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STRUCTURAL HEALTH MONITORING IN A JACKET-TYPE WIND TURBINE FOUNDATION: A MINIMUM DISTORTION EMBEDDING APPROACH

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Abstract. The extreme environmental conditions to which offshore wind turbine foundations are subjected make reliable monitoring methods necessary to predict possible structural damage. A data-driven approach was used to perform the structural health monitoring of a laboratory-scaled jacket-type wind turbine foundation. A white noise signal simulating the waves and wind in the sea was applied and amplified to the structure. The vibration-only response was measured by eight tri-axial accelerometers distributed in the structure. Five different structural classes, composed of the healthy and 4 unhealthy, were correctly classified using the following approach. 2460 measurements were acquired for the healthy structure and 820 by each one of the four unhealthy structures for 5740 measurements in total. The data was arranged using an unfolded procedure resulting in a two-dimensional matrix. This resulting matrix has a size of 5740 x 58008. This resulting data has a high dimensionality. Therefore, using the minimum distortion embedding (MDE) approach, a dimensionality reduction procedure transforms the original data into a low dimensional space with fewer features. The low dimensional representation given by different distortion functions was compared changing the repulsive and attractive penalties. The reduced feature matrix serves as input to a machine learning classifier. Several tree-based classifiers like decision trees, random forest and Adaboost were compared. A 5-fold cross validation procedure was executed to reduce the overfitting. Finally, classification accuracy was calculated as performance measure. The developed structural damage classification methodology yields high classification accuracies.

1 INTRODUCTION

Sustainable development is an important topic to preserve the world and live in harmony with the environment. The seventh sustainable development goal sets forth target 7.2, which aims to achieve a substantial increase in the percentage of renewable energy within the global energy mix by the year 2030 [1]. Wind energy is one of the most important renewable energies. Predictive maintenance in wind turbines is a crucial strategy for ensuring the reliability, efficiency, and safety of wind energy production,besides, predictive maintenance helps reduce costs by preventing unplanned downtime and minimizing the need for reactive, costly repairs [2].

Artificial intelligence have been used to perform these predictive maintenance taking advantage of processing condition monitoring data acquired from wind turbines. Particularly, the offshore wind turbines are subject to extreme environmental conditions due to wind and sea waves. The structural health monitoring of the wind turbine foundation can be assessed analyzing vibration only data using accelerometers [3]. A drawback for analyzing accelerometer signals is the high dimensionality that they have. Previous works have treated this issue using Principal Component Analiysis (PCA)[4], Laplacian Eigenmaps [5], autoencoder [6]. However, the dimensionality reduction problem is still open in order to obtain an embedding of the original high dimensional data into a lower subspace dimension.

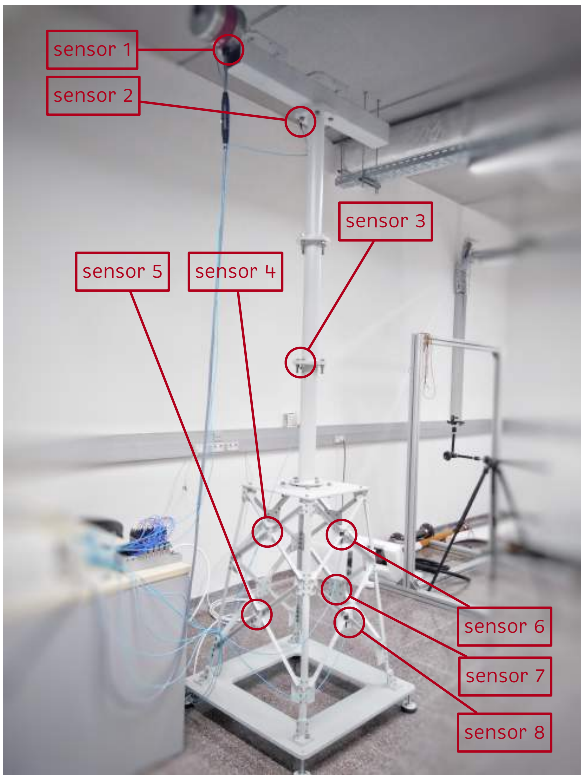
Dimensionality reduction methods start with either weights that describe the similarity of a pair of items, or distances that describe their dissimilarity. The analysis is performed for each pair of items. If two items are similar, their vectors should be close to each other; if two items are dissimilar, their vectors should be far from each other. The minimum distortion embedding (MDE) method generalizes the common cases in which similarities between items are described by weights or distances [7]. MDE has a framework backend in pytorch. The MDE method takes advantage of graphic processing units (GPUs), which improves the computational cost of obtaining a final low-dimensional representation of the data.

This work exhibits a novel damage classification methodology compose of different stages including data organization, data scaling, dimensionality reduction using the MDE algorithm, machine learning classification comparing the behavior of three different tree based algorithms, a 5-fold cross validation and accuracy classification as performance measure. The methodology was satisfactorily tested in a laboratory scales wind turbine foundation. As knowledge of the authors this is the first time that MDE is use to reduce the dimensionality of accelerometer data and perform structural damage classification in wind turbine foundations. This article is organized as follows: the second section describes the materials and methods including the experimental setup, a theoretical background of the MDE and machine learning classifiers, then the third section shows the obtained results of the embeddings and confusion matrices in the structural damage classification problem. Finally, the fourth section contains the Conclusions detailing the principal insights of this study.

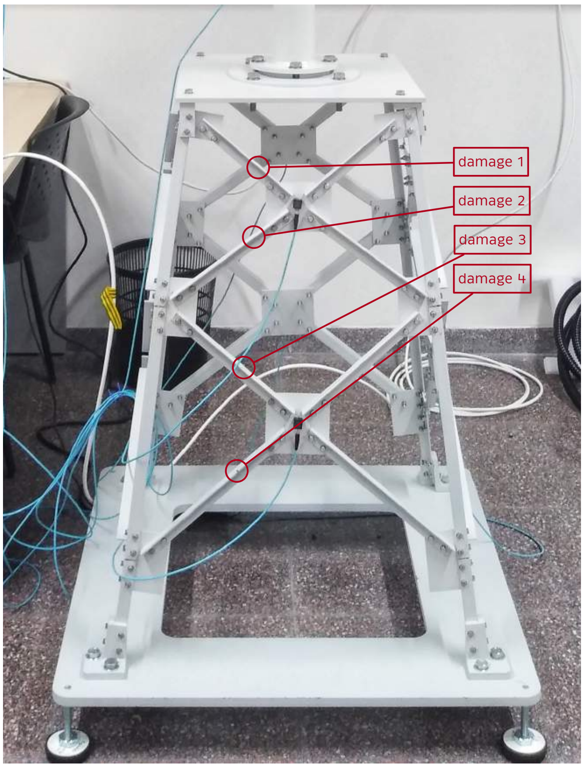
2 MATERIALS AND METHODS

2.1 Experimental setup

A laboratory scale jacket-type wind turbine foundation is used in the experiments. This structure is 2.7m height and it is composed by three parts the nacelle, the tower and the foundation. The foundation is made of steel bars. The structure is instrumented with 8 triaxial accelerometers as can be seen in the Figure 1a. The accelerometers measure the vibration produced in the structure by applying an amplified white noise signal in a shaker. The experimental setup has 5 classes in a structural damage classification problem. First the healthy structure is measured. Then a crack of 5mm is applied in a four different bars belong to the foundation. These four bars with cracks are used one at a time. The damaged bars corresponding each one to the damage classes are shown in Figure 1b.



(a) Location of the sensor within the structure.



(b) Damaged links in the foundation structure.

Figure 1: Experimental setup of the wind-turbine structure [5].

Four distinct amplitudes were employed to apply a white noise signal to the structure, namely 0.5, 1, 2, and 3, to emulate the influence of marine waves and wind. For the undamaged structure, 615 experiments were conducted for each amplitude, amounting to a total of 2460 experiments. Likewise, for each damaged structure, 205 experiments were conducted at each amplitude, resulting in a total of 820 experiments for each of the four damage classes. The number of experiments is detailed in Table 1.

The experiments in the wind turbine foundation used a sampling frequency of 275Hz. The duration of each experiment was 8.789 s. Then a total of M=2417 time measures were acquired by each experiment per sensor. The data from each sensor can be represented by equation 1 in a matrix X with L rows according to Table 1 and $M = 2417$ columns. 8 triaxial accelerometers were attached to the structure resulting in 24 sensors in Total. An unfolding procedure ordering the data of each sensor one after the other was executed. In this way, each experiment had 2417×24= 58008 data points. Finally, the total size of the dataset was 5740×58008. These

Table 1: Number of experiments in the structural damage classification problem

Class	Number of experiments
Undamaged	2460
Damage 1	820
Damage 2	820
Damage 3	820
Damage 4	820
Total	5740

data was scaled using the mean centered unitary group scaling method (MCUGS) [4] due to the magnitude variations obtained by each sensor.

$$X = \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1M} \\ \vdots & \vdots & \ddots & \vdots \\ x_{l1} & x_{l2} & \cdots & x_{lM} \\ \vdots & \vdots & \ddots & \vdots \\ x_{L1} & x_{L2} & \cdots & x_{LM} \end{pmatrix} \in \mathcal{M}_{L\times M}(\mathbb{R}) \tag{1}$$

2.2 Minimum Distortion Embedding-MDE

The scaled data have a high dimensionality. In this study the minimum distortion embedding (MDE) algorithm is used to reduce this high dimensionality to obtain a low dimensional representation of the data. The MDE algorithm was used due to its excellent capabilities to separate the data of different classes and agglomerate the data of each class, these properties ultimately facilitate the task of a machine learning classifier. Presented below is a concise overview of the MDE algorithm. For an in-depth understanding, the reader is encouraged to consult [7].

The new representation of the data in the reduced-dimensional space is called embedding. This embedding can be represented by a matrix $X \in R^{L\times m}$. Where $L = 5740$ are the rows of the total dataset and m are the target dimensions. In this study we set m=30. The set of pairs is denoted as σ. The average distortion (γ) of the embedding is calculated using the equation 2 . The distortion is defined by distortion functions (f_{ij}) of a pair of experiments and their euclidean distance $d_{ij} = \|x_i - x_j\|_2$ as follows [7] .

$$\gamma(X) = \frac{1}{\sigma} \sum_{(i,j)\in\sigma} f_{ij}(d_{ij}) \tag{2}$$

The dimensionality reduction process in the MDE approach consists on minimize the average distortion in the final embedding as showed in equation 3 , the embedding can be subject to some constraints. In this study the standardize and centered constraints[7] were compared.

$$\begin{aligned} &\min\ \gamma(X) \\ &s.t.\ X \in \varphi \end{aligned} \tag{3}$$

Where $\varphi \subseteq R^{Lxm}$ is the set of allowable embeddings. A projected quasi-Newton method is used to solve this optimization problem. MDE has the capability to identify similar experiments to minimize the intra-class distance, in addition the MDE method can identify dissimilar items to maximize the inter-class distance.

Two different distortion functions were compared in this study. First the Quadratic attraction function showed in equation 4. Second a combination between the log1p attraction function showed in equation 5 and the log repulsion function showed in equation 6.

$$f_{ij}(d_{ij}) = d_{ij}^2 \tag{4}$$

$$f_{ij}(d_{ij}) = \log(1 + d_{ij}^{1.5}) \tag{5}$$

$$f_{ij}(d_{ij}) = \log(1 - e^{-d_{ij}}) \tag{6}$$

2.3 Classifiers and 5-fold cross-validation

The reduced feature matrix is used at the entrance of a machine learning classifier. In this study, three different tree-based [8] machine learning classifiers were compared: decision trees, random forest, and AdaBoost. Principal advantages of these classifiers include their simplicity, versatility, and adaptability. A 5-fold cross validation [9] procedure is executed in order to avoid overfitting. The final confusion matrix is derived by aggregating the results from each individual confusion matrix obtained in every fold. Classification accuracy is calculated as performance measure in the final confusion matrix. The stages of developed structural classification methodology are shown in Figure 2.

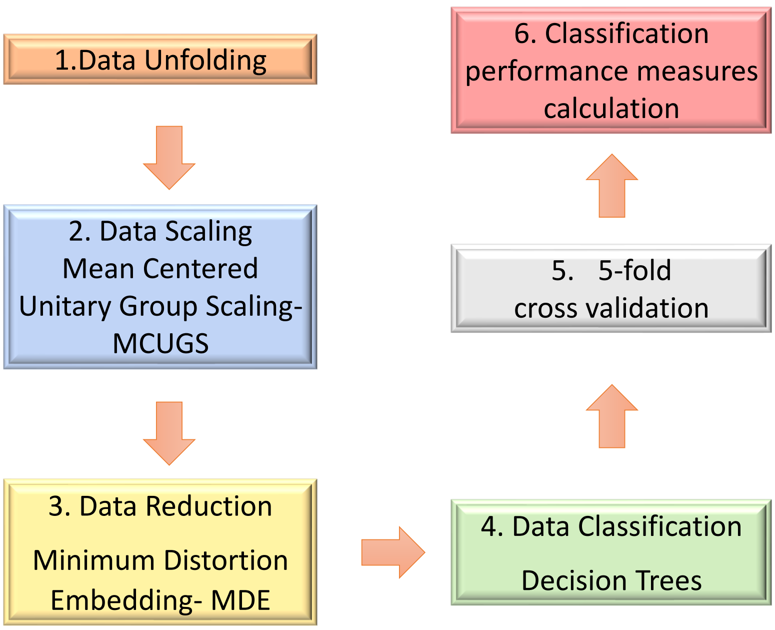


Figure 2: Stages of the developed structural damage classification methodology.

3 RESULTS

3.1 Embeddings

As a preprocessing method, the preserve neighbors method was used, which inspects the local structure of raw data and helps determine pairs of items that are similar if they are close and dissimilar if they are far away. This preprocessing method is based on the construction of a neighborhood graph that has a parameter k. As a first experiment, the MDE algorithm was used with the neighbors parameter k= 30, a standardize constraint, and a Quadratic attraction function as distortion function. The 3D scatter plot of the resulting embedding can be seen in the Figure 3. A mixture of data from the Undamaged, Damage 2, Damage 3 and Damage 5 classes forming a Ring is evident. It is also observed how the Damage 1 class spreads from the center outwards, forming a sphere.

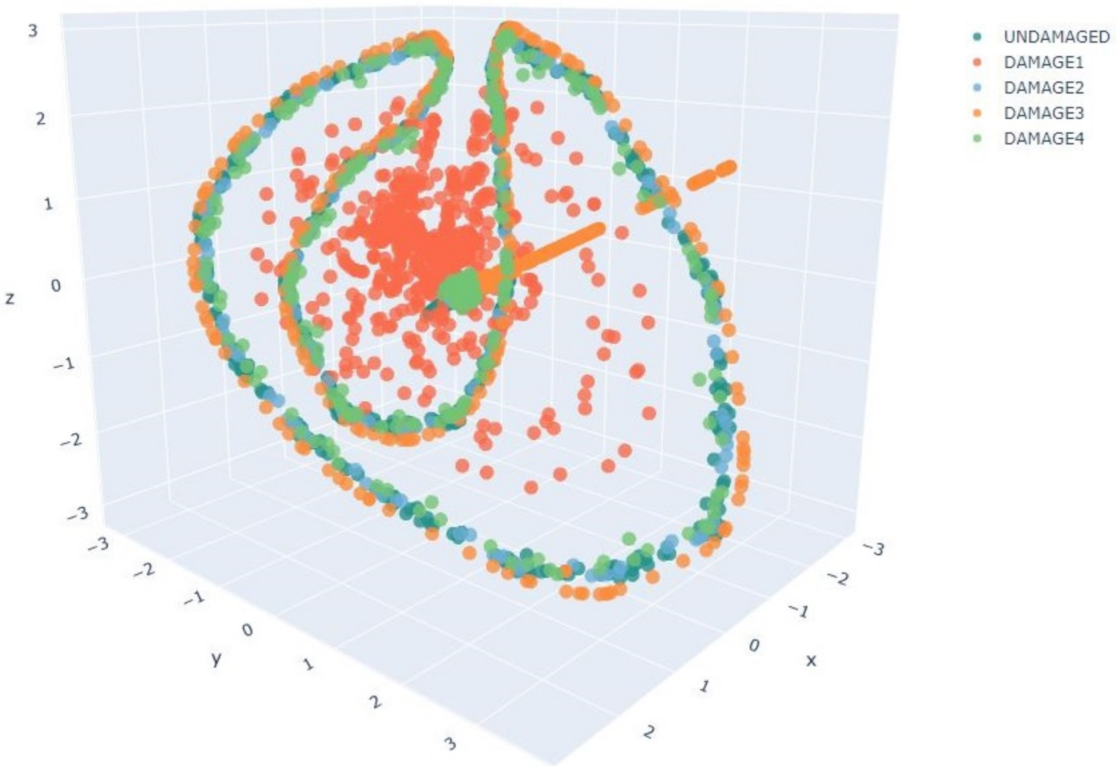


Figure 3: MDE embedding, standardize constraint, Quadratic attraction function and k=30.

The goal was to achieve a clear distinction among classes in the embedding obtained through the use of the MDE algorithm. This involved ensuring that the data associated with each class would not only agglomerate but also distinctly separate from data belonging to other classes. In a subsequent experiment, the parameter for preserving neighbors, denoted as k and set to 200, was increased. A centered constraint was applied, and two distortion functions—a log1p function for attraction and a log function for repulsion—were combined. The outcome of this second experiment is illustrated in Figure 4. It is evident that the classes are perfectly separated, and the data within each class is appropriately grouped together.

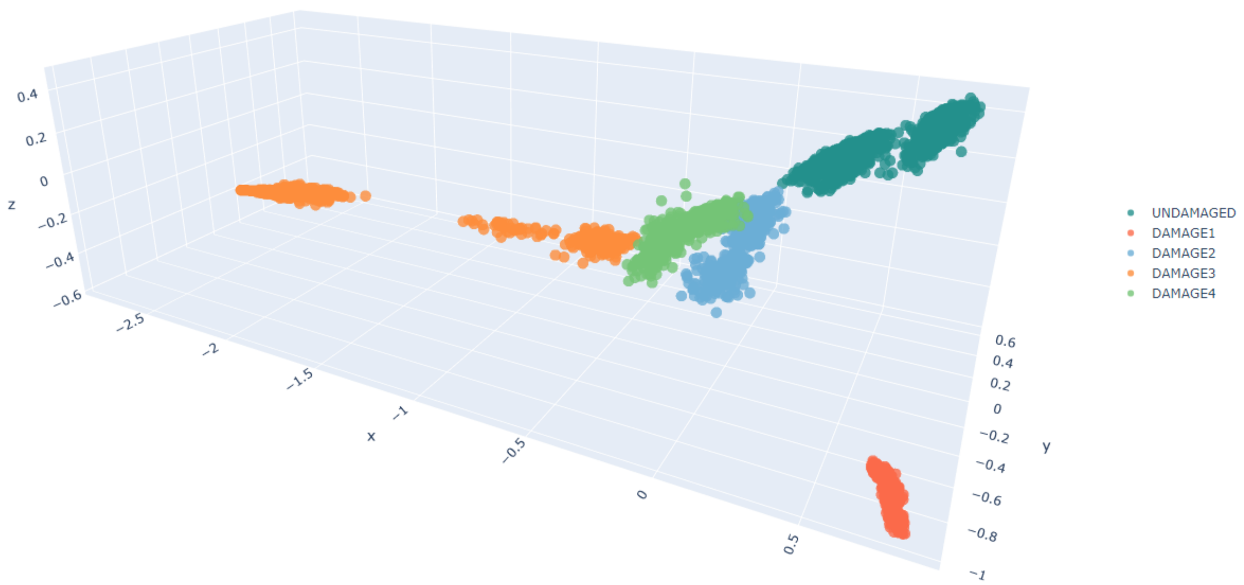


Figure 4: MDE embedding, centered constraint, log1p attraction function, log repulsion function and k=200.

3.2 Classification

The reduced matrix obtained in the second embedding experiment was used at the entrance of the following machine learning classifiers. The first classification was obtained using the AdaBoost machine learning algorithm. The parameter n-estimators was set to 100. After five-fold cross validation the total confusion matrix showed in Figure 5 was obtained. The 2460 data belonging to the Undamaged class are classified perfectly well. This is important because the Undamaged class is not confused with any other class. The 820 data belonging to the Damage 1 class are also correctly classified in their entirety. However, the Damage 2 and Damage 3 classes are quite confused, and no data from the Damage 4 class was correctly classified. The classification accuracy obtained by the AdaBoost algorithm reached a value of 70.52%.

Actual Class	Predicted Class				
	Undamaged	Damage 1	Damage 2	Damage 3	Damage 4
Undamaged	2460	0	0	0	0
Damage 1	0	820	0	0	0
Damage 2	1	0	300	519	0
Damage 3	0	0	352	468	0
Damage 4	0	0	310	510	0

Figure 5: Confusion matrix results of Adaboost classifier with an accuracy of 70.52%.

The second classification was obtained using the random forest machine learning algorithm. The parameters of the random forest algorithm were max depth=8, n-estimators=100, max-features=1. After five-fold cross validation the total confusion matrix showed in Figure 6 was obtained. An improvement of the classification of Damage 2, Damage 3 and Damage 4 is exhibited causing more than 735 samples of these classes to be correctly classified. Conversely, the Undamaged and Damage 1 classes were accurately classified without errors. The classification accuracy obtained by the random forest algorithm reached a value of 95.83%.

Actual Class	Predicted Class				
	Undamaged	Damage 1	Damage 2	Damage 3	Damage 4
Undamaged	2460	0	0	0	0
Damage 1	0	820	0	0	0
Damage 2	1	0	752	0	67
Damage 3	0	0	6	735	79
Damage 4	0	0	83	2	735

Figure 6: Confusion matrix results of random forest classifier with an accuracy of 95.83%.

The third classification was obtained using the decision trees machine learning algorithm. The parameter of the decision trees algorithm was max depth=8. After five-fold cross validation the total confusion matrix showed in Figure 7 was obtained. The best classification was exhibited by the decision trees algorithm with a classification accuracy of 99.26%. The classification of Damage 2, Damage 3, and Damage 4 is demonstrated, resulting in the correct classification of more than 800 samples from these classes. On the flip side, there were no errors in the accurate classification of the Undamaged and Damage 1 classes.

Actual Class	Predicted Class				
	Undamaged	Damage 1	Damage 2	Damage 3	Damage 4
Undamaged	2460	0	0	0	0
Damage 1	0	820	0	0	0
Damage 2	1	0	803	0	16
Damage 3	0	0	0	815	5
Damage 4	0	0	17	3	800

Figure 7: Confusion matrix results of decision tree classifier with an accuracy of 99.26%.

4 CONCLUSIONS

This study demonstrates the successful development of a methodology for classifying structural damage. The methodology comprises various stages in the processing of data acquired through accelerometers, including data unfolding, scaling, reduction, classification, and cross-validation. The achieved high classification accuracy, particularly in a laboratory-scaled jacket-type wind turbine foundation, underscores the effectiveness of the developed methodology. Notably, the undamaged structure was consistently and accurately distinguished from damaged structures, with data collected from four structures featuring a 5 mm crack inserted into a foundation bar.

It is crucial to emphasize the effective representation of data in the low-dimensional space achieved through the Minimum Distortion Embedding (MDE) algorithm. This is evident in the clear separation between classes and the cohesive grouping of data within each class. Such representation significantly facilitates the task of the machine learning-based classification algorithm. The best classification accuracy of 99.26% was obtained by the decision trees machine learning algorithm. Looking ahead, there is an anticipation of developing a semi-supervised methodology for structural damage classification.

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