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SEMI SUPERVISED DETECTION OF STRUCTURAL DAMAGE USING MACHINE LEARNING

[1]Mrs. G. Padma, [2]Sriram Sri Chandana, [3]Vakati Romitha, [4]Yerragudi Vanditha Reddy, [5]Maddi Sukanya

[1]Assistant Professor, Department of CSE(DS), Malla Reddy Engineering College for Women (Autonomous Institution – UGC, Govt. of India), Hyderabad, INDIA.

[2345]UG,Department of CSE(DS), Malla Reddy Engineering College for Women (Autonomous Institution – UGC, Govt. of India), Hyderabad , INDIA.

ABSTRACT

In recent years, Artificial Neural Networks (ANNs) have been introduced in Structural Health Monitoring (SHM) systems. A semi-supervised method with a data-driven approach allows the ANN training on data acquired from an undamaged structural condition to detect structural damages. In standard approaches, after the training stage, a decision rule is manually defined to detect anomalous data. However, this process could be made automatic using machine learning methods. This paper proposes a semi-supervised method with a data-driven approach to detect structural anomalies. The methodology consists of: 1) a Variational Autoencoder (VAE) to approximate undamaged data distribution and 2) a One-Class Support Vector Machine (OC-SVM) to discriminate different health conditions using damage-sensitive features extracted from VAE's signal reconstruction. The method is applied to a scale steel structure that was tested in nine damage scenarios by IASC-ASCE Structural Health Monitoring Task Group.

INDEX TERMS Semi-supervised damage detection, structural health monitoring, variational autoencoder, one-class support vector machines, machine learning.

I. INTRODUCTION

Anomaly detection is a key research problem within many diverse research areas and application domains (see, for example, [1], [2], [3]). Anomalies (also said abnormalities, deviants, or outliers) can be viewed as data instances which move away, are dissimilar, from the large part of collected data. Errors in the data can be the cause of anomalies, but sometimes they can be indicative of a new, previously unknown, underlying process [4]. Anomaly detection tasks have been tackled by several Machine Learning (ML), and in particular Deep Learning (DL), techniques [5], [6], [7]. However, a substantial part of anomaly detection approaches is based on Autoencoder (AE) architectures [4], [8], [9], [10], [11], [12], [13]. AEs correspond to neural networks composed of at least one hidden layer and logically divided into two components, an encoder and a decoder. From a functional point of view, an AE can be seen as the composition of two functions E and D: E is an encoding function (the encoder) which maps the input space onto a feature space (or latent encoding space), D is a decoding function (the decoder) which inversely maps the feature space on the input space. A meaningful aspect is that by AEs, one can obtain data representations in terms of fixed latent encodings $\vec{h}$. In a nutshell, in anomaly detection tasks AEs are trained to minimize reconstruction error only on normal data instances, thus involving high reconstruction error on anomalous data. Then, the reconstruction error is considered as an anomaly score to classify the input data as anomalous or not, using a user-defined decision rule.

2 LITREATURE SURVEY

In recent decades, the attention to procedures for anomaly detection due to damage phenomena in civil constructions and infrastructures is more and more growing. Indeed, (i) safety standards for new constructions have increased - and therefore existing constructions could not comply with these standards for little degradation phenomena (ii) both new and existing structures are becoming increasingly smart with the use of several embedded sensors providing real-time information. For this reason, the research aimed at finding procedures that allow the set up of a Structural Health Monitoring (SHM) system for structures and infrastructures, i.e., for both buildings and bridges, are very numerous. Bridges are strategic structures for which important and expensive management and maintenance activities are foreseen because they are structural types particularly subject to environmental phenomena and variations in use conditions (loading-unloading cycles, temperature, etc.).

Moreover, they do not have reserves of resistance capacity, which are characteristic of other structural types such as, for example, buildings. On the one hand, a proper model of the physics behavior of this type of structures in operational condition is not easy. This stimulates the use of automatic monitoring systems that can continuously and rapidly detect anomalous conditions due to damage, to ensure a quick response from the infrastructure manager. On the other hand, it is necessary to consider that (i) the high variability of the boundary conditions in which the bridge structure functions can alter the estimate of the anomaly (e.g., variable vibrations induced by wind actions, highly variable traffic load during the functioning of the structure, highly non-linear mechanical behavior of the materials that constitute the bridge) (ii) any algorithm implemented for a structural monitoring system hardly detect damage conditions if trained on an extensive database of measurements performed mainly in the operating conditions of the structure, namely in the absence of structural damage. This second aspect is crucial because the difficulties of measuring damage conditions are due to the intrinsic assumption made in the structural design approach, which expects the use of high safety factors to ensure that the operational conditions are well far from the structural limit condition. Therefore it is evident that investigating the use of damage detection algorithms that accurately provide warnings for structural monitoring is particularly challenging and interesting, regardless the subsequent necessity of damage quantification and structural prognostics.

3 METHODOLOGY

In this work we propose a framework to perform a semi-supervised damage detection using a VAE followed by a OC-SVM. The main aim of our proposal consists in identifying the presence of damages regardless their intensity, thus producing outcomes from the application of this framework that can be interpreted in terms of a binary classification response. A supervised method for identifying structural damage requires labeled data during the training phase, which means data must be recorded both in the undamaged and damaged states of the structure.

However, in a real case study, the available data is assumed to be undamaged during the training phase. Therefore, the use of data on the damaged structure is subordinated to the adoption of Finite Element (FE) numerical models of the structure, which can simulate potential damage conditions.

It should be noted that, for existing structures, the FE model is based on simplifying assumptions that may not fully match the experimental behavior of the structure. Updating the FE model can improve the accuracy of the simulation (e.g. by calibrating the matrix of masses and stiffnesses of the structure), but this process is time-consuming and requires extensive analysis. The described procedure, which uses a semi-supervised approach, circumvents this issue by relying solely on undamaged data during the training stage to detect structural decay without utilizing FE numerical models. According to its definition, training a VAE on undamaged data involves the approximation of their intractable true posterior through their latent representation. In [7], an anomaly is defined as an observation that differs from regular data that it is considered to be generated by a different mechanism.

This definition induces to consider distinct true posterior between undamaged and damaged data. Leveraging on this aspect, different latent distributions are generated by the probabilistic encoder if data are heterogeneous (i.e. including both undamaged and damaged data), thus inducing the probabilistic decoder to an erroneous data reconstruction if latent distributions are different from that of the undamaged data. Then, after a feature extraction stage, data are fed into a OC-SVM in order to learn a decision boundary to separate undamaged data from damaged data, and thus to classify new input datapoints as damaged or not. A representation of the framework is shown in Figure 1. In the following subsections VAE and OC-SVM models are explained.

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FIGURE 1. Photo of the experimental setup.

4. EXPERIMENTAL ASSESSMENT

The architecture proposed in this work was evaluated on the benchmark dataset from the case study related to the steel frame tested in Phase II of the SHM benchmark problem [8], whose results were published in 2003 by the International Association for Structural Control (IASC) - American Society of Civil Engineers (ASCE) Structural Health Monitoring Task Group. The results of the experimental assessment are compared with the performances obtained by the method proposed in [7] on the same dataset and with the performances obtained by substituting VAE with a standard AE, thus following the approach proposed in [5]. In this Section, firstly details on the benchmark dataset are provided. Then, details regarding how data were arranged and specifics about the model selection stage involved in the experimental phase are described. Finally, results are shown and discussed.

	X_Minimum	X_Maximum	Y_Minimum	Y_Maximum	Pixels_Areas	X_Perimeter	Y_Perimeter	Sum_of_Luminosity	Minimum_o
0	42	50	270900	270944	267	17	44	24220	76
1	645	651	2538079	2538108	108	10	30	11397	84
2	829	835	1553913	1553931	71	8	19	7972	99
3	853	860	369370	369415	176	13	45	18996	99
4	1289	1306	498078	498335	2409	60	260	246930	37

Fig 1: Dataset

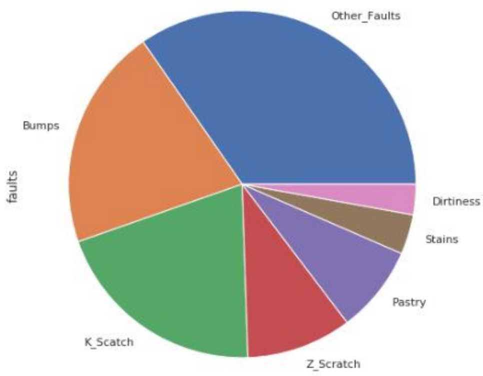

Fig 2: Faults identifeid

In this work, we proposed a framework to perform a semi-supervised damage detection in an SHM system based on a VAE and a OC-SVM in order to minimize human interactions during the data classification process. It is important to note that, even though we have focused our studies on MLP, VAEs can be implemented using various other architectures, such as CNNs and RNNs. While we acknowledge that different implementations of VAEs can potentially impact the overall performance of the pipeline, our study primarily focused on examining the functionality of the entire framework to gain insights into its operation

5 CONCLUSION

In this work, we proposed a framework that allows to automate the entire damage identification process (from the training stage to the testing stage) requiring less time than a traditional SHM technique. In particular, if we consider a typical SHM technique (i.e. FDD) that compares the frequency of vibration of the structural system in different conditions to identify anomalies, we have to highlight that (i) the frequency identification is not always unique (ii) the threshold to define if there is an anomaly is completely arbitrary. The probabilistic aspects of a VAEs allow to model data heterogeneity with different generating distributions. In the case of undamaged/damaged data, the probabilistic encoder models different data distribution thus involving an implicit capture of damaged states of a structure and resulting in a more robust damage-detection system than using a standard AE. Moreover, the KL divergence, which is generally implied in VAE's training stage, could be evaluated for the cases in which a damage is detected in order to quantify it.

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