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Application of artificial neural networks in the damage identification of structural elements

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The paper presents a structure test system developed for monitoring structural health, and discusses the results of laboratory experiments conducted on notched strip specimens made of various materials (aluminium, steel, Plexiglas). The system takes advantage of elastic wave signals actuated and sensed by a surface-mounted piezoelectric transducers. The structure responses recorded are then subjected to a procedure of signal processing and feature's extraction, which includes digital filters, wavelets decomposition, Principal Components Analysis (PCA), Fast Fourier Transformation (FFT), etc. A pattern database defined was used to train artificial neural networks and to establish a structure diagnosis system. As a consequence, two levels of damage identification problem were performed: novelty detection and damage evaluation. The system's accuracy and reliability were verified on the basis of experimental data. The results obtained have proved that the system can be used for the analysis of simple as well as complex signals of elastic waves and it can operate as an automatic Structure Health Monitoring system.

Keywords: artificial neural networks, damage detection, structural health monitoring, elastic waves.

1. Introduction

There is a large group of structures such as aircraft, bridges and dams whose operational safety requires periodic inspections or even continuous monitoring of their condition. Nowadays more and more often the structures are equipped with Structural Health Monitoring (SHM) systems providing information about their current state [11, 14]. The application of such systems improves operational safety since damage detected early can prevent the future disaster.

One very promising nondestructive technique that is suitable for SHM systems employs the phenomenon of elastic wave propagation in solids [1, 7, 9, 16]. For the purpose of wave excitation and sensing the structure is usually equipped with piezoelectric transducers that can be used as wave actuators and sensors. Application of piezoelectric transducers in the field of Nondestructive Tests (NDT) means that sensing and actuating devices can be easily integrated into the monitored structure. It can be done during its construction, so control points can be set up in the areas that are hidden or inaccessible for most NDT techniques.

In general, the analysis of elastic wave signals consists of quantitative and qualitative descriptions of their changes (e.g. attenuation, distortion, reflection) caused by damage appearance and growth. The frequency of the excitation signal is usually tuned in order to trigger propagation of selected waveform (mostly the antisymmetric A_0 or the symmetric S_0) [10]. This is performed because of the sensitivity of certain elastic wave forms to changes caused by an expected type of damage [6]. However, a very important issue is the clarity of the signal to be analysed since a large majority of known approaches deal only with impulse-echo signals where excitation wave package and occurring reflections from a model boundaries (or existing damage) are well distract and visible enough to be recognized. Unfortunately, measurements conducted on a real structure or in service conditions may lead to quite complex signals, useless for the techniques in question and, consequently, to damage detection.

Complex signals were recorded also during the laboratory tests performed. Some factors that are responsible for these circumstances include the fact that small dimensions of the monitored specimen or neighbourhoods of structure elements (like joints, stiffeners, bearings) may cause many imposed reflections. Limitations of the equipment used (power of transducers and amplifiers; excitation frequency, signal repeatability, precision of the bonding layer, interference of transducers and cables with other electrical devices may lead to unsatisfactory signal quality. Finally, environmental effects may cause very low signal-to-noise ratio. As a consequence, a damage 'hidden' behind the excitation signal or other predominant reflections may remain undetected or misclassified. Thus, the research presented in the paper is focused on the approach that can be used for the analysis of both simple and complex signals on one hand, and enable automatic examination of structures tested on the other. The system proposed here is composed of three main components:

- algorithm of signal de-noising (filtering) and features extraction/compression (PCA),
- damage/novelty detection (Auto-associative Neural Networks, ANNs),
- damage prediction/evaluation (feedforward Neural Networks).

Structure reliability depends on the precision of the diagnosis systems employed and hence signal processing plays a major role in damage detection. Since the reflection and dispersion effects may produce quite complex signals, determination of parameters suitable for such purpose more and more often requires the application of advanced signal processing techniques. In this case wavelet decomposition, data filtering, Fourier transformation and statistical analysis are commonly used [3, 12, 15].

The main advantage of current development of SHM systems is their ability to perform automatic signal analysis and damage identification, significantly reducing the human factor. For this purpose the approach of novelty detection and damage evaluation is proposed in the paper. The idea is to use a data set of signal parameters obtained from a reference structure (e.g. undamaged structure, numerical models, laboratory tests) and to use *soft computing methods* [13] to warn about the damage appearance and predict its type, location and extent. In this manner Neural Networks (NNs) can perform automatic analysis of the elastic waves and accelerate the process of structure diagnosis.

The inverse problem discussed deals with identification of the current state of the structure based on an analysis of recorded elastic wave signals caused by known excitation. The results of the performed investigations prove that the proposed approach makes automation of structure testing possible and can be applied to SHM systems. Its robustness and sensitivity were examined during the laboratory tests performed on specimen strips made of various materials.

2. Intelligent damage identification

Damage identification can be found as a hierarchical structure of increasingly precise stages, viz. damage detection, its localization, assessment, etc. [14]. The first stage use methods which provide a qualitative indication that damage may be present in the structure. It can be accomplished without prior knowledge of how the system behaves when damaged. These methods are referred as *novelty detection* [3, 14]. To solve the task the application of ANNs [13] is studied in the present paper. This type of neural network is known also as a *replicator* [2].

Later stage methods of damage detecting provide information about the probable position of the damage and estimate its type or extent. Here the idea of pattern recognition can be used, although it typically requires large amounts of data whose acquisition requires a huge effort in both computational and experimental investigation. However, in the approach described here, standard NNs were trained to recognize the patterns obtained from slightly damaged laboratory models.

A well-defined SHM system should be able to evaluate the damage parameters. However, damage detection and identification are possible only when the measured signals are affected by the presence of damage and its severity, so the application of suitable signal processing techniques is a crucial part of the diagnosis system.

To combine these tasks into an integrated diagnosis system, a two-level SHM algorithm was designed which signals the presence of a failure and can predict its parameters (damage height and width). A simple scheme of the system's functioning is shown in Fig. 1. With measurement of the elastic wave signals at every control point, signal processing techniques have to be applied. At this stage, environmental and measurement noise is removed and signal parameters suitable for damage identification are computed. Then the first level identification is performed by the Neural Network (NN) trained for novelty detection. When the signal differs from normal condition, the system will indicate the presence of damage (by a flashing red light). Then the second identification level can be conducted using the NN trained for damage prediction. The resulting output vector will evaluate the extent of the damage or will declare a false alarm.

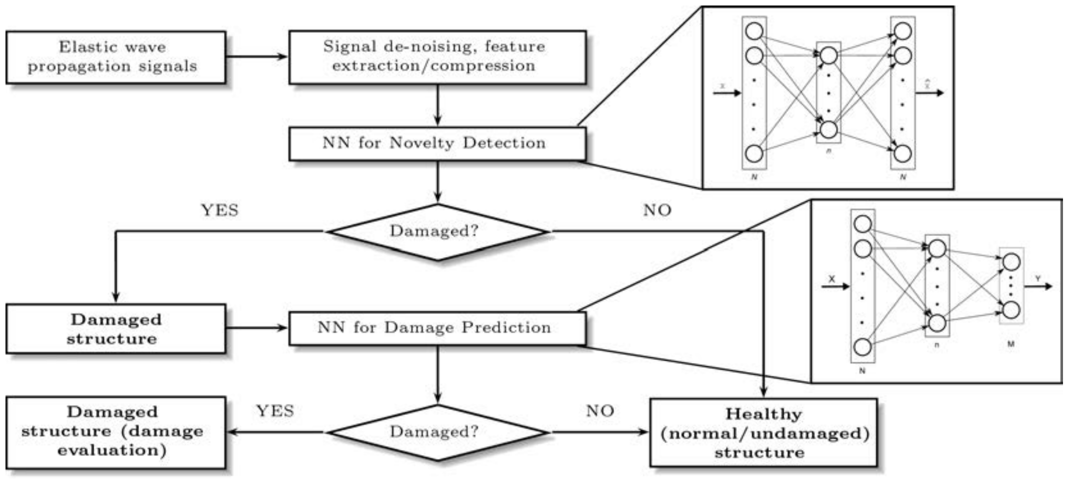

Fig. 1. Scheme of damage detection and the prediction system.

2.1. Signal processing

During the laboratory tests it was found that both environmental conditions and equipment precision may significantly affect the elastic wave signals measured from the models. The signal disturbances identified were usually related to sensor and cable noise, ambient vibration, environmental conditions, incidental events, etc. Fortunately, because of the wide range of data processing techniques available, the influence of signal noise can be minimized.

The first stage of the proposed signal processing algorithm employs wavelet transformation in order to effect decomposition of the signals into their approximations and details. Assuming a certain threshold level we can reject some of those details since they are mainly related to high frequency noises. The application of 1D wavelet de-noising gives smooth approximation of the measured data and the effect of the digital nature of the recorded signal can be diminished (Fig. 2a). In the research study outlined in the paper the signal decomposition level was set to eight and the wavelet family *sym4* used.

The next step in signal processing concerned the application of digital filters. A high-pass Chebyshev filter was used in order to attenuate low frequency bins. Since the sampling frequency of the signals was relatively high (up to 2.5 GHz) filter application followed the signal decimation procedure. Resampling of the measured data at a lower rate caused a significant reduction of the designed filter's order. Examples of both decimated and filtered signal is shown in Fig. 2b.

Afterwards, feature extraction was done by the application of many different techniques. Computed parameters, such as wave amplitudes, spectral densities, correlation factors, etc., defined vectors which were then used for training the diagnosis system. In such a way the suitability of the

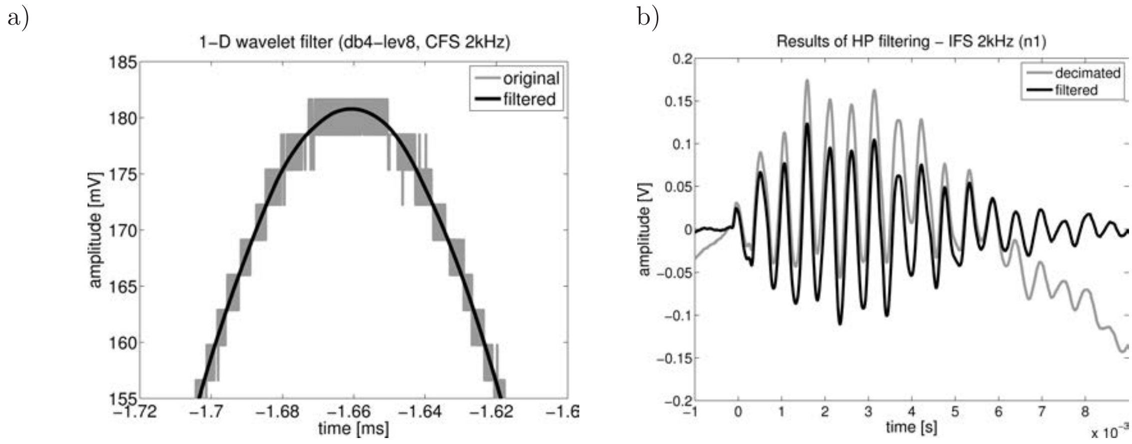

Fig. 2. Wavelet de-noising (a) and digital filtering (b) of the measured signals.

excitation signals used and the wave features were studied. However, the damage prediction accuracy presented in the paper refers to the best results obtained at the present stage of investigation.

As an alternative, a statistical algorithm of PCA was used for the purpose of feature extraction and signal compression [5]. As a result, signals length was decreased from 2501 to 16 principal components. The number of components selected ensured that the reconstruction of the elastic wave signals could be performed with less than 0.5% error. The computed principal components were then used for training neural networks designed for novelty detection.

2.2. Neural Networks for damage identification

NNs are used in many interesting areas and tasks. In engineering applications they are especially attractive in solving the so-called *inverse problems*. The assumption is that NNs are able to learn an unknown relation between input and output data (even when the data are incomplete or fuzzy).

The learning process consists of minimizing the computed error value between the target and the network outputs obtained for successive iterations. Testing is carried out based on the data that the network has never seen before. The ability to produce such a prediction for the training set is called network generalization.

What is a crucial issue in damage identification is the correct selection of features that describe the damage and then improving the accuracy of the neural algorithm (i.e. by tuning the architecture, data preprocessing, or using a different training algorithm). For the mentioned task feedforward NNs are commonly used. They consist of an input (first) layer, usually one or two hidden layers and an output layer. The number of elements in the input and output layers is determined by the size of the learning and testing data sets. It is recommended that the training process be started with one hidden layer and a small number of neurons in that layer [13].

Sometimes the main factor limiting a network's performance is a small number of patterns. Learning the relation between input and output is more difficult in this case. The second issue is that the function that we are trying to simulate should be smooth, i.e. a small change in the inputs should produce a small change in the outputs.

One of the regularization techniques that may improve network generalization is based on the addition of small amounts of artificial noise (jitter) into the inputs during training. In other words, if we have two cases with similar inputs, the desired outputs will usually be similar. As long as the amount of jitter is sufficiently small, we can assume that the output will not change enough to be of any consequence, so we can use the same target value. It should be noted that too much jitter will obviously produce garbage, while too little will have hardly any effect.

The validity of a neural network-based damage detection approach also depends on the initial weights and biases, the order of input elements, choice of transfer function, training algorithm, etc. Thus, to achieve sufficient efficiency, the training procedure was repeated at least fifty times. As a convergence precision mean square error (MSE) [13] was introduced to calibrate network performance.

2.3. Novelty detection

The idea of novelty detection is that only training data obtained from normal operating condition of the structure is used to establish the diagnosis [3, 14]. First, a model of the normal condition is created and then the newly acquired data are compared with those of the model. If there are any significant deviations, then the algorithm indicates novelty. It means that the system has departed from the normal condition and can be damaged. This approach is recognized as a damage detection algorithm and gives mainly qualitative indication that damage might be present in the structure.

For the purpose of novelty detection ANNs were used here. They were learned using the Levenberg-Marquardt algorithm. When the trained network is fed with the inputs obtained from a damaged state, the novelty index $NI(\mathbf{x}) = \|\mathbf{x} - \widehat{\mathbf{x}}\|$ (defined as the Euclidean distance between the target outputs $\mathbf{x}$ and the outputs $\widehat{\mathbf{x}}$ of the NN) will increase [3]. If the learning was successful, the index will be $NI(\mathbf{x}) \approx 0$ for the data obtained from the undamaged state. However, if data are obtained from a damaged structure, the novelty index will indicate an abnormal condition by providing a non-zero value.

Although novelty detection provides in general a two-level classification (damaged, undamaged), it can be regarded also as a multilevel classification indicating e.g. type, severity and extent of damage. Obviously, improved classification accuracy involves the application of a NN designated to multilevel classification. However, such an approach requires prior knowledge about possible damage scenarios, since the algorithm is based on the class labels assigned to a sample of measured data. It was proved that, for instance, when based on one of the laboratory models, the application of this type of NN can provide very good classification results.

2.4. Damage evaluation

The damage evaluation task is often related to a regression problem and provides an approximation of damage extent, location, etc. In the proposed approach feedforward NNs were used to predict the extent of damage in laboratory models of strip elements.

Based on the laboratory tests conducted a damage pattern database, corresponding to both healthy and damaged structures, was defined. Then the NN architecture was designed and customized by minimizing a test Mean Square Error (MSE) [13]. The obtained results followed many repetitions of NN training with various input vectors related to the extracted wave parameters, type of excitation signal (continuous, impulse), frequencies, location of control points, etc.

The common problem associated with such tests, and damage detection in particular, is that only a relatively small number of patterns can be obtained from a single specimen during the laboratory tests. In order to improve the NN's generalization ability and prove its robustness, the number of damage patterns was extended by adding measurement or artificial noise to the measured signals. Next, the signal parameters were computed and used for NN learning. Although the training data were noised, the trained NNs retained the same prediction accuracy. It proved the reliability of the designed system in the case when the measured signals were affected by insignificant deviations of the excitation frequency or by the addition of artificial noise to the evaluated signal parameters.

3. Laboratory tests

The idea on which the application of elastic wave propagation phenomena is based is the assumption that any obstacles will cause wave reflections and affect their transition through damaged areas.

In order to illustrate the signal variations, let us consider a strip with piezoelectric transducers attached at one of its edges. A simplified scheme of the model is shown in Fig. 3a. An incident wave was introduced at the left edge of the model and the structure response was measured simultaneously at these control points (No. 1). Close to the right hand side of the model a damage was introduced in the form of a drilled hole. The measured signal is shown in Fig. 3b.

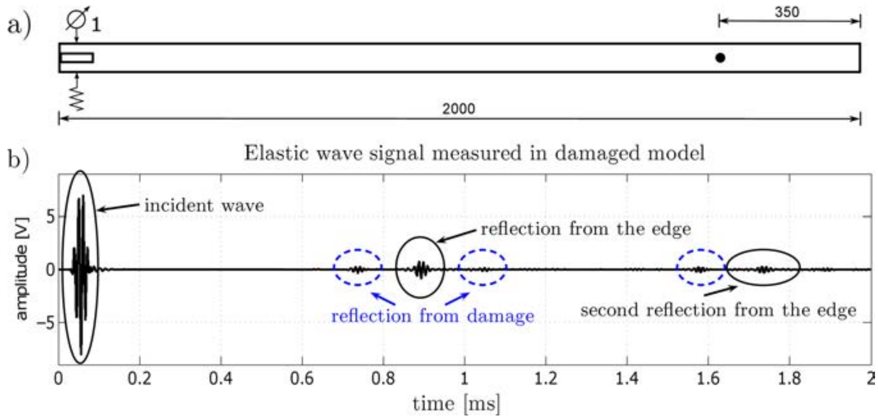

Fig. 3. Elastic wave measured in damaged model.

In this plot the first wave package resulted from the excitation signal that was introduced to the model. Next, the elastic wave propagated through the model and a second wave package was caused by the reflection from the damage. The next wave package was the first reflection from the right end of the model. The elastic wave came back to the left end and a second reflection from the damage can be recognized. This scenario is repeated until the elastic wave is completely attenuated.

The elastic wave signals measured at each control point installed can then be subjected to the identification procedure that deals with damage location and prediction of its extent and nature. It is important to adjust the excitation parameters so that the damage significantly influences the measured signals.

3.1. Laboratory set-up

The laboratory apparatus applied for the purpose of actuating and sensing elastic waves as well as the test idea are shown in Fig. 4.

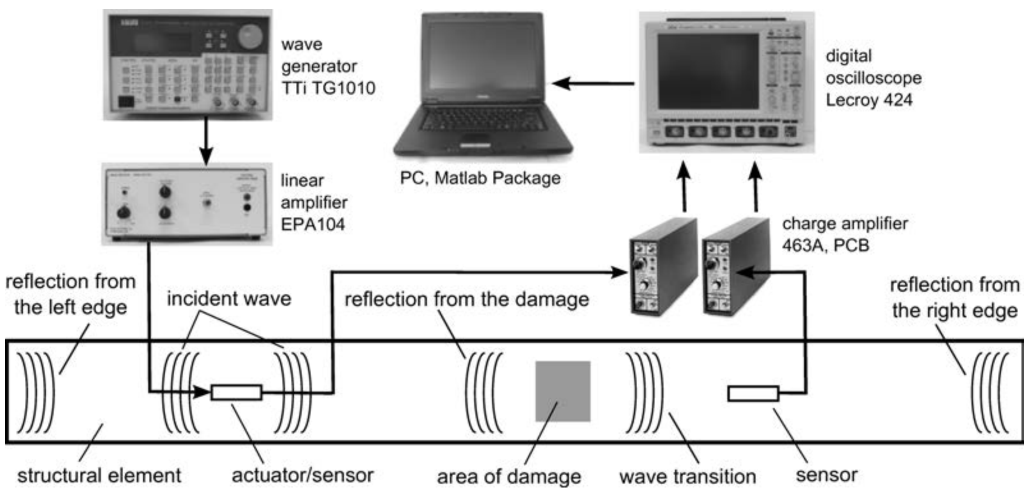

Fig. 4. Test idea and laboratory set-up.

First, the excitation signals were adjusted using the wave generator TTi TG1010. After amplification by the linear amplifier EPA-104, the incident wave was introduced to the specimen using a piezoelectric transducer (QuickPack, Mide). The structure response signals were then measured by sensors and amplified by charge amplifiers (Model 463A, PCB). Since the piezoelectric material in the applied transducers was two-layered, it was possible to measure the signals at the position of both the actuator and sensor. Then the signals were stored in a digital oscilloscope (Lecroy 424) together with the reference signal received from the wave generator. Data analysis was performed using a personal computer (PC) and Matlab Package [8].

3.2. Laboratory models

The proposed NDT approach was studied on laboratory specimens consisting of strips made of various materials. In particular, the experiments were conducted on strips of aluminium (2000 × 10 × 1 mm), steel (808 × 32 × 2 mm) and Plexiglas (1206 × 60 × 3.8 mm). Preliminary tests were performed on undamaged models, where damage was simulated by attaching an additional mass or by adding external forces [4]. In such a way disturbances of the local stress field were induced and could be identified. Next, a few damage scenarios were considered and introduced at certain locations for each model. The severity of damage changed between the initial and final stages (Fig. 5).

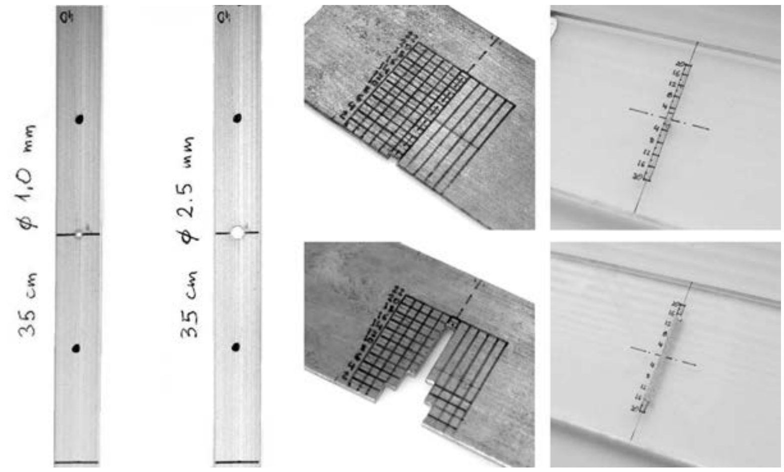

Fig. 5. Damage scenarios showing the initial and the final stages.

First of all, the damage in the form of drilled holes was introduced to the aluminium strip and the wave propagation signals were recorded for three subsequent damage positions and respective hole diameters ranging from 1.0 to 3.2 mm. The results of these tests are shown in Fig. 6, where the elastic wave signals, propagating in both the healthy and damaged aluminium strip, were compared. In particular, it can be seen from this plots that the introduced excitation, the reflection from the strip end and the additional reflections (between the excitation and the first reflections) related to the respective damages are clearly indicated. The analysis of the reflection arrival times and their amplitudes can be used for damage detection, location and evaluation.

Similar experiments were conducted on both steel and Plexiglas strips. The damages in these cases were introduced by creating notches across the entire thickness of the strips (see Fig. 5). For the steel strip the notching extended up to 20 mm height and 10 mm width, starting from one edge to the opposite side; for the Plexiglas up to 32 mm height and 2 mm width, starting from the centre interchangeably to the outer edges. However, the analysis of the recorded signals was much more difficult than expected. An example of the comparison of the elastic wave propagation in the healthy and damaged steel strip is shown in Fig. 7.

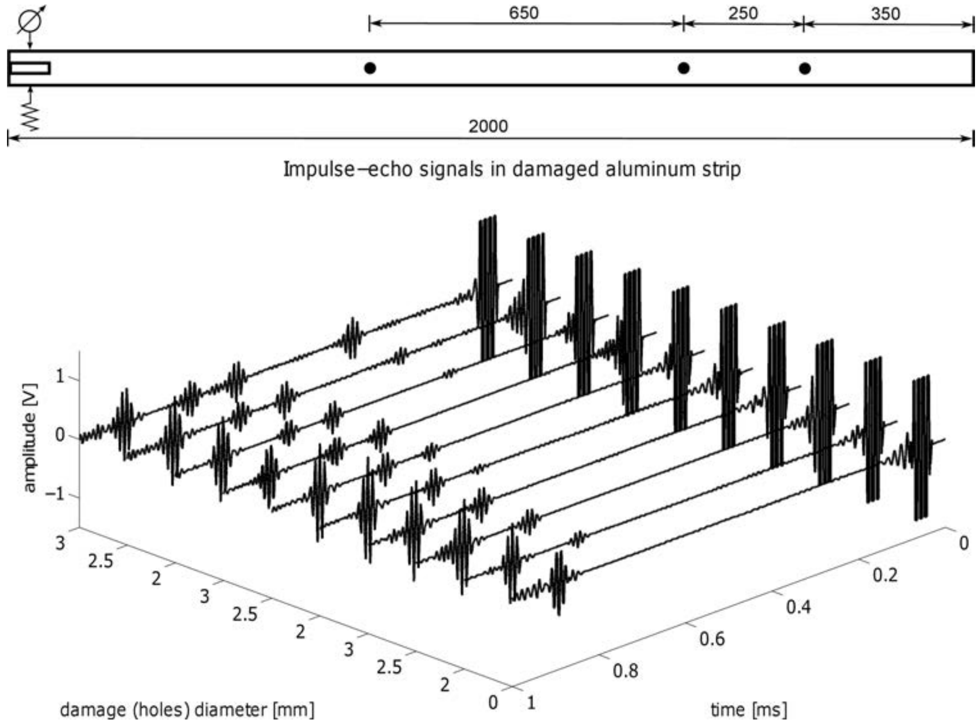

Fig. 6. Elastic wave signals recorded in a healthy (hole diameter = 0) and damaged aluminum strip.

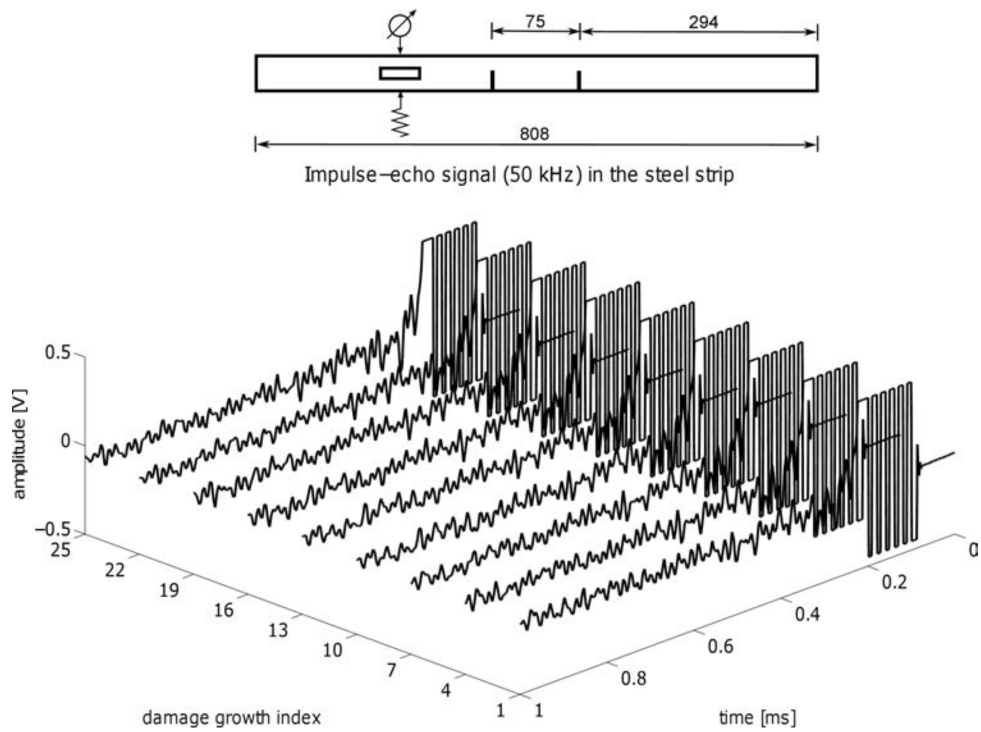

Fig. 7. Elastic wave signals recorded in the steel strip, 6 sine waves, 50 kHz.

Although the damage increased, its occurrence, position and extent could not be estimated by visual inspection, even if the plots were closely examined. Obviously, there were some changes in the signals, but it was very difficult to relate them to the damage extent or position. In addition, because of the large number of signal reflections, those originating from the model ends could not be identified. There are several possible explanations: the models lengths were relatively short (compared with the aluminium strip), the piezoelectric transducers were bonded along the models and the elastic wave frequency of the impulse excitations was limited to 50 kHz due to constraints of the applied control equipment.

As shown in Figs. 6 and 7, the performed tests can be divided, in general, into two classes: those where the reflections from the existing obstacles (e.g. damaged areas, model limits) are well separable and those where they are quite complex or even non-separable. The analysis of the first group of signals is fairly clear and simple to apply in damage detection investigations, whereas in the case of short models, equipment limitations, low frequency excitations and noise existence can make it a very difficult problem. However, it is proved in the paper that a solution can be reached by the application of advance signal processing techniques and NNs.

4. Damage detection and evaluation

The damage database obtained from the laboratory tests was used here for training the diagnosis system designed to detect damage and estimate its severity. A huge computational effort was made to improve the training procedure with particular attention paid to various definitions of the input vectors, tuning the architecture of the NNs, parameter adjustment and repetitions of the learning algorithm, etc. The main objective of this effort was to decrease the damage identification error and improve the generalization ability of the system.

4.1. Training novelty detection

The first step of the proposed diagnosis system was damage detection. For the purpose of novelty detection the a replicator was applied. From the total number of 91 patterns obtained from the simple model (the aluminium strip) and stored in the damage database, 22 patterns corresponding to the undamaged case were used for learning the replicator. The remaining 67 patterns were used for NN testing. It can be seen in Fig. 8 that through the application of PCA and NNs, extremely accurate pattern classification was achieved, even for patterns relating to incipient damage.

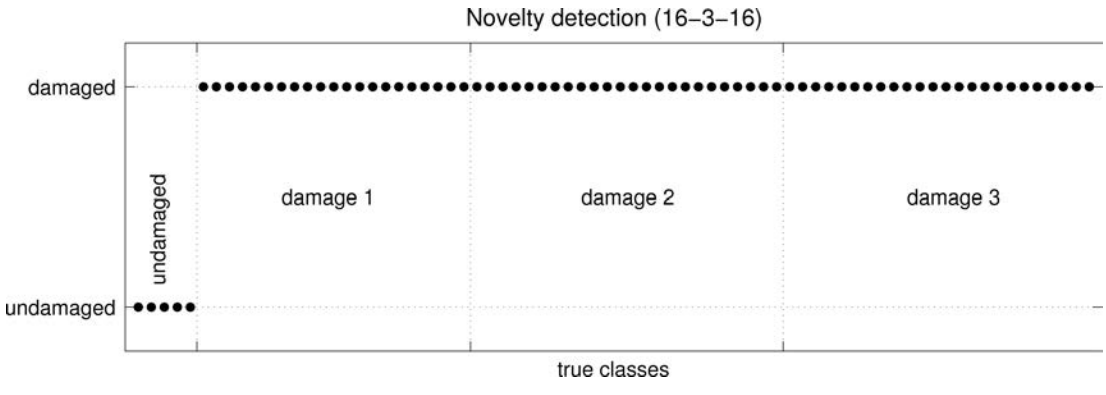

Fig. 8. Results of pattern classification using NN (16-3-16) and novelty index (aluminium strip).

It was proved that the replicator of architecture 16-3-16 could correctly separate the classes of damaged and undamaged structures for all the damage scenarios considered. In this case, the threshold level was set to $thr = 2$ while the novelty index NI varied in the ranges (0.105, 1.094) and (4.738, 41.167) respectively for undamaged and damaged patterns.

Next, a novelty index was used for multilevel classification and separation of particular structure classes (undamaged, one damage, two damages). The results obtained are shown in Fig. 9 while a matching confusion matrix was compiled and is shown in Table 1.

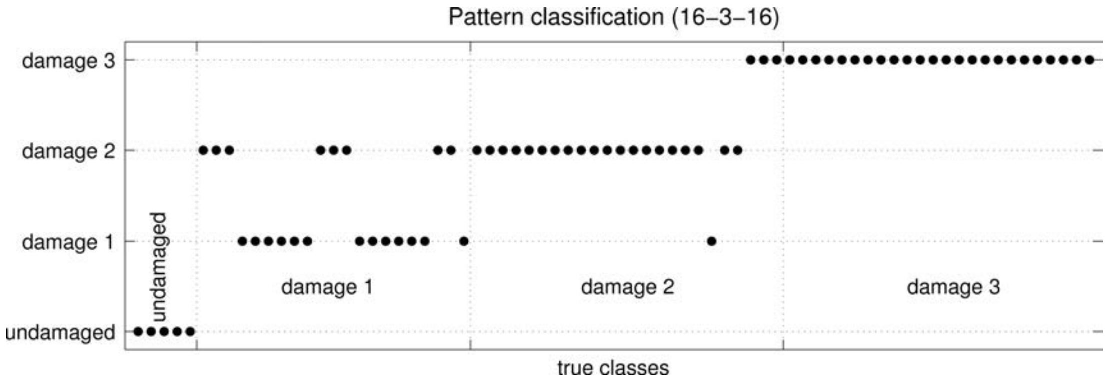

Fig. 9. Results of pattern multilevel classification using NN (16-3-16) and novelty index (aluminium strip).

Table 1. Confusion matrix of multilevel classification results (aluminium strip): NN testing.

True classes	Pattern classification (16-3-16)			
	undam.	dam. 1	dam. 2	dam. 3
undam.	**100%**	0%	0%	0%
dam. 1	0%	**89.2%**	10.8%	0%
dam. 2	0%	1.4%	**94.5%**	4.1%
dam. 3	0%	0%	0%	**100%**

The biggest classification errors were associated with separation of inter-classes. In case of the aluminium strip the accuracy was approximately 90% for one and two damages classes, whereas the undamaged and three damages cases were classified with excellent (100%) accuracy. The novlety index NI for the certain damage scenarios varied in the ranges (4.738, 17.846), (8.194, 38.998), (38.716, 41.167) while the threshold levels were set to $thr = \{2, 8.5, 35\}$.

The same classification algorithm was used for the complex signals obtained from the laboratory tests of the steel and Plexiglas strips. In the first case the total number of 31 patterns was extended to 2000, adding to the source signals various time histories of measurement noise. As before, the results of the two-level classification (damaged, undamaged) proved excellent (with 100%) accuracy for both models.

In the case of multilevel classification of damage patterns for complex signals the results obtained are shown in Fig. 10, while the corresponding confusion matrix complied is given in Table 2.

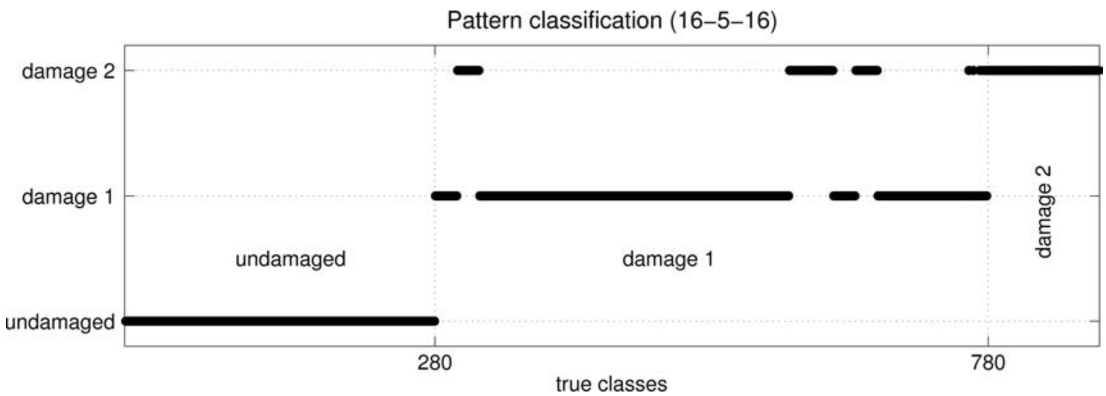

Fig. 10. Results of multilevel pattern classification using NN (16-5-16) and novelty index (steel strip).

Table 2. Confusion matrix of multilevel classification results for the steel (and Plexiglas) strips: NN testing.

True class	Pattern classification (16-5-16)		
	undam.	dam. 1	dam. 2
undam.	**100%**	0%	0%
dam. 1	0%	**89.0%** (66.7%)	11.0% (33.3%)
dam. 2	0%	0%	**100%**

It can be seen that the classification accuracy for the aluminium (Table 1) and steel strips proved to be very similar (about 90%), while for the Plexiglas strip it was slightly lower (about 67%).

To improve these results, classifying NNs (16-3-1) were designed and trained using patterns for the Plexiglas strip. It increased the pattern separation accuracy to 100%, even for inter-classes. The results of this study are shown in Fig. 11.

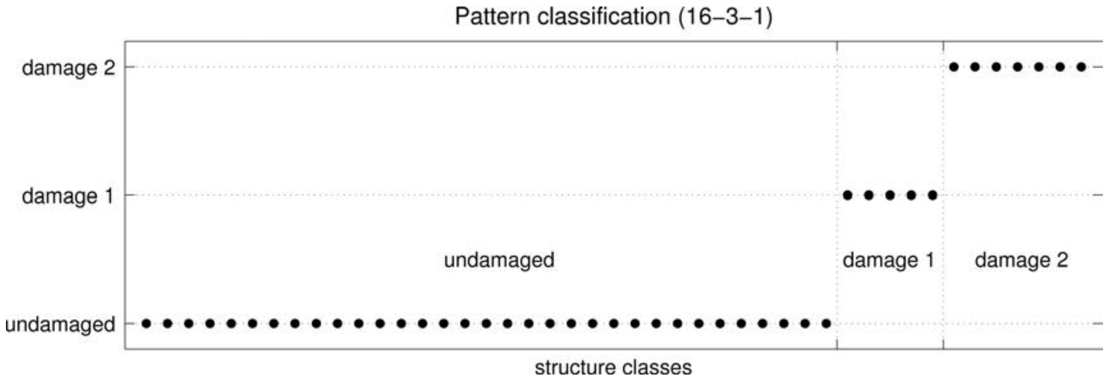

Fig. 11. Results of pattern multilevel classification using NN (16-3-1) in the Plexiglas strip.

It proves that a damage detection subsystem can work properly for both *simple* and *complex* signals.

4.2. Training the damage evaluation subsystem

In the case when the diagnosis system warns that an anomaly has been detected, another type of NN can be applied to evaluate the damage parameters. Since the position of any damage was considered constant, the only parameter which it was necessary to identify was the damage extent (height and width).

First of all, the suitability of the defined input vectors was examined for the purpose of damage evaluation and NN training. To achieve this, various frequencies (2 to 50 kHz) and different types of excitation signal were studied. Although impulse excitations are the most frequently used, the application of Continuous Sine Waves (CSWs) was also analysed. It was found during the laboratory tests that such signals can be useful when the damage is located close to the actuator and reflections from the damage overlap with the excitation signal.

Following signal processing, a set of CSW parameters was computed. The input vector consisted of the following parameters: (i) the wave's dynamic amplitudes Ad, (ii) amplitude factors Af (defined as the ratio of the dynamic amplitudes measured at two control points), (iii) correlation factor Cf (related to signals received from the actuator and sensor). The results obtained from the learning and testing a selected NN based on these input vectors and the computed MSEs of damage identification are shown in Fig. 12. A statistical characteristic of the MSE computed for all the patterns after training the NN is also provided.

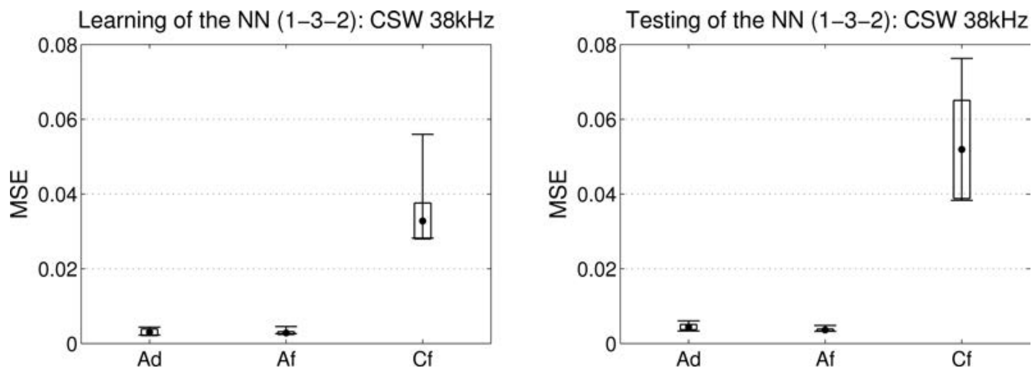

Fig. 12. MSE of damage extent identification obtained from NN (1-3-2) trained using CSW parameters: mean value (dot), minimum and maximum errors reached among all patterns (stem), standard deviation (rectangle).

As the best results related to the first two input vectors, a new input vector was defined as a combination of those parameters and selected frequencies. The results obtained from the cases studied are shown in Table 3, where it can be seen that the additional information included in the input vectors has the damage identification results. The real values of the predicted parameters, related to the best accuracy achieved in the case of CSWs, are shown in Fig. 13, where both the target and calculated values of the damage parameters are given in millimeters.

Table 3. NN testing results for combinations of input vectors (InV) and selected frequencies of the CSWs.

InV type & size	Frequency combination	MSE of testing ($\times 10^{-3}$)			
		mean	min	max	std
$\mathrm{Ad}_{(1\times N)}$	38	**4.41**	**3.36**	6.08	0.69
$\mathrm{Af}_{(1\times N)}$	38	**3.63**	**3.46**	4.83	0.30
$\mathrm{Ad}_{(2\times N)}$	18-38	**3.092**	**1.952**	4.286	0.807
$\mathrm{Ad}_{(2\times N)}$	38-44	**2.079**	**1.100**	3.277	0.698
$\mathrm{Ad}_{(3\times N)}$	18-38-44	**1.513**	**0.889**	2.967	0.565

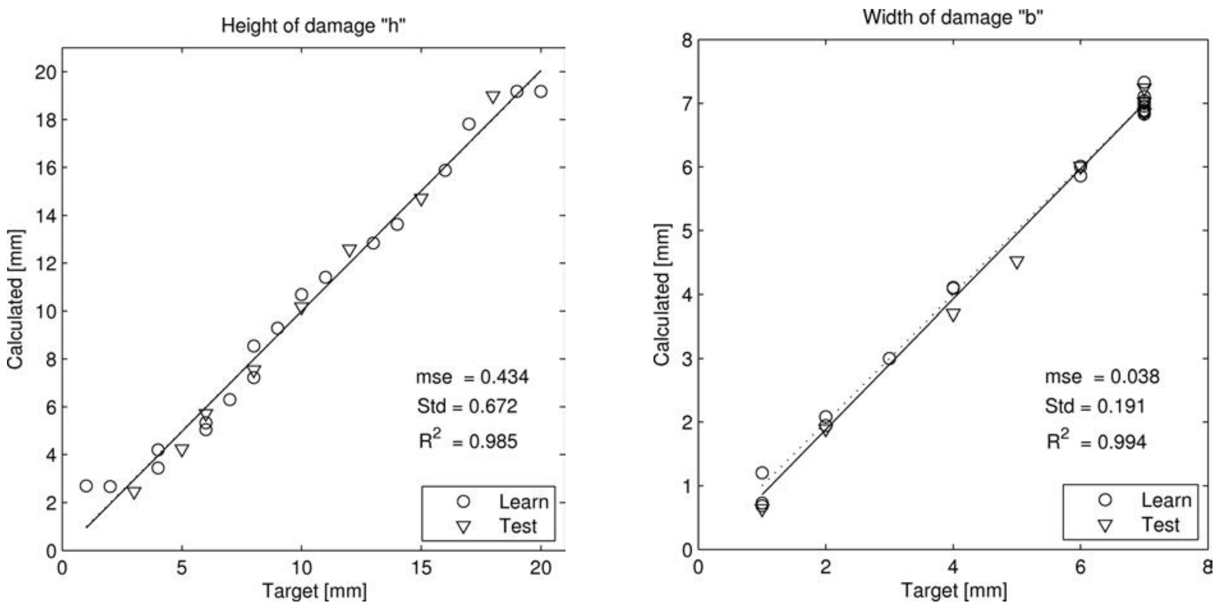

Fig. 13. Results of damage parameter prediction using CSW and the NN (3-3-2): damage height and width.

A similar training procedure was repeated for the Impulse Sine Waves (ISWs) with an even larger set of signal parameters. Mainly, the additional input vectors consisted of spectrum magnitudes and threshold amplitudes were defined. The excitation signals were composed of one, four and six sine periods, while the signal frequency ranged from 2 to 50 kHz. The final results of the performed tests are shown in Fig. 14 for both learning (circle) and testing (triangle) damage evaluation. It can be seen that the testing accuracy for the steel strip varied between 0.10 and 1.13 mm. In comparison with the other results relating to the wide range of signals studied and their parameters (Table 4, where Ad8Ad9 means the eighth and the ninth Ad of a signal, M_1 denotes the maximum value of a frequency magnitude, Ad_{1to3} refers to first three Ad of a signal) the accuracy obtained for both CSWs and ISWs was very good and they remained at the same level. Consequently, it should be noted that CSWs can be useful for damage evaluation, although for continuous monitoring systems can be very energy consuming.

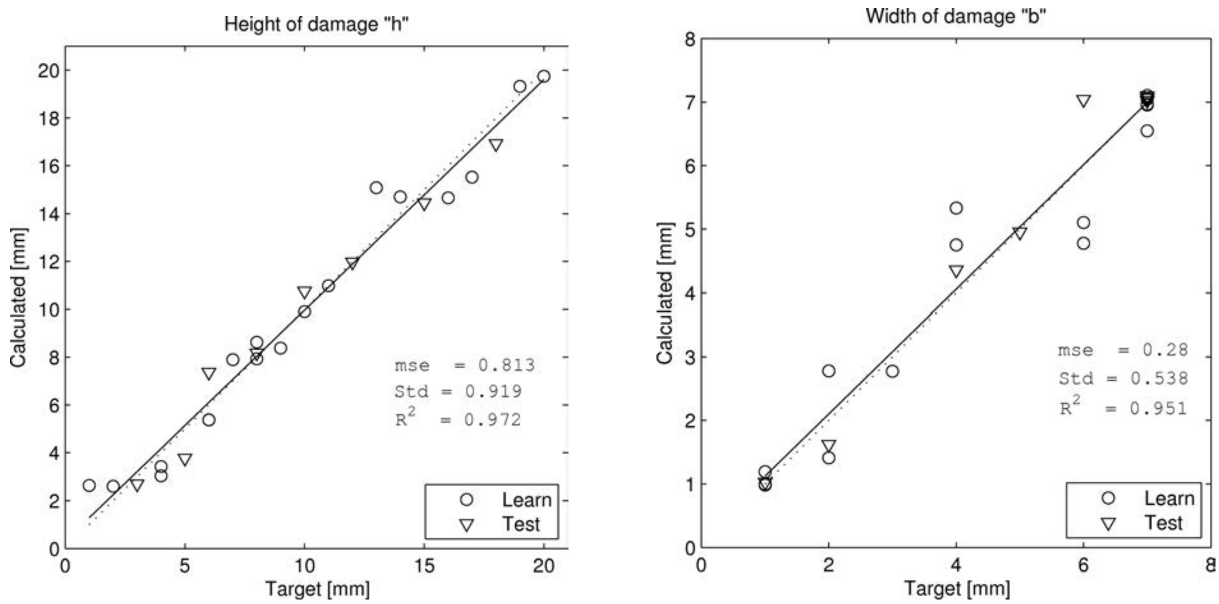

Fig. 14. Results of the damage parameter prediction using ISWx4 and NN (1-3-2): damage height and width.

Table 4. Real values of predicted damage parameters for testing the NNs using CSW and ISW.

Signal type	Input vector (InV)	Width [mm]			Height [mm]		
		mean	min	max	mean	min	max
CSW 38 kHz	$Af_{(1\times N)}$	0.37	0.003	1.35	0.57	0.09	1.26
CSW 18-38-44 kHz	$Ad_{(3\times N)}$	0.21	0.007	0.48	0.51	0.17	0.99
ISWx1 38 kHz	$Ad8Ad9_{(2\times N)}$	0.28	0.002	0.85	0.52	0.02	1.66
ISWx4 42 kHz	$M_{1\,(1\times N)}$	**0.12**	0.011	0.55	0.51	0.10	1.13
ISWx6 38 kHz	$Ad_{1to3\,(3\times N)}$	0.22	0.001	0.88	**0.26**	0.03	0.55

Taking into account the mean accuracy obtained of the predicted extent of the damage it is worth mentioning that the most suitable signals, among all the experiments performed on the steel strip, were the impulse signals consisting of four and six sine waves. The optimal excitation frequency for the considered model was 38 kHz.

In the case of the Plexiglas strip, where the damage width was constant, the accuracy of the damage height evaluation varied from 0.5 to 12.2 mm for all the patterns considered. The lower precision level can have been caused by the material parameters (wave attenuation, time of flight) and measurement uncertainty (transducers type, thickness of bonding layer, etc.). Hence in future work attention should focus on better precision of model preparation and proper adjustment of the laboratory equipment.

5. Conclusions and final remarks

The performed investigations have proved that:

- Damage detection and evaluation are possible by using elastic wave propagation.
- Difficulties can be caused by relatively short models, damage located in the neighbourhood of excitation, superposition of many reflections, operating limitations of piezoelectric transducers and testing equipment.
- NNs have been shown to be useful for the analysis of both *simple* and *complex* signals.
- PCA is useful for both feature extraction and data reduction of elastic wave signals applied to structure tests.
- Two levels of damage identification process were established: novelty detection and damage size estimation.
- The approach presented here allows automation of structure testing and seems very useful for on-line SHM systems.

Further work in the field of novelty detection should be focused on system validation during laboratory tests performed on real structures or their elements. What is also worth studying is the application of other types of NNs, such as Support Vector Machines (SVM) or Bayesian NNs, in order to improve the accuracy of both pattern classification and prediction of damage parameters.

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