Dear reader, this is part of the literature review from my thesis, the course was cancelled in my year but my supervisor was kind enough to sign me up for the literature review part of the course as I write my thesis. If you feel like only reviewing ~1500 words which I believe is the limit, then you can stop at Section 3.

1 Damage Identification

Methods of damage identification that monitor changes in civil infrastructure include methods based on modal properties, methods based on a model-updating procedure, probabilistic approaches e.g. using Bayes theorem, and pattern recognition approaches such as artificial neural networks.

A significant amount of the early research into damage identification of civil infrastructure is based on modal properties, attempting to detect damage by classifying changes in natural frequency or mode shape.

Damage was applied to the I-40 bridge, a 130m girder bridge over the RIO Grande river, before it's demolition, and data recorded from ambient vibration tests. The damage was intended to simulate fatigue cracking and was inflicted with torch cuts in a girder. In the fourth and most severe damage state the web of the girder contained a 6 foot cut and the flange was completely cut through. In [1] it is noted that changes in dynamic properties were only observed in the fourth damage state. Furthermore, changes of similar magnitude were observed from repeated ambient vibration tests on the undamaged structure.

In [2] introduced the use of the curvature of mode shapes which is obtained by differentiating the displacement mode shape twice. Changes in the curvature of the mode shape are localized to the damage and furthermore the absolute difference of the curvature mode shapes of the damaged and undamaged structures increase with damage severity [3]. However the [2] study was on a computer model of a beam, and did not consider robustness to noise.

In [4] changes in mode shapes, from the same I-40 experimental data, were shown to be statistically different from the undamaged state for all damage states, however the analysis could not discriminate whether the source of the change was structural damage. The damage in the fourth damage state was localized, however at this point the bridge was sagging by 2cm at the damage location, and according [5] the bridge would have collapsed under a live load.

In [6] changes in natural frequency and mode shapes from numerical simulations are used to determine the location and the extent of damage on a rigid frame and then to assess the safety of the structure. However this paper highlights two issues common in the literature. Modal parameters corresponding to a baseline or "healthy" state are required, and robustness to noise is not addressed in the work. The requirement of "baseline" data is not a fatal flaw and could be addressed in a number of ways: 1) the baseline state comes from sensor measurements taken for newly built structures, 2) existing structures could be monitored for *any* changes after sensor installation, not knowing whether the structure was already damaged or not, 3) a FEM is used to generate an approximation of the baseline state. The robustness to noise is a more crucial problem because civil structures will be subjected to environmental factors such as temperature changes. The work [6] simply states "the existence of noise in the data processing should be addressed".

The 64m concrete Dogna bridge in Italy was built in 1978 and suffered from a strong flood in 2003. In 2008, prior to demolition, an experimental campaign was carried out where six damage configurations were applied to the bridge in the form of notches cut with a hydraulic saw. In [7] changes in modal curvature were succesfully used to identify the location of the damage. However the dynamic tests were all carried out under similar environmental conditions, thus the robustness to noise was not investigated.

In concrete structures with reinforcing steel bars, the bars are tensioned such that the concrete remains in compression. Once the steel bars have corroded and failed the concrete bridge is liable to collapse. However the stiffness of the bridge is mostly contributed by the concrete, the corrosion of the steel has little influence on the dynamics, until the steel bars and bridge have failed [8].

In [9] a model-updating approach is applied which minimizes the difference in mode shapes. This approach is validated on the Z24 highway bridge in Switzerland, which is a 58m pre-stressed concrete bridge. The damage scenario considered was the lowering of one of the supporting piers (originally at a height of 44m) by 95mm. In this study only a single damage scenario was considered and environmental effects such as temperature which could represent a false positive damage scenario were not considered.

Model-updating approaches compare measurement data with responses from an analytical model, and attempt to minimize the difference by updating model parameters. One problem with optimization algorithms used to update model parameters is that they may find a local rather than a global optimum. Evolutionary algorithms are good candidates for such problems and in [10] the particle swarm optimization algorithm is used as a model-updating approach using vibration data. The approach was experimentally verified against data from a 129m railway viaduct.

Health monitoring based on an analytical model imposes a challenge because an analytical model is required and the necessary data for building an analytical model is not always available. This is because civil infrastucture is not always built precisely to the original design, due to changes in orders or due to on-site construction constraints. Moreover, in the case of concrete, uniform material properties are not guaranteed.

A Bayesian probabilistic approach was applied in a laboratory test to a reinforced-concrete bridge column [11], this method compared the relative damage probabilites of different damage events based on data from vibration tests. The method has the potential advantage of not requiring an accurate analytical model, yet the study was only on a single column of a bridge and it was a laboratory experiment that did not account for environmental noise.

2 Machine Learning

Machine learning based approaches map inputs to outputs based on previously given input-output pairs, known as training data. Supervised learning methods require the existence of data corresponding to damage states, which is unlikely in the case of civil infrastructure. Unsupervised learning methods classify data into clusters without pre-existing labels. One-class classification is a form of outlier detection that can be considered a special case of supervised-learning, where only one class of training data is present in the training data.

In [12] a number of damage identification experiments were applied that attempted to identify damage on an aircraft wing. The study showed damage localization and assessment to be possible with machine learning methods however the experiments were in a controlled laboratory setting without any environmental factors present. In the same paper it is argued that "damage prediction cannot be addressed by machine learning methods in general".

In [5] a FEM of the 214m Clifton suspension bridge in Bristol, England is used to generate data corresponding to healthy and damaged states, namely damage to the girders. Environmental factors were considered by heating one side of the model by 30 °C. In order to generalize the classification problem, data was generated by simulating a vehicle moving at 3 different speeds. The vehicle was simulated using 2 concentrated loads, one per axle. Features were extracted from simulated vibration data and given as input to two unsupervised neural networks. The better-performing of the two was DIGNET [13] with a damage detection rate of [illegible]%.

An ANN is used to detect damage from dynamic responses from a FEM of a railway bridge in [14]. To accomplish this an ANN is trained on past acceleration responses from the healthy bridge and then used to predict future values, the difference between predicted and measured data are used as a damage indicator. While prediction of subsequent acceleration data was possible, the only loading applied was one moving vehicle, a train, no additional vehicles or second lane of traffic. Furthermore the authors suggest further work regarding the effect of environmental and operational effects.

The Syndey Harbour Bridge (SHB) is a steel-reinforced concrete bridge built in 1932. The SHB consists of 800 jack arches in longitudinal direction. In an experimental campaign each jack arch was fitted with 3 accelerometers. It was known that one of the arches was cracked. Two very interesting papers applied damage detection to acceleration data collected from the sensors on the SHB. Both of these papers, unlike any of the works discussed so far, make use of structural information of the bridge.

[15] uses the idea that if an arch on the SHB is healthy then accelerometers would move together, if there is a crack then they would move differently. An SVM was trained using labeled data from features combining data from sets of 3 accelerometers on an arch. A one-class SVM (OCSVM) which is an unsupervised variant of the SVM that is trained only on the healthy data, was also tested. The supervised variant achieved an accuracy of approximately 0.97 and the unsupervised approximately 0.71.

Two methods were applied in [16] using the idea that similar substructures should behave similarly. k-means clustering was applied to the features collected from each joint. With k-means k=2 and only considering 6 joints, including one known damaged joint, a cluster was formed containing primarily features from the damaged joint. This method did not perform well when the amount of joints considered was increased to 71. The other method applied in [16] considered a "joint representative", a feature that is the mean of the features from one joint. Then a pairwise map was created using the euclidean distance between each pair of joint representatives. This method detected the known damaged joint, another joint with a known faulty sensor and a third joint with unknown damaged state.

3 Practical Considerations

Any SHM system that is deployed on a real-life structure must consider the environmental and operational effects that will affect the responses of the bridge. Temperature changes the stiffness properties of a bridge deck resulting in different responses throught a day or year, and noise from traffic on another lane will also make damage identification more difficult.

A regression analysis was applied to acceleration data from the Alamosa Canyon Bridge in New Mexico in [17]. The natural frequency varied approximately 5% during the 24 hour interval when measurements were taken and the frequency was well correlated with temperature. Measured temperatures exceeded 45 celcius and the eastern and western sides of the bridge showed a large temperature gradient, because the bridge is oriented north to south. In [18] a linear relationship is shown between the 1st and 2nd eigenfrequencies of the Z24 bridge in Zwitzerland and temperature above 0 celcius, and a separate linear relationship below temperature below 0 celcius. The linear relationship was related to the presence of the asphalt on the bridge.

An integrated machine learning algorithm, combining techniques including PCA, is presented in [19] for separating the individual components of the deflection signal into componenets with separate frequencies. When the noise level was under 10%, each component (temperature, live load, structural damage) was succesfully separated based on data from a computer model of a long-span bridge. A linear relationship between temperature and deflection was assumed. Temperature was decomposed into two sinusoidal components, daily and annual. An auto-associative neural network is employed for separating the effect of damage in extracted features from responses caused by environmental variations of the system [20]. However the experiment was on a numerical simulation of a hard drive, and a laboratory test on a spring-mass system. The authors admit that several issues are to be addressed before the approach can be used on real structures.

In a real-life installation the possibility that a sensor has developed a fault and that the received signal is incorrect must be considered, in the work on the SHB [16] one of the sensors was faulty, which was detected as damage. Damaged sensors can be detected via sensor data reconstruction. In this approach sensor data is reconstructed based on spatial and temporal correlations among the sensor network. If there are discrepancies between the measurement data and reconstructed data then the sensor may be faulty. Spatial correlations are used to reconstruct sensor data via PCA [21], minimum mean square error estimation [22], and support vector regression [23]. A recurrent neural network (RNN) was used that includes both spatial and past temporal data [24]. More recently in 2019 a bidirectional RNN includes more information by considering spatial and both past and future temporal correlations [25]. This method outperformed a number of existing methods on their test set, however the test data was from numerical simulation of an unvalidated model.

4 Conclusion

Early work on damage identification of civil infrastructure was largely focused on the analysis of modal properties such as mode shapes while recent work tends to employ machine learning, with particular use of unsupervised methods such as the OCSVM. Feature extraction is arguably the most important and difficult step in ML-based health monitoring [12]. Much of the existing research suggests promising results in a simulated or laboratory setting, and does not consider the difficulties that environmental or operational effects provide. Two works that succesfully detected aprioi known damage on the SHB combined machine learning techniques with knowledge about the behaviour of the structure.

{TODO: more on: anomaly detection. SHM installations in real life, and anomaly detection of non-bridge structures e.g. levees. and conclusion.}

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