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Wavelet Usage for Feature Extraction for Crack Localization

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***Abstract*—In this research work we investigate the analysis of Acoustic Emission (AE) signals using wavelet decomposition to locate a single event (crack), which usually takes place in three typical areas in a ship hull. The problem is a typical classification problem relying on the use of novel features extracted from the AE time series. As in most classification problems the extraction and selection of the most appropriate set of features plays a major role in the overall performance of the method and it is by no means a trivial task. Once a suitable set of features is extracted even "simple" classification models can perform adequately whereas a non-informative set of features even combined with sophisticated classifiers can lead to disappointing results. Here, we exploit the multi-resolution capabilities of wavelet decomposition, so that a set of features is extracted which it is then combined with a simple classifier. The proposed method gives superior classification rates for noisy environments compared to our previous work where conventional methods for feature extraction were deployed.**

Keywords-component; wavelet decomposition; accoustic emmisio, feature extractio, classification

I. INTRODUCTION

Corrosion and fatigue cracking are the most pervasive types of structural problems that appear in ship structures. Each of the damage modes, if not properly monitored and rectified on time, could potentially lead to catastrophic failure or unanticipated out-of-service time. Especially in the case of a ship, which transports crude oil, the consequence of an oil spill due to a broken weld would be -among other reasons- environmentally disastrous. Therefore the structural health monitoring of a ship is of very critical concern. Most of the existing techniques for the inspection of ship structures require them to be taken out of service. A technique that could detect damage while the ship is in normal operation is greatly desired - keeping in mind that ships' downtime is extremely costly- while the identification of the extent and the location of the damage is an even more complex problem.

Non-Destructive Testing (NDT) methods are widely used for damage identification [1]. In particular, NDT techniques are necessary to detect damage in high stressed and fatigue-loaded spots and areas of complex structures, i.e. aircrafts, bridges, ships etc.. NDT methods are extensively used for the manufacture and the maintenance of ship structures. Of particular interest is the inspection of ship welding. The qualitative control of welding, as is generally called the inspection of the surface and the interior of welding, aims to identify and confirm, that they do not have any cracks, inclusions, or/and other defects that can compromise the resistance of the ship. However, the use of most of the well-known NDT methods may not be feasible when the structure is in operation.

Acoustic Emission (AE) is among the most well known and successful NDT methods for the detection and location of damages in a variety of metal structures [2], [3]. AEs are commonly defined as transient elastic waves within a material caused by the release of localized stress energy. Hence, an event source is the phenomenon which releases elastic energy into the material, which then propagates as an elastic wave.The processing of AE signals is based on the detection and conversion of these elastic waves to electrical signals by directly coupling piezoelectric transducers on the surface of the structure under examination. AE is sensitive enough to track newly formed crack surfaces down to a few hundred square micrometers and less.

A number of analytical and experimental works investigating fatigue damage occurrence in ships have been proposed in recent years [3]. The theoretical formulation for the assessment of the reliability of a ship hull with respect to fatigue failure of the longitudinal members is presented in [4]. The model accounts for multiple cracks both in the side longitudinal and in the side shell and also models the crack growth process. Usually, the dynamic characteristics of the structure change when structural damage occurs. Five full-scale specimens representing side longitudinal of floating production storage and offloading units were fatigue tested in [5]. The connections were very similar to connections currently in use, and they were fabricated according to typical ship-yard practice. The specimens have also been modeled by finite elements and some of the results from the most complex connections have been compared with measured data. Zybaydi et al. proposed an autocorrelation function to identify damage in the side shell of ship structures using a combination of experimental and numerical studies [6]. The damage occurrence in the side shell of ship structures, modeled as a stiffened plate, was identified using the random decrement technique.

Zubaydi et al. [7] also proposed a Neural Network (NN) technique to identify the damages in the side shell of a ship's structure with the autocorrelation function of the structure vibration response being the input to the NN. The theoretical response was obtained using a finite element model of the structure. A considerable amount of all fatigue damage in ship hulls occurs in the side shell plating, especially at the connection between longitudinal and heavy transverse parts, as reported in [8], [9]. The studies by Strathaus et al. [8] and Sucharski [9] have shown that fatigue due to wave-induced loads is the main cause of ship structural damage, especially for structures having high stress concentrations at the connection between the longitudinal and the heavy transverse members of the side shell. Recently Kappatos et al. [10] presented an evolutionary algorithm as a means to select relevant features from a larger set of "primitive" features [11].

In this research work we examine and test the effectiveness of a different set of features extracted from AE signals using the discrete time wavelet transform (DTWT). During the last 20 years, researchers from the field of applied mathematics and signal processing have developed powerful wavelet methods for the multiscale representation of signals [12]. This kind of representation allows the decomposition of a signal into a number of scales, each scale representing a particular "coarseness" of the signal under study [13]. This approach can be quite useful when we try to extract information from signals that contain more than one component. In the proposed here approach, we use the DTWT to condense the information from quite long time series in order to feed a simple, but nevertheless, effective classifier.

The remainder of the paper is organized as follows: Section II is a brief introduction to wavelet transform and DTWT. Section III describes the experimental structure, which was used to test a metal structure and the data acquisition system. In Section IV the proposed classification procedure and how it was used in the experimental data set is presented. Section V discusses the classification results, and in Section VI some conclusions and future directions are drawn.

II. Wavelet Tranform

In the past few years, wavelet analysis has been found to be particularly useful as an alternative -and sometimes even more suitable- to the short-time Fourier transform. The intrinsic property of the wavelet transform to localize well both in time and frequency domain makes it very appealing in case of nonstationary signals. Even for stationary signals, it can be sometimes difficult to choose a good resolution to analyze the signal. This is the case when the signal contains a mixture of features at different resolutions [13].

The continuous wavelet transform (CWT) of signal $s(t)$ is produced taking the inner product of the signal with translated and scaled versions of a (real or complex) analyzing function, also called mother wavelet ψ.

Translations and dilations of this "mother" (or analyzing) wavelet (Eq. 1) are used to transform the signal into another form (time-scale representation).

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \tag{1}$$

In the case of discrete parameter wavelet transform (DPWT) [14], the dilation and translation parameters α, b are restricted only to discrete values leading to the following expression:

$$\psi_{m,n}(t) = a_0^{-m/2}\psi\left(\frac{t-nb_0a_0^m}{a_0^m}\right) \tag{2}$$

The choice of $a_0=2$ and $b_0=2$ (dyadic grid arrangement) is quite usual:

$$\psi_{m,n}(t) = 2^{-m/2}\psi\left(2^{-m}t-n\right) \tag{3}$$

For discrete time signals the discrete time wavelet transform (DTWT) [14] is given by:

$$T_{m,n} = 2^{-m/2}\sum_k x(t)\psi\left(2^{-m}k-n\right) \tag{4}$$

As it is obvious, different mother wavelets give rise to different classes of wavelets, and thus, the characteristics and features of the decomposed signal can be quite different. In this work, we have experimented using Daubechies, symmlets, coiflets and biorthogonal families trying different number of vanishing moments. All the aforementioned wavelets were developed by Daubechies [12] and they demonstrate the appealing property of having compact support and the wavelet transform can be computed with finite impulse response conjugate mirror filters using a fast filter bank algorithm.

III. EXPERIMENTAL SETUP

The side shell of a ship hull was modeled using a stiffened plate model (SPM) whose dimensions are shown in Fig. 1. The outside side shell was dyed with oil-paint in order to simulate as closely as possible the ship's outer side.

Reflections at the end of the SPM were reduced by wrapping the ends in putty. The fixed boundary condition of the model was obtained by clamping the side shell using three heavy bases. Insulation material was placed between: a) the SPM and the three bases, b) the three bases and the bottom of the tank, and c) the bottom of the tank and the floor to eliminate external noise. The SPM and its supports were fixed in a water tank. The putty at the edges of the SPM prevents water from passing in the inside side shell of the plate. The putty was dyed with oil-paint for better water-tightness and to prevent putty corrosion.

The Physical Acoustics Corporation (PAC) R15-Alpha sensors were used to detect the wave in the steel stiffened plate. The sensors were stuck on the plate with grease-couplant.

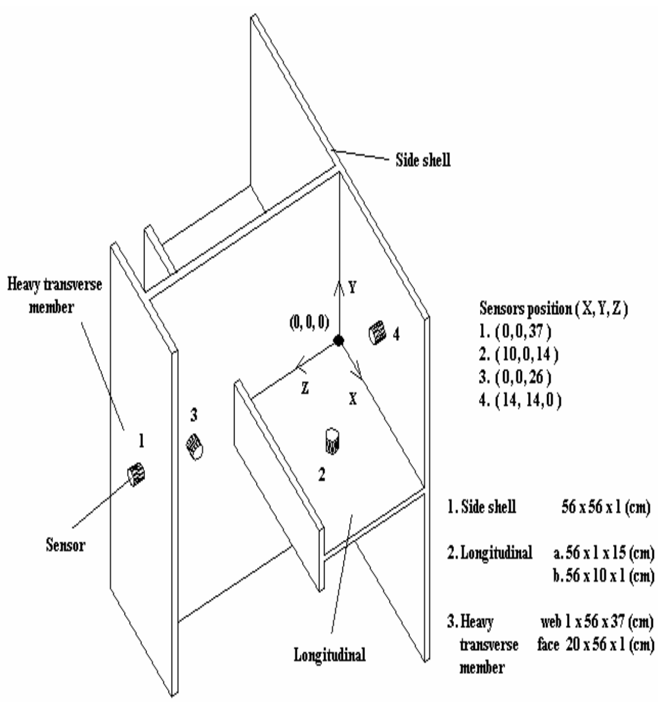

Figure 1. The SPM under test along with the sensors' positions

In order to detect the AE-signal coming from any possible position, the four sensors were set into symmetrical positions, taking into account the structure of the ship-hull. The first, the second and the third sensor were located in the middle of the face plate of the heavy/longitudinal/side shell respectively, minimizing the total distance between the welding seam points and the nearest sensor. The fourth sensor was located in the middle of the distance between the heavy transverse face and the faceplate of longitudinal. A detailed description of the sensor types and their configuration can be found in [10].

The studies by Strathaus et al. [3] and Sucharski [4] have shown that fatigue due to wave-induced loads is the main cause of ship structural damage, especially for structures having high stress concentrations at the connection between the longitudinal and the heavy transverse members of the side shell.

IV. LOCALIZATION OF AE SOURCES IN SHIP HULLS

In this research work, we propose a new method for AE-source localization, which consists of three modules:

- the feature extraction module, where a set of features is derived from the AE signal based on the wavelet decomposition of the signal,
- a dimensionality reduction stage based on the well-known technique of principal component analysis (PCA) and
- a classification module.

In the remainder of this section each one of the three modules is presented in brief along with the data sets involved in this work.

A. *Data sets*

In this research work, we put much emphasis in locating the AE source coming from 3 "distinct" locations:

1. AE source in the welding seam between the longitudinal and the heavy transverse member (web) (class-A),
2. AE source in the welding seam between the longitudinal and the side shell (class-B),
3. AE source in the welding seam between the heavy transverse member (web) and side shell (class-C).

Data for each class (A, B, C) were generated at 90 different positions almost uniformly distributed in the welding-seam areas. At each position the pulser is triggered five times to simulate the signal variance of AE events at the same position.

During continuous monitoring, time-frames of 32 msecs are used to extract the features set. In this time-frame the direct crack signal and the most important reflections are included. The complete set of recordings consists of 450 signals, 150 from each class (A, B, C). Taking into account the high levels of noise encountered in ship hulls, emphasis should be placed for the case of low SNRs. Therefore the localization method was evaluated in the presence of white Gaussian noise with zero mean value at -20, -10, 0, 10, SNR (dB).

B. Feature Extraction

The most appealing characteristic of wavelets is that they have the ability to decompose a signal into a number of scales, where each scale represents a particular “coarseness” of the signal under study [13]. As a result different scales capture different intrinsic characteristics of the signal.

For this work we performed DTWT up to level 12 using various mother wavelets. Fig 2 shows the detail coefficients of a signal coming from the first sensor produced using a Daubechies mother wavelet with 14 vanishing moments.

For each level we have calculated the standard deviation of the detail coefficients. The standard deviation at each scale is a means to quantify the “energy” concentration of the signal at this particular level. Having four sensors and by performing wavelet decomposition up to scale 12 automatically creates a feature vector of dimension 48. Due to the quite large number of features a dimensionality reduction stage was also incorporated.

C. Dimensionality Reduction

In pattern recognition tasks, usually, potential improvement (better generalization) can be achieved by using fewer features than those available [15]. Actually, in order to build a classifier we tend to extract several features, which may convey redundant information about the pattern-class of interest. Therefore, in this proposed approach, we have incorporated a PCA stage in order to both decorrelate the input features and possibly reduce the dimension of the input vector.

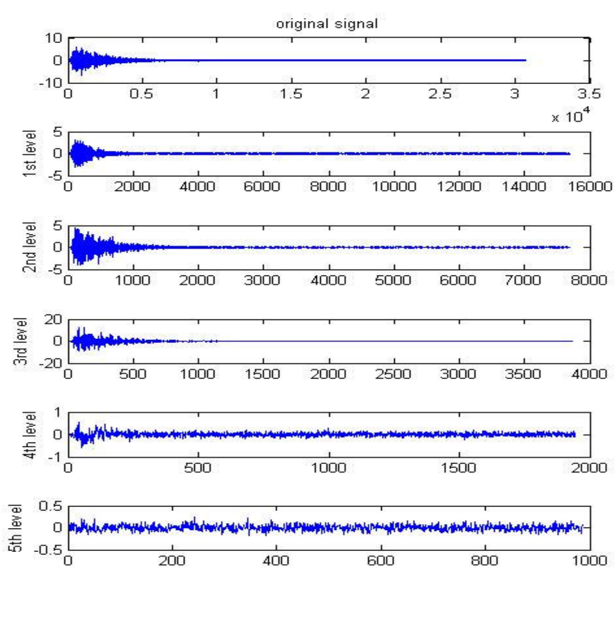

Figure 2. The original signals and the detail coefficients up to level 5 produced using a Daubechies wavelet with 14 vanishing moments

PCA, or Karhunen-Loeve transformation, is a well known approach to perform dimensionality reduction by linear combination of the original features in such a way that preserves as much of the relevant information as possible [15], [16]. This method computes eigenvalues of the correlation matrix of the input data vector and then projects the data onto the subspace spanned by the eigenvectors (principal components) corresponding to the dominant eigenvalues. Even if the whole set of the eigenvectors is retained, this can also lead to an improvement of the classification performance, because the new set has features that are uncorrelated and this, in general, improves the classification capabilities of a classifier.

D. Classification stage

In this research work we are not interested in detecting the exact location of the crack. Our aim is to classify the signal into one of the three classes described previously in subsection IV.C. Thus, we treat the crack location problem using a pattern recognition approach. Therefore, having a (reduced) feature vector we fed a classifier to assign them to one of the three predefined classes.

Many algorithms and models have been developed over the past years to tackle the supervised pattern recognition problem [17]-[19]. New variants and improvements of existing methods are developed every day. However the improvements attributed to the more advanced and recent methods and algorithms are usually small and in real life problems the theoretical or “empirically” proven advantages are irrelevant or even unreal [20].

As a result in this research, we put attention to the selection and extraction of features and we decided to use a simple linear classifier, the minimum Mahalanobis distance classifier and a nonlinear k-nearest neighbor classifier (with k=1 and k=5) [17], [18].

V. RESULTS

In order to test the performance of the proposed approach we divided the 450 cases into 6 (non-overlapping) subsets; each one consisting of 25 examples from each class (A, B and C) (i.e. 75 cases in total). The classifier was trained on all subsets except for one, and the validation error was measured by testing it on the subset left out. We repeated this procedure 6 times, each time using a different subset for testing and we averaged the performance over the 6 experiments. We tried different number of principal components (PCs) and different number of vanishing moments for each one of the wavelet families. It must be noted that the selection of the configuration (number of vanishing moments and number of retained PCs) was performed based on the training set and then applied to the testing set in order to avoid “optimistic” results. Fig 3 depicts the performance (accuracy / location rate) as a function of the number of PCs retained and the number of vanishing moments of the Daubechies wavelet for the case of -10 dB of additive Gaussian noise using the linear classifier.

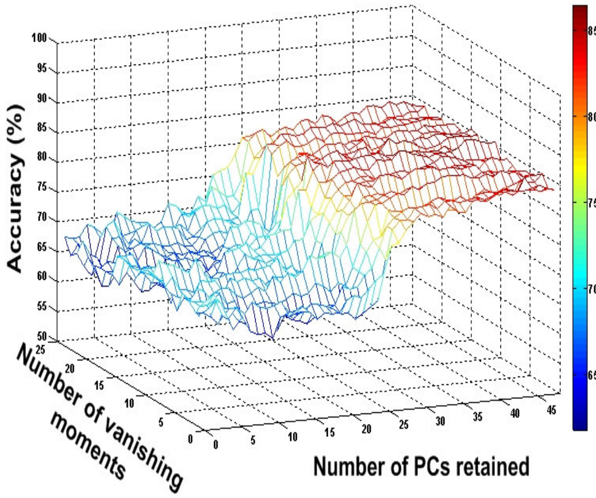

Figure 3. Classification accuracy of the minimum Mahalanobis distance classifier for the case of -10 dB additive noise for the Daubechies family.

Tables I to III summarize the best location rate achieved for each wavelet family and each noise level for the 3 different classifiers employed in this research work

TABLE I. LINEAR

wavelet families	SNR (dB)			
	10	**0**	**-10**	**-20**
Daubechies	89.1111	89.7778	83.5556	68.6667
Symmlets	88	89.1111	83.7778	68.4444
Coiflets	89.7778	90.6667	83.1111	67.7778
Biorthogonal	89.5556	90.4444	88.2222	70.8889

TABLE II. NEAREST NEIGHBOR (NN)

wavelet families	SNR (dB)			
	10	**0**	**-10**	**-20**
Daubechies	87.5556	77.1111	68.6667	66
Symmlets	86.2222	80.4444	70.2222	66.8889
Coiflets	84.6667	77.7778	68.4444	69.7778
Biorthogonal	80.6667	79.7778	75.5556	72.2222

TABLE III. 5-NN

wavelet families	SNR (dB)			
	10	**0**	**-10**	**-20**
Daubechies	87.7778	81.3333	72.4444	73.3333
Symmlets	87.7778	78.2222	73.1111	72.4444
Coiflets	86	77.7778	70.6667	68.8889
Biorthogonal	89.1111	80.8889	76.4444	72.8889

VI. CONCLUSIONS

In this research work, a novel set of features based on the wavelet transform was extracted and used in order to locate cracks by monitoring AE events in the presence of additive white-Gaussian noise. This set of features is quite robust giving satisfactory localization rates of a single event in very noisy environments. The proposed features could be embodied in real-time crack monitoring systems of large and complex structures improving the performance reliability in noisy environments. From an industrial point of view, the development of fast and efficient monitoring machines can be easily achieved using few features in low-cost hardware. The crack characterization rate of the extent of damage is very promising; however, more work has to be done for accurate location of crack using fewer sensors.

The results show that the use of wavelet based features and a simple classifier can give remarkable results even in the presence of large levels of noise. These results outperform our previous work [10], [21] where evolutionary approaches and NNs (a multilayer perceptron in [10] and a probabilistic NN in [21]) were combined to perform the same task using conventional features for every noise level except for the case of 10 dB SNR [10]. This indicates that a good set of features is more important than the use of extremely complex models that sometimes tend to uncover artificially hidden relations among the input-output data.

In almost all cases the use of biorthogonal wavelets resulted in the optimal or near optimal performance (Tables I-III) without however completely overwhelming the other families. This indicates that the selection of the wavelet family is not that crucial after all. For very high levels of noise the performance of all three classifiers is comparable and in addition the number of PCs doesn't play such an important role. However in general for lower noise levels more PCs give better results.

Moreover in this research work only one type of features has been investigated (standard deviation). This is by no means the only choice and there are other transformations that can be applied to the wavelet coefficients in order to come up with useful features. Furthermore a level selection process, in other words a mechanism to pinpoint the levels that contain the most relevant information instead of using the details of each level could be beneficial. In addition, the use of global statistics (standard deviation in this work) even though quite useful as it is proven by our results, does not exploit the time scale capabilities of the wavelet transform. In other words the evolution of the phenomenon is not captured and only the scale information is used. In future work we will also examine more thoroughly this matter.

We must also note that the propagation behaviour of crack and crack growing signals are influenced by the kind and size of ship-hull, materials etc. leading not necessarily to the same set of features for detection of AE events. This means that the proposed method has to be tailored for the specific application. Nevertheless, the methodology is generic enough and can be used as it is.

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