Automatic Evaluation of Aerospace CFRP Structures Based on Ultrasonic Echo Signals

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Abstract. Components made of carbon-fibre reinforced plastics (CFRP) used for aircraft construction are tested with ultrasonic sensors to guarantee their required stability. Topic of this paper is the automatic evaluation of the backscattered signals received by the sensors. The evaluation system is based on a statistical classifier using most discriminative features extracted from the backscattered echo signals. By this means we aim for an automatic characterization of the material mainly used for a reliable defect detection.

1. Introduction

Carbon-fibre reinforced plastics (CFRP) materials have many advantages for airplane construction and application due to their high stability and low weight. The material stability is tested in a non-destructive way with ultrasonic sensors and the backscattered echo signals are analyzed in detail to recognize defects and production errors within the material like porosity or delamination defects (disbanding of adjacent material layers). For the time being human inspectors evaluate the received data by surveying many C- and D-scan images, but this visual inspection is subjective and dependent on the typical human factors.

Therefore an evaluation system is considered which is able to detect and identify defects within the material automatically. This system is based on a statistical classifier that analyzes the received echo signals. Due to the direct evaluation of all ultrasound echo signals, more details of the echo signals can be taken into consideration than being visualized in C- and D-scans for manual examinations. Different types of material defects can occur: porosity, delamination, inclusion of foreign objects. Here we mainly consider delamination defects. Delamination is the effect of disbanding two adjacent CFRP layers of this composite material.

Each recognition system is split into two main steps, the echo signal feature generation and the classification technique. Based on the measured ultrasonic echo signals passed through the examining CFRP structure some characteristic signal features will be generated from the high resolution signal profile. The challenge is to identify those features, which are characteristic for a particular defect, because the reliability of a classifier increases with the discriminative power of selected features. Many classification methods are well known and can be used; for our task the polynomial classifier is considered using polynomial regression for classification. The evaluation system has been tested using real ultrasonic measurements of CFRP component parts of vertical tail planes.

First an overview of the classification system is given in this paper including the most important processing steps like segmentation, feature extraction and classification procedure. Second, selected features are investigated for their discriminative power using measured training data. Afterwards a few classification results are given.

2. Defect Recognition System

Figure 1 shows an overview of considered evaluation system. After ultrasonic data have been received from the sensors, several steps concerning signal processing like normalization, filters or other conversion steps are applied. Some other important steps are event detection, segmentation and contour detection.

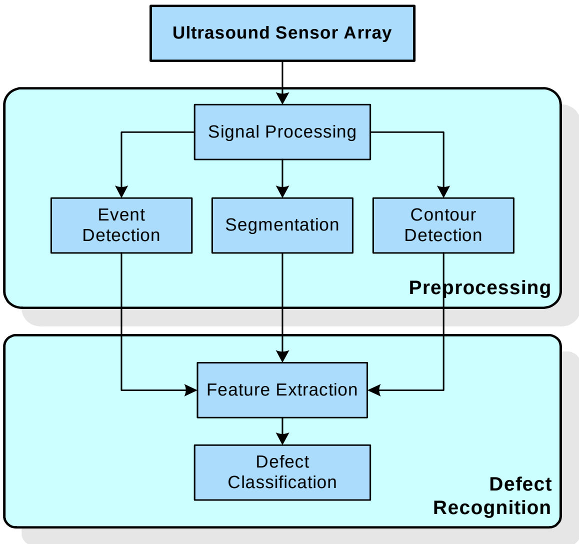

Figure 1. Overview of the Evaluation System

Event detection is the process of detecting and extracting the ultrasonic events from the echo signals. One event indicates a suspected case of being an occurrence caused by a material defect. For example events can be single peaks detected by a peak detection algorithm determining all possibly relevant echo peaks. For the investigation presented in this paper we use a peak detection based on a calculated reference amplitude [2].

The contour detection process estimates the structure of the component to be evaluated. It is very helpful for feature calculation to know where surface and back wall are situated and where these regions with special material occurrences (stringer, ribs, etc) are located. **Figure 2** outlines a part of the structure with a stringer to imagine the structures complexity.

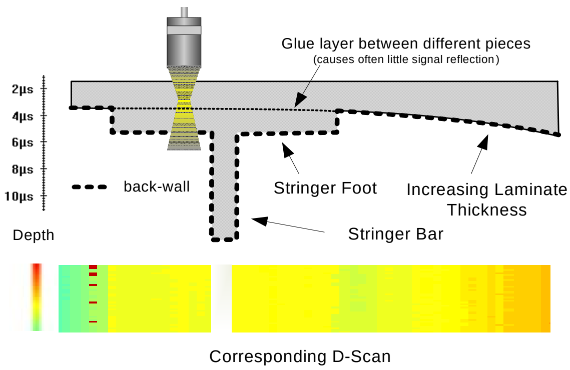

Figure 2. Lateral cut of a component’s structure

The idea of the segmentation process is to detect regions that may correspond to real defects or to zones with special material characteristics like stringers. Stringers are CFRP-stripes glued to the back wall for stability reasons (**Figure 2**). Ideally this process surrounds the defective and stringer areas from other error free areas, so that the classification procedures only needs to classify these areas.

3. Feature Extraction

The most challenging task for the classification is the identification and selection of proper features. While C- and D-scan images for manual examinations take mostly the echo signal's amplitude into consideration, a more complex feature scheme is used for automatic classification. Few most descriptive features are described in the following.

3.1 Echo Signal Amplitudes

The ultrasonic echo signal is reflected by different kinds of occurrences within the material. The highest reflection factor is observed at the coupling of the material and the couplant (e.g. water). In the case of flawlessness the reflection of the back wall is observed. The amplitude value should be normalized beforehand.

$$v_1 = \frac{|\widehat{r}_e|}{a_{\text{ref}}(t_e)} \tag{1}$$

The numerator $|\widehat{r}_e|$ is the absolute value of the echo signal peak amplitude belonging to event *e*. The denominator $a_{\text{ref}}(t_e)$ describes the reference amplitude value calculated during the event detection process.

3.2 Contour Features

The geometric contour features expresses the proximity of an event to the material surface or back wall. For calculation of these values the information resulting from the contour detection process is used.

$$v_2 = 2 - 2\sigma\left(\frac{|t_e - t_{\text{surface}}|}{T_{\text{tol}}}\right) \tag{2}$$

$$v_3 = 2 - 2\sigma\left(\frac{|t_e - t_{\text{bw}}|}{T_{\text{tol}}}\right) \tag{3}$$

$$v_4 = \sigma\left(\frac{t_e - t_{\text{bw}}}{T_{\text{tol}}}\right) \tag{4}$$

$$\sigma(x) = \frac{1}{1 + e^{-x}} \tag{5}$$

Hereby σ corresponds to the sigmoid function (5). Parameter t_e describes the propagation time corresponding to the detected event, whereas t_{surface} and t_{bw} depict the propagation time of the signal peak detected as a surface or as a back wall peak respectively during the contour detection process. T_{Tol} is a tolerance time which determines how fast the function increases or decreases. **Figure 3** displays the behaviour of these functions for $T_{\text{Tol}} = 1$.

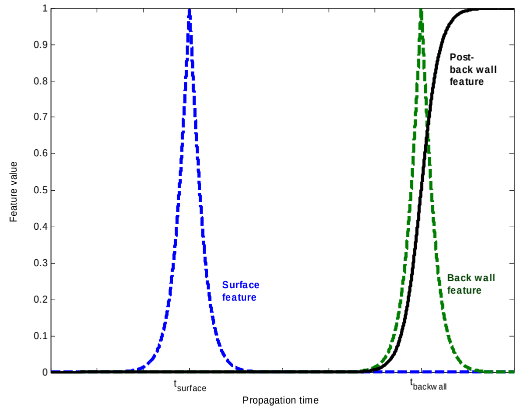

Figure 3. Geometric Features

The discriminative power of the feature and thus the classification ability improves with the accuracy of the contour recognition.

Another set of features can be obtained using the back wall amplitude. When the echo signal reaches the back wall it has passed through nearly the complete material. So almost every type of defect affects the value of the back wall amplitudes.

$$v_5 = |r(t_{\mathrm{bw}})| \tag{6}$$

$$v_6 = \frac{|r(t_{\mathrm{bw}})|}{a_{\mathrm{ref}}(t_{\mathrm{bw}})} \tag{7}$$

The value of r(t) indicates the amplitude value of the echo signal at time *t* and $a_{\mathrm{ref,bw}}$ constitutes a reference amplitude of the back wall echo. It is defined to be the maximum amplitude of all back wall echo amplitudes within a specified spatial area.

If we set the event echo signal amplitude in relation to the backwall amplitude features, we obtain three further feature values for classification.

$$v_7 = \frac{|r(t_e)|}{r(t_{\mathrm{bw}})} \qquad v_8 = \frac{\frac{|r(t_e)|}{a_{\mathrm{ref}}(t_e)}}{\frac{|r(t_{\mathrm{bw}})|}{a_{\mathrm{ref}}(t_{\mathrm{bw}})}} \qquad v_9 = \frac{|r(t_e)|}{a_{\mathrm{ref}}(t_{\mathrm{bw}})} \tag{8}$$

3.3 Correlation Features

The correlation between spatially neighboured signals characterizes their similarity. This feature takes into account that two signals corresponding to the same defect appear to be more similar than two signals of different defect classes. If two echo signals f(t) and g(t) in discrete time domain are represented by the vectors **f** and **g** (considering the non-shifted case) the correlation value of these two signals is synonymous with the inner product of the vectors. For the next feature the mean of the correlation value between the evaluating event signal f_e and all signals $\mathbf{g}_{1..n}$ with a distance of specific *d* from the evaluating signal $\mathbf{f}_e$ is calculated (9).

$$v[..]_d = \frac{1}{N_n} \sum_{n=1}^{n} \mathbf{f}_e^T \mathbf{g}_n^{(d)} \tag{9}$$

The vector $\mathbf{f}_e$ contains the discrete amplitude values of the evaluating event signal and $\mathbf{g}_{1..n}$ denotes all n echo signals with distance of d pixels to $\mathbf{f}_e$. In [1] the behaviour of the correlation value has been investigated. The decrease of this value differs dependent on the defect type (**Figure 4**).

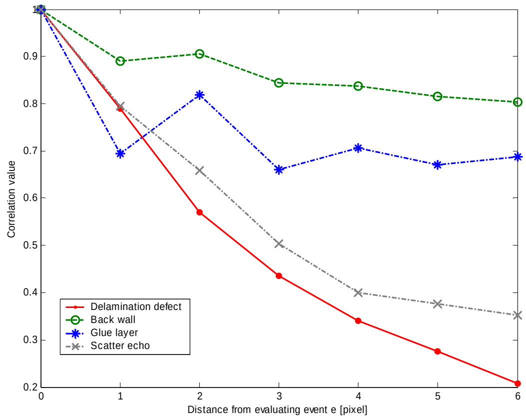

Figure 4. Behaviour of normalized correlation value [1]

The solid line indicates the expected continuous decrease of the correlation value in case of a delamination defect.

3.4 Region Features

After the segmentation process (**Figure 1**) the examining component has been virtually divided into many regions, so we can consider *geometrical characteristics* of these regions:

- *Width* (W) and *Length* (L) measured in pixels of the region.
- *Shape*: Length in relation to width ($S = L / W$).
- *Area* (A): The number of signals in the region.
- *Perimeter* (P): Number of signals in the boundary of the region.
- *Roundness*: Another measurement for the shape of the region, $R = \frac{A \cdot \pi}{P^2}$.

For every signal related feature (e.g. contour and correlation) *statistical moments* can be defined.

$$\mu_k = E\left((X - \mu)^k\right) \tag{10}$$

Equation (10) defines the kth central moment of the random variable X. The variable X can describe every feature value listed in paragraph 3.1 and 3.2. This way we can characterize the statistical distribution of different feature values of one region. For example we can use the mean amplitude value or the variance of all amplitude values of each region.

4. Classification

4.1 Feature Selection

In the feature selection process we decide for a set of features which mostly contribute to a good distinction between the defect classes. The intention is to compress the feature set as much as possible into a feature vector without loosing too much of the descriptive and discriminative power of the original feature set [3]. Reducing the feature dimension reduces drastically the computation complexity and allows higher order polynomial classifiers.

The *descriptive power* is the potential of reconstruction to retrieve the original feature vector from its compressed version (i.e. the selected feature set). One method to find the most descriptive feature is the *Principal Component Analysis* (PCA). Besides the PCA has the effect to decorrelate the features. The definition of this transform is given in [4].

By contrast the *discriminative power* is necessary to discriminate data between the *K* classes of the classification task. In other words it defines the "separability" of the feature. The selection results are given below.

4.2 Statistical Classifier

In the field of pattern recognition there are many classification techniques well known like neural networks, support vector machines or polynomial classifiers. Unlike the neural networks which tries to reconstruct a natural brain's structure the polynomial classifier is based on statistical decision theory using polynomial regression. All mentioned techniques have in common that supervised learning is applied before classification (**Figure 5**).

A set of labelled representative feature vectors is presented to the classifier together with the class membership information for training purpose. Based on the principle of polynomial approximation a decision matrix (discriminating function) is calculated, which is applied to the feature vector extracted from the unknown measurement data to get the classifier's result.

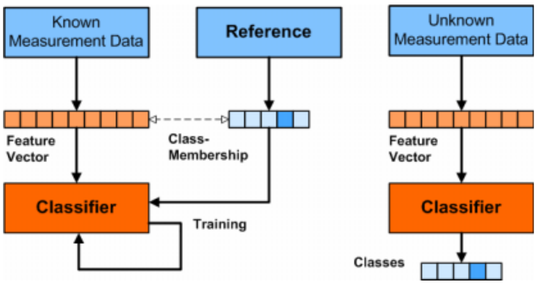

Figure 5. Classification in general

5. Results

Proposed classification scheme and features have been applied on real ultrasonic measurements of real CFRP airplane components. The data have been recorded with an sensor array with 80 conventional ultrasonic probes working in 5 MHz frequency domain. The considered components are parts of vertical tail planes and are structured like in Figure 2. The ultrasonic echo signals received from the sensors are A/D converted and ALOK compressed. As mentioned in **Figure 1** this data is received by the pre-processing and extraction module where the features are calculated. Resulting feature vectors are labelled with three different class labels (**Table 1**) to determine the features with most descriptive and discriminative power for feature selection.

No.	Class
1.	Error free scatter echo
2.	Back wall echo
3.	Delamination

Table 1. Three classes for defect classification

5.1 Descriptive Power

By means of the principal component analysis the principal components have been calculated.

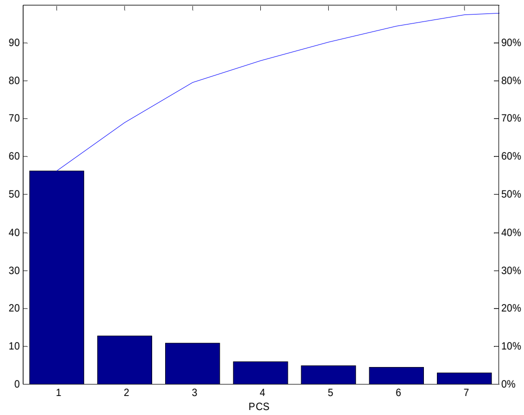

Figure 6. Variances of the PCS

Feature	PC 1	PC 2	PC 3
1.	*0.32049*	*0.2381*	*-0.033209*
2.	0.27875	-0.1288	0.21239
3.	0.2358	-0.016147	0.17138
4.	0.31848	0.25124	-0.046348
5.	0.28148	-0.17769	-0.051138
6	0.19741	-0.32174	-0.080706
7	0.2642	0.36877	0.24396
8	0.20789	-0.1545	-0.5831
9	0.20789	-0.1545	-0.5831
10	*0.30359*	*0.25044*	*-0.070328*
11	*0.31359*	*-0.060435*	*0.20798*
12	*0.31907*	*0.24695*	*-0.047107*
13	-0.24163	0.29516	-0.21377
14	0.17412	-0.36402	0.2385
15	0.084236	-0.44443	0.14355

Table 2. Principal Components

Figure 6 shows that about 95% of the variances are explained by the first 7 principal components. The weights of the first three components are displayed in **Table 2**. It turns out that the most descriptive features are “1. Region Size”, “4. Standard Deviation of Regions Amplitudes” and “12. Backwall Amplitude”. The “(Post-) Backwall” features (10, 11) follow them closely.

5.2 Discriminative Power

Concerning the classification with minimum squared error the discrimination power of the features is even more interesting. It describes how good the features can distinguish between classes with minimum error. There are many ways to determine the discriminative power. In this case the features are selected by applying the training algorithm of polynomial classifier with the residual variance as optimization criterion. Using this techniques the features which contribute most to the reduction of the classification error are automatically selected.

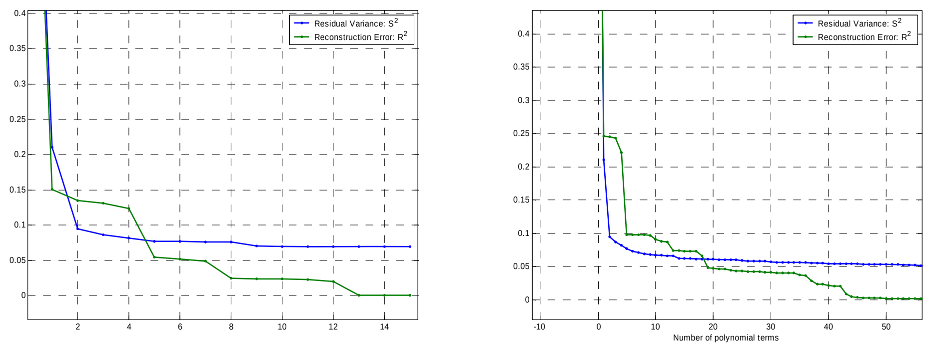

Figure 7. Development of the training error using polynomial regression
with degree 1 (left) and degree 2 (right)

The blue line of **Figure 7** indicates the training error (residual variance) dependent on the features automatically selected by the training mechanism of the polynomial classifier. The green line refers to the reconstruction error representing the descriptive power. The most discriminating features resulted using this technique are listed in **Table 3**.

No.	Feature Name	Δ RV
10.	Contour: Backwall Feature	-0.7894
13.	Contour: Peak / Backwall Amplitude	-0.1162
11.	Contour: Post-Backwall Feature	-0.0078
1.	Region: Area	-0.0048

Table 3. Features contributing most to residual variance (RV)

5.3 Validation

In this section the classification result of a cross-validation is given. The labelled training set has been split into two parts. The classifier is trained using the first part and evaluated on the second part. This is done several times whereby the feature vectors joining to first and second part are chosen randomly. **Table 4** shows the results.

Class		Classified		
No.	**Name**	**0**	**8**	**9**
0	No decision	n/a	n/a	n/a
8	Backwall Echo	0.0020	0.9716	0.0264
9	Delamination	0.0011	0.0053	0,9936

Table 4. Classification result considering back wall echo and delamination class.

It is important that more than 99% of the delamination signal have been detected and classified correctly, because the classifier should be designed to fulfil the absolute critical requirement for CFRP testing: Every critical material defect must be detected. It is also clear that the number of false positives should be as low as possible.

5.4 Material Defect Detections

These calculations have been performed on signal level, i.e. every single event extracted from every single signal have been labelled, trained and classified. In this section we would like to show the performance in form of a result image.
In Figure 8 the results are represented in a result map. Every occurrence that has been classified (e.g. as back wall echo or defect echo) is marked in one specific color. The red markings labelled with F1 to F3 are real defects detected by the classification system. The other red markings are false positives. Some of them result because of the small intermediate echo signal caused by "glue layers" (**Figure 2**).

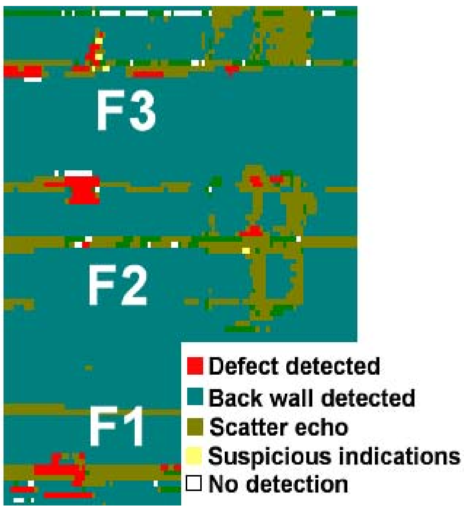

Figure 8. Classification result

6. Conclusion

A classification system for detecting defects in CFRP material is proposed. The design of the underlying classifier including the used features based on echo signals is introduced.

Because of the irregularities of the material it is a technical challenge to distinguish automatically and with high reliability between echo signals resulting from real defects or from some legal occurrences within the material's structures. But the results are quite promising. We always have to keep in mind, that no possibly critical defect must not ignored. The classification scheme can be designed or tuned in the way that rather a few false positives are detected than real defects are missing in the classification results. So the performance and the advantageousness of this system increases with the decrease of false positives. There are some possibilities for improvement we have in mind like a more sophisticated back wall detection or the usage of full echo signals rather than compressed ones.

7. References

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