Author:
Alamdari, M. M.; Dang Khoa, N. L.; Wang, Y.; Samali, B.; Zhu, X.

Article Title:

A multi-way data analysis approach for structural health monitoring of a cable-stayed bridge

Journal Title: Structural Health Monitoring

Date: 01 Jan 2019

Journal Title
XX(X):1–12

DOI: 10.1177/ToBeAssigned
www.sagepub.com/
SAGE

A Multi-Way Data Analysis Approach for Structural Health Monitoring of a Cable-Stayed Bridge

Mehrisadat Makki Alamdari[1], Nguyen Lu Dang Khoa[2], Bijan Samali[3], Xinqun Zhu[3]

Abstract

A large scale cable-stayed bridge in the state of New South Wales, Australia has been extensively instrumented with an array of accelerometer, strain gauge and environmental sensors. The real-time continuous response of the bridge has been collected since July 2016. This study aims at investigating three aspects of structural health monitoring in this bridge including, damage detection, damage localization and damage severity assessment. A novel data analysis algorithm based on multi-way data analysis is proposed to analyse the dynamic response of the bridge. This method applies incremental tensor analysis for data fusion and feature extraction, and further uses one-class support vector machine on this feature to detect anomalies. Fifteen different damage scenarios were investigated; damage was physically simulated by locating stationary vehicles with different mass at various locations along the span of the bridge. The effect of damage on the fundamental frequency of the bridge was investigated and a maximum change of 4.4% between the intact and damage states was observed which corresponds to a small severity damage. Our extensive investigations illustrate that the proposed technique can provide reliable characterisation of damage in this cable-stayed bridge in terms of detection, localization and assessment. The contribution of the work is three-fold; first, an extensive structural health monitoring system was deployed on a cable-stayed bridge in operation; second, an incremental tensor analysis was proposed to analyse time series responses from multiple sensors for online damage identification; and finally, the robustness of the proposed method was validated using extensive field-test data by considering various damage scenarios in presence of environmental and operational variabilities.

Keywords

Cable-Stayed Bridge, Tensor Analysis, Damage Detection, Damage Localization, Damage Severity Assessment, Structural Health Monitoring.

1 Introduction

Cable-stayed bridges have gained popularity in design of long-span bridges since they offer a more economical option due to their reduced material requirements and shorter construction time[1]. In cable-stayed bridges, cables are the most critical load carrying members and are highly vulnerable to adverse long term load effects, e.g. fatigue, and environmental actions, e.g. corrosion and their coupled effects. In addition, stay cables are prone to various vibration effects such as vortex-induced or wind and rain-induced vibrations[2]. These effects inevitably result in damage accumulation that may impair the bridge. It is thus critically important to develop robust and efficient monitoring systems to pro-actively detect bridge defects.

Various monitoring systems by adopting different types of sensors have been deployed on the cable-stayed bridges which can be classified into global or local techniques. Vibration-based monitoring by measuring the acceleration response at several locations and identifying the modal parameters using output-only modal analysis techniques[3–5] is one of the widely-used approaches for monitoring the cable-stayed bridges[6,7]. In previous studies, the measured modal parameters, e.g. natural frequencies or mode shapes were often used with novelty detection techniques[8] such

[1]School of Civil and Environmental Engineering, University of New South Wales, Australia
[2]Data 61, Commonwealth Scientific and Industrial Research Organisation (CSIRO), Australia
[3]School of Computing, Engineering and Mathematics, Western Sydney University, Australia

Corresponding author:
Mehrisadat Makki Alamdari
Email: m.makkialamdari@unsw.edu.au

as neural network or other machine learning methods, or they are combined with finite element analysis to get useful information about presence, location and severity of damage[9]. Although vibration based monitoring offers relatively low-cost system, the modal parameters of a structure are highly influenced by operational and environmental conditions, e.g. traffic, wind or temperature[10]; as a result, it requires a significant effort to identify damage effect from the changes in the modal parameters[11]. Furthermore, vibration-based approaches lack a sufficient resolution for health monitoring of the cable stays[12].

Measuring the changes in the cable-forces or cable-stresses is another alternative for damage assessment in the cable-stayed bridges, as damage causes a redistribution of forces and stresses in the stay cables[13,14]. For example, a significant drop in a tension force of a cable as a result of loss of cross section or slippage at the anchorage, increases forces in the adjacent cables[15]. Application of load cells or elasto-magnetic sensors have been proposed for this purpose[16], however, they are only suitable for static measurement and not capable for real-time monitoring. Fiber optical sensors have been proposed to overcome this limitation but they are quite expensive and hard to install or replace[17]. In[12], a distributed strain monitoring based on the Fiber Bragg Grating sensors was used to identify any tension loss in the cables. Application of magnetic flux leakage has also been employed for stress monitoring in the cables. However, the technique suffers from temperature effects; furthermore, it requires extensive field calibrations using identical cables to determine the relationship between magnetic permeability and strain in the cables[18]. Techniques based on the non-contact measurement using image processing or computer vision algorithms have also gained attraction for cable force monitoring[19]. Furthermore, application of various localized non-destructive testing (NDT) techniques, e.g. acoustic emission[20], thermography[21], X-ray radiography[22] and guided waves[23] has shown to be effective for monitoring the cable-stayed bridges. From the literature, methods involving cable-force measurement and NDT seem to be quite effective in identification of damage in cable-stayed bridges. Application of new sensing technologies such as smart wireless sensing has also been deployed on several large scale cable-stayed bridges to monitor the dynamic response of the bridge[24] or the cable forces[25]. However, these systems suffer from several problems including, the energy cost, e.g. battery-powered nodes, time synchronisation and wireless channel stability[26].

In this study, the vibration response of the cables in terms of the tension force under the ambient excitation is adopted to detect, localize and assess various emulated damages on the bridge. The rationale behind the technique lies in the fact that any potential damage on the structure will change the distribution of cable forces compared to a benchmark state. The measured time series data from the cable forces are integrated with a novel data analysis technique based on incremental tensor learning to identify damage. These sensors' measurements usually have a high redundancy and correlation, thus, approaches based on two-way matrix analysis may fail to capture all of these correlations and relationships together[27,28]. These approaches usually involve a matricisation of a multi-way tensor followed by the use of techniques such as principal component analysis (PCA) or singular value decomposition (SVD) to further analyse the data. For example, we can concatenate the frequency data from multiple sensors at a certain time to form a single data instance at that time for anomaly detection in time dimension. However, unfolding the multi-way data and analysing them using two-way methods may result in information loss and misinterpretation since it breaks the modular structure inherent in the tensor data[27]. In contrast, tensor analysis allows the learning from these highly correlated data in multiple modes at the same time[29]. It has contributed to successes in many domain applications such as social network and brain data analysis, web mining and information retrieval, or health care analytics[30]. In this work, tensor analysis is used to fuse and extract information collected from multiple sensors instrumented on the bridge cables. Our approach detects the change in the structure compared to its baseline state. Localization is carried out by comparing the changes of sensor in the tensor space and, finally assessment is performed by comparing the anomaly scores obtained from different structural states.

The remainder of the paper is organized as follows. Section 2 explains our novel multi-way data analysis approach using incremental tensor learning. Section 3 presents the details of the cable-stayed bridge and an implemented structural health monitoring (SHM) system on this bridge. Section 4 focuses on the details of the 15 emulated damages on this bridge and the corresponding impact on the characteristic features of the bridge. Section 5 provides damage identification results and discussions. We concludes the paper in Section 6 with a summary of our contributions and suggestions for future work.

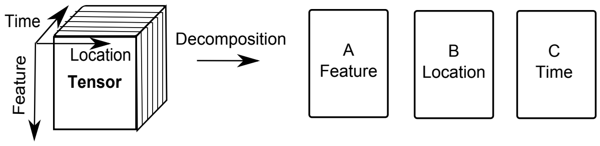


Figure 1. Tensor data with three modes in SHM.

2 Methodology: Incremental Tensor Analysis for Online Damage Identification

2.1 *Tensor Analysis for SHM Data*

In SHM, data are usually collected from a large number of sensors, especially for large civil structures like a long span bridge or a high-rise building. For instance, several accelerometers may be put along a bridge's spans to measure vibration signals excited by traffic or ambient loadings over long periods of time. One excitation event at a specific time produces multiple signals measured by different sensors. These SHM data can be considered as a three-way tensor, i.e. a three dimensional array of $(feature \times location \times time)$ as described in Figure 1. Feature is the information extracted from the raw signals in time domain (e.g. strain in strain gauges). Location represents sensors, and time is data snapshots at different timestamps. Each slice along the time axis shown in Figure 1 is a frontal slice representing all feature signals across all locations at a particular time. For simplicity, in this paper we represent a tensor as a three-way array, which is often the case in SHM. However, it is also possible to generalize all the theories for a n-way array.

Two typical approaches for tensor decomposition are CP decomposition and Tucker decomposition[29]. After a decomposition from a three-way tensor, three component matrices can be obtained representing latent information in each mode. In the case of SHM data as in Figure 1, they are associated with feature (denoted matrix A), location (matrix B) and time modes (matrix C). In CP method, it is easy to interpret the artifact in each mode separately using its associated component matrix. In Tucker method, any component can interact with other components in other modes quantified by a core tensor[31]. This makes the interpretation of a Tucker model more difficult than CP. Therefore, we only use CP method in this paper for our SHM applications.

2.1.1 *CP Decomposition*

The CP decomposition factorizes a tensor as a sum of a finite number of rank-one tensors. In case of a three-way tensor $\mathcal{X} \in \mathbb{R}^{I \times J \times K}$, it is expressed as

$$\mathcal{X} = \sum_{r=1}^{R} A_{:r} \circ B_{:r} \circ C_{:r} + \mathcal{E}, \tag{1}$$

where R is the latent factor, $A_{:r}$, $B_{:r}$ and $C_{:r}$ are r-th columns of component matrices $A \in \mathbb{R}^{I \times R}$, $B \in \mathbb{R}^{J \times R}$ and $C \in \mathbb{R}^{K \times R}$. Noted that A, B and C have the same R columns. The symbol '$\circ$' represents a vector outer product. $\mathcal{E}$ is a three-way tensor containing the residuals.

CP decomposition is typically solved using ALS technique. The technique iteratively solves each component matrix using a least square method by fixing all the other components and the procedure is repeated until it converges[29]. The results by CP are unique provided that we permute the rank-one components[32]. The algorithm for CP decomposition using ALS is described in Algorithm 1.

Algorithm 1 Tensor decomposition CP-ALS

Input: Tensor $\mathcal{X}$, number of components R
Output: Component matrices A, B and C

Initialize A, B and C
repeat
  $A = \text{argmin}_A \frac{1}{2} \left\| X_{(1)} - A(C \odot B)^\top \right\|^2$ (fixing B and C)
  $B = \text{argmin}n_B \frac{1}{2} \left\| X_{(2)} - B(C \odot A)^\top \right\|^2$ (fixing A and C)
  $C = \text{argmin}_C \frac{1}{2} \left\| X_{(3)} - C(B \odot A)^\top \right\|^2$ (fixing A and B)
  ($X_{(i)}$ is an unfolding matrix of $\mathcal{X}$ in mode i and $\odot$ is the Khatri-Rao product)
until convergence

2.2 *Incremental Tensor Update*

In many SHM applications, an ongoing monitoring and a real-time response of the SHM system are required. It is time consuming to do the tensor decomposition in a batch manner when new data come in. Therefore, incremental tensor learning is investigated to update the decomposed component matrices (i.e. matrices A, B and C) of a new tensor when new data arrive without decomposing the whole tensor as in Section 2.1.1. In this work, we will use a technique called onlineCP-ALS[33] to incrementally track component matrices decomposed by CP over time. Assuming that we only have a three-way tensor as in a typical SHM problem with component matrices A, B and C. The authors proposed a technique to incrementally update these matrices as the followings.

2.2.1 *Update temporal mode C*

Due to an arrival of new information (new frontal slices in time mode), additional rows will be added to component matrix C. By fixing A and B, we can solve C as[34],

$$C = \text{argmin}_C \frac{1}{2} \left\| X_{(3)} - C(B \odot A)^\top \right\|$$
$$= \text{argmin}_C \frac{1}{2} \left\| \begin{bmatrix} X_{old(3)} - C_{old}(B \odot A)^\top \\ X_{new(3)} - C_{new}(B \odot A)^\top \end{bmatrix} \right\|.$$

Thus,

$$C = \begin{bmatrix} C_{old} \\ C_{new} \end{bmatrix} = \begin{bmatrix} C_{old} \\ X_{new(3)}((B \odot A)^\top)^\dagger \end{bmatrix}, \tag{2}$$

where $\dagger$ is a matrix pseudo-inverse. Therefore, new rows added to C can be estimated using only new information in time mode,

$$C_{new} = X_{new(3)}((B \odot A)^\top)^\dagger \tag{3}$$

2.2.2 Update non-temporal mode A and B By fixing B and C, the optimization function can be written as $\frac{1}{2}\left\|X_{(1)} - A(C \odot B)^\top\right\|^2$. Taking the derivative of this function with regard to A and setting it to zero, we have

$$A = \frac{X_{(1)}(C \odot B)}{(C \odot B)^\top (C \odot B)} = PQ^{-1}$$

where $P = X_{(1)}(C \odot B)$ and $Q = (C \odot B)^\top (C \odot B)$.

Directly calculating P and Q is costly since $(C \odot B)$ is a big matrix. By representing $X_{(1)}$ and C with *old* and *new* information, we can have [34]:

$$P = P_{old} + X_{new(1)}(C_{new} \odot B)$$

Likewise, Q can be estimated as

$$Q = Q_{old} + C_{new}^\top C_{new} \circ B^\top B$$

Therefore, A can be computed as,

$$A = \frac{P_{old} + X_{new(1)}(C_{new} \odot B)}{Q_{old} + C_{new}^\top C_{new} \circ B^\top B} \tag{4}$$

Similarly,

$$B = UV^{-1} = \frac{U_{old} + X_{new(2)}(C_{new} \odot A)}{V_{old} + C_{new}^\top C_{new} \circ A^\top A} \tag{5}$$

We can see that by storing information from previous decomposition (i.e. P, Q, U and V), components matrices A and B are updated using only new information arriving in time mode.

2.2.3 onlineCP-ALS For a three-way tensor that grows with time (C mode), based on the above formulation, a two-staged procedure is proposed to incrementally update tensor component matrices. First, P, Q, U and V are initialized using a training tensor. Then when new data arrive, component matrices C, A and B are updated using Equations 2, 4 and 5, respectively. A, B and C are iteratively updated until convergence. Since the computational complexity for each iteration is only dependent on new data, this ALS style update is much faster than the batch version of ALS tensor decomposition. The technique, which is called onlineCP-ALS, is described in Algorithm 2 [33].

Algorithm 2 Incremental Tensor Update: onlineCP-ALS

Input: Train tensor data $\mathcal{X}_{train}$
Output: Component matrices A, B, C when new data arrive

1: **Initialization/training stage:**
$P = X_{train(1)}(C \odot B)$
$Q = C^\top C \circ B^\top B$
$U = X_{train(2)}(C \odot A)$
$V = C^\top C \circ A^\top A$
2: **Update/testing stage:** when new data come in as new slices appended to time mode
Repeat
C is updated using Equation 2 (fixing A and B)
A is updated using Equation 4 (fixing B and C)
B is updated using Equation 5 (fixing A and C)
Until convergence

2.3 Online Damage Identification

Damage identification was classified by Rytter into four different levels of complexity [35]: damage detection (level 1), localization (level 2), severity assessment (level 3) and failure prediction (level 4). Among the four, level 4 requires an understanding of the physical characteristics of the damage progression in the structure. Level 1 can be solved using a one-class learning while levels 2 and 3 usually require a supervised learning approach [36].

Since we usually only have data associated with healthy states of structures, a one-class approach is more practical. In this work, using incremental tensor analysis and one-class support vector machine (SVM) [37], we are able to detect, localize and assess damage progress online in a one-class manner. One-class SVM finds a small region to cover most data from one-class (i.e. healthy data) and anomalies elsewhere. It is done by mapping the data into a feature space using a kernel and then separating them from the origin with maximum margin [37]. It has been used as a robust anomaly detection method in many application domains, including in SHM [38].

This section describes an approach to identify damage in real-time using incremental tensor analysis as shown in Figure 2. Vibration responses of the structure are measured over time by strain gauges or other kinds of sensors. Next,

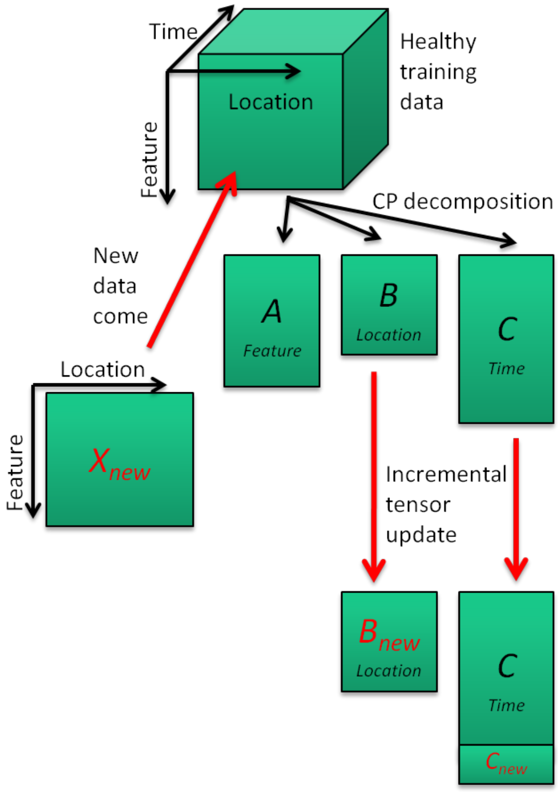


Figure 2. Incremental tensor analysis for online damage identification.

features are extracted from the raw data of all sensors, which form a three-way tensor data. Then the tensor is decomposed into matrices of different modes as described in Section 2.1. A benchmark model is built and when new data arrive, the tensor component matrices will be updated for damage identification.

2.3.1 Building a Benchmark Model Given a three-way tensor $\mathcal{X}_{train}$ $(feature \times location \times time)$ which represents data in a healthy condition of a structure. $\mathcal{X}_{train}$ is decomposed into three component matrices A, B and C using CP decomposition (Section 2.1.1). Each row of C represents an event in time mode. Using a one-class SVM[37], we build a model using healthy training events which are represented by rows of the component matrix C.

In this stage, matrices P, Q, U and V are initialized as described in Algorithm 2.

2.3.2 Damage identification Due to an arrival of a new event (a new frontal slice X_{new} in time mode), an additional row C_{new} is added to the component matrix C, and matrices A and B are also incrementally updated as described in Algorithm 2.

After having C_{new}, this new row will be checked if it agrees with the benchmark model built in the training stage, indicating the condition of the structure. In case of one-class SVM, a negative decision value indicates that the new event is likely a damaged event.

Figure 3. Illustration of the cable-stayed bridge.

In order to localize the positions of damage, location matrix B, where each row captures meaningful information for each sensor location, is analyzed. By analyzing B_{new} when each new data instance arrives, it is able to find anomalies, which correspond to damaged locations. In this work, a distance from a sensor obtained from a new tensor (a row in B_{new}) to the same sensor obtained from the training data (the same row in B) is used as an anomaly score to localize damage.

To estimate the extent of the damage, we analyze decision values returned from the one-class SVM model. The rationality is that a structure with a more severe damage (e.g. a longer crack) will behave more differently from a normal behaviour. Different ranges of the decision values may present different severity levels of damage.

3 Case Study: Cable-Stayed Bridge

A cable-stayed bridge over the Great Western Highway in the state of New South Wales, Australia (33°45′ 50.49″S, 150°44′31.14″E) has been considered as a case study in this research[26]. Figure 3 shows an illustration of the bridge. The cable-stayed bridge has a single A-shaped steel tower with a composite steel-concrete deck. The bridge is composed of 16 stay cables with semi-fan arrangement. The span and the tower height are 46m and 33m, respectively. This bridge carries one traffic lane and one side-walk with maximum loading capacity of 30t. The deck has a thickness of 0.16m and a width of 6.3m and it is supported by four I-beam steel girders. The girders are internally attached by a set of equally-spaced cross girders (CG) as depicted in Figure 4.

Figure 4. Illustration of the longitudinal and lateral girders under the deck.

3.1 Instrumentation

A dense array of sensing system, including strain gauge and accelerometer sensors has been deployed on this bridge since July 2016[5,39]. All the sensors are timely synchronised and are continuously measuring the dynamic response of the bridge under normal operation at 600 Hz. The measured data are recorded in a file every 10 minutes. An HBM Quantum-X data acquisition system is used for signal conditioning and data logging. The Quantum system provides an integrated and reliable device to log high quality data with 24 bit resolution with bandwidth capability of 0 to 3kHz.

3.1.1 Strain Gauge Sensors: Each cable has been instrumented with a full axial Wheatstone bridge to measure the dynamic strain response of the cables. The sensors have been mounted 1m above the cable end. Figures 5a and 5b schematically show the location of strain gauges SA1 to SA8 which are, respectively, installed on cables 1 to 8. After the test, it was realised that sensor SA4 was not operational, thus, this sensor was eliminated from the analysis. The strain gauges were configured to be positive in tension with a suitable coefficient of thermal expansion for steel to be immune to thermal creep. In this study, the strain response of the cables under ambient excitation is employed for damage identification.

3.1.2 Accelerometer Sensors: A grid of 24 uniaxial accelerometers has been installed under the bridge deck at the intersection of the longitudinal girders and the floor beams (corss girders). Figure 5c schematically illustrates the location of the mounted accelerometers. They are low-noise Silicon Designs accelerometers and can detect accelerations within the range of 62g with an output noise of 10mg/Hz and sensitivity of 2,000mV/g.

In this research the acceleration response of the bridge under ambient excitation is employed to identify the dynamic characteristics of the bridge at each damage case. To this aim, operational modal analysis (OMA) using the covariance-driven stochastic subspace (SSI-Cov) technique is adopted to process the output-only acceleration responses[5].

4 Description of Damage Scenarios

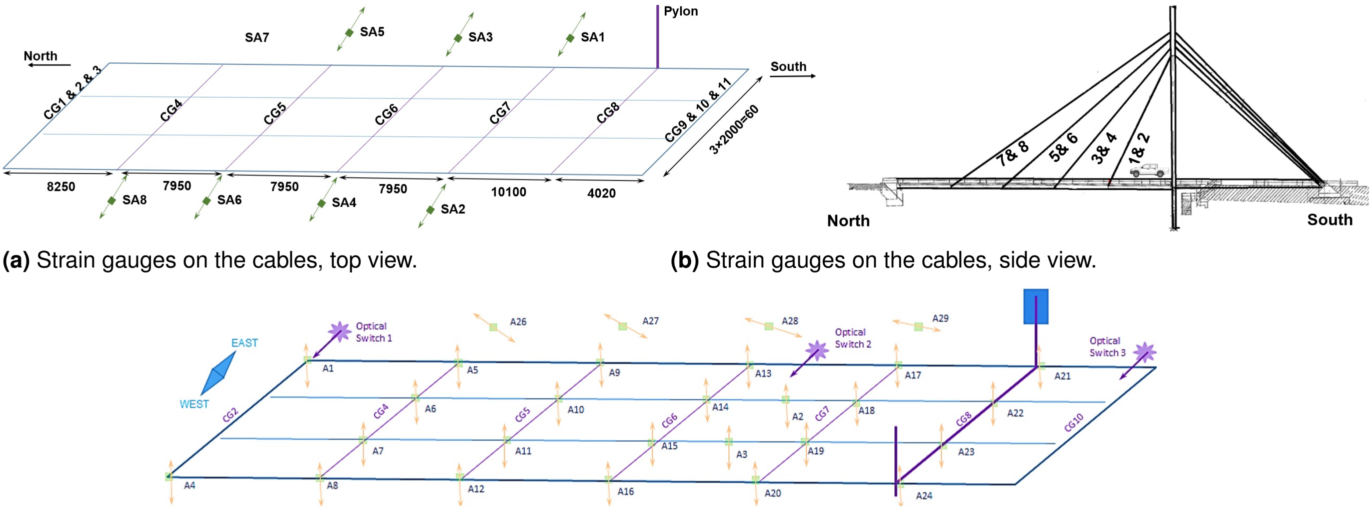
In total 16 different states of the structure including, intact condition and 15 damage conditions are considered to investigate the robustness of the proposed framework for damage identification. The acceleration responses of the bridge at each 16 state are obtained from all 24 accelerometers and processed using SSI-Cov to extract the fundamental frequency of the bridge.

4.1 Emulated Damage

In this study, we emulated damage by locating stationary mass on the bridge at different locations as real damage was not available. In the context of SHM of bridge structures, it is quite a common practice to emulate damage by locating stationary lumped mass on the bridge[40,41]. Two extensive field experiments were conducted on this bridge which are refereed to ”Bus Damage Test” and ”Car Damage Test” .

The Bus Damage Test was conducted on 28^{th} of October 2016 in which a 13t three-axle bus was placed at stationary location at mid-span of the bridge for duration of five minutes. This damage scenario is referred to Damage Case 1 (DC1). During this test a temperature variation of 16° to 19° was observed. Figure 6 shows an illustration of test vehicle in DC1. Due to the distributed effect of mass in DC1, this dataset is not suitable for damage localization and it will be solely adopted for detection and assessment of damage.

In order to ensure the proposed method is capable of locating damage, a separate experiment was considered which is referred to Car Damage Test. It was conducted on 23^{rd} of February 2018. A test vehicle e.g. Holden Colorado Ute was utilised as lumped mass to physically simulate damage. The gross vehicle weight is 2.4t and the distance between the axles is 3.1m. The bridge span was hypothetically divided into 14 equal sections where the length of each section is equal to the length of the vehicle. In each damage case, e.g. Damage Case 2 (DC2) to damage case 15 (DC15), the vehicle was placed in one section for duration of five minutes and the dynamic response of the bridge was recorded under ambient excitation sources.



(a) Strain gauges on the cables, top view.

(b) Strain gauges on the cables, side view.

(c) Accelerometers under the deck.

Figure 5. Schematic illustration of the sensors installed on the bridge including deck and cables.

Figure 6. Illustration of the test vehicle in DC1.

Figure 7. Illustration of the test vehicle in DC2 to DC15.

During each damage test, the bridge was open for people to walk on the bridge, however, due to the narrow width of the bridge, it was impossible to have two passing vehicles on the bridge. Figure 7 illustrates a typical damage test when the vehicle is sat at stationary position on the bridge. The location of the test vehicle at each damage case is specified by the distance of the front axle from the expansion joint at the south end of the bridge when the traffic direction is from the south to the north, see Figures 5a and 5b. For example, in DC2, this distance is equal to 6.2m, in DC3 it is 9.3m (6.2m+3.1m) and in DC15, it is 46.5m (6.2m+13 $\times$3.1m). During the entire test, temperature varied between 27° and 32°. The dataset obtained from this experiment is adopted to validate the performance and robustness of the proposed technique in damage detection and damage localization.

4.2 *Damage Effect on Dynamic Response*

For each damage case, the five-minute vibration response under the ambient excitation was processed to identify the fundamental frequency of the bridge. The bridge is located on top of a hill, thus, it is subjected to wind-induced excitation. Further, it is located over a busy highway, e.g. Great Western HWY which provides adequate source of excitation for the bridge. Figures 8a and 8b respectively, show the 5-minute dynamic response of the bridge in DC7 obtained from accelerometer A14 and strain gauge SA6, (see Figures 5a and 5c). As seen, the bridge is vibrating with its natural frequencies under the ambient excitation. To further investigate this, the first singular value of the power spectral density (PSD) matrix[42] obtained from all the accelerometer sensors was plotted in Figure 8c. From Figure 8c, the presence of the first several dominant modes of the bridge in the frequency range of [0-20 Hz] is clear; in higher frequencies up to 50 Hz, still the vibration modes can be tracked, however as expected, they are less-excited. This investigation demonstrates that the ambient excitation provides adequate source of energy to excite the vibration modes.

Fully automated OMA[5] is adopted to analyze the acceleration response of the bridge at each damage case. The fundamental frequency of the bridge was extracted and compared with the healthy state where no additional mass is located on the bridge. Table 1 presents the fundamental frequency at each damage case and the corresponding change in (%) compared to the healthy state . The natural frequency of the bridge in its intact condition is 2.07 Hz and by locating the small car at different locations on the bridge (DC2 to DC15), a variation between 0.9% and 4.4% in the natural frequency is obtained. As expected, when the car is sitting close to the either end of the bridge, minimum change is observed whereas when the car is sitting close to the cross girder 5, where maximum of the first bending mode occurs, maximum change of 4.4% happens. In DC1, a considerable change of 13% in the first frequency compared to the intact state happens.

5 Damage Identification Results

5.1 Feature Extraction for Tensor Analysis

In this research, the change in the cable-forces is adopted for damage identification as any damage in the structure changes the distribution of the cable-forces. Ambient strain responses from each cable sensor in both healthy and damage cases were split into events of 5 seconds for analysis. Then the following steps were applied to extract feature for our damage identification.

First, the dynamic strain responses due to the live load effects from each cable (except SA4 which has been eliminated due to the sensor issue, see Section 3) were normalized by subtracting the average strain from the same cable in the healthy training data. Then the normalized strain was transformed into a unique direction by taking into account the orientation of each cable and then the contribution from the cables at east side of the bridge and at west side of the bridge was averaged. This resulted in four time series responses e.g. SA1&2, SA3, SA5&6 and SA7&8. Since each strain response had 3000 samples (5 seconds at 600 Hz) and there were 4 locations of strain feature, the data formed a tensor of $(3000\ feature \times 4\ locations \times 928\ events)$ where 928 were the number of healthy events and damage events (including 14 car damage cases and 1 bus damage case).

5.2 Damage Detection and Severity Assessment

Eighty percent of the healthy events were randomly selected as a training tensor for building a healthy benchmark model using tensor decomposition and one-class SVM (Section 2.3.1). The remaining healthy events and all damage events were used as test data. Using the approach in Section 2.3.2, all test data were evaluated against the training model. For all experiments, we have used the core consistency diagnostic technique (CORCONDIA) method described in[43] to decide the number of latent factors R in the CP method. This method suggested $R = 2$ for all experiments. The Gaussian kernel with $\gamma = 0.01$ and $\nu = 0.05$ was used in one-class SVM for anomaly detection.

Figure 9 shows the decision values returned by the one-class SVM model for test data, including healthy events, car damage events and bus damage events. The black 'X' is the average decision value for each type of events. The results show that the method successfully detect damage with high accuracy ($F_1 score = 99.86\%$). It also show that bus damage events had more negative decision values than car damage events, which can be used to assess the severity of damage.

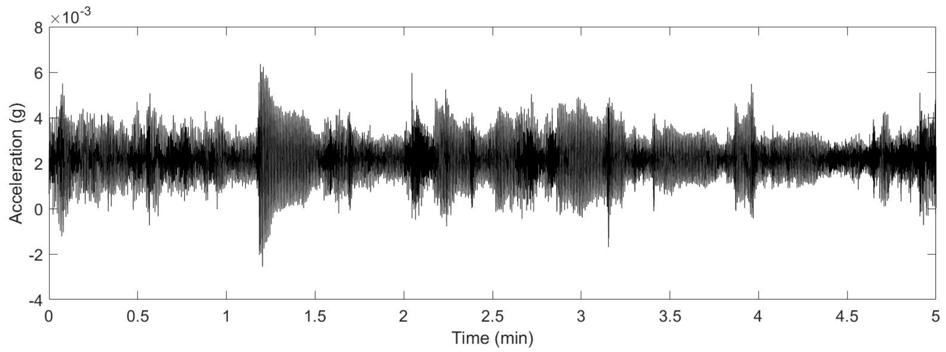
5.3 Damage Localization

Using the approach in Section 2.2, component matrix B_{new} was incrementally updated for every new test event. For each test event, sensor scores at each location were computed as described in Section 2.3.2. Figure 10 shows the sensor scores for different damage cases including, DC2 (where the car is close to CG8 (see Figure 5c for cross girder (CG) locations)), DC5 (where the car is close to CG7), DC8 (where the car is close to CG6) and DC11 (where the car is close to CG5).

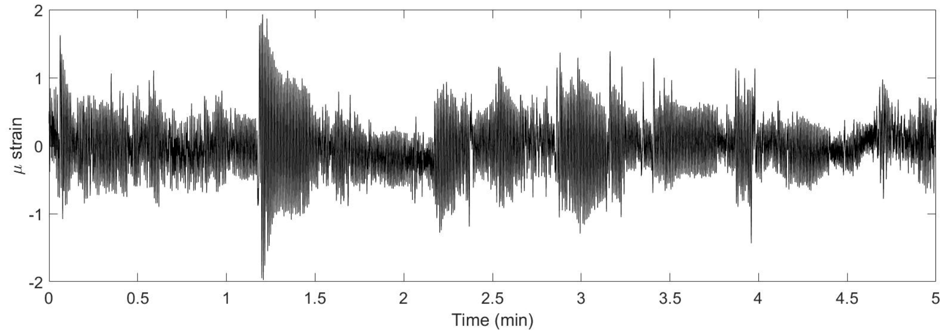
In test DC2, SA1&2 which are the closest strain gauges to the car locations were captured as a sensor with the most change. Test DC5 was also successfully localized as SA1&2 was picked up. However, in test DC8 (close to SA3), SA5&6 were captured while SA3 was the sensor with the second most change. Note that SA3&4 signals were not averaged as other pair of cable sensors due to the sensor issue in SA4. Finally, DC11 was successfully localized by identifying SA5&6 as damage location. Similar trends were obtained for the other damage cases. In short, our investigation results show that tensor analysis has potential to localize damage.

6 Conclusion

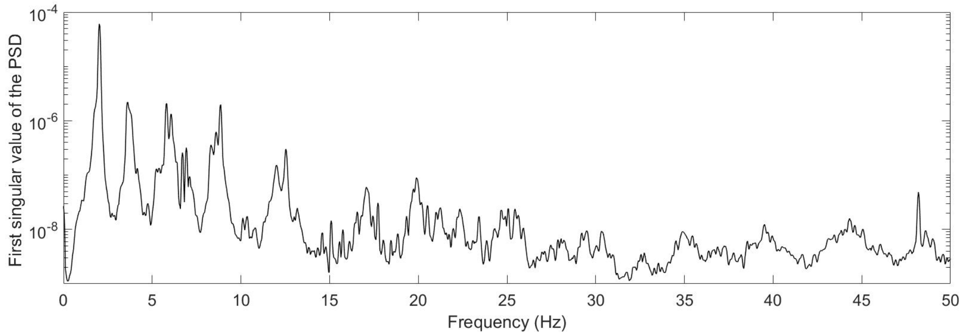
This paper presented a novel method to use a multi-way tensor analysis to identify damage for SHM, including



(a) The acceleration response obtained from sensor A14.



(b) The strain response obtained from sensor SA6.



(c) The first singular value of the PSD matrix obtained from all the accelerometers.

Figure 8. Dynamic response of the bridge in damage case 7 (DC7).

Table 1. The fundamental frequency and the corresponding change compared to the healthy state in each damage case.

H	DC1	DC2	DC3	DC4	DC5	DC6	DC7	DC8	DC9	DC10	DC11	DC12	DC13	DC14	DC15
2.07	1.80	2.05	2.05	2.05	2.05	2.01	2.01	1.98	1.98	1.98	1.98	2.01	2.01	2.05	2.05
0%	13%	0.9%	0.9%	0.9%	0.9%	2.7%	2.7%	4.4%	4.4%	4.4%	4.4%	2.7%	2.7%	0.9%	0.9%

detection, localization and severity assessment in an unsupervised manner. The technique forms healthy sensing data as a tensor and uses tensor analysis to fuse data from different sensors and build a benchmark model using one-class SVM. When new data arrive, tensor component matrices are incrementally updated and used for online damage identification.

The proposed technique was evaluated using data collected from our deployed extensive SHM system on a cable-stayed bridge in operation in Western Sydney. The technique was able to detect emulated damage on the bridge with an $F_1 score$ of 99.86%. It is also able to assess different damage severity. Moreover, the damage was successfully located in many damage cases.

The contribution of the work is three-fold; first, an extensive structural health monitoring system was deployed on a cable-stayed bridge in operation; second, an incremental tensor analysis was proposed to analyze time series responses from multiple sensors for online damage identification; and finally, the robustness of the proposed method was validated using extensive field-test data by considering various damage scenarios in presence of environmental and operational variabilities. In the future, we will investigate more robust feature extraction and abnormality measure to improve damage localization and

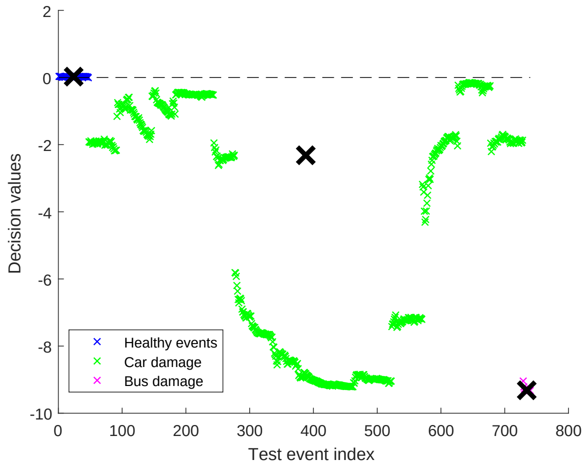


Figure 9. Damage detection and severity assessment.

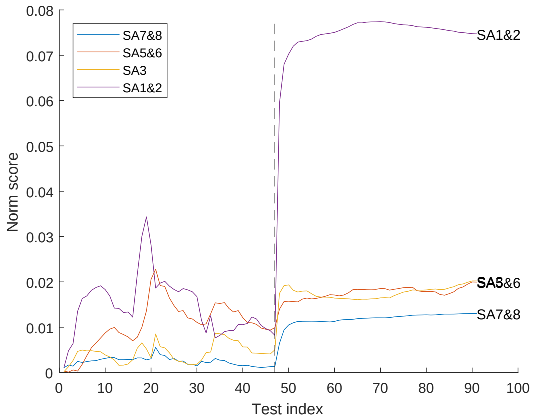
damage assessment. Also, a tensor fusion approach, which integrates signals from different type of sensors (e.g. accelerometers and strain gauges), has a potential to improve damage identification compared with the use of one type of sensor.

Acknowledgements

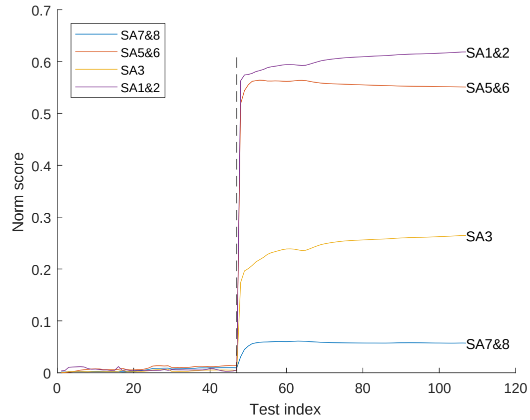
NICTA is funded by the Australian Government through the Department of Communications and the Australian Research Council through the ICT Centre of Excellence Program. CSIRO's Digital Productivity business unit and NICTA have joined forces to create digital powerhouse Data61. The instrumentation of this bridge has been planned and conducted by researchers at Data61. The authors also would like to thank the Western Sydney University and University of New South Wales for facilitating the field tests and data collection process.

References

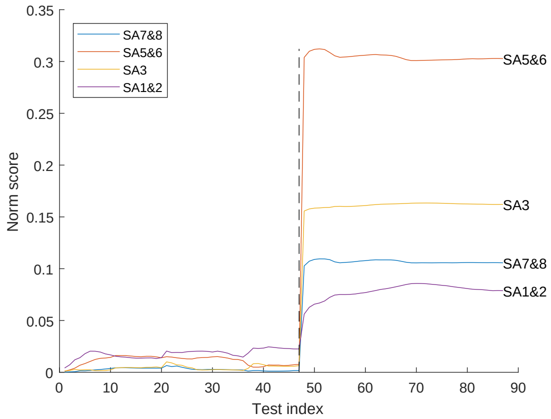
1. Ren WX and Peng XL. Baseline finite element modeling of a large span cable-stayed bridge through field ambient vibration tests. *Computers & structures* 2005; 83(8-9): 536–550.
2. Li H and Ou J. The state of the art in structural health monitoring of cable-stayed bridges. *Journal of Civil Structural Health Monitoring* 2016; 6(1): 43–67.
3. Diord S, Magalhães F, Cunha Á et al. High spatial resolution modal identification of a stadium suspension roof: Assessment of the estimates uncertainty and of modal contributions. *Engineering Structures* 2017; 135: 117–135.
4. Cunha A, Caetano E and Delgado R. Dynamic tests on large cable-stayed bridge. *Journal of Bridge Engineering* 2001; 6(1): 54–62.
5. Sun M, Makki Alamdari M and Kalhori H. Automated operational modal analysis of a cable-stayed bridge. *Journal of Bridge Engineering* 2017; 22(12): 05017012.
6. Asadollahi P and Li J. Statistical analysis of modal properties of a cable-stayed bridge through long-term wireless structural health monitoring. *Journal of Bridge Engineering* 2017; 22(9): 04017051.
7. An Y, Zhong Y, Tan Y et al. Experimental and numerical studies on a test method for damage diagnosis of stay cables. *Advances in Structural Engineering* 2017; 20(2): 245–256.
8. Ding YL, Li AQ and Deng Y. Structural damage warning of a long-span cable-stayed bridge using novelty detection technique based on wavelet packet analysis. *Advances in Structural Engineering* 2010; 13(2): 291–298.
9. Ko J, Sun Z and Ni Y. Multi-stage identification scheme for detecting damage in cable-stayed kap shui mun bridge. *Engineering structures* 2002; 24(7): 857–868.
10. Mao JX, Wang H, Feng DM et al. Investigation of dynamic properties of long-span cable-stayed bridges based on one-year monitoring data under normal operating condition. *Structural Control and Health Monitoring* 2018; .
11. Soo Lon Wah W, Chen YT, Roberts GW et al. Separating damage from environmental effects affecting civil structures for near real-time damage detection. *Structural Health Monitoring* 2017; : 1475921717722060.
12. Nazarian E, Ansari F, Zhang X et al. Detection of tension loss in cables of cable-stayed bridges by distributed monitoring of bridge deck strains. *Journal of Structural Engineering* 2016; 142(6): 04016018.
13. Lin SW, Yi TH, Li HN et al. Damage detection in the cable structures of a bridge using the virtual distortion method. *Journal of Bridge Engineering* 2017; 22(8): 04017039.
14. Haji Agha Mohammad Zarbaf SE, Norouzi M, Allemang RJ et al. Stay force estimation in cable-stayed bridges using stochastic subspace identification methods. *Journal of Bridge Engineering* 2017; 22(9): 04017055.
15. Mehrabi AB. In-service evaluation of cable-stayed bridges, overview of available methods and findings. *Journal of Bridge Engineering* 2006; 11(6): 716–724.
16. Zhang R, Duan Y, Or SW et al. Smart elasto-magneto-electric (eme) sensors for stress monitoring of steel cables: design theory and experimental validation. *Sensors* 2014; 14(8): 13644–13660.
17. Li H, Ou J and Zhou Z. Applications of optical fibre bragg gratings sensing technology-based smart stay cables. *Optics and Lasers in Engineering* 2009; 47(10): 1077–1084.
18. Christen R, Bergamini A and Motavalli M. Three-dimensional localization of defects in stay cables using magnetic flux leakage methods. *Journal of nondestructive evaluation* 2003;



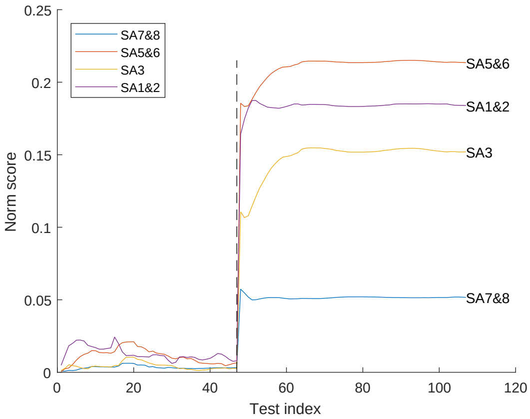
(a) Test DC2



(b) Test DC5



(c) Test DC8



(d) Test DC11

Figure 10. Damage localization results for four investigated damage cases.

22(3): 93–101.

19. Xu Y, Brownjohn J and Kong D. A non-contact vision-based system for multipoint displacement monitoring in a cable-stayed footbridge. *Structural Control and Health Monitoring* 2018; .
20. Zejli H, Gaillet L, Laksimi A et al. Detection of the presence of broken wires in cables by acoustic emission inspection. *Journal of Bridge Engineering* 2012; 17(6): 921–927.
21. Mehrabi AB. Assessment of in-service cable stayed bridgesapproach and findings. In *Structures Congress 2006: Structural Engineering and Public Safety*. pp. 1–8.
22. Sukhorukov V, Sukhorukov D, Slesarev D et al. Nondestructive testing of bridge stay cables. In *Structural Materials Technology 2012*. pp. 347–352.
23. Zhang S, Shen R, Wang T et al. A two-step fem-sem approach for wave propagation analysis in cable structures. *Journal of Sound and Vibration* 2018; 415: 41–58.
24. Weng JH, Loh CH, Lynch JP et al. Output-only modal identification of a cable-stayed bridge using wireless monitoring systems. *Engineering Structures* 2008; 30(7): 1820–1830.
25. Liao W, Wang D and Huang S. Wireless monitoring of cable tension of cable-stayed bridges using pvdf piezoelectric films. *Journal of Intelligent Material Systems and Structures* 2001; 12(5): 331–339.
26. Anaissi A, Makki Alamdari M, Rakotoarivelo T et al. A tensor-based structural damage identification and severity assessment. *Sensors* 2018; 18(1): 111.
27. Acar E and Yener B. Unsupervised multiway data analysis: A literature survey. *IEEE Transactions on Knowledge and Data Engineering* 2009; 21(1): 6–20.
28. Khoa NLD, Zhang B, Wang Y et al. *PAKDD 2015, Vietnam, May 19-22, 2015, Proceedings, Part I*, chapter On Damage Identification in Civil Structures Using Tensor Analysis. Cham: Springer International Publishing. ISBN 978-3-319-18038-0, 2015. pp. 459–471.
29. Kolda TG and Bader BW. Tensor decompositions and applications. *SIAM Review* 2009; 51(3): 455–500.
30. Papalexakis EE, Faloutsos C and Sidiropoulos ND. Tensors for data mining and data fusion: Models, applications, and scalable algorithms. *ACM Transactions on Intelligent Systems and Technology (TIST)* 2016; 8(2): 16.

31. Acar E, Aykut-Bingol C, Bingol H et al. Multiway analysis of epilepsy tensors. *Bioinformatics* 2007; 23(13): i10–i18.
32. Kolda TG and Sun J. Scalable tensor decompositions for multi-aspect data mining. In *ICDM 2008: Proceedings of the 8th IEEE International Conference on Data Mining*. pp. 363–372.
33. Khoa NLD, Anaissi A and Wang Y. Smart infrastructure maintenance using incremental tensor analysis: Extended abstract. In *Proceedings of the 2017 ACM on Conference on Information and Knowledge Management*. CIKM '17, New York, NY, USA: ACM. ISBN 978-1-4503-4918-5, pp. 959–967.
34. Zhou S, Vinh NX, Bailey J et al. Accelerating online cp decompositions for higher order tensors. In *Proceedings of the 22Nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. KDD '16, New York, NY, USA: ACM. ISBN 978-1-4503-4232-2, pp. 1375–1384.
35. Rytter A. *Vibration-based inspection of civil engineering structures*. PhD Thesis, University of Aalborg, Denmark, 1993.
36. Worden K and Manson G. The application of machine learning to structural health monitoring. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* 2007; 365(1851): 515–537.
37. Schölkopf B, Williamson RC, Smola AJ et al. Support vector method for novelty detection. In *NIPS*. pp. 582–588.
38. Khoa NL, Zhang B, Wang Y et al. Robust dimensionality reduction and damage detection approaches in structural health monitoring. *Structural Health Monitoring* 2014; 13(4): 406–417.
39. Kalhori H, Alamdari MM, Zhu X et al. Traffic data collection using a bridge-weigh-in-motion system in a cable-stayed bridge. In *Austroads Bridge Conference, 10th, 2017, Melbourne, Victoria, Australia*.
40. Kody A, Li X and Moaveni B. Identification of physically simulated damage on a footbridge based on ambient vibration data. In *Structures Congress 2013: Bridging Your Passion with Your Profession*. pp. 352–362.
41. Lederman G, Wang Z, Bielak J et al. Damage quantification and localization algorithms for indirect shm of bridges. In *Proc. Int. Conf. Bridge Maint., Safety Manag., Shanghai, China*.
42. Brincker R, Zhang L and Andersen P. Modal identification from ambient responses using frequency domain decomposition. In *Proc. of the 18*International Modal Analysis Conference (IMAC), San Antonio, Texas*.
43. Bro R and Kiers HA. A new efficient method for determining the number of components in parafac models. *Journal of chemometrics* 2003; 17(5): 274–286.