Application of the elastic waves and neural networks as a tool of damage detection and health monitoring in aircraft’s structures

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Abstract

There exist a large group of structures like e.g. aircraft, which operational safety requires periodical inspections or even continuous monitoring of its health. Sometimes the structures are equipped with Structural Health Monitoring systems which usually utilizes the phenomena of elastic waves propagation in solids. The analysis of elastic waves signals consists in general of quantitative and qualitative description of theirs changes (e.g. attenuation, distortion, reflection) caused by a damage appearance and growth. Since the reflections and dispersion effects may produce pretty complex signals, therefore the determination of parameters suitable for damage detection requires the application of advance signal processing techniques. For this purpose an approach of novelty detection and damage evaluation based on soft computing methods (for example - Neural Networks) was proposed in this paper. Two levels of the damage identification problem were realized: novelty detection and damage assessment. The system accuracy and reliability were verified during laboratory tests. It was proved that the system can be used for the analysis of simple as well as complex signals. One of the important factors in the structural health monitoring systems is the amount of data that need to be analysed in real time. This study investigated the use of artificially deteriorated signals of elastic waves in training the novelty detection (ND) system. In this system auto-associative neural networks were trained using the principal components calculated on the basis of experimentally measured signals. It was found that the designed ND system remained sensitive and robust even when it uses raw signals with a relatively low sampling rate, on a fairly narrow time window and even noisy signals.

Keywords: Structural Health Monitoring ; Neural Network ; novelty detection ; damage assessment ;

1. Introduction

There are many engineering structures like e.g. aircraft, which operational safety requires periodical inspections or even continuous monitoring of its health. Nowadays more and more often the structures are equipped with Structural Health Monitoring systems providing information about theirs present state. Application of such the systems improves operational safety, since the early detected damage can prevent the further disaster. One of a very promising non-destructive technique that is suitable for the mentioned SHM systems utilizes the phenomena of elastic waves.

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propagation in solids. For the purpose of the waves excitation and sensing the structure is usually equipped with the piezoelectric transducers that can be used as the waves actuators and sensors. The non-contact methods like the laser vibrometry can be used for the elastic waves sensing and theirs multidimensional analysis. The analysis of elastic waves signals consists in general of quantitative and qualitative description of theirs changes (e.g. attenuation, distortion, reflection) caused by a damage appearance and growth. Since the reflections and dispersion effects may produce pretty complex signals, therefore the determination of parameters suitable for damage detection requires the application of advance signal processing techniques. For this purpose an approach of novelty detection and damage evaluation was proposed in this paper. The idea is to use a data set of signals parameters obtained from a reference structure (e.g. undamaged structure, numerical models, laboratory tests) and use soft computing methods in order to warn about the damage appearance and predict its type, location or extent. In such a way Neural Networks (NNs) can perform the automatic analysis of the structures diagnosis process. The obtained results proved that the proposed approach enable an automation of the structure test and may be applied for SHM systems, while its robustness and sensitivity was examined during laboratory test performed on specimens made of various composite. Two levels of the damage identification problem were realized: novelty detection and damage assessment. The system accuracy and reliability were verified during laboratory tests. It was proved that the system can be used for the analysis of simple as well as complex signals. Moreover, the designed system can be fully integrated with the monitored structure and can operate on-line as an automatic Structural Health Monitoring system. The phenomenon of elastic wave propagation is used in non-destructive tests and structural health monitoring systems. The main task of such the systems is novelty detection (ND). Apart from the issue of sensitivity to potential damage, others posed requirements are the throughput and efficient operation in real time. This is largely related to the amount of data that need to be processed. For this reason, various methods are used to compress signals (PCA, ICA [1,2]), which further in the present study was preceded by an attempt to reduce the dimensionality of a set of measurement data.

Continuous monitoring systems require the elimination of the human factor and that is why many such the systems based on artificial intelligence algorithms, which include artificial neural networks. This approach allows primarily to process data in an automatic way. This is especially important with regard to large amounts of measurement signals, which are usually quite complex and are susceptible to errors of various origin. Hence, an attempt was made to determine the sensitivity and robustness of such the ND system.

Subsequent studies of the ND training system were performed using a database of real signals measured in the laboratory for two similar specimens of aluminium strips [3]. Originally, these signals were received by the piezoelectric transducer and then recorded on a digital oscilloscope (DO) at a high sampling rate of 5 MHz. This high resolution is justified in carrying out laboratory experiments, but consequently leads to a significant computational effort due to the length of the signal, in this case reaching 25 001 samples. Therefore, in view of the design of ND systems, for real-time operation and low hardware requirements of the measurement systems a reduction in signal quality to some acceptable level of measurement uncertainty becomes inevitable. Reducing the sampling frequency may also result in greater susceptibility of the system to ambient noise and it also requires appropriate investigation. For this reason, the scope of this work was limited to a rather simple signals (e.g. discarding the problem of multi-dimensionality, complex geometry, the presence of joints, environmental and operational conditions) where the reflections from damage area were clearly visible. However, the correct operation of the ND system used was confirmed in the past also in relation to more complex signals [6].

2. Tested structures

2.1. Scope of the research

A set of laboratory tests was carried out on samples which consisted of strips as well as plate specimens made of various materials used in the aviation industry (including the real covering and wing fragments). In the group of studied surfaces there were both undamaged and damaged parts of the analysed samples. At an early stage of the research, the existence of damage was also simulated through sticking to the model an additional masses (e.g. aluminium or steel plates). A list of all the samples analysed and the study scopes are presented in Table 1. Some details of the measurement set-up and selected models (carbon fibre laminate, aluminium plate with stiffeners, aluminium strips)
Fig. 1. Laboratory set-up with a laser vibrometer: devices used, examples of models tested, faults introduced and additional masses.

are shown in Fig. 1. In the study, time signal of elastic waves were recorded by laser Doppler vibrometer (Polytec PSV-400) and a digital oscilloscope (LeCroy WaveRunner 104MXi).

Table 1. A summary of the experiments conducted and the research scopes

<table>
<thead>
<tr>
<th>Models investigated</th>
<th>Undamaged</th>
<th>Scope of the reasearch</th>
</tr>
</thead>
<tbody>
<tr>
<td>Strips (aluminum, steel, plexiglasa)</td>
<td>✓ ✓</td>
<td>✓ ✓</td>
</tr>
<tr>
<td>Aluminum panel</td>
<td>✓ ✓</td>
<td>✓ ✓</td>
</tr>
<tr>
<td>Carbon fiber composite</td>
<td>✓ ✓</td>
<td>✓ ✓</td>
</tr>
<tr>
<td>Glider wing</td>
<td>✓ ✓</td>
<td>✓ ✓</td>
</tr>
</tbody>
</table>

2.2. Exemplary results

Visual analysis of elastic waves in time domain is usually quite complex, therefore maps of signal root-mean-square (RMS) value are commonly used in the damage detection. This allows to locate both the source generating a reflecting signals (position of the inductor) and location of other discontinuities.

A carbon fibres composite plate with dimensions $270 \times 940$ mm is the first example of the investigated specimens. On a selected fragment of the plate a grid of measurement points was established. Elastic wave propagation was induced by a piezoelectric transducer (Noliac CMAP) permanently attached in the middle of the plate. A package of 4.5 sine wave with operating frequency 5 kHz and modulated by Hanning window was used as the pattern of extortion.

One of the effects that can be observed in the time domain is an asymmetry in elastic waves generated, which may be caused by inaccuracy in transducer’s bonding layer or certain individual features of the transmitter used. In this case it was also possible to observe a much higher attenuation of the waves travelling in the diagonal directions, while wave’s portion propagating along fibre reinforcement had a higher velocity.

The nature of wave propagation in the tested composite was clearly visible in the task with additional mass attached inside scanned area, where a wave reflected from a zone of altered properties can be clearly identified (Fig. 2). Because the additional mass was glued on the sample side scanned by the vibrometer, the measurement points in this area were removed and it can be seen on the charts as a circular opening. Results of the experiment are shown in the time domain by the values of the elastic wave propagation velocity at selected instance of time. On the first image (Fig. 2a) the elastic wave forming can be seen which then passes through the zone with additional mass (Fig. 2b). Next, abnormal wave amplitude due to reflections from the attached mass can be noticed (Fig. 2c), which finally are already very clear (Fig. 2d).
3. Methodology of signal processing

3.1. Study case description

The measuring signals of elastic waves taken into consideration were obtained during laboratory tests of two identical samples of aluminium strips with dimensions $2000 \times 10 \times 1$ mm. At one side of the model a piezoelectric transducer Mide QP22B was glued. Because it has two stacks arranged in two parallel layers, one served as an actuator, the other as a sensor. Location of the transducer is shown schematically in Fig. 1.

The excitation signals in the form of five sine waves modulated with a Hanning window and operating frequency equals to 108 kHz were used. After leaving the function generator (TTi TG1010), the signal was amplified (Linear amplifier EPA-104), and then was supplied to an actuator. Signals received from the model as well as reference signals from the signal generator were stored on the digital oscilloscope.

There is also shown the location of the holes simulating the appearance of anomalies in Fig. 1. The holes diameter was varied depending on the size of the used drill and was equal to 1.0, 1.5, 2.0, 2.3, 2.5, 3.0, 3.2 mm. In the first case the damage was located 60 cm from the top (Specimen A), in the second 60 cm from the bottom (Specimen B).

In experiments performed on the first strip (Specimen A) a set of patterns was obtained and it consisted of 23 signals related to the undamaged specimen and 42 signals related to the specimen with a drilled hole (of different diameters). Whereas in case of the second strip (Specimen B) this set consisted of 28 and 42 signals respectively. Hence, a total of 135 patterns were available.

3.2. Elastic waves in novelty detection

One of the commonly developed non-destructive measurement technique, which is widely used in structural health monitoring, is based on the phenomenon of elastic wave propagation. This approach assumes that the anomaly appears in the structure (fault condition) can be detected and identified on the basis of the measured signal analysis. In this work the results of previous laboratory experiments were used [3], where measurements were performed on two samples of aluminium strips. In order to actuate and to sense the elastic wave signals a surface-mounted piezoelectric transducers were used and the anomaly (damage) was modelled by drilling holes of different diameter. The structure responses recorded by digital oscilloscope were then subjected to a procedure of signal processing (decimation, windowing, etc.) and features extraction (Principal Components Analysis, PCA). A defined pattern database was then used to train Auto-associative Neural Network (AaNN) for the purpose of novelty detection. When such a trained AaNN is fed with the inputs obtained from a damage state of the system, the novelty index $NI$, which measures the distance between the known input and output of the AaNN, will increase [1,2].

Signal processing as well as neural networks simulations were performed in Matlab environment [4]. Each time the AaNN training was repeated 50 times, and depending on the value of the calculated index $NI$ the binary classification of structure (undamaged, damaged) was made. One indicator of the suitability assessment was the number of properly trained classifiers (PTC). It shows how many classifiers were trained flawlessly in each series of simulations. If even one particular pattern has been incorrectly classified, the classifier is considered to be acting in an improper manner.

Another indicator used which measures the classifier’s usefulness is a confusion matrix (CM) calculated for the whole set of repetitions. The matrix values represent the percentage of the number of samples correctly assigned to a specific class [3].
3.3. Training the ND using poor quality signals

Research conducted in the laboratory are generally carried out with the greatest possible accuracy. However, in conditions of complex systems with a network of sensors located in the most sensitive areas of construction, a very important factor is the amount of information to be processed. Hence there is a need to examine the stability and reliability of diagnostic systems considering the possibility of using measurement signals of degraded quality characteristics, which ultimately can significantly improve the performance and throughput of diagnostic systems.

Another important factor is the fact that processing the signal of elastic waves which were originally measured (sampling frequency of 5 000 kHz, signal length of 25 001 samples, measurement time of 5 ms), unfortunately poses in practice some difficulties due to the hardware requirements, the computation time and the possibility of the use of certain numerical procedures (e.g. a required the filter order when its slope is steep). Hence, there is sometimes the need to adjust the parameters of signals and determine their scope, which guarantees the reduction of the task dimension without compromising the information contained in the data.

The idea of this work is to simulate training diagnostic system developed on the basis of signals with reduced quality characteristics. Therefore, for the purposes of this study, several methods of artificial deterioration of elastic waves signals were adopted. In order to estimate of such the scope, simulation of training diagnostic system were carried out assuming the following cases:

1. Signals decimated at a lower rate.
2. Signals with a shorter time basis (cutting off the end of the signal).
3. Signal portions of the predetermined width of the time window, sliding along the time axis.
4. Signals cluttered by a random noise.

Concept and scope of these activities is shown in Fig. 3, where an example of the original signal and a corresponding fragment of degraded characteristics were shown.

Studying the different configurations of signal parameters a pattern database was obtained, which was next used to simulate a neural network training in order to estimate the sensitivity and robustness of the ND system investigated. For simplicity it was assumed that in spite of changes in the number of the signal samples (when signal was decimated or trimmed), the number of principal components remained constant; it was 16 in both the previous studies [1,3] and all the cases investigated in this paper. AaNN architecture is therefore fixed and it can be describe as $16-h-16$, where $h = 3$ is a number of neurons in the hidden layer, which in previous investigations was considered optimal. The range of each individual tasks as well as the results obtained were discussed in next sections.
4. The results of the diagnostic system training

4.1. Signal decimation

First, the signal decimation was carried out by reducing the number of samples, and input signals were downsampled by preserving every \(N\)th sample (starting with the first). In earlier measurements the decimation rate was set to \(R = 20\), which simultaneously changes the sampling frequency (250 kHz) and length of the signal (1251 samples). Obtained in this way the signal is not much different from the original, which allowed the detection of anomalies in their early stages. However, until now, it was never attempted to train the AaNN based on the significantly deteriorated signals.

Signal decimation essentially means data resample at a lower rate. The resulting resampled vector \(Y\) is \(R\) times shorter than the original signal \(X\). In Matlab, there are at least a few functions that sample the signal at a lower resolution, such as `downsample`, `resample`. When for this purpose `decimate` function is used, the data are filtered with lowpass filter, before resampling [4].

Starting from the initial value of the decimation factor equal to \(R = 20\), each time the sampling frequency was lowered by half. Both the signal parameters and the results obtained after AaNNs training have been collected in Table 2.

<table>
<thead>
<tr>
<th>Decimation factor (R)</th>
<th>20</th>
<th>40</th>
<th>80</th>
<th>160</th>
<th>320</th>
<th>640</th>
<th>1280</th>
</tr>
</thead>
<tbody>
<tr>
<td>SF (kHz)</td>
<td>250.0</td>
<td>125.0</td>
<td>62.5</td>
<td>31.3</td>
<td>15.6</td>
<td>7.8</td>
<td>3.9</td>
</tr>
<tr>
<td>Samples</td>
<td>1251</td>
<td>626</td>
<td>313</td>
<td>157</td>
<td>79</td>
<td>40</td>
<td>20</td>
</tr>
<tr>
<td>PTC</td>
<td>50</td>
<td>50</td>
<td>50</td>
<td>50</td>
<td>50</td>
<td>50</td>
<td>0</td>
</tr>
<tr>
<td>CM Undamaged</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>98.0%</td>
</tr>
<tr>
<td>CM Damaged</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>98.8%</td>
</tr>
</tbody>
</table>

Analysing the results it can be seen that only in the last case, it failed to properly train any classifier. This means that it was not possible to separate all the patterns correctly, even though the vast majority of patterns were correctly classified, with an efficiency of 98%. In other cases, in each of the 50 trials, the classification efficiency was flawless — the number of PTC is 50 and classification accuracy is 100%.

4.2. Trimming the signal

Another considered approach to reduce the dimension of measurement data was trimming the signals. This consisted in rejecting the final part of the signal, which seems to be very complex in visual assessment due to overlapping reflections of waves propagating in the specimen.

Starting from the comparison signal decimated by a factor of \(R = 20\), in each case of the signals considered here, their length were shorter by the time of necessary for the transition of the incident wave to the specimen end and back (i.e. 1 ms, 250 samples).

Since all these signals were recorded in the specimen with a hole of 3.2 mm in diameter, it is easy to identify in the shortest signal that: the first wave packet is an incident wave registered, the last is the wave package reflected from the end of the specimen, and in the middle there is the wave reflected from the simulated damage area.

After trimming, each of the signals obtained were processed and thus defined the pattern databases were used to train the novelty detection system. The obtained results were collected in Table 3 together with basic parameters of the signal used. It turns out that on the basis of the shortest signals, the correct anomaly detection was possible, but it depended on the starting point of randomly matched weights in the neural network connections. Stable solutions were obtained for the signals whose length is at least 3 ms. This may prove that although the tail signal is complex, it carries very valuable information resulting from the signal passed several times through the area of damage.
Table 3. Identification results for trimmed signals.

<table>
<thead>
<tr>
<th>Trimmed</th>
<th>0</th>
<th>250</th>
<th>500</th>
<th>750</th>
<th>1000</th>
</tr>
</thead>
<tbody>
<tr>
<td>Samples</td>
<td>1251</td>
<td>1001</td>
<td>751</td>
<td>501</td>
<td>251</td>
</tr>
<tr>
<td>Time</td>
<td>5 ms</td>
<td>4 ms</td>
<td>3 ms</td>
<td>2 ms</td>
<td>1 ms</td>
</tr>
<tr>
<td>PTC</td>
<td>50</td>
<td>50</td>
<td>50</td>
<td>23</td>
<td>40</td>
</tr>
<tr>
<td>CM Undamaged</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>98.7%</td>
<td>99.6%</td>
</tr>
<tr>
<td>CM Damaged</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>97.8%</td>
<td>99.1%</td>
</tr>
</tbody>
</table>

4.3. Signal windowing

Analysing the results presented in the previous section it was concluded that most of the information about possible structural damage may be located just at the tail of the signal recorded. For this reason, the next experiment will involve shifting a time window of predetermined length along the measured signal. The aim is to find a source of valuable information.

In this task were adopted three variants of a case study, which differed in the width of the selected time window. It was assumed that the largest window in this test will have the length of 251 samples (1 ms). At this time the incident wave travels the entire length of the sample, reflects from its end and then returns back to the starting point, where it is received by the piezoelectric sensor. Any other of the windows defined was shorter by about half. The signals’ parameters obtained in this way were collected in Table 4. Based on the results, it is difficult to identify the optimal location of the window with the greatest amount of information about the samples examined. Therefore, in next tests overlapping of windows was eliminated and the registered signals of elastic waves were artificially noised.

Table 4. Parameters of the signals windowed.

<table>
<thead>
<tr>
<th>Case study</th>
<th>Time (samples)</th>
<th>Time shifting (ms)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>251</td>
<td>1.0</td>
</tr>
<tr>
<td>2</td>
<td>125</td>
<td>0.5</td>
</tr>
<tr>
<td>3</td>
<td>51</td>
<td>0.2</td>
</tr>
</tbody>
</table>

4.4. Decimation of windowed signals

It was assumed in this experiment that the signal of 1 ms (251 samples) window length can be further reduced by its decimation. The considered decimation levels were equal to $R = \{40, 100, 200, 300\}$. It has finally led to the signal length of respectively $L = \{126, 51, 26, 17\}$, which in the last case is even comparable to the length of the input vector containing 16 principal components.

Based on the obtained results it can be concluded that the correct training of the ND system is possible even if the windowed signal has been significantly distorted by its decimation. Moreover, it seems that in the present case (window length of 1 ms) the most information about the structural health of the test specimens is contained in the central part of the signals.

4.5. Artificial random noise disturbances

Noisy signals have been obtained by adding to the measured signals a noise artificially generated. For this purpose, a matrix of normally distributed pseudorandom numbers was prepared in Matlab. Its size was 3 times larger than the primary patterns database. Adding this noise with zero mean and an assumed standard deviation, the patterns database...
obtained was consequently four times larger and it included both the original and the noisy patterns (540 patterns in total).

During the simulations of training the ND system different levels of artificial noise were considered. It was expressed by its standard deviation, which was taking values from the set \( \sigma = \{5.0, 1.0, 0.8, 0.6\} \cdot 10^{-3} \). Every time, on the basis of the signals obtained, the principal components were calculated and then they were used to train the ND system. Simulations carried out in this experiment was limited only to the case of a window of 21 samples, sliding along the time axis with a step equal to the window length. Final classification results achieved in this way proved that the most information about a failure is contained in the wave packet associated with the second and the third transitions of the incident wave through the entire length of the specimen tested.

5. Conclusions and final remarks

The study shows that it is possible to signal the occurrence of damage on the basis of a raw signal, even at a relatively low sampling frequency. Moreover, it seems that the apparently illegible signal parts (due to multiple reflections from the edge of the specimen) carry a significant amount of information about the occurrence of damage. Thus, from the point of view of training the ND system, representative information about the state of the tested structure should not be expected in the initial part of the signal (first pass), but in its subsequent sections.

Taking into account the results of the classification in the case of a sliding window, the system has detected the damage even under fairly complex signals, which are completely unsuitable for visual evaluation. It was also demonstrated that the length of windowed signals can be reduced by its further decimation and proper inference of ND system studied was possible. Selection of a fairly narrow time windows as well signal decimation were significantly accelerated the calculations on the signal processing stage.

The most important conclusion from the research carried out is that most of the information about the state of the tested specimens can be obtained from the analysis of the time windows in which appears the wave packet associated to the next transitions (second or third) of the incident wave through the entire length of the specimen. It was most apparent when the pattern database has been extended to signals with artificially generated random noise.

Acknowledgements

Financial support of Structural Funds in the Operational Programme - Innovative Economy (IE OP) financed from the European Regional Development Fund - Project ”Modern material technologies in aerospace industry”, Nr POIG.01.01.02-00-015/08-00 is gratefully acknowledged.

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