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.

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1. INTRODUCTION

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.

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).

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

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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-weighing 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   Ququa 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   (Ququa et al. 2020). Although leading to more robust estimates, their sparsity would not allow

139   accurate localization of curvature variations. In another paper, Ququa 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.

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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.

2. PROCEDURE OUTLINE

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:

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

176   where $u(z,t)$ is the structural displacement, z and t are the space and time variables, μ 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), δ

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 $\hat{z} = vt$.

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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 ζl 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):

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

196   with

$$\alpha = \frac{vl}{\pi}\sqrt{\frac{\mu}{EI}} \tag{3}$$

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:

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

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 τ 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:

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

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:

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

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 ζ 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 ζ. 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:

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

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

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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:

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

2) The DSF and the damage index are spatially dense and not available only at the 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 ζl:

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

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

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

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

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 μ_S

317   and σ_S are the mean and standard deviation of the amplified areas of the samples included in the

318   set S, while β 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.

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).

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.

3.2 Discussion

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

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

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

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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

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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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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

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