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A systematic method from influence line identification to damage detection: Application to RC bridges

Zhiwei Chen*[1], Weibiao Yang[1], Jun Li[2], Qifeng Cheng[3,4] and Qinlin Cai[1]

[1]Department of Civil Engineering, Xiamen University, Xiamen, China
[2]Centre for Infrastructural Monitoring and Protection, School of Civil and Mechanical Engineering, Curtin University, Kent Street, Bentley, WA 6102, Australia
[3]Holsin Engineering Testing Co., LTD, Xiamen, China
[4]College of Civil Engineering, Huaqiao University, Xiamen, China

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Abstract. Ordinary reinforced concrete (RC) and prestressed concrete bridges are two popular and typical types of short- and medium-span bridges that accounts for the vast majority of all existing bridges. The cost of maintaining, repairing or replacing degraded existing RC bridges is immense. Detecting the abnormality of RC bridges at an early stage and taking the protective measures in advance are effective ways to improve maintenance practices and reduce the maintenance cost. This study proposes a systematic method from influence line (IL) identification to damage detection with applications to RC bridges. An IL identification method which integrates the cubic B-spline function with Tikhonov regularization is first proposed based on the vehicle information and the corresponding moving vehicle induced bridge response time history. Subsequently, IL change is defined as a damage index for bridge damage detection, and information fusion technique that synthesizes ILs of multiple locations/sensors is used to improve the efficiency and accuracy of damage localization. Finally, the feasibility of the proposed systematic method is verified through experimental tests on a three-span continuous RC beam. The comparison suggests that the identified ILs can well match with the baseline ILs, and it demonstrates that the proposed IL identification method has a high accuracy and a great potential in engineering applications. Results in this case indicate that deflection ILs are superior than strain ILs for damage detection of RC beams, and the performance of damage localization can be significantly improved with the information fusion of multiple ILs.

Keywords: influence line; damage detection; RC bridge; inverse problem; information fusion; experimental verification

1. Introduction

A great amount of bridges has been built throughout the world in the past few decades to meet the economic and social needs of communities. The number of highway bridges in China has exceeded 779,000 by the end of 2015, and 90% of them are short- and medium-span bridges which accounts for the vast majority. Among these bridges, the ordinary reinforced concrete (RC) and prestressed concrete are most widely used to build bridges. Corrosion is regarded as one of the primary causes of deterioration in RC bridge decks and piers, and the occurrence of surface and in-depth cracks accelerate the rate of corrosion of steel reinforcement (Vu and Stewart 2000). Due to the combined actions of the ordinary (or overweight) traffic loading and corrosive environmental effect, cracks are prone to initiate in the tensile regions of RC bridges at the early stage and then gradually propagate. The cost of maintaining, repairing or replacing degraded existing RC bridges is immense. In the Unite States, up to US$3 billion is spent annually on the repair of RC bridge decks and it is estimated that the improved maintenance practices can reduce this amount by up to 46% (Stewart and Mullard 2007). To this end, detecting the abnormality of RC bridges at an early stage and taking the protective measures in advance are effective ways. Therefore, an efficient damage detection method sensitive to early damage is essential for the maintenance of RC bridges.

In the past few decades, civil engineers and researchers have studied several types of methods for condition and damage assessment of bridge structures. As a typical routine inspection for the surface condition of local bridge damage, visual inspection has been carried out by experienced engineers especially after overloading, accidents, or when codes change. The development of non-destructive testing (NDT) technologies, such as ultrasonic, sonics, conductivity, eddy current and radar, enable engineers to detect in-depth damage and describe damage in a visual way (McCann and Forde 2001). Visual inspections and NDT do find signs of damage such as cracks, spalls, chemical deterioration, and corrosion when these become "visible" by naked eyes or instruments. However, the relation between such signs of damage and the corresponding ‘‘condition’’ of the structure is often very difficult to establish (Aktan and Catbas 2002). Based on the fundamental idea that damage-induced changes in the physical properties (mass, damping, and stiffness) will cause detectable changes in the modal properties (notably

∗Corresponding author, Associate Professor
E-mail: cezhiwei@xmu.edu.cn

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frequencies, mode shapes, and modal damping), the vibration-based damage detection techniques went through a rapidly development in the civil engineering society (Doebling *et al.* 1998, Fan and Qiao 2011, Li *et al.* 2014, Li and Hao 2016). A well-known family of them is based on structural dynamic characteristics and their derivatives, such as frequencies, mode shapes, damping ratios, and strain mode shapes, whereas their representative derivatives include frequency response function, modal strain energy, energy transfer ratio, and flexibility matrix, etc. (Chen and Xu 2007, Fang *et al.* 2012, Fang and Perera 2009, Yan *et al.* 2012, Yi *et al.* 2013a, Li and Hao 2014). Although these methods demonstrated varying degrees of success in previous studies, detecting early damage of bridge structures remains a big challenge. One of the main obstacles is that structural dynamic characteristics are either insensitive to early damage or too sensitive to measurement noises and changes in the operational environment conditions, such as temperature.

Conversely, relatively rare attention has been paid to static damage detection techniques, although they actually offer direct measure of stiffness or flexibility matrix. Moreover, displacement and stress influence coefficients are conceptual, physics-based indices representing structural characteristics that are meaningful to engineers, and they are often analytically predicted for designing or evaluating structural performance. The influence line (IL) is a static property that describes the variation of reaction, internal loading, displacement, or stress at one location if a bridge structure is subjected to a moving unit load. ILs (or slowly moving pre-weighted truck-induced responses) are widely used in the design and characterization of the behavior of bridges (Hibbeler 2009, AASHTO 2010, 2011, Ding *et al.* 2016). It allows the bridge designers to discover quickly where to place a live load in order to calculate the maximum unfavorable response for each of the following functions: reaction, displacement, or stress, etc. Bridge ILs used in the design stage can be determined by the design model of a bridge. Given to the necessary simplifications and uncertainties of material parameters in bridge modeling, the “design” IL could be quite different from the “actual” IL which is determined by the field testing of a built bridge. Comparing with the design IL, the actual IL normally lies on the safe side for condition evaluation of newly-built bridges. Due to the long-term effects of traffic loading and harsh environmental conditions, these bridges begin to deteriorate once built and continuously accumulate damage during their long service life, and bridge ILs gradually change along with structural deterioration. Therefore, monitoring bridge IL in different stages of service life and its changing tendency can be utilized to evaluate bridge condition and detect damage.

Several studies on IL-based damage detection method have been carried out for applying to bridge structures. Aktan and Catbas (2002) have demonstrated that unit influence lines (UIL) of strain or displacement could be a promising structural condition index. Furthermore, integrating with video images and sensor data, UIL was identified and then utilized to detect damage with an experimental setup of four-span steel bridge structure (Zaurin and Catbas 2010). Recently, the methodology was applied to detect and locate common damage scenarios on a steel bascule bridge (Zaurin *et al.* 2016). Chen *et al.* (2015) also applied the stress IL based method to detect local damage of a long suspension steel bridge, and its efficacy was successfully validated by case studies. Other influence line related studies were included in some recent literatures, such as Choi *et al.* 2004, Yi *et al.* 2011, Chen *et al.* 2012, Yi *et al.* 2013b, Sun *et al.* 2015 and Ding *et al.* 2017. Although above studies have proved that IL is a promising damage index for bridge structures and applied the methods to steel bridges, few studies involve RC bridges that are widely used in practice. Comparing with steel bridges, RC bridge has much more complicated modes of internal force distribution and structural failure, and thus damage-induced variations on influence line indices of RC bridge deserve a careful and in-depth investigation.

This paper first introduces key issues in establishing a systematic methodology framework for damage detection based on bridge ILs. A regularization method is proposed to identify IL based on vehicle information and the corresponding moving vehicle induced bridge response time history. By introducing cubic B-spline functions to make an alternative representation of IL, a new IL identification method is proposed for obtaining a more reasonable solution. Subsequently, a damage index is defined for bridge damage detection, and both of displacement and strain ILs are utilized to detect the occurrence and location of damages on bridges. To improve the efficiency of damage localization, information fusion technique that synthesizes ILs of multiple locations is used for damage detection. Finally, the feasibility of the systematic method from IL identification to damage detection is verified through experimental tests of a three-span continuous RC beam.

2. Methodology framework from IL identification to damage detection

To establish a systematic methodology framework for damage detection based on bridge ILs, some key issues need to be considered. The identification of bridge IL that exactly represents current bridge condition is the foundation of IL-based damage detection method. Furthermore, how to comprehensively make use of ILs identified from multiple sensors installed at the critical bridge locations is the main problem for the application to damage detection. Therefore, a systematic research framework should contain proper methods to perform steps from IL identification to damage detection.

The bridge ILs can be roughly determined by a trial load test that uses heavy trucks and often performed before a built bridge opening to the public. With the aid of a temporary or permanent structural monitoring system, the test examines the initial ILs of the bridge under planned load conditions and provides baseline information for future inspection and monitoring. Similar tests can be periodically scheduled in the bridge service life for damage detection purposes. However, it is often more preferable to identify the ILs of the bridge under in-service conditions, because such a measure: (1) does not require suspending bridge operations; and (2) can capture the change of influence lines in a more timely manner. Thus, it is necessary to develop a quick and precise method to identify IL by using real-time monitoring data of moving vehicle and vehicle-induced bridge response.

To evaluate the bridge condition in a comprehensive and reliable way, it is required to install various types of multiple sensors on pre-determined critical sections for obtaining more local damage information. Although an individual IL can be exacted from typical bridge responses monitored by only one sensor, damage detection based on a single IL has conspicuous drawbacks. Given to environmental noises and measurement errors are inevitable in sensor data, the detection of small damage is very difficult, if not impossible. Normally, only sensors locating in a close vicinity of damage locations are sensitive to the local damage, and thus the detectable range of a single IL (or sensor) is limited. In addition, it is likely to make conflicting conclusions on damage condition based on different ILs (or sensors). Therefore, comprehensive IL information of multiple sensors should be used for damage detection.

3. Quasi-static IL identification

3.1 Mathematical model of IL identification

If the vehicle is assumed to run on the bridge along a given straight line and individual axles of the vehicle act on the bridge independently, then the vehicle-induced bridge response can be approximately represented by the superposition by a summation the actions of all individual axles

$$R_s(x) \approx \sum_{i=1}^{N} A(i) \times \Phi\left(x - D(i)\right) \tag{1}$$

where $R_s(x)$ is the bridge response induced by the vehicle loading at location x (the location of the first vehicle axle), $\Phi(x)$ is the IL function corresponding to the location of unit force, N is the number of axles, $A(i)$ is the ith axle load of the vehicle, and $D(i)$ is the distance between the ith axle and the first axle. According to the sampling frequency or finite element intervals, the functions $R_s(x)$ and $\Phi(x)$ can be discretized into vectors $\mathbf{R}_s$ and $\mathbf{\Phi}$. As a result, Eq. (1) can be rewritten in a matrix form as

$$\mathbf{R}_s = \mathbf{L}\mathbf{\Phi} \tag{2}$$

or

$$\begin{Bmatrix} R_s(1) \\ R_s(2) \\ \vdots \\ \vdots \\ R_s(p) \end{Bmatrix}_{p\times 1} = \begin{bmatrix} A_{1,1+D(1)} & 0 & \cdots & A_{1,1+D(2)} & \cdots & \cdots & A_{1,1+D(k)} & 0 & \cdots & \cdots \\ 0 & A_{2,2+D(1)} & 0 & \cdots & A_{2,2+D(2)} & 0 & \cdots & A_{2,2+D(k)} & 0 & \cdots \\ \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots \\ \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots \\ 0 & 0 & 0 & 0 & A_{p,p+D(1)} & 0 & \cdots & A_{p,p+D(2)} & 0 & \cdots \end{bmatrix}_{p\times q} \begin{Bmatrix} \phi(1) \\ \phi(2) \\ \vdots \\ \vdots \\ \phi(q) \end{Bmatrix}_{q\times 1} \tag{3}$$

where $\mathbf{R}_s$ is the quasi-static response vector for a given location, $R_s(1)$ and $R_s(2)$ are the 1st and 2nd sample of measurement responses. p is the number of samples in the response measurement. $\mathbf{L}$ is the loading matrix constructed according to vehicle information such as axle spacing and axle loads, $\mathbf{\Phi}$ is the influence coefficient vector, and q is the number of influence coefficients in the IL.

Not only the quasi-static component but also the fluctuation component exists in the measured bridge response induced by the moving vehicle. The fluctuations mainly arise from dynamic impact effect, road roughness, disturbance from other loadings, measurement noise and so on. Therefore, the response measurement $\mathbf{R}_m$ can be expressed as the sum of two parts

$$\mathbf{R}_m = \mathbf{L}\mathbf{\Phi} + \boldsymbol{\eta} \tag{4}$$

where the first term represents the quasi-static response that can be estimated by static IL, and $\boldsymbol{\eta}$ denotes the disturbance vector accounting for the dynamic and noise effects. If $\mathbf{R}_m$ and $\mathbf{L}$ in Eq. (4) are constructed by the measurement information, then the identification of $\mathbf{\Phi}$ could be regarded as a classic inverse problem. It is not easy to exactly identify IL from the measured bridge response and vehicle information, especially when disturbances are considered in the responses. Although $\boldsymbol{\eta}$ is normally very small compared with the peak value of $\mathbf{R}_s$, the former may lead to enormous errors in the estimation of bridge IL.

Tikhonov regularization (or l_2-regularization) is a commonly used method for dealing with ill-conditioned inverse problems, and thus it is utilized to develop a mathematical model of IL identification by representation as follows (Vogel 2002)

$$\mathbf{\Phi} = \arg\min_{\mathbf{f}\in R^n} \left\|\mathbf{R}_s - \mathbf{L}\mathbf{\Phi}\right\|_2^2 + \lambda\left\|\mathbf{\Phi}\right\|_2^2 \tag{5}$$

where $\{\arg\min\}$ stands for the argument of the minimum (i.e., the set of the given argument minimizing the given function), $\left\|\mathbf{R}_s - \mathbf{L}\mathbf{\Phi}\right\|_2^2$ is the sum of the square of the error term, $\left\|\mathbf{\Phi}\right\|_2^2$ is the penalty function, and λ is weighting factor of the penalty function. The selection of λ is often challenging in the Tikhonov regularization method if the true solutions are unknown, and a variety of parameter selection methods has been proposed in the past (Vogel 2002). In this study, the weighting factor λ is determined by means of the L-curve (Hansen 1992).

3.2 Cubic B-spline based method for IL identification

In the above section, a mathematical model of IL identification is proposed, and then the optimal solution of IL can be determined based on the objective function defined in Eq. (5). Although the obtained IL solution conforms to the optimization of mathematical expression, it cannot fulfill the physical meaning of IL. In the physical world, real IL for a typical bridge location should be a relatively smooth curve. Even when bridge structures suffer a minor or medium level of damage, internal force redistribution enables local damage effect to spread over the surrounding components, and thus guarantees the relatively smooth of ILs. However, IL identified by the aforementioned model usually contains lots of periodic fluctuations, which mainly attribute to the assumption that influence line is composed of several influence coefficients which are unrelated to each other. The correlation between the influence coefficients of two points that are close to each other should be significant. Therefore, a cubic B-spline based method is proposed for resolving the above problem.

In mathematics, a spline is a numeric function that is piecewise-defined by polynomial functions, and which possesses a high degree of smoothness at the places where the polynomial pieces connect, which are known as knots (Judd 1998). The most commonly used splines are cubic splines, i.e., of order 3-in particular, cubic B-spline (or basis spline), which is equivalent to C2 continuous composite Bézier curves. In the previous study, the cubic B-spline interpolation has been proved to suitable for constructing deflection or strain ILs of a long-span bridge (Sun *et al.* 2016). In this study, the basis function expansion method is introduced to make an alternative representation of IL, and thus IL can be regarded as a linear combination of a series of cubic B-spline functions as follows

$$\mathbf{\Phi} = \mathbf{N}\mathbf{w} \tag{6}$$

where $\mathbf{N}=[N_{0,3} \ldots N_{i,3} \ldots N_{n,3}]$ is the cubic B-spline function matrix, in which $N_{i,3}$ denotes the ith cubic B-spline basis function of order 3; $\mathbf{w}=[\mathrm{w}_0 \ldots \mathrm{w}_i \ldots \mathrm{w}_n]^T$ is the weighting coefficient vector. By means of the Cox-de Boor recursion formula, the cubic B-spline basis functions $N_{i,k}$ can be derived by following equations

$$N_{i,0}(\xi) = \begin{cases} 1 & \xi_i \le \xi < \xi_{i+1} \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

$$N_{i,k}(\xi) = \frac{\xi - \xi_i}{\xi_{i+k} - \xi_i} N_{i,k-1}(\xi) + \frac{\xi_{i+k+1} - \xi}{\xi_{i+k+1} - \xi_{i+1}} N_{i+1,k-1}(\xi) \tag{8}$$

where ξ_i is defined as knots, and $\Xi = \{\xi_0, \xi_1, \cdots, \xi_{n+k+1}\}$ is the knot vector, which is a non-decreasing sequence of real numbers, i.e., $\xi_i \le \xi_{i+1}$.

Introducing Eq. (6) into Eq. (5), the objective function of IL identification can be rewritten as

$$\mathbf{w} = \arg\min_{\mathbf{f}\in R^n} \|\mathbf{R}_s - \mathbf{L}\mathbf{N}\mathbf{w}\|_2^2 + \lambda\|\mathbf{w}\|_2^2 \tag{9}$$

The weighting coefficient vector $\mathbf{W}$ is determined by obtaining the optimal solution of the above equation, and then the influence coefficient vector $\mathbf{\Phi}$ can be constructed by Eq. (6). In this way, the variables for optimization are transformed from a large number of influence coefficients to a small number of weighting coefficients, which would be beneficial for achieving a smooth IL as well as keeping it close to the real one.

4. Damage identification based on comprehensive information of multiple ILs

4.1 Damage index based on IL change

After a certain service period, a RC bridge may have local damage, such as cracks, spalls, chemical deterioration, and corrosion. ILs can provide a suitable comparison of bridge response under the same load, a moving unit force, between the current and original states of the bridge. The bridge deflection or strain responses of a healthy bridge to a unit vertical force are taken as the baseline ILs. When a bridge is subject to several severe local damages, ILs may exhibit apparent changes that can be detected through a comparison with baseline ILs. Therefore, the IL change can be regarded as a damage index as follows

$$\Omega(x) = \Phi(x) - \Phi_{BL}(x) \tag{10}$$

where $\Phi(x)$ and $\Phi_{BL}(x)$ are the newly obtained ILs and baseline ILs, respectively, both of which are function of the abscissa x of unit force in the longitudinal direction. If the bridge does not suffer any damages or the location of damage is far away from the measurement location of ILs, the damage index $\Omega(x)$ of ILs should be minimal and negligible. Otherwise, the magnitude of $\Omega(x)$ may increase when a unit force moves on the bridge. Member stiffness loss in statically determinate structures leads to a change in displacement IL, but no change in strain IL takes place unless a strain gauge is directly installed at the damage location. Fortunately, most bridges are statically indeterminate. In this study, both of displacement and strain ILs are adopted to detect the occurrence and location of damages on RC bridges.

4.2 Damage localization based on information fusion of multiple ILs

Multiple ILs are identified from sensors installed on different locations of a bridge, and thus it is necessary to propose a damage localization approach which could synthesize ILs of multiple locations through information fusion technique. By assuming n sensors installed in the concerned region of bridge and m candidate locations of interest $x_j (j=1,2,\ldots,m)$ for damage localization, IL information from multiple sensors are available, thus the mass function matrix of ILs can be defined as

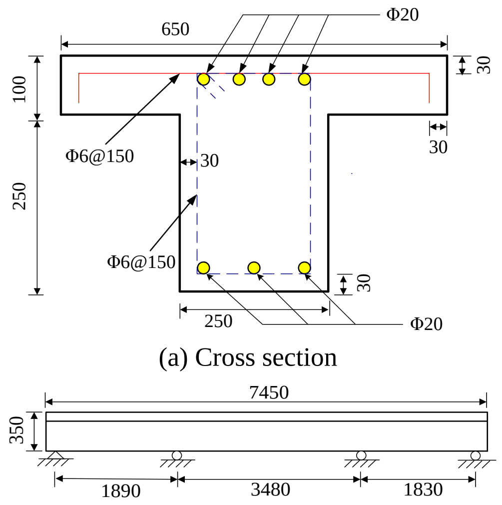
$$\mathbf{m} = \begin{bmatrix} m_1(x_1) & m_1(x_2) & \cdots & m_1(x_m) \\ m_2(x_1) & m_2(x_2) & \cdots & m_2(x_m) \\ \cdots & \cdots & m_i(x_j) & \cdots \\ m_n(x_1) & m_n(x_2) & \cdots & m_n(x_m) \end{bmatrix} \tag{11}$$

in which, the mass function coefficient $m_i(x_j)$ denotes the degree of belief regarding the damage at jth location according to the IL change from the ith sensor, and can be calculated by the equation as follows

$$m_i(x_j) = \frac{|\Omega_i(x_j)|}{\sum_{j=1}^{m}|\Omega_i(x_j)|} \tag{12}$$

A greater value of $|\Omega_i(x_j)|$ implies a higher probability of damage occurrence at the location x_j, and thus is assigned with a greater mass function coefficient. The evidence from multiple information sources (i.e., sensors) can be combined using Dempster's combination rule (Basir and Yuan 2007). By fusing information of n sensors, the joint mass function coefficient corresponding to the jth candidate location can be computed by

$$m(x_j) = \prod_{i=1}^{n} m_i(x_j) \Big/ \sum_{j=1}^{m}\left(\prod_{i=1}^{n} m_i(x_j)\right) \tag{13}$$



(a) Cross section

(b) Front view

Fig. 1 Layout of a continuous RC beam (unit: mm)

Fig. 2 Loaded vehicle moving on continuous RC beam

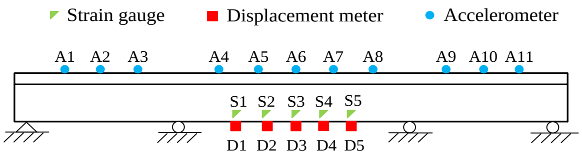


Fig. 3 Layout of sensors installed on the beam

When the ith sensor location is distant from the candidate location x_j, the evidence $m_i(x_j)$ may not be reliable even though a great value is detected; when a sensor is mounted very close to the concerned location x_j, the measurement is more sensitive to the possible damage and the provided evidence information should be treated more credible than those from other distant sensors. To account for this distance effect, a weighted joint mass function coefficient is proposed to take into account the relative credibility of each strain sensors in the information fusion process

$$m(x_j) = \prod_{i=1}^{n} w_{ij} m_i(x_j) \Big/ \sum_{j=1}^{m} \left(\prod_{i=1}^{n} w_{ij} m_i(x_j) \right) \tag{14}$$

where w_{ij} is the weighting factor determined based on the distance D_{ij} between the ith sensor and the jth location. Given that totally n sensors are involved in the information fusion, the relationship between w_{ij} and D_{ij} is established

$$w_{ij} = \frac{1/D_{ij}}{\sum_{i=1}^{n} \left(1/D_{ij} \right)} \tag{15}$$

in which

$$D_{ij} = \left| x_i - x_j \right| \tag{16}$$

where x_i is the location of the ith sensor, and x_j stands for the jth location. By introducing the weighting factor into calculation, information from sensor at a small distance can be assigned with a great weighting factor; whereas the distance is very far, a minimal weighting factor should be assigned and the contribution of the corresponding sensor should be nearly ignored. To avoid infinite or extremely large weighting factor in the data fusion, D_{ij}=0.1 m is taken when the sensor is very close to the concerned damage location (i.e., D_{ij}<0.1 m).

By integrating IL-based damage detection and information fusion technologies, the weighted joint mass function coefficient is defined after a comprehensively consideration of multiple ILs, and a greater value of the coefficient (between 0 and 1) indicates a larger probability of damage. Therefore, it could be a promising method for determining local damage locations in a more accurate and reliable way.

5. Experimental verification on a three-span continuous RC beam

5.1 Experimental setup

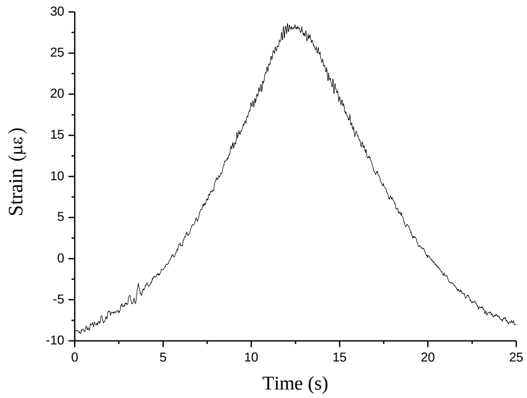
As the simplification of RC bridges in real-world, a three-span continuous RC beam is used for verifying the feasibility and performance of the proposed approach for applications to damage detection in RC bridges. A T-shaped beam is specially designed for the convenience of a steel-made loaded vehicle moving on it. Layout of steel bars in the upper and bottom surfaces of the beam is designed to prevent concrete fractures if applying dead load or construction load. More detailed information on the design scheme of the experimental testing RC beam can be found in Fig. 1.

The three-span continuous RC beam was fabricated in the laboratory, and a pulling force generated by an electric motor was applied to pull a steel-made loaded vehicle to cross the bridge, as shown in Fig. 2. Many steel plates are superimposed on the vehicle to ensure a reasonable vehicle bridge mass ratio and make the deflections or strains of beam large enough for a precise measurement.

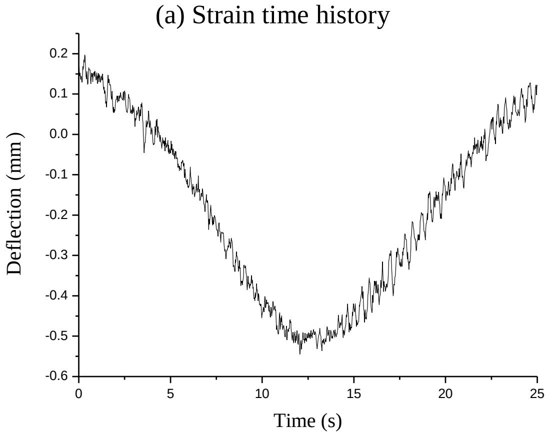
To identify the quasi-static strain and deflection influence lines, five strain gauges and five displacement meters were installed on the middle span of the beam. For a better comparison between the dynamic and static properties of the beam, eleven accelerometers are installed to identify the first few modal frequencies. The layout of the sensor installing on the beam are displayed in Fig. 3.

5.2 Verification of IL identification method

To verify the proposed approach of quasi-static IL



(a) Strain time history



(b) Deflection time history

Fig. 4 Moving vehicle induced dynamic response time history

identification based on multiple monitoring data, the moving vehicle testing and static single-point loading testing are respectively performed to determine the baseline IL and identified IL.

The strain or deflection time histories are required to construct response vector for IL identification. The strain and deflection time histories induced by a loaded vehicle moving from one end of beam to the other, were measured by strain gauges and displacement meters installed in the middle span of this three-span continuous RC beam. The dynamic strain and deflection time histories measured by sensors installing at the mid-span are shown in Figs. 4(a) and (b). It can be found from both figures that a peak value occurs when vehicle approaches the sensor location at the mid-span. In addition, obvious fluctuations are found from the measured strain and deflection time histories, and this phenomenon mainly attributes to the vehicle-bridge dynamic interaction effect and measurement noises. Although vehicle weight has been increased to 1 ton and responses at the mid-span are larger than other locations, the response peaks of time histories recorded at the mid-span (shown in Fig. 4) are still very small, which indicates that the RC beam has high rigidity. For the same level of measurement noise, using small amplitude of response leads to a decrease of signal-to-noise ratio which makes a precise IL identification more challenging.

In addition to the response vector, IL identification requires to construct loading matrix in Eq. (9) based on the

Table 1 Basic information of loaded vehicle

Axle spacing (m)	Axle loading (N)			Real-time location (m)
	1st axle	2nd axle	Total	
0.4	4825	4825	9650	*

*Real-time location of moving vehicle is determined by background subtraction technique

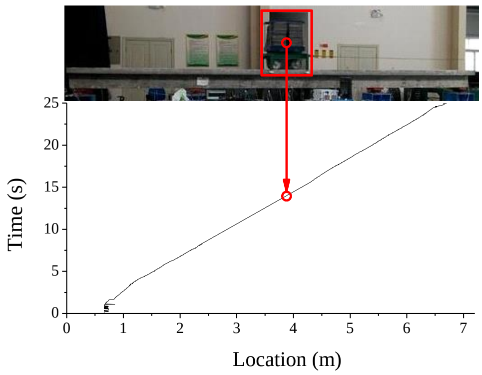
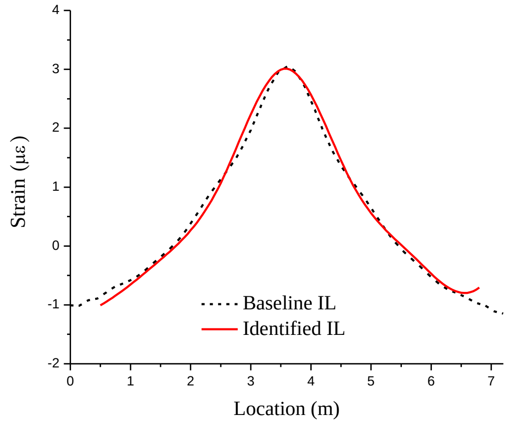


Fig. 5 Real-time location of moving vehicle

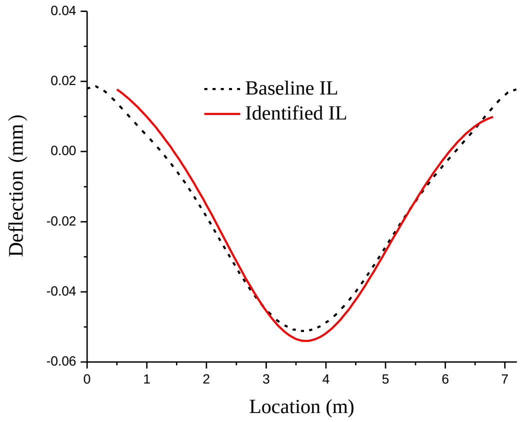
information of loaded vehicle, including axle spacing, axle loads and real-time locations of moving vehicle. The basic information of the loaded vehicle is listed in Table 1.

In this study, the real-time location of moving vehicle is determined by background subtraction technique. Background subtraction is a widely-used approach for detecting moving objects in videos from static cameras. The rationale in the approach is based on detecting the moving objects from the difference between the current frame and a reference frame, often called “background image”. Pixels in the current frame that deviate significantly from the background frame are clustered to determine the moving object, and then the centroid of moving object can be calculated by the locations of related pixels. Taking a stationary point in the background image as the reference point, the time-varying location of vehicle centroid in the whole procedure of moving vehicle testing is identified by background subtraction method. To establish a relationship between the vehicle location and its corresponding strain or deflection responses, the location of time-varying vehicle and the time of deflection or strain measurement must be synchronously recorded. In Fig. 5, the abscissa of the curve represents the distance from the centroid of the vehicle to the left end of the beam, and the ordinate denotes the time of deflection and strain measurement. By integrating vehicle information of the real-time location, axle spacing and axle loads, the loading matrix **L** in Eq. (2) can be constructed.

Based on the cubic B-spline basis function matrix that is constructed by the Cox-de Boor recursion formula, as well as the response vector and loading matrix, ILs can be identified by Eqs. (6) and (9). The identified strain and deflection ILs at the mid-span of beam are shown in Fig. 6(a) and (b), respectively. The horizontal axis represents the location of an unit force (1 kN) acting on the beam, and the vertical axis indicates the strain or displacement caused by an unit force at the corresponding location. In addition to IL

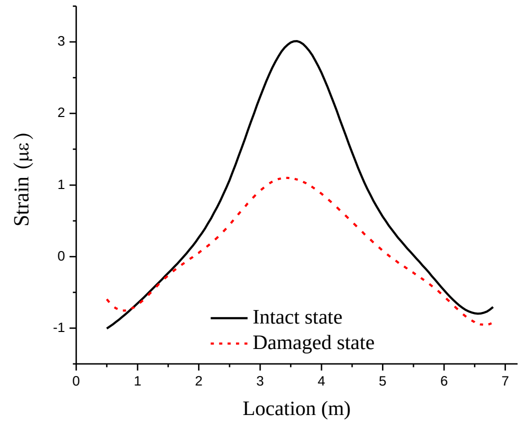


(a) Strain IL

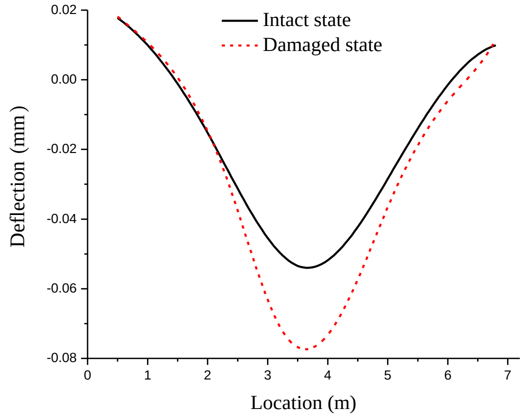


(b) Deflection IL

Fig. 6 Comparison of baseline IL and identified IL



(a) Strain IL



(b) Deflection IL

Fig. 8 ILs in the intact and damaged state

(a) Electro-hydraulic servo loading system

(b) Tiny cracks in local zoom

Fig. 7 Loading tests of a RC beam

identified from the moving vehicle testing, the baseline IL is identified from static single-point loading testing, in which a strip-shaped vertical loading is applied to the beam at each time and then successively moves in longitudinal direction with a small interval. The baseline ILs are also shown in Fig. 6 for the comparison. It can be observed from Fig. 6(a) that the identified strain IL can perfectly fit with the baseline IL not only for its shape but also its peak value. The identified result of deflection IL is not as good as strain IL, and the relative change ratio between the identified and baseline strain ILs is 5.6%, but it is still acceptable for application to damage detection. The results demonstrate that the proposed IL identification method has a high accuracy and thus has great potentials in engineering applications.

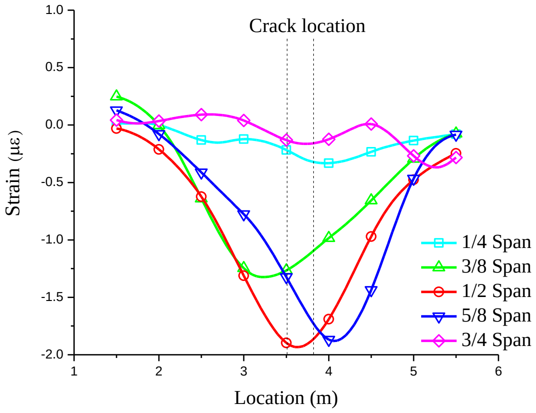
5.3 Verification of damage detection method

To verify the efficacy and performance of applying the proposed damage detection approach for RC bridges, a minor damage was generated by applying external vertical loadings on the mid-span of the laboratory beam through an electro hydraulic servo loading system, as shown in Fig. 7(a). The system stopped loading when two tiny cracks appeared at the bottom of the loading region as shown in Fig. 7(b). Cracks are located in the sections at distances of 3.51 m and 3.82 m from the left end of the beam. After unloading, the cracks will close and become so inconspicuous that make them rather difficult to detect by naked eyes.

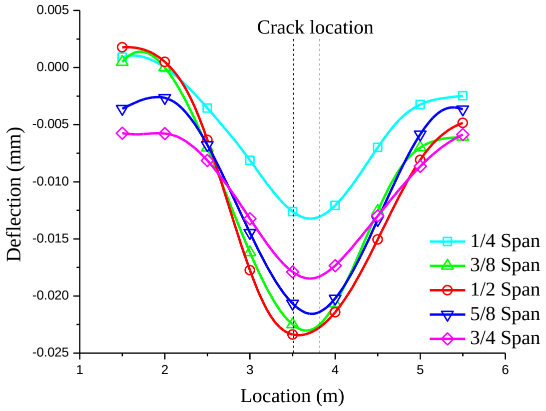
Table 2 Comparison of indices in the intact state and damaged state

Indices	Modal frequencies							Peak values of IL	
	1st mode (Hz)	2nd mode (Hz)	3rd mode (Hz)	4th mode (Hz)	5th mode (Hz)	6th mode (Hz)	7th mode (Hz)	Stress IL ($\mu\varepsilon$)	Deflection IL (mm)
Intact	36.7	85.4	135.9	199.8	296.4	402.6	488.4	3.01	0.054
Damaged	33.7	81.4	132.6	190.6	286.7	389.0	476.5	1.13	0.079
CRI*	8.3%	4.7%	2.4%	4.6%	3.3%	3.4%	2.4%	62.5%	46.8%

*CRI: Changing rate index between the intact and damaged state



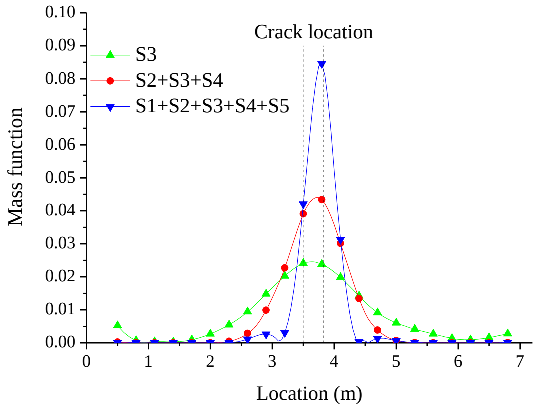
(a) Strain ILs



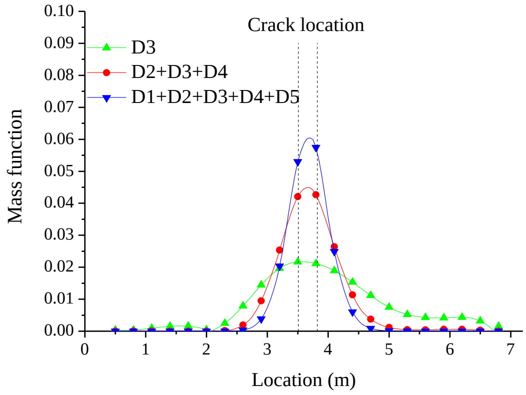
(b) Deflection ILs

Fig. 9 Changes in ILs at different monitoring locations

In order to make comparisons with modal frequencies of the continuous beam before and after damage, dynamic tests have been carried out on the beam as shown in Fig. 2. The excitation is provided by an impact hammer applied at the mid-span and 1/4 span of the beam. Eleven force-balance accelerometers are installed on locations as shown in Fig. 3 and used to measure the dynamic responses. The frequency domain decomposition method is adopted to identify the modal frequencies of the intact and damage states. The frequency domain decomposition is one of the non-parametric methods that have some similarities with the pick-peaking and complex mode indicator function methods. In this technique, the power spectral density of a structure’s response is calculated and then the singular value decomposition. The frequency results of the first seven modes are listed in Table 2, and the changing rate



(a) Strain ILs



(b) Deflection ILs

Fig. 10 Damage localizations by information fusion of ILs at different locations

index (CRI) between the intact and damage state for each mode is calculated. It can be found that the largest CRI is only 8.3% and the second largest one is less than 5%. This phenomenon indicates that modal frequency change indices are not sensitive to the minor damage at the early stage, and the frequency change induced by the temperature variation may be even greater than that caused by the minor damage, as reported by previous studies.

A similar procedure that is used to identify IL in the intact state, is also applied to identify IL in the damaged state. Figs. 8(a) and (b) show the identified strain and deflection ILs in the mid-span of the beam under the intact and damaged states. Significant differences can be observed in the ILs from these two states, and the largest difference appears at the peak value of ILs, which is just located in the damage region. The CRI values for peak value of the above two ILs are also calculated and listed in Table 2. Comparing with CRI values of modal frequency, CRI values of IL peak are found to be much higher.

For a comprehensive study of understanding the change in ILs induced by the occurrence of minor damage, ILs before and after damage are compared among different monitoring locations. The monitoring data collected by strain gauges and displacement meters installed at five critical locations (as shown in Fig. 3) are used to identify strain and deflection ILs. Using the baseline and the newly-obtained ILs, IL change defined as a damage index is calculated by Eq. (10) and shown in Fig. 9. Taking the

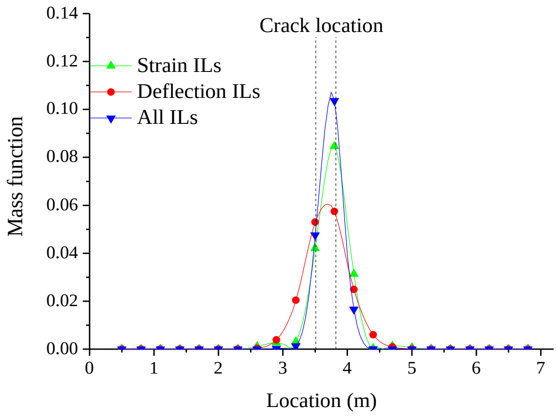


Fig. 11 Damage localizations by information fusion of all ILs from different sensors

deflection IL change curves for example, some uniform observations are obtained by comparing five curves in Fig. 9(b), which include that all curves have apparent fluctuations and the locations of their peaks are close to each other. The obvious fluctuation can be regarded as an indicator to detect the occurrence of damage, and the location of apparent peaks can be used to roughly determine the damage location. Peak values of the five curves fall in the main damage region without exception, which indicates deflection IL change could be an excellent index for damage localization. Comparing with deflection IL, only the change of strain IL at the location of 1/2 span in Fig. 9(a) can be used to accurately localize damage based on its peak location, and strain ILs at the location of 1/4 span and 3/4 span are almost impossible for accurately judging the existence of damage. This phenomenon could be explained by the fact that strain/stress is sensitive to local damage but it is limited to a small region around damage.

Without prior knowledge of damage, it will be very difficult to make a reliable decision on damage detection because conflicts are likely to exist in the findings from single ILs of different locations. Thus, the information fusion of multiple ILs proposed in Section 4.2 is applied to localize damage of the RC beam. Based on the IL change before and after damage, each mass function coefficient is calculated by Eq. (12) to construct mass function matrix defined in Eq. (11). By fusing information of multiple sensors, the weighted joint mass function coefficients for all the candidate locations are computed by Eq. (14). 127 candidate locations of interest at an interval of 0.05 m are selected from the experimental beam. Damage localizations by information fusion of different numbers of sensors (as shown in Fig. 3) are subsequently examined and compared. The results are shown in Fig.10, with the number of sensors measured for strain and deflection IL information fusion varying from one, three to five. The joint mass function value at the damage location around the mid-span increases along with the number of sensors. By contrast, after fusing information of three or five sensors, the joint mass function around the damage location can be easily distinguished from the other non-damage locations, and the mass function at the locations faraway from damage is reduced to near zero.

Furthermore, the efficiency of damage localization is validated by considering the information fusion with different types of sensors. In this study, the joint mass function values are calculated by information fusion of only strain ILs, only deflection ILs and all ILs, and then three curves are demonstrated in Fig. 11 for comparison. The identification results indicate that different types of sensors adopted for information fusion are beneficial to damage localization with a certain extent. In conclusion, the information fusion technique can effectively strengthen the consistent information (such as damage-induced structural change) and eliminate non-consistent information (such as "noise" effect) from multiple sensors installed around the damage.

6. Conclusions

A methodology framework from IL identification to bridge damage detection has been proposed for applications to RC bridges in this paper. To obtain a IL solution which not only satisfies mathematical optimal but also conforms to the physical meaning, the basis function expansion method is introduced to make an alternative representation of IL, and a method integrating with cubic B-spline function and Tikhonov regularization is proposed to identify IL based on the vehicle information and the corresponding moving vehicle induced bridge response time history. By checking IL change through a comparison with baseline IL, both displacement and strain ILs are utilized to detect the occurrence and location of damages on bridges. Furthermore, information fusion technique is used to synthesize ILs of multiple locations/sensors and thus improve the efficiency of damage localization. Finally, the feasibility of the systematic method from IL identification to damage detection is validated by experimental tests on a three-span continuous RC beam. Major conclusions drawn from this investigation can be summarized as follows:

- The identified ILs can well match with the baseline ILs, which demonstrates that the proposed IL identification method has a high accuracy and great potentials in engineering applications.
- Through applying IL indices to detect the occurrence and location of damage on a RC beam, deflection ILs are found to be superior than strain ILs. It could be explained by the fact that strain/stress is sensitive to local damage but it is limited to a small region around damage.
- The information fusion of multiple ILs can effectively strengthen consistent information (such as damage-induced structural change) and eliminate non-consistent information (such as "noise" effect) from multiple sensors installed around the damage.

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