Wavelet Transform Based Feature Extraction for Ultrasonic Flaw Signal Classification

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Abstract—In this paper, an automatic system is designed to classify the ultrasonic flaw signals from carbon fiber reinforced polymer (CFRP) specimens with void, delamination and debonding. In such system, different methods based on discrete wavelet transform (DWT) and wavelet packet transform (WPT) are first utilized for feature extraction. After that, the linear mapping is applied for dimensionality reduction. Artificial neural networks (ANNs) and support vector machines (SVMs) are trained to validate the effectiveness of different wavelet transform based features for flaw signal classification. Experimental results show that the normalized energy of WPT coefficients coupled with the statistical parameters of WPT representation of original signals can be taken as the reliable features to effectively classify different ultrasonic flaw signals with lower training elapsed time.

Index Terms—discrete wavelet transform, wavelet packet transform, feature extraction, ultrasonic flaw signal classification

I. INTRODUCTION

Considerable advancement and development in the last few decades have enabled ultrasonic nondestructive 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, which are increasingly applied in many applications for the recognition of flaws in engineering materials. The overall classification process often consists of three major steps, preprocessing of the original signal, feature extraction by using various digital signal processing methods, and pattern classification. One of the most important techniques of the system is feature extraction, which directly affects the accuracy and reliability of flaw classification. The potential of different signal processing analysis techniques in ultrasonic testing has been investigated by many researchers.

Anastassopoulos et al. [1] conducted an extensive discrimination study on ultrasonic signals very similar to each other obtained from artificial inserts in a carbon fiber reinforced polymer (CFRP) plate. The performance of fifteen classification schemes composed of non-parametric pattern recognition and artificial neural network (ANN) algorithms was assessed, and a 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.

Simone et al. [2] presented discrete Gabor transform (DGT), discrete wavelet transform (DWT) and clustered DWT methods for the classification of ultrasonic signals from inspection regions with weld flaw. The results from trained ANN demonstrated the effectiveness of the clustered DWT method for feature extraction.

Matz et al. [3] used the DWT based method for filtering of ultrasonic signal to suppress the echoes from grains. Support vector machine (SVM) was applied to automatically classify ultrasonic signals in the form of different fault echoes from materials used for constructing airplane engines.

Schulz et al. [4] focused on the automatic evaluation of the backscattered signals received from 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 the CFRP materials.

Lee [5][6][7] critically reviewed popular feature extraction techniques in ultrasonic flaw signal classification, including fast Fourier transform (FFT) and DWT, identified the critical issues, and compared the reported approaches to point out their strengths and weaknesses.

Cacciola et al. [8][9] proposed an heuristic approach for classifying the ultrasonic echoes measured on defective CFRP specimen. The proposed method was based on the use of DWT and PCA for feature extraction and selection. Experimental results assured good performances of the SVM classifier trained by these features.

Zhang et al. [10] proposed empirical mode decomposition (EMD) based feature extraction method for ultrasonic flaw signals classification. The original ultrasonic flaw signals were first decomposed into a finite number of stationary intrinsic mode functions (IMFs) by EMD. After that, Fourier transform was used for analyzing and constructing the feature vector on frequency domain. Finally, BP neural network was made as decision-making classifier. Experimental results showed that the method had better performance for detecting ultrasonic flaw signals.

Sambath et al. [11] improved the sensibility of defect detection in ultrasonic testing by using ANN and wavelet based signal processing techniques. Wavelet transform (WT) was used to derive feature vectors which contain two-dimensional information on four types of defects, namely porosity, lack of fusion, tungsten inclusion and non defect. These vectors were then utilized to train the BP neural network. By using the wavelet features and ANN, accurate rate with 94% for defect classification was obtained

Yadav et al. [12] used six time-frequency representation techniques, i.e., short time Fourier transform, continuous wavelet transform, Wigner-Ville spectrum, Hilbert-Huang transform, Williams-Choi transform and Stransform to extract features out of time domain based signals obtained from a plate with and without cracks. A comparison study was carried out to assess their ability for describing the characteristic of different cracks.

Iyer et al. [13] presented an automatic classification system, which includes preprocessing of the signal, multi-resolution analysis for feature extraction, and neural network classification, to process A-scan signals acquired with the ultrasonic transducer from a pipe region of interest (ROI). By taking into consideration some priori knowledge of the problem, the system can classify the ROI into an appropriate flaw class.

Similar work can refer to [14][15][16]. As mentioned above, wavelet transform based methods are mostly adopted for feature extraction due to the non-stationary characteristics of ultrasonic flaw signals. The objective of this contribution is to show the advantages and disadvantages of different wavelet transform based feature extraction technique in ultrasonic flaw signal automatic classification application. The rest of this paper is organized as follows. Section 2 describes the methodologies of WT, including DWT and wavelet packet transform (WPT). Section 3 presents the experimental setting and section 4 analyzes the experimental results. Section 5 addresses the conclusions.

II. WAVELET TRANSFORM METHODS

Once the ultrasonic flaw signals acquired in the form of digitized data are preprocessed, various digital processing techniques can be used for feature extraction from these signals. Note that ultrasonic signals contain numerous non-stationary or transitory characteristics, which are often the most important part of signal. Fourier analysis is not suitable to describe such characteristics since it can be processed only in frequency domain. To overcome these deficiencies, WT based techniques are developed for processing signals simultaneously in time and frequency domains. WT adopts a windowing technique with variable-sized regions, in which long time intervals are used where more precise low-frequency information is required, while shorter regions are used where high-frequency information is required. In mathematics, WT refers to the representation of a signal in terms of a finite length or fast decaying oscillating waveform, which is scaled and translated to match the input signal. In this way, it is possible to split local and global dynamics for a signal by a multi-resolution analysis (MRA) in a wavelet domain, proving less sensitive to noise than Fourier transform [8].

Especially, DWT has been widely used in the ultrasonic signal analysis as a fast algorithm to obtain the wavelet transform of signals sampled in discrete time. The DWT analyzes the signal by decomposing it into its coarse approximation and detailed information, which is accomplished by using successive high-pass and low-pass filtering operations in the frequency domain.

Given signal $v(t) \in L^2(\Re)$, the DWT approximation coefficients and detail coefficients are evaluated as $cA_j(k) = \sum_m h(m-2k)cA_{j-1}(m)$ and $cD_j(k) = \sum_m g(m-2k)cA_{j-1}(m)$, where j is the level of decomposition, k is the time location, m is the number of samples, $h(.)$ and $g(.)$ are the half-band low-pass filter and high-pass filter respectively. Note that at each level j, only the approximation coefficients are filtered leaving the detail coefficients unaltered. The DWT decomposition tree with three level for signal $v(t)$ is shown in figure 1.
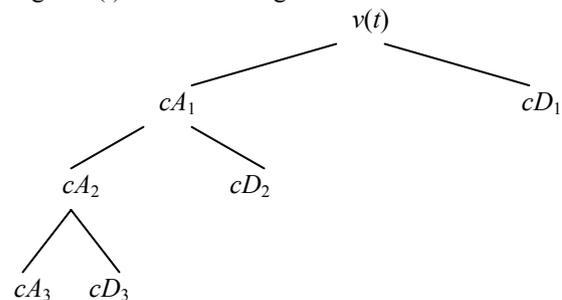
Fig.1. Three level DWT decomposition tree

Since the DWT coefficients are not time invariant, an extension method of DWT, i.e., wavelet packet transform (WPT), has been proposed to overcome the problem. The WPT analysis has the same frequency bandwidths in each resolution since it can simultaneously break up detail and approximation versions. WPT decomposition does not increase or lose the information within the original signals, and the middle as well as high frequency signals can also offer superior time-frequency analysis [17]. At each level j in WPT decomposition, there is no difference between approximation and detail coefficients because the detail coefficients are also filtered. In this case, the WPT coefficients are uniformly indicated with $d_{j,i}(k)$, where j is the scale level and i is their corresponding position in the decomposition tree at that level. The WPT decomposition tree with three level for signal $v(t)$ is shown in figure 2.

Note that there are exist different WPT decompositions for the given signal $v(t)$, classical entropy based criteria can be used to efficiently search the best decomposition tree. The entropy associated to signal $v(t)$ is defined as follow.

$$Epy(v(t)) = -\sum_{j=1}^{L}\sum_{i} Epy(d_{j,i}) \qquad (1)$$

where $Epy(d_{j,i}) = -\sum_k d_{j,i}^2(k) \log d_{j,i}^2(k)$, $d_{j,i}(k)$ is the WPT coefficients and L is the maximal decomposition level. The decomposition tree whose corresponding $Epy(v(t))$ is minimum will be taken as the best one.
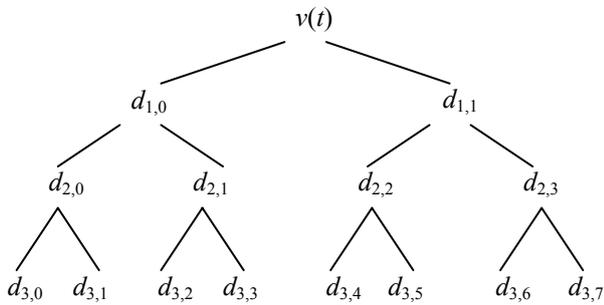
Fig.2. Three level WPT decomposation tree

III. EXPERIMENTS

A. Signal Acquisition

In this study, two carbon fiber reinforced polymer (CFRP) specimens are used for experiment. CFRPs are manufactured by mixing carbon fibers and plastic resin under prescribed conditions. Because of their excellent mechanical properties, CFRP materials have been widely used for critical components and structures. Under complex environments and loading states, damage in the form of void, debonding, delamination and/or transverse cracking may occur in these materials during manufacture process and service. The flaw identification of CFRP components plays a key role in the service function and safety of the systems [18]. A PXU T227 digital detector was used to send ultrasonic waves into CFRP specimens with different flaws through a transducer operating at the central frequency of 5 MHz. An echo was reflected back each time when the ultrasonic wave encountered a discontinuity in the propagation medium. The A-scan signal was digitized at a sampling frequency of 100 MHz and sample length of 512 using a Sonotek STR 8100 A/D board, and then stored in a personal computer. We collected the following 100 ultrasonic signals for our classification experiments. The typical signal samples with different flaw are shown in figure 3.
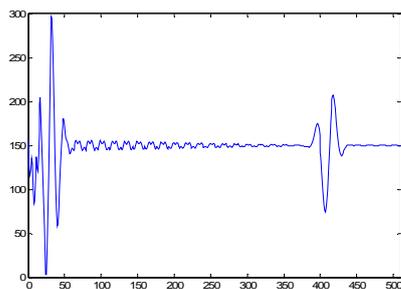
(a)
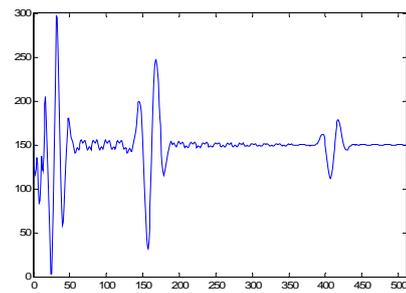
(b)
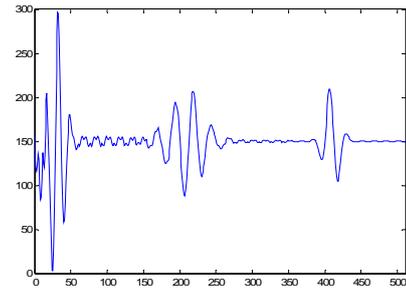
(c)
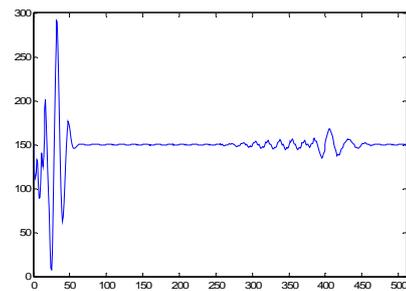
(d)

Fig.3. Time domain based ultrasonic signals with different flaws
(a) No flaw (b) Delamination (c) Debonding (d) Void

B. Features Extraction

If there are flaws appearing within the in-study specimen, the amplitude and frequency of its corresponding ultrasonic echo signal will change with different degree. The signal energy in some frequency sub-band can be enhanced and that in other frequency sub-band will be reduced. Therefore, the signal energy of different frequency components contains much information about flaws, i.e., the energy change of some frequency component may represent a kind of flaw. By using WPT decomposition, we can extract such energy features for ultrasonic flaw signals.

Let $d_{j,i}(k)$ be the WPT coefficients of the ith position at the jth level of the decomposition tree, its corresponding signal energy can be calculated as follow.

$$E_{j,i} = \sum_k d_{j,i}^2(k) \qquad (2)$$

For ultrasonic signals with different flaws, the energy distributions at given scales are always varied. Therefore, $E_{j,i}$ can be considered as an important feature for classification. In consideration of the inconvenience of

numerical analysis due to large value of $E_{j,i}$, a normalization should be taken.

As is shown in figure 4, since the 64 WPT coefficients at the low frequency sub-band can completely describe the macro-trend of each signal, the following eight statistical parameters [11] of representation of signal by the WPT can also be taken as useful features for classification.

(a)

(b)

(c)

(d)
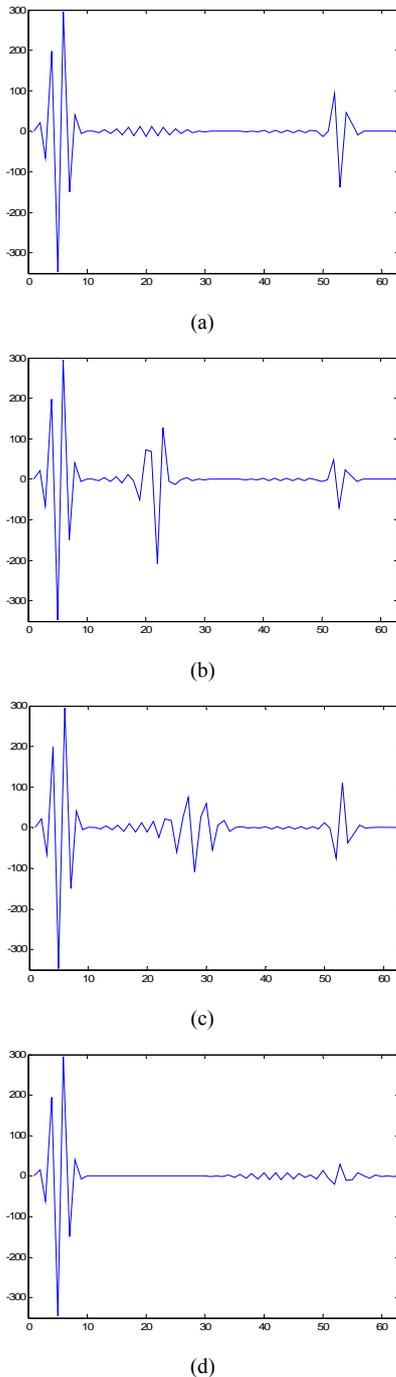
Fig.4. Ultrasonic signal of d3,0 coefficients representation for different flaws (a) No flaw (b) Delamination (c) Debonding (d) Void

(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: $MAX = \underset{1 \le i \le N}{\mathrm{Max}}(x_i)$

(4) Minimum amplitude: $MIN = \underset{1 \le i \le N}{\mathrm{Min}}(x_i)$

(5) Maximum energy: $\mathrm{Max}^2(|MAX|, |MIN|)$

(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.

In this study, the best WPT decomposition was at level 3 by applying the entropy minimization criterion, and Daubechies's wavelet of order 5 was used for filtering. As mentioned above, $E_{3,0}$, $E_{3,1}$, $E_{3,2}$, $E_{3,3}$, $E_{3,4}$, $E_{3,5}$, $E_{3,6}$, $E_{3,7}$, could be taken as the energy features. However, only $E_{3,0}$, $E_{3,1}$, $E_{3,2}$, $E_{3,3}$ were selected since they accounted for more than 97.4% of the total energy of signal $v(t)$. Finally, four normalized energy features $E_{3,0}/E$, $E_{3,1}/E$, $E_{3,2}/E$, $E_{3,3}/E$ where $E=E_{3,0}+E_{3,1}+E_{3,2}+E_{3,3}$, and eight statistical parameters of $d_{3,0}(k)$ coefficients representation, called WPT_Egy features below, were stored as a 12 dimensional feature vector.

To further reduce the feature space, the principal components analysis (PCA) method was exploited. PCA is a quantitatively rigorous method for dimension reduction. The method generates a new set of variables, called principal components (PCs). Each PC is a linear combination of the original variables. All the PCs are orthogonal to each other, so there is no redundant information. The PCs as a whole form an orthogonal basis for the space of the data. The full set of PCs is as large as the original set of variables. But it is commonplace for the sum of the variances of the first few PCs to approximate the total variances of the original data. In this study, we only select the PCs whose contributions to total variation of the whole set of PCs are greater than 1%. Figure 5 shows that about 99% of the variances are explained by the first 6 PCs. In this way, the dimensionality of input feature vector for classification can be reduced from 12 to 6.
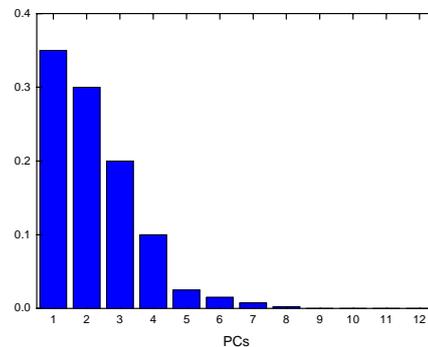
Fig. 5. Variances of the PCs

The main purpose of this study is to investigate the effectiveness of extracted WPT_Egy features for ultrasonic flaw signals classification. For comparison, other three kinds of features extracted by different

strategy are also applied to the classification experiments, which are listed as follows.

(1) WPT_Coe features

Transform the original time domain signal into the WPT coefficients with 3 level decomposition by using Daubechies5 wavelet. The 256 coefficients, i.e., $d_{3,0}$ to $d_{3,3}$, are stored as features while discarding $d_{3,4}$ to $d_{3,7}$, which do not contain much information but mainly noise. After PCA processing, 117 PCs will be selected as the final inputs for classification.

(2) DWT_Sta features

Transform the original time domain signal into the DWT coefficients with 3 level decomposition by using Daubechies5 wavelet. As is shown in figure 6, since the 64 cA_3 coefficients completely describe the macro-trend of each signal, the same eight statistical parameters mentioned above of such coefficients representation are stored as features. After PCA processing, 3 PCs will be selected as the final inputs for classification.

(3) DWT_Coe features

Transform the original time domain signal into the DWT coefficients with 3 level decomposition by using Daubechies5 wavelet. The 256 coefficients, i.e., cA_3, cD_3, and cD_2, are stored as features while discarding cD_1, which do not contain much information but mainly noise. After PCA processing, 106 PCs will be selected as the final inputs for classification.

C. ANN Classification

In this study, feed-forward neural networks with one hidden layer were trained by using the back-propagation algorithm in batch mode for classifying the ultrasonic signals into no flaw, delamination (at the top, middle or bottom of the in-study specimen), void or debonding. To compare the four kinds of features, i.e., WPT_Egy, WPT_Coe, DWT_Sta and DWT_Coe features, four ANN architectures respectively having 6, 117, 3 and 106 input nodes were designed. Kolmogorov's theorem was used for determining the number of neurons at hidden layer. The learning rate was set to 0.2 and the topological order was applied as the update mode of the networks. The 5-fold cross-validation was carried out for assessing classification performance of all ANNs. The 100 ultrasonic signals were shuffled and randomly divided up into 5 subsets. In turn, 4 of these subsets were used to train the network, and the remaining subset was used to validate the network. The process did not terminate until every subset was taken as training set and test set. Moreover, we got a average of the network training ability by assigning 10 different initial weights to the network. The classification performance with the four kinds of features extracted by different strategies could be compared using the result of each cross-validation test. The mean square error (MSE) limit was set to 0.001 for stopping the training process, and the epoch limit was set to 200,000 for those occasional cases where training failed to converge. The values of main parameters for training ANNs are resumed in table I.
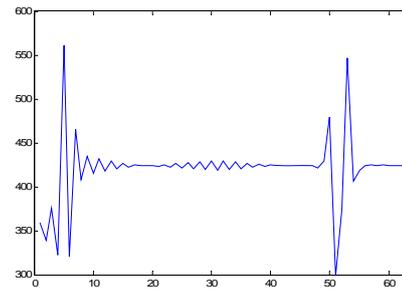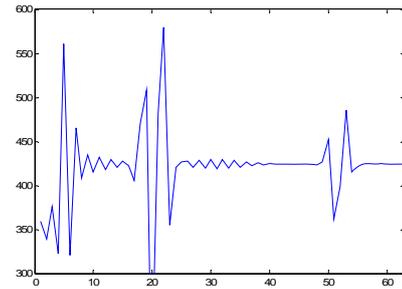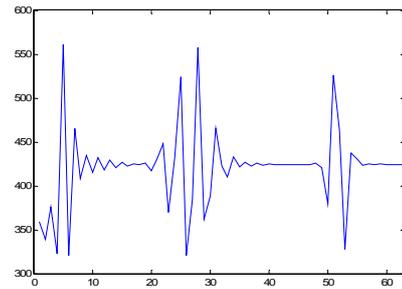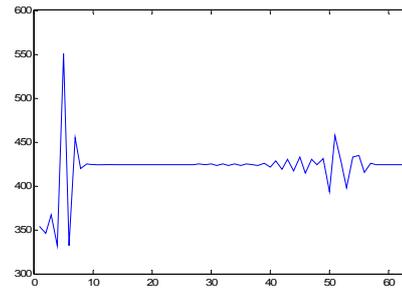
Fig.6. Ultrasonic signal of cA3 coefficients representation for different flaws (a) No flaw (b) Delamination (c) Debonding (d) Void

TABLE I.

THE PARAMETERS OF ANNs

Parameter	Value
No. of neurons at input layer	6/117/3/106
No. of neurons at output layer	6
No. of neurons at hidden layer	13/235/7/213
Activation function at hidden layer	tansig
Activation function at output layer	tansig
Training algorithm	trainlm
Performance goal	0.001

D. SVM Classification

   While using SVMs for classifying the ultrasonic flaw signals, the one-against-one method was adopted to solve the multi-class problem (6 kinds of flaws). Such method constructs all possible pairwise hyperplanes, where each hyperplane is constructed using the training samples from two classes chosen out of k classes [19]. The decision function for class pair ij can be defined by $f_{ij}(x) = \phi(x) \cdot w^{ij} + b^{ij}$, and there exist $k(k\text{-}1)/2$ different decision functions for a k-class problem. In this study, each SVM classifier casts one vote for its preferred class, and the final result is the class with the most votes. Sample x will be assigned to class i if we have

$$\arg \max_i \sum_{j \neq i, j=1}^{k} sign(f_{ij}(x)) \qquad (3)$$

where sign(f_{ij}) is the sign function, whose value is 1 when f_{ij} is positive and 0 otherwise.

   The corresponding 6, 117, 3 and 106 PCs of WPT_Egy, WPT_Coe, DWT_Sta and DWT_Coe features described in section 3.2 were taken as input vectors of SVMs. Linear, polynomial, and RBF kernels were used to train the SVMs with the best performances by a convenient variation of the training parameters. In all cases, the penalty parameter C was varied from 0.001 to 100. Polynomial kernel was evaluated by varying the degree d of the polynomial between 2 and 5. RBF kernel was evaluated by varying the value of σ between 0.01 and 100. The value sets of different parameters for training SVMs are resumed in table II. Analogously, the 5-fold cross-validation was also carried out for assessing classification performance of SVMs, and different feature extraction strategies could be compared using the result of each cross-validation test.

TABLE II.

THE PARAMETERS OF SVMS

Kernel function	Parameter C	Parameter d	Parameter σ
Linear	{0.001, 0.01, 0.1, 1, 10 100}	-	-
Polynomial	{0.001, 0.01, 0.1, 1, 10 100}	{2, 3, 4, 5}	-
RBF	{0.001, 0.01, 0.1, 1, 10 100}	-	{0.01, 0.1, 1, 10, 100}

IV. RESULTS AND ANALYSIS

   The classification accuracy in percentage and training elapsed time of ANN classifiers by using different features (their corresponding PCs are taken as the inputs for ANN) are summarized in table III. Moreover, the confusion matrices are shown in table IV to VII, where the class1 to class6 stands for top delamination, middle delamination, bottom delamination, void, debonding and no flaw respectively. Among the four kinds of features, DWT_Sta shows the worst performance, whose classification accuracy is only 90%, although it needs the least training elapsed time (31.06s). Obviously the statistical features of DWT coefficients representation can not effectively describe the characteristics of different ultrasonic flaw signals because it is hard to select the

features with the best discrimination power. Furthermore, the time-variance problem of DWT coefficients also degrades the classification performance. In contrast, the comparatively high performance of WPT_Egy and WPT_Coe (their classification accuracy are 96.25% and 98.75% respectively) indicates that applying WPT decomposition for ultrasonic flaw signals can effectively overcome the time-variance problem, and hence increasing the classification accuracy. The relatively low performance of DWT_Coe (91.25% classification accuracy with 100.1 second for training) implies that DWT coefficients are somewhat meaningless features due to their time-variance and high dimensionality.

TABLE III.

THE CLASSIFICATION RESULTS OF ANN BY USING DIFFERENT FEATURES

Features	Classification accuracy	Training elapsed time
WPT_Egy	96.25	56.8s
WPT_Coe	98.75	107.18s
DWT_Sta	90	31.06s
DWT_Coe	91.25	100.1s

TABLE IV.

CONFUSION MATRIX USING WPT_EGY FEATURES FOR CLASSIFICATION

	Class1	Class2	Class3	Class4	Class5	Class6
Class1	7	0	2	0	0	0
Class2	0	8	0	0	0	0
Class3	1	0	5	0	0	0
Class4	0	0	0	16	0	0
Class5	0	0	0	0	17	0
Class6	0	0	0	0	0	24

TABLE V.

CONFUSION MATRIX USING WPT_COE FEATURES FOR CLASSIFICATION

	Class1	Class2	Class3	Class4	Class5	Class6
Class 1	8	0	1	0	0	0
Class 2	0	8	0	0	0	0
Class 3	0	0	6	0	0	0
Class 4	0	0	0	16	0	0
Class 5	0	0	0	0	17	0
Class 6	0	0	0	0	0	24

TABLE VI.

CONFUSION MATRIX USING DWT_STA FEATURES FOR CLASSIFICATION

	Class1	Class 2	Class 3	Class 4	Class 5	Class 6
Class1	5	0	4	0	0	0
Class2	0	8	0	0	0	0
Class3	2	0	4	0	0	0
Class4	0	0	0	15	0	1
Class5	0	0	0	0	17	0
Class6	0	0	0	1	0	23

TABLE VII.

CONFUSION MATRIX USING DWT_COE FEATURES FOR CLASSIFICATION

	Class1	Class 2	Class 3	Class 4	Class 5	Class 6
Class1	5	0	4	0	0	0
Class2	0	8	0	0	0	0
Class3	2	0	4	0	0	0
Class4	0	0	0	16	0	0
Class5	0	0	0	0	17	0
Class6	0	0	0	1	0	23

   Note that the comprehensive performance of WPT_Egy features for classification is the highest, which achieve 96.25% classification accuracy with only 56.8

second for training ANN. On one hand, extracting features from statistical parameters of representation of WPT coefficients can remarkably reduce the dimensionality of feature vector. Although the accuracy by using WPT_Coe features for classification is slightly higher (98.75%), almost doubling time (107.18s) is needed for training ANN. On the other hand, energy features of WPT_Egy can effectively describe the local characteristic of flaw signals by analyzing the same frequency sub-bands in each resolution, which does not lose any useful information. Compared to DWT_Sta, WPT_Egy features are more reliable for classifying similar flaw signals due to the additional four energy features. Figure 7 shows the energy diagrams by using Daubechies5 wavelet to perform the WPT for signals with various delamination flaws. The horizontal axis stands for the number of frequency sub-bands and vertical axis stands for the value of the corresponding normalized energy. As is shown in the figure, the variation of each subspace is apparent, and the first four energy features is particularly useful for distinguishing delamination flaws since the related energy distribution is very different from the others. While using DWT_Sta features for classification, among total 8 misclassified signals, 6 misclassifications are between top delamination and bottom delamination signals , which is shown in table VI.

The classification accuracy in percentage of SVM classifiers by using different features (their PCs are taken as the inputs for SVM) are summarized in table VIII. Note that for SVMs with different kernel function, only the best results and the corresponding parameters are recorded in the table. Due to the lack of space, we do not list the confusion matrices. Again, the classification performance of WPT based features for classification is better. Comparing the results of table III and table VIII, the SVM with polynomial kernel or RBF kernel function outperforms the ANN due to its higher generalization capability for classification problem with small sample size.

V. CONCLUSIONS

This paper presented a ultrasonic flaw signal classification system by using wavelet transform based strategies for feature extraction. A digital flaw detector was first used to acquire the signals of defective CFRP specimens with void, delamination and debonding. After that, the time domain based ultrasonic signals could be processed by DWT and WPT to extract different features. Finally, the feature vectors selected by PCA method were taken as inputs to train ANN and SVM classifiers. Experimental results showed that the WPT_Egy features, constructed by normalized energy of WPT coefficients and statistical parameters of WPT representation of original signals, were informative features to deal with classification for ultrasonic flaw signals.
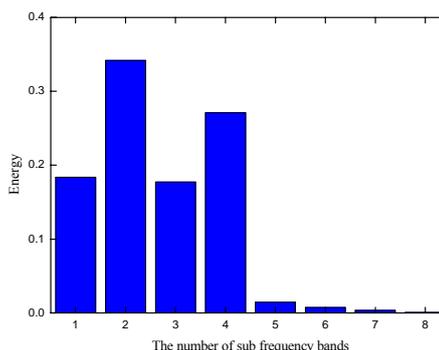
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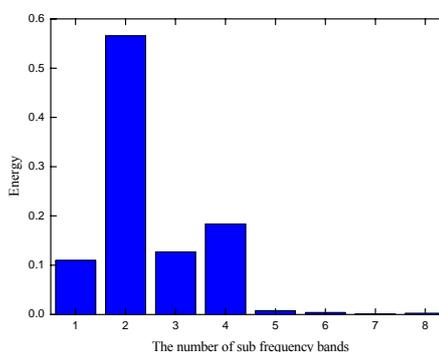
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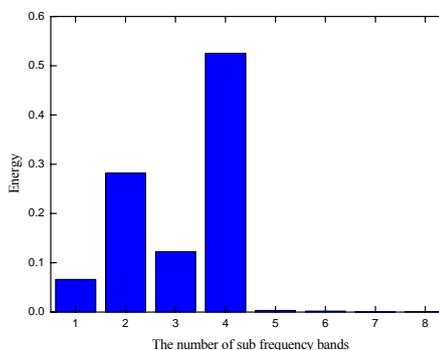
(c)

Fig. 7. Energy distribution (a) Top delamination (b) Middle delamination (c) Bottom delamination

TABLE VIII.
THE CLASSIFICATION RESULTS OF SVM BY USING DIFFERENT FEATURES

Features	Classification accuracy with linear kernel (C=1)	Classification accuracy with polynomial kernel (C=0.1, d=3)	Classification accuracy with RBF kernel (C=1, σ=0.1)
WPT_Egy	93.75	97.5	98.75
WPT_Coe	95	98.75	100
DWT_Sta	86.25	90	91.25
DWT_Coe	87.5	91.25	92.5

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