Automatic Detection of Defects in Riveted Lap-joints using Eddy Current

Fredrik Lingvall   Tadeusz Stepinski

January 29, 1998

Address:
Signals and Systems Group
Uppsala University
P O Box 528
SE-751 20 Uppsala, Sweden
URL:
http://www.signal.uu.se

Abstract

A method for detection and classification of defects originating from rivet holes in a riveted lap-joint using eddy current (EC) inspection is presented in this paper. The EC-signals were acquired from a number of lap-joints using a tailor-made deep penetrating probe, and a digital single frequency EC-instrument. A number of rivets in the lap-joints had defects located in the second layer of the lap-joint. The problem consisted in detecting and classifying defect signals in presence of strong interference due to rivet responses. The preprocessing before detection consisted of median filtering, rotation and de-biasing of the eddy current pattern. The rotation was performed so that the signal energy from the rivet responses was maximized along the quadrature direction, and the defect response energy was maximized in the in-phase direction of the EC-signal. Feature extraction was then performed using wavelets, PCA and block-mean values of the defect signal. The classification was performed using a standard multi-layer perceptron neural network.

Introduction

A modern civil aircraft has a large number of riveted lap-joints incorporating some 10 to 30 thousands rivets. Manual inspection of these rivets is not only tedious but it is also time consuming and therefore expensive. An automated inspection system does not only reduce the inspection cost but it also increases reliability—decreases the risk of making human faults.

In this paper an artificial neural network (ANN) based eddy current (EC) detector/classifier is purposed. A number of complex valued EC data vectors were collected by AeroSpatiale in France which then were used for both testing and evaluation.

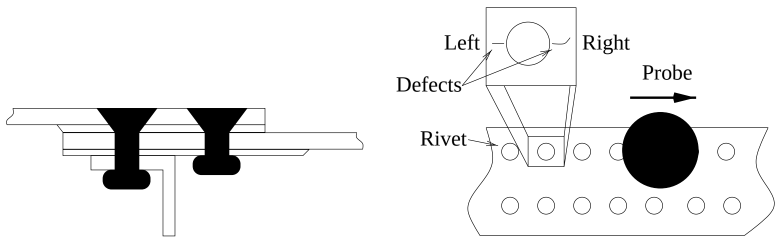
Using this data suitable pre-processors, features extractors, and ANN structures were examined. The proposed classifier, shown in Figure 1, consists of pre-processing (bias compensation, normalization etc.), feature extraction for efficient classification, and detection/classification by means of an ANN.

Figure 1: *Outline of the classifier.*

Data Acquisition

The data were acquired using a deep penetrating probe tailor-made for the purpose of detecting defects in riveted lap-joints.[1] The probe was constructed in such a way that the rivet response and the defect response at the working point (frequency ≈ 2 kHz) were almost perpendicular in the impedance plane.

The defects were created by applying a large number of fatigue cycles on the lap-joints in a way similar to what arises in real aircrafts. Due to the direction of the applied force the defects were only located on the left and/or the right side of the rivets in the second layer of the lap-joint, see Figure 2.



(a) (b)

Figure 2: *(a) Cross section of a lap-joint and (b) Defect location and probe movement in a lap-joint.*

After the acquisition of the EC signals the lap-joints were taken apart and the defects were inspected manually and labeled (left or right crack, length, angle of crack etc).

Three different data series were available for this study. In total 43 complex valued vectors were used, each vector containing data from 18–30 rivets. The data can roughly be divided in three groups; 1) data with no defects, 2) data with large defects, and 3) data with small or medium defects. The second group is not so interesting for this study since large defects can easily be detected—by simply thresholding.

The aim with this investigation has therefore been to detect and if possible to classify small to medium sized defects.

[1]The probe that was used was a multi-differential probe similar to the MKD 43-18 from Rohmann Gmbh.

Pre-Processing

Before feature extraction and detection the signal must be normalized. The rivet response present in all data takes the form of a complex valued sinusoidal-like signal. This signal could be used for normalization since the distance between all rivets (22 mm) was constant and since the probe was able to separate rivet and defect responses well.

It was also necessary to filter the signal—due to disturbances—and remove offsets before reliable classification could be made.

Median filtering

The EC signal was first filtered with a median filter. This step was necessary because the digital acquisition device had imperfections which introduced spikes in the signal.

Rotation

A common way for manual EC inspection is to rotate the complex valued signal so that the defect response lies mainly along one axis (in-phase or quadrature) and then observe only this signal. In our case this means placing the response from the rivets along one axis and the response from defects along the other axis. Most of the the energy in the signal comes from the periodic response of the rivets and this information can be used to rotate the signal, that is, we simply rotate the signal denoted by a column vector $\mathbf{x}$, ϕ radians so that the energy in the imaginary part of the signal is maximized, see Eq. (1).

$$\max_{\phi} \| \operatorname{Im}\{\mathbf{x}e^{i\phi}\} \|^2 \tag{1}$$

Figure 3 shows one signal before and after rotation.

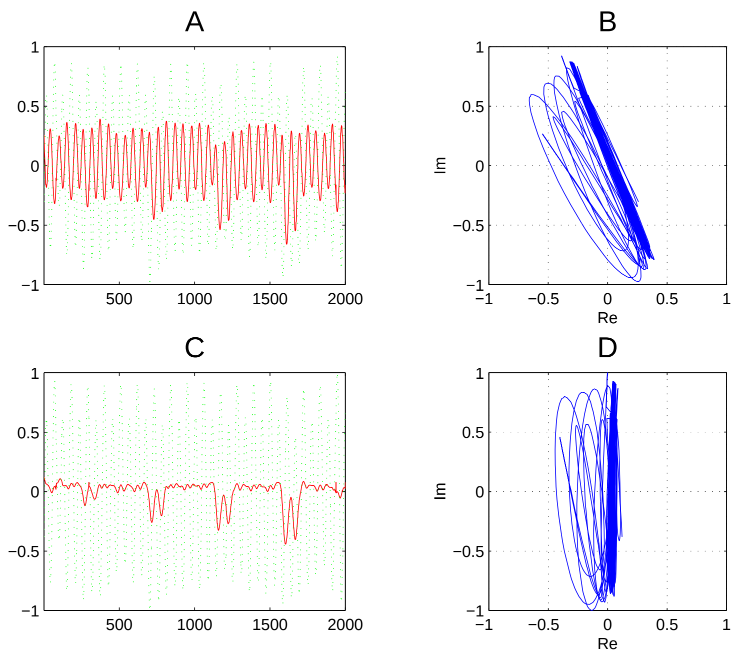


Figure 3: *A - Original signal (solid - real part, dotted - imaginary part). B - Complex plane plot of original signal. C - Rotated signal. D - Complex plane plot of rotated signal.*

Normalization

In order to be able to accurately characterize defects the complex valued signals must first be normalized in a proper way. Here we assume that the responses from rivets should be the same in all data. Therefore, after rotation, the positive part of the quadrature signal—the one containing rivet responses—is used for the normalization. The mean value of this part is used for the actual normalization, which is done to get a more robust normalization. One can consider it as the mean value of a half wave rectified signal. We noted that when large defects occur the quadrature part is also affected which degrades the performance of the normalizing procedure. Therefore, before the normalization we detect large defect by thresholding and then remove these parts of the signal.

Adjusting Bias

Compensating the bias of an EC signal (i.e. its real part, corresponding to defects) is important since it can affect later processing and detection (thresholding). For the EC signals encountered here subtracting the mean value may not be the best way to adjust the bias. Signals containing no defects look rather sinusoidal and therefore a simple mean value subtraction would be sufficient, but for the signals containing many defects this would result in an offset level which would depend on the size and the number of defects present in the signal.

This problem has been solved by analyzing the histogram of the signal and simply using the signal value at the maximum of the histogram (i.e., the most likely amplitude) for bias compensation. An example of this procedure is shown in Figure 4.

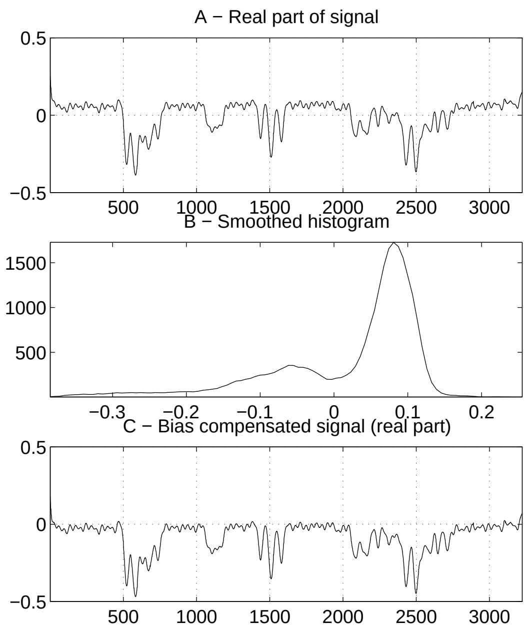


Figure 4: *A - Real part of an EC signal. B - Smoothed histogram of the signal. C - Real part of the signal compensated with the value at the maximum of the histogram.*

Feature Extraction

The task of this operation is to extract information (or features) that is relevant for the detection and/or classification of the EC signals. It is also desirable to keep the dimension of the feature vector as low as possible since this results in a simpler classifier. If the feature vector is too large it may even be impossible to construct or train a feasible classifier since the number of parameters in the classifier may be to large in comparison to the number of data available.

The extracted features should be relevant, which means that they enable detection of different classes of defects. Examples of classes considered here are: large defects, defects on left (or right) side of the rivet etc. Large defects are easily detected by thresholding, but to be able to distinguish between left or right defects we must have features which preserve information about location. Three types of feature extractors investigated by us are presented below: block-mean values, wavelets and PCA.

Window Centering

This is an important step because all later processing relies on it. All the features are extracted from a window which is centered around each rivet. The window centering is currently based on the observation that the rivet response is a periodical sinusoidal-like signal with two positive peaks for each rivet, where one of the peaks is significantly larger that the other one. Thus, the rivet response (imaginary part of the EC signal) includes the information needed to position the analyzing window around each rivet, which is illustrated in Figure 5. After the centering, the window width is increased slightly (by 50

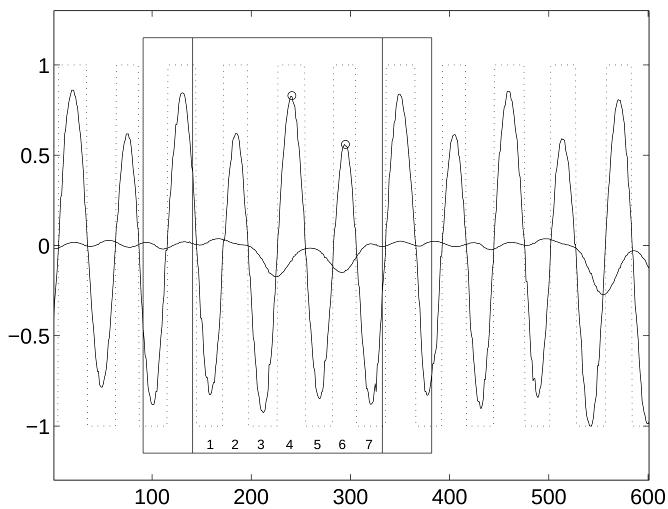


Figure 5: *Window centering.*

samples) because defect responses from the adjacent rivets overlap. Also, the signal vector in this window is down sampled (from about 300 samples) to a length of 128 samples since later feature extractors (e.g. wavelets) require input vectors of dyadic length (power of two).[2] Furthermore, the data vector is windowed by a sigmoid-like window in order to remove edge effects.

Block-Mean Values

This is a very simple technique where the window is divided into a number of sections (blocks) and a mean value is calculated in each block. Other possibilities is to take the

[2]A length of 256 could also have been used, but this did not improve classification so a length of 128 were used here for simplicity.

energy or absolute value of the signal in each block.

The Discrete Wavelet Transform

A disadvantage of the crude block-averaging method presented above is the risk of loosing information that is important for classification. We could of course increase the number of blocks, but this would also increase the length of the feature vector. Therefore, the signal should be represented as compactly as possible without loosing vital information in the signal (data compression). One way to do this is to transform the EC vector denoted $\mathbf{x}$ to another vector $\mathbf{y}$ with a linear transform, $\mathbf{y} = \mathbf{A}\mathbf{x}$. The trick is then to choose the matrix $\mathbf{A}$ in such way that only a few coefficients in $\mathbf{y}$ are needed for the classification.

The most common way to choose $\mathbf{A}$ is to let the elements $a_{m,n}$ of $\mathbf{A}$ be of the type $a_{m,n} = e^{-jmn}$ (where $j = \sqrt{-1}$), that is, $\mathbf{y}$ is the discrete Fourier transform (DFT) of $\mathbf{x}$. However, this particular choice of $\mathbf{A}$ is not suitable for this application since the basis functions (sin and cos functions) have infinite duration, and when using basis functions of the this type short pulses in $\mathbf{x}$ will be distributed over all coefficients in $\mathbf{y}$ and no compression is obtained. The basic task for the classifier, to distinguish between positions of EC defect responses relative to the position of the rivet, would be difficult to fulfill if the DFT was used. In this paper we are proposing two alternative linear transforms for compressing the EC data: the discrete wavelet transform and principal component analysis (which uses basis functions based on data). Both of them have the properties desired for this application.

The discrete wavelet transform (DWT) is interesting here because it uses basis functions that are localized and have a finite support [1, 2]. This gives us the ability to, at different scales and position, examine where the signal has a significant energy. Other attractive features of the DWT is that by removing some (wavelet) coefficients, small scale components of the signal can be removed (noise or high frequency disturbances) while still keeping the overall signal shape. Moreover, very efficient algoritms ($O(n)$) for computing the DWT are available. Figure 6a shows the first 16 basis functions of the DWT used for analysis of the EC signals.

Principal Component Analysis

The basic idea behind the PCA approach is that the defect response data should be expressed as a superposition of a set of basis functions determined (learned) from examples. This means that, basis functions that are tailored for the data at hand are used.

The learned basis functions are the eigenvectors of the covariance matrix of the data vector $\mathbf{x}$ regarded as a stochastic column vector (variable). After collecting the basis functions (eigenvectors of the covariance matrix in descending order of their eigen values) as the columns of the matrix Φ, the EC data vector denoted by $\mathbf{x}$ can also be expressed using the new basis as:

$$\mathbf{y} = \Phi^T \mathbf{x} \tag{2}$$

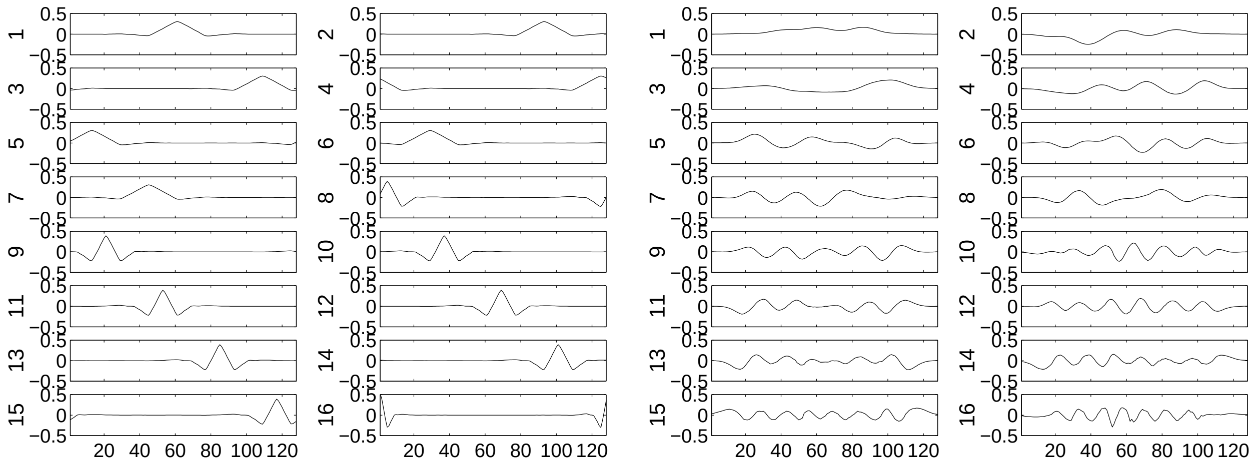
where $\mathbf{y}$ denotes the EC data column vector expressed in the new basis. Or

$$\mathbf{x} = \sum_i y_i \phi_i = \Phi \mathbf{y} \tag{3}$$

where ϕ_i are the columns in Φ.

Through the PCA approach we obtain an "intelligent" system which from examples of EC data extracts a suitable orthogonal set of basis functions. The extraction of the suitable eigenvectors can be realized by means of artificial neural networks. One should note that the eigenvectors form a complete set of orthogonal basis functions which means that they are as powerful as the sinusoids or polynomials. The only important difference is that the basis functions obtained from PCA are better fit to the particular problem from which the data originates than the other bases.

In our case $\mathbf{x}$ has a length of 128 samples, but the elements in $\mathbf{x}$ are strongly correlated so the actual dimension of the data is much lower than 128. Analysis of the eigenvalues of the covariance matrix reveals that, in this case, the dimension is approximately 10–15. This means that, the other eigen values are negligible (compared to the first one). Therefore, it is sufficient to use only the 10 to 15 first elements in $\mathbf{y}$ as features. Figure 6b shows the first 16 basis functions obtained from data with principal component analysis.



(a) (b)

Figure 6: *The first 16 basis functions of (a) the Discrete wavelet transform (coiflet 2) and (b) obtained by principal component analysis.*

Detection/Classification

The classifier is implemented as a two-layer artificial neural network (ANN). The ANN has two outputs; one for defects on the right side of the rivets and one for defects on the left side. It appeared that it was sufficient to use only 3 neurons in the hidden layer which is good since this implies fast training and a low number of coefficients in the net (good if the amount of data is low).

The data set was divided into two subsets, one set for training, and one for cross validation and evaluation. All data with large defects were removed from both the training set and the evaluation set. Large defects are detected using thresholding as mentioned earlier.

Results

The evaluation data set contained 640 examples of which 68 had defects. In the Block-mean method using 15 blocks resulted in the best performance for this method. For the wavelet method 15 coefficients where used and for the PCA method 13 coefficients were used. Table 1 shows the performance of the different methods. The percentage of missed

	Block-Mean	Wavelet	PCA
Missed detections	7.4 %	7.4 %	7.4 %
False detection	1.9 %	1.3 %	1.5 %
Wrong classification	16 %	12 %	13 %

Table 1: *Classification/detection results on evaluation data.*

detections are rather high (5 of 68), but a closer analysis of the examples which were missed, leads to the conclusion that the signal amplitude was very low for all of them.

Conclusions

A method for detecting and classifing defects in a lap-joint using EC testing was presented in this paper. Reliable defect classification required a certain amount of pre-processing. The EC signals were normalized and rotated, and the bias (dc-offset) was compensated. Rivet responses were used for both the rotation and the normalization procedures, which appeared to be a reliable and robust solution. Precise window centering around the rivets was also required for efficient classification to extract features that carry the information on the defect location. The imaginary part (quadrature) of the rotated EC signal was used to position the analyzing windows. The three feature extractors which were used here all utilized the real part of the complex EC signal and they all provided information about the location and amplitude of the defects.

The feature extractors based on the DWT and PCA are the ones that performed best on the given evaluation data. Their feature vectors had approximately 10–15 elements. A simple two-layer feed forward perceptron ANN with 3 hidden units appeared to be sufficient when using these features for the classification. The simple ANN architecture (obtained due to efficient pre-processing) results in a low number of weight coefficients to train which is desired if the number of training data available is low. This means also a lower risk for overfitting the network to the training data set.

Acknowledgements

This work has been supported by the Brite Euram III project CANDIA [3]. The authors would like to acknowledge D. Simounet and P. Auge from AEROSPATIALE Suresnes for providing the EC data.

References

[1] M. Yves. *Wavelets Algorithms & Applications.* siam, 1993.

[2] G. Strang and T. Nguyen. *Wavelets and Filter Banks.* Wellesley - Cambridge Press, 1996.

[3] F. Lingvall and T. Stepinski. Neural network classifier for EC signals—theoretical study. Technical report, Signals and Systems Group, Uppsala University, October 1997.