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Ultrasonic Flaw Signal Classification using Wavelet Transform and Support Vector Machine

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Abstract

This paper presents a ultrasonic flaw signal classification system by using wavelet transform and support vector machine (SVM). A digital flaw detector is first used to acquire the signals of defective carbon fiber reinforced polymer (CFRP) specimen with void, delamination and debonding. After that, the time domain based ultrasonic signals can be processed by discrete wavelet transform (DWT), and informative features are extracted from DWT coefficients representation of signals. Finally, feature vectors selected by PCA method are taken as input to train the SVM classifier. Furthermore, the selection of SVM parameters and kernel function has been examined in details. Experimental results validate that the model coupled with wavelet transform and SVM is a promising tool to deal with classification for ultrasonic flaw signals.

Keywords: ultrasonic signal classification, support vector machine, feature extraction, wavelet transform

1. Introduction

Ultrasonic methods are the most successful non-destructive testing (NDT) techniques for quality assessment and detection of flaws in engineering materials. Conventional ultrasonic testing techniques, however, are based on manual or experiential pattern identification, which easily brings about costly, lengthy and erratic analysis. Considerable advancement and development in the last few decades have enabled ultrasonic testing to change from a Black-Smith profession to an advanced multidisciplinary engineering profession. Modern signal processing techniques and artificial intelligence tools can be integrated as automatic ultrasonic signal classification systems (AUSCS) [1]. In AUSCS, ultrasonic flaw signals acquired in a form of digitized data are preprocessed firstly, and informative features are extracted using various digital signal processing and pattern recognition techniques. Finally, the set of selected features becomes the basis of flaw identification by training the proper classifier. Therefore, extraction of features and design of classifier play critical roles in AUSCS.

The objective of this contribution is to show that advanced signal processing and pattern recognition techniques can aid ultrasonic testing to correctly identify different flaws found in carbon fiber reinforced polymers (CFRPs). The rest of this paper is organized as follows. Section 2 reviews the previous related work. Section 3 describes the methodologies of wavelet transform (WT) and support vector machine (SVM). Section 4 describes the experimental procedure and section 5 analyzes the experimental results. Section 6 addresses the conclusions.

2. Related Work

The potential of signal processing and pattern recognition analysis on ultrasonic testing has been investigated by several authors.

Lee critically reviewed popular feature extraction techniques in AUSCS, including fast Fourier transform (FFT) and discrete wavelet transform (DWT), identified critical issues in feature extraction, and compared the reported approaches to draw their strengths and weaknesses [2, 3].

Yamani et al. developed a database of ultrasonic A-scan signals by using an out-of-service pressure vessel with lots of high temperature hydrogen attach defects. The basic

feature extraction method coupled with principal component analysis (PCA) were used to represent these sets of A-scan signals. Experimental results showed that a priori trained classifier based on nearest-neighbor criterion can distinguish accurately the hydrogen attack from geometrically similar defects [4].

ISA et al. provided a continuous system for oil and gas pipeline condition monitoring. The raw ultrasonic signals were first processed using DWT and then classified using SVM. Preliminary tests showed that the SVM algorithm was able to classify the signals as abnormal in the presence of wall thinning [5].

Matz et al. used the DWT based method for filtering of ultrasonic signal to suppress the echoes from grains. SVM was used to automatically classify ultrasonic signals, with fault echo, echo from weld and back-wall echo, measured on material used for constructing airplane engines [6].

Anastassopoulos et al. conducted an extensive discrimination study on ultrasonic signals very similar to each other obtained from artificial inserts in a CFRP plate. The performance of fifteen classification schemes consisting of non-parametric pattern recognition and Artificial Neural Network (ANN) algorithms was assessed, and an upper bound for the classification error expected with similar ultrasonic signals was defined. Moreover, the Wilk's Λ criterion was proved efficient for feature selection in their experiments [7].

Cacciola et al. proposed an heuristic approach for classifying the ultrasonic echoes measured on defective CFRP. The proposed method was based on the use of DWT and PCA for feature extraction and selection [8]. Experimental results assured good performances of the implemented SVM classifier. They also developed a software package, which allowes users to perform the cross wavelet transform, the wavelet coherence and the fuzzy inference system for implementing a data-independent classifier [9].

Sambath et al. improved the sensibility of flaw detection in ultrasonic testing by using an ANN and signal processing technique. Wavelet transform was used to derive a feature vector which contains two-dimensional information on four types of defects, namely porosity, lack of fusion, tungsten inclusion and non defect. These vectors were then classified by an ANN trained with the back propagation algorithm. Using the wavelet features and ANN, good classification at the rate of 94% was obtained [10].

Schulz et al. focused on the automatic evaluation of the backscattered signals received by the ultrasonic sensors. The evaluation system was based on a statistical classifier using most discriminative features extracted from the backscattered echo signals according to their amplitudes, contour, correlation and region. By this means they implemented reliable defect detection for an automatic characterization of the CFRP material [11].

Liu et al. proposed algorithms for defect detection based on discrete wavelet packet transform and BP network. Furthermore, the reconfigurable architecture of the defect detection in embedded system was discussed. According to the experiments of ultrasonic signal processing, such architecture could provide a flexible and efficient solution to embedded reconfigurable signal processing system [12].

As mentioned above, there are two strategies for feature extraction in AUSCS.

(1) Choose features from different domains of ultrasonic signals. The derived features mainly include statistical parameters extracted from statistical moments of the time-domain or/and frequency-domain based ultrasonic signals, such as mean, variance, skewness and kurtosis. Using such strategy, users need effective feature selection schemes to evluate the discrimination of features, reduce the redundancy and optimize the feature set.

(2) Use directly the whole signal section derived from the ultrasonic scans as input to the classifier. The input features mainly include FFT coefficients and DWT coefficients. Such strategy demands minimum preprocessing, i.e., not much feature selection schemes are employed. However, coefficient features are often high dimensional.

Moreover, there are two conventional classifiers used in AUSCS, namely ANN and SVM. Generally, SVM has superior prediction and generalization performance in view of small sample size problem.

3. Methodology
3.1. Wavelet Transform

Fourier transform can be used to improve the performance of feature extraction for flaws by mapping the time domain based signals into frequency domain based signals. However, the frequency domain characteristics of transient signals would not be reflected by Fourier transform due to its global property. Yet wavelet transform (WT) is a kind of time-frequency domain method with multi-resolution analysis, which can adjust the time and frequency property as required. The decomposed parts of the signal are resolved such that the higher the frequency, the finer the resolution [13]. WT has powerful ability for denoting local signal characteristics both in time and frequency domain. WT can be considered as a special filtering operation, and the frequency segmentation is obtained by dilating the wavelet. It is a windowing technique with variable sized regions, which allows the use of long time intervals to obtain more precise low frequency information and shorter regions where high frequency information is needed.

Note that as a fast algorithm to obtain the wavelet transform of a discrete time signal, discrete wavelet transform (DWT) has been widely used in the ultrasonic signal analysis. The DWT analyzes the signal by decomposing it into its coarse approximation and detailed information, which is accomplished by using successive highpass and lowpass filtering operations in the frequency domain [14]. The original signal $x[n]$ is first passed through a half-band highpass filter $g[n]$ and lowpass filter $h[n]$, where $g[n]$ and $h[n]$ are quadrature mirror filters of each other. After the filtering, half of the samples of the two output signals are discarded by downsampling since the signals now have a bandwidth of $\pi/2$ radians instead of π. This constitutes one level of decomposition and it is expressed mathematically as:

$$y_{high}[k] = \sum_n x[n] \cdot g[2k-n] \tag{1}$$

$$y_{low}[k] = \sum_n x[n] \cdot h[2k-n] \tag{2}$$

Where $y_{high}[k]$ and $y_{low}[k]$ are the outputs of the highpass and lowpass filters after downsampling by 2. The above procedure is repeated for further decomposition of the lowpass filtered signals.

3.2. Support Vector Machine

Support vector machine (SVM) is a structural risk based learning machine, which constructs N-dimensional hyperplane to optimally separate the input data into different categories. A sigmoid kernel function model of SVM is equivalent to a two-layer, feed-forward neural network. Furthermore, SVM can use polynomial function or radial basis function (RBF) in which the weights of the network are found by solving a quadratic programming problem with linear constraints [15]. Since SVM is robust in high dimensional spaces with a sparse set of samples, it may be used either to classify or predict some arbitrary patterns from a set of labeled data while avoiding over-fitting the data at the convergence of the training [16, 17].

Let $\{x_i, y_i\}$ be a dataset, where x_i is a d-dimensional sample (i=1,2,…l) and y_i is the corresponding bipolar label ($y_i \in \{-1,1\}$). Assume that we have defined a linear separating hyperplane by $w \cdot x + b$ for training samples, then it should meet:

$$y_i(w \cdot x_i + b) \geq 1, \quad \forall i \in \{1,2,..,l\} \tag{3}$$

The optimal separating hyperplane (OSH) can not only correctly separate the samples, but also maximize the margin between the closest positive samples and negative samples. The separable margin can be calculated as follow:

$$d(w,b) = \min_{\{x_i | y_i = 1\}} \frac{w \cdot x_i + b}{\|w\|} - \max_{\{x_i | y_i = -1\}} \frac{w \cdot x_i + b}{\|w\|} = \frac{1}{\|w\|} - \frac{-1}{\|w\|} = \frac{2}{\|w\|} \tag{4}$$

Obviously the maximum of $d(w,b)$ may be achieved through the minimization of $||w||^2/2$. By using a number of nonnegative slack variables ξ_i, the training of SVM can be formulated as solving a quadratic optimal problem:

$$\min_{w,b,\xi_i} \frac{1}{2} || w ||^2 + C \sum_{i=1}^{l} \xi_i \quad \text{s.t.} \quad y_i(w \cdot x_i + b) \geq 1 - \xi_i, \quad \xi_i \geq 0 \tag{5}$$

According to Lagrangian theory, it yields $w = \sum_i \alpha_i y_i x_i$ with constraints $C \geq \alpha_i \geq 0$ and $\sum_i \alpha_i y_i = 0$, where i=1,2,…l. Note that α_i can be found after the following problem is maximized:

$$L_D = \sum_i \alpha_i - \frac{1}{2} \sum_{i,j} \alpha_i \alpha_j y_i y_j x_i x_j \tag{6}$$

The samples with value α_i>0 are called support vectors (SVs). The decision function can be derived as follow:

$$f(x) = \text{sgn}(w \cdot x + b) = \text{sgn}(\sum_{i=1}^{N_s} \alpha_i y_i x_i x + b) \tag{7}$$

Where, N_s is the number of SVs.

Linear separation of datasets can not be achieved successfully all the time. Therefore the points in original space should be expanded to a feature space with higher dimensionality and hence linear separation can be retried [18]. This expansion process is realized with operator $\phi(\cdot)$ and the OSH turns into the form $f(x) = w \cdot \phi(x) + b$. We may consider an augmented space by utilizing kernel function in the form of $K(x_i, x) = \phi(x_i) \cdot \phi(x)$ [19].

4. Experimental procedure
4.1. Specimens

Carbon fiber reinforced polymers (CFRPs) are manufactured by mixing carbon fibers and plastic resin under prescribed conditions. The most common form of CFRPs is the cross-ply laminate, such as laying up a sequence of unidirectional plies [21]. The materials have high elastic modulus and tensile strength with low density as well as thermal expansion. They have been widely used for various components and structures, such as aircraft fuselage as well as wing structures, helicopter rotors and windmill blades, due to their excellent properties. However, the CFRPs are relatively brittle comparing with metallic materials [22]. Flaws in form of void, delamination and debonding may occur in CFRPs during the manufacturing process or under complex environments and loading states.

In this study, two CFRP specimens were used for experiment. An artificial defective CFRP specimen measures 300mm×300mm×5mm, with void (ϕ3mm), top delamination, middle delamination and bottom delamination, which are depicted in Figure 1. Another defective CFRP specimen is a panel with natural debonding.
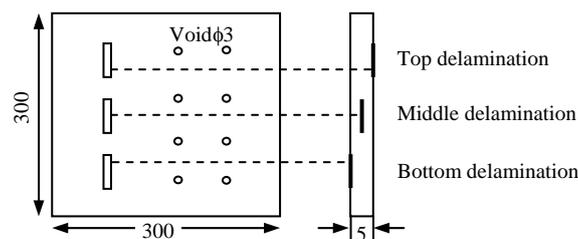
Figure 1. The Specimen with Void and Delamination

4.2. Signal Acquisition

A PXU T227 digital flaw detector was used to send ultrasonic waves into the CFRP specimens under test through a transducer operating at the central frequency of 5MHz. An echo was reflected back each time when the ultrasonic wave encountered a discontinuity in the propagation medium. The A-scan signal was digitised at a sampling frequency of 100 MHz and sample length of 4k using a Sonotek STR 8100 A/D board, and then stored in a personal computer (PC). The ultrasonic testing system is shown in Figure 2.

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┌──────────────────┐      ┌──────────────────┐
│ Personal Computer │◁═══▷│  Digitizer card  │
└──────────────────┘      └──────────────────┘
         ▲
         ║
         ▽
   ┌───────────────────────┐
   │ Ultrasonic flaw detector │
   └───────────────────────┘
```
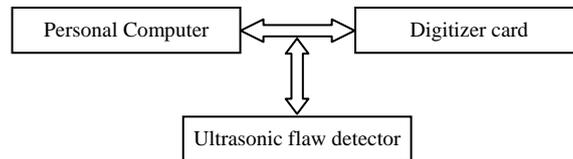
Figure 2. The Ultrasonic Testing System

As the dataset for further classification experiments, the collected signals are composed by:

(1) 30 ultrasonic pulses affected by delamination-like flaws at the top, middle and bottom of the in-study specimen repectively;

(2) 20 ultrasonic pulses describing void of the in-study specimen;

(3) 20 ultrasonic pulses describing debonding of the in-study specimen;

(4) 30 ultrasonic pulses showing absence of defect.

4.3. Feature Extraction and Selection

After pre-processing, the signals describing different flaws can be characterized by wavelet coefficients which are the successive continuation of the approximation coefficients and detail coefficients by using DWT. In this study, each signal was decomposed into 3 levels using Daubechies wavelet. The signals for three types of flaws (delamination, void and debonding) and the representation of their corresponding 512 samples of DWT coefficients are shown in Figure 3 to Figure 5 respectively. Obviously, these DWT coefficients completely describe the macro-trend of each signal.
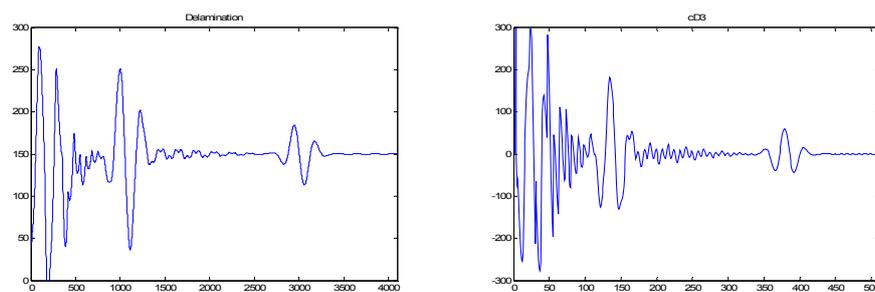
Figure 3. Ultrasonic Signal for Delamination and its DWT Coefficients Representation
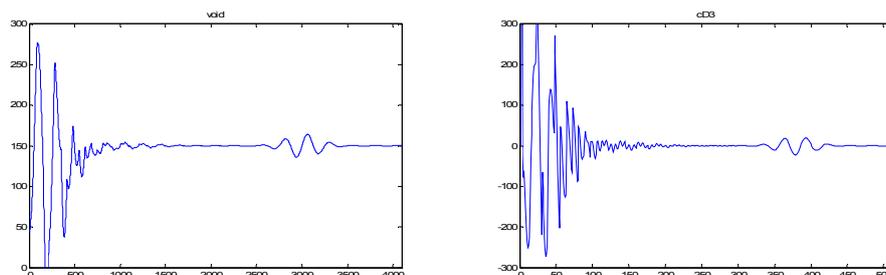
Figure 4. Ultrasonic Signal for Void and its DWT Coefficients Representation
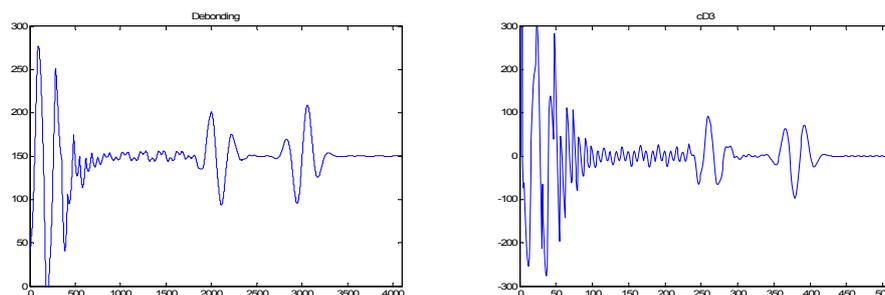
Figure 5. Ultrasonic Signal for Debonding and its DWT Coefficients Representation

Eight informative features were extracted from the DWT coefficients representation of each signal:

(1) Mean value: $AVG = \dfrac{1}{N}\sum_{i=1}^{N} x_i$

(2) Standard deviation: $STD = \sqrt{\dfrac{1}{N-1}\sum_{i=1}^{N}(x_i - AVG)^2}$

(3) Maximum amplitude
(4) Minimum amplitude
(5) Maximum energy
(6) Average frequency
(7) Frequency of minimum energy samples
(8) Half point (HaPo): the frequency that divides up the spectrum into two parts of same area.

Moreover, the conventional time-domain based statistical parameters of each signal, including the mean value, root mean square value, standard deviation and absolute value, were also calculated and taken as another four features.

Due to the still large dimensionality of feature space, the PCA method was exploited to reduce the number of inputs into classifier by only considering the principal components (PCs) whose contributions to total variation of the whole set of PCs are greater than 2%. Finally, the input number of elements for classifier has been reduced from 12 to 6.

4.4. SVM Classification

The training set and test set for classification experiments were composed by 100 signals collected in section 4.2. Six PCs mentioned in section 4.3 were taken as the input vector for training SVM classifier. We conducted the one-against-one method for multi-class classification (6 classes in this study, i.e., top delamination, middle delamination, bottom delamination, void, debonding, no defect) and adopted five fold cross validation assessment for training. First, the samples were randomly divided into five groups. In the training stage, one group was left out as test samples for verifying the SVM classifier, and the other remaining four groups were used as training samples. The process did not terminate until every group was taken as test sample set. Finally, average of the five recorded results was taken as the result of the trained SVM classifier.

5. Results and Analysis

In this study, three classical kernel functions used for SVM training were as follows:

(1) Linear kernel: $K(x_i, x) = x_i \cdot x$

(2) Polynomial kernel: $K(x_i, x) = (x_i \cdot x + 1)^p$

(3) RBF kernel: $K(x_i, x) = \exp(-\gamma \| x_i - x \|^2)$

The recognition rates and training times of SVMs with various kernel functions are resumed in Table 1. As is shown in the table, the mean recognition rates of SVMs with RBF kernels are higher than those with linear and polynomial kernels. However, SVMs with RBF

kernels had the maximum training times due to their exponential computational complexity. Let us focus on the SVMs with polynomial kernel (p=3) and RBF kernel (γ=0.1), denoted as Poly3SVM and RBF0.1SVM respectively. Poly3SVM achieves 97.5% of training recognition rate within 81.4s. In this case, two top delamination flaws of the CFRP specimen were classified as middle delamination flaws, which was not affected by false positive or negative at all. Compared to RBF0.1SVM, 98.75% of training recognition rate within 270.1s, Poly3SVM gains 230% improvement for training efficiency whereas 1.25% loss for recognition rate. Therefore, Poly3SVM can perfectly achieve the trade-off between the computational complexity and classification performances.

Table 1. Recognition Rates and Training Times of SVMs with Different Kernel Functions

Kernel function	Recognition rate of training data (%)	Recognition rate of test data (%)	Training time (s)
Linear (*C*=1)	91.25	87.5	21
Polynomial, *p*=2 (*C*=0.1)	95	90	67.5
Polynomial, *p*=3 (*C*=0.1)	**97.5**	**92.5**	**81.4**
Polynomial, *p*=4 (*C*=0.1)	97.5	93.75	101.3
RBF, *γ*=10 (*C*=1)	96.25	91.25	218.5
RBF, *γ*=1 (*C*=1)	97.5	92.5	230.3
RBF, *γ*=0.1 (*C*=1)	**98.75**	**93.75**	**270.1**

For further comparation, we also implemented the back propagation (BP) network by using MATLAB NN Toolbox for classifying the flaw signals from CFRP specimen. The output of BP network was a 6 component vector. A component value in the $1\pm\delta$ interval was considered as 1 and a component value in the $0\pm\delta$ interval was considered as 0, where δ>0. The optimal BP network architecture was selected based on the average of the best classification results for the 6 classes of flaws. The values of all parameters for training the BP network are resumed in Table 2. Table 3 displays the classification accuracy results obtained by using SVMs and BP network. Obviously, the SVM classifier yields better classification performance than that of the BP neural network. In the CFRP flaw identification case, we can conclude that the SVM outperforms the BP network due to its higher generalization capability for classification problem with small sample size.

Table 2. The Parameters of BP Network

Parameters	Values
No. of input features	6
Activation function at hidden layer	tan-sigmoid transfer function
Activation function at output layer	tan-sigmoid transfer function
Training algorithm	trainscg
No. of neurons at hidden layer	13
Performance goal	0.001
Network structure	6-13-6

Table 3. Comparison between BP Network and SVMs

Classifier	Recognition rate of training data (%)	Recognition rate of test data (%)	Training time (s)
BP network	91.25	86.25	85
Standard SVM	98.75	93.75	170.5

6. Conclusion

In this paper, we used the digital flaw detector to acquire ultrasonic signals from CFRP specimen with void, delamination and debonding, and utilized advanced signal processing and pattern recognition techniques to implement automatic classification for these flaw signals. DWT and PCA were first used for feature extraction and selection. In classification process, we trained the SVM to identify different flaws. Moreover, the selection of kernel function was discussed detailly so as to train the SVM classifier with the best comprehensive performance.

Experimental results showed that the proposed SVM can efficiently classify different ultrasonic flaw signals with high recognition rate.

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