

Investigation on the use of artificial neural networks to overcome the effects of environmental and operational changes on guided waves monitoring

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Abstract. Intelligent feature extraction and advanced signal processing techniques are necessary for a better interpretation of ultrasonic guided waves signals either in structural health monitoring (SHM) or in nondestructive testing (NDT). Such signals are characterized by at least multi-modal and dispersive components. In addition, in SHM, these signals are closely vulnerable to environmental and operational conditions (EOCs), and can be severely affected. In this paper we investigate the use of Artificial Neural Network (ANN) to overcome these effects and to provide a reliable damage detection method with a minimal of false indications. An experimental case of study (full scale pipe) is presented. Damages sizes have been increased and their shapes modified in different steps. Various parameters such as the number of inputs and the number of hidden neurons were studied to find the optimal configuration of the neural network.

1. Introduction

The aim of SHM is to detect, localize and identify early stage damages in operating structures in order to increase their life service, reduce maintenance cost and avoid catastrophic failure [1]. Ultrasonic guided waves are considered as a good candidate for such an application because they can travel over long distances with relatively small attenuation. Hence, they can cover large areas using only small number of permanently mounted sensors. The acquisition system continuously (or periodically, where the acquisition period is related to different factors which are not detailed in the present paper) stores data from *in-situ* structures. Consequently, signal processing and analysis are necessary to convert the acquired data into information reflecting the state of the structure. However, the collected data may contain not only information about damage but also the effect of EOCs [2]. Thus, to ensure a reliable damage detection approaches, these effects must be eliminated or at least reduced. In literature, issues (analytical and statistical) relating to the effects of EOCs have been addressed by many researchers [3,4]. By following an analytical approach, it is difficult to provide a global and reliable solution for this problem. Indeed, each environmental and operational factor should be studied carefully to demystify its effects. Once effects are known, solutions can be provided (example temperature effect in reference [7]). Since these effects are various, it becomes a challenging task to implement a solution per parameter. An alternative approach can be found in statistical methods, specifically in pattern recognition paradigm [5].

This paper starts by describing the effects of EOCs on ultrasonic guided waves monitoring technique. Time-shift, amplitude drift, distortion and dilation were determined as drastic effects of these EOCs.



Afterward, a damage detection technique based on a supervised learning algorithm, namely Artificial Neural Networks (ANNs) will be investigated. The last section will be devoted to the conclusion of the paper.

2. Environmental and operational effects

The propagation of guided ultrasonic waves can be affected by some environmental and operational factors (e.g. temperature, humidity, vibration loads, etc.). For instance, temperature variation induces generally a thermal expansion or compression of the structure which impacts the wave propagation. In the case where only single non-dispersive mode propagates through the medium, the effect of temperature has been demystified by mathematical formulations [3]. The assumption of single-mode excitation reduces the complexity of the received signals and thus makes their interpretation much easier. However, its generation depends highly on the type of transducers and the geometry of the host structures [6]. Theoretically, it has been shown that change in wave velocity, caused by temperature variation, is the main cause of time shift in signals [3]. This time shift will have an impact on the detection system because it will result in an unacceptable high residual signal if two baseline signals are subtracted. This is due to the fact that even if there is no damage, the baseline and the current signal do not match. Besides, literature review, performed recently by the authors, showed that time shift is not the only effect of temperature. In addition, the assumption of single mode propagation is often idealistic because the generation and propagation of a unique mode is not always straightforward especially in in-situ structures. Guided waves are characterized by multi-modal, dispersive and multipath components; hence it is difficult to establish a mathematical relationship between EOCs effects and wave propagation. To overcome this problem, researchers have performed empirical studies by exposing the structure to different temperature variation in an environmental chamber [7]. Results shown in Figure 1 (left) confirmed that the effect of temperature is not only a change in the arrival time but also in the amplitude of signal response. It has been also found that changes in signal shape namely distortion and dilation can be eventually noticed when dealing with diffuse ultrasonic signals [8]. These results are quite controversial because damages might be detected via algorithms which can extract information by comparing exactly the amplitude, the shape and the arrival time of signals before and after damage. In other words, the effects which result on signals, and can have a drastic consequence on the damage detection system are: time shift, amplitude drift, distortion and dilation. Even if the other EOC factors, such as liquid loading, are not studied in this paper, the effects might be the same. As a consequence, techniques that can remove temperature effect could possibly be utilized for other EOCs factors. Therefore, the damage detection algorithm should be able to recognize if the monitored structure is damaged or not even under harsh EOCs. That's to say the algorithm should make difference between damage presence and EOCs since both impact the signal. To this end, some compensation method have been developed, but they are limited to some specific cases, and had been only designed to compensate the effect of time shift as it is illustrated in Figure 1 (right).

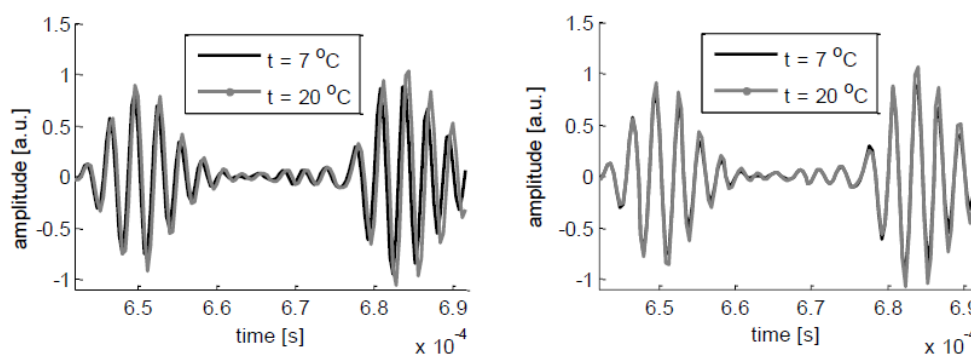


Figure 1. Example of temperature effect on sensor signals (left), and temperature compensation (right) [7]

The solution to the EOCs problem is inspired from pattern recognition paradigm (e.g. face and speech recognition) where the algorithm is capable of detecting a pattern even it includes some changes. The most utilized algorithm is the Artificial Neural Network (ANN) [9,10]. The next section will provide an analysis of this algorithm and how it can be utilized in the context of SHM applications.

3. Artificial Neural Network (ANN)

ANN is an algorithm inspired from biological neural networks. It has been initially designed for solving problems of pattern recognition, and it has been extended then to other artificial intelligence applications such as prediction, control and optimization [11,12]. In the context of SHM and non-destructive evaluations, this method has been successfully utilized for damage detection and classification [9]. It is considered as a supervised learning algorithm, because data from both system states (damaged and undamaged) are needed and should be available for classification tasks. The basic architecture of an ANN consists of three components: inputs, hidden layers and outputs. All these components must be interconnected and process information in parallel. In this study, inputs are the damage-sensitive features calculated from ultrasonic guided waves signals. It's a measure that quantifies the presence and severity of damages. The algorithm of ANN is implemented by two elementary steps: training and validation. The first step also known as learning provides the network with the desired output for specific types of inputs. Since the damage-sensitive features are dependent on damage type, the objective of this step is to learn to the detection system the relation between the features and the type of damage. The second step tests the ability of the network to recognize the type of damage whenever a new feature value is presented. Figure 2 shows the ANN architecture that has been adopted, which is the Feed Forward Back Propagation (FFBP) [13].

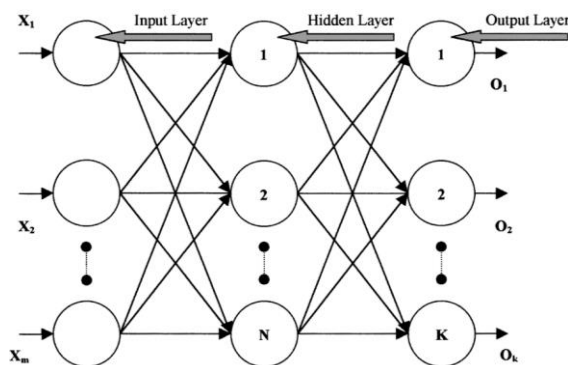


Figure 2. Feed Forward Back Propagation network.

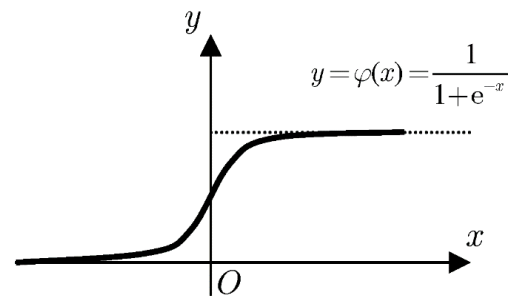


Figure 3. Sigmoid transfer function.

The input layer receives the inputs as damage-sensitive features. The hidden layer processes the data by multiplying the input vector by weights and adding biases. The results are set as input parameter of a transfer function (Figure 3). Since the output targets are generally coded with binary digit, this function returns a float between 0 and 1. The output layer provides the network with the outputs and compares them with targets. The error is calculated as:

$$E = \frac{1}{N} \sum_{i=1}^N \sum_{j=1}^m (y_{ij} - \hat{y}_{ij})^2 \quad (1)$$

where N is the number of training samples, m is the number of output nodes, y_{ij} is the desired target and \hat{y}_{ij} is the network output. If the error E is bigger than a certain value, the training is continued by transmitting the errors backwards from the output layer, and adjusting the weight and biases. Otherwise, the learning process is stopped. Finally, it is worth noting that the performance of the network depends greatly on several parameters such as: dimension of the input vector, type of damage

sensitive features and number of hidden layers. Therefore, it is recommended to test multiple combinations of these parameters in order to find the optimal configuration of the network.

4. Case of study

Experiments were conducted on a pipeline structure using ultrasonic guided waves. Damage was simulated physically by adding a mass of magnets to the surface of the pipe, as it is shown in Figure 4. This technique has been found in the literature as an acceptable way to simulate damage non-permanently in a structure [14–16]. In fact, damage is normally detected in guided waves-based systems due to the local change in the density ratio of the structure causing a wave reflexion. By adding the mass to the structure, a simulated damaged region is created. Besides, the reflexion coefficient of the incident wave is more sophisticated than the case of a realistic damage.



Figure 4. Different types of defects (circumferential configuration)

A single acquisition of the baseline and all damage types was acquired. To account for environmental and operational conditions changes (EOC), a stochastic noise was added to each type of damage including the baseline. For each case (for example the baseline), 199 signals is constructed from the original signal (which has not been contaminated with noise) as it is shown in Figure 5. Four damages-sensitive features were extracted: RMS, Variance, Peak to Peak amplitude and Maximum amplitude.

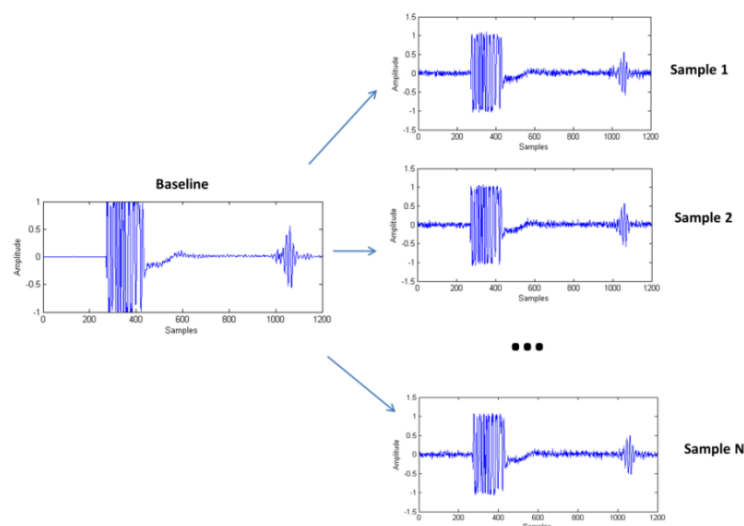


Figure 5. Database building

Table 1. Classes with codifications

Classes	Binary number
1 defect	00
2 defects	01
3 defects	10
4 defects	11

Table 1 illustrates the classes that have been considered in this algorithm. Each class of damage type was coded with a 2 digit binary numbers. Fifty signals were used as training data and 150 for validation. The network performance is quantified by the number of correctly classified samples. In order to find best network configuration, a huge and extensive number of tests of different parameters combination were accomplished. For each input vector, the number of hidden layers was changed from 1 to 40. Results illustrated in Figure 6 have shown that the best network configuration was found with twenty nine hidden layers and the four damages-sensitive features, because the accuracy of classification is 100%, it follows that all samples from different types of damages have been correctly classified. An example of a poor result has been noticed when only six hidden layers were utilized (Figure 7).

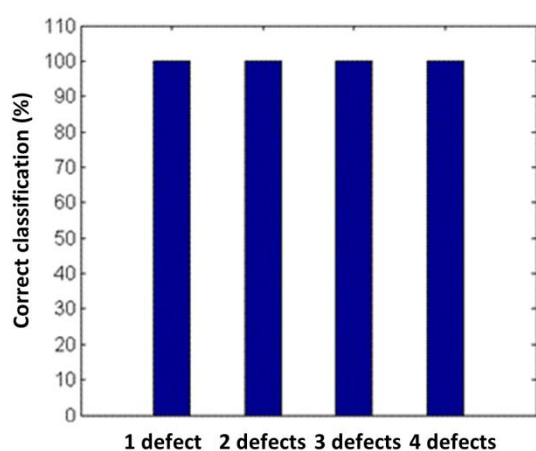


Figure 6. Accuracy of classification with the best network configuration.

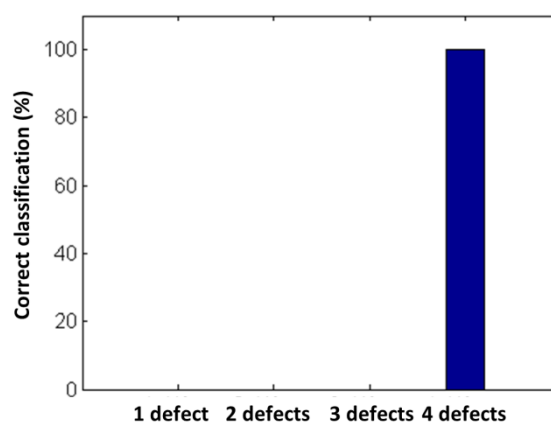


Figure 7. Accuracy of classification with 6 hidden layers.

5. Conclusion

ANN algorithm has proven its efficiency as a promising algorithm for damage detection and classification even in the presence of EOCs changes, which were simulated by a random and stochastic noise. However, there are many issues making its real-world application very limited. These issues can be summarized as follows:

- A huge and extensive set of trials must be verified to find the optimal network configuration which has the best classification performance in terms of number, type of input parameters and the number of hidden layers.
- ANN data learning requires information from damage state, which is impractical because it is generally difficult to acquire damaged data during in-situ monitoring of structures.

Finally, it must be noted that, the aim of this study was not to apply the ANN to detect and classify defects but to verify if this method can resist to the EOCs effects. Indeed, the added noise could simulate some effects of EOCs but not all of them. However, the results have shown that this approach has found to be robust. Hence, even if the other EOCs effects have not been investigated, the results would be the same.

6. References

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