# An Investigation of the Effect of Measurement Interval on the Autoencoder Based Damage Detection in Uncontrolled Structural Health Monitoring

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## ABSTRACT

Unsupervised damage detection in uncontrolled, outdoor environmental and operational conditions (EOCs) is crucial for practical structural health monitoring. While previous research has explored autoencoder-based unsupervised damage detection methods, they require training data only from pristine conditions. In long-term monitoring, irregular environmental and operational conditions, as well as variations in damage, may make it difficult to satisfy this requirement. In this paper, we propose a novel autoencoder-based approach that uses training data containing regular and irregular environmental and operational conditions, as well as damage variations. We also investigate the impact of various factors, such as training epoch, damage duration, and measurement interval on the accuracy of damage detection. Our results indicate that our proposed framework achieves an AUC score of over 0.95 when the measurement interval is around 860 seconds per measurement. Interestingly, this score decreases both when we sampling faster and slower.

## INTRODUCTION

Mechanical systems and civil infrastructures are subject to continual deterioration over time as a result of their exposure to operational and environmental conditions, such as applied static/dynamic loads, temperature variations, and strong winds. This degradation can manifest in various forms, such as corrosion, fatigue cracks, erosion, and strength reduction. As the number and complexity of large and costly engineering structures (e.g., bridges, wind turbines, and aircraft) continue to increase, there is a growing demand to improve their safety and reliability and reduce design, operating, and maintenance costs. To address this demand, structural health monitoring (SHM) has been extensively developed [1, 2].

In structural health monitoring, damage diagnosis techniques based on ultrasonic guided waves (UGW) have garnered significant interest owing to their numerous promising capabilities, such as their ability to cover large inspection areas, high sensitivity to detecting small-sized damage, and the ability to continuously monitor in-service structures on-site [1, 3]. However, it's important to note that changes in guided waves may not only be attributed to structural changes in the monitored system but may also result from various environmental and operational conditions (EOCs), such as moisture, vibration, and especially temperature [2, 4]. Recent research has demonstrated the success of supervised machine learning and deep learning algorithms in ultrasonic guided wave-based structural health monitoring in various conditions [5–12]. However, these algorithms require well-established, labeled, and balanced datasets, typically obtained in controlled lab environments using simple structures. Generating all possible damage scenarios in varying environmental and operating conditions is often cumbersome, time-consuming, and costly [13]. Therefore, Unsupervised learning algorithms, such as deep convolutional autoencoders, are better equipped to handle such situations [14].

The autoencoder-based structural health monitoring system with guided waves has

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been implemented in some research. Rautela et al. transformed guided waves into a time-frequency domain using continuous wavelet transformation and then delamination in aerospace composite panels was identified using a convolutional autoencoder algorithm that has been trained on healthy signals [13, 14]. Abbassi et al. compared four unsupervised dimensionality reduction-based damage detection methods with $Q$ and $T^2$ statistics for computing the compressed representation of the monitoring data (DI plot), including principal component analysis, kernel principal component analysis, t-distributed stochastic neighbor embedding, and autoencoder. Results indicated the autoencoder trained by guided waves from various health conditions showed the best performance in detecting and locating the position of the damage with varying temperature conditions [2]. Similar usage is implemented in detecting rail flaws and plate structures based on the reconstruction error with an autoencoder trained by guided waves obtained from pristine structures [15]. Yu et al. enhanced damage localization with denoised guided waves generated by denoising autoencoder trained by healthy guided waves from complex composite structures [16]. Lee et al. also further presented an automatic technique for detecting and classifying fatigue damage in composite structures using a deep autoencoder. The autoencoder model is trained using guided waves collected from pristine specimens, and its architecture and hyperparameters are optimized to improve the accuracy and sensitivity of the damage diagnosis. The damage-sensitive features are automatically extracted from the bottleneck layer of the DAE model and then analyzed using a density-based spatial clustering of applications for damage classification. [3].

Although these autoencoder models achieve remarkable performance in damage detection, few of them are validated in uncontrolled, outdoor environments in the existence of highly variable conditions, such as rain and snow [17, 18]. In addition, all these autoencoder models are required to be trained by data collected from pristine specimens. In this way, this work will propose a novel autoencoder-based damage detection without requiring clean training only from pristine structures. Furthermore, our previous experiment, as highlighted in [19], revealed that decreasing the measurement interval leads to a decrease in correlation among nearby collected guided waves. Consequently, this can lead to increased variations within the collected data, thereby hindering damage detection due to the impaired reconstruction of guided waves. Surprisingly, experiments mentioned in the paper also demonstrate that increasing the measurement interval can have a negative impact on damage detection. However, there is a lack of knowledge on the impact of measurement interval on damage detection. Therefore, our study aims to investigate the influence of frequency on damage detection and provide valuable guidelines for selecting an appropriate frequency for measuring guided waves in practical structural health monitoring scenarios.

## DAMAGE DETECTION FRAMEWORK

The framework comprises two components: a short-term PCA-based guided wave reconstruction and an autoencoder-based guided wave reconstruction. The framework can differentiate between regular and irregular environmental and operational variations (EOCs) as well as damage variations by comparing the guided wave reconstruction results from the two components. The reconstruction coefficient, which measures the correlation between a guided wave and its corresponding reconstructed guided wave, is

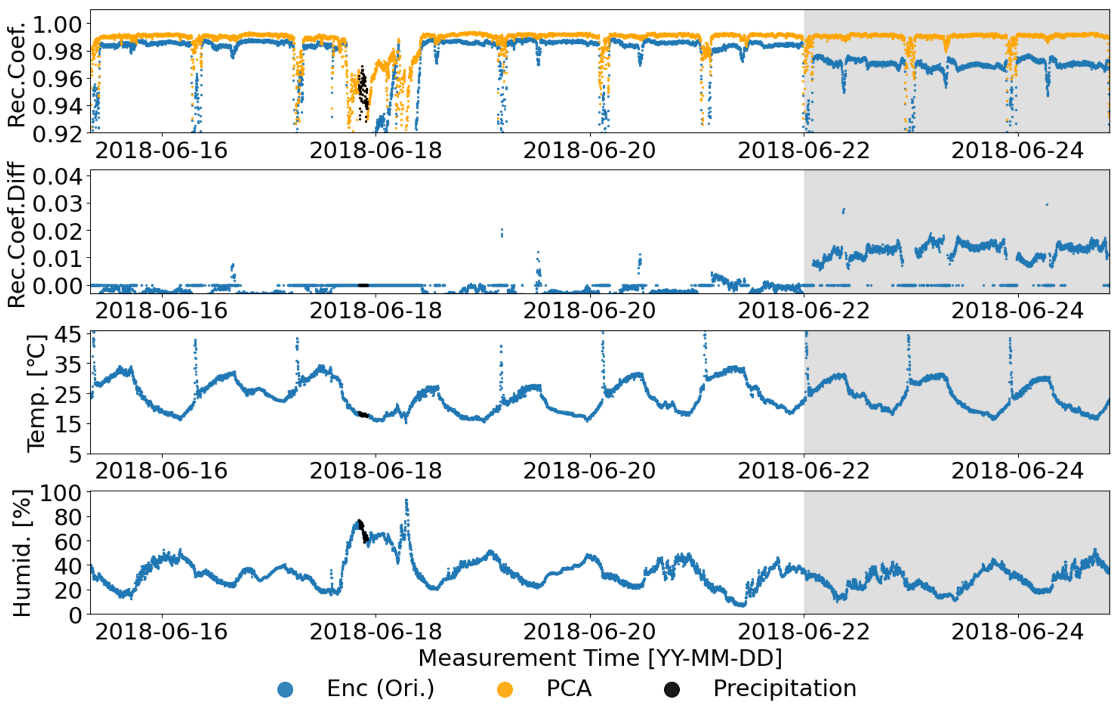


Figure 1. The damage detection index is the difference between the short-term PCA and autoencoder reconstruction coefficients, as shown in the second subplot. The short-term PCA and autoencoder (after the 3-rd epoch training) reconstruction coefficients, marked with orange and blue color, respectively, are shown in the first subplot. The corresponding temperature and humidity are shown in the third and fourth subplots. The damage region is shadowed with a gray region and the recorded precipitation period from the weather website is marked with black color. The measurement interval is 86 seconds per measurement.

used to evaluate the reconstruction performance. The short-term PCA reconstruction coefficients can distinguish irregular EOC variations, such as rain and snow, from regular EOC variations, such as temperature and humidity, and damage variations, such as crack and delamination in composite structures [17, 18]. Meanwhile, the autoencoder-based reconstruction coefficients can detect damage variations from regular EOC variations.

## Irregular Variation Detection

To implement short-term PCA reconstruction in guided wave structural health monitoring, the continuously monitored guided waves are divided into non-overlapping batches. For example, the 80-day guided waves are divided into 80 batches, each containing 1-day guided waves. PCA is then applied to decompose and reconstruct each batch of guided waves using the first 15 principal components. This is called short-term PCA because the time window is relatively small compared to long-term monitoring. This parameter setting has been previously used in our work [17, 18] and has proven to efficiently detect irregular EOC variations, as illustrated in Fig. 1 where short-term PCA reconstruction coefficients remain close to 1 during regular and damage variations but decrease during irregular variations such as rain, snow, and direct sunlight conditions.

### Damage Detection

Guided waves that can not be reconstructed by the autoencoder and not from irregular EOC variations (as identified by short-term PCA reconstruction) will be inferred to be from damage variations. Thus, the damage detection is based on the difference between short-term PCA and autoencoder-based reconstruction coefficients, as shown in Fig. 1. When those reconstruction coefficient differences are far from 0, the corresponding measurements will be regarded as damage variations. To avoid false alarms from irregular EOC variations, we set reconstruction differences to 0 for guided waves detected from irregular variations. To further reduce false alarms from regular and irregular variations, we apply a 3-hour long-running median filter to process reconstruction differences before detecting damage to mitigate some unexpected bad reconstructions caused by dynamic regular and irregular EOC variations.

### Damage Detection Evaluation

The detection model's ability to distinguish between positive and negative samples across a range of thresholds, rather than a specific threshold, is indicative of good performance. As such, the evaluation of damage detection performance is based on the receiver operating characteristics (ROC) curve and the area under the ROC curve (AUC), which are calculated by sweeping across possible thresholds to obtain true positive rate (TPR) and false positive rate (FPR) [17, 18].

## EXPERIMENTAL SETUP

Experiments were conducted at the University of Utah in Salt Lake City. The monitoring system was placed in a small room with three walls and a gate, exposed to various weather conditions, such as rain and snow, due to the lack of a roof. We use synthetic damage as described in our prior work [18] to evaluate the performance of our damage detection framework. We created a total of 20 regions of 80-day guided waves, each containing synthetic damage ranging from 1 to 20 days. It's worth noting that the training data is also used as test data in our study. We utilized the autoencoder's learning ability difference in guided waves from regular, irregular, and damage variations.

## RESULTS AND DISCUSSION

In this section, we explore the effect of changing the measurement interval (the time between each measurement) on the autoencoder's performance. We also demonstrate this our choice of measurement interval is related to the number of epochs for which the autoencoder is trained. In the first subplot of Figure 2, the measurement interval is set to 17.2 seconds per measurement. It can be observed that during the presence of synthetic damage (indicated by the gray region), the reconstruction differences are larger compared to the healthy conditions when training for only one epoch training. These differences tend to decrease with continued training with more epochs, likely due to overfitting. When the measurement interval is decreased to 86 and 860 seconds per

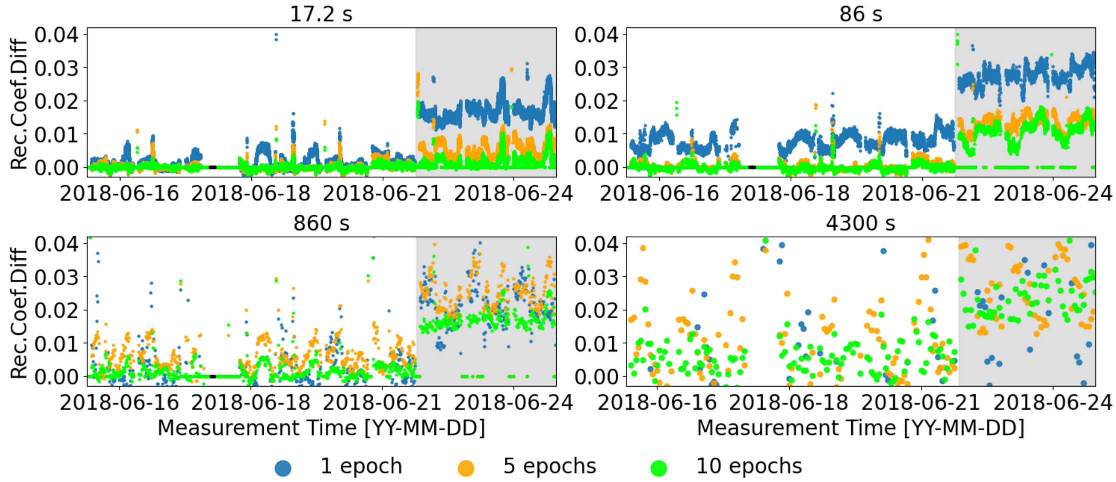


Figure 2. The four subplots display the normalized reconstruction difference between the short-term PCA and autoencoder-based reconstruction coefficients at different measurement frequencies, ranging from 17.2 seconds per measurement to 4300 seconds per measurement, as indicated in the title of each subplot. For each subplot, the reconstruction difference using the 1st, 5th, and 10th epoch autoencoder reconstruction coefficients is shown. The damage region, which lasts for 3 days, is shaded in gray.

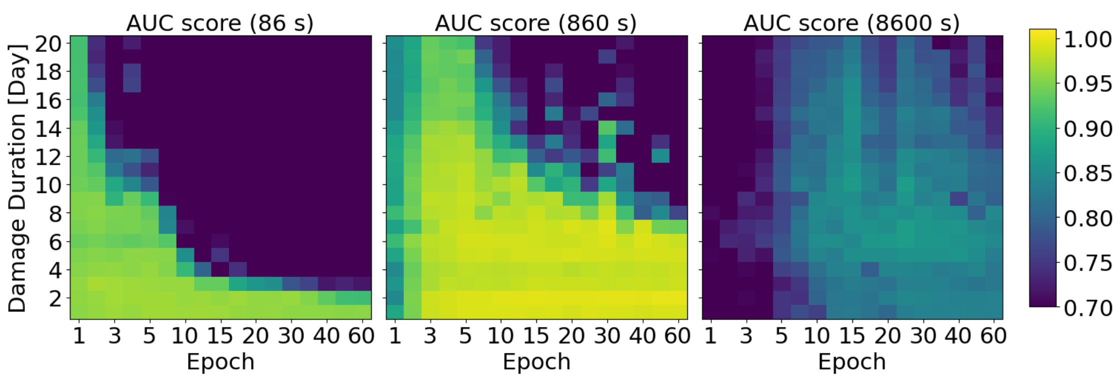


Figure 3. The three subplots depict the AUC score obtained by calculating the reconstruction difference between the short-term PCA and autoencoder reconstruction coefficients. Each subplot corresponds to a different measurement interval, ranging from 86 to 8600 seconds per measurement. For each subplot, the AUC scores were calculated for damage durations ranging from 1 to 20 days, using the reconstruction coefficients obtained after training the autoencoder for 1 to 60 epochs.

measurement, the reconstruction difference between the healthy and damaged regions still persists even after 10 training epochs. This suggests that decreasing the measurement interval results in the autoencoder being trained with fewer guided waves reflecting damage variations, leading to larger reconstruction differences. Moreover, reducing the frequency also helps reduce false alarms caused by transient EOC variations, such as direct sunlight, as shown in Fig. 1. However, at even lower measurement frequencies, such as 4300 s, it becomes challenging to reconstruct even regular guided waves, thus diminishing our ability to effectively detect damage.

Further evidence can be observed in Figure 3, where an increase in the training epoch (x-axis) or the duration of damage in the training data (y-axis) leads to a decrease in the AUC score when the measurement interval is set to 86 seconds per measurement. This suggests that prolonging the autoencoder training duration or introducing more instances of damage variations for the autoencoder to learn worsens the damage detection performance due to a reduction in reconstruction differences within the damaged region. Consequently, the autoencoder learns fewer guided waves that contain damage variations, while still acquiring sufficient regular guided waves to enhance damage detection.

On the contrary, an improvement in performance is observed when increasing the measurement interval from 86 to 860 seconds per measurement. For instance, the best AUC score across training epochs increases from $0.94$ to $0.98$ when the damage duration spans 10 days. Additionally, higher AUC scores are achieved for larger training epochs and longer damage durations. However, when further reducing the measurement interval to 8600 seconds per measurement, the damage detection framework fails to achieve high AUC scores under any conditions. This can be attributed to the inadequate learning (reconstruction) of regular guided waves, resulting from the scarcity of regular guided waves available for the autoencoder to learn.

## CONCLUDING

Our proposed damage detection framework demonstrates its effectiveness in detecting damage in uncontrolled, outdoor environments, without relying solely on training data from pristine conditions. Our findings indicate that excessively long damage durations and large training epochs can have a detrimental effect on performance. However, by appropriately reducing the measurement interval, we can improve both the accuracy of damage detection and the robustness concerning variations in training time and damage duration, as it reduces the number of learning instances from damage variations. Further reducing the measurement interval worsens the damage detection performance due to the limited availability of regular guided waves for training the autoencoder.

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