Unsupervised Damage Detection for Smart Extraterrestrial Habitats Using Autoencoders and Information Fusion

ZIXIN WANG, MOHAMMAD R. JAHANSHAHI, ILIAS BILIONIS, YUGUANG FU, AMIN MAGHAREH and SHIRLEY J. DYKE

ABSTRACT

In the context of smart and resilient extraterrestrial habitats, the structural health monitoring (SHM) of habitats is crucial and challenging due to the harsh space environments. To this end, a novel anomaly detection framework is developed based on active sensing and information theory. Active sensing involves the excitation of the structure at specific locations and collecting acceleration data using sensors. The collected data from different excitation points and sensor locations are analyzed, and the extracted information is fused to further enhance anomaly detection. More specifically, an unsupervised anomaly detection framework using autoencoders (AEs) has been developed. Continuous wavelet transforms (CWTs) of acceleration signals are utilized to train AEs. Information fusion strategies are proposed to enhance the robustness of the approach to both aleatoric and epistemic uncertainties. Two unsupervised learning approaches developed by standard AE and variational autoencoder (VAE) are systematically compared. The numerical study based on the ASCE benchmark model and the experimental study based on a geodesic dome testbed have been carried out to validate the performance of the proposed framework and study its limitations. The framework's ability to extract information from multiple sources allows it to identify anomalies that might have been missed by traditional detection methods. For instance, it is shown that the proposed approach increases anomaly detection accuracy by up to 39.8% under a relatively small damage scenario compared to state-of-the-art approaches.

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INTRODUCTION

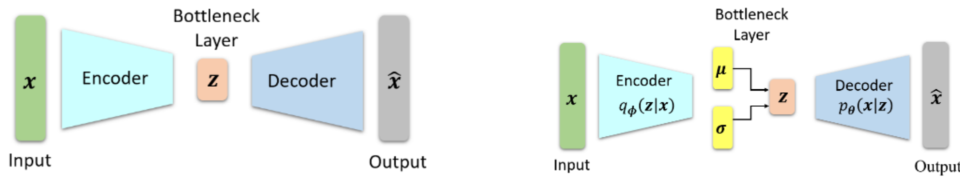
SHM plays an essential role in developing smart extraterrestrial habitats, and it is more challenging than the regular civil infrastructures on Earth due to the harsh space environments. Therefore, it is an urgent need to develop a damage detection approach for space habitats. Specifically, the approach should be able to deal with uncertainties due to environmental and operational conditions, as well as non-ideal boundary conditions. The developed approach is also applicable to the structures on Earth.

Supervised learning requires the labeled data under the structure's healthy and damaged states [1]. In this regard, how to generate the dataset under different damaged states of the structure to train the data-driven approach becomes a critical problem. Unsupervised learning addresses this problem since it does not require the labels of the data under different structural scenarios, and it only needs the data under the healthy state to train the damage detection approach [2]. Among different unsupervised learning methods, AE is the most widely adopted one. However, there is no record of developing AE for damage detection in extraterrestrial habitats, and the robustness of AEs to aleatoric and epistemic uncertainties is not comprehensively considered in the current studies. VAE is an unsupervised learning method in a probabilistic manner, which can be utilized for anomaly detection. But there is still a lack of a systematic comparison between the damage detection performance of AE and VAE.

In this work, an unsupervised damage detection approach for extraterrestrial habitats is developed using AEs, active sensing, and information fusion. A numerical study based on an ASCE benchmark problem is carried out using a 120-degree-of-freedom (120-DOF) model. Two unsupervised learning approaches developed by standard AE and VAE are systematically compared. To enhance the robustness of the approach to aleatoric and epistemic uncertainties, three information fusion strategies are proposed. Furthermore, the proposed approach is experimentally validated using a geodesic dome that is designed to emulate an extraterrestrial habitat under real-world uncertainties.

METHODOLOGY

AE is an unsupervised neural network model that is used for data compression, dimensionality reduction, and feature extraction. The architecture of AE consists of two parts, an encoder and a decoder, as shown in Figure 1(a). The encoder extracts the features representing the most important information in the input data, and the decoder reconstructs the input data using the latent representation generated by the encoder. AE is trained only using the data under the healthy state of the structure. Consequently, the reconstruction error, i.e., mean squared error (MSE), is small under the healthy state. However, since AE does not learn the data under the damaged state during the training, MSE will be increased if the data under the damaged state is poured into AE. The threshold τ for anomaly detection is determined by specifying a percentile of the distribution fitted to the MSE of the training data under the healthy state. If MSE is larger than this threshold, it can be inferred that the structure is probably changed from its healthy state. VAE is a probabilistic generative model that can perform efficient approximate inference with continuous latent variables. The architecture of VAE contains a probabilistic encoder defined by the guide $q_{\phi}(z|x)$ and a probabilistic decoder defined by the likelihood $p_{\theta}(x|z)$, as shown in Figure 1(b). In the detection



(a) Standard autoencoder.

(b) Variational autoencoder.

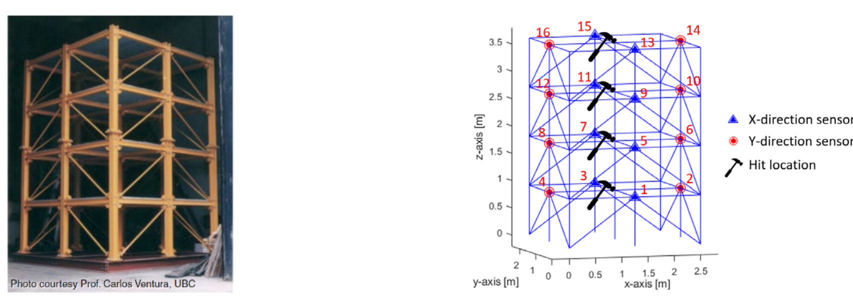
Figure 1. Schematic representation of autoencoders.

phase, similar to standard AE, if the reconstruction error of VAE quantified by MSE is larger than the specified threshold τ, it can be inferred that the structure is probably damaged. The CWT is good at capturing the time-frequency information of signals, which provides advantages for the analysis of nonstationary signals. Therefore, the CWT of acceleration responses is utilized to train AEs.

Information fusion refers to the process of integrating information from multiple resources to enhance the robustness of the damage detection approach to real-world uncertainties. In this work, hierarchical decision fusion is developed, including three decision-level fusion strategies: ‘sensor fusion’, ‘sequential sensor and hit fusion’, as well as ‘combined sensor and hit fusion’. Suppose M accelerometers are attached to the structure, and the structure is hit N times by the hammer. In ‘sensor fusion’, structure damage is detected if over m out of M sensors predict the structure is damaged. In ‘sequential sensor and hit fusion’, based on the results from ‘sensor fusion’, structure damage is detected if over n out of N hits predict the structure is damaged. In ‘combined sensor and hit fusion’, structure damage is detected if over k out of $M \times N$ samples predict the structure is damaged.

NUMERICAL STUDY: ASCE BENCHMARK MODEL

The benchmark structure, as shown in Figure 2(a), is a four-story, two-bay by two-bay quarter-scale steel frame constructed at the University of British Columbia. A 120-DOF model is built to simulate the response measurement of the real structure [3]. The sensor and hit locations are shown in Figure 2(b). Structural damage is emulated by



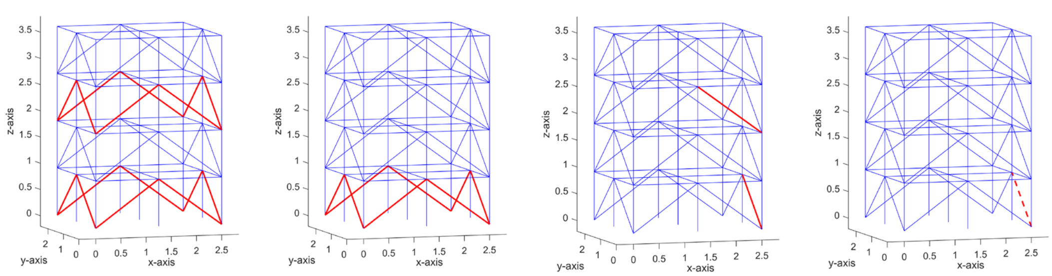
(a) Real structure

(b) 120-DOF model

Figure 2. ASCE benchmark model.

removing the braces or reducing the stiffness of a specified brace. In this study, seven damaged scenarios (DSs) are utilized, as shown in Figure 3. DS-4 to DS-7 refers to 100%, 75%, 50%, and 25% stiffness reduction of one brace. To simulate the real-world uncertainties, 5% aleatoric uncertainty and 10% epistemic uncertainty are added to the data. The dataset information is summarized in Table I.

The damage detection performance of standard AE and VAE with the optimal architectures shown in Table II are comprehensively evaluated under all structural scenarios. The threshold τ for anomaly detection is determined based on the 95$^{\text{th}}$ percentile of MSE distribution. The parameters m, n, and k in the information fusion strategies are selected as 8 out of 16, 2 out of 4, and 32 out of 64, respectively, which enables the information fusion process to be equivalent to the majority vote. The damage detection accuracy is shown in Figure 4. It can be observed that under larger damaged scenarios (i.e., DS-1 and DS-2), both standard AE and VAE can achieve almost 100% accuracy without information fusion. However, as the damage severity decreases, the accuracy will be decreased. Standard AE performs better than VAE in smaller damaged scenarios (i.e., DS-4 to DS-6), where the aleatoric and epistemic uncertainties will pose challenges for damage detection. But information fusion strategies can effectively enhance the robustness of the approach to those uncertainties. For instance, the accuracy of standard AE under DS-6 can be increased from 60.19% to 100% by leveraging information fusion. However, if the damage is too small (i.e., DS-7), both standard AE and VAE cannot make accurate predictions even with information fusion strategies. This is because the effect of uncertainties on the change of vibration signatures is much larger than the effect of structural damage, which makes the approach fail.



(a) DS-1 (b) DS-2 (c) DS-3 (d) DS-4 to DS-7

Figure 3. Damaged scenarios in the ASCE benchmark model. The unit for the x, y, and z axes is in meters.

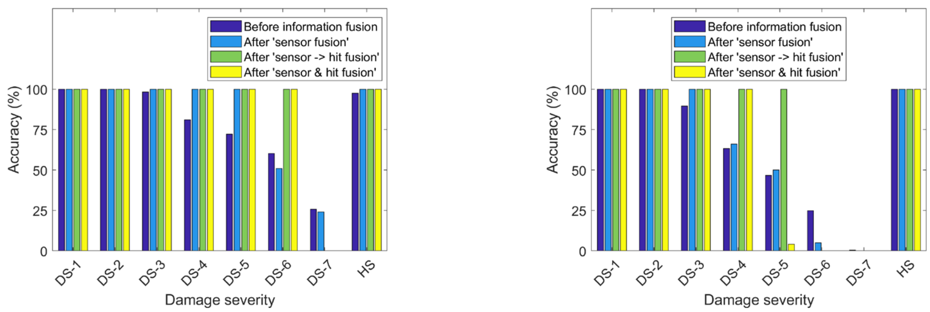
TABLE I. ASCE DATASET INFORMATION

Structural scenario	Dataset	Number of samples
HS	Training, testing	4000, 1600
DS-1 to DS-7	Testing	1600 for each DS

HS: healthy scenario, DS: damaged scenario

TABLE II. ARCHITECTURES OF AE AND VAE IN NUMERICAL STUDY.

AE Model	Encoder	Trainable parameters	Training time (min)	Inference time per sample (sec)
Standard AE	9152 − 64 − 32 − 16	1,185,936	14.3	3.0×10^{-4}
VAE	9152 − 1024 − 3	18,763,718	10.2	1.5×10^{-2}

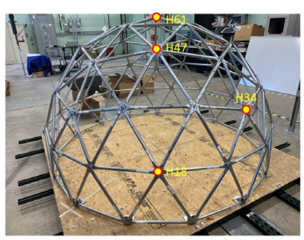


(a) Accuracy of standard AE (b) Accuracy of VAE

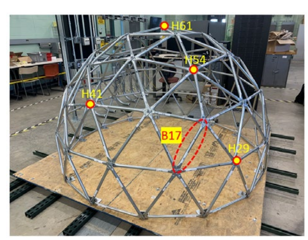
Figure 4. Damage detection of ASCE benchmark model. The legend ‘sensor → hit fusion’ means ‘sequential sensor and hit fusion’. The legend ‘sensor & hit fusion’ means ‘combined sensor and hit fusion’.

EXPERIMENTAL VALIDATION: GEODESIC DOME TESTBED

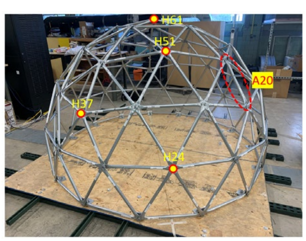
An extraterrestrial habitat can be built as a dome-shaped structure. A geodesic dome is constructed at Purdue University. The diameter and height of the dome are 2.5 *m* and 1.5 *m*, respectively. Structural damage is introduced by removing one strut or loosening bolts. Three damaged scenarios are generated at three different locations by



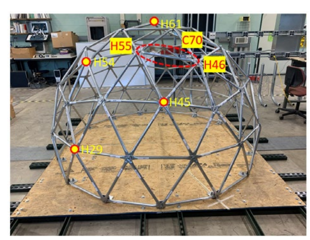
(a) Intact structure



(b) DS-B17



(c) DS-A20

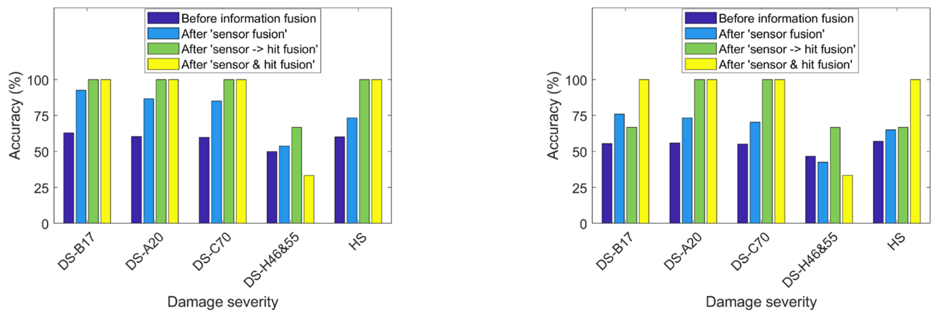


(d) DS-C70 or DS-H46&55

Figure 5. Sensor and damage locations. The yellow dots denote the sensor locations, and the red ellipses denote the damageable struts.

TABLE III. ARCHITECTURES OF AE AND VAE IN EXPERIMENTAL STUDY.

AE model	**Encoder**	**Trainable parameters**	**Training time (min)**	**Inference time per sample (sec)**
Standard AE	7198-784	11,294,446	3.2	1.4×10^{-4}
VAE	7198-1024-3	14,759,972	11.5	3.7×10^{-3}



(a) Accuracy of standard AE (b) Accuracy of VAE

Figure 6. Damage detection of the geodesic dome. The legend ‘sensor → hit fusion’ means ‘sequential sensor and hit fusion’. The legend ‘sensor & hit fusion’ means ‘combined sensor and hit fusion’.

removing strut B17, A20, and C70, respectively. A smaller damaged scenario is created by loosening the bolts at two ends of strut C70 (i.e., H46 and H55). The sensor and damage locations are shown in Figure 5. The proposed approach is experimentally validated using the geodesic dome testbed.

The architectures of standard AE and VAE used in the experimental study are summarized in Table III. The damage detection accuracy is shown in Figure 6. Before applying information fusion, the accuracy is not good due to the large uncertainties in the testbed. However, after employing information fusion strategies, the performance can be enhanced significantly. It is shown that the damaged scenario DS-H46&55 by loosening two bolts is so small that both standard AE and VAE cannot detect it correctly even with information fusion. Overall, standard AE provides higher accuracy than VAE either with or without information fusion.

CONCLUSION

An unsupervised damage detection framework for extraterrestrial habitats using AEs and information theory is developed in this study. Both numerical and experimental studies have validated the effectiveness of the proposed framework. It has been shown that standard AE outperforms VAE in terms of the higher detection accuracy achieved by a simpler network with a smaller number of trainable parameters, as well as faster training and inference time. The framework's ability to extract information from multiple sources allows it to identify anomalies that might have been missed by traditional detection methods. For instance, it is shown that the proposed approach increases anomaly detection accuracy by up to 39.8% under a relatively small damage scenario compared to state-of-the-art approaches.

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