AUSTRALIAN NETWORK OF STRUCTURAL HEALTH MONITORING

Newsletter

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Contents

President's Message

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Dear All,

First of all, let us join together to congratulate Prof Mark Stewart of UTS, one of our ANSHM Advisory Board members together with Prof Chun-Qing Li of RMIT as the first CI, and other researchers, has been awarded an amount of $5m to establish the ARC Training Centre for Whole Life Design of Carbon Neutral Infrastructure, with Mark as the 2nd CI of this ARC ITTC.

For the month of August, I think one of the hot topics in the news and social media is about FIFA Women's World Cup 2023. Our hearts melted when the Matildas was defeated by the European champion, England, in the semi-final. In the match defeating France on 12th August 2023, the attendance at the Suncorp Stadium, Queensland was 49,461, reaching almost 95% of its full capacity

(52,500). This leads to the discussion about the existing facilities for the Olympics. Actually, regarding the preparation for the Olympic Games in 2032, there are different voices about how we plan for the facilities, to upgrade or build new ones for this world event, especially when Victoria in July pulled out of hosting the Commonwealth Games 2026. All these are not related to something that I am familiar with, so I intend not to make any comments. However, one thing we could consider is how SHM could help us prepare for the Olympic Games 2032 in Queensland. We have more than eight years to prepare for this world event. How could current SHM technologies help the design, construction, and maintenance of all these to be upgraded or built facilities and the associated infrastructure? How are the research and development we should focus on so that the findings can be timely achieved for implementation at the facilities and the associated infrastructure to deliver the best benefits? As an example, let us see an interesting "quake" caused by a recent stadium event at Lumen Field, a multi-purpose stadium in Seattle, Washington, USA.

In mid-August, Pacific Northwest Seismic Networks (PNSN) reported an exciting "seismic" event which was triggered, not by a fault, but by a concert at Lumen Field, during the performance of a pop megastar, Taylor Swift[1]. The quake now known as "Swift Quake" was registered on a nearby PNSN strong-motion station KDK, located just outside Lumen Field. The signals recorded by a PNSN station, known as KDK station, were roughly equivalent to a magnitude 2.3 earthquake. It broke the record of "Beast Quake" of 2011, during an athletic event and the activity at the time was close to a magnitude 2.0 earthquake, recorded by the same seismic station, KDK. Below shows a comparison of the ground vibration of the two quakes.

[1] Marczewski, K. (2023), "Beast Quake (Taylor's Version) (From The Vault)", PNSN, https://pnsn.org/blog/2023/08/15/beast-quake-taylor-s-version-from-the-vault

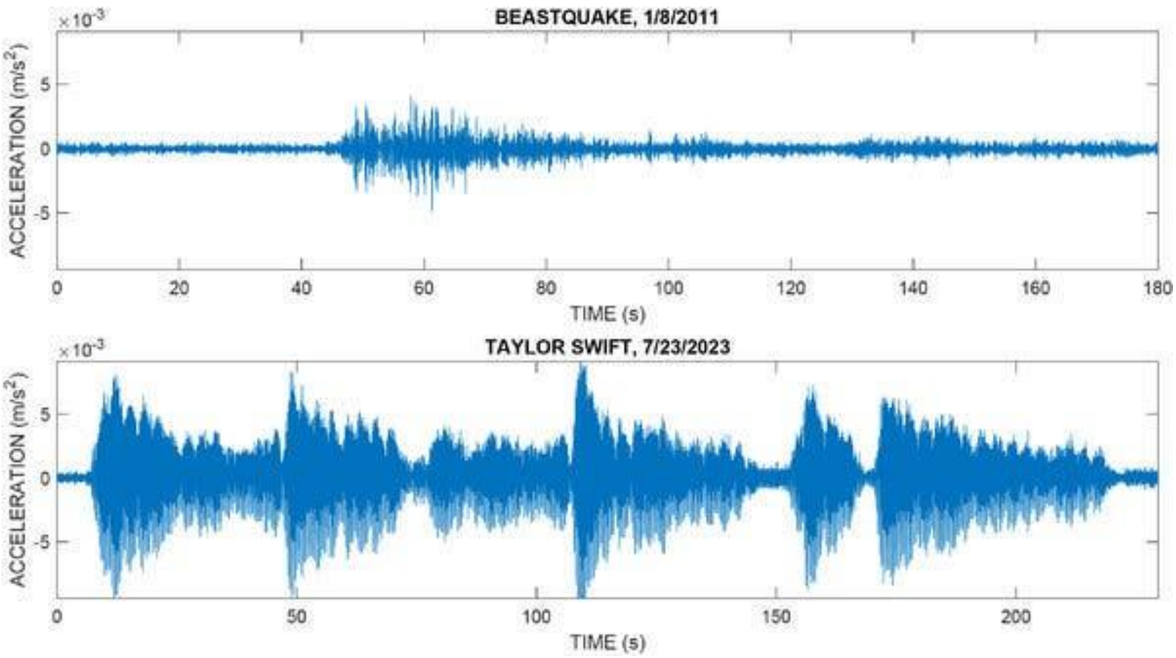

Figure 1: A comparison of the two quakes at a stadium: Top - Beast Quake (2011); and Bottom - Swift Quake (2023) PNSN[1]

It can be seen that the magnitude and duration of the Beast Quake are much smaller and shorter than those of the Swift Quake, but the Beast Quake was only 0.3 magnitude smaller than the Swift Quake, as the Richter scale is logarithmic. Although the two events both happened in the same stadium and were packed full of 70,000 plus people, Prof Jackie Caplan-Auerbach of Western Washington University stated in the report that the comparison may not be fair. She considered "Taylor's concert had the additional help of extremely loud music, which could have given the concert attendees an advantage of coordinating the random jumping and dancing into a more synchronous reaction." This report could give us some insight into our preparation for the Olympic Games 2032. It can be seen that quakes could be caused by activities in a stadium when fans are chanting, jumping, swaying, and cheering, as seen in the game in 2011 and the concert in 2023 at Lumen Field, respectively. Prof Jackie called these quakes Fan Quakes. The same two questions that we, as those working in the field of SHM, should really consider:

1. How current SHM technologies could help the design, construction, and maintenance of all these to-be-upgraded or newly-built facilities and the associated infrastructures?

2. How are the research and development we should focus on so that the findings can be timely achieved for implementation at the facilities and the associated infrastructure to deliver the best benefits?

I addressed those two questions mentioned-above in a special lecture given in a Summer School, entitled “Intelligent Construction” for all graduated students in Jiangsu Province, PRC, organised by Nantong University (NTU). One of my former PhD students, joined NTU after he completed his PhD, is now an Associate Professor in this University. He invited me to give a special lecture about the SHM development in Australia in the Summer School. After Covid 19, we opened a new opportunity and now we do not have to travel overseas and could give a lecture online virtually using a remote meeting platform. On 17th August 2023, I gave a 90-minute lecture to the students and the talk was well received.

Figure 2 Opening Ceremony of the Summer School

In the lecture, besides publicising our book celebrating ANSHM 10th Anniversary (Figure 3), I also stated one of the directions of SHM to address those two questions mentioned-above is to deliver real digital twins for the facilities (upgraded or newly built) and the associated infrastructures.

Figure 3 - Prof Tommy Chan delivering the Special Lecture introducing ANSHM 2nd Monograph, "SHM Research in Australia"

Most often, we can see that many so-called digital twins are only reflecting the spatial properties of a physical entity but could not truly capture its structural behaviours. SHM could help to develop a real digital twin of a structure. With the use of advanced modelling techniques like concurrent multi-scale modelling[2], and substructural modelling[3], we are able to install a smaller number of sensors for digital twinning using SHM techniques. Besides, the use of machine-learning based and/or

[2] Chan, T.H.T., Li, Z.X., Yu, Y. and Sun, Z.H. (2009) "Concurrent Multi-scale Modeling of Civil Infrastructures for Analyses on Structural Deteriorating – Part II: Model Updating and Verification" Finite Elements in Analysis and Design Vol. 45, pp. 795-805.

[3] Jamali, S., Chan, T.H.T., Koo, K.Y., Nguyen, A., and Thambiratnam, D.P. (2018), "Capacity estimation of beam-like structures using substructural method", International Journal of Structural Stability and Dynamics, Vol. 18, No. 12, https://doi.org/10.1142/S0219455418501626.

optimisation-based model updating and damage/deterioration detection techniques[4], we are able to use the digital twins developed to achieve true performance monitoring and health status evaluation for SHM. In the keynote lecture that I am going to present in the forthcoming SHMII-12 in October in Hangzhou, PRC, I will give further discussion on this.

In the last monthly updates, when I mentioned the ANSHM special issues in Structural Health Monitoring, an International Journal (SHMIJ) and the Journal of Civil Structural Health Monitoring (CSHM), I missed one special issue in SHMIJ. To be correct, in the past, we published 3 special issues in CSHM: Vol. 8, No. 5 (2018), Vol. 6, No. 3 (2016), Vol. 3, No. 2 (2013) and 2 special issues in SHMIJ: Vol. 13, No. 4 (2014), Vol. 18, No. 1 (2019). The ANSHM website has also been updated to include the missing SHM special issue. I am really sorry for the confusion which might be generated by this.

Below are the updates for the month.

ANSHM 15th Workshop

Please note the following details for the forthcoming ANSHM 15th Workshop, our annual important event.

Title: The 15th Australian Network of Structural Health Monitoring Workshop &
The Smart Infrastructure Summit 2023
Theme: Infrastructure Digitisation for Net Zero Transition
Hosts: Rockfield Technologies Australia Pty Ltd and James Cook University
Organisers: Dr Govinda Pandey, the CEO of Rockfield, and
A/Prof Ragbin Tuladhar, Head of Engineering,
College of Science and Engineering, JCU
Dates: 23rd - 24th November 2023
with the 25th (Saturday) as an optional day trip to Magnetic Island
(Please mark the dates on your calendar)
Venue: Townsville (exact location to be advised soon)

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[4] Nguyen, A., Kodikara, K.A.T.L, Chan, T.H.T., and Thambiratnam, D.P. (2018), "Deterioration assessment of buildings using an improved hybrid model updating approach and long-term health monitoring data", Structural Health Monitoring, 18 (1), pp. 5-19.

Dr Ulrike Dackermann, ANSHM Workshop Coordinator and I had a meeting with the two organisers of the Workshop, Dr Govinda Pandey and A/Prof Rabin Tuladhar. I am pleased to let you know that the preparation for the Workshop has been progressing very well and the organisers have progress meetings weekly. Day 1 is called the Smart Infrastructure Summit 2023 and the presentations will be by invitation only. Day 2 will follow the ANSHM's traditional Workshop style and the flyer for the call for abstracts of presentations will be distributed soon.

As in previous ANSHM Workshops, ANSHM Advisory Board Meeting (ABM) will be held on the 1st day of the Workshop and the ANSHM Annual General Meeting (AGM) on the 2nd Day. ANSHM Rule 6.5 states that *the quorum for the AGM meetings shall be one half of the number of Core Members plus one*. In order to ensure the quorum requirement could be satisfied, Ulrike conducted a survey to ask the EC/AM members of ANSHM to indicate whether they will attend the forthcoming 15th ANSHM Workshop. I am pleased to let you know that according to the survey, 72% of the Core Members will attend the Workshop.

SHMII-12

I am pleased to let you know that so far we have eight papers/extended abstracts accepted to be presented at the ANSHM Special Session, entitled "Towards Sustainable and Resilient Infrastructure" (SS121) in the 12th International Conference on Structural Health Monitoring of Intelligent Infrastructure (SHMII-12), which will be held on 19th - 22nd October 2023, in Hangzhou, Zhejiang, China. If you still like to join this special session, when submitting papers/extended abstracts using the Conference's official link, https://www.shmii-12.com/, please choose the special session under Australian Network of Structural Health Monitoring (ANSHM): Towards Sustainable and Resilient Infrastructure. However, make sure you will submit it on 31st August 2023, the Final Papers/Extended Abstracts' Submission Deadline.

Please note that the conference registration and hotel reservation portals are now open. SHMII-12 Secretariat encourages those who would like to attend the conference to take advantage of the early bird discount (before September 1, 2023) and greatly reduced conference room rate. For more information concerning the program of the conference, please see the conference website (https://www.shmii-12.com). The website also provides other details, such as information about the Keynote Speakers apart from myself. For any queries, please contact the conference organiser at shmii-12@zju.edu.cn.

ANSHM WebForum
We had our 1st ANSHM Webinar held on 24th August 2023. Many thanks to Brad Dalton, Structural Health Consultant of Furgo presenting Digicampus Computer Vision techniques developed by Fugro, which could be used for Remote Surveying, Thermal Imaging and Visual Vibrometry. There were around 30 ANSHM members from the industry, road authorities, and universities attending the Webinar. We also had a very good discussion after the presentation.

Figure 4 – Brad Dalton presenting how the Imetrum System used to measure a rail bridge

It is interesting to find that after the Webinar, there were many trying to log in to the corresponding Zoom meeting. The recording of Brad's Presentation and the subsequent discussion have been uploaded to ANSHM Youtube Channel. For those who have missed the Webinar or would like to watch it again, the Youtube link is provided below: https://www.youtube.com/watch?v=moZBl5WW7oI.

ANSHM will keep organising this kind of Webforum for SHM Sensor/Service providers to introduce their sensors/services for practical implementation and research collaboration. We will also organise some other forums to discuss SHM-related topics.

ANSHM Executive Committee Meeting

At the time (31st August 2023), I am preparing this President Message, we are going to have our Executive Committee Meeting in the afternoon. Hence, I could only provide outcomes of the meeting as updates of ANSHM in the next monthly updates.

In the next sections, we will have two articles from our members. The first article is titled as A linear universal filter for input and state estimation of structural systems co-authored by Zihao Liu, Mohsen Ebrahimzadeh Hassanabadi and Daniel Dias-da-Costa from School of Civil Engineering, The University of Sydney, Sydney and the second one is a short technical note co-authored internationally by Vahid Reza Gharehbaghi, School of Civil Engineering, University of Kansas, USA and Ehsan Noroozinejad Farsangi, Urban Transformations Research Centre, Western Sydney University with a title of A Breakthrough in Deterioration and Damage Detection for Building Structures.

With kind regards,
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Research profile | **Research publications** | **Google Scholar citations**

A linear universal filter for input and state estimation of structural systems

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ABSTRACT

This paper presents a recursive filtering method for simultaneous input and state estimation of linear structural systems. The proposed method falls within the category of Minimum-Variance Unbiased (MVU) estimators. In contrast to the Augmented Kalman Filter (AKF), the proposed method does not require any assumptions or statistics for estimating unknown input, resulting in a low-cost hyperparameter tuning process. Furthermore, the existing MVU filters, such as Gillijns and De Moor Filters (GDFs), can only be used in either systems without acceleration measurement or systems where the number of accelerations is greater than the number of unknown inputs. On the contrary, the proposed method is universally applicable to any sensor network as long as the number of measurements (of any type) is no less than the number of unknown inputs. Because of this unique characteristic, the proposed method is designated Universal Filter (UF). Numerical tests not only reveal that the UF outperforms the AKF and the GDFs in well-conditioned problems but also demonstrate the ability of the UF to handle ill-conditioned systems where these systems cannot be covered by GDFs.

INTRODUCTION

Recursive filtering methods are widely utilised signal processing techniques that offer real-time frameworks for approximating target quantities in mechanical and infrastructural systems. The approximations are achieved by integrating data from infrequent measurements with a physical model. Applications of filtering estimation methods span structural health monitoring, structural system identification, model updating, and vibration control. Kalman Filter (KF) (Kalman, 1960) is the most frequently employed for structural system identification and monitoring. It had various applications, including predicting fatigue in metal structures (Papadimitriou et al., 2011) and offshore wind turbines (Maes et al., 2016), monitoring structural displacement (Ma et al., 2023), and decoupling physical changes caused by structural damage and varying environmental conditions (Erazo et al., 2019). However, structural system identification presents challenges due to operational dynamic input loads, such as seismic activity, blast loads, vehicular traffic, and wind, as directly measuring these inputs is either costly or unfeasible. In this context, output-only recursive filtering methods offer potential advantages (Lourens & Fallais, 2019). One outstanding output-only input and state estimation technique is the Augmented KF (AKF) (Lourens, Reynders, et al., 2012), which regularises the input estimation problem. The AKF involves augmenting the state vector with unknown inputs and integrating a supplementary fictitious random walk into the process equation with an attributed virtual process noise. This allows the AKF to estimate both the inputs and the state of the system via the routine prediction and update processes of the KF.

The requirement of modelling input evolution (e.g., a random walk) or assigning statistical properties like covariances to inputs may not always be feasible, as such details about inputs are typically unknown. This limitation can be solved by another category of filtering methods that do not rely on input assumptions. Within this group, a pioneering linear Minimum Variance Unbiased (MVU) filter was proposed by Kitanidis (1987). In contrast to the AKF, the input evolution is not involved in the estimation process such that Kitanidis' filter avoids complex hyperparameters tuning related to inputs. However, this filter can only estimate the state and is constrained to system observations without direct transmission. Gillijns and De Moor (2007a) proposed an MVU filter for simultaneous estimation of inputs and states in linear systems, which is only applicable to systems without direct feedthrough – in the context of structural dynamics, this refers to systems without acceleration measurements. This filter is referred to as GDF-WNDF in this paper. To accommodate systems with direct feedthrough, another algorithm was proposed by Gillijns and De Moor (2007b) for joint input and state estimation, referred to as GDF-WDF; this filter requires a full-rank feedforward matrix, implying that the minimum quantity of acceleration measurements must be equal to or more than the number of unknown inputs. A significant limitation of these filters is the rank condition of the feedforward matrix. Therefore, the aforementioned algorithms can only be applied to systems with no direct feedthrough or with a full-rank feedforward matrix.

This paper presents a novel four-step MVU filter for the simultaneous estimation of inputs and states within the field of structural dynamics. The proposed MVU filter eases the requirement of a full-rank feedforward matrix or the absence of a feedforward matrix; in other words, the algorithm is applicable universally, regardless of the rank condition of the feedforward matrix. Based on this feature, the proposed filter will be hereafter referred to as Universal Filter (UF). It should be mentioned that no assumption is made on the input model or statistics, and the input regularisation is not needed within the inverse analysis. Solutions to the estimation errors and the error propagation are derived in their closed form without any simplifications. The optimal input gain is derived from weighted least squares, and the optimal state gain is computed by minimising the trace of the state estimation error covariance. To illustrate the estimation quality of the UF for different inputs and sensor networks, two numerical case studies are presented, and the performance of the UF is compared with AKF and GDFs.

FILTER FORMULATION

System equations

The discrete-time recursive process equation of a linear structural system can be defined by:

$$\mathbf{x}_k = \mathbf{A}_{k-1}\mathbf{x}_{k-1} + \mathbf{G}_{k-1}\mathbf{d}_k + \mathbf{w}_{k-1}. \tag{1}$$

In the above equation, $\mathbf{x}_k \in \mathbb{R}^n$ is the state vector, $\mathbf{d}_k \in \mathbb{R}^m$ is the input vector, and the zero-mean white noise vector $\mathbf{w}_k \in \mathbb{R}^n$ represents the modelling error. Matrices $\mathbf{A}_k \in \mathbb{R}^{n\times n}$ and $\mathbf{G}_k \in \mathbb{R}^{n\times m}$ stand for the system matrix and input matrix. Note that the Zero-Order-Hold assumption in Eq. (1) is different from the existing MVU filters where the input vector is evaluated at timestep $k-1$, which creates one timestep lag between the state and the input.

The observation equation can be written as:

$$\mathbf{y}_k = \mathbf{C}_k\mathbf{x}_k + \mathbf{H}_k\mathbf{d}_k + \mathbf{v}_k, \tag{2}$$

where $\mathbf{y}_k \in \mathbb{R}^p$ is the output vector containing the sensory measurements; the output matrix $\mathbf{C}_k \in \mathbb{R}^{p\times n}$ and the feedforward matrix $\mathbf{H}_k \in \mathbb{R}^{p\times m}$ relates the state and unknown input to the measured quantities $\mathbf{y}_k$. The zero-mean white noise $\mathbf{v}_k \in \mathbb{R}^p$ stands for the measurement noise. Note that in the absence of acceleration measurement, $\mathbf{H}_k = \mathbf{0}$, leading to a system without direct feedthrough, whereas acceleration measurements imply a system with direct feedthrough in which $\mathbf{H}_k \neq \mathbf{0}$.

Filtering steps

A four-step filtering framework is developed for the system defined by Eqs. (1) and (2). First, a biased state estimate $\hat{\mathbf{x}}_{k|k-1}$ of the true state $\mathbf{x}_{k-1}$ is obtained based on the information from the previous timestep:

$$\hat{\mathbf{x}}_{k|k-1} = \mathbf{A}_{k-1}\hat{\mathbf{x}}_{k-1|k-1}. \tag{3}$$

By fusing the biased state estimate $\hat{\mathbf{x}}_{k|k-1}$ and the observation $\mathbf{y}_k$, a minimum-variance unbiased estimate $\hat{\mathbf{d}}_k$ of the true input $\mathbf{d}_k$ can be obtained as:

$$\hat{\mathbf{d}}_k = \mathbf{M}_k\left(\mathbf{y}_k - \mathbf{C}_k\hat{\mathbf{x}}_{k|k-1}\right), \tag{4}$$

where $\mathbf{M}_k$ is the input gain obtained by using weighted least squares. The biased state estimate $\hat{\mathbf{x}}_{k|k-1}$ and the estimate of the input $\hat{\mathbf{d}}_k$ are used to obtain an unbiased a-priori state estimate $\hat{\boldsymbol{x}}_{k|k-1}$:

$$\hat{\boldsymbol{x}}_{k|k-1} = \hat{\mathbf{x}}_{k|k-1} + \mathbf{G}_{k-1}\hat{\mathbf{d}}_k. \tag{5}$$

The a-posteriori state estimate $\hat{\mathbf{x}}_{k|k}$ is calculated by incorporating $\hat{\boldsymbol{x}}_{k|k-1}$, the optimal state gain $\mathbf{K}_k$ and the innovation $\mathbf{y}_k - \mathbf{C}_k\hat{\boldsymbol{x}}_{k|k-1} - \mathbf{H}_k\hat{\mathbf{d}}_k$ by using:

$$\hat{\mathbf{x}}_{k|k} = \hat{\boldsymbol{x}}_{k|k-1} + \mathbf{K}_k\left(\mathbf{y}_k - \mathbf{C}_k\hat{\boldsymbol{x}}_{k|k-1} - \mathbf{H}_k\hat{\mathbf{d}}_k\right). \tag{6}$$

Summary of the filter

The filtering steps and relevant error covariances are presented in Table 1. For detailed derivations of the proposed filter, readers can refer to the work by Ebrahimzadeh Hassanabadi et al. (2023).

Table 1 Summary of the filtering scheme

A. Initialise at $t = t_o$

- Assign $\hat{\mathbf{x}}_{0|0}$
- Assign $\mathbf{P}_0^{\mathbf{x}}$

B. For $t = t_k,\ k = 1,2,\ldots,N$

➢ Input estimation

- $\hat{\mathbf{x}}_{k|k-1} = \mathbf{A}_{k-1}\hat{\mathbf{x}}_{k-1|k-1}$
- $\mathbf{P}_k^{\varepsilon} = \mathbf{C}_k\left(\mathbf{A}_{k-1}\mathbf{P}_{k-1}^{\mathbf{x}}\mathbf{A}_k^T + \mathbf{Q}_{k-1}\right)\mathbf{C}_k^T + \mathbf{R}_k$
- $\mathbf{P}_k^{\mathbf{d}} = \left[\mathcal{G}_k^T(\mathbf{P}_k^{\varepsilon})^{\dagger}\mathcal{G}_k\right]^{\dagger}$
- $\mathbf{M}_k = \mathbf{P}_k^{\mathbf{d}}\mathcal{G}_k^T(\mathbf{P}_k^{\varepsilon})^{\dagger}$
- $\hat{\mathbf{d}}_k = \mathbf{M}_k\left(\mathbf{y}_k - \mathbf{C}_k\hat{\mathbf{x}}_{k|k-1}\right)$

➢ State estimation

- $\hat{\boldsymbol{x}}_{k|k-1} = \hat{\mathbf{x}}_{k|k-1} + \mathbf{G}_{k-1}\hat{\mathbf{d}}_k$
- $\mathbf{P}_k^{\mathbf{xd}} = \left(\mathbf{P}_k^{\mathbf{dx}}\right)^T = -\mathbf{P}_{k-1}^{\mathbf{x}}\mathbf{A}_{k-1}^T\mathbf{C}_k^T\mathbf{M}_k^T$
- $\mathbf{P}_k^{\mathbf{dw}} = \left(\mathbf{P}_k^{\mathbf{wd}}\right)^T = -\mathbf{M}_k\mathbf{C}_k\mathbf{Q}_{k-1}$
- $\mathbf{P}_k^{\boldsymbol{x}} = \mathbf{A}_{k-1}\mathbf{P}_{k-1}^{\mathbf{x}}\mathbf{A}_{k-1}^T + \mathbf{G}_{k-1}\mathbf{P}_k^{\mathbf{d}}\mathbf{G}_{k-1}^T + \mathbf{Q}_{k-1} + \mathbf{A}_{k-1}\mathbf{P}_k^{\mathbf{xd}}\mathbf{G}_{k-1}^T + \mathbf{G}_{k-1}\mathbf{P}_k^{\mathbf{dx}}\mathbf{A}_{k-1}^T + \mathbf{G}_{k-1}\mathbf{P}_k^{\mathbf{dw}} + \mathbf{P}_k^{\mathbf{wd}}\mathbf{G}_{k-1}^T$

- $\mathbf{P}_k^{\mathbf{d}x} = \mathbf{P}_k^{\mathbf{dx}}\mathbf{A}_{k-1}^T + \mathbf{P}_k^{\mathbf{d}}\mathbf{G}_{k-1}^T + \mathbf{P}_k^{\mathbf{dw}}$
- $\mathbf{P}_k^{\mathbf{dv}} = \left(\mathbf{P}_k^{\mathbf{vd}}\right)^T = -\mathbf{M}_k\mathbf{R}_k$
- $\mathbf{P}_k^{\mathbf{v}x} = \mathbf{P}_k^{\mathbf{vd}}\mathbf{G}_{k-1}^T$
- $\mathbf{Y}_k = \mathbf{C}_k\mathbf{P}_k^{x} + \mathbf{H}_k\mathbf{P}_k^{\mathbf{d}x} + \mathbf{P}_k^{\mathbf{v}x}$
- $\mathbf{\Psi}_k = \mathbf{C}_k\mathbf{Y}_k^T + \mathbf{H}_k\left(\mathbf{P}_k^{\mathbf{d}x}\mathbf{C}_k^T + \mathbf{P}_k^{\mathbf{d}}\mathbf{H}_k^T + \mathbf{P}_k^{\mathbf{dv}}\right) + \mathbf{P}_k^{\mathbf{v}x}\mathbf{C}_k^T + \mathbf{P}_k^{\mathbf{vd}}\mathbf{H}_k^T + \mathbf{R}_k$
- $\bar{\mathcal{K}}_k = \mathbf{Y}_k^T\mathbf{U}_k\left(\mathbf{U}_k^T\mathbf{\Psi}_k\mathbf{U}_k\right)^{-1}$
- $\mathbf{K}_k = \bar{\mathcal{K}}_k\mathbf{U}_k^T$
- $\hat{\mathbf{x}}_{k|k} = \hat{\boldsymbol{x}}_{k|k-1} + \mathbf{K}_k\left(\mathbf{y}_k - \mathbf{C}_k\hat{\boldsymbol{x}}_{k|k-1} - \mathbf{H}_k\hat{\mathbf{d}}_k\right)$
- $\mathbf{P}_k^{\mathbf{x}} = \mathbf{K}_k\mathbf{\Psi}_k\mathbf{K}_k^T - \mathbf{Y}_k^T\mathbf{K}_k^T - \mathbf{K}_k\mathbf{Y}_k + \mathbf{P}_k^{x}$

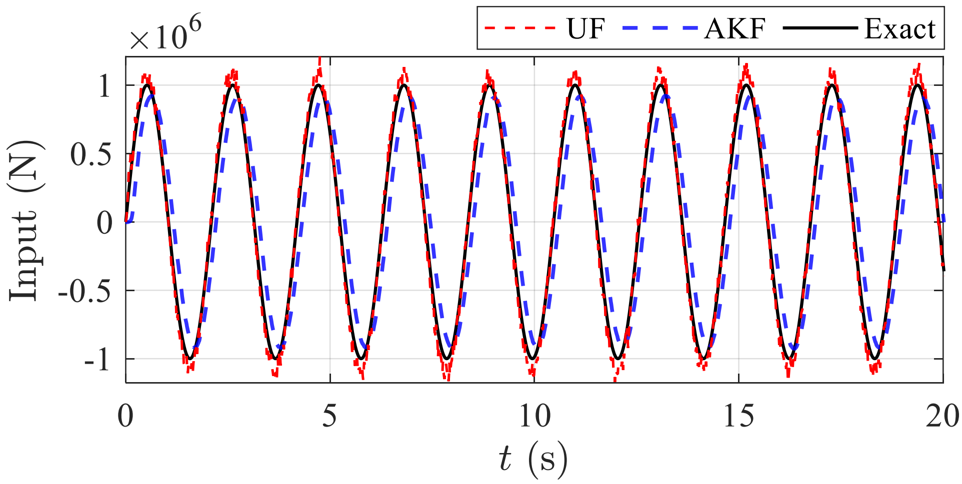
NUMERICAL VALIDATIONS

Two case studies are selected to illustrate the proposed filter. First, a numerical model of an eight-storey shear frame is used to compare the performance of the UF and AKF. Next, the 39-storey Pirelli tower is used to compare the UF with GDFs. Finally, a rank-deficient feedthrough scenario is also presented. Rayleigh damping is assumed with Rayleigh factors $\alpha = \beta = 0.01$ for the following numerical examples, and filters are optimised using a grid search method.

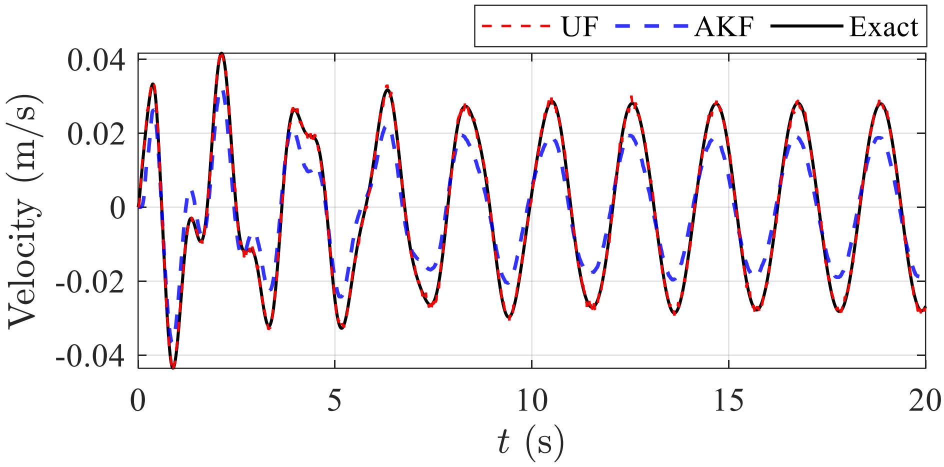
Eight-storey shear building

The purpose of the first numerical model consisting of an eight-storey shear building is used to highlight a known limitation of the AKF (Lourens, Papadimitriou, et al., 2012) stemming from its input regularisation, whereas the UF is an input regularisation-free framework. The parameters of the shear building frame model are taken from De Callafon et al. (2008). The building has eight levels with an inter-storey stiffness of 10^9 N/m and a lumped mass of 625 tonnes at each level. A sinusoidal load defined by $\mathbf{d}(t) = \{10^6 \sin(3t)\}$ N is applied on the top level for an analysis time duration of 20 s. The natural frequencies of the structure range from 7.38 to 78.64 rad/s. Only the first two vibrational modes are considered in the process equation of both AKF and UF to create the modelling error. The sensor network includes a displacement measurement at the 4th level, a velocity measurement at the top level, and an acceleration measurement at the first level.

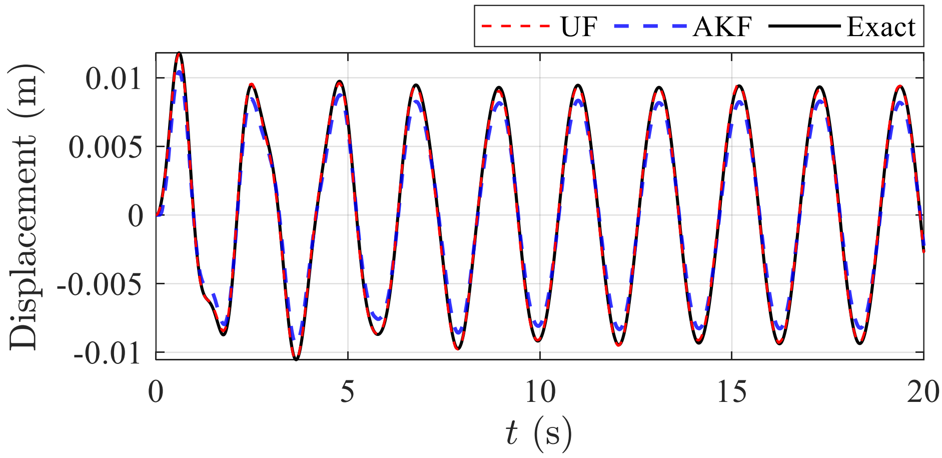
To evaluate the estimation quality, the estimated inputs by the AKF and UF are illustrated in Figure 1(a). While the AKF provides a relatively smooth input estimation compared to the UF, it has delay and underestimation, an issue not found with the UF. Figure 1(b) and (c) present the estimated velocity and displacement, respectively. The displacement estimated by the UF matches the exact values in contrast with the AKF estimation, which is biased and underestimates the displacement. The underestimation is significant in the AKF velocity estimation, whereas the quality of UF estimation should be highlighted is substantially superior.



(a)



(b)



(c)

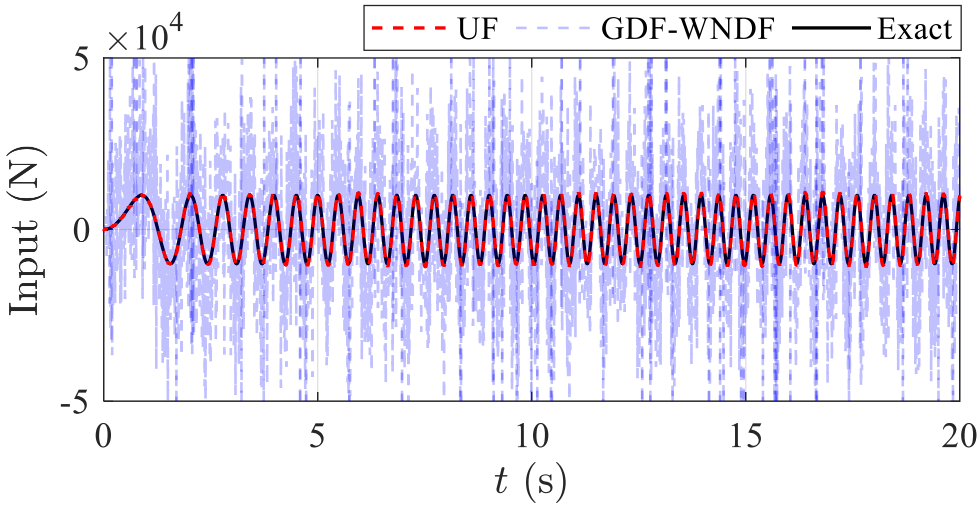
Figure 1 Estimation results by UF and AKF: (a) input, (b) velocity and (c) displacement.

Pirelli tower

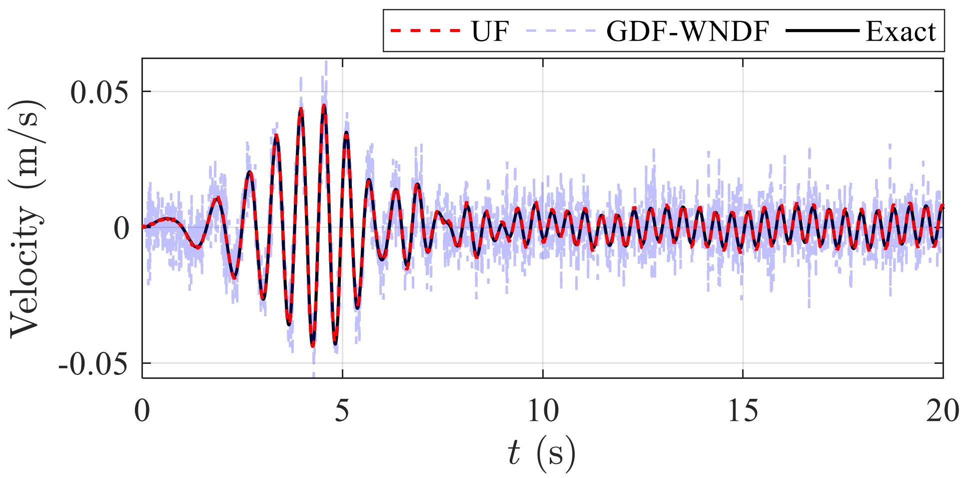
The second numerical example presents the joint input-state estimation using a finite element model of the 39-storey Pirelli tower shown in Figure 2, which was previously studied by Barbella et al. (2011). All nodes in the 3-D model are restrained in the vertical direction, and the study focuses on the lateral vibration of the tower along its longer dimension of the floor plan. The first eight natural modes are used in the process equation of the filter with the natural frequencies ranging from 1.999 to 100.078 rad/s.

Figure 2 Pirelli tower in Milan, Italy

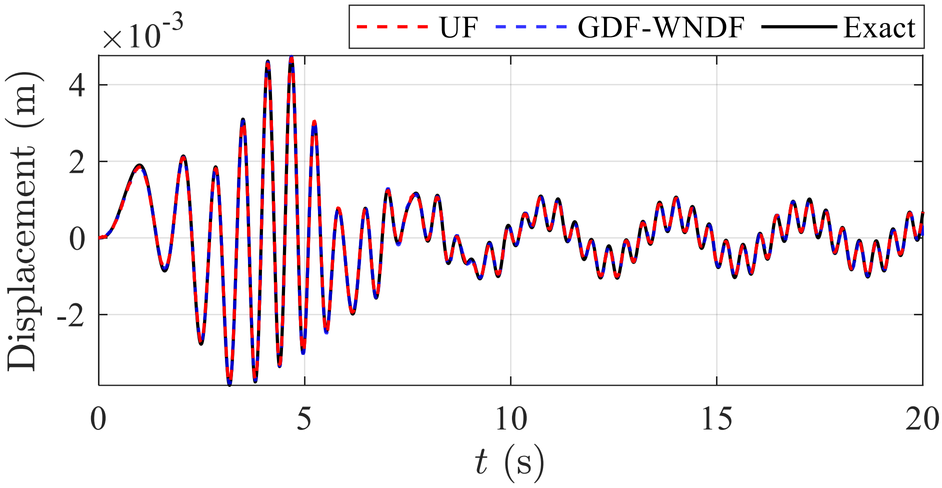
To compare the UF with GDF-WDF, a swept sine load defined by $\mathbf{d}(t) = \{10^3 \sin(\Omega(t)t)\}$ N is applied on the 10^{th} level, in which $\Omega(t) = 10\tan^{-1}(0.2t)$. The observation includes displacement measurements at the 1^{st}, 6^{th}, 22^{nd}, and the 34^{th} levels; and velocity measurements at the 1^{st}, 5^{th}, 15^{th}, 20^{th}, 25^{th}, 30^{th}, 35^{th} and the 39^{th} levels. Only one acceleration measurement is placed at the 1^{st} level leading to a full-rank feedthrough matrix. Fig. 3(a) shows that the noise of input estimation by the GDF-WDF is significantly amplified compared to the UF. Figs. 3(b) and (c), despite both filters correctly predicting the displacement, the velocity estimated by the GDF-WDF is much noisier than the UF. This outcome stems from the different inversion mechanisms embedded within the specific structures of the two filters. The system inversion in the UF is well-conditioned, resulting in enhanced estimation quality.


UF
GDF-WNDF
Exact
$\times 10^4$
5
0
-5
Input (N)
0
5
10
15
20
t (s)

(a)


UF
GDF-WNDF
Exact
0.05
0
-0.05
Velocity (m/s)
0
5
10
15
20
t (s)

(b)



(c)

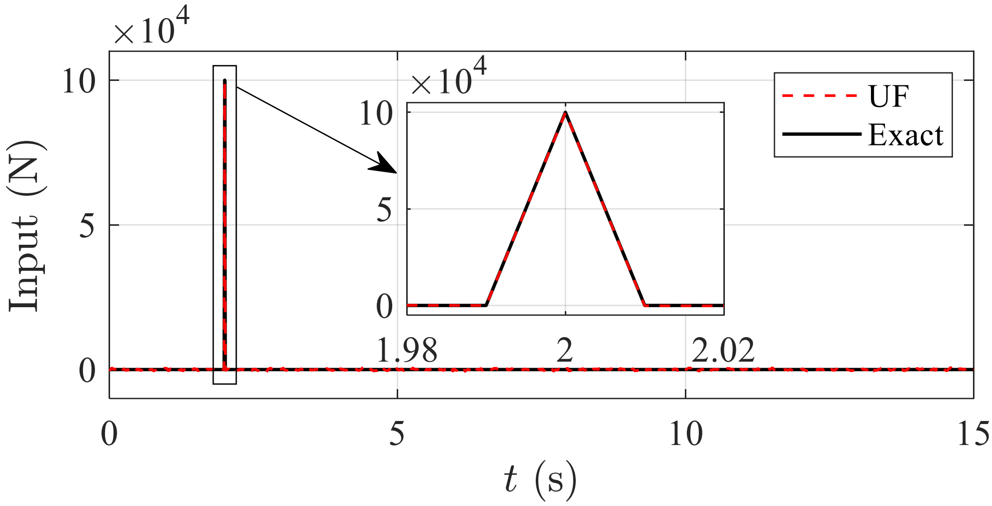
Figure 3 Estimation results by the UF and GDF-WNDF: (a) input, (b) velocity and (c) displacement.

Rank-deficient feedforward matrix

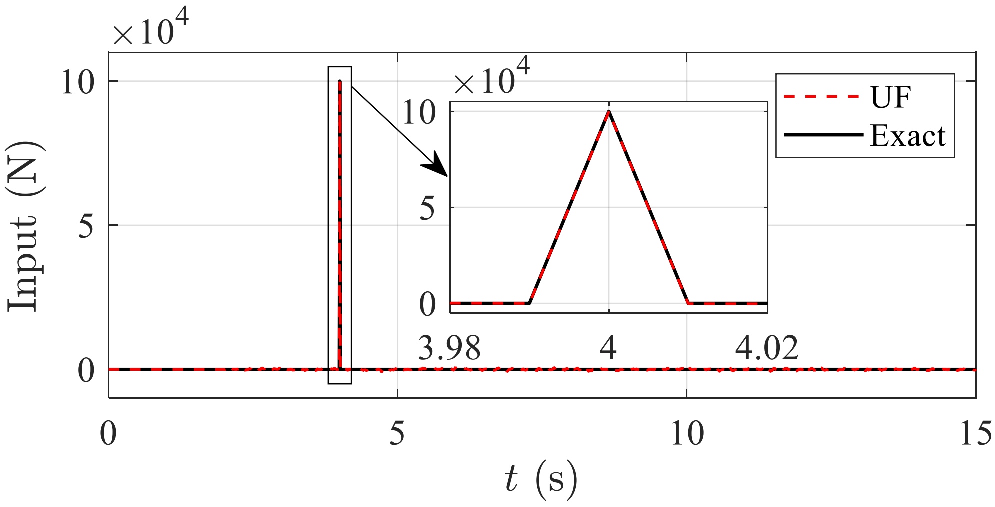
The GDF-WNDF is only applicable to systems without direct feedthrough, i.e., no acceleration measurements. The GDF-WDF can only be used for systems with a full-rank feedforward matrix; that is, the minimum number of acceleration observations must be equal to or greater than the number of unknown inputs. However, the developed UF consistently remains applicable as long as the minimum number of measurements (of any type) is equal to or greater than the number of unknown inputs.

The eight-storey shear frame is again considered to demonstrate the performance of the UF for a rank-deficient feedforward matrix. The structure is excited by two triangular impact loads applied on the first and the top levels. The duration of the two impacts is 0.02s, with the same peak value of 10^5 N. The impact on the first level occurs at $t = 2$ s, whereas the impact on the top level occurs at $t = 4$ s.

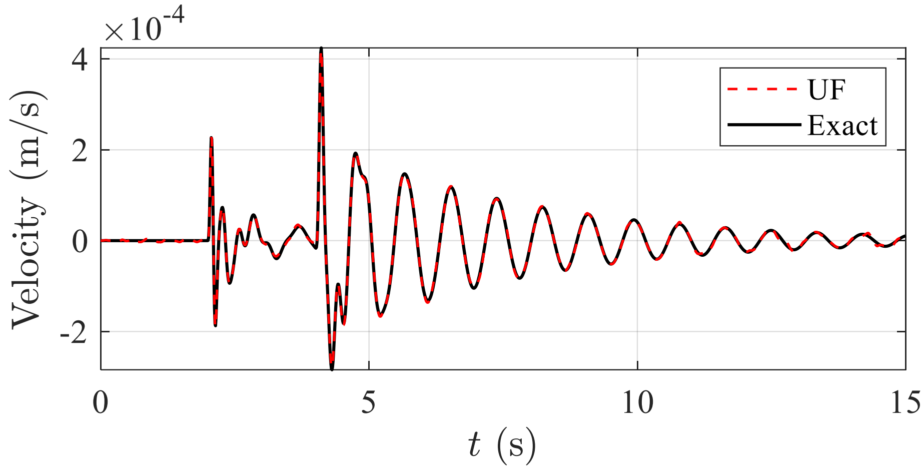
Given that the impact load efficiently excites all the structural modes, a full-order model that integrates all eight modes is used as the process equation. The arrangement of sensors includes a displacement measurement and an acceleration measurement at level 1, a velocity measurement at level 8, and a displacement measurement at level 7. Since there are two unknown inputs and only one acceleration measurement, neither the GDF-WDF nor the GDF-WNDF can be deployed. On the contrary, the UF keeps numerical stability under this sensor network. As shown in Fig.4, the estimations of displacement, velocity, and loads match closely the correct values.



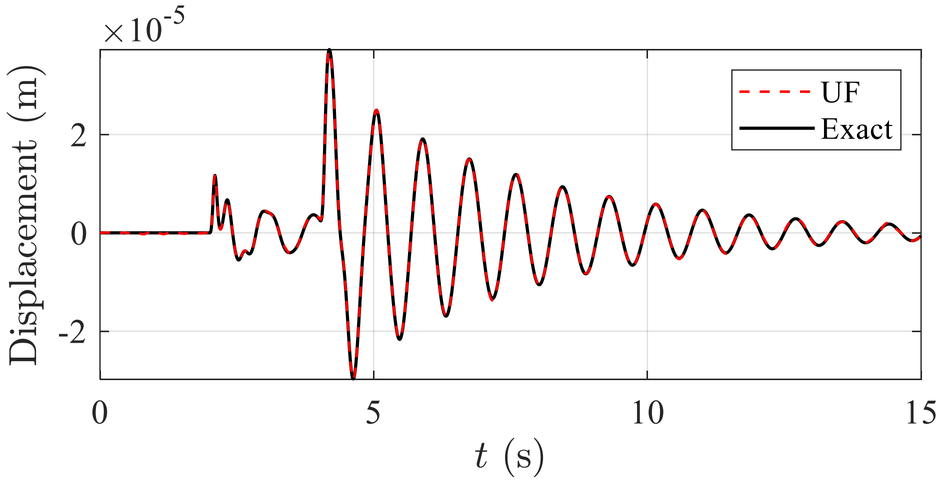
(a)



(b)



(c)



(d)

Figure 4 Inverse analysis by the UF: (a) the first impact load, (b) the second impact load, (c) velocity of the 4^{th} level, and (d) displacement of the 4^{th} level.

CONCLUSIONS

A novel recursive filtering method designated Universal Filter (UF) was proposed to jointly estimate the inputs and state of a linear structural system. The presented algorithm does not require any assumption in the process equation or statistics for unknown inputs. Estimation error equations were derived, and the corresponding covariance equations were presented in a closed form without simplifications. Furthermore, the input and state gains were formulated to minimise the estimation error variances, thus achieving a minimum-variance unbiased estimation. The proposed algorithm was shown to have universal applicability to systems with and without acceleration measurements disregarding the rank condition of the feedforward matrix. Two numerical models were used to demonstrate the efficiency of the algorithm, and the results showed the presented method has an enhanced performance over those existing algorithms.

REFERENCES

Barbella, G., Perotti, F., & Simoncini, V. (2011). Block Krylov subspace methods for the computation of structural response to turbulent wind. *Computer methods in applied mechanics and engineering*, *200*(23-24), 2067-2082.

De Callafon, R. A., Moaveni, B., Conte, J. P., He, X., & Udd, E. (2008). General realization algorithm for modal identification of linear dynamic systems. *Journal of engineering mechanics*, *134*(9), 712-722.

Ebrahimzadeh Hassanabadi, M., Liu, Z., Eftekhar Azam, S., & Dias-da-Costa, D. (2023). A linear Bayesian filter for input and state estimation of structural systems. *Computer-Aided Civil and Infrastructure Engineering*. https://doi.org/10.1111/mice.12973

Erazo, K., Sen, D., Nagarajaiah, S., & Sun, L. (2019). Vibration-based structural health monitoring under changing environmental conditions using Kalman filtering [Article]. *Mechanical Systems and Signal Processing*, *117*, 1-15. https://doi.org/10.1016/j.ymssp.2018.07.041

Gillijns, S., & De Moor, B. (2007a). Unbiased minimum-variance input and state estimation for linear discrete-time systems. *Automatica*, *43*(1), 111-116. https://doi.org/10.1016/j.automatica.2006.08.002

Gillijns, S., & De Moor, B. (2007b). Unbiased minimum-variance input and state estimation for linear discrete-time systems with direct feedthrough. *Automatica*, *43*(5), 934-937. https://doi.org/10.1016/j.automatica.2006.11.016

Kalman, R. E. (1960). A New Approach to Linear Filtering and Prediction Problems. *Journal of Basic Engineering*, *82*(1), 35-45. https://doi.org/10.1115/1.3662552

Kitanidis, P. K. (1987). Unbiased minimum-variance linear state estimation. *Automatica*, *23*(6), 775-778. https://doi.org/10.1016/0005-1098(87)90037-9

Lourens, E., & Fallais, D. J. M. (2019). Full-field response monitoring in structural systems driven by a set of identified equivalent forces. *Mechanical Systems and Signal Processing*, *114*, 106-119. https://doi.org/10.1016/j.ymssp.2018.05.014

Lourens, E., Papadimitriou, C., Gillijns, S., Reynders, E., De Roeck, G., & Lombaert, G. (2012). Joint input-response estimation for structural systems based on reduced-order models and vibration data from a limited number of sensors. *Mechanical Systems and Signal Processing*, *29*, 310-327. https://doi.org/10.1016/j.ymssp.2012.01.011

Lourens, E., Reynders, E., De Roeck, G., Degrande, G., & Lombaert, G. (2012). An augmented Kalman filter for force identification in structural dynamics. *Mechanical Systems and Signal Processing*, *27*, 446-460. https://doi.org/10.1016/j.ymssp.2011.09.025

Ma, Z., Choi, J., & Sohn, H. (2023). Three-dimensional structural displacement estimation by fusing monocular camera and accelerometer using adaptive multi-rate Kalman filter [Article]. *Engineering Structures*, *292*, Article 116535. https://doi.org/10.1016/j.engstruct.2023.116535

Maes, K., Iliopoulos, A., Weijtjens, W., Devriendt, C., & Lombaert, G. (2016). Dynamic strain estimation for fatigue assessment of an offshore monopile wind turbine using filtering and modal expansion algorithms [Article]. *Mechanical Systems and Signal Processing*, *76-77*, 592-611. https://doi.org/10.1016/j.ymssp.2016.01.004

Papadimitriou, C., Fritzen, C.-P., Kraemer, P., & Ntotsios, E. (2011). Fatigue predictions in entire body of metallic structures from a limited number of vibration sensors using Kalman filtering. *Structural Control and Health Monitoring*, *18*(5), 554-573. https://doi.org/10.1002/stc.395

A Breakthrough in Deterioration and Damage Detection for Building Structures

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Abstract

In the field of structural health monitoring (SHM), the detection of structural anomalies in intricate systems remains a paramount challenge. A novel signal-based supervised approach is proposed for the precise detection of deterioration and damage in building structures. Central to this method is the signal simulation-based feature selection (SSFS) algorithm, which effectively extracts sensitive features solely from baseline signals across diverse structure types. The findings demonstrate the method's efficacy, presenting it as a promising alternative to conventional techniques requiring additional data. The introduced damage identification procedure (DIP) approach integrates the SSFS methodology, emphasizing its reliance on baseline signals and obviating the need for structural information. Leveraging wavelet transform and statistical indices, the study showcases the method's success in real-world case studies, highlighting its potential for widespread application and future research to address the critical task of identifying structural defects in complex systems within the realm of SHM.

Case Studies

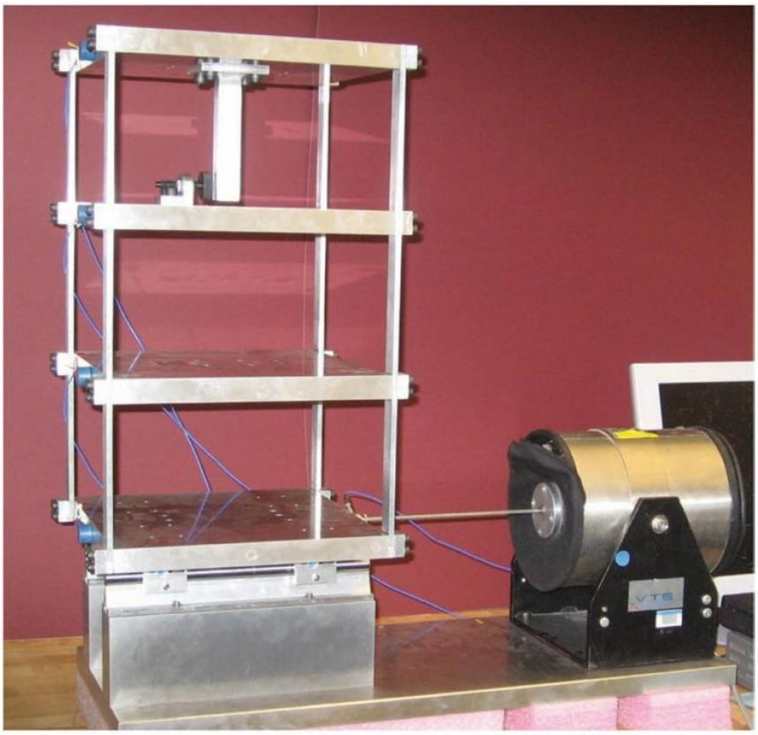
There are two case studies in this study as shown in Figure 1:

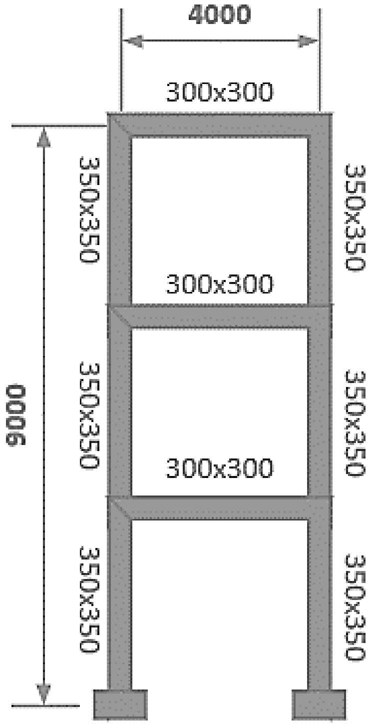
a) Damage Case

A complete three-storey reinforced concrete framework was simulated utilizing the IDARC software. In this illustrative case study, deterioration is defined as a consistent reduction in the cross-sectional area of the structural elements.

b) Deterioration Case

The experimental setup comprises a framework featuring aluminium columns and floor panels. Various simulations of damage were executed through alterations in mass substitution and adjustments in column stiffness.





(a) Damage Case (b) Deterioration Case

Figure 1 (a) Damage case and (b) Deterioration Case

Damage Identification Procedure (DIP)

As shown in Fig. 2, the initial step involves deriving a structural pattern solely from baseline responses. Subsequently, this pattern, indicative of the structure's condition, is employed in the subsequent stage for defect identification based on present responses. After elucidating each stage, the method is then implemented on two distinct models to evaluate its effectiveness.

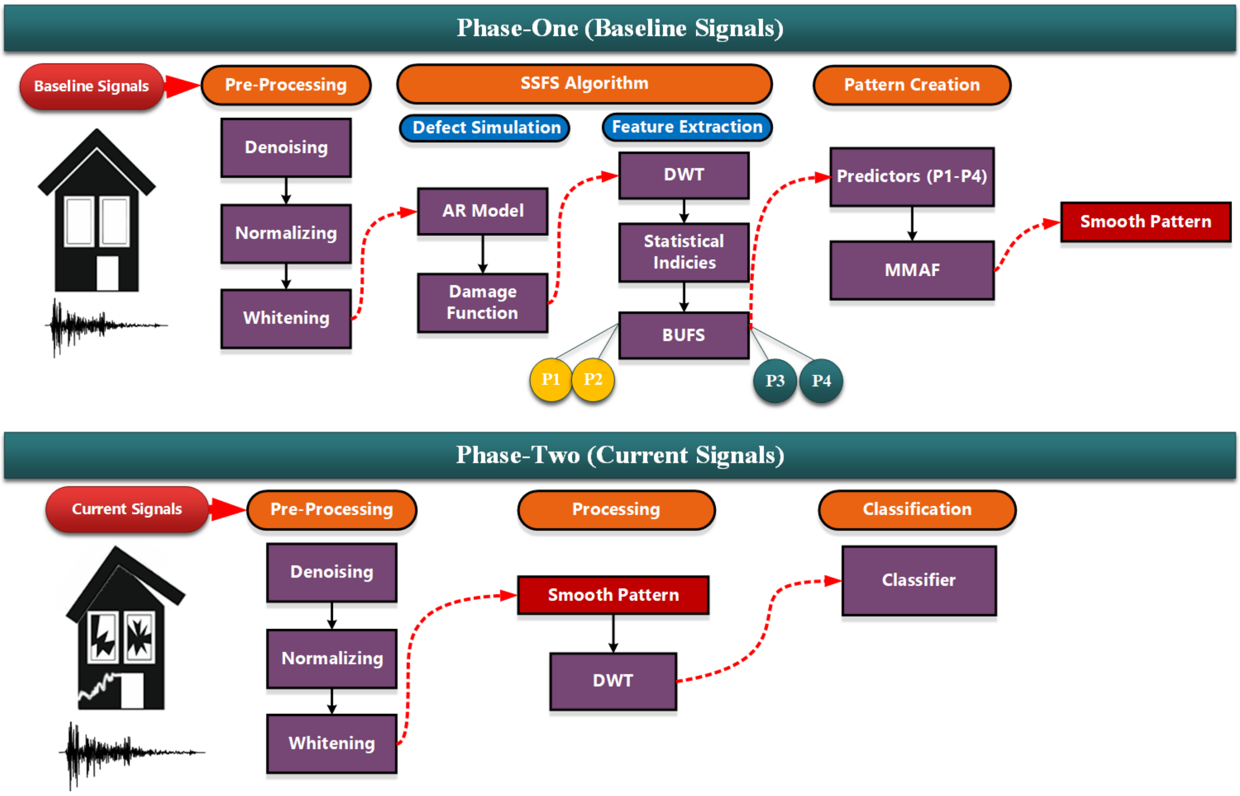


Figure 2 Flowchart of Damage Identification Procedure (DIP)

Phase One

The intricate nature of buildings arises from interconnected responses across multiple tiers, adding complexity compared to simpler structures. Some attributes can adeptly differentiate between baseline and damage signals, while others lack the required sensitivity. In response, a fresh approach, denoted as signal simulation-based feature selection (SSFS), is introduced. It facilitates the extraction of precise features from baseline signals, encompassing distinct response categories.

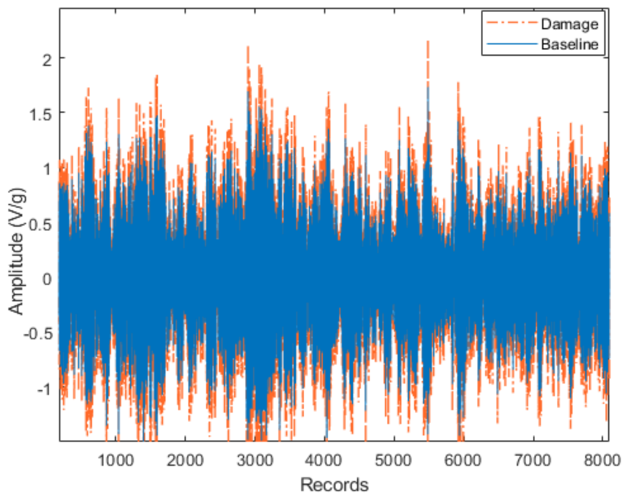
By utilising baseline responses, the simulation of damage and deterioration conditions is executed, obviating the necessity for current system state knowledge. These simulated signals are then harnessed to extract sensitive features capable of discerning diverse structural conditions. This is achieved through parameter adjustment of the autoregressive (AR) time series model, presented as follows:

$$S_j = \sum_{i=1}^{p} a_i s_{j-1} + \varepsilon_j \qquad (1)$$

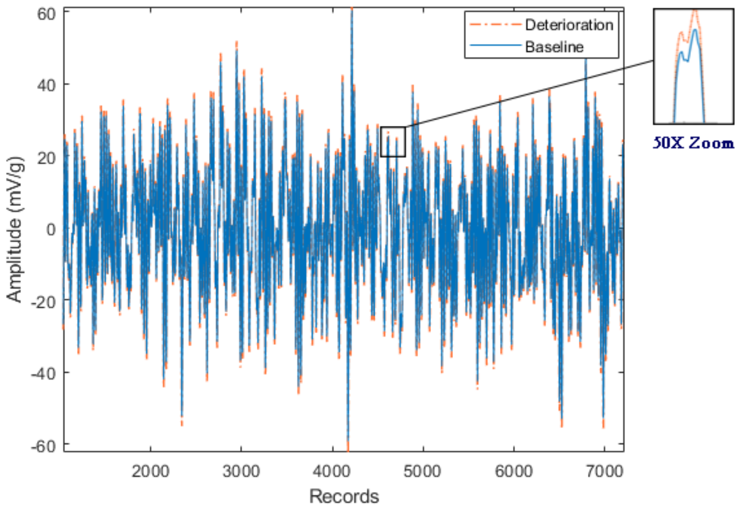
In the context of the formula, s_j denotes the standard acceleration signal during the j^{th} time interval. The term ε_j corresponds to the residual parameter at the same time step. The coefficient α_i pertains to the i^{th} degree of p, while s_{j-i} signifies the prior response at $(j-i)^{th}$ instance. To establish the baseline state, a simulation of deterioration and damage is accomplished by channelling the AR parameters through a damage function, expressed as:

$$Z(t) = \theta \times s(t) + \delta \qquad (2)$$

where, θ represents magnitude, and δ signifies bias in the function. We assume values of 0.01 for magnitude and 0.1 for bias in both deterioration and damage cases. Figure 3 illustrates simulated signals from the baseline structure. In contrast to damage simulation, deterioration-induced variations are less prominent.



(a) Damage Records



(b) Deterioration Records

Figure 3 Simulated signals from the baseline structure

Phase-Two

In this phase, the seamless pattern derived from the prior stage is engaged to assess the structure's conditions through present responses. In pursuit of this objective, the current responses undergo preliminary processing, as previously explained. In this processing phase, the smooth pattern is applied to the signals employing Discrete Wavelet Transform (DWT) to unveil the inherent signal behaviours. Subsequently, pattern recognition is executed using three distinct supervised machine learning algorithms: Artificial Neural Network (ANN), Support Vector Machine (SVM), and K-Nearest Neighbors (KNNs).

Results and Discussion

The subsequent outcomes demonstrated the adeptness of the proposed methodology in accurately detecting damage and deterioration. Consequently, this approach holds promise as a feasible substitute for conventional techniques demanding supplementary information.

***Table 1** The overall accuracy of classification of deterioration in scenario 3*

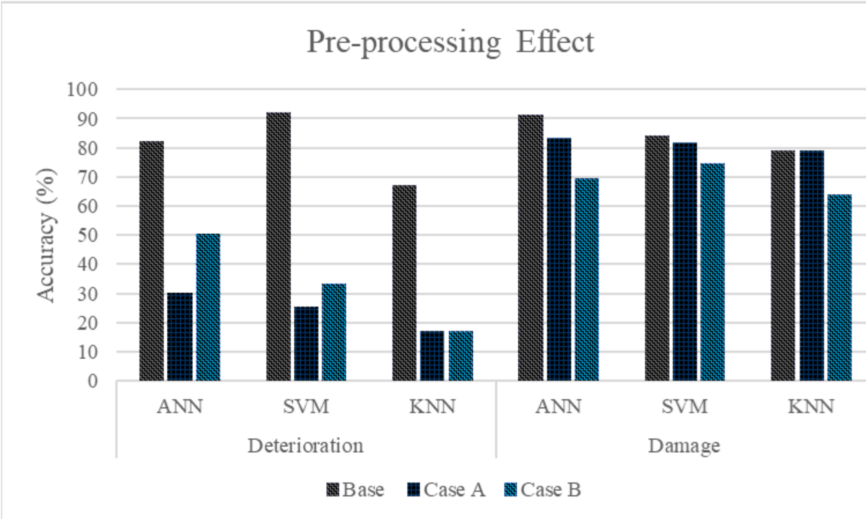
Overall accuracy (%)	ANN	SVM	KNN	Average
Story 1	98.0	75.0	75.0	82.6
Story 2	100.0	91.7	91.7	94.4
Story 3	96.0	91.7	100.0	95.9
Average	98.0	86.1	88.9	

***Table 2** The overall accuracy of classification in damage*

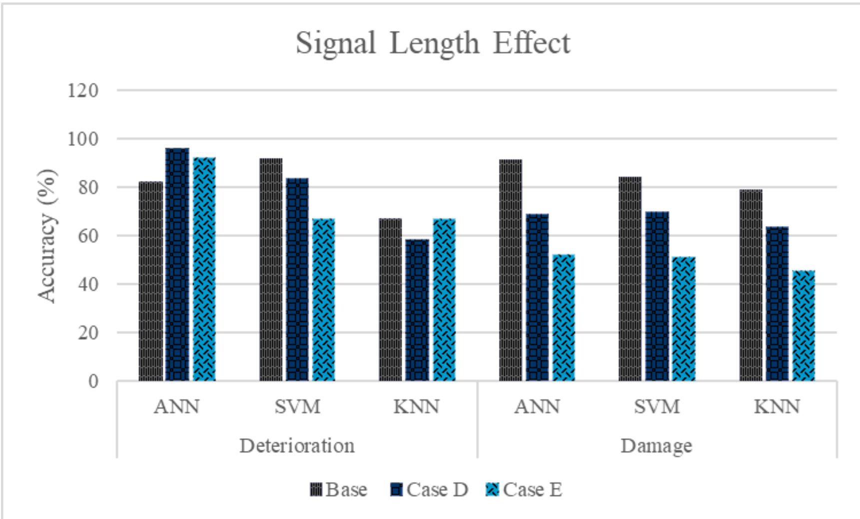
Overall accuracy (%)	ANN	SVM	KNN	Average
Story 1	92.2	92.0	86.6	92.2
Story 2	90.9	87.5	85.7	88.1
Story 3	90.9	83.9	78.6	84.4
Average	91.3	87.8	83.6	

Finally, to study the effects of distinct signal conditions and the robustness of the method, distinct scenarios were explored as shown in Fig. 4:

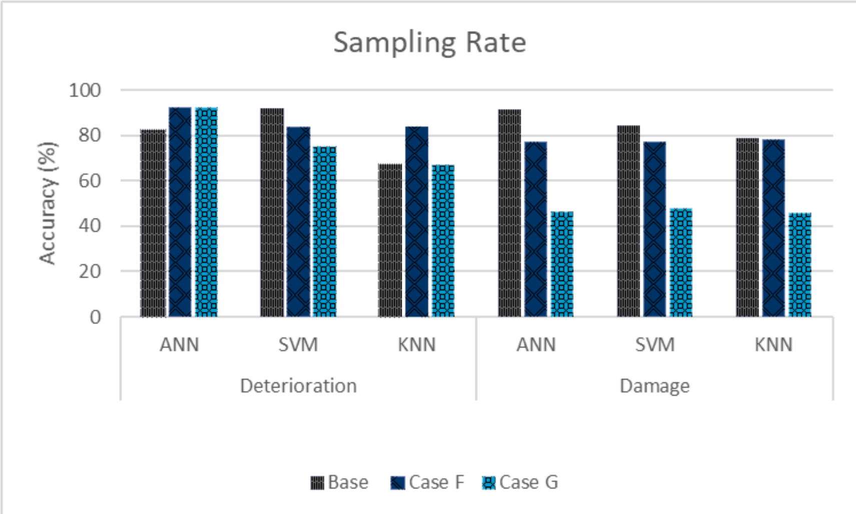
- Case A: Raw data without whitening
- Case B: Un-processed data
- Case C: Non-smooth pattern (omitting the moving average filter)
- Case D: One-half of the original data
- Case E: One-fourth of the original data
- Case F: Sampling rate reduced by half
- Case G: Sampling rate reduced by a quarter



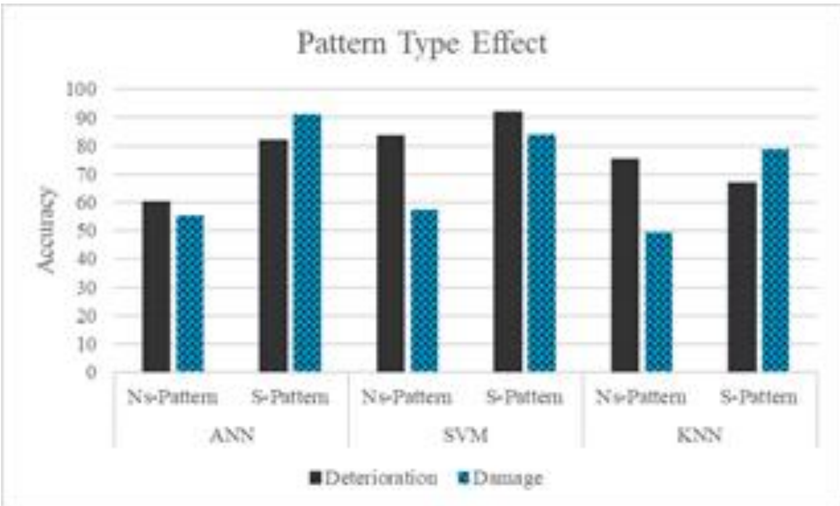
(a) Processing effect



(b) Signal length effect



(c) Sampling rate effect



(d) Pattern type effect

Figure 4 Effects of distinct signal conditions

Concluding Remarks

In the annals of algorithmic research, the novel feature selection methodology elucidated in this manuscript proffers advantages that are poised to catalyze future investigations. The SSFS, a salient outcome of our rigorous research endeavours, possesses an array of distinctive attributes, as delineated below:

- Its adaptability is manifest in its compatibility with an array of clustering algorithms, notably the Self-Organizing Map (SOM), Hierarchical Clustering, and the quintessential k-Means Clustering.
- It accommodates diverse signal processing paradigms, spanning the gamut from HHT and PCA to CWT and STFT, demonstrating its inherent versatility.
- Eschewing constraints with regard to structural taxonomy, the SSFS is efficacious across diverse infrastructural entities – be it the expansive realm of bridges, the intricate lattice of space frames, or the mechanistic realms of rotary motors.
- A cardinal feature of the SSFS is its autonomous capability to discern and extrapolate sensitive features pertinent to both incipient and overt structural anomalies.
- The analytical metrics adopted in our treatise exhibit modularity, allowing the facile integration of alternative signals or sophisticated statistical indices.

In conclusion, the SSFS stands as a paragon of innovation, auguring propitious avenues for subsequent academic explorations.

Conference News

- The 15th Australian Network of Structural Health Monitoring Workshop & The Smart Infrastructure Summit 2023, 23rd - 24th November 2023, Townsville, Australia, https://www.anshm.org.au/.
- The 12th International Conference on Structural Health Monitoring of Intelligent Infrastructure (SHMII-12), ANSHM Special Session, entitled "Towards Sustainable and Resilient Infrastructure" (SS121), 19th - 22nd October 2023, Hangzhou, Zhejiang, China, https://www.shmii-12.com/.
- The 10th Asia-Pacific Young Researchers and Graduates Symposium, 6th – 8th December 2023, Perth, Australia, https://yrgs2023.com/.
- Technology Convergence 2023 "Setting the Wheels in Motion – Reimagining the Future of Heavy Vehicles, Roads and Freight", jointly organised by the International Society for Weigh-In-Motion (ISWIM) and the International Forum for Heavy Vehicle Transport & Technology (HVTT Forum), 6th -10th November 2023, Brisbane, Australia, https://www.techconverge23.org/.
- The 26th Australasian Conference on the Mechanics of Structures and Materials, 3rd - 6th December 2023, Auckland, New Zealand, https://www.acmsm26.com/.
- The 14th International Workshop on Structural Health Monitoring (IWSHM), "Designing SHM for Sustainability, Maintainability, and Reliability." will be held on September 12th - 14th, 2023, at Stanford University, United States, https://iwshm2023.stanford.edu/.
- SPIE SSN06: Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems 2024, 25 - 28 March 2024, Long Beach, California, United States, https://spie.org/SSN06.

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