NEURAL NETWORK BASED CLASSIFIER FOR ULTRASONIC RESONANCE SPECTRA

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Abstract

In this paper we present a neural network based spectrum classifier (NSC) and its application to ultrasonic resonance spectroscopy. The use of an Artificial Neural Network (ANN) is proposed to meet the requirements of high sensitivity for small but relevant changes in the spectra, and simultaneous robustness against measurement noise. Provided with enough training examples, the ANNs are known to be able to find features representative for different classes and to generalize in order to cope with the measurement noise. Among several types of ANNs that could be used for classifying the spectra we have chosen a multi-layer perceptron (MLP). Although the MLP itself can perform feature extraction, we included an optional pre-processor for this purpose. The NSC is essentially model free and can be trained using real and modeled spectra. The classifier uses both amplitude and phase information in the spectra. The performance of the classifier has been verified using a number of practical applications, here we present results of its application to detection of disbonds in adhesively joint multi-layer aerospace structures using Fokker Bond Tester resonance instrument. In this case the classifier is capable of detecting very small disbonds (larger than 25% of the sensor area) and correct identifying their position in the structure (identifying the defected joint).

Introduction

Recently ultrasonic spectroscopy has become a more common NDE technique and specialized instruments are commercially available now for inspection of aerospace structures, ball bearings, and even concrete [2],[3].

Ultrasonic resonance spectroscopy is a method for testing materials with relatively low acoustic absorption per wavelength by exciting the sample under test into mechanical resonance. By progressively sweeping the frequency of a driving transducer across a range and recording the amplitude and relative phase of a receiving transducer one can build up a spectrum of the sample under test. Solid objects have many resonances or modes of vibration with peak frequencies that depend upon the mechanical properties of the sample, its geometry and the presence of any flaws. A spectrum therefore contains information about the sample that is of interest for the purpose of inspecting it. The challenges of the technique are to sample the spectrum accurately and to interpret it correctly.

The spectrum acquired in this way can be used for characterization of the inspected object or detection of flaws in it. Since the spectrum gathered by the modern instrument can consist of several thousand points and can contain many resonance peaks the user demands tools for spectrum classification. Since classifying spectra is a common task in many practical applications general software tools have been developed for this purpose during Brite/EuRam Project BE-5029-92. The software was used there to classify ultrasonic resonance spectra from pavement blocks, carbon fiber composite structures and ball bearings. To meet the requirements of high sensitivity for small but relevant changes in the spectra and simultaneous robustness against measurement noise, the use of an Artificial Neural Network (ANN) was proposed. Since the software was meant to be evaluated by different industrial participants, a user friendly Graphical User Interface (GUI) was also developed. The software, referred to as the Neural Spectrum Classifier (NSC), was written in MATLAB to run under MS-Windows.

Neural Spectrum Classifier

In the Neural Spectrum Classifier (NSC) a multi-layer perceptron (MLP) has been used for classifying spectra. Although the MLP can perform feature extraction, an optional pre-processor was included for this purpose (see Figure 1).

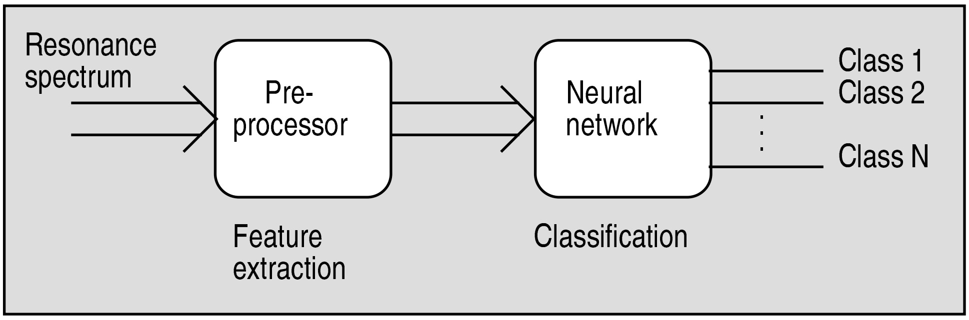

Figure 1: *General structure of the Neural Spectrum Classifier*

The pre-processor can be used to incorporate the a priori knowledge about the physics involved in the creation of data. This makes it work as a model based feature extractor, extracting data relevant for the classification. A big benefit when using the pre-processor is data-reduction. Making the input vector (spectrum) smaller means reducing the number of input weights in the ANN, which allows the number of training examples to be reduced. On the pavement block spectra, rational function approximations of the spectra were used. However, the best results were obtained when not using the pre-processor, probably due to the spectra being very complex in combination with big in-class variations caused by spread in acoustic velocity.

The MLP network was trained to produce a positive signal at the output associated to the presented class, and zero on all other outputs. Theoretically the outputs are capable of estimating the a posteriori probability ($P(Class\ i \mid \boldsymbol{x})$ where $\boldsymbol{x}$ is the input pattern vector). If the estimates are good, this is exactly what is needed to make a classifying decision. Furthermore, if a pattern (spectrum) is presented that looks much different from those in the training set, normally the sum of the outputs will not be one (as expected for probabilities). This indicates a hazardous classification and can be used to automatically warn the operator. Another piece of information given to the operator during training is the cross-validation error. This shows, while training, how well the classifier performs on data not included in the training set. If care is not taken, overtraining/overfitting (increase in cross-validation error) can become a problem when using a high degree of freedom in the net together with too little training data.

The NSC program is controlled through the use of menus and dialogue boxes which make possible to configure the neural network and to define the training and the validation sets. When all preparations are done the training can start. As training progresses, curves are plotted to show the current training and cross validation error (see Figure 2). In this example the training should be interrupted after about 55 iterations after reaching minimum in the cross-validation curve. By terminating the training at its minimum we protect the network from overtraining resulting in ”memorizing” the training data and ensure good generalization ability.

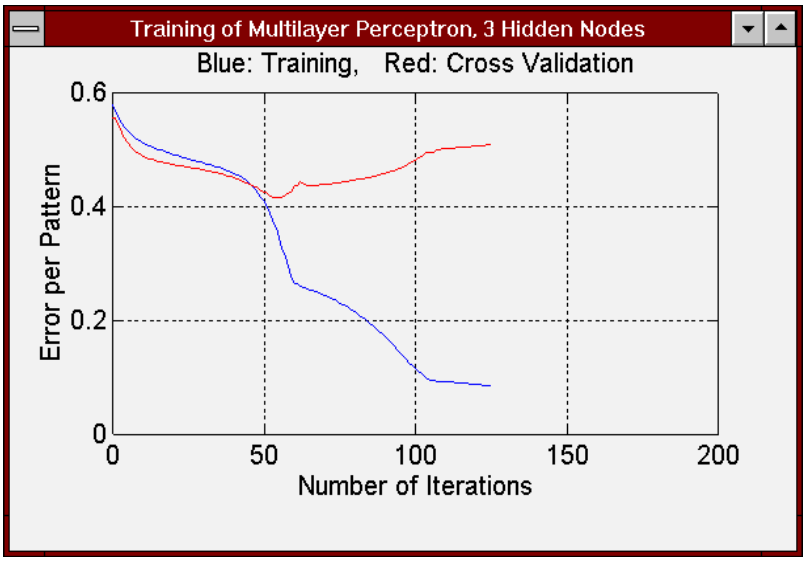

Figure 2: *Error plot during training. Training should be terminated when minimum in the validation curve occurs.*

When network weights have been trained to appropriate values, the NSC is ready to start classifying. The data set to be classified is specified in the same manner as previously used for the training and validation sets. The classifier is applied to data through the use of a menu and generates a list including filenames, suggested class and the neuron outputs from the output layer (used for decision). The result is currently presented in a simple text editor, from which it can be saved and included in other documents.

Application examples

The performance of the classifier has been verified using a number of practical applications, such as civil engineering [3], inspection of aerospace composite structures, ball bearings and aircraft multi-layer structures. Here we present shortly some results, focusing on detection of disbonds in adhesively joint multi-layer aerospace structures using Fokker Bond Tester resonance instrument, details can be found in [1].

Aerospace structures made of composite. As part of the evaluation of the developed ultrasonic spectroscopy system the NSC software was tested on ultrasonic resonance spectra from composite panel samples. Spectra were collected with four different types of damages, and from flawless samples. The damages included: a small cut in one of the carbon fiber layers, with and without delamination (14 spectra), heat damage (5 spectra) and indentation with a hammer (10 spectra). From the flawless samples 23 spectra were acquired. Each spectrum consisted of 1000 frequency samples in the range from 50 kHz to 3 MHz. After training on data with all different types of damages, plus the flawless spectra, the classifier was able to correctly classify 82% of the spectra not used for training. This result looks promising and the performance might be improved if larger training sets were to be used.

Ball bearings. The NSC software was also tested on a large set of ultrasonic resonance spectra from spot weldings in commercial ball bearings. The spectra were collected from 50 ball bearings, of which 20 were labeled flawless and the remaining 30 had different kinds of artificial defects in the weld, resulting in a training set consisting of 130 spectra from flawless ball bearings and 208 spectra from flawed specimens. The spectra consisted of 100 frequencies in the range from 1 kHz to 10 MHz. After training, 96.5% of the spectra were correctly classified. Furthermore, the conclusion could be made that the testing has a global character, i.e., ball bearings can be classified as flawless or flawed based on a single spectrum, acquired from an arbitrary point.

Fokker Bond Tester. An ultrasonic inspection technique commonly used for aircraft structures is based on ultrasonic spectroscopy [2]. Commercially available instruments (bond testers) used for this test operate on the principle of mechanical resonance in a multi-layer structure. A piezoelectric probe shown in Figure 3b, excited by a variable frequency sine signal is placed on the surface of the inspected structure. A frequency spectrum in the range of some tens of kHz to several MHz is acquired by the instrument, see Figure 3a.

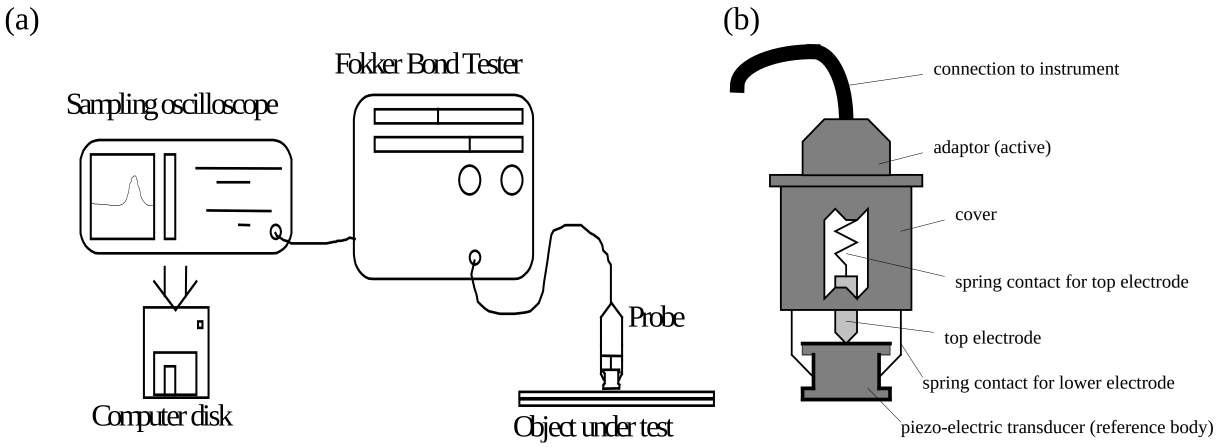

Figure 3: *Experimental set-up for bond inspection (a) and probe for the Fokker Bond Tester (b).*

Commercially available instruments (bond testers) used for this test operate on the principle of mechanical resonance in a multi-layer structure. A piezoelectric probe shown in Figure 3b, excited by a variable frequency sine signal is placed on the surface of the inspected structure. A frequency spectrum in the range of some tens of kHz to several MHz is acquired by the instrument, see Figure 3a.

A resonance in the layered structure occurs when echoes between two boundaries travel back and forth due to differences in acoustic impedances at the boundaries. For multi-layer structures a number of resonances can be observed depending on their geometry and condition. For each particular defect-free structure and given transducer we obtain a characteristic resonance pattern, an ultrasonic signature, which can be used as a reference.

During the inspection of an unknown object its surface is scanned by the probe and ultrasonic spectra are acquired for many discrete points. Disbond detection is performed by the operator looking at some simple features of the acquired spectra, such as center frequency and amplitude of the highest peak in a pre-selected frequency range. This means that the operator has to perform spectrum classification based on primitive features extracted by the instrument.

Our task in this project was to develop an automatic classifier capable of detecting and classifying defects in multi-layer structures based on ultrasonic spectrum acquired by Fokker Bond Tester. Our belief was, that by using the entire spectrum (i.e., within the frequency range used during the measurement) we would have enough information not only to detect a disbond but also to identify in which layer it was located. The detection is normally possible for a well trained human operator, but when it comes to small defects not big enough to cover the area of the transducer, maximum amplitude and center frequency are not sufficient to locate the disbond. But primarily, our method would serve as a way of automating the inspection procedure.

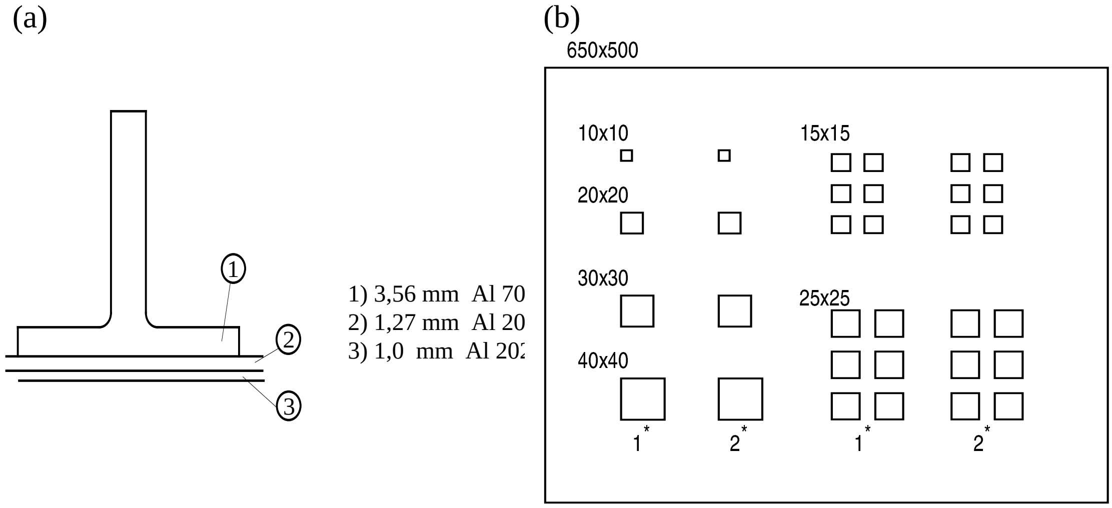

Figure 4: *Structure of the real object "Lower wing skin"(a). Test object "Cargo door" (b) (*: interface containing disbond)*

A number of real objects with artificially made disbonds were tested using the Fokker Bond Tester and spectra were stored in a PC for the classification. One of the objects, "Lower wing skin " is shown in Figure 4. As can be seen, the positions and sizes of flaws are marked. The same marks were also drawn on the actual objects to facilitate measurements.

The NSC was trained using labeled data acquired during inspection of objects with known defects. Examples of spectra for the object ”Lower wing skin” are shown in Figure 5, the spectra measured for the flawless structures for different number of layers in the upper panel, the spectra corresponding 100% and 50% disbonds in the middle and lower panel, respectively. The size of the disbonds is given as a percent of active surface of the probe used for the test.

Classifier structures resulting from the training were verified in a blind test. To evaluate the reliability and performance of the NSC it was subjected to a blind test using unknown data containing spectra measured for various sizes and locations of the disbonds (from 50% to over 100% of the probe size).

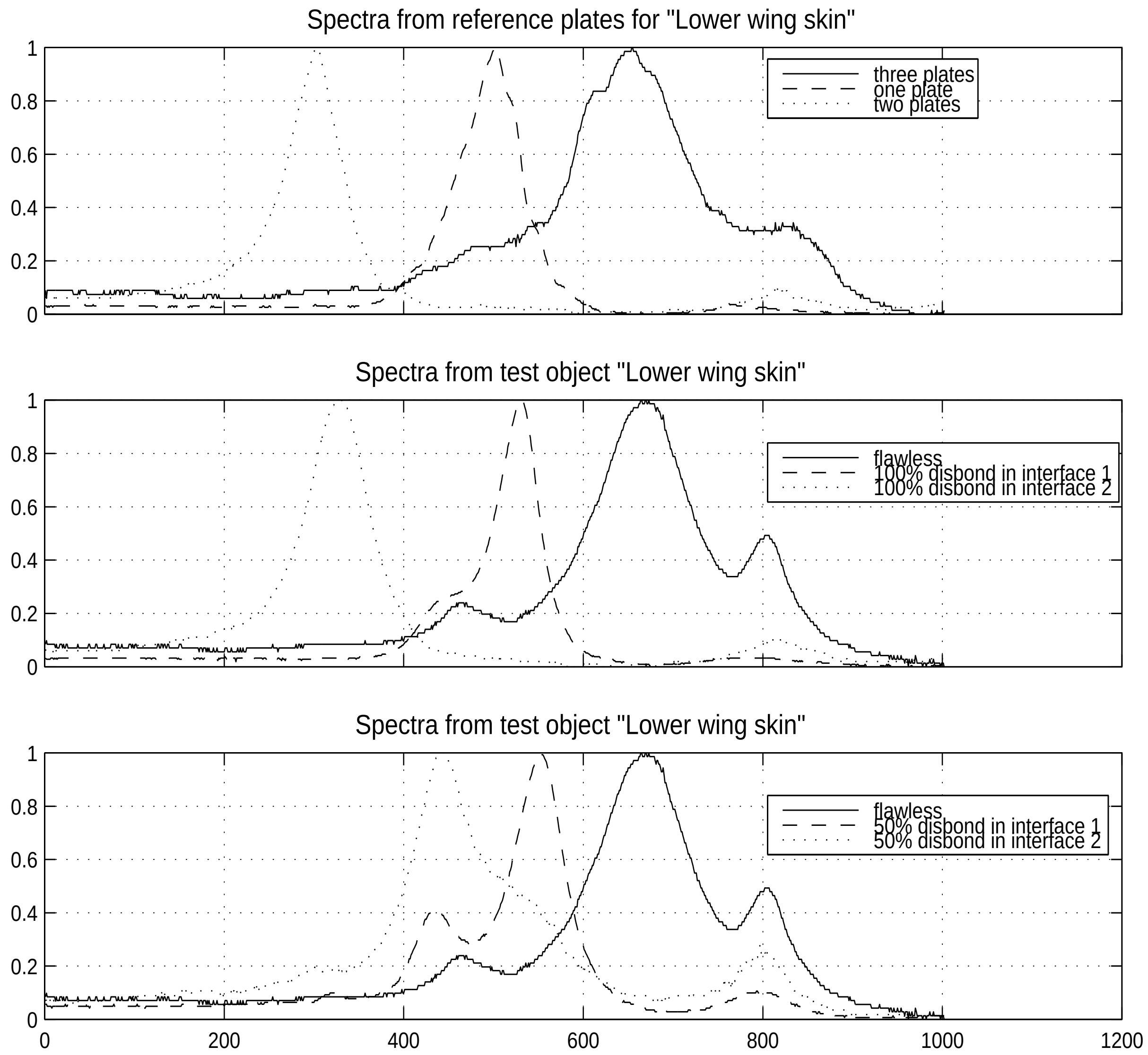

Figure 5: *Normalized spectra from test object "Lower wing skin".*

A simple MLP with 3 hidden nodes in one hidden layer was sufficient for the job. The network had 3 to 5 outputs depending on the number of layers in the inspected object. The classification result for the object ”Lower wing skin” is presented in Table 1, where outputs of the network corresponding to different signals (files) acquired in blind test are shown in columns Class 1, 2 and 3, respectively. The output signals are in the range 0 to 1 and each output indicates the probability of delamination in the layer assigned to it. This makes possible evaluating uncertainty of the classification result; if two outputs had high values the classification result was uncertain.

Table 1: *Blind test results for "Lower wing skin" using network with 2 hidden nodes and training for 2000 iterations*

"Lower wing skin"				
Filename	Suggested Class	Confidence index		
		Class1	Class2	Class3
O_SC1.234	1	0.997	0.000	0.003
O_SC1.235	3	0.003	0.003	0.996
O_SC1.236	2	0.000	0.998	0.002
O_SC1.237	1	0.997	0.000	0.003
O_SC1.238	2	0.000	0.998	0.002
O_SC1.239	1	0.997	0.000	0.003
O_SC1.240	1	0.997	0.000	0.003
O_SC1.241	3	0.003	0.003	0.996
O_SC1.242	2	0.000	0.997	0.003
O_SC1.243	1	0.997	0.000	0.003
O_SC1.244	3	0.003	0.003	0.996
O_SC1.245	2	0.000	0.998	0.002
O_SC1.246	1	0.997	0.000	0.003
O_SC1.247	3	0.003	0.003	0.996
O_SC1.248	3	0.003	0.003	0.996

Blind test data was classified 100% correctly between flawless and defect samples. Layer containing flaw was determined correctly in 97.2% of the cases (see Table 2 for details).

Table 2: *Blind test results (54 spectra) using final networks obtained from training set TS 1.*

Object	Classification ok/defect	Defect positioning
Lower wing skin	100 %	100 %
Window frame 1	100 %	100 %
Window frame 2	100 %	100 %
Cargo door	100 %	94.1 %
Total performance	100 %	97.2 %

Generally, it has been shown that the NSC is capable of detecting very small disbonds (larger than 25% of the sensor area) and correctly identifying their position in the structure (identifying the defect joint).

Conclusion

We have presented a neural network based spectrum classifier (NSC) aimed at ultrasonic resonance spectroscopy. The ultrasonic spectroscopy and the NSC has been evaluated in many industrial applications, such as concrete inspection, testing of aerospace composite structures, ball bearings, and aircraft multi-layer structures. The latter application has been presented in some detail.

The results obtained with NSC in different applications show that both flaw detection and localization can be performed automatically by the use of a neural network classifier.

The evaluation of the proposed algorithms for the classification of ultrasonic resonance spectra clearly indicated that an adequate classifier can in many practical cases be obtained by applying the multi-layer perceptron directly to the measured spectra, without any pre-processing. The proposed pre-processor, in the form of a rational function approximation, put constraints on the characteristics of spectra and require knowledge about the measurements that may not be available. Therefore experiments were concentrated on the MLP, applied directly to the spectra without pre-processing. It is worth noting however, that in some applications where the amount of training data is very limited, but a priori information about the spectra is available, the pre-processor may be useful.

The parallel structure in the NSC allows for rapid computations of output signals. Although training takes some time, it can be done once on a representative set of data. When training has been completed the classification process is fast and easy to implement in a real-time application.

Another benefit in using this kind of automatic classifier is that the output data gives an indication of the classification reliability. This information could be used to inform the operator which classifications are less reliable.

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