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Deep Learning-based Unsupervised Methods for Real-Time Condition Monitoring of Structures: A State-of-the-Art Survey

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ABSTRACT

Real-time unsupervised condition monitoring of civil infrastructures has gained a great deal of attention during the past decade. This practice has been challenged by several factors such as the lack of a robust feature extraction strategy, scarcity of baseline data collected from the intact structure, the lack of information from missing data, and the hardship of specifying a dynamic threshold strategy. Thanks to the advances in deep learning techniques, the condition monitoring practice of civil infrastructures benefits largely from the strength of deep learning for feature extraction, amending missing information, and developing dynamic threshold settings. This survey studies some of the recent advances in real-time unsupervised condition monitoring of civil infrastructures. As such, it has been noted that the variational auto-encoder and generative adversarial networks are two main deep learning models that can address the aforementioned challenges. Therefore, a possible future path for research in this field can be towards mixing these deep learning models to address all the challenges of real-time unsupervised condition monitoring of civil infrastructures at once.

Keywords: Structural condition monitoring, Unsupervised learning, Variational auto-encoder, Generative adversarial networks

1. INTRODUCTION

The health condition monitoring of the civil infrastructures has been made possible through the installation of SHM systems on structures, during the past decade. This has made the structural health condition assessment possible through the tracking of abnormality in structural response data. The numerous sensors deployed on a structure provides a huge monitoring data that can be analysed to investigate the in-service condition of the structure. Advanced data processing methods aim to convert the recorded multi-source heterogeneous data into meaningful physical indicators for structural health assessment, as discussed in Ref. 1. This will further facilitate the effective decision making about the maintenance and management of the target structure. Conventional data analysis methods are limited in dealing with: (1) the effect of noise on structural characteristic information, (2) the Environmental and Operational Variations (EOV) effect, (3) analysing a large volume of measurement data, (4) the lack of baseline information, and (5) errors stemming from the missing data stemming from sensors failure. The advancement of data processing units and deep learning based algorithms during the past decade has made the analysis of massive data obtained from an SHM system possible. This paves the way towards accurate, autonomous, and robust condition monitoring of civil infrastructures through the recorded data. Therefore, the SHM community have been focusing on exploring the capabilities of deep learning-based strategies for various challenges involved with the structural condition monitoring, as discussed in Ref. 2.

Real-time condition monitoring of a structure is an unsupervised process that does not rely on any information from abnormal states of the structure. However, there are some challenges involved with the unsupervised structural health monitoring. Some of these challenges are studied in Ref. 3. This survey is aimed at presenting some of these challenges and the ways of addressing them from reviewing recent studies conducted in this field of research.

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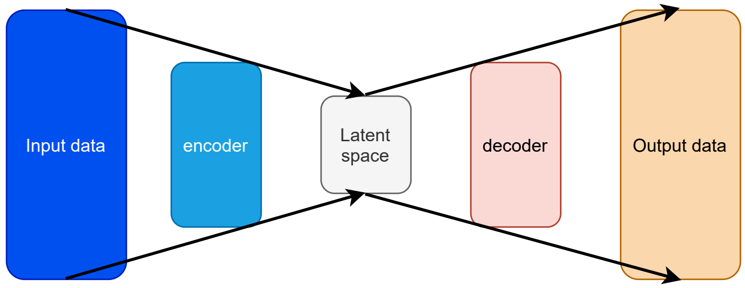

Figure 1: Diagram of a vaiational auto-encoder (VAE).

2. FEATURE EXTRACTION USING VARIATIONAL AUTO-ENCODER

Traditional feature extraction algorithm mostly focus on signal processing of vibration data and extracting features from either the time domain analysis of recorded data such as coefficients of a time series model of the structural vibration data, as discussed in Ref. 4, frequency domain such as structural modal information, as dicussed in 5, or time-frequency domain such as Gabor's analytical signal's characteristics, as discussed in Ref. 6. In the recent decades, advances of deep learning methods made it possible to extract high-level abstract features form raw vibration data. Variational Auto-Encoder (VAE) is one of the most widely used generative DL models for solving unsupervised problems. VAE has been used to reduce the high-dimensional structural vibration data to low-dimensional latent space, and then the original data from the low-dimensional representations is restored, as shown in Ref. 7. The procedure of an VAE module is depicted in Fig. 1. As such, the encoder unit is a deep learning module that transfers input data to a latent space in a bid to discard useless information in it. The transferred data in the latent space is a dimensionaly reduced version of the input data. The decoder unit aims at reconstructing the input data as output through transforming the cleaned data in the reduced latent space. As such, one of the potential application of an VAE module is to denoise the input data, as shown in Ref. 8. Condition monitoring of civil infrastructures under the EOV effects is another challenging task, as discussed in 9, 10. A VAE module can be developed to discard the unwanted effect of the EOV effects on the structural vibration data, while preserving useful information about the damage state of the structure.

3. MIMICKING REAL DATA USING GENERATIVE ADVERSARIAL NETWORKS

Another challenge for real-time damage detection of structures stems from the lack of enough data objects associated with different structural conditions. In general, it is not practical to gather this data from a structure in operation, as it is a costly process. Generative Adversarial Network (GAN) is a class of machine learning frameworks that is developed to generate new data that follows the same statistics as the data in training set. As can be seen from Fig. 2, the discriminator unit in a GAN is a classifier that discriminates between real data (training data) and fake data (generated by the generator unit). The aim of a GAN is to mimic the training data through constantly modifying the generated model until the discriminator fails to distinguish between the fake and training data. Recently, a novel strategy based on multi-GAN's discriminators was proposed to mimic a dynamic-class novelty detection framework, as shown in Ref. citenumsoleimani2021system.

Data loss upon monitoring of a structure is the most common type of sensors failure. This issue is more common in wireless sensors. Since the transferred data is greatly important for real-time monitoring of structures, a procedure needs to be developed to regenerate this missing information. Recently, a GAN architecture was developed for imputation of missing strain response of a bridge structure for unsupervised health monitoring, as shown in Ref. 11.

4. THRESHOLD SETTING BASED ON GAN

Real-time condition monitoring of structures is reliant on a dynamic threshold setting strategy. Probabilistic threshold setting has been proven to be effective for early damage detection of structures, as discussed in Ref. 12,

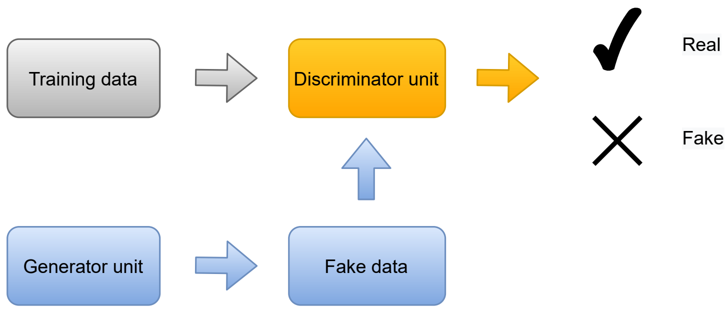

Figure 2: Diagram of a Generative Adversarial Network (GAN).

13. However, machine learning algorithms are not capable of learning meaningful features from big data and exploring a more complex data structure for the automatic fault detection. Recently, a self-setting threshold strategy was developed based on deep convolutional GAN (DCGAN) for condition monitoring of generator bearings in a wind turbine, as shown in Ref. 14.

5. CONCLUSIONS AND FUTURE WORK

The state-of-the-art of deep learning approaches for real-time unsupervised condition monitoring of civil infrastructures has been investigated. As such, three main challenges involved with this practice, reported in the literature, include: (1) denoising, removing the EOV effects, (3) automatic feature extraction, (4) amending missing information in the recorded data, (5) the lack of baseline data, and (6) an automatic dynamic threshold setting strategy. Some recent studies in the realm of real-time unsupervised condition monitoring of civil infrastructures indicate that two different deep learning models, namely VAE and GAN have been recently employed for addressing the above issues. However, it was noted that in non of the investigated studies all the aforementioned challenges were addressed together. Hence, future studies can focus on developing deep learning architectures based on a mixture of VAE and GAN for addressing the real-time unsupervised condition monitoring of civil infrastructures, where all the above challenges are addressed at once.

REFERENCES

[1] Entezami, A., Sarmadi, H., and Mariani, S., "An unsupervised learning approach for early damage detection by time series analysis and deep neural network to deal with output-only (big) data," in [*Engineering Proceedings*], **2**(1), 17, Multidisciplinary Digital Publishing Institute (2020).

[2] Ye, X., Jin, T., and Yun, C., "A review on deep learning-based structural health monitoring of civil infrastructures," *Smart Struct. Syst* **24**(5), 567–585 (2019).

[3] Soleimani-Babakamali, M. H., Sepasdar, R., Nasrollahzadeh, K., and Sarlo, R., "System-reliability based multi-ensemble of gan and one-class joint gaussian distributions for unsupervised real-time structural health monitoring," *arXiv preprint arXiv:2102.01158* (2021).

[4] Entezami, A. and Shariatmadar, H., "An unsupervised learning approach by novel damage indices in structural health monitoring for damage localization and quantification," *Structural Health Monitoring* **17**(2), 325–345 (2018).

[5] Hassani, S. and Shadan, F., "Using incomplete frf measurements for damage detection of structures with closely-spaced eigenvalues," *Measurement* **188**, 110388 (2022).

[6] Hassani, S., Mousavi, M., and Gandomi, A. H., "Damage detection of composite laminate structures using vmd of frf contaminated by high percentage of noise," *Composite Structures* , 115243 (2022).

[7] Ma, X., Lin, Y., Nie, Z., and Ma, H., "Structural damage identification based on unsupervised feature-extraction via variational auto-encoder," *Measurement* **160**, 107811 (2020).

[8] Yan, X., Xu, Y., She, D., and Zhang, W., "Reliable fault diagnosis of bearings using an optimized stacked variational denoising auto-encoder," *Entropy* **24**(1), 36 (2021).

[9] Mousavi, M. and Gandomi, A. H., "Prediction error of johansen cointegration residuals for structural health monitoring," *Mechanical Systems and Signal Processing* **160**, 107847 (2021).

[10] Mousavi, M. and Gandomi, A. H., "Structural health monitoring under environmental and operational variations using mcd prediction error," *Journal of Sound and Vibration* **512**, 116370 (2021).

[11] Jiang, H., Wan, C., Yang, K., Ding, Y., and Xue, S., "Continuous missing data imputation with incomplete dataset by generative adversarial networks–based unsupervised learning for long-term bridge health monitoring," *Structural Health Monitoring* , 14759217211021942 (2021).

[12] Sarmadi, H. and Yuen, K.-V., "Early damage detection by an innovative unsupervised learning method based on kernel null space and peak-over-threshold," *Computer-Aided Civil and Infrastructure Engineering* **36**(9), 1150–1167 (2021).

[13] Daneshvar, M. H. and Sarmadi, H., "Unsupervised learning-based damage assessment of full-scale civil structures under long-term and short-term monitoring," *Engineering Structures* **256**, 114059 (2022).

[14] Chen, P., Li, Y., Wang, K., Zuo, M. J., Heyns, P. S., and Baggeröhr, S., "A threshold self-setting condition monitoring scheme for wind turbine generator bearings based on deep convolutional generative adversarial networks," *Measurement* **167**, 108234 (2021).