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AUTOMATIC STRUCTURAL DAMAGE ISOLATION USING SUPPORT VECTOR MACHINE CLASSIFICATION

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Abstract. *Structural Health Monitoring uses several signal processing techniques to detect and classify damages in engineering flexible structures. These techniques are usually based on vibration analysis, originated from real structures by adequately positioned sensors. This results in a huge number of signals, making this task virtually impossible for human analysis, consequently demanding efficient data science methods. This paper proposes a machine learning architecture for damage isolation in composite structures, constituted by an unsupervised feature extraction using an autoencoder neural network, and a supervised learning classification based on a Support Vector Machine (SVM) algorithm. Aiming a continuous monitoring system, a Lamb wave method is adopted to generate the signals and preprocessing the data to be classified. Periodic inspection is performed by means of an arrangement of piezoelectric transducers forming a circular array of eight sensors with a central actuator, dividing the monitored area into eight regions. Discrete wavelet and Hilbert transforms are applied to the acquired signals, in order to minimize noise and dispersion effects as well as to improve peak amplitude and location estimation. Damage indexes, which result from the autoencoder model, are used as attributes for an SVM classifier. An experimental dataset is used to train both, autoencoder and the SVM algorithm, in order to predict the target structural integrity by comparing a new input data obtained during the inspection phase with a set of healthy signatures and, if there is any damage, it proceeds to effectively find its localization.*

Keywords: *Structural Health Monitoring, Support Vector Machine, Machine Learning, Autoencoder, Symptom Learning*

1. INTRODUCTION

Structural Health Monitoring (SHM) encompasses several damage detection techniques that may be applied mainly to monitor mechanical, aerospace and civil engineering flexible structures, representing tools of great importance for safety reasons as well as for the economic benefits they can generate. The development of several techniques in the past decades is a result of an intense research effort to detect and analyse damages in these complex structures. Lamb wave propagation analysis is one of these techniques to assess structures' integrity that has been very successful (Lu and Wang *et al*. 2008). Signal processing techniques, such as discrete wavelet transform (Lemistre and Balageas, 2001) and Hilbert transform (Feldman, 2011) are commonly applied on the measured signals to minimize the noise influence in the measurements and emphasize signal features that can be used to detect the onset of a damage. However, considering the application of an SHM method to a real structure, in a aircraft wing for example, the number of sensors and respective amount of generated data tends to be huge, which turns its analysis into a big data problem, demanding machine learning techniques in order to be efficiently analysed.

A global SHM is indeed a System of Systems (SoS) that may present one or more applications (Jaradat, 2011) with the objectives of damage detection, localization, diagnosis and prognosis. Damage detection is the basic goal, with the monitoring system interrogating the sensors periodically, looking for any abnormality detection, which, if found, will fire an alarm and change the respective machine status. Only then it will progress to new stages, where the other goals are now searched. The next question is in general to find where is the damage localized, which makes it possible to have eventually some maintenance or interactive tests programmed. The following goals are to determine a diagnosis for the detected abnormality and its respective severity and prognosis analysis, which should give the estimated remaining useful life (RUL) of the structure (Ramasso and Saxena, 2014). Our scope in this work is to detect and isolate the damage, indicating a probable region of the structure where it is localized.

Each of the above mentioned goals may be the subject of a classification system based on signal interpretation that can be represented in Figure 1 by three key blocks: signal preprocessing, feature extraction and classification itself. To implement a diagnosis or a prognosis systems, the same block structure may be repeated, probably using different techniques for each block. In the present case, Lamb wave propagation in a composite structure is the basic interrogation method, implemented through piezoelectric patch transducers. Scattering of the waves resulting from the presence of a damage shall be interpreted comparing the respective measured signals to sensor healthy signatures in order to achieve to its detection and isolation.

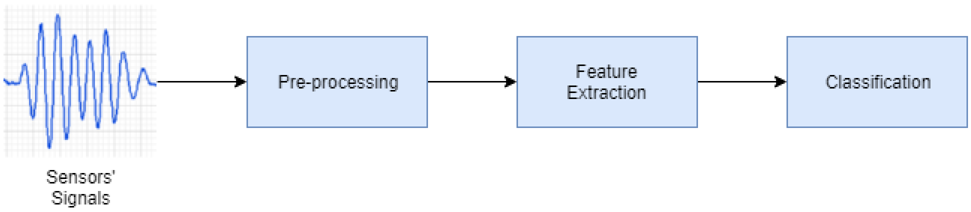


Figure 1: Classification process block diagram

Several publications show the efficiency of SHM methods where Lamb wave-based fault detection and diagnosis for flexible structures, based on traditional signal analysis approaches, have been successful (Su, Lemistre and Balageas, 2001). The methods' development results in general from a research team effort, tested in a laboratory considering its application to a structure model, or part of it. However, if a real structure is to be considered, the number of sensors and periodical measurements will necessarily be much bigger, turning the handcrafted methods impossible to be applied. This is typically the case of a big data problem, which demands automatic classification using a machine learning technique.

Methods using artificial intelligence have been successfully used in a wide variety of engineering fields to solve difficult problems. Recently, deep learning methods have been the preferred way to solve big data problems (LeCun, Bengio and Hinton, 2015), and are beginning to be used to condition monitoring (Nick *et al.*, 2014, and Finnoti, Cury and Barbosa, 2019). This paper introduces an automatic support vector machine (SVM) approach to a structural damage detection and isolation problem as part of an SHM system, discussing pattern recognition in signals, model reduction, feature extraction and SVM classification and algorithms.

Based on deep learning methods, the feature extraction, an important aspect of the classification process described in Figure 1, has been given an interesting solution. This stage of the classification process is usually implemented by a handcrafted developed mathematical model, following one or more of the several existing signal processing techniques, which demands an expert support to be effectively used. However, a logical model may be also used, via a machine learning application, *e.g.* a neural network model. Traditional machine learning methods is based on supervised learning, where a set of samples with the respective labels are available for training. The labels must be normally provided by the work of one or more human expert. However, based on some deep learning new methods, unsupervised learning is becoming common, mainly applied to the feature extraction block. It means that the learning techniques are now being used twice in the classification process: for the classification itself, but also for the feature extraction, now known as feature learning. These recently introduced techniques make a great difference for the treatment of the big data problems.

Deep learning methods are constituted by some recent introduced machine learning algorithms that represents data-driven models through multiple processing network layers, mining the complex information hidden in the dataset. One of the deep learning unsupervised methods introduced by (Hinton and Salakhutdinov, 2006) is the autoencoder (AE), which yields the reduction of the model dimensionality.

Traditional SHM methods executes a classification process through signal processing human expertise in order to manually extract the features, or symptoms, using acquired knowledge from similar previous experiences. Based on the set of symptoms that was raised, the expert may achieve to a diagnosis, also using his/her experience or by some problem solving method. This procedure is bonded by the human limited memory and inference capability, which are the same reasons why artificial intelligence is today winning all complex traditional games.

The contribution of this paper is the originality of the deep learning architecture proposed for an SHM system, combining an AE for feature learning with SVM for classification. Eight sensor signatures, represented by AE network reduced models, are compared to periodically repeated measurements. Their results are then submitted to an SVM algorithm for classification, which detect a possible damage, and indicates its respective localization.

The second section presents the adopted Lamb wave and preprocessing techniques. The third section briefly introduces the autoencoder network, followed by an introduction of the classification SVM method in the fourth section. The description of the composite plate and experimental setup are in the fifth section, which includes also the description of the acquired signal dataset. In the sixth section the respective experimental results and discussions are presented, followed by the conclusions in the seventh section.

2. STRUCTURAL ASSESSMENT

Lamb waves have been widely used on non-destructive evaluation techniques to assess the structural integrity on SHM systems (Dsouza *et al*, 2018). Piezoelectric transducers attached to the structure under inspection, generate and measure these waves. Information about the presence of damage, its location and its severity are obtained by analysing the parameters of the reflected and transmitted waves resulting from the interaction between the incident wave and the damage. There are two general methods for using Lamb waves to detect damage, known as pitch-catch and pulse-echo (Su and Ye, 2009). The simplest pitch-catch approach uses at least two transducers to inspect the region between them, as illustrated in Figure 2. It is seen in this figure an actuator and a sensor, both piezoelectric patches, where the actuator generates a burst signal captured by the sensors, which incorporates the medium characteristics. Damage onset on this region causes scattering of the waves, which modifies some measured signal parameters. Comparison between a known signature of the healthy structure and a recently measured signal may conduct to detection and identification of damage. Figure 3 shows how the signal may be affected by damage localized between the sensor and actuator. In this case, signal amplitudes measured by the sensor decreases due to attenuation of incoming wave on the damage. A different change of parameters may also occur if the damage is not in the direct line between the transducers.

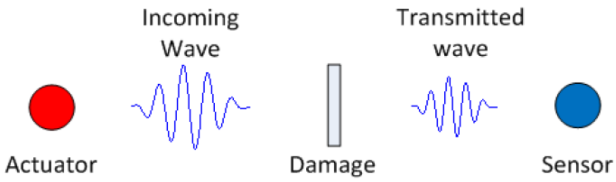


Figure 2: Positioning of transducers to the pitch-catch approach

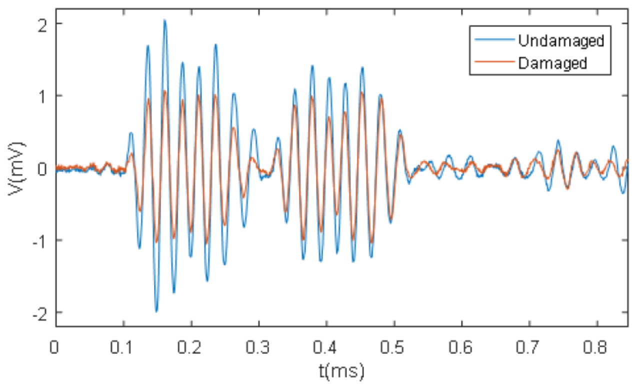


Figure 3: Acquired signals using the pitch-catch approach for damage and undamaged cases

Signals from the measuring system need to be processed by specific algorithms to separate information from noise, regular reflections and other interferences in the system. The wavelet transform is a signal processing technique used to represent signal features in time and frequency domains simultaneously. It has the ability to detect aperiodic short-time events, unlike the Fourier transform which is particularly useful for the analysis of periodic signals. These transient events are detected through the similarity between its shape in time domain and a waveform known as mother wavelet. This approach fits well to analyze non-stationary signals, because its spectral components vary along time. The propagation of Lamb waves is an example of signal with punctual occurrences. (Mallat, 1989) presented an efficient method to implement the wavelet transform in discrete time, through multi-resolution analysis and digital filter banks. This theory relates the Discrete Wavelet Transform (DWT) with a filter bank composed by high and low pass quadrature mirrored filters, through which the signal is successively decomposed in several stages into details and approximations. The approximation is obtained as the output of the last low pass filter and is related to the smoothed signal. The output of the same stage high pass filter provides the details of the signal, related to transient events contained in the signal.

Higher frequency signal components are located at lower level details. Analysing the decomposed signal into several details provides information that could be hidden in the original signal, probably masked by noise from the measurement system. Considering a tone burst containing five cycles of a 40 kHz sine wave multiplied by a Hanning window applied to the actuator to excite Lamb waves at the structure, the main component of the signal measured by sensors with a sample rate of 1.21 MHz corresponds to the fourth level detail coefficients of DWT.

Hilbert transform can be used to highlight some specific points of the processed signal, for example, the amplitude and the instants that peaks occurs. This signal processing technique creates an analytical signal from a real signal (Feldman, 2011). The absolute value of the analytical signal corresponds to signal envelope.

In order to illustrate the effect of applying these signal processing techniques, Figure 4 shows the raw signal measured by a sensor, the detail coefficients of fourth level of its DWT with the mother wavelet Daubechies 40 and its envelope. It clearly minimizes the noise and eliminates the continuous voltage level present in the measurement system, enhancing the desired signal attributes. The peak amplitude and the instant they occur are much more evident on the signal envelope. These parameters can be used to monitor the integrity of the structure.

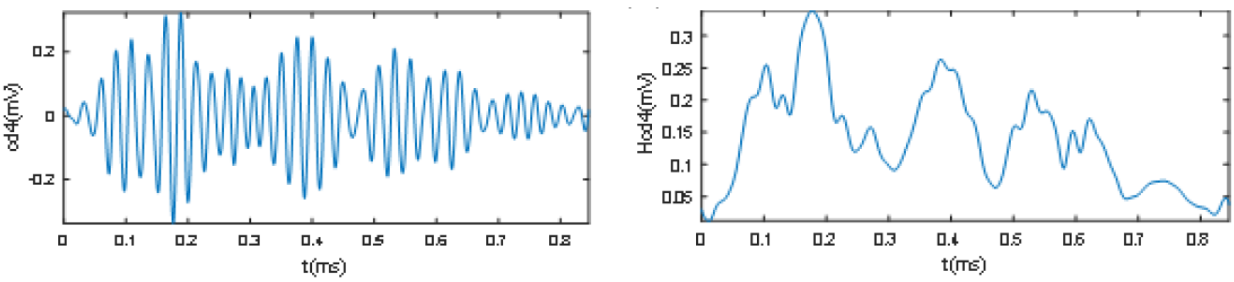


Figure 4: DWT detail coefficients (cd4) and respective Hilbert transform (Hcd4)

3. AUTOENCODER

Autoencoders, while conceptually simple, play an important role in machine learning. They are unsupervised learning networks that aim to transform inputs into reduced outputs with the least possible amount of distortion. Autoencoders were first introduced in 2006 by (Hinton and Salakhutdinov, 2006) to address an unsupervised learning problem, following the work of (Rumelhart *et al.*, 1986), which provided one of the fundamental paradigms for unsupervised learning and for addressing the mystery of how synaptic connections changes, induced by local biochemical.

Consider an n-dimensional vector given by $X^T = \{x^{(1)}, x^{(2)}, \ldots x^{(n)}\}$ where $x^{(i)} \in \Re$, which we want to reduce its dimension to $r < n$. An autoencoder neural network, given for example the architecture in Figure 5, where the input layer is the vector X and the output layer is the vector y, is trained in order to reproduce the input in the output, such as $y^{(i)} \approx x^{(i)}$. As depicted in Figure 5, the autoencoder may be separated in two parts, the encoder, and the decoder. Note that the encoder output is given by $z = \phi(W^{(1)}x)$ and the decoder output is given by $y^{(2)} = \psi(W^{(2)}z)$, where $W^{(i)}$ is the weight matrix of layer i, and $\phi(\cdot)$ and $\psi(\cdot)$ are the activation functions of the encoder and decoder, respectively. As such, the encoder output z has dimension r, which corresponds to the reduced model of the data, after the successful training of the autoencoder network. Then, the encoder output may be used as the input of the classifier.

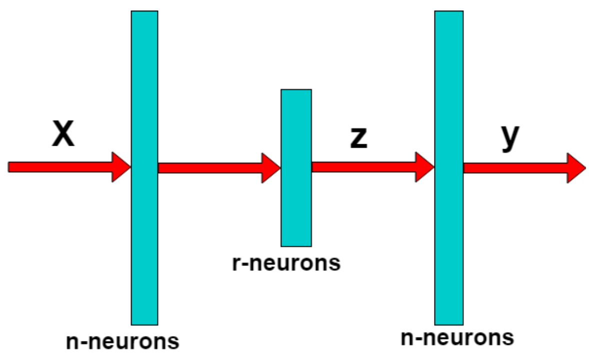


Figure 5: Autoencoder configuration

The most important motivation brought recently by the autoencoders is due to its capacity of reduction of linear and nonlinear models, using an unsupervised learning approach that brings the power to automatize a problem's feature extraction. This is an important characteristic in classification problems when there are a big number of data to classify, and specially in the case of diagnosis, which, in traditional handcrafted methods, leads usually to a tedious and error prone analysis of a lot of data to find anomalies.

4. SUPPORT VECTOR MACHINE

This section describes succinctly basic SVM concepts that can be found in (Scholkopf, 2000), (Cristianini, 2000) and (Kecman,2001).

Having in hands a training set of instance-label pairs $(x_i, y_i), i = 1,2,,m$ where $x_i \in R^n$ and $y_i \in +1,-1$, for the linearly separable case, a correct data points classification is given by:

$$\langle w.x_i \rangle + b \geq +1 \quad for \quad y_i = +1 \tag{1}$$

$$\langle w.x_i \rangle + b \leq -1 \quad for \quad y_i = -1 \tag{2}$$

One set of inequalities can be achieved combining Equations (1) and (2) .

$$yi(\langle w.x_i \rangle + b)1 \geq 0 \quad \forall i = 1,...,m \tag{3}$$

Solving the following optimization problem leads to the hyperplane with the maximum margin:

$$Min_(w,b)\frac{1}{2}w^T w \quad subject\,to: \; y_i(\langle w.x_i \rangle + b)1 \geq 0 \tag{4}$$

To solve this problem one must find the saddle point of the Lagrange function:

$$L_p(w,b,a) = \frac{1}{2}w^T. - \sum_{i=1}^{m}(\alpha_i y_i(\langle w.x_i \rangle + b) - 1) \tag{5}$$

On Equation (5) α_i represents the Lagrange multipliers, hence $\alpha_i \geq 0$. An optimal saddle point is needed because the L_p must be minimized with respect to the primal variables w and b and maximized with respect to the non-negative dual variable α_i. By differentiating L_p with respect to w and b:

$$\frac{\partial}{\partial b} = 0\,,\, w = \sum_{i=1}^{m} \alpha_i y_i \tag{6}$$

$$\frac{\partial}{\partial b} = 0\,,\, \sum_{i=1}^{m} \alpha_i y_i = 0 \tag{7}$$

The Karush Kuhn-Tucker (KTT) conditions for the optimum constrained function are necessary and sufficient for a maximum of Equation (5). The corresponding KKT complementarity conditions are:

$$\alpha_i[y_i(\langle w.x_i \rangle + b) - 1] = 0 \quad \forall i \tag{8}$$

Substituting Equations (6) and (7) into (5), then L_p is transformed to the dual Lagrangian $L_D(\alpha)$:

$$Min_\alpha L_D(\alpha) = \sum_{i=1}^{m}(\alpha_i \alpha_j y_i y_l \langle x_i.x_j \rangle)\; Subject\,to: \; \alpha_i \geq 0 \quad i = 1,...,m \; and \; \sum_{i=1}^{m}(\alpha_i y_i) \tag{9}$$

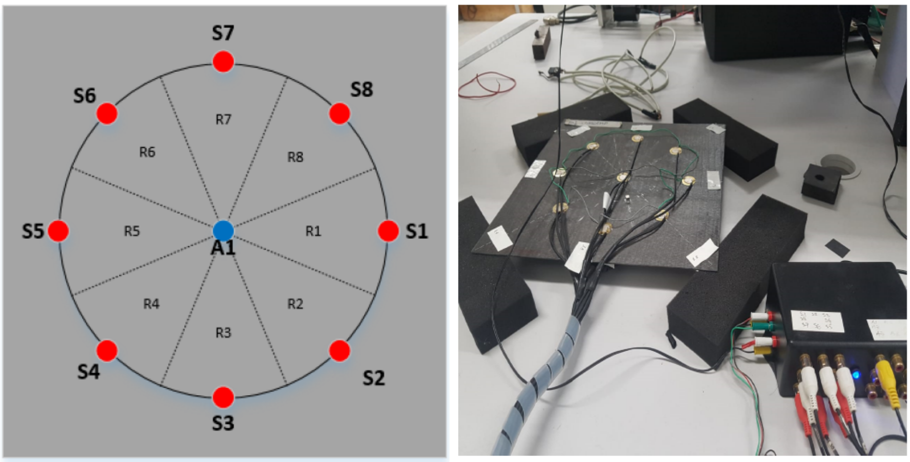
The $L_D(\alpha)$ must be maximized with respect to non-negative α_i to find the optimal hyperplane. In order to determinate the dual optimization problem parameters w^* and b^* of the optimal hyperplane, one must find the solution α_i. Finally, we obtain an optimal decision hyperplane $f(x,\alpha^*,b^*)$ Equation (10) and an indicator decision function sign $[f(x,\alpha^*,b^*)]$.

$$f(x,\alpha^*,b^*) = \sum_{i=1}^{m}[(\alpha_i^* y_i(\langle x_i.x \rangle + b^*) = \sum_{(i \in sv)}^{m} \alpha_i^* y_i(\langle x_i.x \rangle + b^*) \tag{10}$$

Only small subsets of the Lagrange multipliers α_i usually tend to be greater than zero in a typical classification task. These vectors are the closest to the optimal hyperplane, regarding geometrically aspects. The support vectors are the respective training vectors having nonzero α_i, given that the optimal decision hyperplane $f(x,\alpha^*,b^*)$ depends on them exclusively.

5. EXPERIMENTAL PROCEDURE

The experiments were conducted on a carbon fiber square plate of 300 mm x 300 mm x 1 mm to experimentally assess structural integrity. The experimental setup, shown in Figure 6 consists of nine circular buzzers of 20 mm diameter forming a circular arrangement with a centered actuator with 100mm radius. A Labview® instrumentation system were developed to apply a tone burst containing five cycles of a 40 kHz sine wave, multiplied by a Hanning window, to the central actuator. This system was also used to acquire the signals measured by the eight sensors, with a sample frequency of 1.2 MHz. Raw data were processed and analyzed using MatLab®. Mother wavelet Daubechies 10 was adopted in the DWT for all signals and the detail coefficients of fourth level corresponds to the Lamb wave propagation. A pair of magnetic cubes with 5x5x5 mm were used to obtain a punctual mass change on the plate, which simulated damage. This artificial damage was placed randomly within a monitored region to demonstrate the ability to isolate the damaged region inside the circular area, with each region tested separately.



(a) Array of transducers and monitored regions (b) Experimental setup

Figure 6: Plate's disposition of transducers and experimental setup

For each sample, a set of 8 DWT signal envelopes, representing the 8 sensors, were stored in arrays for further analysis in the *symptom extraction* phase.

The *symptom extraction* phase consisted in a deep learning method that creates a *healthy condition signature*, a baseline representation that can be compared with a database of training signals in order to identify patterns in the differences between them, regarding each one of the 8 composite plate pre-defined regions.

The signature was created, in this work, by passing the DWT envelope signal through an autoencoder model. The autoencoder efficiently learns a reduced data coding that is also capable of reconstructing the original information to its original size, if necessary.

In this case, as represented by Figure 7 the autoencoder was developed on the *Keras* framework was trained using 100 healthy samples. A model was developed for each one of the 8 sensors and reduced the signal dimension from 1024 to 155 data points.

Finally, after submitting all the samples through the autoencoder models the complete preprocessed data was obtained by means of a damage index. The damage index was calculated by the difference between the healthy signature and the actual measurement.

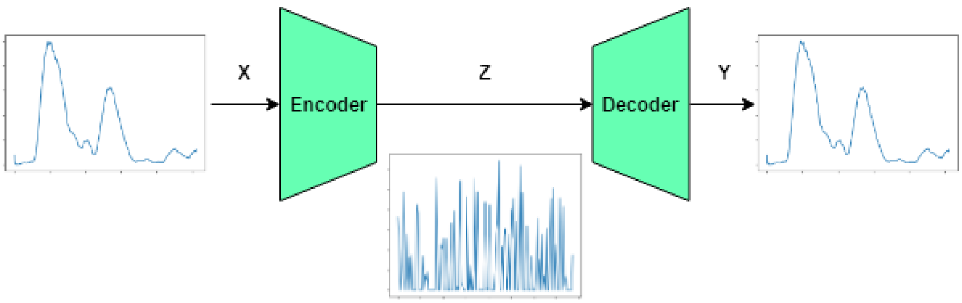


Figure 7: Autoencoder unsupervised symptom learning

All the 8 damage indexes were concatenated in a single line and were used as input for an eight-class SVM classifier algorithm, implemented in Python using *sklearn* package (Pedregosa *et al.*). The algorithm's hyper-parameters were chosen using a technique called grid search. It tests the algorithm implementation with different values for the function parameters. The parameters tested were:

- Kernel Trick: Linear, RBF, Polynomial and Sigmoid;
- C-Parameter: a range from 1e-3 to 1e3;
- Gamma-Parameter: a range from 1e-7 to 1e3.

In this set up, several experiments were made using different combinations of parameters and, with every test made, the closer it was getting from the optimum combination.

The Adaboost ensemble technique (Freund, 1997) was also implemented and tested, however it did not presented satisfactory results.

To reduce the variance problem, it was also used the K fold cross validation technique, with K equal to 5. In this technique, the data is divided in K-folds. Out of K folds, K-1 sets are used for training while the last set is used for testing. The algorithm is trained and tested K times and, with every loop, a new set is used as testing set while the others are used as training. The results obtained by the K fold cross validation technique is the average of the results obtained by each set.

Finally, the best results were optimized utilizing the standard linear kernel with the C-parameter value equals to 127.

The experimentally gathered dataset was compounded by 900 measurements divided equally by all the 9 SVM algorithm classes, being R1 to R8 for damaged regions and R0 for the healthy structure class. The test-train split was made utilizing 80% of the total data for training and the remaining 20% for testing.

6. RESULTS AND DISCUSSION

The algorithm presented a global accuracy of 85.0%, and its confusion matrix is shown in Table 1. Also, the bar chart presented on Figure 8 shows, in percentage, the accuracy of the classifier per class. Observing Table 1, one can see that, regarding the presence or absence of damage, out of 180 tests, the algorithm had a performance of no false positives (0%) and little more than 2% (4 cases) of false negatives.

Table 1: SVM algorithm's confusion matrix

	R0	R1	R2	R3	R4	R5	R6	R7	R8
R0	20	0	0	0	0	0	0	0	0
R1	2	16	1	0	1	0	0	0	0
R2	1	0	18	1	0	0	0	0	0
R3	0	0	1	18	1	0	0	0	0
R4	0	0	2	1	16	0	0	1	0
R5	0	0	0	1	1	18	0	0	0
R6	0	0	0	0	0	0	17	0	3
R7	1	0	0	0	0	0	3	14	2
R8	0	0	0	0	0	0	3	1	16

A visual analysis of the classifier's behavior can be a challenge as the algorithm works with an 1024-dimension input. Even though one cannot clearly see the hyperplane that divides all the SVM classes, it is clear that the feature extraction phase managed to effectively reduce the input dimension, emphasizing the most notable patterns in the differences between the healthy signature and the input signal. It is also clear to see that, despite the high number of dimensions, the classifier could present satisfactory results by finding a hyperplane that best segregate all the classes.

Example of three sensors (S2, S3 and s4) DWT envelopes are presented in Figure 9. This example represents damage located in Region 3, regarding the reference in Figure 6a. The signals in black represent the healthy plate and the colored signals represent the damaged plate cases. It is easy to see that the healthy signals follow a pattern and, making a thorough comparison between the healthy and damaged cases, one can clearly see that the sensor S3's signal suffers a notable decay in its first peak, followed by a second peak amplitude increase. These patterns are frequently repeated in all the other damage regions.

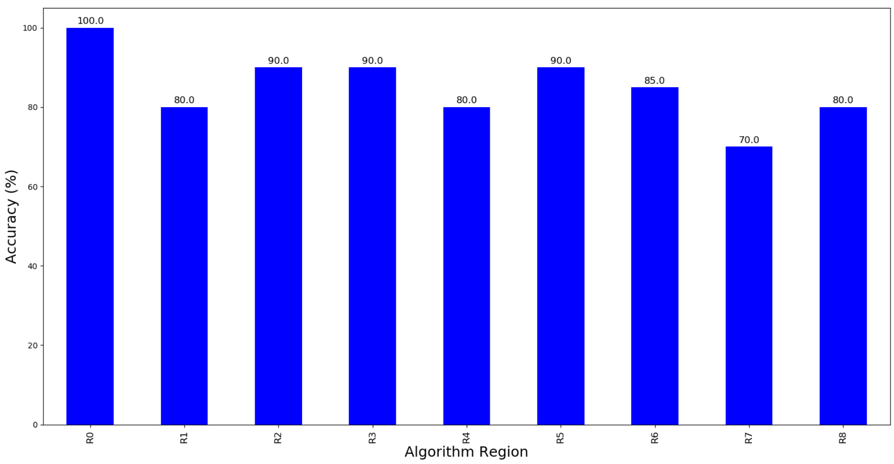
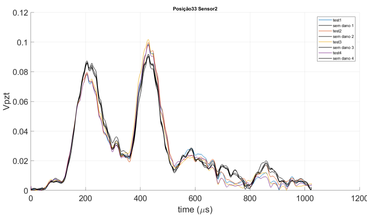
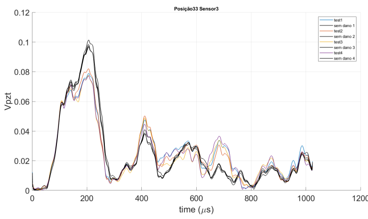


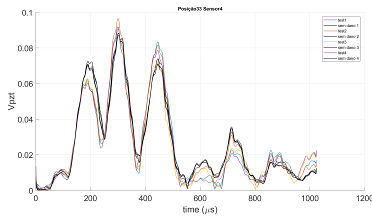
Figure 8: Algorithm's accuracy per class



(a) P33 Sensor 2



(b) P33 Sensor 3

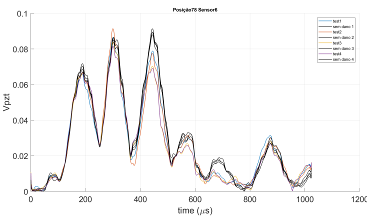


(c) P33 Sensor 4

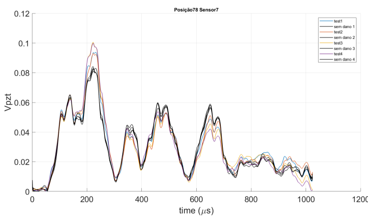
Figure 9: Region 3 DWT envelopes for all the 8 sensors

When the damage is positioned in a region intersection, like the example that shows damage presence between the regions 7 and 8 presented in Figure 10, the readings show a different pattern, increasing the amplitude of the second peak of signals 7 and 8. These are the most likely cases to have a misclassification.

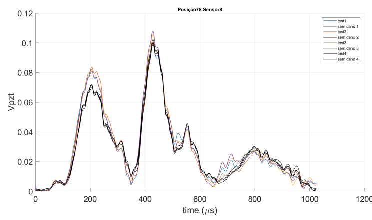
Also, there are several other patterns that may pass unnoticed by a human eye, even for the sensors that are relatively distant from the damage. Taking sensor S5 as example (not shown in the figure), because of its distance from the damage, the signal shows little change. The goal in the next phases is to take all of this changes, no matter how subtle, in consideration.



(a) P78 Sensor 6



(b) P78 Sensor 7



(c) P78 Sensor 8

Figure 10: Region 7 DWT envelopes for all the 8 sensors

It is worth mentioning that in most of the incorrect prediction cases, the classifier predicted damage in the neighbour region. For instance, for the six wrong predictions of region 7, three of them indicated damage in region 6 and two of them indicated damage in region 8. Thus, although giving a wrong classification, in a real situation the classifier would at least give the user information of damage presence and a strong direction in which region it might be.

Another important aspect that can be mentioned is that, in a deep analysis, even though the damage index of most regions present an expected behavior, like the ones observed by (Souza and Nobrega, 2017) for aluminum plates, they can differ from the expected outcome in some regions. Nevertheless, the classifier still works its ways to automatically identify notable pattern and predict the plate's damaged region in the majority of the cases. Finally, it may be noticed in all envelope curves that there are a shape consistence for all the measurements from the same sensor, independently of the damage region, and also that there are different patterns among sensors curves. These changes in the expected behavior could be attributed to the anisotropy property that are due to the composite layers.

7. CONCLUSION

This paper presented an effective technique for reducing data dimensionality using an autoencoder network to synthesize the incoming multisensor signals, which is then presented as an input vector of to a support vector machine classifier, as a strategy to automatically assess the structural integrity of a composite material plate. In general, despite the material's anisotropy, good results were obtained, achieving a classification accuracy rate of 85.0%.

An important goal of this work is achieved when it explicitly shows the use of feature learning as a powerful strategy in a continuous monitoring SHM technique, utilizing unsupervised learning. The proposed configuration is able to point out subtle differences that occur on signals that propagates on structure, and detect structural changes caused by the presence of damage. The main advantage of the proposed approach was to develop a continuous monitoring system that automatically detects and isolates damages in one of the eight pre-defined regions. The classification method using SVM, as in all methods based on machine learning, can extract meaningful data present in a huge amount of data, in order to optimize the models. These methods show synergy with SHM applications, which, in more traditional approaches, tends to have unbalanced incoming data and processing speed. Results have shown that machine learning techniques brings a good solution for the SHM system data analysis problem. Finally, it also should be noticed that despite the similarity between different measurements of the sensors, they present slight different among peak patterns that can yield to damage detection and isolation.

Future work will keep on investigating and developing supervised and unsupervised learning approaches as a means to continuously increase their effectiveness. Specifically, an alternative configuration to be designed will consider a deep stacked autoencoder based on a convolutional neural network, to better characterize the signal reduced model at the feature learning stage.

8. AKNOWLEDGEMENTS

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