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Identification of Structural Dynamic Loads- From Physical Methods to Physics Informed Deep Learning Paradigm

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ABSTRACT: In this study, some progresses on the identification of structural dynamic loads are reported. First, a series of improved Kalman filter with unknown inputs developed by the authors for the identification of joint structural dynamic systems and dynamic loads are briefly reviewed. Then, some identification of structural dynamic loads using the physical guided deep learning paradigm are presented, including the identification of multi dynamic load positions and time histories using physics informed and enhanced Generative adversarial neural network (GAN) and Convolutional Long Short-Term Memory (ConvLSTM), respectively, the identification of full-field wind loads on buildings using physical informed recursive convolutional neural network (CNN), and the identification of stochastic fluctuating wind power spectrum on high- rise buildings using physical guided CNN with partial structural responses. The load type of the network during testing can be different from that during training. Through numerical simulation, it is proved that the proposed methods can learn the nonlinear mapping relationship between the structural responses and the external dynamic loads, and can reconstruct the load time histories well. The proposed methods are verified by numerical simulation and the results show that the deep learning methods can identify the unknown multi dynamic load positions and time histories, full-field wind loads on buildings and the stochastic fluctuating wind power spectrum on high-rise buildings.

KEY WORDS: Identification of structural dynamic loads; Physics informed deep learning; Physical methods.

1 INTRODUCTION

Identification of structural dynamic load is one of the core issues in the fields of structural health monitoring, vibration control and safety assessment. Its goal is to infer the dynamic loads acting on the structure (such as vehicle loads, wind loads, earthquake loads, etc.) from the response signals of the structure (such as displacement, acceleration, strain, etc.). With the development of technology, the methods in this field have gradually evolved from traditional methods that rely on physical models to data-driven deep learning methods.In this study, some progresses on the identification of structural dynamic loads are reported.

2 STRUCTURAL DYNAMIC LOAD IDENTIFICATION—PHYSICAL METHODS

2.1 *Kalman filter with unknown input (KF-UI)*

The Kalman Filter (KF) [1] is a recursive estimation method for structural states based on partial observations. As long as the estimated value of the state at the previous moment and the observation value of the current state are known, the optimal estimation value of the current state can be calculated. It is suitable for real-time online estimation of structural states and can consider the uncertainty of the model and the influence of observation noise. Therefore, it is widely used. However, when applying KF, the external inputs information of the structure needs to be known. In fact, the input information is often difficult to be fully observed. To overcome the limitations of the traditional KF, we proposed Kalman filter with unknown input (KF-UI) [2].

State equation

$$\boldsymbol{X}_{k+1}=\boldsymbol{A}_k\boldsymbol{X}_k+\boldsymbol{G}_k\boldsymbol{f}_k+\boldsymbol{w}_k \quad (1)$$

Observation equation

$$\boldsymbol{y}_k=\boldsymbol{C}_k\boldsymbol{X}_k+\boldsymbol{H}_k\boldsymbol{f}_k+\boldsymbol{v}_k \quad (2)$$

1) Time update for estimated states from k△t to (k+1)△t :

$$\tilde{\boldsymbol{x}}_{k+1/k}=\boldsymbol{A}_k\hat{\boldsymbol{x}}_{k/k}+\boldsymbol{G}_k\hat{\boldsymbol{f}}_{k/k} \quad (3)$$

The smallest variance estimator of state vector at (k+1)△t :

$$\hat{\boldsymbol{x}}_{k+1/k+1}=\boldsymbol{K}^*_{k+1}\tilde{\boldsymbol{x}}_{k+1/k}+\boldsymbol{K}_{k+1}\boldsymbol{y}_{k+1} \quad (4)$$

$$\boldsymbol{K}^*_{k+1}\tilde{\boldsymbol{x}}_{k+1/k}=\tilde{\boldsymbol{x}}_{k+1}-\boldsymbol{K}_{k+1}(\boldsymbol{C}_{k+1}\tilde{\boldsymbol{x}}_{k+1}+\boldsymbol{H}_{k+1}\hat{\boldsymbol{f}}_{k+1}) \quad (5)$$

2) The final update equation of the smallest variance estimator of state vector at (k+1)△t :

$$\hat{\boldsymbol{x}}_{k+1/k+1}=\tilde{\boldsymbol{x}}_{k+1/k}+\boldsymbol{K}_{k+1}(\boldsymbol{y}_{k+1}-\boldsymbol{C}_{k+1}\tilde{\boldsymbol{x}}_{k+1/k}-\boldsymbol{H}_{k+1}\hat{\boldsymbol{f}}_{k+1}) \quad (6)$$

The final update equation of error covariance matrix of the estimated state vector:

$$\begin{aligned}\tilde{\boldsymbol{P}}^x_{k+1/k}&=\tilde{\boldsymbol{\varepsilon}}^x_{k+1/k}\tilde{\boldsymbol{\varepsilon}}^{xT}_{k+1/k}\\&=\begin{bmatrix}\boldsymbol{A}_k & \boldsymbol{G}_k\end{bmatrix}\begin{bmatrix}\boldsymbol{P}^x_{k/k} & \boldsymbol{P}^{xf}_{k/k}\\ \boldsymbol{P}^{fx}_{k/k} & \boldsymbol{P}^f_{k/k}\end{bmatrix}\begin{bmatrix}\boldsymbol{A}_k{}^T & \boldsymbol{G}_k{}^T\end{bmatrix}+\boldsymbol{Q}\end{aligned} \quad (7)$$

3) The final update equation of unknown input at (k+1)△t:

$$\begin{aligned}\boldsymbol{f}_{k+1}=&\left[\boldsymbol{H}_{k+1}{}^T\boldsymbol{R}^{-1}\left(\boldsymbol{I}-\boldsymbol{C}_{k+1}\boldsymbol{K}_{k+1}\right)\boldsymbol{H}_{k+1}\right]^{-1}\\&\boldsymbol{H}^T_{k+1}\boldsymbol{R}^{-1}\left(\boldsymbol{I}-\boldsymbol{C}_{k+1}\boldsymbol{K}_{k+1}\right)\left(\boldsymbol{y}_{k+1}-\boldsymbol{C}_{k+1}\tilde{\boldsymbol{x}}_{k+1}\right)\end{aligned} \quad (8)$$

To minimize the value of $\mathbf{P}^x_{\mathbf{k}+1/k+1}$:

$$\boldsymbol{P}^x_{k+1/k+1}=\boldsymbol{\varepsilon}^x_{k+1/k+1}\boldsymbol{\varepsilon}^{xT}_{k+1/k+1} \quad (9)$$

$$\boldsymbol{K}_{k+1}=\tilde{\boldsymbol{P}}^x_{k+1/k}\boldsymbol{C}^T_{k+1}(\boldsymbol{R}_{k+1}+\boldsymbol{C}_{k+1}\tilde{\boldsymbol{P}}^x_{k+1/k}\boldsymbol{C}^T_{k+1}) \quad (10)$$

Data fusion is applied to prevent the drifts in the identification caused by low-frequency noise.

$$\boldsymbol{y}_{k+1}=\boldsymbol{h}(\boldsymbol{Z}_{k+1},\boldsymbol{f}_{k+1},\boldsymbol{f}^u_{k+1})+\boldsymbol{v}_{k+1} \quad (11)$$

2.2 *Numerical simulation*

Numerical simulation of the identification of unknown excitations for trusses verified the effectiveness of the method.

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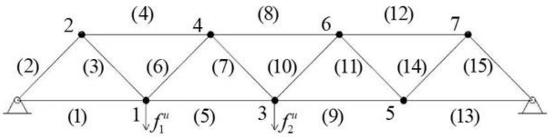


Figure 1. Truss structure

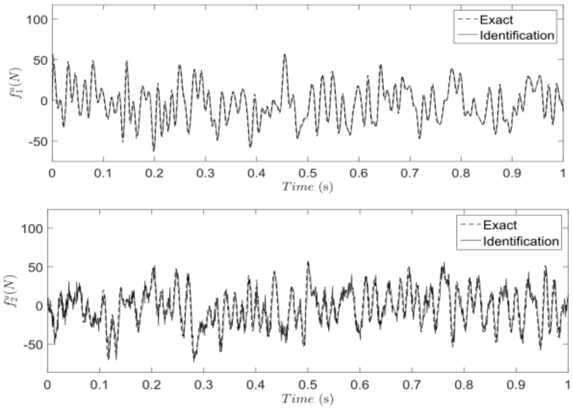


Figure 2. Identification results of unknown forces

2.3 A series of methods for Klaman Filter with Unknown Inputs

A series of methods for Klaman Filter with Unknown Inputs have been proposed by authors.

1) (Extended) Kalman filter under unknown input (KF-UI；EKF-UI)
2) Kalman filter/Extended Kalman filter under unknown input without direct feedback (KF-UI-WDF; EKF-UI-WDF)
3) Unscented Kalman filter under unknown input(UKF-UI)
4) Unscented Kalman filter under unknown input (UKF-UI-WDF)
5) Particle filter under unknown input (PF-UI)
6) Unscented Kalman particle filter under unknown input (UKPF-UI)

3 STRUCTURAL DYNAMIC LOAD IDENTIFICATION—DEEP LEARNING METHODS

The data-driven method for dynamic load identification, which does not require a structural model, is more in line with the needs of actual engineering. Data-driven deep learning methods can establish functional mapping between network inputs (structural responses) and outputs (structural dynamic loads). Machine learning approaches with clear physical interpretability often demonstrate enhanced performance.

3.1 Physics-Guided Deep Learning for Multi Dynamic Load Identification

Existing methods require identical load distributions during training and testing, resulting in poor network generalizability and restricted applicability.

When a single load acts at *j*, the response at the structural measurement point *i*:

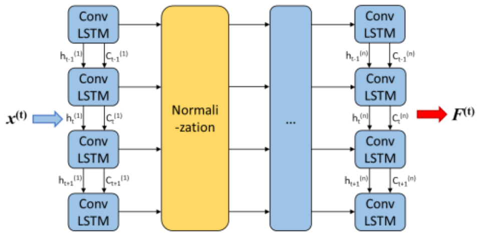
$$z_i^j\left(t\right)=\int_o^t h_i^j\left(t-\tau\right)f_j\left(\tau\right)dt \tag{12}$$

$$\boldsymbol{z}_i^j=\boldsymbol{H}_i^j\boldsymbol{f}_j \tag{13}$$

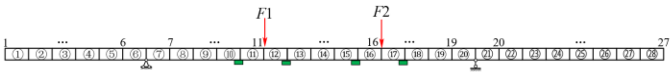
Multiple loads $f_n(n=1,2,\ldots,n_f)$ acts on the structure, where n_f is the number of loads. The formula for the response of the *i*-th measurement point can be expressed as:

$$\boldsymbol{z}_i=\sum_{j=1}^{n_f}\boldsymbol{H}_i^j\boldsymbol{f}_j \tag{14}$$

To solve the problem of identifying dynamic loads, it is necessary to find the inverse matrix of H. Since positive definite conditions need to be satisfied, it is essential to ensure that the observed number is greater than the number of unknown forces.



Numerical simulation of the identification of unknown excitations for outward-extending beams verified the effectiveness of the method.



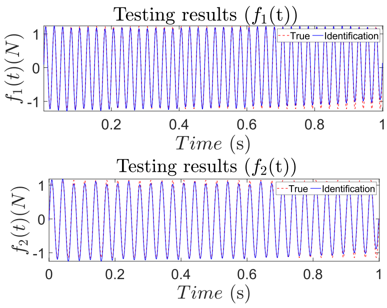


Figure 3.Identification results of unknown forces

3.2 *Physics Guided Deep Learning for Wind Load Identification of Tall Buildings*

It is more challenging to identify wind loads, because Wind load is a type of complex distributed dynamic load. Currently, methods for identifying wind loads mainly rely on theoretical inverse identification [3-4]. In this paper, a scheme for identifying full-field wind loads using a recursive convolutional neural network (CNN) inspired by physical mechanisms is proposed.

The wind load is discretized and sampled spatially. Based on spatial correlation to represent the wind profile. If the floor height is 3 meters. The correlation between the adjacent two floors is 0.954 and that between the three floors is 0.911. It can be assumed that the adjacent two floors are completely correlated. Therefore, spatial correlation can reduce the number of independent loads. The recursive form of the network, as well as the inspiration for its inputs and outputs, is inspired by the spatial correlation and the mapping relationship between wind loads and structural responses.

In this study, a 306-meter-high Australian office building is utilized, which is the 76-story Benchmark building established by IASC-ASCE [5]. In this case, the network is tested using

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structural responses generated by the stationary Davenport spectrum, Harris spectrum and Kaimal spectrum.

To verify the accuracy of spatial identification results, wind load profiles at four time moments are shown in Figure 4. The time histories of wind loads at three heights are presented in Figure 5. The self-power spectrum of the wind load at the 60th floor and the cross-power spectrum between the 60th and 62nd floors are shown in Figure 6. The identification results of the power spectrum align well with the true values.

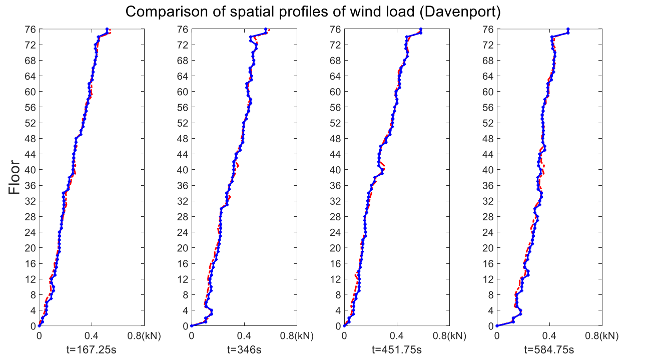


Figure 4. Identification of wind loads profiles (Davenport spectrum)

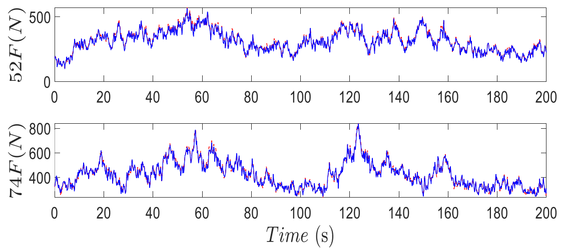
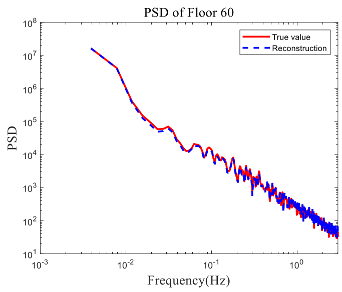
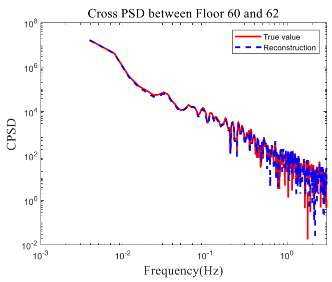


Figure 5. Identification of wind loading time histories (Davenport spectrum)



(a) PSD



(b) CPSD

Figure 6. Identification of the PSD and CPSD (Davenport spectrum)

4 CONCLUSIONS

In this study, some progresses on the identification of structural dynamic loads are reported. To overcome the limitations of the traditional KF, A series of methods for Klaman Filter with Unknown Inputs have been proposed by authors. The physical method is applicable to problems with clear models and simple scenarios. The deep learning method, on the other hand, breaks through the bottleneck of model dependence and is more suitable for complex scenarios in actual engineering. Machine learning approaches with clear physical interpretability often demonstrate enhanced performance. Physics-Guided deep learning for multi dynamic Load identification and for wind load identification of tall buildings are proposed respectively.

In the future, the integrated method of "physical model + data-driven" will become the mainstream. It will not only leverage the explanatory power of physical theories but also utilize the strong fitting ability of deep learning, promoting the development of dynamic load identification towards greater accuracy, robustness, and universality.

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