

Article

Application of Vehicle Scanning Method to Jointed Shield Tunnels: Damage Identification Using an Enhanced Driving Component Extraction Strategy

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Abstract

The vehicle scanning method (VSM) enables indirect structural damage detection using onboard sensors, but its application to shield tunnels remains challenging due to the high stiffness-to-mass ratio of tunnels and the presence of segmental joints. This study investigates whether segmental joints produce false-positive damage indications and evaluates a modified signal extraction strategy. A refined vehicle–tunnel coupled finite element model incorporating shear and rotational springs at segment interfaces is established. Instead of applying Variational Mode Decomposition (VMD) before filtering, the proposed strategy applies low-pass filtering prior to VMD to extract a purer driving component (DC). The DC is quantitatively compared with the previously identified optimal component (D2) in terms of energy amplitude, background suppression, and noise robustness. Results show that (1) segmental joints produce no spurious wavelet energy peaks above the detection threshold in undamaged tunnels; (2) the DC substantially outperforms D2, achieving a signal-to-background ratio of 83.1 (vs. 18.8 for D2) and a 12% higher detection rate for 5% damage under SNR = 10 dB noise; and (3) liner and support damage produce single sharp wavelet energy peaks, while joint damage produces a broadened peak spanning two adjacent elements, suggesting a potential signature for distinguishing joint-related damage from element-related damage in the cases examined. These findings suggest that the method may be applicable to jointed shield tunnels within the range of conditions considered in this numerical study, without requiring joint-specific calibration. The modified DC extraction offers a simpler and more sensitive damage indicator for practical inspection.

Keywords: vehicle scanning method; shield tunnel; segmental joint; damage identification; wavelet energy; variational mode decomposition



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1. Introduction

Tunnel structures are vital components of urban rail transit systems, operating under complex geological conditions, high traffic densities, and long-term cyclic loading. During their service life, shield tunnels inevitably develop various defects, including liner cracking, joint loosening, support degradation, and water leakage [1–4]. If not detected in a timely manner, these defects can progressively deteriorate, compromising structural safety and operational reliability. Conventional inspection methods—such as visual inspection [5–7], the impact-echo method [8], ground-penetrating radar [9,10], and ultrasonic testing [11]—suffer from inherent limitations: low efficiency, high subjectivity, limited penetration depth,

and difficulty in detecting concealed damage [12–14]. Consequently, there is a pressing need for rapid, cost-effective, and reliable techniques for tunnel health monitoring.

The vehicle scanning method (VSM), first proposed by Yang et al. [15], offers a promising alternative to conventional inspection approaches. The core idea of VSM is to use a moving vehicle as both an exciter and a sensor carrier; by analyzing the vibration responses measured from onboard accelerometers, the dynamic characteristics and damage states of the underlying structure can be indirectly identified. This method requires no sensors installed on the structure itself, making it highly mobile, operationally efficient, and non-disruptive to traffic [16]. Over the past two decades, VSM has been extensively developed in the field of bridge engineering. Successful applications include indirect identification of structure properties [15–20], modal information [21–25], the road roughness effect [19,21,26–31] and, more recently, damage localization and quantification [32–35]. And Yang found that the acceleration of the contact point between the vehicle and the bridge is effective in terms of representing structural responses [19–21]. It is now well recognized that the signal components most sensitive to localized damage are those associated with the vehicle's driving frequency [33,36].

Despite the remarkable success of VSM in bridge applications, its direct extension to tunnel structures is non-trivial. Compared with bridges, shield tunnels are embedded in soil or rock masses and possess substantially higher overall stiffness and mass. As a result, the vibration responses induced by vehicle excitation are considerably weaker, leading to lower signal-to-noise ratios and making it more difficult to detect the damage. The use of high-order driving components for tunnel damage identification via wavelet energy was first introduced in [36]. In that work, the CPR was first decomposed by Variational Mode Decomposition (VMD), followed by low-pass filtering applied to individual Intrinsic Mode Functions (IMFs) to extract driving components of different orders. Continuous wavelet transform was then performed on these components, and the resulting wavelet energy distribution was used for damage localization. The method was validated through finite element simulations on a continuous-beam tunnel model, demonstrating excellent sensitivity to minor stiffness reductions (as low as 5%) and robust performance under measurement noise [36].

However, the continuous-beam idealization adopted in our previous study—and indeed in most existing VSM-based tunnel studies—does not fully represent the actual structural characteristics of shield tunnels [37,38]. A shield tunnel is composed of precast concrete segments connected by circumferential and longitudinal joints. The mechanical properties of these joints (both shear and bending stiffness) are typically lower than those of the segment body, introducing periodic stiffness variations along the tunnel length. Such periodic discontinuities raise a critical question: do these joints generate spurious responses in the wavelet energy spectrum that could be misinterpreted as damage? More broadly, does the presence of segmental joints alter the conclusion that “the second-order driving component is optimal” for damage identification? To date, these questions remain unanswered, as virtually all VSM-based tunnel studies have adopted continuous-beam models that neglect joint effects. Addressing this gap is essential for bridging the gap between laboratory-based method development and practical engineering applications.

The present study aims to fill this gap by systematically investigating the applicability of the previously proposed wavelet-energy-based method to shield tunnels with segmental joints. To this end, a refined vehicle–tunnel coupled finite element model is established, in which adjacent tunnel segments are connected by shear and rotational springs to realistically represent joint behavior. The damage identification procedure follows the same wavelet-energy framework as in our previous study, with one methodological refinement: instead of applying VMD first and then filtering individual IMFs, the CPR is first low-

pass-filtered and then subjected to VMD. This modified strategy, although a relatively straightforward adjustment of the processing order, yields a more compact extraction of the driving component and improves the signal quality for subsequent damage identification. The contribution of the present work relative to [38] lies not in the filtering strategy alone, but in its combination with the jointed tunnel model and the systematic evaluation of joint effects on damage identification.

Using this refined model and improved extraction strategy, three specific research questions are addressed: (1) Do segmental joints produce spurious wavelet energy peaks that could be misidentified as damage? (2) How does the DC extracted by the modified strategy compare with the D2 component (previously identified as optimal) in terms of energy amplitude, background suppression, and noise robustness? (3) Can the wavelet energy signature distinguish between liner damage (single-element stiffness reduction) and joint damage (spring stiffness reduction at the segment interface)? Through systematic numerical simulations, we demonstrate that the proposed method maintains its effectiveness in jointed tunnels, with no false positives induced by the joints themselves, and that the wavelet energy distribution provides preliminary information for distinguishing damage types.

The structure of this paper is as follows. The vehicle–tunnel interaction model, CPR reconstruction, and wavelet-energy-based identification framework are briefly revisited in Section 2, with particular focus on the modified extraction strategy for the driving component. Section 3 describes the refined finite element model incorporating segmental joints. Section 4 presents numerical results and discusses the effects of joints on damage identification performance. Section 5 provides concluding remarks.

2. Materials and Methods

2.1. VTI Model and CPR

The vehicle is represented by a two-axle half-car model (Figure 1), with the body treated as a rigid beam of mass m_v and inertia J_v , with wheelbase d . The tunnel is modeled as an Euler–Bernoulli beam on an elastic foundation. The key parameters follow the same definitions as in our previous work [36]. The governing equation of the tunnel under the moving vehicle is

$$EI \frac{\partial^4 y(x, t)}{\partial x^4} + \rho \frac{\partial^2 y(x, t)}{\partial t^2} + K_r y(x, t) = f_c(t) \quad (1)$$

where $f_c(t)$ is the contact force; under the assumption $m_v \ll \rho$, the contact force is

$$f_c(t) = \sum_{j=1,2} p_j \delta[x - v(t - t_j)] [H(t - t_j) - H(t - t_j - T)] \quad (2)$$

with δ and H denoting the Dirac delta and Heaviside functions, respectively.

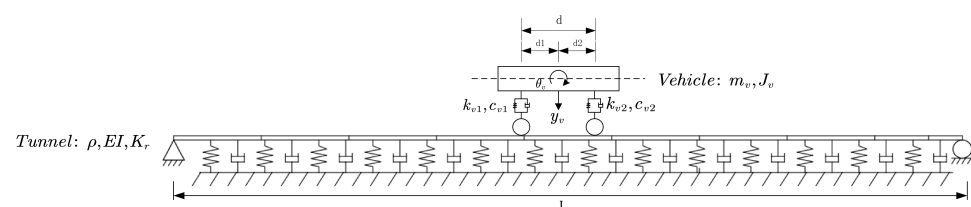


Figure 1. Vehicle–tunnel interaction model.

For the front and rear wheels, the CPR takes the following form:

$$u_{cj}(t) = \sum_{n=1}^N \sum_{i=1,2} \frac{\Delta_{stn,i}}{1-S_n^2} \left[\sin \frac{n\pi v(t-t_i)}{L} - S_n \sin \omega_{tn}(t-t_i) \right] [H(t-t_i) - H(t-t_i-T)] \sin \frac{n\pi v(t-t_i)}{L}, j=1,2. \quad (3)$$

where ω_{tn} is the n th modal frequency of the tunnel, S_n is the speed parameter, and $\Delta_{stn,i}$ is the static deflection. The detailed derivation is available in our previous work. It is worth noting that the CPR contains the tunnel's natural frequencies ω_{tn} and the driving frequencies $\frac{n\pi v}{L}$, but is free of vehicle-related frequency components—a desirable property for indirect structural identification.

The coupled system equations solved in the FE analysis are

$$\begin{bmatrix} \mathbf{M}_v & 0 \\ 0 & \mathbf{M}_t \end{bmatrix} \begin{Bmatrix} \ddot{\mathbf{q}}_v \\ \ddot{\mathbf{q}}_t \end{Bmatrix} + \begin{bmatrix} \mathbf{C}_v & 0 \\ 0 & \mathbf{C}_t \end{bmatrix} \begin{Bmatrix} \dot{\mathbf{q}}_v \\ \dot{\mathbf{q}}_t \end{Bmatrix} + \begin{bmatrix} \mathbf{K}_v & 0 \\ 0 & \mathbf{K}_t \end{bmatrix} \begin{Bmatrix} \mathbf{q}_v \\ \mathbf{q}_t \end{Bmatrix} = \begin{Bmatrix} \mathbf{F}(t)_v \\ \mathbf{F}(t)_t \end{Bmatrix} \quad (4)$$

The vehicle matrices $\mathbf{M}_v$, $\mathbf{C}_v$, and $\mathbf{K}_v$ are defined in our previous work [36] and follow the standard two-axle half-car formulation. The tunnel matrices are assembled from the segment and joint contributions described in Section 3.2. The force vectors $\mathbf{F}(t)_v$ and $\mathbf{F}(t)_t$ represent the interaction forces between vehicle and tunnel subsystems.

2.2. Back-Calculation of CPR

In field measurements, the CPR cannot be directly measured; instead, only the vehicle body accelerations at the front and rear axle positions, denoted as $\ddot{y}_{v1}$ and $\ddot{y}_{v2}$, are recorded by onboard accelerometers. The CPR can be back-calculated from these vehicle responses using the equilibrium equations of the vehicle body in vertical and rotational directions. Following the procedure established in [36], the back-calculated contact point accelerations $\ddot{u}_{c1}$ and $\ddot{u}_{c2}$ are given by

$$m_v \ddot{y}_v(t) + c_{v1} [\dot{y}_v(t) + d_1 \dot{\theta}_v(t) - \dot{u}_{c1}(t)] + c_{v2} [\dot{y}_v(t) - d_2 \dot{\theta}_v(t) - \dot{u}_{c2}(t)] + k_{v1} [y_v(t) + d_1 \theta_v(t) - u_{c1}(t)] + k_{v2} [y_v(t) - d_2 \theta_v(t) - u_{c2}(t)] = 0, \quad (5)$$

$$J_v \ddot{\theta}_v(t) + c_{v1} d_1 [\dot{y}_v(t) + d_1 \dot{\theta}_v(t) - \dot{u}_{c1}(t)] - c_{v2} d_2 [\dot{y}_v(t) - d_2 \dot{\theta}_v(t) - \dot{u}_{c2}(t)] + k_{v1} d_1 [y_v(t) + d_1 \theta_v(t) - u_{c1}(t)] - k_{v2} d_2 [y_v(t) - d_2 \theta_v(t) - u_{c2}(t)] = 0, \quad (6)$$

Here, $y_v(t)$ and $\theta_v(t)$ denote the vertical displacement and pitch rotation of the vehicle body, with dots indicating time derivatives. The accelerations at the center of mass relate to the wheel-end accelerations $\ddot{y}_{vj}$ ($j = 1, 2$) as follows:

$$\ddot{y}_v(t) = \frac{\ddot{y}_{v1}(t)d_2 + \ddot{y}_{v2}(t)d_1}{d}, \ddot{\theta}_v(t) = \frac{\ddot{y}_{v1}(t) - \ddot{y}_{v2}(t)}{d} \quad (7)$$

By solving the above system of differential equations, the CPR can be obtained as follows:

$$\ddot{u}_{cj}(t) = \frac{1}{c_{vj}} e^{\frac{-k_{vj}}{c_{vj}} t} \int_0^t G_j(\tau) e^{\frac{k_{vj}}{c_{vj}} \tau} d\tau, j=1,2. \quad (8)$$

where

$$G_1(t) = \left(\frac{d_2^2 m_v + J_v}{d^2} \right) \frac{d^2 \ddot{y}_{v1}(t)}{dt^2} + \left(\frac{d_1 d_2 m_v - J_v}{d^2} \right) \frac{d^2 \ddot{y}_{v2}(t)}{dt^2} + k_{v1} \ddot{y}_{v1}(t) + c_{v1} \frac{d \ddot{y}_{v1}(t)}{dt} \quad (9)$$

$$G_2(t) = \left(\frac{d_1 d_2 m_v - J_v}{d^2} \right) \frac{d^2 \ddot{y}_{v1}(t)}{dt^2} + \left(\frac{d_1^2 m_v + J_v}{d^2} \right) \frac{d^2 \ddot{y}_{v2}(t)}{dt^2} + k_{v2} \ddot{y}_{v2}(t) + c_{v2} \frac{d \ddot{y}_{v2}(t)}{dt} \quad (10)$$

The discrete form for the field test is

$$\ddot{u}_{cj}(t) = \frac{1}{c_{vj}} \sum_{s=0}^{t/\Delta t} \left(G_{j|s} \right) e^{\frac{k_{vj}}{c_{vj}}(s\Delta t - t)} \Delta t, j = 1, 2, \quad (11)$$

where $G_{j|s}$ are functions of the measured vehicle accelerations and their derivatives, and Δt is the sampling interval. The detailed expressions of $G_1(t)$ and $G_2(t)$ are omitted here for brevity and can be found in our previous work. This back-calculation strategy has been validated through both theoretical derivation and numerical simulation [20,21,36].

2.3. Damage Identification Framework

The damage identification framework consists of three stages: (1) extraction of driving components from the back-calculated CPR, (2) continuous wavelet transform to generate the wavelet energy spectrum, and (3) damage localization using a statistically derived detection threshold. The key methodological refinement introduced in this study lies in the first stage, where the order of VMD and filtering operations is rearranged to achieve cleaner extraction of driving components. This modification is detailed in the following subsection.

2.3.1. Extraction of Driving Components

In our previous study, the driving components were extracted through a “VMD-before-filtering” strategy; Variational Mode Decomposition (VMD) [39,40] was then applied to the reconstructed CPR, which was accordingly decomposed into a series of Intrinsic Mode Functions (IMFs) characterized by distinct frequency bands. In tunnel structures, the high stiffness-to-mass ratio substantially weakens the driving frequency components, causing them to be distributed across multiple IMFs instead of appearing as a single isolated IMF. Consequently, a low-pass Butterworth filter (cutoff frequency 10 Hz) was applied to each IMF individually to extract the embedded driving components. Specifically, the first-order driving component was obtained from IMF1, the second-order from IMF2, and so forth. While this strategy was theoretically sound and proved effective in continuous-beam tunnel models, it is operationally indirect and requires post-processing of multiple IMFs.

VMD was applied with the following settings: number of modes $K = 4$, penalty parameter $\alpha = 2000$, tolerance $\varepsilon = 1 \times 10^{-6}$, and uniform initialization of center frequencies. These values were selected following the recommendations in [41] and were kept constant throughout all analyses. For the low-pass filter, the 10 Hz cutoff was selected because (i) the vehicle driving frequency is approximately 2.25 Hz, (ii) the first tunnel natural frequency is approximately 9.1 Hz, and (iii) 10 Hz lies in the spectral valley between the driving harmonics and the first tunnel mode.

In this study, we adopt a modified “filtering-before-VMD” strategy, as illustrated in Figure 2. The key difference is that the low-pass filter is applied before VMD rather than after. The procedure is as follows:

1. The filtered signal is generated by applying a fifth-order low-pass Butterworth filter (cutoff: 10 Hz, same as [36]) to the back-calculated CPR.
2. The filtered signal, in which the driving frequency components now dominate, is then subjected to VMD.
3. Because the driving frequency has become the dominant content in the filtered signal, VMD automatically separates it as the first IMF (IMF1), which directly serves as the driving component (DC) used in this study.
4. If higher-order driving components are of interest, they can be obtained by applying VMD to the residual signal after removing IMF1.

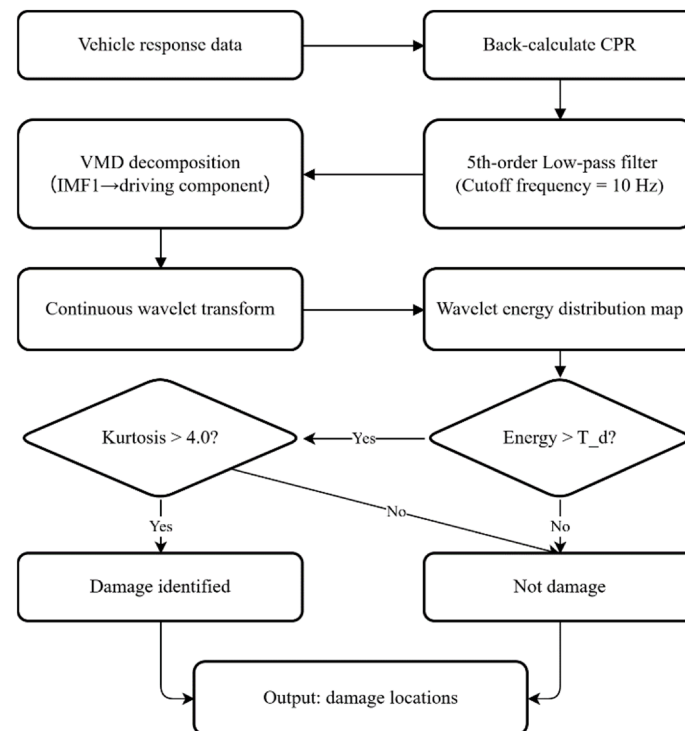


Figure 2. Damage identification procedure.

The advantages of the modified strategy are twofold. First, the extraction process is more compact: rather than filtering each IMF individually, a single filtering operation followed by VMD yields a directly usable driving component. Second, the physical interpretation is clearer: the filtering step intentionally isolates the frequency band of interest, and VMD subsequently separates the dominant component within that band as IMF1. Quantitative comparison shows that the DC achieves higher energy concentration at the driving frequency than the D2 component extracted by the previous approach (see Section 4.3). This improvement in signal purity benefits the subsequent wavelet-based damage identification, particularly in low signal-to-noise-ratio tunnel environments. It should be noted, however, that the modification itself is a relatively straightforward adjustment of the processing order; its value lies primarily in the improved performance demonstrated through the numerical studies rather than in conceptual novelty.

2.3.2. Continuous Wavelet Transform and Wavelet Energy

For time-frequency analysis of the extracted DC, the continuous wavelet transform (CWT) is employed. The mother wavelet selected is the Mexican Hat (mexh), which offers a balanced resolution between time and frequency domains—a desirable property for detecting localized transients. For any signal $f(t) \in L^2(\mathbb{R})$, its CWT is defined as

$$W_x(a, b) = \langle f(t), \psi_{a,b}(t) \rangle = \int_{-\infty}^{\infty} f(t) \psi_{a,b}^*(t) dt = \int_{-\infty}^{\infty} f(t) \frac{1}{\sqrt{a}} \psi^*\left(\frac{t-b}{a}\right) dt \quad (12)$$

where a and b are the scale and translation parameters, respectively, and $\psi^*(t)$ denotes the complex conjugate of the mother wavelet $\psi(t)$. The coefficient $W_x(a, b)$ quantifies the signal's energy content at scale a and time b .

An important property of the wavelet transform is its energy-preserving nature:

$$\int_{-\infty}^{+\infty} |x(t)|^2 dt = \frac{1}{C_\psi} \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} |W_x(a, b)|^2 \frac{da db}{a^2} \quad (13)$$

This allows for the definition of a time-dependent energy function:

$$E(b) = \int_{-\infty}^{+\infty} \frac{|W_x(a, b)|^2}{a^2} da \quad (14)$$

Physically, $E(b)$ reflects how the signal's energy varies over time. A localized stiffness reduction—caused by liner cracking, support degradation, or joint loosening—produces a sudden change in the dynamic response, which manifests as a sharp energy concentration in $E(b)$. Thus, the appearance of a distinct peak in $E(b)$ indicates the presence of damage. Moreover, summing the wavelet energy across multiple scales enhances the detectability of such peaks, as suggested by Hester and González [35]. The CWT was implemented with the same parameters as [36]: a scale range from 1 to 100, with a linear scale resolution of 100 scales. The wavelet energy values $E(b)$ were computed by numerical integration over the scale domain using the trapezoidal rule. All cases used identical scale settings to ensure comparability. The wavelet energy values computed from the above formulation are dimensionless and are used for relative comparison among different elements and cases.

2.3.3. Damage Detection Threshold

A statistical criterion is employed to distinguish actual damage peaks from background fluctuations. Let $\tilde{E}$ represent the vector of wavelet energies computed for all elements along the tunnel. A robust threshold is constructed as

$$T_d = \text{median}(\tilde{E}) + 5 \cdot \text{MAD}(\tilde{E}) \quad (15)$$

where MAD denotes the median absolute deviation:

$$\text{MAD}(\tilde{E}) = \text{median}(|\tilde{E} - \text{median}(\tilde{E})|) \quad (16)$$

A coefficient of 5 is selected to provide a conservative detection boundary, minimizing false positives under the assumption of Gaussian-distributed background noise.

However, due to the inherent energy spread of the wavelet transform, multiple consecutive elements may exceed T_d even when only a single damaged element exists. To pinpoint the exact damaged element, an additional sharpness filter based on kurtosis is applied:

$$K_i = \frac{\mu_4}{\sigma^4} \quad (17)$$

where μ_4 and σ^4 are the fourth central moment and standard deviation of the local energy distribution, respectively. An element i is flagged as damaged if and only if: (1) $E_i > T_d$, and (2) $K_i > 4$.

In subsequent figures, T_d is shown as a horizontal dashed line, and elements satisfying both criteria are highlighted with red dots. This two-stage strategy—thresholding followed by kurtosis screening—was validated in our previous work across various noise and roughness scenarios, and has proven effective without requiring a priori knowledge of damage locations or severity.

2.3.4. Research Questions Revisited

With the theoretical background and methodological framework established, we now recapitulate the specific research questions addressed in this study. These questions arise from the gap identified in the Introduction: the absence of systematic evaluation of joint effects on VSM-based tunnel damage identification. The following three questions guide the numerical investigation presented in Sections 3 and 4:

Q1—False-positive risk: Do segmental joints produce spurious wavelet energy peaks that could be misinterpreted as structural damage?

Q2—DC vs. D2: How does the DC extracted by the modified strategy compare with D2 (previously identified as optimal) in terms of energy amplitude, background suppression, and noise robustness in jointed tunnels?

Q3—Damage type discrimination: Can the wavelet energy signature distinguish between liner damage (single-element stiffness reduction) and joint damage (spring stiffness reduction at the segment interface)? Specifically, does liner damage produce a single sharp peak, while joint damage produces a broadened peak spanning two adjacent elements with comparable energy levels?

Each question is addressed through specifically designed finite element simulation cases in Section 4. Before presenting these results, the next section describes the refined finite element model incorporating segmental joints.

3. Refined Vehicle–Tunnel FE Model with Segmental Joints

3.1. Vehicle Model

A two-axle half-car representation is used for the test vehicle. Its two degrees of freedom are the vertical displacement y_v and the pitch rotation θ_v of the body. The vehicle parameters, summarized in Table 1, are kept consistent with our previous study to ensure comparability of results. The vehicle body has a mass $m_v = 4000$ kg and a moment of inertia $J_v = 3000$ kg·m². The front and rear suspension stiffnesses are $k_{v1} = k_{v2} = 300$ kN/m, with damping coefficients $c_{v1} = c_{v2} = 1.04 \times 10^4$ N·s/m (corresponding to a damping ratio of approximately 0.15). The wheelbase is $d = 2$ m, with $d_1 = d_2 = 1$ m. The vehicle travels at a constant speed $v = 10$ m/s throughout the simulation, unless otherwise specified. These parameters are representative of a typical medium-sized inspection vehicle. The vehicle matrices are:

$$\mathbf{M}_v = \begin{bmatrix} m_v d_2/d & m_v d_1/d \\ J_v/d & -J_v/d \end{bmatrix}, \mathbf{C}_v = \begin{bmatrix} c_{v1} & c_{v2} \\ c_{v1}d_1 & -c_{v2}d_2 \end{bmatrix}, \mathbf{K}_v = \begin{bmatrix} k_{v1} & k_{v2} \\ k_{v1}d_1 & -k_{v2}d_2 \end{bmatrix} \quad (18)$$

The choice of 4000 kg vehicle mass and 10 m/s speed reflects a balance between two practical considerations. On the one hand, larger mass and higher speed enhance vehicle–tunnel coupling excitation, improving the SNR of damage-induced responses. On the other hand, operational constraints in actual subway tunnels impose upper bounds on these parameters. The selected values fall within the typical range of light-duty inspection vehicles used in tunnel monitoring practice.

Table 1. Parameters for vehicle and tunnel.

Category	Parameter	Symbol	Unit	Value
Vehicle	Lumped mass	m_v	kg	4000
	Inertia	J_v	kg·m ²	3000
	Stiffness for suspension	k_{v1}, k_{v2}	kN/m	300
	Damping for suspension	c_{v1}, c_{v2}	N·s/m	1.04×10^4
	Axle distance	d_1, d_2	m	1
	Running speed	v	m/s	10
Shield Tunnel	Elastic modulus	E	MPa	2.75×10^4
	Moment of inertia	I	m ⁴	27.5
	Foundation stiffness	k_r	kN/m ³	4.4×10^4
	Per-unit-length mass of beam	ρ	kg/m	13,430
	Length	L	m	400
Segment Joints	Shear stiffness	k_s	N/m	7×10^{10}
	Rotation stiffness	k_θ	N·m/rad	4×10^{10}

3.2. Tunnel Model with Segmental Joints

In our previous study, the tunnel was idealized as a continuous Euler–Bernoulli beam on an elastic foundation—a simplification commonly adopted in VSM-based tunnel studies. While this idealization facilitates theoretical derivation and reveals the fundamental mechanism of the proposed method, it does not capture the inherent discontinuities of actual shield tunnels, which are composed of precast concrete segments connected by circumferential and longitudinal joints. To represent this structural characteristic, a series of Euler–Bernoulli beam segments interconnected by shear and rotational springs are employed (Figure 3). Each beam segment represents one tunnel ring of length $l_e = 1.0$ m, and the total tunnel length $L = 400$ m is discretized into 400 identical beam elements. The adjacent segments are connected through a shear spring with stiffness k_s and a rotational spring with stiffness k_θ .

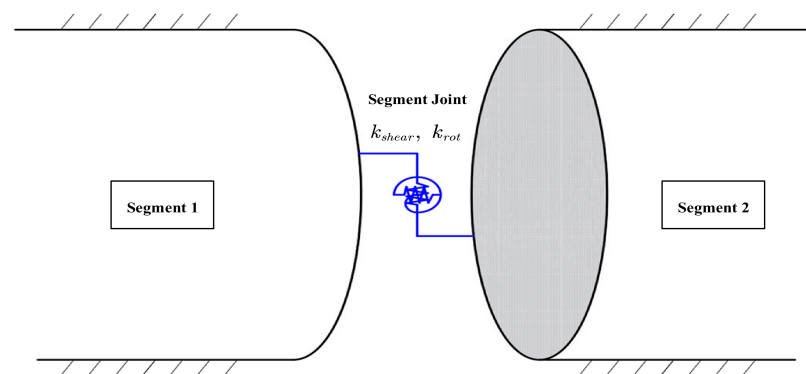


Figure 3. Tunnel segment joints.

The rotational stiffness is taken as $k_\theta = 4 \times 10^{10}$ N·m/rad. The stiffness of segmental joints is a complex nonlinear problem involving joint type, bolt preload, axial force level, and loading direction [41,42]. Experimental studies have proposed nonlinear moment–rotation models based on full-scale tests [42], but no standardized guideline exists for selecting simplified stiffness values in beam–spring models. In practice, the equivalent stiffness method is commonly adopted, where the joint stiffness is treated as an equivalent parameter calibrated to represent the overall lining behavior. Wang et al. reported that the ratio $k_\theta / (EI \cdot l)$ typically falls in the range of 0.04 to 0.08 for equivalent models without axial force. The adopted value yields a ratio of approximately 5.3% (0.053), which falls within this range and is representative of a tunnel in normal service conditions. For the shear stiffness, fewer experimental studies are available; it is taken as $k_s = 7 \times 10^{10}$ N/m, consistent with the stiffness level used in previous numerical studies on segmental tunnel joints.

Two sets of joint stiffness values are used for different purposes. For model validation against the analytical continuous-beam solution (Section 4.1), both stiffnesses are increased by a factor of 10 to $k_s = 7 \times 10^{11}$ N/m and $k_\theta = 4 \times 10^{11}$ N·m/rad, ensuring that the joints behave nearly as rigid connections so that the jointed model degenerates to the continuous-beam limit. This verifies the correctness of the numerical implementation rather than claiming physical realism for the high-stiffness joint. For damage identification studies (Sections 4.2–4.5), the nominal values of $k_s = 7 \times 10^{10}$ N/m and $k_\theta = 4 \times 10^{10}$ N·m/rad are used to investigate joint effects under service-level parameters.

The spring connection matrix $\mathbf{k}_j$ for a joint connecting two adjacent beam elements is expressed as

$$\mathbf{k}_j = \begin{bmatrix} k_s & 0 & -k_s & 0 \\ 0 & k_\theta & 0 & -k_\theta \\ -k_s & 0 & k_s & 0 \\ 0 & -k_\theta & 0 & k_\theta \end{bmatrix} \quad (19)$$

where the degrees of freedom at each node correspond to vertical displacement and rotation. This matrix is assembled into the global stiffness matrix at the corresponding interface nodes.

Assembly of joint contributions. In the global stiffness matrix $\mathbf{K}_t$, each joint contribution $\mathbf{K}_j$ is assembled at the degrees of freedom corresponding to the two adjacent nodes. Specifically, consider a joint connecting the i -th and $(i + 1)$ -th beam elements, with nodes I and $i + 1$ sharing the interface. The degrees of freedom at these nodes are $[u_i, \theta_i, u_{i+1}, \theta_{i+1}]$, where u denotes vertical displacement and θ denotes rotation. The joint stiffness matrix $\mathbf{K}_j$ is added to the corresponding 4×4 block of the global stiffness matrix at these DOFs. This assembly procedure is equivalent to connecting the two Euler–Bernoulli beam elements with a zero-length spring element at the shared interface. The same assembly rule applies to all 399 joints along the 400-element tunnel discretization.

For each individual beam segment, the mass matrix $\mathbf{m}_i^e$ and stiffness matrix $\mathbf{k}_i^e$ follow the standard Euler–Bernoulli beam formulation with elastic foundation. The mass matrix is

$$\mathbf{m}_i^e = \frac{\rho l}{420} \begin{bmatrix} 156 & -22l & 54 & 13l \\ -22l & 4l^2 & -13l & -3l^2 \\ 54 & -13l & 156 & 22l \\ 13l & -3l^2 & 22l & 4l^2 \end{bmatrix}, \quad (20)$$

The element stiffness matrix $\mathbf{k}_i^e = \mathbf{k}_b^e + \mathbf{k}_r^e$ consists of two parts: the beam bending stiffness $\mathbf{k}_b^e$ and the foundation support stiffness $\mathbf{k}_r^e$.

$$\mathbf{k}_b^e = \frac{EI}{l^3} \begin{bmatrix} 12 & -6l & -12 & -6l \\ -6l & 4l^2 & 6l & 2l^2 \\ -12 & 6l & 12 & 6l \\ -6l & 2l^2 & 6l & 4l^2 \end{bmatrix}, \quad \mathbf{k}_r^e = \frac{k_r l}{420} \begin{bmatrix} 156 & -22l & 54 & 13l \\ -22l & 4l^2 & -13l & -3l^2 \\ 54 & -13l & 156 & 22l \\ 13l & -3l^2 & 22l & 4l^2 \end{bmatrix}, \quad (21)$$

The tunnel bending stiffness is $EI = 2.75 \times 10^4 \text{ MPa} \times 27.5 \text{ m}^4 = 7.5625 \times 10^{11} \text{ N} \cdot \text{m}^2$, and the foundation stiffness is $k_r = 4.4 \times 10^4 \text{ kN/m}^3$. The mass per unit length is $\rho = 13,430 \text{ kg/m}$. Rayleigh damping with a damping ratio of 0.05 was assigned.

3.3. Damage Simulation

Damage is simulated as a localized reduction in tunnel properties, including bending stiffness EI , foundation stiffness k_r , joint shear stiffness k_s and rotation stiffness k_θ at selected element(s), following the same approach as in our previous study. The damage severity is quantified by a parameter α ($0 < \alpha \leq 1$), representing the fractional reduction in stiffness:

$$EI_{\text{damaged}} = (1 - \alpha)EI_{\text{intact}}, \quad k_{r,\text{damaged}} = (1 - \alpha)k_{r,\text{intact}}, \quad (22)$$

A severity of $\alpha = 0.1$ (10% reduction) is used as the default damage level unless otherwise specified. This level is representative of incipient damage that is difficult to detect by conventional visual inspection but has already caused measurable changes in structural dynamic response.

3.4. Solution Procedure and Analysis Settings

Solution of the coupled vehicle–tunnel system equations is obtained through the Newmark- β method, adopting $\beta = 0.25$ and $\gamma = 0.5$ (the average acceleration scheme), which is unconditionally stable for linear structural dynamics problems. A time step of $\Delta t = 0.001$ s (sampling frequency 1000 Hz) is adopted throughout all simulations. The vehicle is assumed to enter the tunnel at $t = 0$ with a constant speed and exits after $T = (L - d)/v = 39.8$ s. All numerical simulations and signal processing procedures were implemented in MATLAB R2023a (The MathWorks, Inc., Natick, MA, USA).

A preliminary convergence study was conducted using element lengths of 2.0 m, 1.0 m, and 0.5 m. The results obtained with 1.0 m and 0.5 m elements were nearly identical (frequency deviation $< 1\%$), so the 1.0 m mesh was adopted for all simulations. The time step of 0.001 s was chosen to ensure at least 10 samples per period of the highest tunnel frequency of interest.

To avoid the boundary effects inherent in wavelet transform analysis, the first and last 100 m of the tunnel (corresponding to 100 elements each) are excluded from the damage identification results, consistent with the treatment in our previous study. Only the middle 200 m segment (elements 101 to 300) is analyzed for damage identification. This region is sufficiently far from the tunnel ends to ensure that wave reflections do not contaminate the wavelet energy spectrum, and it excludes the vehicle acceleration and deceleration zones (if any). All reported damage localization results are based on this central analysis window.

All vehicle and tunnel parameters are summarized in Table 1 for quick reference. The joint parameters are listed separately in the same table to distinguish them from the continuous-beam parameters used in the previous study.

4. Numerical Results and Discussion

4.1. Model Validation

Before investigating the influence of segmental joints on damage identification, it is essential to validate the baseline behavior of the refined finite element model. For this validation, the joint stiffnesses are set to high values ($k_s = 7 \times 10^{11}$ N/m, $k_\theta = 4 \times 10^{11}$ N·m/rad) so that the jointed model degenerates to the continuous-beam limit.

Figure 4 compares the frequency spectra of the vehicle acceleration response and the CPR obtained from the analytical solution and the jointed FE model. The corresponding time-domain responses are shown in Figure 5, which also demonstrates close agreement between the theoretical and FE models. The first four tunnel frequencies identified from both models are summarized in Table 2. This confirms that the numerical implementation of the jointed FE model is correct: the spring connection matrices are properly assembled, and the Newmark- β solver produces dynamically consistent responses. The time-domain CPR waveforms also exhibit close correspondence. With the numerical model validated, the joint stiffnesses are reduced to realistic levels ($k_s = 7 \times 10^{10}$ N/m, $k_\theta = 4 \times 10^{10}$ N·m/rad) for all subsequent damage identification studies.

The time-domain CPR waveforms also exhibit close correspondence, with the jointed model showing negligible additional oscillations at the segment interfaces. The validated baseline confirms that the refined FE model is suitable for the subsequent damage identification studies.

Strictly speaking, this validation confirms the correctness of the numerical implementation. The jointed model under representative nominal stiffnesses—which incorporates physical assumptions about joint behavior—is validated indirectly through the sensitivity study described below and through the consistency of its dynamic response with expected behavior of segmented tunnels. Full experimental validation is left for future work.

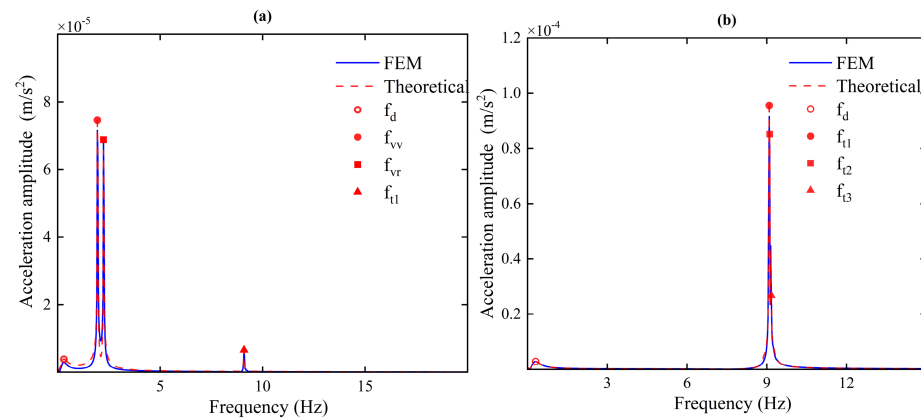


Figure 4. Frequency spectra comparison between theoretical and FE models: (a) vehicle acceleration; (b) CPR at the vehicle–tunnel contact point.

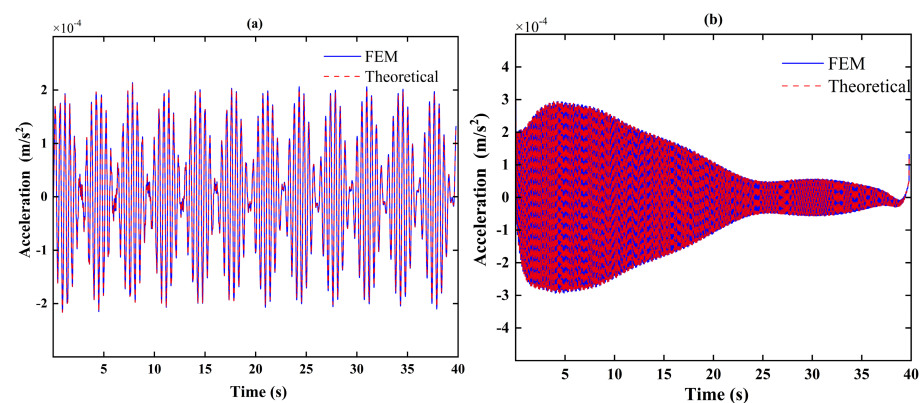


Figure 5. Time-domain response comparison between theoretical and FE models: (a) vehicle acceleration; (b) CPR at the vehicle–tunnel contact point.

Table 2. Natural frequencies identified from theoretical and FE models.

	f_{vv}	f_{vr}	f_{t1}	f_{t2}	f_{t3}	f_{t4}
Theoretical	1.95	2.25	9.110	9.115	9.134	9.186
FEM	1.95	2.26	9.095	9.112	9.136	9.184

4.2. Q1—Do Segmental Joints Produce Spurious Damage Indications?

To answer Q1 (whether segmental joints generate false-positive indications)—The undamaged jointed tunnel is first analyzed using the representative nominal values ($k_s = 7 \times 10^{10}$ N/m, $k_\theta = 4 \times 10^{10}$ N·m/rad). A single liner damage case ($\alpha = 0.1$ at element 200) is then introduced to establish the baseline damage signature. Three signal types are compared: (a) the raw CPR, (b) the D2 component extracted via the previous VMD-before-filtering strategy, and (c) the DC extracted via the modified filtering-before-VMD strategy. The detection threshold $T_d = \text{median}(E) + 5 \times \text{MAD}(E)$ is applied to each signal type, with the kurtosis criterion ($K_i > 4$) used to pinpoint damage elements.

Figure 6 presents the wavelet energy distributions for the three signal types. The raw CPR (Figure 6a) performs poorly: no distinct peak is observed at the damage location, and the threshold is elevated due to strong background fluctuations. This confirms that the raw CPR, while effective for bridge applications, is inadequate for tunnel structures with much higher stiffness-to-mass ratios. In contrast, both processed signals—D2 and DC—yield clear detection. The background energy is substantially reduced, with thresholds on the order of 10^{-14} , and the kurtosis criterion successfully identifies the damaged element (marked as a red dot in the figure).

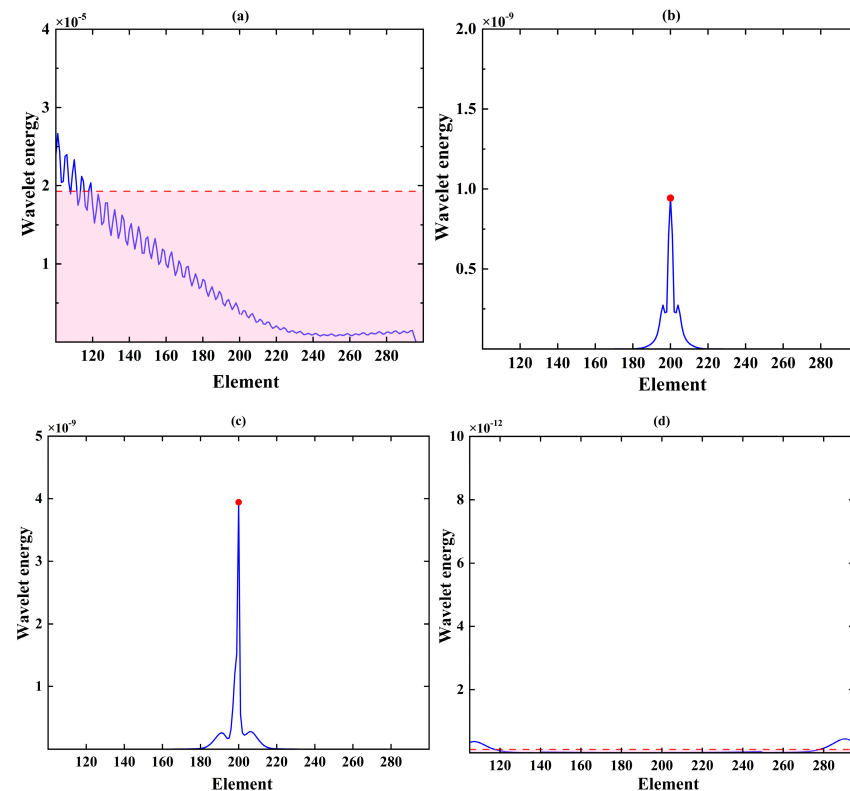


Figure 6. Wavelet energy distributions: (a) CPR with damage, (b) D2 with damage, (c) DC with damage, (d) DC in undamaged tunnel. The red dot indicates the element identified as damaged by the kurtosis criterion. The horizontal dashed line indicates the detection threshold T_d . The red dot marks the element identified as damaged (satisfying both $E_i > T_d$ and $K_i > 4$).

To directly examine whether normal segmental joints themselves generate false-positive indications in the absence of any damage, the undamaged jointed tunnel was analyzed using the DC under the same processing procedure. The result is shown in Figure 6d. The wavelet energy remains consistently low throughout the tunnel, with the energy at any joint position well below the detection threshold $T_d = 1.06 \times 10^{-13}$. No elements satisfy both the threshold and kurtosis criteria, confirming that no spurious damage is identified in the undamaged tunnel.

The key difference between D2 and DC lies in the peak energy: DC achieves approximately 2–3 times higher peak energy than D2 at the damage location, while the energy spread to adjacent elements is comparable between the two. This difference is physically reasonable: D2 is extracted from the driving component coupled with the second tunnel mode after VMD, representing only a portion of the driving-related energy; DC, obtained by filtering before VMD, concentrates the full driving-frequency energy within the passband into a single IMF. The higher peak energy of DC is advantageous for damage extraction under environmental interference, as will be further quantified in Section 4.3.

Importantly, under the joint stiffnesses used in this study, no spurious wavelet energy peaks are observed at any joint location in either D2 or DC—including in the undamaged case shown in Figure 6d. Although the jointed model is slightly more flexible than the continuous-beam idealization, the joints represent periodic, global stiffness variations rather than localized anomalies. Their wavelet energy distributes broadly across the time-scale plane rather than concentrating at individual positions. This inherent distinction ensures that joints do not produce false positives. Q1 answer: No false positives. Both D2 and DC correctly identify the damage without spurious indications at joints, and the DC also produces no false indications in the completely undamaged tunnel.

4.3. Q2—DC vs. D2: Quantitative Comparison

As shown in the previous section, both D2 and DC achieve effective damage identification, but they differ in peak energy. To quantitatively investigate this difference, a single damage case ($\alpha = 0.1$ at element 200) is analyzed under 15 dB noise. Gaussian white noise was generated using the `randn` function in MATLAB and added to the vehicle acceleration time histories before CPR back-calculation. The SNR was defined as $\text{SNR} = 10 \log_{10} (P_{\text{signal}} / P_{\text{noise}})$, where P_{signal} and P_{noise} are the mean powers of the clean signal and the noise, respectively.

Three metrics are used: peak energy E_{peak} , mean background $E_{\text{bg,mean}}$ (elements 101–300 excluding damage and neighbors), and signal-to-background ratio $\text{SBR} = E_{\text{peak}} / E_{\text{bg,mean}}$.

Figure 7 shows the results. Both signals successfully identify the damage peak, and despite some background fluctuations induced by noise, the threshold and kurtosis criteria effectively screen out false detections. D2 (Figure 7a) yields a clear peak at element 200 with $E_{\text{peak}} = 9.49 \times 10^{-10}$, $E_{\text{bg,mean}} = 5.06 \times 10^{-11}$, and $\text{SBR} \approx 18.8$. The DC (Figure 7b) yields a significantly sharper peak with $E_{\text{peak}} = 5.47 \times 10^{-9}$, $E_{\text{bg,mean}} = 6.58 \times 10^{-11}$, $\text{SBR} \approx 83.1$ —approximately 4.4 times higher than D2.

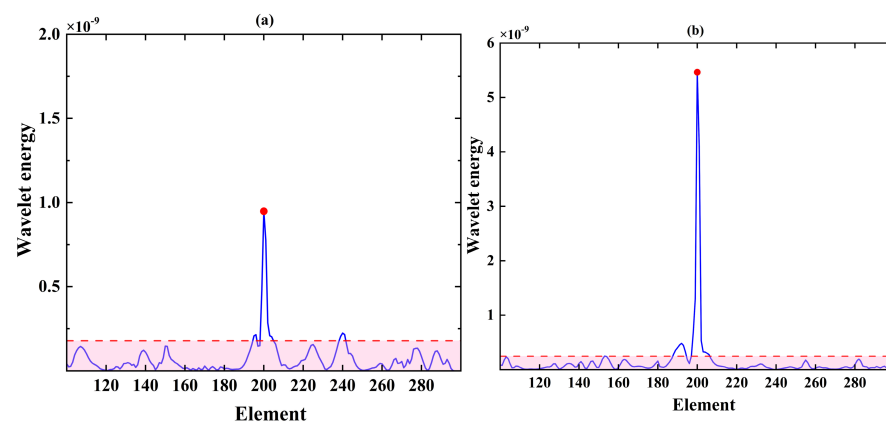


Figure 7. Damage identification results under 15 dB noise using (a) D2 and (b) DC. The horizontal dashed line represents the detection threshold T_d . The red dot marks the identified damaged element.

Interpretation. The improvement is attributable to the modified extraction order. In the previous VMD-before-filtering strategy, driving energy was distributed across multiple IMFs; D2 captured only the portion coupled with the second tunnel mode. In the modified strategy, filtering before VMD isolates the driving frequency band, enabling VMD to concentrate all driving-related energy into a single IMF (the DC). This explains the higher peak energy.

Both D2 and DC serve as effective signal sources for damage identification in this example. The background energy levels are comparable between the two, but DC exhibits higher peak energy due to its concentrated energy distribution, resulting in a superior SBR. This advantage is beneficial for damage identification under noisy conditions. However, it is also noted that some noise-induced fluctuations exceed the threshold in both cases, though the kurtosis criterion successfully screens them out in this example. Under higher noise levels, more severe fluctuations may still be misidentified as peaks—a limitation that will be examined in the Monte Carlo study below.

Noise robustness. Monte Carlo simulations (100 runs) at SNR = 15 dB and 10 dB were performed for both D2 and DC, with three damages of varying severity (5% at element 150, 10% at element 200, 30% at element 250). Figure 8 presents the Monte Carlo results in terms of three metrics: (a) detection rate (DR)—the percentage of runs in which the damage was correctly identified at the true location; (b) missed detection rate (MDR)—

the percentage of runs in which the damage was not detected; and (c) false-positive rate (FPR)—the percentage of runs in which at least one spurious peak was identified in an undamaged region. The detection criterion for each run follows the threshold and kurtosis procedure described in Section 2.3.3. Figure 8a shows the detection rates for the three damage locations. Higher noise levels (lower SNR) reduce detection performance. For the 10% and 30% damages, both methods maintain high detection rates across both noise levels. For the 5% minor damage, DC consistently outperforms D2 due to its higher energy concentration: at SNR = 10 dB, DC achieves 87% detection while D2 achieves 75%. Figure 8b,c show the missed detection rates and false-positive rates, respectively. The results show that DC produces fewer missed detections and fewer false positives than D2, particularly for minor damage under high noise, because its higher intrinsic energy makes the damage-induced peak less susceptible to noise-induced fluctuations.

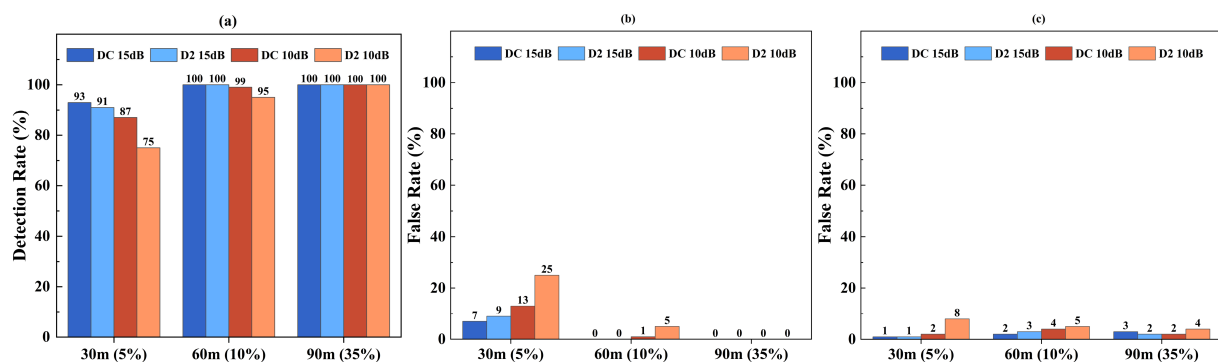


Figure 8. Monte Carlo simulation results: (a) detection rates, (b) missed detection rates, and (c) false-positive rates.

Q2 answer: DC substantially outperforms D2 in terms of peak energy ($4.4\times$ higher SBR) and noise robustness (12% higher detection for 5% damage at SNR = 10 dB).

4.4. Q3—Preliminary Observation on Damage Type Signatures

It should be emphasized that the following analysis is based on a limited set of simulation cases (a single damage severity $\alpha = 0.1$ at specific locations). The purpose of this section is to explore whether different damage types exhibit distinguishable wavelet energy signatures, rather than to establish a general classification criterion. The observations reported here are therefore preliminary and should be verified with additional cases in future work.

Three damage scenarios are designed with identical severities ($\alpha = 0.1$):

Liner damage: Single-element stiffness reduction in EI at element 200 (mid-segment). The result is shown in Figure 6c and is not repeated here.

Support damage: Single-element support stiffness k_r reduction at element 200 (mid-segment).

Joint damage: Reduction in the spring stiffness k_s and k_θ at the interface between elements 199 and 200, simulating joint loosening.

All three scenarios use the DC and identical wavelet parameters.

Figure 9 presents the wavelet energy distributions for support damage (Figure 9a) and joint damage (Figure 9b). Support damage produces a single sharp peak at element 200, with rapid energy decay to adjacent elements (Figure 9a). Joint damage produces a broadened peak covering both elements 199 and 200, with comparable energy levels at the two adjacent positions. In Figure 9b, the red dot marks the highest peak identified by the detection criterion at element 199, while the hollow circle marks the energy at element

200. The two are in close proximity, forming a plateau-like distribution that is distinctly different from the single-peak pattern of liner and support damage.

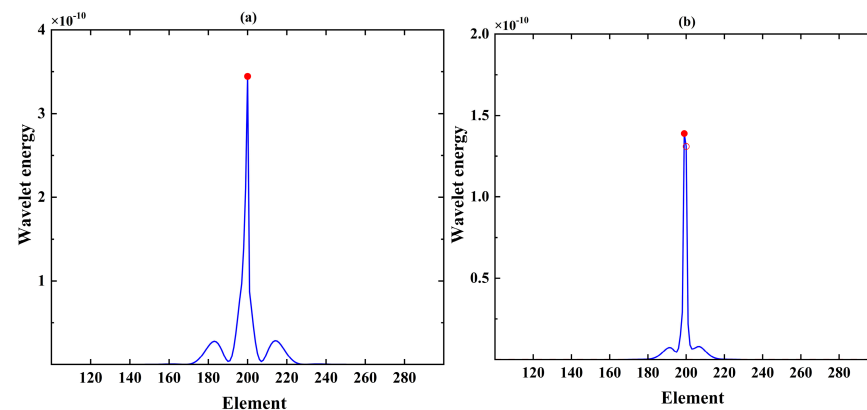


Figure 9. Wavelet energy distributions for different damage types: (a) support damage; (b) joint damage. The horizontal dashed line indicates the detection threshold T_d . The red dot marks the highest peak identified by the detection criterion. The hollow circle marks the energy level at the adjacent element, showing the plateau-like distribution for the joint damage case.

This two-element broad peak is physically interpretable: the weakened spring connects two independent beam elements, and its stiffness reduction affects the dynamic response of both elements simultaneously. The wavelet transform captures this bilateral effect as a contiguous energy concentration spanning the two-element region, rather than as two separate peaks. Importantly, this broadened pattern is distinct from the wavelet energy spread observed in single-element damage (liner or support), where adjacent elements show only residual energy. In joint damage, both adjacent elements exhibit comparable energy levels, forming a plateau-like distribution in the cases examined.

Q3 answer: In the cases examined, liner and support damage both produce single sharp peaks and are not distinguished from each other. Joint damage, however, exhibits a broadened two-element peak pattern, suggesting potential discrimination between joint-related and element-related damage. This observation is limited to the current discretization (1.0 m elements) and requires further verification with mesh refinement studies; complete classification among the three damage types is not achieved by the current method.

4.5. Sensitivity to Joint Stiffness

To assess the robustness of the proposed method to variations in joint stiffness, the nominal joint stiffness values ($k_s = 7 \times 10^{10}$ N/m, $k_\theta = 4 \times 10^{10}$ N·m/rad) were varied by $\pm 50\%$. A single joint damage case ($\alpha = 0.1$ at the interface between elements 199 and 200) was analyzed using the DC under each stiffness level. A single joint damage case was chosen for this sensitivity study because it represents the most direct test of whether the method can reliably detect damage at joints under varying baseline joint stiffness conditions—the very scenario that the proposed method is designed to address. The sensitivity of liner damage detection to joint stiffness variations was verified to be even less critical, as liner damage occurs away from the joints and is therefore less affected by joint stiffness changes.

Table 3 summarizes the results. Several observations can be made from the sensitivity analysis. First, at all three stiffness levels, the joint damage was correctly identified at the interface between elements 199 and 200, with the characteristic broadened two-element peak pattern. This indicates that the detection of joint damage is not contingent on the exact joint stiffness values chosen.

Table 3. Sensitivity of damage identification results to joint stiffness variation.

Joint Stiffness Level	E_{peak}	$E_{bg,mean}$	SBR	Localization Error
Low (0.5×)	1.66×10^{-10}	2.32×10^{-12}	71.6	0
Nominal (1.0×)	1.39×10^{-10}	1.77×10^{-12}	78.5	0
High (1.5×)	1.21×10^{-10}	1.50×10^{-12}	80.7	0

Second, the peak energy at the damage location (E_{peak}) varied with joint stiffness. A lower overall joint stiffness led to slightly higher E_{peak} , while a higher stiffness reduced it. This trend is physically reasonable: when the entire tunnel becomes stiffer, the relative perturbation caused by a local stiffness reduction becomes less prominent. Importantly, the SBR of the two adjacent elements remained comparable (within 13%) across all cases.

Third, and most critically, even when the overall joint stiffness was varied by $\pm 50\%$, no false-positive peaks were observed at any healthy joint location across the entire stiffness range. This confirms that the conclusion that “segmental joints do not produce false-positive damage indications” (Q1) is robust to reasonable variations in joint stiffness.

These results demonstrate that the main conclusions of this study are stable under reasonable variations in joint stiffness ($\pm 50\%$). The detection and localization of joint damage remain accurate, the characteristic broadened two-element peak pattern is preserved, and no false positives are generated at healthy joints. This indirectly supports the selection of joint stiffness values: although the nominal values are representative estimates rather than experimentally calibrated values, the conclusions do not critically depend on their exact magnitudes.

5. Discussion

The numerical results presented in Sections 4.1–4.5 provide consistent answers to the three research questions, summarized in Table 4.

Table 4. Research questions and answers.

Research Question	Answer
Q1: Do segmental joints produce false-positive indications in the wavelet energy spectrum?	No false positives. Both D2 and DC correctly identify the damage without spurious indications at joints, and the DC also produces no false indications in the completely undamaged tunnel.
Q2: How does the DC compare with D2 in terms of energy amplitude, background suppression, and noise robustness?	DC outperforms D2. SBR: DC ≈ 83.1 , D2 ≈ 18.8 (4.4× higher). At SNR = 10 dB, DC achieves 87% detection for 5% damage (vs. 75% for D2).
Q3: Can the wavelet energy signature distinguish between different damage types?	In the cases examined, liner and support damage both produce single sharp peaks and are not distinguished from each other. Joint damage, however, exhibits a broadened two-element peak pattern, suggesting potential discrimination between joint-related and element-related damage. This observation is limited to the current discretization (1.0 m elements) and requires further verification with mesh refinement studies; complete classification among the three damage types is not achieved by the current method.

Practical implications. Three implications follow. First, within the range of joint stiffness values and simulation conditions considered in this study, no joint-specific calibration appears to be necessary. Second, the DC is recommended over D2 for field applications due to its higher SBR (83.1 vs. 18.8) and simpler extraction (one filter + VMD, rather than VMD + multiple filtering operations). Third, the wavelet energy signature provides preliminary qualitative information for distinguishing joint-related damage from element-related damage (liner or support). It should be emphasized, however, that liner damage and support damage are not distinguished from each other by the current method.

Limitations. Several limitations are acknowledged: (1) This study assumes healthy joint conditions; degraded joints may become detectable, which requires further investiga-

tion. (2) The present study assumes idealized measurement conditions, constant vehicle speed, uniform support conditions, and a 2D tunnel model. Practical implementation would need to address sensor synchronization, speed control, spatial variability of support stiffness, and 3D effects such as longitudinal and circumferential joint interactions. These factors are not accounted for in the current study and should be examined in future work. (3) The study is purely numerical—experimental validation is the necessary next step. (4) The cubic relationship between wavelet energy and damage severity has not been re-examined in jointed tunnels. (5) The joints are modeled as linear shear and rotational springs, which simplifies the actual nonlinear behavior of segmental joints (e.g., bolt slip, contact nonlinearities, and gap opening). This idealization is acceptable for the service-level conditions considered in this study but may not capture the full range of joint behavior under severe loading. (6) The joint stiffness values used in this study are representative estimates based on literature ranges and are not calibrated to a specific tunnel case. Experimental validation and calibration of the joint model are necessary steps before field application. These will be addressed in future work.

Relation to previous and companion studies. This study builds upon our previous continuous-beam work [36] by introducing the filtering-before-VMD strategy and evaluating joint effects. A companion study further enhances localization accuracy through a time-frequency persistence algorithm. Together, these studies form a coherent progression from foundational method to practical validation.

6. Conclusions

This study has systematically investigated the applicability of a wavelet-energy-based vehicle scanning method for damage identification in shield tunnels with segmental joints. A refined finite element model incorporating shear and rotational springs at segment interfaces was established, and a modified filtering-before-VMD strategy was introduced to extract a purer DC. The main conclusions are as follows:

- (1) Segmental joints do not produce false-positive damage indications. In the undamaged jointed tunnel, neither DC nor D2 produce wavelet energy peaks above the detection threshold at any joint location. Joints introduce periodic, stationary stiffness variations that are inherently distinguishable from localized, non-stationary damage-induced perturbations. Within the range of joint stiffness values and simulation conditions considered in this study, no joint-specific calibration appears to be necessary.
- (2) The DC substantially outperforms the D2 component. The DC achieves a signal-to-background ratio of 83.1, approximately 4.4 times higher than D2 ($SBR \approx 18.8$) under 15 dB noise. Under $SNR = 10$ dB noise, the DC maintains 87% detection for 5% stiffness reduction, while D2 achieves 75%. The improvement is attributed to the modified extraction order: filtering before VMD concentrates the full driving-related energy into a single IMF, whereas the previous approach distributes it across multiple IMFs.
- (3) The wavelet energy signature provides preliminary discrimination between joint-related and element-related damage. In the cases examined, liner and support damage both yield single sharp peaks and are not distinguished from each other. Joint damage yields a broadened peak covering two adjacent elements with comparable energy levels, which differs from the single-peak pattern of element-related damage. This suggests a potential signature for identifying joint deterioration, but complete classification among all three damage types is not achieved.
- (4) The modified ‘filtering-before-VMD’ strategy simplifies the extraction procedure and, in the cases examined, produces a cleaner damage indicator with improved sensitivity and background suppression compared with the previous ‘VMD-before-filtering’

approach. This improvement is attributed to the concentration of driving-frequency energy into a single IMF. The modification itself is straightforward, but its benefit is demonstrated through the quantitative improvements reported in Section 4.3.

Future work should address experimental validation using scaled tunnel models or real operational tunnels, investigation of degraded joint conditions, three-dimensional modeling, and quantitative severity estimation in jointed tunnels.

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Data Availability Statement: The data will be made available on request.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

VSM	Vehicle Scanning Method
CPR	Contact Point Response
VMD	Variational Mode Decomposition
IMF	Intrinsic Mode Function
DC	Driving Component
D2	Second-Order Driving Component (from previous VMD-before-filtering strategy)
CWT	Continuous Wavelet Transform
SBR	Signal-to-Background Ratio
SNR	Signal-to-Noise Ratio
FE	Finite Element
DOF	Degree of Freedom

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