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In-situ Health Monitoring for Bogie Systems of CRH380 Train on Beijing–Shanghai High-Speed Railway

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Abstract

Based on the authors' research efforts over the years, an *in-situ* structural health monitoring (SHM) technique taking advantage of guided elastic waves has been developed and deployed via an online diagnosis system. The technique and the system were recently implemented on the China's latest high-speed train (CRH380CL) operated on Beijing−Shanghai High-Speed Railway~~, the world's longest high-speed line constructed in a single phase~~. The system incorporated modularized components including active sensor network, active wave generation, multi-channel data acquisition, signal processing, data fusion, and results presentation. The sensor network, inspired by a new concept—"decentralized standard sensing"—was integrated into the bogie frames during final assembly of CRH380CL, to generate and acquire bogie-guided ultrasonic waves, from which a wide array of signal features were extracted. Fusion of signal features through a diagnostic imaging algorithm led to a graphic illustration of the overall health state of the bogie in a real-time and intuitive manner. The *in-situ* experimentation covered a variety of high-speed train operation events including startup, acceleration/deceleration, full-speed operation (300 km/h), emergency braking, track change, as well as full stop. Mock-up damage affixed to the bogie was identified quantitatively and visualized in images. This *in-situ* testing has demonstrated the feasibility, effectiveness, sensitivity, and reliability of the developed SHM technique and the system towards real-world applications.

Keywords: structural health monitoring; signal processing; guided-wave-based damage detection; high-speed train bogie system; Beijing−Shanghai High-speed Railway; CRH380CL

Nomenclature

Acronyms

pld	point-line distance
AE	acoustic emission
ANP	acoustic nonlinearity parameter
BSHSR	Beijing–Shanghai High-Speed Railway
DI	damage index
GW	guided wave
HAT	hollowed axle testing
NDT	nondestructive testing
PXI	PCI extensions for instrumentation
PZT	lead zirconate titanate
RANP	relative acoustic nonlinearity parameter
RWI	rail wheel inspection
SHM	structural health monitoring
TOF	time of flight

Symbols

a_X	magnitude scaling factor of signal X
f_E	excitation frequency
k	wavenumber
x_p	wave propagation distance
A_1, A_2	amplitudes of the fundamental and second harmonic modes
$\mathbf{A}_{\boldsymbol{m}}$	antisymmetric Lamb wave modes ($\boldsymbol{m}$ = 0, 1, 2…)
$\mathbf{E}$	expected value
$\mathbf{F}$	flexural modes in tubes
$\mathbf{L}$	longitudinal modes in tubes
N	number of sensors in a network
R	sensing path weight factor
$\mathbf{S}_{\boldsymbol{m}}$	symmetric Lamb wave modes ($\boldsymbol{m}$ = 0, 1, 2…)
T	transducer
W	signal weight coefficient

X, X_{comp}, X_{τ}	baseline signal, compensated baseline signal, time-shifted baseline signal
Y	current signal

Greek symbols

γ	Lamb wave nonlinearity scaling factor
λ	wavelength
μ	mean of a signal
ρ	signal correlation coefficient
ς	scaling parameter for RANP based imaging
τ	time lag
Δ	difference of the current and baseline signals

Subscripts

$(\ )_{accum}$	accumulated *DI* after fusion
$(\ )_{corr}$	*DI* genre using correlation
$(\ )_{final}$	final *DI*
$(\ )_{i}$	actuator
$(\ )_{i,j}$	sensing path $T_i – T_j$
$(\ )_{j}$	sensor
$(\ )_{RANP}$	*DI* genre using *RANP*

1. Introduction

The period from the 1990s up to the present day has witnessed unprecedented prosperity in railway industry globally, and especially in ~~greater~~ Greater China. Of particular interests ~~is~~ are the high-speed trains with an operational speed over 200 km/h. However, potential threats behind such a rapid expansion of railway network must be envisaged: possible failure of train structures during their operation can result in immense life and monetary loss, leading to irretrievable and catastrophic consequences. Trains in many countries, in spite of approaching the designed service life, are anticipated to remain in service for an extended period. The longer a train is in service the more critical defects it may suffer. This concern is doubly accentuated for high-speed trains because of the higher speed, more intensive use, and more complex structures, compared to ordinary trains. Exposed to a wide array of hazards such as detrimental impacts, atrocious climate, complex rail conditions, and unexpected events, high-speed trains are highly prone to structural damage, which can initiate under repetitious loads during their operation, and then deteriorate at an alarming rate without sufficient warning. For instance, the German Eschede train crash in 1998—the first high-speed train disaster in history leading to 200 casualties and also the world's deadliest train accident to date—was attributed to the cracks in the wheel rims [1]; earlier, Sydney's Granville train derailment in 1977, killing 83 people, was a consequence of the damage in the poorly maintained railway structures [2].

With safety being a paramount priority in public transportation, criteria of reliability, integrity, and durability must be met strictly by all train structures. To this end, routine maintenance and inspection work in virtue of nondestructive testing (NDT) (*e.g.*, radioscopy, ultrasonics, electromagnetic inspection, laser interferometry, thermography, and eddy-current [3]) has to be carried out on key train structures, such as bogies and axles, on a regular basis. Although playing a significant role in preventing structural failure, most of the NDT-based inspection is conducted at a periodical interval, regardless of the working condition changes and progressive deterioration of train structures (*i.e.*, non-condition-based). They cost a lot but deliver low efficiency. For example, the ultrasonic inspection, one of the dominant NDT implementations in railway industry, is manipulated at a low speed, consuming a considerable amount of time in order to fully scan an entire train bogie; meanwhile, to ensure the functionality of ultrasonic probes, downtime of vehicles is a prerequisite, incurring high cost in terms of labor and disruption to the traffic. Even so, this technique often neglects the damage small in size until it grows to a conspicuous level.

In contrast to non-condition-based inspection, the condition-based monitoring is targeted at continuous and automated surveillance of structural health condition without suspending the normal operation of structures, which is commonly referred to as *structural health monitoring* (SHM) [4–7]. Using integrated sensors, pre-developed models, and proper signal processing tools, SHM is able to enhance system safety, drive down exorbitant maintenance cost, and extend residual life of aging structures. It has been demonstrated that an effective SHM exercise can reduce the overall maintenance cost of a transportation system by over 30% [8], accompanying substantial improvement of reliability and safety.

Following a recapitulation on the state of the art of prevailing NDT and SHM techniques for train structures at present, this paper recounts the development of an SHM technique specialized for high-speed train bogies, taking advantage of active ultrasonic waves guided by bogie frames. This technique, residing on the authors' intensive research efforts over the years, is deployed via an online diagnosis system in conjunction with a piezoelectric sensor network configured in virtue of a new concept—“decentralized standard sensing”. The technique and the system were implemented on China’s latest high-speed train (CRH380CL) operated on Beijing−Shanghai High-Speed Railway (BSHSR), to monitor the health conditions of the train bogie frames in real time. The *in-situ* experimentation covered a variety of train operating events, including startup, acceleration/deceleration, full-speed operation (300 km/h), emergency braking, track change, as well as full stop. Signal fusion and diagnostic imaging algorithms were developed to facilitate the presentation of monitoring results in images, which are intuitive for users to comprehend the overall health state of the entire bogie structure.

2. NDT and SHM for train structures—the state of the art

In general, an NDT or SHM technique for integrity evaluation of a train structure can be implemented based on either global or local measurements, in terms of a common premise: the damage, if any in a train structure, alters structural properties (local effective stiffness, electric/magnetic conductivity, electro-mechanical impedance, *etc*.), and hence the globally measured dynamic vibration responses of the structure (*e.g.*, eigen-frequency, mode shape, and strain energy) or the locally acquired waves guided by the structure. Any deviation manifested in the captured signals with respect to corresponding baseline signals, can serve as an indication of damage occurrence.

Between these two implementations, most global vibration-based approaches, reflecting damage-induced changes in global responses, are often not deemed sufficiently sensitive to damage until it reaches a notable extent, because damage is a local phenomenon and it would not modulate global responses of a train structure significantly. Moreover, rugged working conditions of trains introduce additional difficulties in extracting damage-induced global vibration changes, hampering perception of damage in its embryo stage. Thus, the effectiveness of global vibration-based techniques towards small damage in large and complex train structures remains questionable. In contrast, local wave propagation-based approaches, represented by those using acoustic emission (AE) and guided waves (GWs), explore local disturbance from the damage [3]. There have been a large number of NDT techniques developed for train structures based on AE and GWs. Representatively, the immersion technique for rail wheel inspection (RWI) [9], as displayed in figure 1(a), is a popular NDT technique in railway industry, whereby the dismounted wheel is immersed in a water tank (for a liquid coupling that warrants wave transmission), and damage in the wheel is deemed existent if abnormal wave propagation is observed. This technique has proven effectiveness in detecting defects in the wheel flange, rim, and entire disk. Another RWI method, called *in-motion ultrasonic testing* [10] shown in figure 1(b), enables wheel tread inspection by exciting Rayleigh waves—a type of GWs guided by the rim—when the wheel is passing over stationary ultrasonic probes mounted on the track at a low speed. In addition to RWI, GW-based techniques for wheel set axels are also available, typified by the hollowed axle testing (HAT) [11] in figure 1(c), which features an extendible probe system operated inside a hollowed axle to generate and acquire GWs along the axle.

Nevertheless, limited by the nature of non-condition-based detection, all the above NDT methods have to be maneuvered offline, entailing the suspension of train service. Meanwhile, most existing techniques are exclusively developed for wheels and axles only, and there has been an obvious lack in SHM techniques that can be manipulated during the normal operation of trains, let along high-speed trains, for not only wheels and axels, but coaches, bolsters, and bogies. In particular, bogies, the most complicated and critical structural component of a train vehicle that support all the dead loads and payloads, are fairly vulnerable to a diversity of damage modalities such as cracks, surface/subsurface fatigue, corrosion, scratch, wheel flat, indentation, wearing and gauge. The integrity of a bogie is among the top concerns pertaining to train safety.

In this regard, the GW-based philosophy, initially proposed for aerospace structures and now on the verge of maturity for real-world SHM applications in various industrial sectors [12–21], can be an excellent candidate to circumvent such insufficiency, by making use of their guided nature and superb characteristics including low attenuation, strong penetration, fast propagation, omnidirectional dissemination, low energy consumption, convenience in actuation/acquisition, and most importantly, superior sensitivity to damage even at a tiny scale or underneath structural surfaces. However, the development and application of GW-based SHM for train bogies is somewhat handicapped, due to the complex geometry and boundary conditions of bogies, as well as the demanding operational environment. In addition to thin plate-like components, tubular structures with larger thickness are commonly used to shape bogie frames, which entail higher magnitudes of GW excitation so as to cover a reasonable inspection area. The highly multimodal and dispersive natures of GWs in tubular structures, together with complex reflections from boundaries, present substantial obstacles for signal feature extraction and interpretation. To model various damage types in bogies aforementioned under different working loads is an intractable issue. In addition, development of compact instrumentation, proper wiring and cabling for actuators/sensors, real-time signal acquisition, and processing of massive signals are some other challenges in practical implementation of GW-based SHM for train bogies.

Subject to these difficulties and challenges, current research efforts on GW-based SHM techniques for train structures are mainly in the form of methodological development, simulation work, or testing in well-controlled laboratorial environment, yet very limited investigations have been fully demonstrated in reality, not mentioning on high-speed trains, with *in-situ* validation.

3. Methodology

A GW-based SHM approach is developed, dedicated to the online integrity monitoring and real-time damage detection for high-speed train bogie frames that serve as a waveguide. This section briefly discusses the theory, principle, and methodology of the approach.

3.1. Principle

Figure 2 shows the dispersion curves of GWs in an A606 steel plate (*i.e.*, Lamb waves—the modality of elastic waves guided by a thin plate- or shell-like waveguide), and their counterparts guided by a tube of the same material. $\mathbf{S}_{\boldsymbol{m}}$ ($\boldsymbol{m}$ = 0, 1, 2…) in figure 2(a) refers to a collection of symmetric Lamb wave modes, while $\mathbf{A}_{\boldsymbol{m}}$ ($\boldsymbol{m}$ = 0, 1, 2…) refers to antisymmetric modes; in figure 2(b), **L** refers to the longitudinal modes in a tubular structure, and **F** refers to the flexural modes. In the case of Lamb waves, for instance, a multitude of GW modes are traveling in the waveguide simultaneously, at different velocities subject to the excitation frequency and waveguide thickness concurrently. Either mode type can be chosen to detect specific forms of damage in the bogie in terms of their respective motion pattern: the symmetric type is known to be more sensitive to through-thickness damage and interior damage (including fatigue damage-driven plastic zones), while the antisymmetric type has a better performance in perceiving surface cracks, scratch or corrosion [3]. The frequency tuning [12] is a process that can be manipulated to select a desired wave mode with dominant energy in GW signals.

To excite and acquire a desired wave mode in the bogie, a network-based sensing strategy is proposed, in which piezoelectric lead zirconate titanate (PZT) wafers are networked and integrated into the bogie during the assembly process of the train, as illustrated schematically in figure 3. Each PZT wafer can act either as an actuator to generate probing GWs, or as a sensor to capture bogie-guided waves. These wafers collectively form different sensing paths in terms of pulse-echo or pitch-catch configurations. The interaction of probing GWs with damage in the bogie, if any, induces linear wave scattering (documented in the time domain such as delay in time-of-flight (TOF) [13–15], wave reflection or transmission [16–19], energy dissipation [20, 21] and mode conversion [22, 23]), or nonlinear wave distortion (manifested in the frequency domain such as higher-order harmonics). With these linear or nonlinear features extracted from GW signals through proper signal processing, various genres of damage index (*DI* hereinafter) can be constructed, linking the changes in GW features to damage parameters such as location, size, shape, and severity. Continuous evaluation of a *DI* enables real-time monitoring of the bogie's overall health condition.

3.2. *DI* based on signal correlation

Damage in a bogie modulates probing GWs, deviating them from baseline signals that are either pre-collected from an intact benchmark bogie or pre-calculated from theoretical models without any damage. If the damage is right on or close to a particular sensing path in the sensor network, the deviation can be significant; otherwise, it can be minute. Therefore, the correlation between a signal captured from the bogie under inspection and its corresponding baseline signal can be used to develop an indicator to damage occurrence in the structure. Let $X = \{x_1, x_2, \ldots, x_n\}$ be the baseline signal acquired via sensing path $\mathrm{T}_i - \mathrm{T}_j$, where T_i and T_j denote respectively an actuator and a sensor in a sensor network with N PZT wafers ($i, j = 1, 2, \cdots, N$, but $i \neq j$), and let $Y = \{y_1, y_2, \ldots, y_n\}$ be the signal collected from the bogie under inspection (called *current signal* in what follows). The correlation coefficient, ρ_{XY}, between *X* and *Y* is calculated as

$$\rho_{XY} = \frac{\sum_{r=1}^{n}(x_r - \mu_X)(y_r - \mu_Y)}{\sqrt{\sum_{r=1}^{n}(x_r - \mu_X)^2 \cdot \sum_{r=1}^{n}(y_r - \mu_Y)^2}}, \tag{1}$$

where μ_X and μ_Y are the means of *X* and *Y*, respectively. The *DI* constructed by T$_i$ – T$_j$ is then defined as

$$DI_{i,j} = 1 - |\rho_{XY}|. \tag{2}$$

Noticeably, the above *DI* is established for a single sensing path rather than at each spatial node (or pixel) in the monitored domain; thus, it may be unable to accurately pinpoint damage in the region where no sensing paths traverse (as a consequence of the sparse configuration of the sensor network). Furthermore, environmental impacts (*e.g.*, temperature variation) in continuous measurement can create discrepancies of a captured current signal from its corresponding baseline signal even when there is no damage in the bogie, manifested by time shifting and/or different amplitude scales, which leads to outdated benchmarking. This is because a baseline signal is pre-acquired under specific environmental conditions, which may vary significantly from the current signals captured later on.

In order to circumvent the above inefficiency of a sparse sensor network, and meanwhile to compensate for continuous changes in ambient conditions, an enhancement tactic can be employed to define the correlation-based *DI*, in which the difference in signals due to the existence of damage in the bogie, designated as Δ, between *Y* and a compensated baseline signal X_{comp}, is calculated first as

$$\Delta = Y - X_{comp} = Y - a_X X_\tau, \tag{3a}$$

where a_X is a magnitude scaling ratio for a time-shifted baseline signal, which reads

$$a_X = \mathbf{E}\left[(Y-\mu_Y)\left(X_\tau - \mu_{X_\tau}\right)\right] \Big/ \mathbf{E}\left[(X-\mu_X)^2\right]. \tag{3b}$$

In the above, **E** signifies the expected value operator; X_τ denotes a lagged signal X with respect to Y that counteracts possible time shift due to environmental effects, with τ being the time lag at which the cross correlation of X and Y reaches its maximum, *viz.*, $\tau = \tau\big|_{\max\left(\mathbf{E}\left[(Y-\mu_Y)(X_\tau-\mu_X)\right]\right)}$. μ_{X_τ} is the mean of X_τ. In addition to taking into account the time shift caused by environmental impacts, equation (3b) calculates a scaling ratio, a_X, between the magnitudes of Y and X_τ, which is also utterly attributed to ambient effects, so that after such an adjustment, the rescaled, time-shifted baseline signal X_{comp} eliminates the discrepancies and is paired to its corresponding current signal as if it were measured under the current environmental conditions throughout the whole testing. It should be noted that this global discrepancy discussed in the above (purely due to environmental effects) is different from and statistically independent of the local deviation of Y from its baseline signal caused by structural damage.

With this enhancement tactic, the *DI* can now be redefined at each pixel in the monitored domain. For a pitch-catch configuration in the sensor network, the *DI* at pixel (x, y) defined by sensing path T_i – T_j, designated as $DI_{i,j}(x,y)$, is

$$DI_{i,j}(x,y)_{corr} = W \cdot |\max(\Delta)| \cdot \frac{\sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}}{\sqrt{(x-x_i)^2 + (y-y_i)^2} + \sqrt{(x-x_j)^2 + (y-y_j)^2}}, \tag{4}$$

where W is a weight coefficient to compensate for wave attenuation over propagation distance; (x_i, y_i) and (x_j, y_j) are the coordinates of T_i and T_j, respectively. The subscript "*corr*" addresses that the cornerstone of such an index is signal correlation.

3.3. *DI* based on nonlinearities of GWs

In parallel, a nonlinear *DI* is established based on the *acoustic nonlinearity parameter* (*ANP*) extracted from GW signals. The incentive of developing a nonlinear *DI* to supplement the signal correlation-based linear *DI* in equation (4) lies on the conclusion drawn from the authors' preceding studies on nonlinear ultrasonic waves [24, 25]: the nonlinearities of GWs possess a higher sensitivity to damage small in size, such as surface/subsurface fatigue damage, corrosion, and thermal degradation, which are otherwise hardly discovered using signal correlation- or TOF-based signal features because no substantial wave scattering would occur in the latter cases [26].

The nonlinear characteristics of GWs used in this approach include primarily the second harmonics. Consider a one-dimensional waveguide bearing a fatigue crack first. Using a perturbation theory [27], the GWs, modulated by the fatigue crack, has the following relationship between A_1 (the amplitude of selected wave mode at excitation frequency f_E) and A_2 (the amplitude of its second harmonic mode at twice the excitation frequency $2f_E$)

$$A_2 = \frac{ANP}{8} A_1^2 k^2 x_p, \tag{5}$$

where k is the wavenumber, and x_p the wave propagation distance. *ANP* is associated with nonlinearities arising from the waveguide material and the damage concurrently [25]. After rearrangement, equation (5) converts to

$$ANP = \frac{8}{k^2 x_p} \frac{A_2}{A_1^2}. \tag{6}$$

With equation (6), *ANP* can be determined directly by measuring A_1 and A_2 from a captured GW signal, and any monotonous increase in its value implies the occurrence of damage in the bogie. For the purpose of damage detection, one is more interested in the change (*i.e.*, monotonous increase) in *ANP* than its absolute value. Allowing for this, at a given x_p, the *relative acoustic nonlinearity parameter* (*RANP*) is further introduced as

$$RANP = \frac{A_2}{A_1^2}. \tag{7}$$

Thus, once any change in *RANP* is perceived, damage is deemed existent in the bogie. In order to extend the above analysis from a one- to three-dimensional waveguide for train bogies, equation (7) is multiplied by a scaling factor γ [28]. Because such a factor remains unchanged regardless of damage existence or propagation distance, γ can be eliminated through appropriate normalization process as with other parameters like k and x_p. Therefore, *RANP* in equation (7) is also applicable for bogie-guided waves.

To develop a RANP-based *DI*, a relationship is first established between (i) the value of *RANP* acquired by a particular sensing path in the sensor network, and (ii) the point-line distance (*pld*) from the damage to that sensing path in Euclidean geometry [24]. Figure 4 shows such a relation for a typical steel plate used in train bogies with a thickness of 4.5 mm, where pld/λ (on the horizontal axis) refers to the above point-line distance normalized by the probing wavelength λ excited at f_E. It can be seen that *RANP* (on the vertical axis) reaches its maximum when the sensing path passes through the damage, which is reduced monotonously as the sensing path moves away from the damage. Meanwhile, high inertness is observed when the path is far away from the damage. These features of *RANP* can be beneficial to the detection of multi-site damage. On the other hand, it has also been proven [24] that such a relation between *RANP* and *pld/λ* is insensitive to the length variation of a sensing path, rendering great flexibility in configuring the sensor network.

Residing on *RANP*, a nonlinear *DI* at a pixel (x, y) in the monitored domain developed by the path $T_i - T_j$ is defined as

$$DI_{i,j}(x,y)_{RANP} = RANP_{i,j}\left[\frac{\varsigma - R_{i,j}(x,y)}{\varsigma - 1}\right], \tag{8}$$

where $RANP_{i,j}$ denotes the *RANP* extracted from the GW signal acquired via $T_i - T_j$, ς is a scaling parameter that controls the size of the effective distribution area, and $R_{i,j}(x,y)$ is a weight factor regulating the area of influence from the damage on a sensing path [21, 24], which reads

$$R_{i,j}(x,y) = \begin{cases} \dfrac{\sqrt{(x-x_i)^2+(y-y_i)^2}+\sqrt{(x-x_j)^2+(y-y_j)^2}}{\sqrt{(x_i-x_j)^2+(y_i-y_j)^2}} & \text{when } R_{i,j}(x,y) < \varsigma \\ \varsigma. & \text{when } R_{i,j}(x,y) \geq \varsigma \end{cases} \tag{9}$$

The subscript of this *DI* reflects that the index is based on the nonlinear feature—*RANP*.

3.4. Signal processing

High-speed trains are operated in harsh environments in which a captured GW signal can be severely contaminated by the complex vibration of running vehicles and wideband noise with unpredictable uncertainties. For a thorough understanding, a typical vibration signal acquired passively (without active generation of probing GWs) by a PZT sensor attached to the bogie frame of a high-speed train running at 300 km/h (to be detailed in following sections) is displayed in the time and frequency domains, in figures 5(a) and 5(b), respectively. As can be seen in figure 5(b), the signal power is distributed in a fairly wide range: a portion of the power is concentrated at a lower frequency band (up to approximately 100 kHz) which can be attributed to the vibration of running vehicles, and the majority is randomly scattered at a higher band (up from 800 kHz) which comes from various noise interferences. Consequently, digital low-pass and high-pass filters are employed to screen the high- and low-frequency components, respectively, creating a working frequency range between 200 and 800 kHz with little noise contamination, in which a probing GW signal can be actively generated and acquired.

Prior to the above filtering, instantaneous averaging is firstly applied to reduce the environment effects and random noise. Different signal processing tools such as Hilbert transform and short-time Fourier transform [24] are used as well, to extract wave components at the active excitation frequency f_E (for establishing the *DI* with equation (4)), and further at twice the excitation frequency $2f_E$ (for establishing the *DI* with equation (8)).

3.5. Diagnostic imaging

Upon signal processing, the correlation- and RANP-based *DIs* are constructed for each sensing path in the sensor network, defined at every pixel in the monitored domain. As a principal objective and a feature of the proposed SHM technique, the monitoring results of the bogie are expected to be presented in images intuitively and promptly using the *DI* value at each pixel. Thus, each sensing path is able to render an image, indicating the probability of damage occurrence at all the pixels from the perspective of that path.

However, it has to be envisaged that in practical measurement, individual images may contain not only the information pertaining to damage but those unwanted features such as ambient noise and measurement uncertainties, multiple wave modes, and boundary reflection, all of which can mask damage-associated features and impede accurate determination of *DI*s. An image fusion algorithm is therefore developed, to amalgamate individual images from all sensing paths in the sensor network. In this approach, the resulting *DI* (written as DI_{final}) at each pixel in the fused image is calculated by accumulating corresponding *DI*s at this pixel contributed by every sensing path, followed by a normalization process with respect to the maximal accumulated *DI* value of the entire domain, in accordance with

$$DI_{final}(x,y) = DI_{accum}(x,y) / \max(DI_{accum}(x,y)), \tag{10a}$$

where

$$DI_{accum}(x,y) = \frac{1}{N \cdot (N-1)} \sum_{i,j=1,\, i \neq j}^{N} DI_{i,j}(x,y). \tag{10b}$$

Note $DI_{i,j}(x,y)$ in equation (10) can be linear $DI_{i,j}\left(x,y\right)_{corr}$ defined by equation (4) or nonlinear $DI_{i,j}(x,y)_{RANP}$ defined by equation (8), or both. The image fusion strengthens damage-incurred linear and nonlinear GW features (commonality in individual images) while weakens noise (random information in individual images).

4. System

The developed SHM technique is deployed via an integrated online diagnosis system, with its final assembly shown in figure 6. The system, designed to fully accommodate the needs of automatic and online SHM for train structures, features the following key components.

4.1. Sensor networks capitalizing on a new concept—“decentralized standard sensing”

A PZT wafer provides substantial weight saving over conventional GW actuating and sensing devices, with low-power consumption, negligible footprints, ease of integration into host structures, high operating frequency, dual roles as an actuator and a sensor, as well as low cost. However, a single wafer performs local acquisition of GWs, and generally tends to supply inadequate information for SHM of train structures, which erodes confidence in the monitoring results. Spatially distributed PZT wafers are thus networked to configure a sensor network. By "communicating" with each other, individual sensors act cooperatively to allow desirable redundancy and to enhance reliability of GW signal acquisition [29].

However, as far as train bogies are concerned, it is often uneconomic and sometimes infeasible to prudentially allocate every sensor in the sensor network towards a cost-effective configuration, due to the complex and diverse geometries of the train bogie. For most field applications, unlike laboratorial experiments, optimization of sensor placement on the case-by-case basis cannot be achieved until the actual test has been done. This would require additional access to the structures in operation in order to modify the current sensor network configuration plan, which is not always feasible and usually costs more. Moreover, to manually affix individual wafers to train structures with adhesives, and solder insulated wires on each of them can unavoidably introduce performance inconsistency from one wafer to one another, leading to discrepancy and monitoring instability. With such inefficiency recognized, a sensor networking approach based on the concept of "decentralized standard sensing" is developed, aimed at an effortless and universal solution to GW excitation and generation in various structures with high flexibility yet a reduced cost.

Conceptually, the "standard sensing" refers to a standardized sensing unit, made up of a PZT wafer and a printed circuit board (both embedded in a polyimide film), as shown in figure 7. The film not only covers the entire area of the wafer and the circuit for protection purpose, but also provides a convenient surface for installation of the unit on bogies. Thin and flexible, the polyimide film can deform to adapt to the curvature of different parts of the bogie. Inside the film, the circuit is connected to the electrodes of the PZT wafer beforehand via soldering and/or conductive adhesives, and a standard microdot connector in the circuit enables a quick connection to controlling hardware through a shielded cable. Each sensing unit features a thickness of less than 0.2 mm and weight less than 3 g, contributing negligible weight and volume penalty to the bogie. With dual piezoelectricity, each unit can alternate its role between an actuator and a sensor through a switch array controller. A multitude of such units are flexibly networked to configure a tailor-made sensor network, which can be permanently integrated into bogies to accommodate their diverse geometrical identities and boundary conditions. Use of the standardized units can avoid deliberate consideration on positioning of individual sensors, saving significant efforts when large-scale sensor networks are concerned. To ensure its functionality in rugged working conditions, each unit is insulated from the environment through an epoxy layer once attached to the structure (to be detailed in section 5.2). *In-situ* testing has demonstrated that such protection can greatly enhance survivability of PZT in atrocious operation conditions of high-speed trains.

Furthermore, the "decentralization" in the concept signifies the self-contained functionality of individual units in the network, including particularly the independence of physical positioning, communication with the system (GW generation and acquisition), signal processing, *etc*. Warranted by certain redundancy, such decentralization effectively de-emphasizes the contribution from individual units, thus enhancing error-tolerance and mal-functionality-resistance of individual sensors in a large-scale network. This trait can be particularly important for real-world applications, without which the erroneous or incomplete perceptions from a few sensors (due to various factors such as measurement noise) may interfere with the correct information perceived by others in the network, delivering inaccurate monitoring results.

4.2. Modularized hardware components and interfaces

In conventional laboratorial tests, GW generation and acquisition can be easily achieved with separate measurement devices such as wedge probes, function generators, oscilloscopes, *etc*; for real-world SHM applications, nevertheless, it is desirable that all the functional units are well integrated with mutual communication to fulfill the designated SHM task. To deploy the proposed SHM method, a compact, integrated online diagnosis system is developed on a PCI eXtensions for Instrumentation (PXI) platform with the virtual instrument technique. In conjunction with the use of the active sensor network, the diagnosis system embraces a sensor network control module, an arbitrary wave generation module (with high-power amplification), a multi-channel data acquisition module, and a central control and data processing module. All these modules are integrated through the PXI bus and controlled by in-house software [30]. Importantly, in order to make the system readily applicable for diverse engineering applications apart from high-speed trains, standard communication interfaces are used throughout the system architecture, with which additional modules can be conveniently introduced for further system expansion.

4.3. Man-machine interface

The in-house software, programmed on LabVIEW® and packaged in one final code for easy manipulation, has the full access and control of each module in the diagnosis system in sequence to accomplish each step of the monitoring, from GW generation, sensing unit role switch, multi-channel acquisition, to signal processing, data fusion, and image construction. Through a user-friendly man-machine interface, the inputs for probing waveforms (*e.g.*, excitation frequency, amplitude, number of cycles), data acquisition and storage (*e.g.*, sampling rate, trigger level, storage path), sensor coordinates, signal processing (*e.g.*, averaging, filter parameter), and damage detection (*e.g.*, *DI* calculation, image construction, resolution control) can be specified easily, and finally the SHM results are presented in images automatically, which are intuitive for users to comprehend the overall health state of the entire train bogie. Continuous monitoring can be achieved by setting an appropriate monitoring interval between each periodic scan.

5. ***In-situ* SHM of trains on Beijing−Shanghai High-Speed Railway**

The developed SHM technique, deployed via the online diagnosis system, was installed on the China's latest high-speed train (CRH380CL) operated along Beijing−Shanghai High-Speed Railway (BSHSR) in January, 2013, for *in-situ* monitoring of the health conditions of the train bogie frames.

5.1. CRH380CL and BSHSR

CRH380CL, as photographed in figure 8(a), was designed based on Siemens® Velaro's high-speed train platform, and manufactured by CNR Changchun Railway Vehicles Co. (China), featuring a maximum design speed of 400 km/h and an operating speed of 380 km/h. The rolling stock consists of 16 coaches, on which there are 32 CW400/CW400D bolsterless bogies with air-spring suspension systems. The conformance testing of this train model was carried out along BSHSR. ~~Upon completion of the conformance testing, CRH380CL will remain on BSHSR for commercial services, providing the fastest scheduled train service in the world.~~ With a length of 1,318 kilometers (figure 8(b)), ~~BSHSR~~ this railway is ~~the world's longest high-speed rail constructed in a single phase (from 2008 to 2010), and also~~ the world's first line designed with a commercial operating speed of 380 km/h~~. The railway began its commercial service in June, 2011~~, which connects Beijing and Shanghai, the two major economic zones in China, in a less than a five-hour journey.

5.2. SHM strategy for CRH380CL bogies

As discussed earlier, bogie frames, made of high-strength low-alloy steel (*e.g.*, SMA490BW for CRH series), are the most crucial components of train vehicles, whose integrity and health condition is among the top concerns pertaining to train safety. Thus, it was accordingly selected as the object to be monitored *in-situ* using the developed SHM technique.

With the selected bogie of CRH380CL, the PZT sensor network was customized in light of the concept of "decentralized sensing" and integrated into the hot-spots of the bogie ("hot-spots" referring to those regions where high intensity of stress concentration is anticipated, based on finite element simulation results [31]) during the manufacturing stage of the bogie frame (before its final assembly with coach), four months prior to the conformance testing. For illustration, a diagram of one quarter of the bogie frame with such a sensor network is displayed in figure 9, encompassing a switch array controller and eleven standard sensing units. Nine of the sensors are on the side panel and the rest on the top surface, distributed in such a way that the geometric features of the bogie frame (*e.g.*, thickness variation, boundaries) as well as GW attenuation in the structure are taken into account. Each sensing unit, once installed, was thoroughly protected by a pre-coating layer, as seen in figure 10(a), before wiring. Industrial tapes with long durability were used to seal the sensing units and cables, as shown in figure 10(b). The sensor network was then connected to the online diagnosis system situated inside the coach through shielded cables, as displayed in figure 11, after the bogie was put together with the coach.

In-situ SHM was manipulated in the manner of periodic scans. After signal processing, various features extracted from GW signals were used to establish linear *DI* with equation (4) and nonlinear *DI* with equation (8). Given a propagation speed of around 5 km/s of the selected GW mode in steel, it generally took no more than 0.5 ms for a probing wave, guided by the bogie frame, to propagate between any two sensing units in the sensor network. The system utilized time division multiplexing through the switch array controller, to independently instruct each sensing unit. In each scan, all the sensing units took turns to act as the actuator with the rest being sensors. Since GW propagation is reversible, the two GW signals acquired between a pair of sensing units, regardless of which one is the actuator, showed considerable similarity. Thus, for a sensor network with N standardized sensing units, the number of unique monitoring paths is ${}_{N}C_{2}$, which in this case was 55, as 11 standard sensing units were used for one quarter of the bogie.

Since the train to be monitored was newly manufactured and carefully inspected before delivery, it was deemed no structural damage existed in the bogie in the first place. In order to comprehensively evaluate the developed technique and the online diagnosis system, the following three scenarios were considered during the *in-situ* monitoring:

(i) static loading – when the train was stationary;

(ii) dynamic loading – when the train was in operation at a speed up to 300 km/h; and

(iii) with mock-up damage – an aluminum mass was added to the side panel of the bogie frame, simulating damage under the static and dynamic loads, respectively.

For all scenarios, ten-time averaging, band-pass filtering, Hilbert transform and short-time Fourier transform were applied to raw GW signals in sequence, as elaborated in section 3.4. In addition, to understand the influence from vibration and environmental noise on GW wave propagation in bogie, pure vibration signals of the bogie when the train was in normal operation was measured beforehand using the mounted sensor network.

5.3 Scenario (i): intact state under static loading

To begin with, *in-situ* monitoring was accomplished under static loading without any mock-up damage, the purpose of which was to validate the setup and optimize system parameters. Five-cycle narrowband sinusoidal tone bursts modulated by a *Hann* window were generated by the waveform generation module, in figure 12(a), and magnified to ±60 $V_{p\text{-}p}$ as the input signal. Frequency tuning was applied to select excitation frequencies within a working band of 200–800 kHz (as explained in section 3.4 and figure 5(b)), and a strong response of generated GW signals could be obtained at a center frequency of circa 400 kHz, which was then determined as the excitation frequency. This corresponds to a frequency-thickness value of about 4 MHz·mm, given that the thickness of the bogie frame inspected was roughly 10 mm, meaning the excitation mode was $\mathbf{S_1}$ according to figure 2(a). In each scan, GW signals were collected from the 55 channels at a sampling rate of 20 MHz through the multi-channel data acquisition module, and the interval between every scan was set to 10 s. For illustration, the GW signal acquired via sensing path $T_3 - T_2$ after signal processing in the central control and data processing module, is shown as an example in figure 12(b).

5.4. Scenario (ii): intact state under dynamic loading

Using the same settings from the static test, *in-situ* monitoring for the bogie was conducted as the train was in operation on BSHSR during the night. On all the testing nights, the outside temperature measured by the train maintained between -3–0 ºC, and the actual maximum speed recorded was 300 km/h.

To investigate the influence of different dynamic loadings due to vehicle motion on the propagation characteristics of actively generated GWs, a group of signals acquired via T_3 – T_2 are displayed in figure 13, covering a variety of operation events including startup, speed-up, full-speed operation (300 km/h), emergency braking, track change, as well as full stop. It can be seen that the discrepancy among GW signals in different operation events were negligible, showing very minor amplitude differences in some cycles and no phase changes at all. This has demonstrated the vehicle vibration and ambient interference have trivial impact on actively generated and acquired GWs, thanks to the filtering and averaging processes as well as the carefully chosen working frequency that masked out the majority of low-frequency vibration and high-frequency environmental noise.

5.5. Scenario (iii): damaged state

During a suspension window of the conformance testing, mock-up damage was created on a side panel of the bogie frame, as photographed in figure 14, by bonding an aluminum mass (measuring roughly 22×13 mm^2) to the bogie frame with superglue, in the area enclosed by sensing units T_1, T_2, T_6, and T_7. The added mass was carefully covered with industrial tape to make sure it would not fall off the bogie when the train was in motion, which was then removed upon the completion of the testing. The mock-up damage, by compromising the structural integrity, would impose twofold modulation on GW propagation in the bogie: linearwise, it would scatter the probing waves and incur delay in TOF and energy dissipation as it blocks GW propagation; nonlinearwise, it would distort the probing waves and generate higher-order harmonics, because the intentional imperfect bonding between the bogie surface and the mass would induce contact acoustic nonlinearity. Thus, linear and nonlinear *DIs* could be established in terms of Eqs. (4) and (8), respectively.

The same testing configurations were retained from the above two scenarios. The discrepancy during measurement between baseline signals obtained from Section 5.2 and current signals from the damaged state (mainly due to temperature variation) was compensated by the correlation-based signal processing technique as elaborated in Section 3.2. A real-time image of the side panel to which the mock-up damage was affixed is shown in figure 15, automatically produced by the system using the diagnostic imaging algorithms detailed in section 3.5 through imaging fusion. In the image, the color scale calibrates the degree of probability of damage occurrence at all pixels across the monitored domain, and the red color corresponds to a higher probability. As can be seen, both the location and approximate size of the mock-up damage were clearly indicated in the image with a satisfactory accuracy. Similar images were continuously produced for different parts of the entire bogie in a real-time manner during the *in-situ* monitoring, which were observed to maintain a high quality and repeatability.

Since the work concerns an industrial application, a relatively big mass was used as the mock-up damage, in order to primarily validate the online SHM system in a real world scenario. Hence in this case, the nonlinear technique did not demonstrate particular superiority over the other. For a detailed comparison of the effectiveness between linear and nonlinear damage detection techniques as well as studies on nonlinear GW-based SHM, one can refer to the authors' other studies [24, 25].

6. Concluding remarks

A GW-based SHM technique was developed and deployed via an integrated online diagnosis system. The system, in conjunction with the use of an active sensor network in virtue of the concept of "decentralized standard sensing", embraces modularized hardware components, and an intuitive man-machine interface. The system was recently installed on the China's latest high-speed train model CRH380CL, and validated by *in-situ* monitoring the health condition of the bogie frames of CRH380CL on Beijing−Shanghai High-Speed Railway. To the authors' knowledge, this is the first time that a fully functional GW-based SHM technique has been experimented *in-situ* on high-speed trains. During the testing, a large number of GW signals were acquired under diverse train operation events, including startup, acceleration/deceleration, full-speed operation, emergency braking, track change, and full stop, revealing that these operating events could hardly impact GWs actively generated in an appropriately selected frequency band. Linear and nonlinear GW features were extracted to establish different genres of damage indices. Assisted with data fusion diagnostic imaging algorithms, the damage indices have proven effectiveness in pinpointing damage in intuitive images in terms of its occurrence probability. With an expandable library of damage indices, the fusion enables a great flexibility to employ the most efficient type of damage indices (linear or nonlinear), or a hybrid index, to optimize health monitoring according to specific applications. Continuous monitoring of the train bogie in a consistent, automatic, and accurate manner, along with the demonstrated capacity of detecting mock-up damage in the bogie, have evidenced the practicality, efficacy, and stability of the developed SHM technique and the online diagnosis system towards real-world engineering applications. With the inborn compatibility, mobility, and expandability, the technique and the system are expected to have a great prospective in other industrial practices.

7. Other resource

The said *in-situ* testing on Beijing−Shanghai high-speed railway was filmed, and a short version of the video can be viewed at http://www.youtube.com/watch?v=4R9BImwH0rI.

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Figure Captions

Figure 1. (a) RWI using immersion technique [9]; (b) RWI using in-motion ultrasonic testing with sensors mounted on railway tracks [10]; (c) hollowed axle testing (HAT) and a close-up view of the extendible probing shaft [11].

Figure 2. Dispersion curves (group velocity) of GWs in A606 steel: (a) plate structure; and (b) tube structure.

Figure 3. Principle of the proposed SHM technique for train bogie frames based on actively generated GWs and sensor networks.

Figure 4. Normalized RANP *vs.* point-line distance normalized by the probing wavelength, obtained from a set of parallel sensing paths on a steel plate.

Figure 5. A pure noise signal acquired by a sensor attached to the bogie frame of a running high-speed train: (a) time history; and (b) frequency domain with selected working band of 200–800 kHz circled.

Figure 6. The integrated, expandable GW-based SHM system developed for train structure monitoring: encapsulation, communication ports, and user interface.

Figure 7. Decentralized standard PZT sensing units with a close-up.

Figure 8. (a) Model CRH380CL for conformance testing. (b) Beijing–Shanghai High-Speed Railway route map.

Figure 9. Sensor networks and control: (a) the switch array controlling the sensor networks on the bogie frame; and (b) schematic diagram of the bogie frame and sensing unit distribution (unit: *mm*).

Figure 10. Sensor installation on the bogie frame: (a) each sensing unit was insulated with epoxy; and (b) industrial tapes were used to cover the sensing units, hold cables in place, and eliminate exposure to external disturbance such as wind.

Figure 11. (a) The sensor network was connected to the SHM system through shielded cables after the coach was mounted on bogies. (b) The system situated inside the coach.

Figure 12. (a) Excitation signal; and (b) a typical signal acquired via sensing path $T_3 – T_2$. The crosstalk was incurred by the electronic interference from the excitation channel, which generally has no impacts on the subsequently acquired signal.

Figure 13. Comparison of signals acquired via path $T_3 – T_2$ for a variety of train events.

Figure 14. The aluminum block was glued onto the side panel as mock-up damage, in the area enclosed by sensing units T_1, T_2, T_6, and T_7.

Figure 15. Real-time diagnostic image presenting the location and approximate size of the mock-up damage using the signal correlation algorithm (the actual position and size of the damage was shown with dashed rectangle).