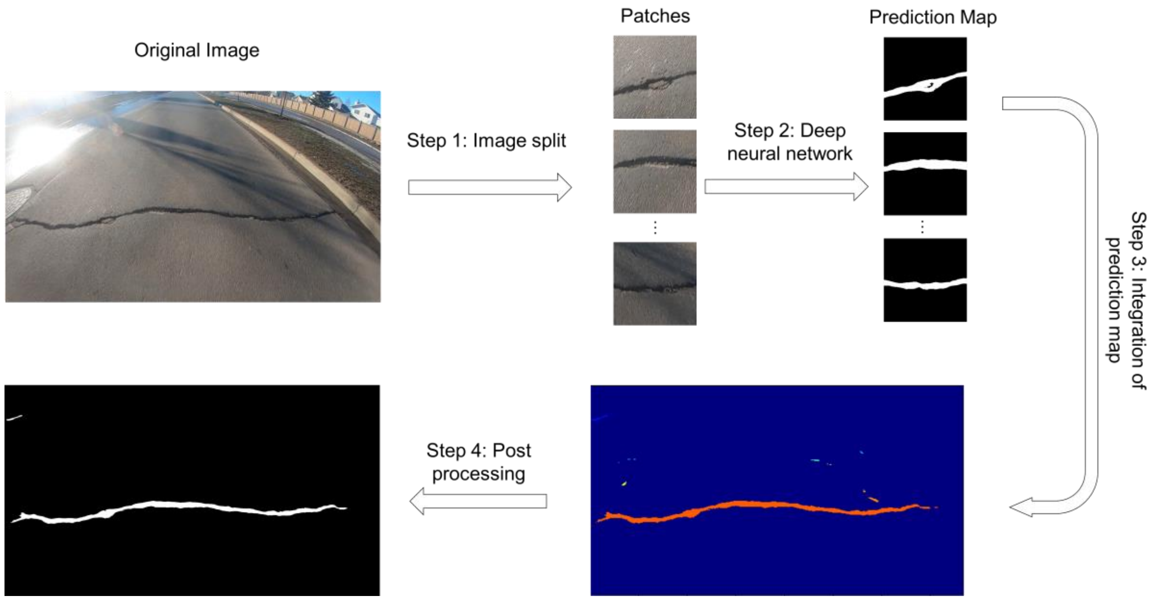

Figure 1. Overview of the crack detection procedure

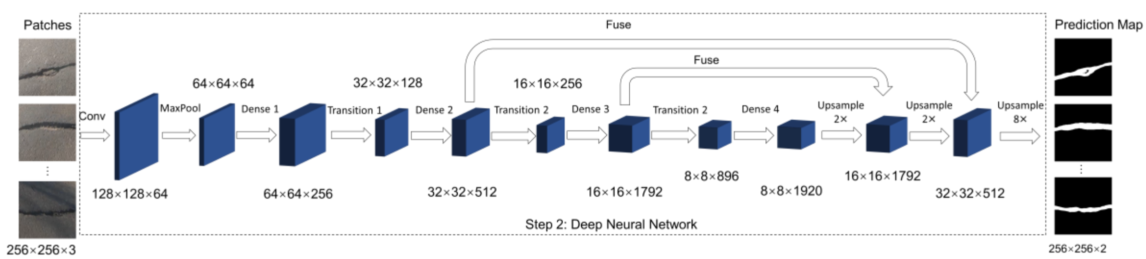

Figure 2. Details of the deep learning model

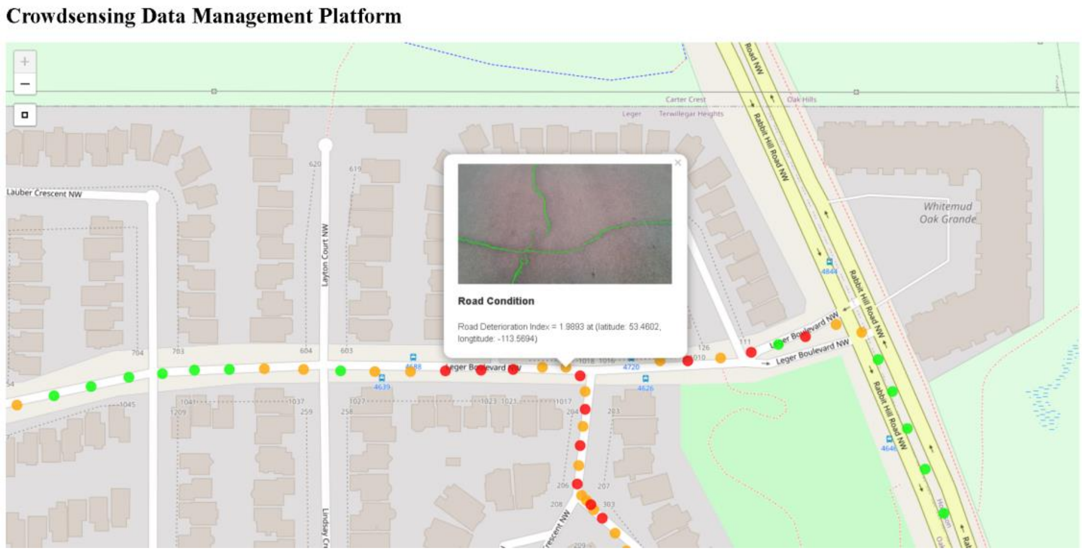

Figure 3. Screenshot of the platform for road condition monitoring

Bridge Monitoring

In this section, two bridge monitoring methodologies integrated in the platform are explained.

1. Mel-frequency Cepstrum Coefficients

Cepstral analysis has been the subject of several studies (Bochud et al., 2011; Dackermann et al., 2014) focusing on monitoring of bridges, mainly using fixed sensors. These studies proved the potential of using cepstral analysis for bridge damage detection, both numerically and experimentally. Meanwhile, the dependency of most delamination detection methods on the environmental noise and the subjectivity of inspectors has motivated many studies to use component analysis and Mel-frequency cepstral (MFC) analysis (Balsamo et al., 2014; G. Zhang et al., 2011). These studies demonstrated the efficiency of using MFC analysis for damage detection of bridge structures, although they only employed direct monitoring methodologies.

The main advantage of using MFC analysis in comparison to traditional cepstral analysis is the idea that MFC considers more weight for lower frequency features. This is a crucial fact in indirect bridge monitoring since the collected mixed data contains both vehicle and bridge features, while the features related to bridges lie mostly within lower frequency ranges. The flowchart of Mel-frequency cepstral analysis proposed in this methodology (Mei et al., 2019) is shown in Figure 4.

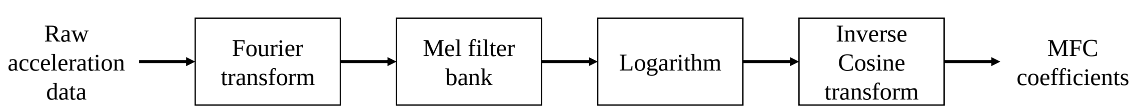

Figure 4. Process of MFC analysis (Mei et al., 2019).

After features are extracted using MFC analysis for each run of a vehicle, they can be stored and plotted in the platform. When a large number of vehicles pass across the bridge, the distribution of the features can be compared using KL divergence to identify the potential damage, as described in (Mei & Gül, 2019). Figure 5 presents a visualization of the features extracted from 8 runs of a single vehicle on the platform.

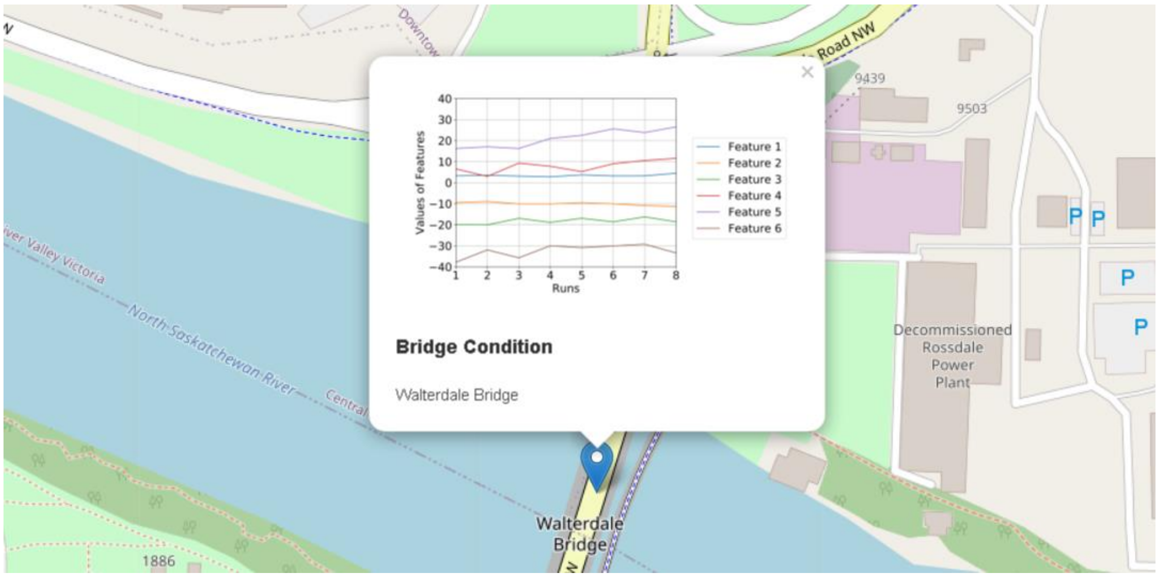

Figure 5. Screenshot of the platform for bridge condition monitoring using Mel-frequency cepstral analysis.

2. Inverse Filtering methodology

As mentioned in the Introduction section, the main challenge in the drive-by monitoring of bridges is the effect of external sources in the recorded, mixed vibrations. Vehicle features, including engine vibrations, suspension system, tire vibrations, etc., as well as road roughness effect, significantly affect the on-vehicle recorded vibrations (Shirzad-Ghaleroudkhani et al., 2020). In terms of spectral analysis, the frequency content of the recorded vibrations is highly dominated by vehicle and roughness level. Thus, detecting bridge features would be challenging. Therefore, a novel methodology of inverse filtering was introduced (Shirzad-Ghaleroudkhani & Gül, 2020, 2021), which focuses on eliminating vehicle and road roughness effects from recorded mixed signals and magnifying bridge frequencies.

Inverse filtering methodology is built upon the fact that vibrations recorded on a vehicle consist of two types of sources: transient and steady sources. Vibration sources related to the vehicle components, e.g., engine vibrations, suspension system, tire vibrations, etc., as well as road roughness effect, are present throughout the vehicle travel history and are thus considered steady sources. On the other hand, for a limited window of the time when the vehicle is passing over the bridge, a transient source, i.e., bridge vibration, will be added to the mixed signal. As a result, any filter capable of suppressing steady sources of vibrations in the recorded signal will amplify transient sources, which are bridge dynamic features.

In the bridge frequency detection point of view, a frequency spectrum of the vibrations recorded on the vehicle while moving off the bridge, hereby called off-bridge spectrum, is employed to design a filter that suppresses vehicle and road roughness effects. This filter will later be applied to the vibration spectrum recorded on the similar vehicle moving on the bridge, hereby called on-bridge spectrum. The resulting filtered spectrum will then amplify bridge frequencies. This process is illustrated in Figure 6 using polynomial equations, which hypothetically represent frequency spectra. In Figure 6 (a), a hypothetical spectrum of the off-bridge case is shown with a black curve. Then, the inverse of that spectrum is calculated and shown using a blue curve, representing the inverse filter shape. As a result, the product of these two curves would be a flat line spectrum with no priority between different frequencies. In other words, it shows that the inverse filter shape is capable of eliminating frequency contents related to the off-bridge case. On the other hand, Figure 6 (b) illustrates the hypothetical on-bridge spectrum with a red curve, similar to the previous off-bridge spectrum with a slight difference in the amplitude corresponding to the bridge frequency, shown with a dashed line. In addition, the inverse filtered on-bridge spectrum is presented in Figure 6 (b) using a blue curve, where a major peak representing target bridge frequency has emerged and other major peaks are suppressed. This hypothetical case shows that as long as all major factors affecting the shape of the spectrum, including the vehicle and road features, are similar between off- and on-bridge cases, it would be possible to detect bridge frequency using inverse filtering methodology.

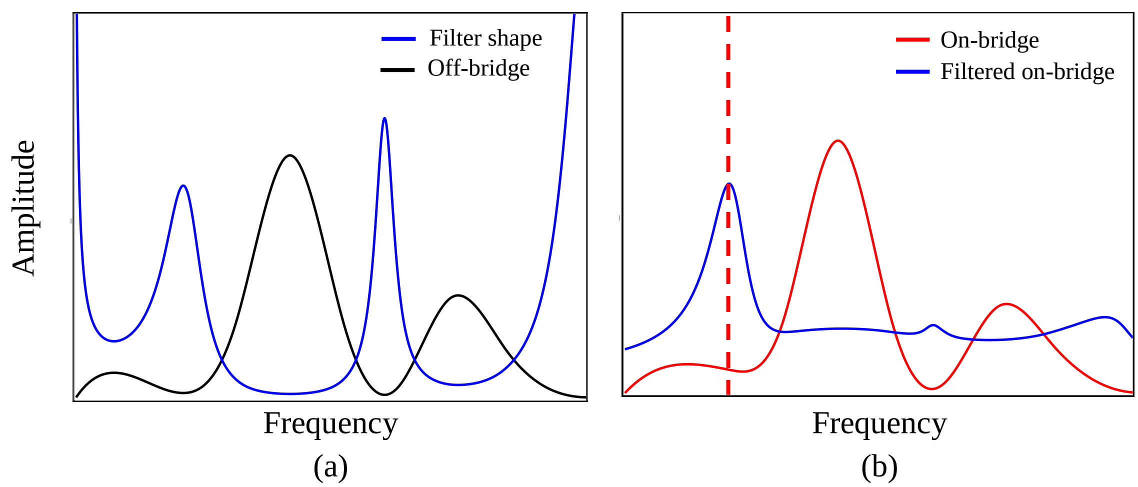

Figure 6. Hypothetical (a) off-bridge spectrum and inverse filter shape and (b) unfiltered and filtered on-bridge spectra using polynomial equations (Shirzad-Ghaleroudkhani & Gül, 2020).

Among all factors affecting the frequency spectrum of recorded vehicle vibrations, vehicle speed and road roughness are of the most importance. Engine vibrations, suspension system, and tire vibrations all depend on the speed of the vehicle. In addition, road roughness has a major effect on the vibrations experienced by the vehicle. As such, a new methodology (Shirzad-Ghaleroudkhani & Gül, 2021) was presented, which constructs a database of vehicle vibrations throughout the travel. Depending on the speed and road roughness experienced by the vehicle while moving over the bridge, the appropriate off-bridge signal will be recalled, and the corresponding inverse filter will be designed. The first step in this process is to detect on- and off-bridge segments of the travel. This process is performed using the GPS history of the vehicle travel, as shown for a sample in Figure 7. GPS coordinates of the start and endpoints of each bridge are employed to detect vehicle location with respect to the bridge. In the next step, constant speed windows of the vehicle travel are stored inside the database. Per each constant speed window of the on-bridge signal, the matching speed off-bridge signals are recalled to be used for inverse filtering design. However, before designing the inverse filter, the effect of road roughness level will be considered as well. The average energy level of acceleration signals, calculated using the mean square of the acceleration values, is used as a representative of the road roughness level. In fact, the closest energy level among off-bridge signals to the on-bridge one will be used to design the appropriate inverse filter. Hence, all major limitations of inverse filtering methodology are addressed. The flowchart of this process is illustrated in Figure 8.

Figure 7. A sample of on-bridge (red) and off-bridge (green) data separation using recorded GPS history (Shirzad-Ghaleroudkhani & Gül, 2021).

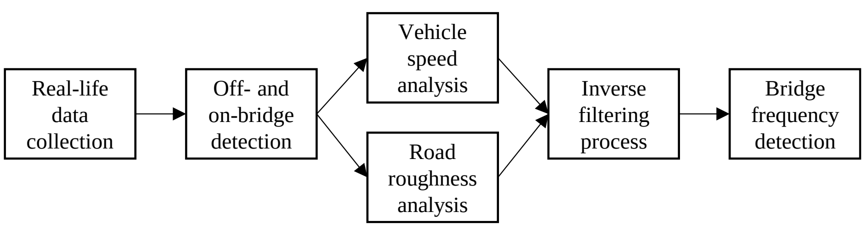

Figure 8. The flowchart of the proposed inverse filtering methodology

Two real-scale bridges in Edmonton, Alberta, i.e., High Level Bridge and Walterdale Bridge as shown in Figure 9, were studied (Shirzad-Ghaleroudkhani & Gül, 2021) to investigate the performance of the proposed methodology in detecting bridge frequency under real-life conditions. Their fundamental frequencies were captured through a separate experiment using fixed sensors, resulting in 2.8 and 2.1 Hz for High Level Bridge and Walterdale Bridge, respectively. In addition, the vibrations and GPS data were collected using a Samsung Galaxy Note 10 plus smartphone mounted on a Honda Civic sedan, as shown in Figure 10.

(a) (b)

Figure 9. Pictures of (a) High Level Bridge and (b) Walterdale Bridge.

Figure 10. Placement of the smartphone inside the vehicle (Shirzad-Ghaleroudkhani & Gül, 2021).

Frequency identification results using inverse filtering methodology for these bridges are presented in Figure 11 and Figure 12. These figures contain two plots, where the top plot illustrates the on-bridge and the corresponding off-bridge spectra required for inverse filtering methodology, and the bottom figure demonstrates the filtered on-bridge spectrum. Note that the previously identified bridge frequencies are shown using dashed lines. As seen, it is not possible to detect bridge frequencies using the on-bridge spectrum, which is dominated by vehicle and road features. However, after applying an appropriate inverse filter, a major peak representing bridge frequency will emerge. It is worth noting that the proposed inverse filtering methodology considers each device and vehicle separately throughout the filtering process and thus is robust against their features. Meanwhile, there are slight differences between the emerged peak frequency and the previously identified frequencies, which are due to the environmental effects. Exposed bridge structures are highly affected by environmental factors, especially temperature. Such effects will be implemented in the methodology to increase the accuracy of frequency detection in the future.

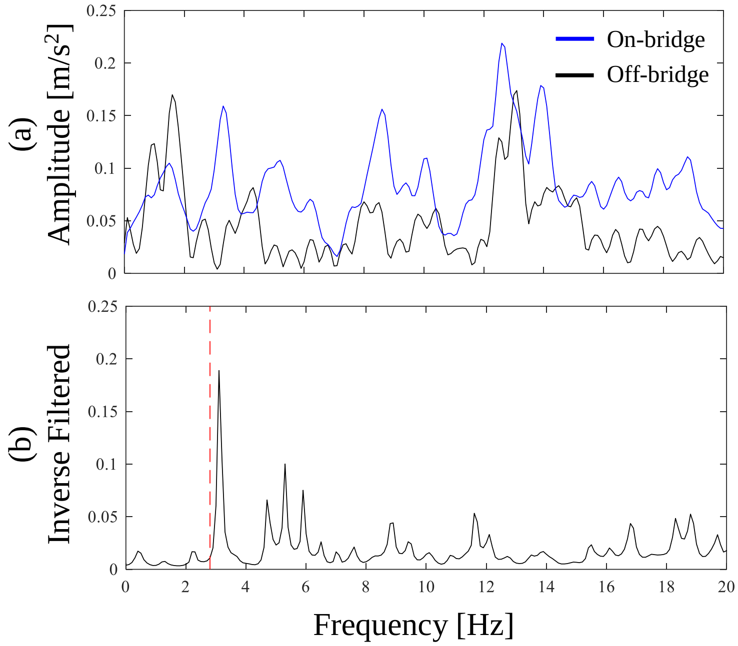

Figure 11. (a) A sample of on-bridge and corresponding off-bridge spectra and (b) the inverse filtered on-bridge spectrum for High Level Bridge.

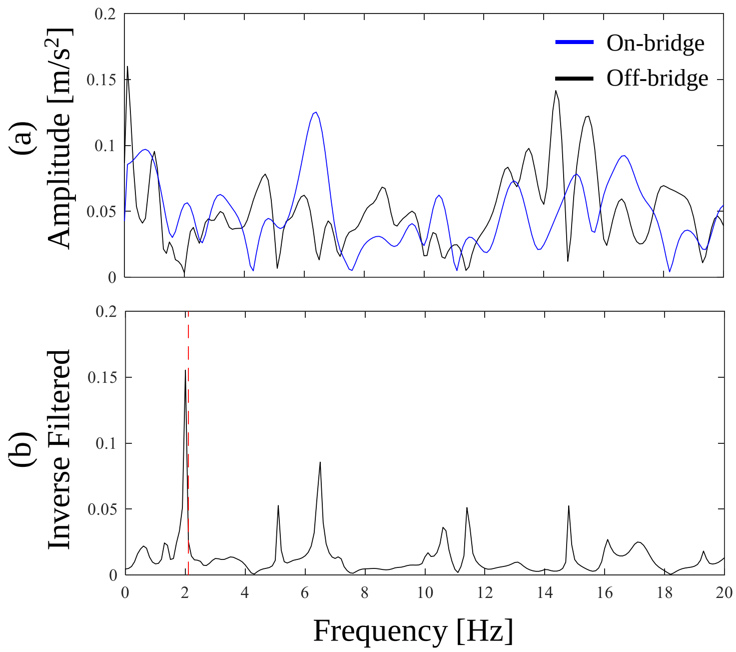

Figure 12. (a) A sample of on-bridge and corresponding off-bridge spectra and (b) the inverse filtered on-bridge spectrum for Walterdale Bridge.

In order to implement inverse filtering methodology in the crowdsensing-based platform, the variations of detected frequencies will be monitored. The identification process will be repeated for all vehicles passing over the bridge, and the seven days average of all frequencies will be calculated inside the platform. Further effects of vehicle types and loads and even traffic distributions along a week will all be eliminated using this averaging technique, although environmental effects throughout the year still need to be implemented in the methodology in future studies. Any significant change in the average detected frequency of each bridge would be a sign of a change in the stiffness of the structure. More detailed monitoring methods could later be applied to those bridges using fixed sensors in serious conditions. The average detected frequency of the bridge would be reported in the platform, as seen in Figure 13. This figure illustrates a hypothetical output of the platform for frequency change detection during eight weeks of data acquisition using the proposed crowdsensed methodology. A permanent change in the detected bridge frequency over time, shown in Figure 13, could be a sign of a serious change in the stiffness of the bridge. As the output of the platform, those cases need to be thoroughly investigated using direct methods in the next phases of bridge monitoring.

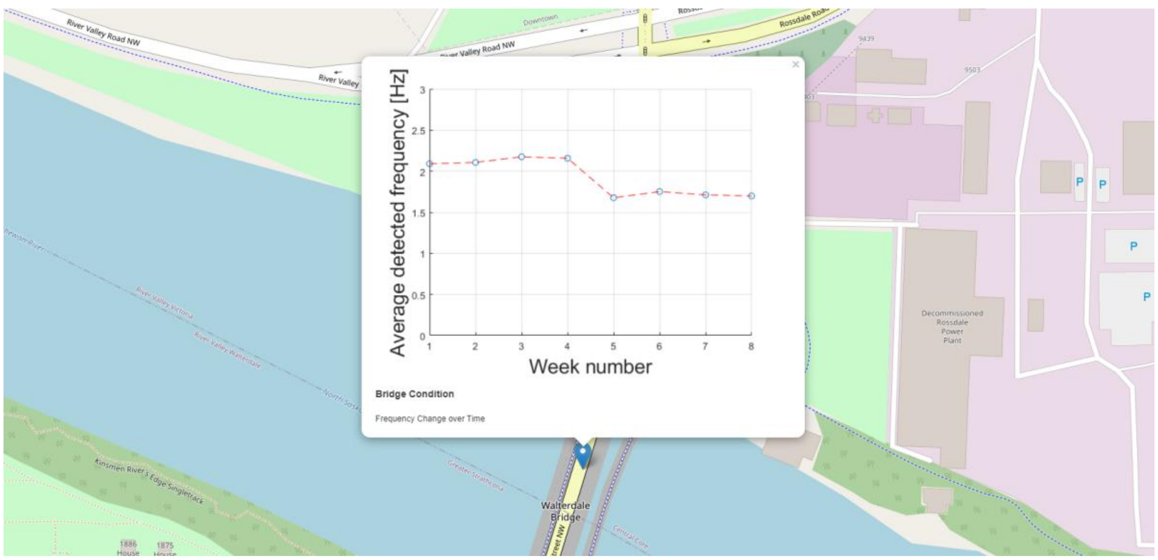

Figure 13. Screenshot of the platform for bridge condition monitoring using inverse filtering for a hypothetical case.

Discussion

This section focuses on the limitations of the proposed crowdsensing-based platform for transportation infrastructure. First, the privacy issues in crowdsensing methodologies are discussed. Later, the limitations of the monitoring methods integrated into the proposed platform are explained.

One of the main challenges facing crowdsensing-based methodologies is the privacy and security of the citizens. Although privacy is considered a human right (Solove, 2011), crowdsensing methods are designed based on the data collected from devices owned by private people. Furthermore, major clients of infrastructure monitoring operations are governmental or municipal agencies. Such issues may raise concern among citizens of future smart cities for sharing their information through proposed platforms, which will be used for the prosperity of their own city. Many studies have focused on providing solutions to this tight relationship through applying effective cryptography and integrating appropriate access control mechanisms (Cilliers & Flowerday, 2014; Gaire et al., 2018). It is important to investigate these concerns for future broad implementations of crowdsensing methods.

Transportation infrastructure is mainly exposed structures, which increases their dependency on environmental effects. For instance, bridge dynamic features are highly dependent on weather parameters, including temperature, humidity, wind, etc. Since bridge monitoring methods rely on detecting the change in dynamic properties of the bridge, such environmental factors play key roles in the accuracy of the results. In addition, road quality monitoring criteria need to be compatible with the weather and environmental features as well. Therefore, it is crucial to implement these effects in the proposed platform using artificial intelligence and machine learning methods (Erazo et al., 2019; Gu et al., 2017; Kostić & Gül, 2017; H. Zhang et al., 2019) in future studies.

Conclusion

This chapter presents a crowdsensing-based platform for collecting citizen data from smart cars and smartphones to be analyzed for monitoring vital transportation infrastructure, i.e., bridge structure and road quality, in smart cities. Three different methodologies that were previously proved effective are implemented in this platform, including a crack detection framework and two bridge damage detection methodologies. Municipalities and urban management administrations can potentially employ this platform to monitor the real-time performance and quality of these components of transportation infrastructure. Since this platform relies on crowdsensed data collection, it significantly reduces monitoring costs and can be applied to a whole metropolitan area at the same time.

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