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# Damage localization in a steel truss bridge using influence lines identified from vehicle-induced acceleration

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## ABSTRACT

In the last few decades, structural health monitoring (SHM) has proven a helpful tool to support the maintenance and management of civil infrastructure. However, typical measurement networks are expensive and require considerable initial efforts. The user-friendliness and interpretability of the outcome of SHM systems is a crucial factor in motivating infrastructure owners and decision-makers to sustain their costs. For this reason, simple algorithms that provide structural parameters with direct physical interpretability for professionals familiar with the typical quantities involved in structural engineering are still the most used in field applications. This paper proposes an original method to identify curvature influence lines of bridges and viaducts only using the structural acceleration response induced by vehicular loads. Acceleration time histories collected at sparse locations through standard accelerometers are employed. In contrast to SHM approaches based on modal parameters, the proposed method does not need strict synchronization, thus being suitable for wireless and low-cost monitoring solutions. Identified influence lines are used to define a spatially-dense damage indicator for accurate localization of structural anomalies with a clear physical meaning. Experimental results obtained for a steel truss bridge analyzed in different damage conditions prove the efficacy of the proposed method also for situations where modal-based approaches may fail.

**KEYWORDS:** damage identification, structural health monitoring, steel bridge, curvature, influence line, accelerometer.

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## 1. INTRODUCTION

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Developed economies depend on complex and capillary transportation infrastructure that guarantees economic exchange and allows the transportation of people and goods. In the last decades, the implementations of structural health monitoring (SHM) systems in civil infrastructure have rapidly grown to inform owners of viaducts and galleries of their structural conditions, thereby supporting maintenance and management operations.

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Traffic is the primary excitation source for road infrastructure and typically induces significant vibration to the structural components. While, in the last decades, operational modal analysis (OMA) for vibration-based SHM has mainly focused on ambient vibration data (Aloisio et al. 2020c; Brincker and Ventura 2015), recent studies have demonstrated that traffic-induced response may enclose valuable information on the structural behavior. For instance, Aloisio et al. (2020a) used traffic vibration to identify the elastic moduli of reinforced concrete (RC) viaducts. Also, Aloisio et al. (2022) highlighted the importance of moving loads to identify structural parameters of railway bridges related to track-ballast-bridge interaction. Khan et al. (2021) used the structural response to vehicular loads to identify damage related to scour. Furthermore, traffic excitation increases vibration amplitude, thus facilitating data collection with relatively low-cost sensing systems (e.g., microelectromechanical systems, MEMS) with a higher noise floor compared to more “traditional” piezoelectric devices (Sabato et al. 2017).

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Due to the ability of traditional sensing systems to collect only the medium-high frequency range of vibration, the first (and still most popular) SHM systems rely on modal parameters (Aloisio et al. 2020b; Bhowmik et al. 2020; Lynch et al. 2006; Sabato et al. 2017; Tronci et al. 2022). However, mode shapes identified using sparse accelerometers are only evaluated at the instrumented locations. Dense sensor networks are thereby necessary for accurate damage

50 localization (Quqa et al. 2022b). Besides, time synchronization between different sensing nodes  
51 is typically required to correctly identify the phase information used to determine the sign of mode  
52 shapes. In addition, SHM approaches based on traffic-induced vibration typically use long time  
53 histories to satisfy the assumption of stationary input at the base of most identification algorithms  
54 (Brincker and Ventura 2015). Together with the data synchronization needs, this aspect may  
55 considerably increase the cost of sensor networks, as they require a constant power supply and  
56 cables or other synchronization strategies to set a common time reference.

57 Although sensing technologies have evolved rapidly, modal parameters and derived  
58 quantities, such as modal flexibility (Toksoy and Aktan 1994) and curvature (Zhang and Aktan  
59 1998), are still the most used damage-sensitive features (DSFs) in SHM due to their intuitive  
60 physical interpretation (Lynch et al. 2006; Sabato et al. 2017). In particular, modal curvature has  
61 always been one of the most effective damage indicators to identify local stiffness reductions in  
62 structural components (Dessi and Camerlengo 2015; Fan and Qiao 2011). However, computing  
63 curvature from modal parameters introduces inaccuracies due to the sparsity of modal estimates  
64 that may amplify the effects of noise (Giordano and Limongelli 2020; Wu and Law 2004).

65 As an alternative to modal parameters, recent studies exploited the spatial information related  
66 to passing vehicles to identify dense structural features (Zheng et al. 2019). The structural  
67 response measured under vehicular loads can be processed to identify the influence lines of a  
68 bridge, representing the variation of a given effect (typically in terms of strain or displacement)  
69 in a structural member due to a moving load, as a function of its location.

70 Zaurin and Catbas (2011) integrated synchronized computer vision data and different sensor  
71 measurements (tiltmeters and strain gages) to identify rotation and strain influence lines during  
72 the passage of vehicles on instrumented bridges. Cavadas et al. (2013) proposed a data-driven

73 method to detect and localize structural damage by analyzing the quasi-static displacement  
74 collected during the passage of a vehicle. The authors used moving principal component analysis  
75 (MPCA) and robust regression analysis (RRA), showing that combining these two methods  
76 provides relevant information on structural conditions. Chen et al. (2015) used train-induced strain  
77 data to identify the stress influence lines of structural elements through regularization approaches,  
78 which proved effective for localizing single and multiple damages of a suspension bridge. Frøseth  
79 et al. (2017) identified the strain influence lines of a railway bridge from sparse measurements  
80 collected under train excitation using deconvolution and stabilizing filters. He et al. (2017)  
81 proposed a damage quantification method based on influence lines identified from displacement  
82 measures of beam structures subjected to loads moving with low speed (i.e., below 1 m/s) to  
83 suppress the dynamic component in the collected dataset. Wang et al. (2017) identified strain and  
84 displacement influence lines by fitting the structural response to piecewise polynomials and  
85 harmonic sinusoids, which model the quasi-static and dynamic parts of the structural response,  
86 respectively. Chen et al. (2018b) presented a damage quantification method based on  
87 displacement influence lines obtained from prior knowledge of the stiffness or flexibility matrix  
88 of the monitored structure, which can be modeled using a numerical model and calibrated on field  
89 data. Wu et al. (2018) identified damage in a continuous concrete girder bridge by analyzing the  
90 areas of influence lines obtained from data collected through distributed long fiber Bragg grating  
91 (FBG) strain sensors. Heitner et al. (2020) presented an iterative method to identify the strain  
92 influence line and the relative axle weights of passing vehicles. Moreover, the authors proposed  
93 the concept of “population influence line” as an elegant and robust synthesis of the bridge  
94 behavior under different loading patterns. Martinez et al. (2020) used a similar iterative approach  
95 to determine the displacement influence line and the axle weight of vehicles in random traffic

96 conditions. Breccolotti and Natalicchi (2022) used displacement and rotation measurements, as  
97 well as WIM data to identify displacement influence lines and the local stiffness of bridges with  
98 different geometrical schemes. The authors tested the method using numerical simulations,  
99 obtaining promising results.

100 All the mentioned studies use strain or displacement data to identify influence lines. However,  
101 several researchers (Alamdari et al. 2019; OBrien et al. 2021a) found that the success of strain-  
102 based methods strongly depends on the closeness of damage to the sensor location. Therefore,  
103 several strain gauges may be necessary to identify damage correctly. On the other hand,  
104 displacement sensors, such as laser doppler vibrometers (LDVs) and linear variable differential  
105 transducers (LVDTs), are typically expensive and need a fixed reference, which is hard to find in  
106 long-term field applications (Nassif et al. 2005).

107 Recently, Martini et al. (2022) used multiple cameras to identify vehicle loads, their location  
108 on the bridge, and the structural displacement at target positions. Dealing with camera recordings  
109 may be particularly challenging due to their sensitivity to light conditions and disturbing objects.  
110 Avoiding strain and displacement measurements, Alamdari et al. (2019) proposed a method to  
111 identify rotation influence lines considering only two instrumented locations at the bridge  
112 bearings. They used this feature to assess cable losses in a cable-stayed bridge. Huseynov et al.  
113 (2020) used accelerometers to retrieve structural rotation and the relevant influence lines for  
114 damage identification in terms of loss in the bending stiffness of the bridge deck. The authors also  
115 found that, for simply supported bridges, the optimal sensor setup involves two sensors at the  
116 supports. A few years later, O'Brien et al. (2021) used rotation measurements collected through  
117 a bridge weigh-in-motion (B-WIM) system for damage identification, observing that when  
118 damage occurs, the rotation-based B-WIM system overestimates vehicle weights. Also, O'Brien

119 et al. (2021b) obtained acceleration influence lines for damage detection using an iterative  
120 approach without the need for pre-weighting of vehicles. The authors showed that a local loss of  
121 stiffness at any bridge location could affect bridge accelerations at every physical point. However,  
122 localization and quantification of damage need further studies.

123        Accelerometers are still the most used sensing solutions for vibration-based SHM due to the  
124 simplicity of use and the availability of a wide set of commercial devices with different technical  
125 specifics and costs, allowing tailored solutions for different case studies. However, several  
126 challenges undermine the direct use of acceleration data to identify influence lines. First, all  
127 measurement amplitudes – including strain and displacements – depend on the vehicle weight  
128 (OBrien et al. 2021b), which is not typically measured in SHM applications. Nevertheless, this  
129 last aspect can be accounted for relatively easily by using WIM systems, which are becoming  
130 increasingly accurate lately (Chen et al. 2018a; He et al. 2019; Huseynov et al. 2022; Sekiya et al.  
131 2018). However, one of the most important aspects that differentiate strain or displacement  
132 measurements from acceleration data is that, in the case of acceleration data, the measurement  
133 amplitude also depends on the vehicle speed and its variations.

134        Quqa et al. (2021) recently proposed a method to obtain curvature influence lines from  
135 acceleration data through simple low-pass filters. The results showed a relatively high variance of  
136 the identified features depending on the vehicle speed and path. A similar filtering approach with  
137 bandpass filters was also applied to the same acceleration signals to identify modal parameters  
138 (Quqa et al. 2020). Although leading to more robust estimates, their sparsity would not allow  
139 accurate localization of curvature variations. In another paper, Quqa et al. (2022a) showed that a  
140 unified monitoring approach based on a filter bank made of both low-pass and bandpass filters

141 can be used to identify different structural features in a computationally convenient fashion  
142 exploiting analog in-memory computing technology.

143 This paper presents the first experimental results obtained for damage localization using only  
144 influence lines identified from acceleration data collected on a real case study with artificially  
145 induced damage. Compared to the proof-of-concept presented by (Quqa et al. 2021), this study  
146 removes the influence line normalization, which hindered the localization of anomalies close to  
147 the instrumented location. A control parameter is introduced instead, based on the area of the  
148 identified feature, and employed to remove outliers generated by anomalous vehicle speeds or  
149 masses, which may affect identification accuracy. Moreover, this study calculates the damage  
150 index by exploiting the superposition principle, considering all the sensors deployed on the  
151 structure and improving robustness in damage localization. The method proposed in this paper is  
152 based on the following assumptions:

- 153 1) One single vehicle is traveling the monitored bridge span,
- 154 2) The vehicle has an approximately constant speed,
- 155 3) Dynamic vehicle-bridge interaction is neglected,
- 156 4) The frequency range of measurement goes down to 0 (i.e., direct current – DC).

157 The first two assumptions can be realistic in the case of relatively small bridges with simply  
158 supported decks and fluid traffic conditions. The third assumption can be considered valid since  
159 the proposed procedure only accounts for the quasi-static part of the structural response, filtering  
160 out all signal components higher than about 1 Hz. The last assumption is respected if particular  
161 accelerometers (e.g., MEMS or force balance) are employed.



162 The main advantage of the proposed method compared to “traditional” approaches, e.g., based  
163 on modal parameters, is that the influence line obtained at a given location carries dense spatial  
164 information of the entire structure. Therefore, by analyzing local variations in the identified  
165 features, damage localization can be achieved using sparse sensors, which do not need strict time  
166 synchronization and can operate almost individually.

167 In this paper, Section 2 presents the outline of the algorithm for identifying influence lines  
168 and calculating a dense damage indicator from sparse acceleration time histories. Section 3  
169 presents the experimental results obtained for the Old ADA Bridge (Japan), tested with artificially  
170 induced damage scenarios. Section 4 reports the main concluding remarks of the study.

## 171 2. PROCEDURE OUTLINE

### 172 2.1 Identification of curvature influence lines

173 Consider a simply-supported beam subjected to a concentrated load  $P$  moving with a constant  
174 speed  $v$  along the axis of the structure. This dynamic system can be described using the following  
175 equation:

$$\mu \frac{\partial^2 u(z, t)}{\partial t^2} + d \frac{\partial u(z, t)}{\partial t} + EI \frac{\partial^4 u(z, t)}{\partial z^4} = P \delta(z - vt) \quad (1)$$

176 where  $u(z, t)$  is the structural displacement,  $z$  and  $t$  are the space and time variables,  $\mu$  is the mass  
177 per unit length of the beam,  $d$  is the damping coefficient, and  $EI$  is the flexural stiffness of the  
178 beam, given by the elastic modulus of the material  $E$  and the inertia of the section  $I$ . In Eq. (1),  $\delta$   
179 represents a Dirac delta function. The solution to Eq. (1) consists of a dynamic and a quasi-static  
180 components, as shown in (Quqa et al. 2021). Specifically, the latter component represents the  
181 displacement of the beam in  $z$  obtained by applying a static load at the (moving) location  $\hat{z} = vt$ .

182 Since  $\hat{z}$  spans the entire beam at the passage of a vehicle, the quasi-static structural response in  $z$   
 183 can be interpreted as the displacement influence line of the beam calculated in the reference  
 184 section  $z$ . A more detailed description of the quasi-static component of the structural response and  
 185 the related equations can be found in (Quqa et al. 2021) and are not reported here for brevity.

186 Assuming the total length of the beam equal to  $l$ , consider an accelerometer installed at a  
 187 section distant  $\zeta l$  from the first support (with  $\zeta \in [0,1]$ ) collecting the structural response in this  
 188 location with a given sampling frequency  $F_s$ . It is worth noting that, in this case, the measure is  
 189 available only at discrete values of time (and thus, of  $\hat{z}$ ). The collected response consists of a  
 190 dynamic and a quasi-static component, represented by the double derivatives of the displacement  
 191 counterparts mentioned above. Since the quasi-static component does not include dynamic  
 192 effects, and the dependence of time only determines the location of the applied load, its double  
 193 derivative over time is proportional to its double derivative over  $\hat{z}$ . Therefore, the quasi-static part  
 194 of the acceleration response represents the influence line of the curvature of the beam computed  
 195 in the instrumented location and can be calculated as (Frýba 1999; Quqa et al. 2021):

$$h^{(\zeta)}[\hat{z}] \approx -\frac{Pl^3}{48EI} \sum_{m=1}^{\infty} \frac{\pi^2 v^2 \sin(m\pi\zeta)}{l^2(m^2 - \alpha^2)} \sin\left(\frac{m\pi\hat{z}}{l}\right) \quad (2)$$

196 with

$$\alpha = \frac{vl}{\pi} \sqrt{\frac{\mu}{EI}} \quad (3)$$

197 Quqa et al. (2021) also demonstrated that  $h^{(\zeta)}[\hat{z}]$  is non-negligible only for the first few terms  
 198 of the summation reported in Eq. (2). Therefore, the frequency spectrum of  $h^{(\zeta)}[\hat{z}]$  is significant  
 199 only in the low-frequency range. On the other hand, if damping is low, the dynamic effects of the

200 structural response are significant only in the proximity of the resonant frequencies of the system,  
 201 the first of which are generally in the order of a few hertz for ordinary RC and steel simply  
 202 supported bridge decks. For this reason, processing the raw acceleration collected during the  
 203 passage of moving loads (i.e., vehicles) through a low-pass filter is generally enough to isolate  
 204 the quasi-static part of the structural response. In this case, the curvature influence line can be  
 205 calculated from the structural acceleration response as:

$$h^{(\zeta)}[\hat{z}] = \left( \frac{\partial^2 u(z, t)}{\partial t^2} \Big|_{z=\zeta l, t=\hat{z}/v} * \bar{b}_0 \right) [\hat{z}] \quad (4)$$

206 where  $*$  is the convolution operator,  $\bar{b}_0[\tau]$  is the impulse response of a low-pass filter with cutoff  
 207 frequency below the first resonant frequency of the monitored structure, and  $\tau$  is the tap index of  
 208 the filter. More details on suitable low-pass filters are provided in Section 3.

209 In this study, passing vehicles are assumed as moving loads. Although real vehicles have two  
 210 or more wheel axles and thus can be more accurately modeled using multiple applied forces, a  
 211 previous study demonstrated that the single-load simplification does not involve significant  
 212 differences at low frequencies if the span length is in the order of 10 times the distance between  
 213 the axles of the considered vehicles (Quqa et al. 2021).

214 Since only the quasi-static part of the structural response is processed in this algorithm,  
 215 suitable sensors that collect vibration at low frequencies (i.e., DC) should be employed. For  
 216 instance, MEMS and force balance accelerometers (FBAs) generally satisfy this condition.  
 217 Moreover, lower sampling frequencies can be set compared to traditional systems employed to  
 218 identify modal parameters since, in this case, the sampling frequency only dictates the

219 discretization rate of  $\hat{z}$ . Furthermore, as each sensor is used to identify an individual influence  
 220 line, strict time synchronization between accelerometers is unnecessary.

221 Quasi-static features identified through low-pass filtering from raw acceleration should be  
 222 cautiously interpreted. Bias, drift, and flicker noise can populate the low-frequency range of the  
 223 acceleration response (Djurić 2000). These phenomena are mainly due to instrumentation noise  
 224 and the effects of road roughness. Herein, a method is proposed to remove a linear trend from the  
 225 identified influence lines to mitigate drifts in the identified features. Specifically, since the beam  
 226 curvature at the instrumented location should be zero when the load is at the supports, a linear  
 227 estimate of the bias and drift that may affect the identified influence line can be calculated as the  
 228 reference line:

$$r^{(\zeta)}[\hat{z}] = h^{(\zeta)}[0] + \frac{h^{(\zeta)}[L] - h^{(\zeta)}[0]}{L} \hat{z} \quad (5)$$

229 where  $h^{(\zeta)}[0]$  and  $h^{(\zeta)}[L]$  indicate the elements of the identified influence line at the instants  
 230 when the load is on the first and last support, respectively. In order to mitigate the effects of bias  
 231 and drift, the estimated reference can be subtracted from the identified influence line as:

$$\bar{h}^{(\zeta)}[\hat{z}] = h^{(\zeta)}[\hat{z}] - r^{(\zeta)}[\hat{z}] \quad (6)$$

232 Moreover, other noise effects can be mitigated by averaging the influence lines identified for  
 233 different vehicles. Since different vehicles may have different speeds,  $\bar{h}^{(\zeta)}[\hat{z}]$  generally has a  
 234 variable length, thus not allowing a direct average. Therefore, each realigned influence line should  
 235 be first interpolated to a grid of fixed locations and then averaged to provide a more robust  
 236 curvature estimate at the grid points (e.g., using spline interpolation (Quqa et al. 2021)).

237 A general identification algorithm for a single estimate of the curvature influence line (called  
238 “sample” hereafter) is thus schematized in Fig. 1 and can be summarized as:

- 239 1) Collect the acceleration time history at a given instrumented location and apply the low-  
240 pass filter,
- 241 2) Cut the filtered signal at the instants where the load enters and leaves the monitored bridge  
242 span,
- 243 3) Subtract the reference line from the obtained estimate,
- 244 4) Interpolate the curvature values to a fixed grid.

245 If the structure is statically determined, the curvature influence line computed in a given  
246 section  $\zeta$  can also be interpreted as the curvature diagram of the structure (which is also  
247 proportional to the bending moment diagram) obtained by applying a static load in  $\zeta$ . As  
248 previously mentioned, the curvature is one of the most used DSFs for SHM, which typically  
249 increases in damaged intervals (Dessi and Camerlengo 2015). Therefore, supposing to identify an  
250 average influence line (using several samples) at the beginning of the monitoring process (namely,  
251 the “baseline” condition) and at periodic intervals (namely, the “inspection” conditions), the  
252 difference between the average inspection and baseline estimates can be effectively employed as  
253 a damage indicator. This difference will be referred to as “difference function” for simplicity.

254 Previous results (Quqa et al. 2021) showed that, for simply-supported beams, clear peaks  
255 appear in the difference function obtained from inspection and baseline influence lines normalized  
256 to their maximum values at the locations where the flexural stiffness was locally reduced.  
257 Moreover, due to normalization, the peak magnitudes were also representative of the damage  
258 entity (assuming particular constraints on the vehicle speed). This approach has shown to be  
259 particularly effective if the damage was not in the proximity of the instrumented location. On the

260 other hand, if the damage was close to a sensor, the maximum value of the inspection influence  
 261 line was in the damaged portion. Therefore, due to data normalization, the difference function was  
 262 close to zero in the damaged interval, making the determination of peaks particularly challenging.  
 263 In truss bridges, sensors are typically deployed at the nodes of the structure, which are locations  
 264 prone to damage. In this study, a different definition of the damage index is proposed, avoiding  
 265 the normalization of identified influence lines and thus providing accurate localization of the  
 266 structural damage even if the anomaly is close to the instrumented locations.

## 267 **2.2 Definition of a damage indicator based on the superposition principle**

268 Assuming a linear-elastic structural behavior during the passage of regular vehicles, the  
 269 superposition principle can be exploited to calculate the curvature diagram of the structure  
 270 subjected to a set of uniform concentrated loads applied at all the instrumented locations. This  
 271 diagram is obtained by summing the influence lines identified at all the instrumented sections. A  
 272 damage indicator is then defined as the difference of the curvature diagrams thus obtained:

$$D[\hat{z}] = \sum_{i=1}^r \bar{h}_d^{(\zeta_i)}[\hat{z}] - \sum_{i=1}^r \bar{h}_b^{(\zeta_i)}[\hat{z}] \quad (7)$$

273 In Eq. (7),  $\bar{h}_d^{(\zeta_i)}[\hat{z}]$  and  $\bar{h}_b^{(\zeta_i)}[\hat{z}]$  denote the average influence lines identified at the  $i$ -th  
 274 instrumented section for the inspection and baseline conditions, respectively, while  $r$  is the total  
 275 number of instrumented locations.

276 Therefore,  $D[\hat{z}]$  represents the increment in the curvature of the structure subjected to a  
 277 uniform set of concentrated loads and is defined at all the values of  $\hat{z}$  regardless of the number of  
 278 instrumented locations. This approach is similar to the case of damage identification using the  
 279 curvature of the uniform load surface (or line, in two-dimensional cases) (Quqa et al. 2020; Wu

280 and Law 2004; Zhang and Aktan 1998) obtained by multiplying the flexibility matrix of the  
281 structure (calculated from identified modal parameters) with a uniform load vector. However, the  
282 proposed approach has two main advantages over the mentioned method:

283 1) Derivation errors introduced by typical methods employed to calculate curvature from  
284 sparse modal estimates (e.g., the central difference approximation (Giordano and  
285 Limongelli 2020; Wu and Law 2004)) are avoided.

286 2) The DSF and the damage index are spatially dense and not available only at the  
287 instrumented locations.

288 However, features identified simply by using filtering operations also have criticalities. First,  
289 each influence line is identified by analyzing a short signal and can be affected by short-term  
290 phenomena (i.e., non-stationarities, such as wind or nearby traffic vibration) and slight variations  
291 in the speed of the passing cars. Moreover, some dynamic effects could be included in the filtered  
292 signal, both due to the imperfect filtering ability of employed filters (thus including signal  
293 components above the selected cutoff frequency) and low-frequency dynamic components in the  
294 structural response. However, all these phenomena have a different influence on each identified  
295 sample; thereby, averaging the influence lines identified at the passage of several vehicles  
296 mitigates the dynamic components.

297 To have a consistent averaging process, however, it is necessary that the individual influence  
298 lines are not substantially different from one another, especially in terms of amplitude. The  
299 amplitude of influence lines mainly depends on vehicle mass and speed. Considering only  
300 vehicles within a given speed and mass range would thus produce similar influence lines. While  
301 speed can be easily calculated from the length of each sample, vehicle weight could be determined  
302 using B-WIM systems, which are becoming very popular for characterizing traffic load (Chen et

303 al. 2018a; He et al. 2019; Huseynov et al. 2022; Sekiya et al. 2018), or roughly estimated using  
 304 regular traffic cameras from the vehicle size or model. Upon selecting influence lines generated  
 305 by a limited set of similar vehicles, anomalous estimates (e.g., due to non-constant speed) can be  
 306 further removed by discarding the samples with an outlier area in a considered time window.

307 At the passage of each vehicle, the area of  $\bar{h}^{(\zeta)}[\hat{z}]$  is calculated at each instrumented location.  
 308 The influence line generally has an amplitude (and an area) that depends on the reference section  
 309 (i.e., the instrumented location). An amplification factor can be calculated to make the areas of  
 310 influence lines comparable based on the relevant instrumented locations. For instance, if the  
 311 stiffness of the beam is almost constant, the amplification factor can be calculated as the ratio of  
 312 the areas of the bending moment diagrams  $M^{(\zeta)}(z)$  obtained by applying the load in  $l/2$  and  $\zeta l$ :

$$\alpha^{(\zeta)} = \frac{\int_0^l M^{(0.5)}(z) dz}{\int_0^l M^{(\zeta)}(z) dz} = \frac{1}{4\zeta(1-\zeta)} \quad (8)$$

313 The amplified area of the curvature diagram can thus be calculated as:

$$A^{(\zeta)} = \alpha^{(\zeta)} \sum_{\hat{z}=0}^L \bar{h}^{(\zeta)}[\hat{z}] \quad (9)$$

314 It is worth noting that, given a vehicle weight,  $A^{(\zeta)}$  should be constant for every  $\zeta$ .

315 In this way, after forming a set  $S$  of  $\bar{h}^{(\zeta)}$  estimates, only the ones with an amplified area  $A^{(\zeta)}$   
 316 included in the range  $[\mu_S - \beta\sigma_S, \mu_S + \beta\sigma_S]$  can be averaged to obtain the final estimate, where  $\mu_S$   
 317 and  $\sigma_S$  are the mean and standard deviation of the amplified areas of the samples included in the  
 318 set  $S$ , while  $\beta$  is a parameter that can be tuned to select the estimates with a user-defined variability  
 319 for the final computation of the damage index. Considering samples calculated at different



320 instrumented locations in the same set  $S$  is necessary to guarantee that the vehicle speed is  
321 uniform.

### 322 **3. EXPERIMENTAL RESULTS**

323 This section briefly describes the experimental case study and then reports the damage  
324 identification results using the proposed approach. The acceleration data for the case study (the  
325 Old ADA Bridge) is freely available online (Kim et al. 2021b) and described in (Kim et al. 2021a).

#### 326 **3.1 Case study**

327 The Old ADA Bridge was a simply supported steel Warren-truss bridge with a main span  
328 length of 59.2 m and a width of 3.6 m. The bridge was built in 1959 and demolished in 2012 in  
329 Japan. A scheme of the case study with the general dimensions is illustrated in Fig. 2. More details  
330 can be found in (Kim et al. 2021a).

331 Before demolition, an experimental campaign was conducted to collect ambient and vehicle-  
332 induced vibration data. Five damage scenarios were artificially induced during the tests while  
333 blocking the traffic and using a single test vehicle. The vehicle was a Nissan Serena having a total  
334 weight of about 21 kN, including passengers and measurement devices. The spacing between the  
335 front and back wheel axles was 2.7 m, and the track width was 1.5 m. The first dominant frequency  
336 of the sprung motion of the vehicle body was identified at 1.7–1.8 Hz, while the first resonant  
337 frequency of the bridge was 2.98 Hz.

338 Four damage scenarios were artificially induced during the experimental campaign, as  
339 reported in Tab. 1. In this study, condition “U” represents the “undamaged” baseline configuration  
340 of the structure. In condition “DC1”, the cross-section of the vertical truss T1 at the bridge  
341 midspan (see Fig. 2) was cut to half and completely cut in condition “DC2”. The central truss was

342 then repaired by lifting the bridge to the original height using a jack and soldering the damaged  
343 element (“DC3”). In this case, however, the bridge was not guaranteed to be restored to its original  
344 state. After recovering the first damaged truss, a second vertical truss (T2 in Fig. 2) was  
345 completely cut in condition “DC4”.

346 It is worth noting that, although the section reductions may seem considerable, DC1 and DC3  
347 can still be considered minor damage, as the element T1 is almost unloaded due to the particular  
348 geometry of the truss structure. Moreover, in DC3, the material continuity was fully restored.  
349 Indeed, (Chang and Kim 2016) noted that identification methods based on modal parameters  
350 could hardly identify damage in this condition.

351 In each condition, an ambient vibration test was carried out first, during which the structural  
352 vibration was collected without vehicle excitation. These tests were followed by vehicle-induced  
353 vibration tests, in which the acceleration response of the structure was acquired while passing  
354 with the test vehicle.

355 Eight uniaxial accelerometers were deployed on the bridge deck, as shown in Fig. 2, five on  
356 the side of the damaged truss member and three on the opposite side, collecting the acceleration  
357 in the vertical direction. The accelerometer model was “ARS-A” by Tokyo Measuring  
358 Instruments, with a nominal responding frequency from DC to 30 Hz. Besides these, two optical  
359 sensors (“PZ-G52” by Keyence Co.) were installed on the two ends of the bridge and one at the  
360 midspan to track the time instants when the vehicle passed in these three instrumented locations.  
361 All sensors were connected to data loggers, guaranteeing time synchronization. All the time  
362 histories were sampled at 200 Hz. During the tests, no substantial temperature change was  
363 observed.

## 364 3.2 Discussion

365 In this study, ten acceleration time histories collected during the passage of the test vehicle at  
366 about 40 km/h (herein called “samples”) are used to calculate the curvature influence lines of the  
367 bridge deck.

368 The low-frequency component of each sample is extracted using a low-pass wavelet filter.  
369 Specifically, the reverse biorthogonal filter with three vanishing moments has proved very  
370 selective in a previous study (Quqa et al. 2022a). Moreover, the modest number of taps of the  
371 impulse response of the mentioned filter makes computations particularly efficient and thus  
372 suitable also for battery-powered sensing nodes. The wavelet filter was obtained by cascading  
373 eight low-pass *rbio3.1* filters, each with a dyadic upsampling with respect to the previous one,  
374 thus resulting in a wavelet transform of level  $n = 8$  (Vetterli and Kovačević 1995). The theoretical  
375 cutoff frequency of the resulting filter, calculated as  $f_{cutoff} = F_s/2^{n+1}$  is thus 0.39 Hz (Quqa et  
376 al. 2021; Vetterli and Kovačević 1995). Fig. 3 shows the response spectra of the acceleration  
377 collected at location A2 during the passage of a single car, the low-pass wavelet filter obtained as  
378 described above, and the related filtered response. It is possible to observe that the filtering  
379 operation mitigates the resonant peaks of the structural response related to the dynamic effects,  
380 and only the quasi-static component below the cutoff frequency has a significant amplitude.

381 A total of 10 influence lines were identified by applying the algorithm described in Section  
382 2.1 for each instrumented location and damage condition, thus collecting and analyzing the data  
383 for 50 different passages of the test vehicle. The left-hand side of Fig. 4 shows the influence lines  
384 identified for each recording, together with their average, organized in different plots for each  
385 damage scenario. The average influence lines are computed after discarding the estimates with a  
386 sample area outside the boundaries described in Section 2. Here, the parameter  $\beta$  was set equal to

387 2, thus assuming to use the 95% of collected samples if their amplified areas are normally  
388 distributed. The left-hand part of the figure reports the amplified areas obtained using Eq. (8) for  
389 all instrumented locations. The sample means and standard deviations of these areas are reported  
390 in Tab. 2. Since the test car is always the same, the amplified areas are almost constant. From the  
391 values shown in the table, it is possible to notice that, in general, the areas of the damaged  
392 conditions are slightly higher compared to those of the baseline, denoting a higher total curvature  
393 of the bridge deck. Moreover, excluding the outliers, the mean area of DC4 is lower than that of  
394 DC2 and DC3, representing the restoring intervention. However, a clear correlation of the total  
395 curvature with the damage entity is not observable in terms of global curvature since DC2 and  
396 DC3 have a similar area, although the damage in DC3 is more severe.

397 The damage index proposed in Section 2.2 was calculated considering two different sensor  
398 setups, i.e., (a) employing all five sensors on one side of the bridge from A1 to A5 and (b) only  
399 the two external sensors, A1 and A5. The spatial distribution of this index in the two mentioned  
400 situations is reported in Fig. 5(a) and 5(b), respectively.

401 Due to the modest number of samples considered in this application (i.e., 10 per damage  
402 condition), the average influence line, and thus the damage indicator, is still affected by local  
403 disturbances, such as the oscillations due to residual dynamic effects. Dashed lines represent the  
404 damage index obtained after the average process in Fig. 5(a-b). In order to consider a more  
405 extensive averaging process over a larger set of samples, Fig. 5(a-b) also reports the moving  
406 average of the damage index considering a kernel length of 40 elements. This “cleaned” diagram  
407 is represented using solid lines.

408 The curvature increment is observable throughout the beam length. However, the maximum  
409 curvature variations (highlighted by arrows) are always close to the locations of the damaged

410 elements, even in the case of sparse sensor setup. It is worth noting that the results obtained in the  
411 two sensor setups are comparable. State-of-the-art studies are generally based on two or more  
412 displacement sensors, dense systems of strain gauges, or vision-based methods capable of  
413 identifying features at all physical points of the structures using images. Here, in the sparse  
414 configuration, only two uniaxial accelerometers were used to localize damage at nodes, which do  
415 not coincide with the instrumented ones.

416 The damage indicator proposed in this paper should be carefully interpreted considering the  
417 structural scheme, especially for truss structures. Indeed, while stiffness reductions in structures  
418 with a constant cross-section would generate a local peak in  $D[\hat{z}]$  in the proximity of the stiffness  
419 loss, damaged elements in truss structures may generate complex patterns of curvature variations.

420 A simple 2D finite element model (FEM) of the case study (schematized in Figure 6) is used  
421 to validate the experimental damage index. In this model, the steel system was assumed as a truss  
422 structure, with the element having the dimensions described in (Kim et al. 2021a). The bridge  
423 deck was modeled as a continuous beam with a cross-section of 0.5×8.0 m. No calibration was  
424 conducted, as the aim of the comparison is only qualitative. The theoretical curvature difference  
425 of the bridge deck loaded with a set of uniform concentrated forces obtained by simulating a  
426 section reduction in T1 and T2 through the FEM is reported in Fig. 5(c), normalized to the  
427 maximum value.

428 It is possible to observe that the experimental damage indicator in conditions DC1, DC2, and  
429 DC3 (Fig. 5(a-b)) has nearly symmetric distributions with a central peak, which is compatible  
430 with the theoretical result shown in Fig. 5(c). As already noted for the areas of the identified  
431 influence lines (see Tab. 2), the curvature distribution in DC1 and DC2 is almost coincident in  
432 Fig. 5(a), while DC2 has a lower magnitude in Fig. 5(b). While this fact may be justified

433 considering a stress redistribution after DC1 and inelastic bridge settlement, the proposed method  
434 was not validated to estimate the damage entity at this stage. Nevertheless, the restoring process  
435 carried out between DC2 and DC3 leads to a curvature reduction for the latter condition. The  
436 curvature difference between conditions DC3 and U is still higher than zero, reflecting a residual  
437 effect of the damage induced in DC1 and DC2 that was not completely recovered. For both the  
438 dense and sparse sensor setups, the peak in curvature difference for DC4 is at the location of T2,  
439 thus reflecting the new damage and being consistent with the theoretical result reported in Fig  
440 5(c).

441 Nevertheless, while the theoretical result has an almost constant curvature except for the  
442 interval between 296 and 444 cm, the experimental result shows higher curvature values  
443 throughout the beam. It is worth noting that the damage of T2 was induced starting from DC3,  
444 which already presents slight damage in T1. Therefore, DC4 can be seen as a combination of the  
445 two theoretical results shown in Fig 5(c). Indeed, in the intervals between 0 and 296 cm, as well  
446 as between 444 and 592 cm, DC3 and DC4 are almost coincident.

447 Chang and Kim (2016) applied different damage identification techniques based on modal  
448 parameters to the data collected on the ADA bridge. Comparing the results presented in this paper  
449 with those of the mentioned study, it is observable that, in general, the proposed approach has  
450 superior sensitivity to small damage (i.e., DC1 and DC3). Indeed, Chang and Kim (2016)  
451 observed that modal parameters (both natural frequencies and mode shapes) change slightly from  
452 U to DC1 and are almost unchanged between U and DC3. Kim et al. (2014) attributed the low  
453 sensitivity of modal parameters to damage to stress redistribution.

454 In (Chang and Kim 2016), outlier analyses were conducted considering different sets of  
455 identified modal parameters to assess their sensitivity to damage. Univariate analyses using a

456 single identified mode frequency resulted in accurate damage identification only for conditions  
457 DC2 and DC4. Similarly, clear damage detection is achieved for the same conditions using the  
458 modal assurance criterion (MAC) on individual mode shapes. Damage is correctly detected in  
459 DC1 only when multivariate analyses are conducted considering multiple natural frequencies or  
460 coordinate MAC (COMAC) values. However, identifying high modes is typically challenging.  
461 Kim et al. (2014) observed that higher modes could only be identified from forced-vibration  
462 responses for the analyzed case study, which generally provide lower precision than the  
463 parameters identified in free vibration.

#### 464 **4. CONCLUSIONS**

465 This paper proposed a new damage indicator based on curvature influence lines identified  
466 only from traffic-induced vibration. The influence lines are determined using individual time  
467 histories, thus not needing strict time synchronization between sensors – which is typically  
468 necessary to identify modal parameters. This damage-sensitive feature is spatially dense and  
469 insensitive to derivation inaccuracies introduced by the central difference approximation or  
470 similar approaches commonly used to calculate curvature from sparse modal estimates.

471 The damage indicator proposed in this study is representative of variations in the curvature  
472 diagram obtained by applying a set of uniform loads to the structure. Using the proposed approach  
473 with acceleration data collected on a steel truss bridge with damaged elements allowed for  
474 accurate damage localization. In the analyzed structure, the damage indicator showed clear peaks  
475 close to the damaged components, even in the case of sparse sensor network (i.e., using only two  
476 sensors). Due to the intuitive physical sense of the damage indicator, the damaged elements can  
477 be accurately identified by interpreting the results with the support of a simple structural model.

478 In the presented monitoring approach, moving vehicles act as concentrated loads applied to  
479 limited structural portions. This is why, compared to other techniques based on modal parameters,  
480 the proposed method has shown superior sensitivity to minor damage. Moreover, while modal-  
481 based approaches generally need to identify high modes to localize minor damage correctly, the  
482 proposed method only consists of filtering the low-frequency component of the structural  
483 response. This makes the algorithm simple and computationally effective, as filtering can be done  
484 as a convolution.

485 In real-life applications, dense sensor setups for vibration-based structural health monitoring  
486 are typically affected by data transmission problems and synchronization. The proposed method,  
487 involving few sensors operating individually, brings enormous benefits, also providing dense  
488 features for accurate localization of structural anomalies. Moreover, compared to typical  
489 controlled loading tests, the proposed approach is based merely on acceleration measurements,  
490 which can be collected with the bridge in operation without interrupting traffic or needing a fixed  
491 reference (necessary for displacement measurements). Traffic intensity (i.e., to understand when  
492 only one vehicle is traveling the bridge) and a rough estimate of vehicle weight can be easily  
493 obtained through one simple traffic camera. The proposed method is meant to be used with a wide  
494 set of measurements in a long-term monitoring process. Therefore, modest vehicle mass and speed  
495 variability would slightly affect the final averaged influence line used for damage identification.

#### 496 **DATA AVAILABILITY**

497 The data used during this study are available online (<https://doi.org/10.17632/sc8whx4pvm.2>)  
498 in accordance with funder data retention policies.

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637 **Tables**

638

**Tab. 1** Description of damage conditions

Damage condition	Description
U	Baseline configuration
DC1	50% cross-section reduction of one truss in T1
DC2	100% cross-section reduction of one truss in T1
DC3	Recovered configuration
DC4	100% cross-section reduction in of one truss T2

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640

**Tab. 2** Statistical parameters of the amplified areas of curvature diagrams

Damage condition	Mean	Standard deviation	Mean excluding outliers
U	3.18	1.14	3.11
DC1	5.73	1.56	5.90
DC2	5.36	1.37	5.43
DC3	5.15	2.60	4.56
DC4	5.09	0.83	5.01

641