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System Identification-based Frequency Domain Feature Extraction for Defect Detection and Characterization

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Abstract—Feature extraction is the key step for defect detection in Non-Destructive Evaluation (NDE) techniques. Conventionally, feature extraction is performed using only the response or output signals from a monitoring device. In the approach proposed in this paper, the NDE device together with the material or structure under investigation are viewed as a dynamic system and the system identification techniques are used to build a parametric dynamic model for the system using the measured system input and output data. The features for defect detection and characterization are then selected and extracted from the frequency response function (FRF) derived from the identified dynamic model of the system. The new approach is validated by experimental studies with two different types of NDE techniques and the results demonstrate the advantage and potential of using control engineering-based approach for feature extraction and quantitative NDE. The proposed approach offers a general framework for selection and extraction of the dynamic property-related features of structures for defect detection and characterization, and provides a useful alternative to the existing methods with a potential of improving NDE performance.

Key Words— Defect detection; feature extraction; frequency response function; structure health monitoring; system identification.

1. Introduction

Active sensing-based non-destructive testing and evaluation (NDT&E) techniques using acoustic (e.g. ultrasonic) and electromagnetic (e.g. eddy current) effects have been widely used for structure health monitoring (SHM) to detect defects inside a structure [1] [2], and different methods have been proposed and studied as can be seen from literature published [3] [4] [5] [6]. A common point in the aforementioned NDT&E techniques is that they all use an output-only approach to perform defect detection where the measured response from a NDT transducer, such as piezoelectric wafer made of Lead Zirconate Titanate (PZT) or pulsed eddy-current (PEC) probe, is analyzed and the features reflecting the health status of the structure/or material under investigation are extracted for defect determination. The general procedure can be summarized as follows: (1) record a baseline/or reference response under a specified excitation, this is normally obtained under defect free condition; (2) measure the response from the transducer installed on the structure/or material to be monitored under the same excitation as used for generating the baseline/or reference response; (3) compare the measured response with the baseline/or reference response for health monitoring and defect detection. The comparison is usually performed by first selecting and extracting some features from both the measured response and the reference response, and then compare these features to determine the health status of the structure under investigation.

A key step for defect detection and characterization using the above approach is the selection and extraction of features from measurements. As can be seen, with the aforementioned procedure, the inspection device was treated as a signal generator where only the response from non-destructive transducer is utilized for feature extraction and it is implicitly assumed that the excitation used in the active sensing inspection is the same as that used for obtaining baseline/or reference response when we perform comparison. Hence any discrepancy between the excitation used for generating baseline response and that used for inspection will affect the accuracy of detection. Also, the features extracted for defect detection will be input-dependent and the different methods have to be employed to select and extract features from the measured response for different types of NDT technique used.

The problem is revisited in this paper and we aim at developing a general framework for feature selection and extraction that can be used with different types of active sensing-based NDT techniques. To this end, the problem is considered from a system perspective and the transducer, such as PZT sensor/or PEC probe, together with the structure under inspection will be viewed as a system (hereafter refer to as an NDT system) where the input to the system is the excitation signal of the NDT device and the output of the system is the corresponding non-destructive transducer's response. Instead of analyzing transducer response alone, we propose to use both input (excitation) and output (response) signals from the system for feature extraction. The proposed method is based on the well-recognized fact that the defects (such as cracks, corrosion) in a structure can change its mechanical/electrical properties, hence the dynamic behavior of the NDT system. Consequently, the basic idea with the new NDE data analysis is to identify such changes in the system's dynamic behaviors with respect to defect-free situations in order to more effectively achieve the objectives of NDT&E.

Based on above discussion, the dynamic property-related features are proposed to be used for defect detection. Specifically, the frequency response function (FRF) of the NDT system derived from input-output measurements is used for feature extraction in this paper because the FRF is less contaminated and can provide more information on defects to be detected. The remainder of the paper is organized as follows. Section 2 discusses the idea behind the new method proposed and present the development of the methodology. This is followed by two experimental studies with different types of NDT techniques in Sections 3 and 4, where a PEC-based system for crack detection and an ultrasonic inspection-based SHM system for corrosion detection using the new method developed are presented. The conclusions and some ideas for future research are presented in Section 5.

2. Methodology

In an active sensing-based NDT system, the system output, or more specifically, the response of the NDT transducer to the excitation (input) depends on both the input signal and the dynamic characteristics of the NDT system itself. As discussed in last section, the basic idea behind the defect detection method proposed in this paper is to detect the changes in dynamic behavior of the NDT system due to a defect. The dynamic behavior of a system is usually described by a parameterized mathematical model. Therefore, in order to capture the dynamic behavior of an NDT system, the system identification technique needs to be applied to identify a model from the measured input-output data for representing the dynamic characteristics of the NDT system under investigation. Once the model is obtained, the defect detection can then be achieved by monitoring the change in the features extracted from the identified model. The general procedure of the proposed method for defect detection is therefore as follows: (1) identify a dynamic model using input-output data obtained from the NDT system; (2) select and extract dynamic behavior-related features of the system derived from the identified model; (3) compare these features of the identified model with those extracted from a reference model representing defect-free conditions. Because there is no requirement for using the same inspecting signal as in the case with traditional NDT&E techniques, and the dynamic behavior-related features can reflect the inherent characteristics of the NDT system, the new method has potential to overcome disadvantages with traditional output only based data analyses and provides more effective solutions to the NDT&E problems in engineering practice.

To facilitate reader and communicate the idea as clearly as possible, the system identification technique used in this paper will be briefly explained before describing the new frequency domain feature extraction method for defect detection and characterization in this section.

2.1. System Identification

System identification is a technique dealing with the problems of constructing mathematical models of dynamic systems from test data. There are in general two types of approaches that can be used to solve this problem and they are referred to as the “Grey-box” modelling approach and the “Black-box” modelling approach. The “Grey-box” modelling approach attempts to combine physical modelling with parameter estimation techniques where the model is constructed from the first-principles up to some unknown parameters and model identification then amounts to the estimation of these unknown parameters using the measurements. The “Black-box” modelling approach, on the other hand, does not assume any prior physical knowledge on the model and the model is identified from input-output measurements only. In this paper, as we aim at developing a general method for feature selection and extraction that can be used with different types of NDT systems based on different physical principles, the “Black-box” identification approach needs to be used. The identification can be performed either in the time domain or in the frequency domain, but for the active sensing-based NDT systems studied in this paper, the measurements are sampled time-domain data, and therefore our attention will focus on the time-domain identification method.

Choosing a model structure is usually the first step in system identification. Clearly, models may come in various forms and complexity. As the identified model in this paper is intended to be used for defect detection, our attention will not focus on the model itself, but rather we are interested in the changes in some features extracted from the identified model which are caused by the defects to be detected. To this end, the ARX (Auto-Regression with eXogeneous input) model structure will be chosen for model identification in this paper, because ARX model is not difficult to be identified, well-suited for modelling the sampled data and can approximate any linear system arbitrarily well if the model order is high enough (see e.g. [7, p.336]). Let $y(t)$ denote the output (response) of the system at the time instant t, $u(t)$ denote the input (excitation) of the system, the ARX model that describes the relationship between the input $u(t)$ and the output $y(t)$ is a linear difference equation of the following form:

$$y(t) + a_1 y(t-1) + \cdots + a_n y(t-n) = b_1 u(t-1) + \cdots + b_m u(t-m) \qquad (1)$$

where $a_1,\cdots,a_n$ and $b_1,\cdots,b_m$ are the model parameters to be estimated. By introducing vectors:

$$\boldsymbol{\theta} = [a_1 \cdots a_n \; b_1 \cdots b_m]^T$$

$$\boldsymbol{p}(t) = [-y(t-1) \cdots -y(t-n) \;\; u(t-1) \cdots u(t-m)]^T$$

Model (1) can be rewritten in a more compact form:

$$y(t) = \boldsymbol{p}^T(t)\boldsymbol{\theta} \qquad (2)$$

Model (2) can be viewed as a way to determine the current output value given previous input and output observations. Such a model structure which is linear in parameter $\boldsymbol{\theta}$ is known in statistics as linear regression. The vector $\boldsymbol{p}(t)$ is called the regression vector and its components are the regressors. Note that, $\boldsymbol{p}(t)$ in (2) contains previous values of the output variable $y(t)$, model (2) is then partly auto-regression and this is where the name of the structure stems from. Given $N + l$, where $l = \max(n,m)$, pairs of input-output observations, the model parameter $\boldsymbol{\theta}$ can be estimated with the least squares (LS) method:

$$\hat{\boldsymbol{\theta}} = [\boldsymbol{P}^T\boldsymbol{P}]^{-1}\boldsymbol{P}^T\boldsymbol{y} \qquad (3)$$

where

$$\boldsymbol{y} = \begin{bmatrix} y(1+l) \\ \vdots \\ y(N+l) \end{bmatrix} \quad \text{and} \quad \boldsymbol{P} = \begin{bmatrix} \boldsymbol{p}^T(1+l) \\ \vdots \\ \boldsymbol{p}^T(N+l) \end{bmatrix}$$

Once the vector $\boldsymbol{y}$ and regression matrix $\boldsymbol{P}$ are defined with input and output measurements, the solution can readily be found by modern numerical software, such as widespread MATLAB. It needs to be pointed out that the model order (i.e. m and n) need to be selected before using LS method for model parameter estimation. In practice, the well-established model order selection procedures [7] for linear system identification which have been coded and available in MATLAB System Identification Toolbox can be applied. Alternatively, the orthogonal forward regression (OFR)-based model identification methods [8], [9] can be used. With an OFR-based model identification method, the model term selection, model order determination, and model parameter estimation can be performed at the same time so that the model identification procedure can be implemented fully automatically. This will allow an automated active sensing NDT&E system to be established using a system identification based approach.

2.2. Input-Output Model Based Feature Selection and Extraction

The ARX model (1) in the last subsection is a discrete time black-box input-output model and the features of the dynamic behaviour of the underlining system are often difficult to be extracted directly from such a model. This is because of the well-known fact that the discrete time representation of a continuous time system is not unique and the parameters in the discrete time ARX model are usually not physically meaningful. However, the frequency-domain properties, such as the frequency response function (FRF) of the system will remain the same whatever form the ARX model has, as long as the model can correctly describe the dynamic behaviors of the system. This implies that the frequency domain features of the ARX model can be a better system representation for the purpose of NDE. This motivates the development of the model frequency analysis-based technique for NDE in the present study.

The FRF can be viewed as a nonparametric model of the system and its values can be evaluated using system transfer function which can be derived from the identified ARX model (1). Once the model (1) is identified, the associated FRF can then be computed over a given set of frequency points as follows:

$$H(e^{j\omega T_s}) = \frac{b_1 e^{-j\omega T_s} + \cdots + b_m e^{-jm\omega T_s}}{1 + a_1 e^{-j\omega T_s} + \cdots + a_n e^{-jn\omega T_s}} \qquad 0 \leq \omega T_s \leq \pi \qquad (4)$$

where ω is the angular frequency (radians/second) and T_s is the sampling period.

Notice that the physical frequency of interest in FRF calculation is from 0 to $f_s/2$, where $f_s = 1/T_s$(Hz) is the sampling frequency, because of the periodic and symmetrical natures of the discrete FRF. If the identified ARX model (1) can well describe the dynamic behavior of the active sensing-based NDT system under investigation, the discrete FRF $H(e^{j\omega T_s})$ computed using (4) will be a good approximation to the original continuous time FRF of the system, from which, features can be selected and extracted for defect detection.

Based on the idea above, the procedure to be used for defect detection with the new method proposed in this paper can be summarized as follows: (i) excite the NDT system under inspection using a broadband inspecting signal and collect both input (excitation) and output (response) data; (ii) identify an ARX model from the collected input-output data using the method introduced in last subsection; (iii) derive the transfer function of the system from the identified model and evaluate the associated FRF from (4); (iv) select and extract features from the computed FRF and compare them with those obtained from defect-free case for defect detection and condition monitoring. The above procedure is depicted in Figure 1 below, where the excitation in the figure is the input to an NDT system which is denoted by $u(t)$ in equation (1) and can be a square-wave in a PEC-based NDT system or a transmit pulse in an ultrasonic inspection-based NDT system, *etc*; and the response in the figure is the output of the NDT system which is denoted by $y(t)$ in equation (1), such as the eddy current picked up by a PEC probe in a PEC-based NDT system, or the acoustic reverberation signal captured by a PZT transducer *etc*. The Model Identification box in Figure 1 performs black-box input-output model identification using the input (excitation) and output (response) measurement data, or more specifically, determines the model order m and n, and estimates the parameter $\boldsymbol{\theta}$ of equation (1). The model-based FRF evaluation box in Figure 1 performs FRF computation using transfer function derived from the identified ARX model (1) in last step via equation (4) and the features for defect detection are eventually extracted from the computed FRF.

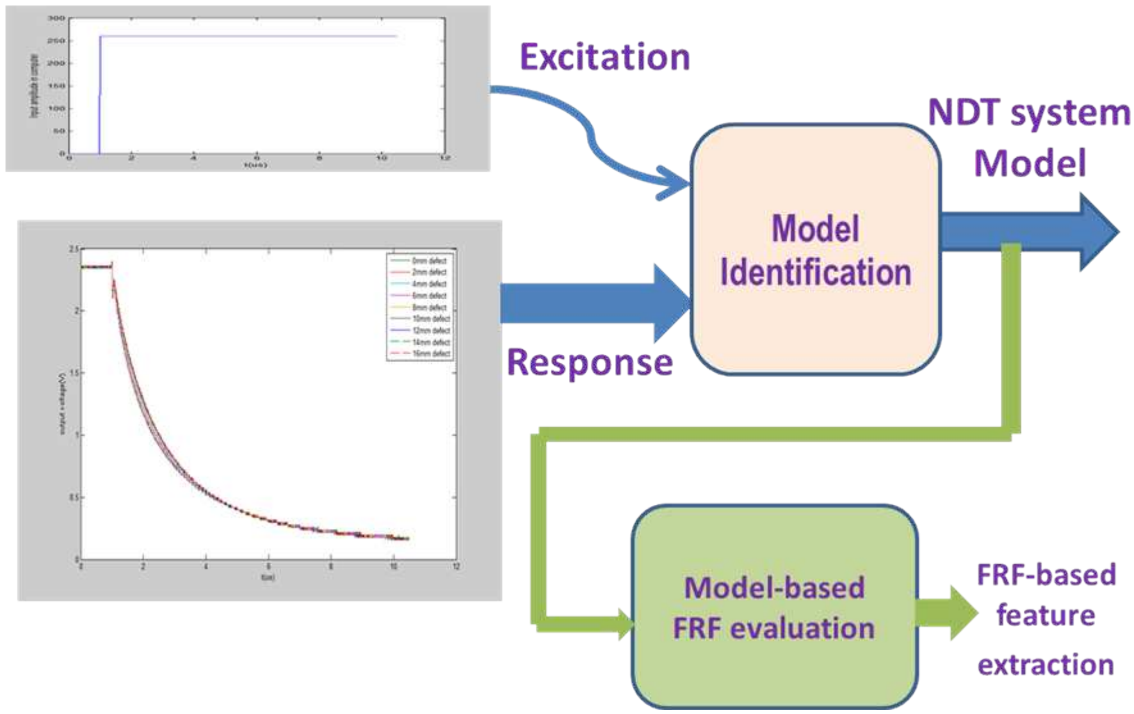

Figure 1. The procedure of system identification-based frequency domain feature extraction for defect detection with NDT techniques

2.3. Remarks

System identification technique was used for PEC system modelling in [21], where it was mainly used for modelling PEC system itself with an aim of simplifying the numerical analysis of PEC systems. Similar ideas that use both input-output data and system identification techniques for defect detection had been proposed in [10], [22] and [23], and a common point of the methods proposed in the above works was that they all took the model parameters as the features for defect detection. As such, it was assumed that the models of the NDT&E system in various faulty and fault-free cases have the same structure (i.e. the same model order and terms), though they used different types of models. For example, a parametrical continuous-time transfer function model was used in [10] and the model parameters identified from input-output data were used as features for defect detection and classification. Whereas, in the method developed in this paper, this assumption is relaxed as features for defect detection are extracted from the nonparametric model FRF derived from the identified ARX model. An added benefit of using FRF-based features instead of model parameter-based features for defect detection is that we have freedom to choose a model structure that is convenient to fit the measured input-output data, and this makes it possible for us to use a relatively simple ARX model structure for the system identification. Furthermore, the substantial interaction from the user required for identification of a continuous-time transfer function model can be avoided by applying OFR-based model identification methods [8], [9] mentioned previously in conjunction with a discrete time ARX model structure and this will facilitate the identification procedure to be implemented fully automatically.

From a signal processing point of view, the FRF evaluation via system identification as described above is equivalent to the autoregressive (AR) based parametrical spectral estimation where the signal (i.e. the response of the NDT transducer) to be analyzed is generated by the NDT system with a given input (excitation) rather than a white noise. In principle, the FRF can also be evaluated using the classical non-parametric method based on direct computation of the Fourier transform of the measured output and input signals and the FRF is obtained as the ratio between the DFT (discrete Fourier transform) of the output and the DFT of the input which can be implemented using FFT. However, this FFT-based FRF evaluation suffers from a poor frequency resolution and a large variance for a short length of data record. Short data records are common in NDT practice due to the hardware limitations, e.g. the limited memory in NDT device, power consumption limitation *etc*. In addition, the FFT-based FRF evaluation is also subject to leakage errors caused by the assumption that the data outside the measurement window is repetitive, and the best solution to avoid leakage is thus the use of periodic excitations and measurements of an integer number of periods, but this is sometimes difficult to achieve in practice and it also reduce the flexibility for users to choose the best excitation for a specific application. On the other hand, the parametrical methods work well with short data records and require much less data than the FFT-based method for the same frequency resolution. Furthermore, the leakage error of the FFT-based method can be avoided with the proposed system identification-based parametrical method and the new method does not assume that the signals outside the measurement window are periodic, hence, the use of periodic excitation is not necessary which enhances the flexibility for selection of excitation. In summary, since processing short data records is the major issue in NDT applications and the new method is developed with the intention of being able to process data from the NDT systems with different types of excitations (both periodic and non-periodic, such as step-like or impulse-like excitations), the system identification-based parametric method is employed for FRF evaluation in this paper.

The selection and extraction of features from FRF for defect detection will be problem-dependent, that is, dependent on how the dynamic behaviour of the NDT system will be changed by the defect to be detected. The features could be selected and extracted from either magnitude or phase response over a certain frequency range, and these will be illustrated in the following experimental studies.

3. Experimental study on PEC-based NDT&E for crack detection

PEC sensing has become an important NDT&E technique and been widely used in SHM system for metal loss and crack detection [5], aircraft structure hidden defects detection and quantification [11], and steel corrosion monitoring [12] amongst others. In most of the previous work, the feature selection and extraction are essentially based on the analysis of the output (response) of the PEC-based SHM system only, and the features used for defect detection are extracted either from transient analysis in the time domain, such as rising, peak and descending points of the differential response (see e.g. [4]), or from spectral analysis in the frequency domain (see e.g. [2] [3]). In the sequel, an experimental study was carried out to detect cracks in a metal plate and the new feature extraction and selection procedure developed in previous section is used for data processing and crack detection so as to verify the idea proposed and demonstrate the effectiveness of the method developed.

3.1 Experimental Setup

The experimental test piece was 3mm thick mild steel and the test procedure are shown in Figure 2. The test case was considered as a simulated growing defect in the test piece, which is 100mm long, 0.5mm wide and 2.1mm deep. To simulate a growing defect, physically a 15mm diameter pancake coil was moved along the defect in 2mm steps from a reference with no defect to the defect length which is approximately equal to the coil diameter. In practice, the sensor tag is fixed and the material under test (MUT) moves over time. The single coil PEC probe was used in the experimental test and this single coil configuration minimises the interface pins required between the sensor and microcontroller. The PEC excitation signal and the coil response were captured by a TDS2024B oscilloscope at 100MS/s. Clearly, only the transient portion of the response contains information about the MUT and, consequently, in practice the sensor tag only acquires this portion of the waveform to minimize power consumption. The complete description of the circuits used for sensor interfacing can be found in [24].

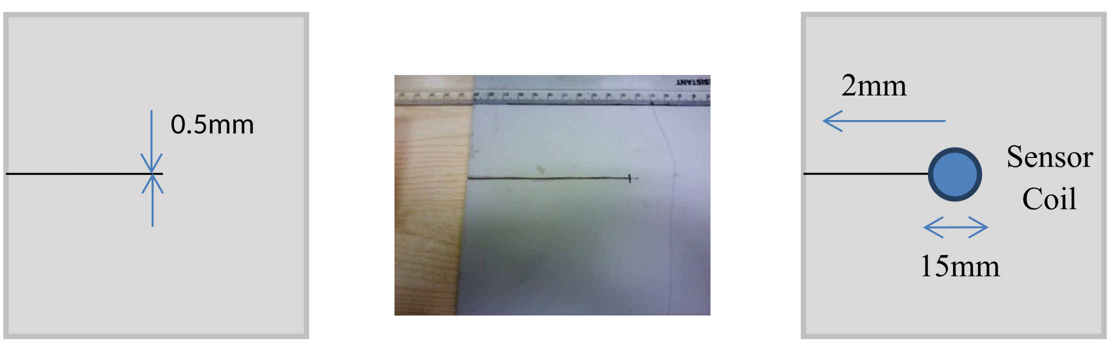

Figure 2. Test piece (left and centre) and experimental procedure (right)

Figure 3 is a schematic diagram of the experimental procedure for acquiring the input-output measurements of a PEC-based NDT system where the PEC sensing module used is shown in the left part of figure. The excitation signal (square wave) generated by the oscilloscope was applied to the PEC sensor to excite the MUT.

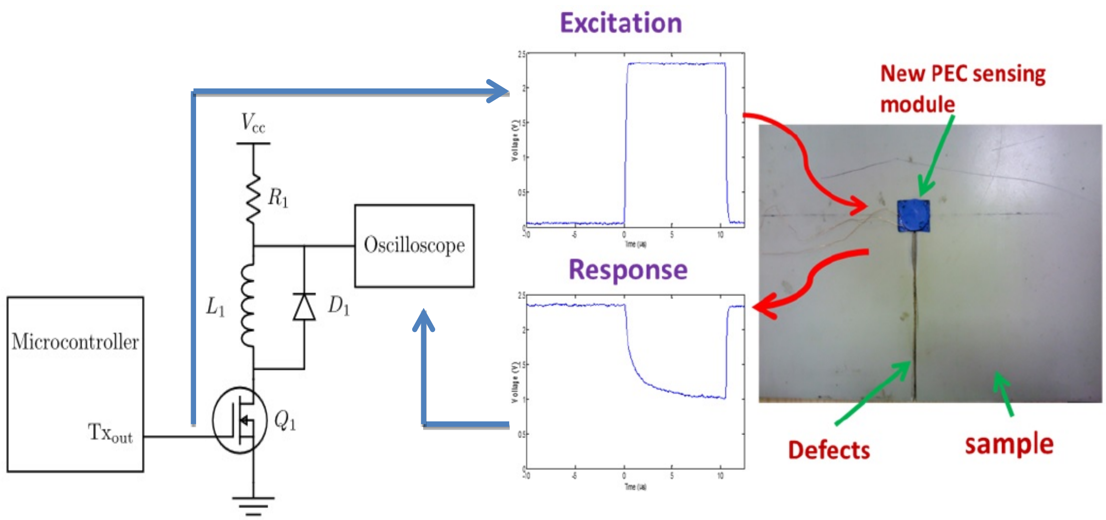

Figure 3. Schematic diagram of experimental procedure

The response of the system was also received by the oscilloscope. Both the input signal and output response of the PEC sensor were acquired by the oscilloscope as shown in Figure 3. Under the experimental set-up as described above, nine experiments were carried out on the test piece, among which the first experiment was for obtaining the reference data with crack length being 0mm (i.e. defect free condition) and the remaining 8 experiments were for acquiring data with the crack lengths starting from 2mm, with incremental step being 2mm, to 16mm respectively, therefore nine sets of input-output data were obtained.

3.2. Feature Extraction and Experimental Data Analysis Results

The new method as depicted in Figure 1 was used to process the input-output data obtained above to extract features for crack detection. Following the remark in the last section, the OFR algorithm [9], which can select model terms and estimate the associated parameters at the same time, was used for model identification so as to minimize the interaction from the user. An ARX model of form (1) with the maximum order $n = 20$ was identified for each case from the corresponding data set and the associated transfer function was then derived, from which the FRF was evaluated using equation (4) for each case, and eventually, the features for defect detection and classification was selected and extracted from these evaluated FRF.

A single-valued index is usually preferred in order to simplify the defect detection and classification. To this end and also to obtain reliable results, the area under the magnitude curve of the FRF $H\left(e^{j\omega T_s}\right)$ is selected as the single-valued index for crack detection and classification, which is defined as:

$$I = \int_0^{\infty} \left| H\left(e^{j\omega T_s}\right) \right| d\omega \qquad (5)$$

The values of index calculated from the nine data sets are shown in Figure 4. It can be seen that there exists a monotonic relationship between the index value and the crack length, and the index value increases as crack grows. This verifies the idea proposed and demonstrates the potential of the developed method for crack detection and classification.

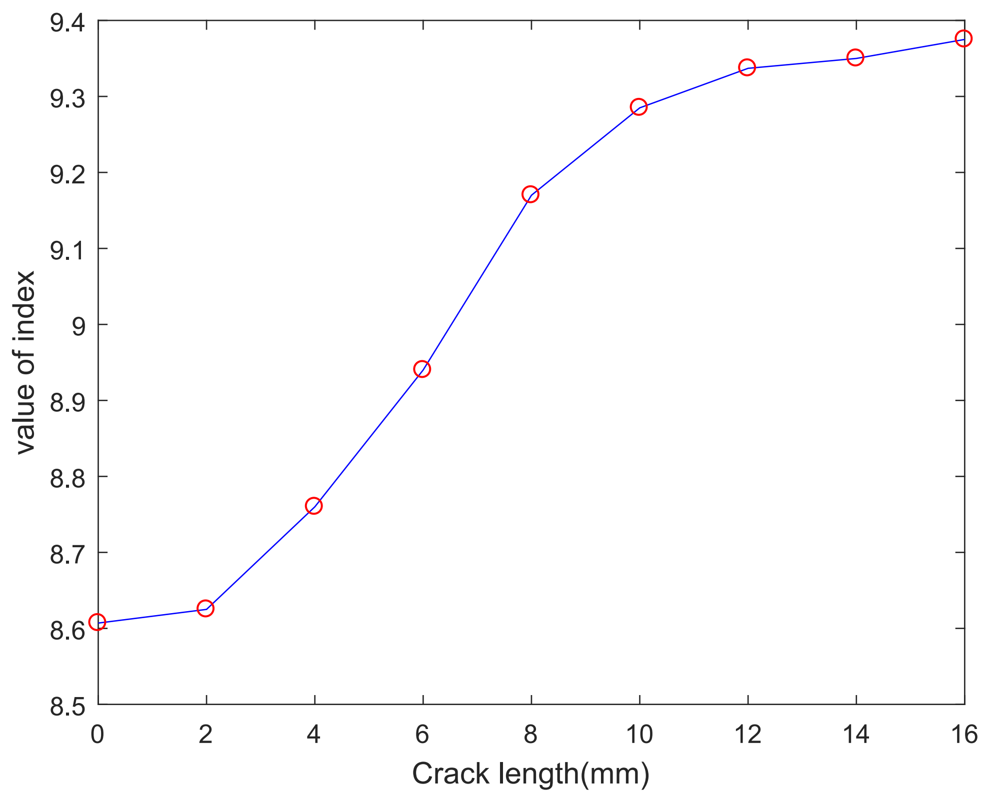

Figure 4. Index value as a function of the crack length

To compare the performance of the new method with existing method, the output signal-based max-slope method had also been used to process the data obtained. Figure 5 illustrates the basic idea behind the max-slope method (see [2], [12]) where typical PEC responses in half excitation period and the associated normalised differential response are depicted. Note that the time has been normalised to the repetition period T of the excitation. In Figure 5(a), B_{REF} is the reference response obtained from a defect-free case; B is the time response from a test case. To simplify detection process and eliminate the lift-off effect of PEC probe [18], the differential normalised response (ΔB_{norm} in Figure 5(b)) defined below is usually used, from which the features can be extracted for defect detection:

$$\Delta B_{norm} = \frac{B}{\max(B)} - \frac{B_{REF}}{\max(B_{REF})}$$

With the max-slope method, the peak value of ΔB_{norm} together with the time to the peak value have been used to characterize defect and the maximum slope, which is defined as the ratio of the peak value of ΔB_{norm} and the time to the peak value, is used as the single-valued index for defect detection. The normalized single-valued indexes from both the new method proposed in this paper and the max-slope method are shown in Figures 6-8 for comparison. In addition, the output and input measurements used for model identification with the new method have also been used for direct computation of FRF via FFT as described in Section 2.3, and the single-valued frequency domain indexes defined by (5) and calculated with the FFT-evaluated FRFs are also shown in these figures where three different windows (i.e. rectangular/or no window, hamming window and hanning window) are applied respectively for comparison.

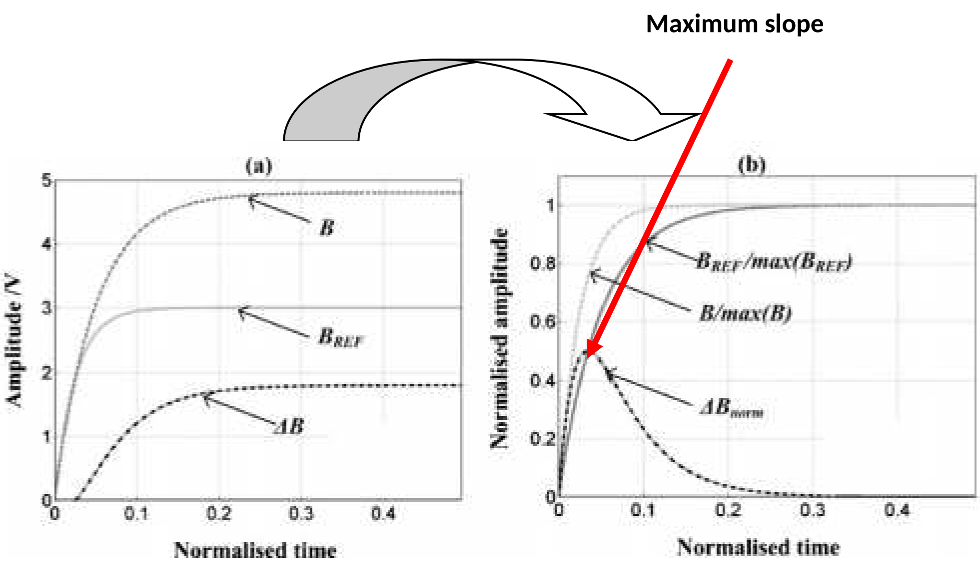

Figure 5. Time domain PEC transient responses in half period

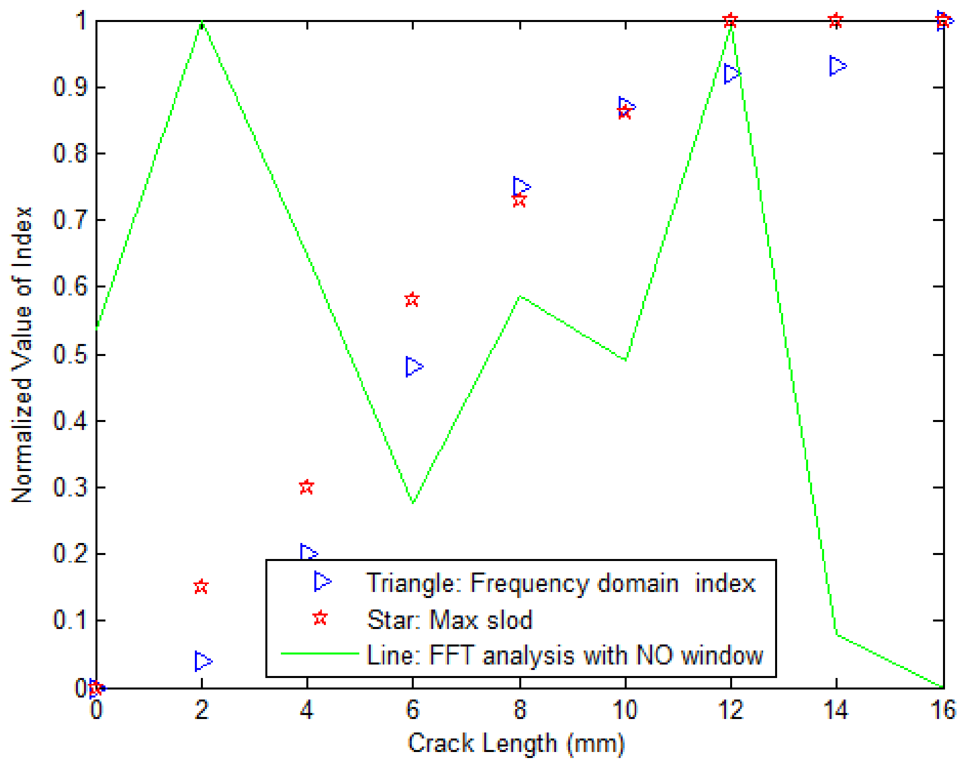

Figure 6. Comparison of the index values calculated with the new method, FFT (without window)-based method and the max-slope method

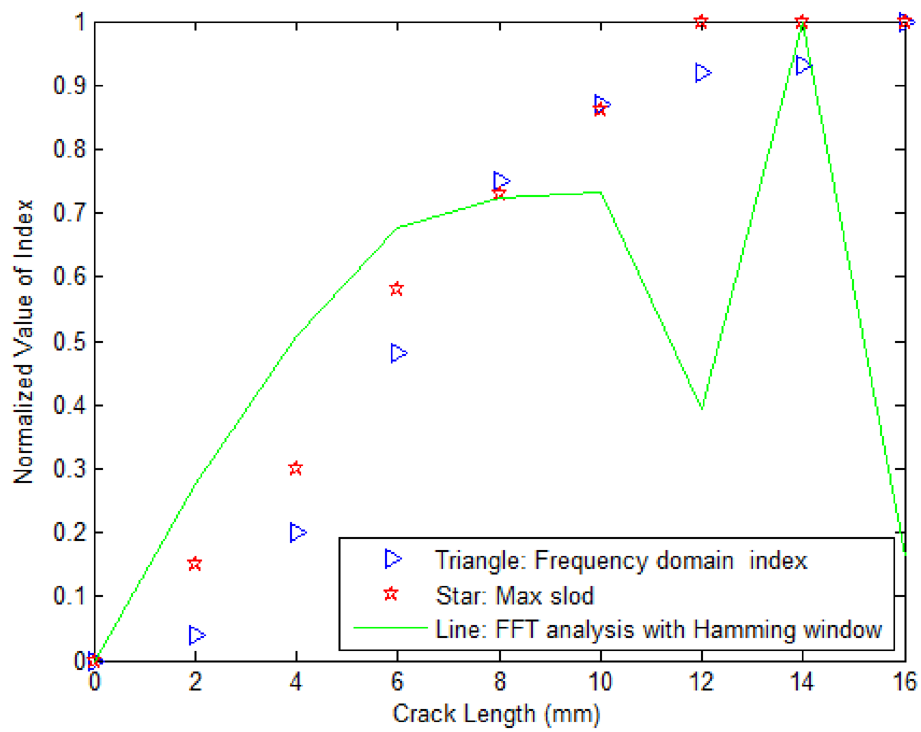

Figure 7. Comparison of the index values calculated with the new method, FFT (with Hamming window) based method and the max-slope method

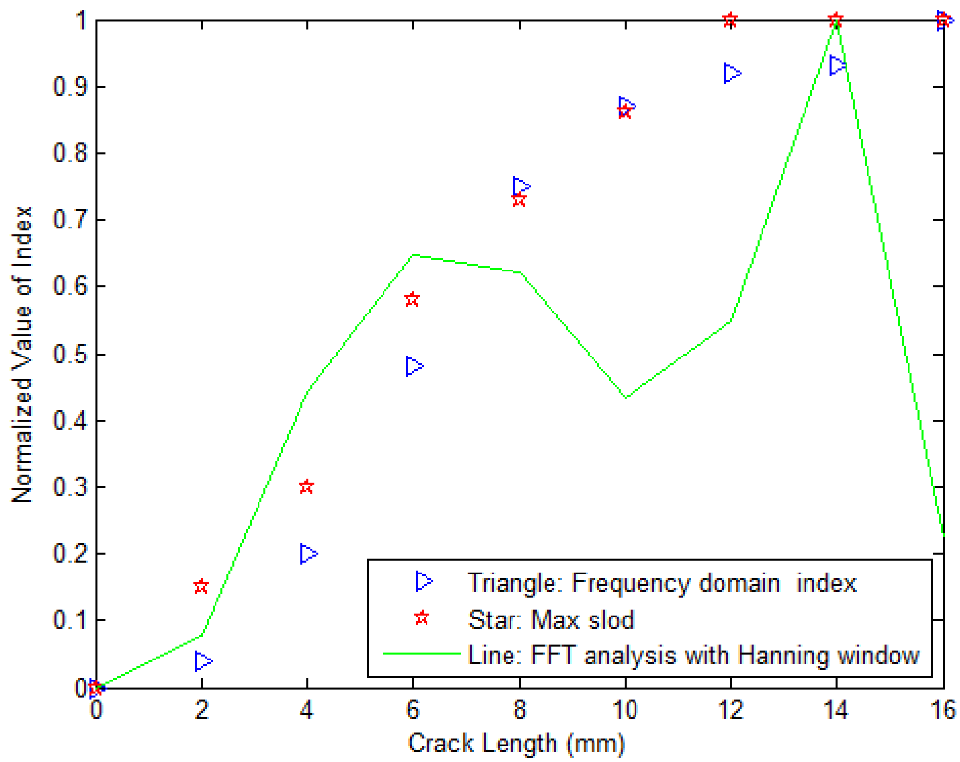

Figure 8. Comparison of the index values calculated with the new method, FFT (with Hanning window) based method and the max-slope method

It can be seen from these figures, the max-slope index saturates more quickly than the frequency domain index obtained from the new method as crack grows. The max-slope index value (represented by red star in Figures 6-8) will remain unchanged when crack length is greater than 12mm, while the frequency domain index value from the new method (represented by blue triangle in Figures 6-8) keeps increasing monotonically. The index values calculated using the FFT (without window)-evaluated FRF (represented by the green line in Figure 6) does not provide useful information for crack detection; while the index values calculated using the FFT (with window)-evaluated FRF (represented by the green lines in Figures 7 and 8) can provide information for detecting relative short crack, they cannot provide reliable information for detecting relative long crack as shown in Figures 7 and 8. This demonstrates the advantage of the new method over the existing output-only time-domain method and the direct FFT-based frequency-domain method for crack detection and classification.

4. Experimental study on corrosion detection using ultrasonic inspection

To test the applicability of the new method with different types of NDT techniques, an experimental study on corrosion detection using ultrasonic inspection is presented in this section. Ultrasonic inspection is a well-established NDT technique and has been widely used in structure health monitoring [1]. Similar to the PEC-based NDT system discussed in last section, the feature extraction in an ultrasonic inspection-based system is conventionally based on analysis of the system response signal only. The defect detection is traditionally performed with the features extracted from the differential signal (i.e. the difference between monitored response and the baseline response) [13], [14], or by correlation analysis where the monitored outputs are compared with the baseline (defect-free) output directly [15]. To demonstrate the effectiveness of the new method developed in this paper with ultrasonic-based NDT technique for defect detection, an experimental study on using a PZT transducer-based ultrasonic inspection system for corrosion detection and classification had been carried out and the associated results obtained with the new method are presented in this section.

4.1. Experimental Setup

Two samples were used for evaluation in the experiment. The first sample was 20mm thick mild steel (S275), polished on one side and shot-blasted on the other. The second sample was identical in dimension and polished on one side, but has since been exposed in marine atmosphere for 10 months of corrosion on the shot-blasted side as shown in Figure 7. The transducer is attached to the polished side and used to assess the state of the other side.

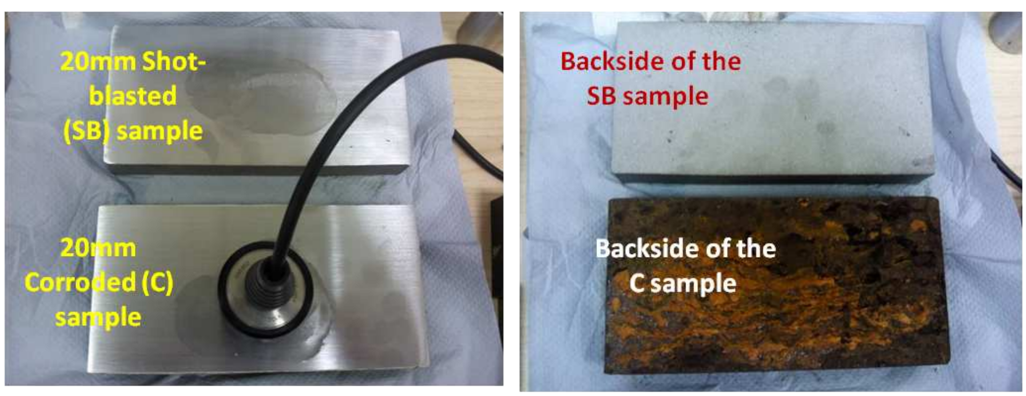

Figure 7. Material under test: coupling side (left) and evaluation side (right); shot-blasted (SB) sample (top) and corroded (C) sample (bottom)

The general arrangement of the sensor tag with a PZT payload and the hardware implementation of the experimental ultrasonic inspection system are shown in Figure 8. The microcontroller initiates a transmit pulse and a bench oscilloscope is used to capture the acoustic reverberation (i.e. response). This arrangement allows the acoustic response to be sampled well above the Nyquist frequency. Once an acquisition has been completed, the acquired data is conveyed to a PC for processing.

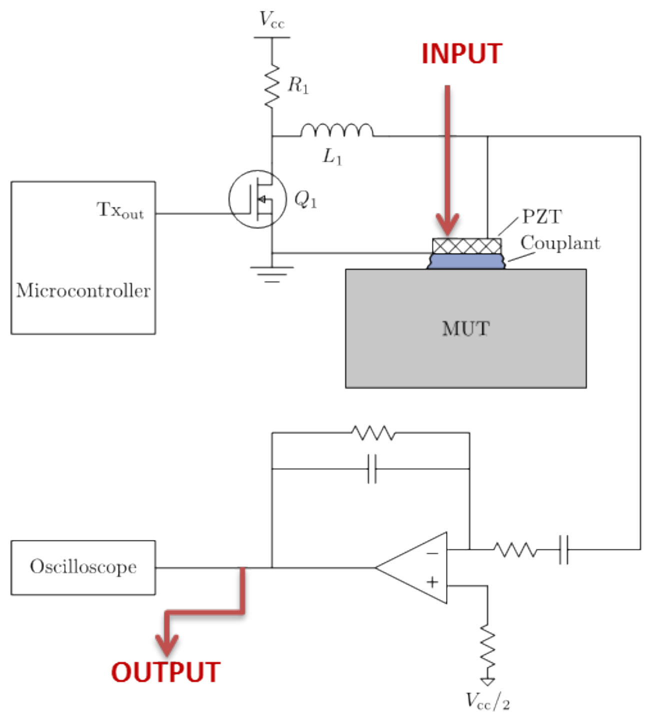

Figure 8. PZT sensor tag consisting of transmit circuitry, sensor payload, receive circuitry and the overall hardware implementation of the experimental system.

The above system was used to capture the response from 5 different positions on each sample. The ten pairs of the captured excitations (inputs) and responses (outputs) are illustrated in Figure 9.

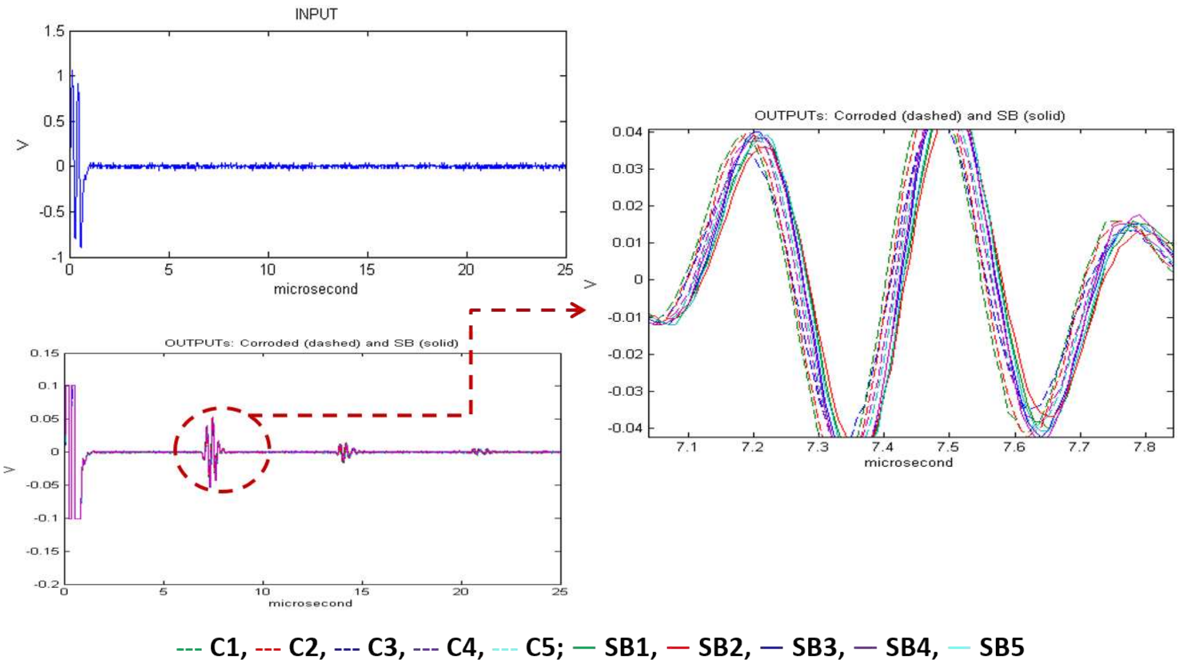

Figure 9. Captured input and output signals

The new method depicted in Figure 1 was used to process these data. Again, the OFR algorithm [9] was used for model identification so as to minimize the interaction from the user and ten ARX models of form (1) with the maximum order $n = 20$ were identified from each of ten input-output data sets. To check the quality of the identified models for describing the dynamic behaviors of the underline systems, the model predicted responses are compared with the actual measured responses and the results are shown in Figure 10.

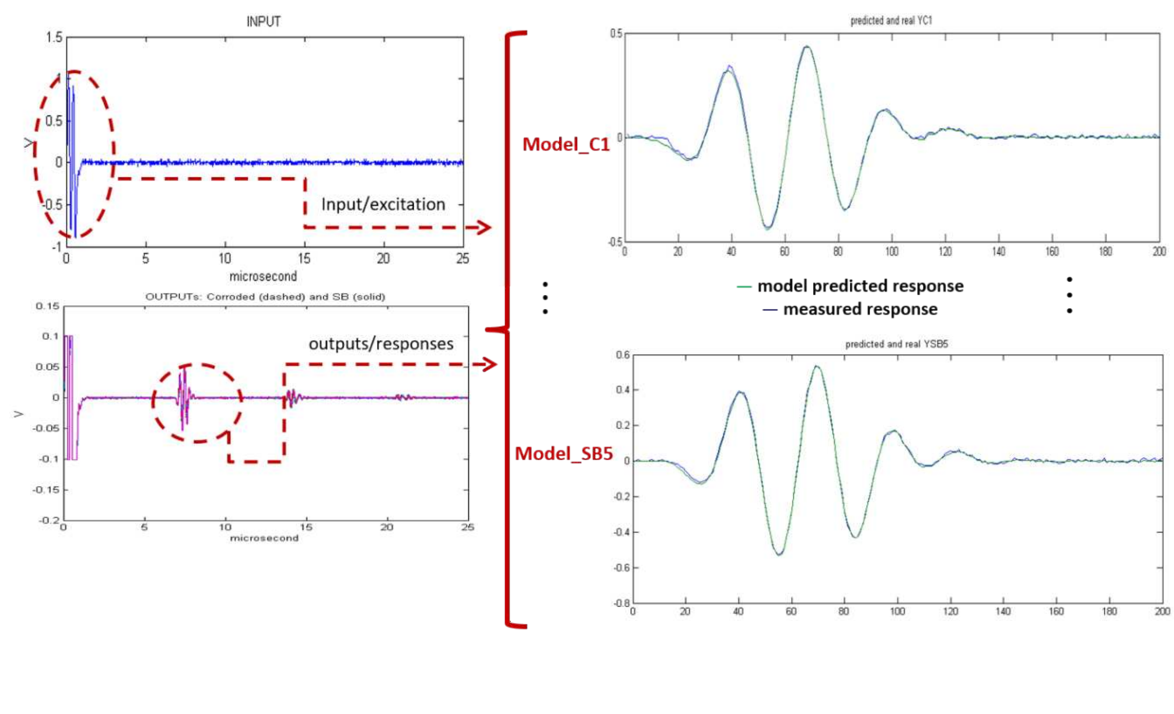

Figure 10. Results of time-domain modelling---comparison between model predicted outputs and the measured responses

It can be seen that the outputs predicted by the identified models fit quite well with the measured responses and the identified models can, therefore, be used to represent the systems under investigation for further analysis.

4.2. Feature Extraction and Experimental Results

Once the models have been identified, following the procedure illustrated in Figure 1, the system FRFs can be derived from the identified models using equation (4), and the results are shown in Figures 11 and 12.

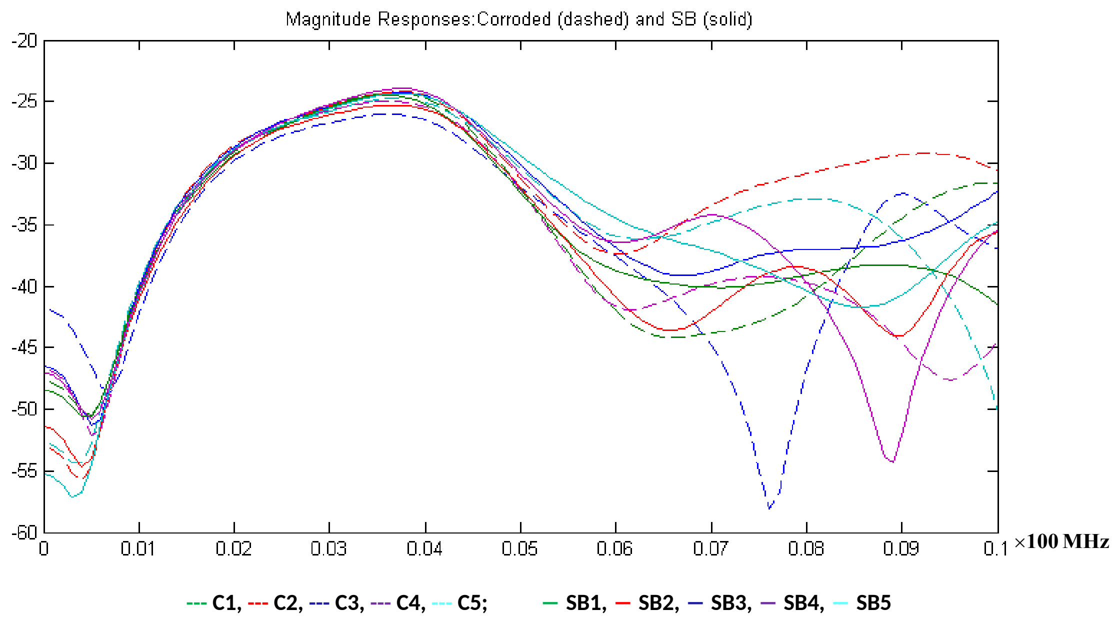

Figure 11. Magnitude curves of the FRFs computed from the identified models

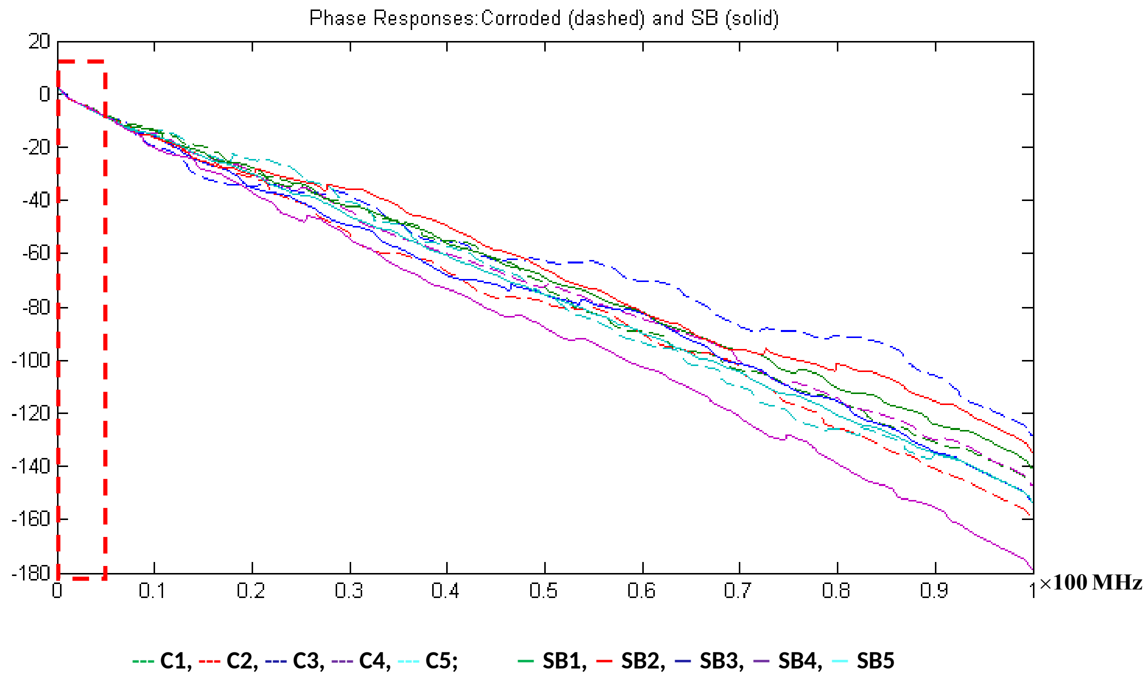

Figure 12. Phase curves of the FRFs computed from the identified models

In Figures 11 and 12, the dashed lines are FRFs obtained from the corroded (C) sample and the solid lines are those obtained from the shot-blasted (SB) samples. It can be observed that the magnitudes of FRFs derived from the identified models are, in general, not reliable indicators for the corroded/non-corroded cases as there is no obvious grouping between corroded/non-corroded cases using the magnitudes of the FRFs as shown in Figure 11. However, the variation in the phase of FRFs due to corrosion is apparent at low-frequency part (dashed box part of Figure 12), and this is shown in Figure 13 where the zoom-in of the dashed box part of Figure 12 is plotted. Hence the phase of the FRF derived from the identified model can be selected as the feature for corrosion detection with the above ultrasonic inspection-based SHM system.

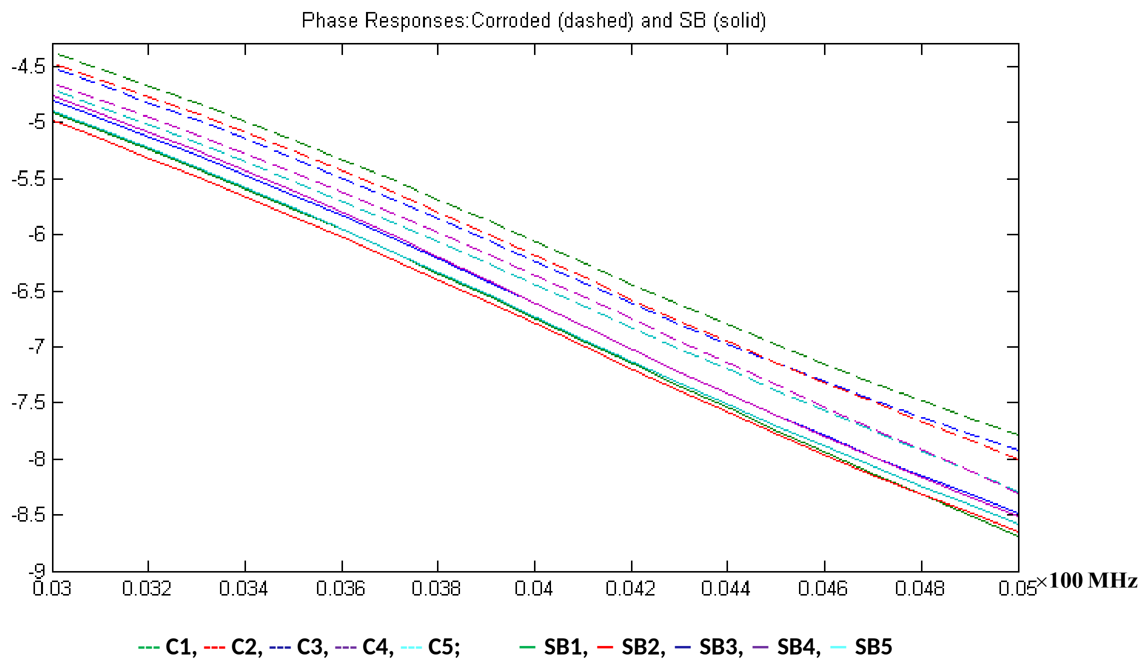

Figure 13. Low-frequency phase curves of the FRFs computed from the identified models

To facilitate detection, the sum of phase angles of the FRF over the frequency range between 3MHz to 5MHz is defined as a single-valued index for corrosion detection. The calculated index values of the FRFs derived from the identified models of the corroded and shot-blasted samples with each sample inspected at five different locations are summarized in Table 1 below.

Table 1. Index values for corrosion detection

sample	corroded sample (C)					shot-blasted sample (SB)				
position	C2	C3	C1	C5	C4	SB5	SB1	SB4	SB2	SB3
index value	-124.01	-126.67	-127.34	-130.82	-132.12	-135.18	-135.50	-137.70	-138.22	-139.22

It can be seen from Table 1 that, in general, the phase lag from the corroded sample is smaller than that from the shot-blasted (i.e. non-corroded) sample and this property of the derived FRF can be used for corrosion detection and characterization.

5. Conclusions

The problem of feature selection and extraction for defect detection and characterization using NDT techniques has been investigated and an input-output model based feature extraction and selection method using system identification technique has been developed for defect detection and characterization in this paper. The main novelty of the proposed solution is that we consider the problem of feature extraction from a system perspective and the features are extracted using both the input and output signals rather than output (i.e. response) signal alone. The new approach provides a general and flexible framework to select and extract features from the system FRF derived from an input-output parametric dynamical model identified using both system input and output data. This is in contrast with the previous methods, where the feature selection and extraction are based on analysis of the system output (response) only. Hence, the new method does not require that the excitation to be used in test is the same as that used in obtaining reference/or baseline response as long as the excitation to be used is persistently exciting of certain order (see e.g. [7]), i.e. it contains sufficiently many distinct frequencies that cover the relevant dynamical modes of the NDT system. This provides a much appreciated flexibility for users, so that the best excitation can be selected for a specific application. The core elements in the new method are the routines for ARX model identification and the associated FRF evaluation which are well-established in control system society, and can be used in conjunction with different types of NDT techniques. In addition, as the FRF represents the inherent characteristics of the inspected system, the defect detection results obtained using the new method can potentially be more robust to the impacts of various disturbances including noises. The new method developed has been applied to process the data from two experimental studies for defect detection using different types of NDT techniques, which verify the idea behind the new method developed and demonstrate the potential of the new approach in NDT&E-based SHM applications. It opens research using control engineering-based method to improve the NDE techniques.

It needs to be pointed out that the linear relationship between excitation and response of the SHM system under investigation has been assumed throughout the current study, if nonlinearity in this relationship is significant, the new method may not work. However, it is possible to extend the idea behind the new method developed to the nonlinear case and a potential solution to the problem is to use the NARMAX (Non-linear AutoRegressive Moving Average with eXogenous input) modelling method [16] [8] [9], instead of using an ARX model structure for model identification as described in this paper. In addition, the Nonlinear Output Frequency Response Function (NOFRF) [17], which can be evaluated from the identified NARX model, needs to be used for describing the frequency-domain characteristics of the nonlinear SHM system under investigation as the linear FRF is not adequate to define the frequency-domain properties of a nonlinear system. The features for defect detection and characterization will then need to be selected and extracted from the NOFRF derived from input-output data. Further research aiming to address these issues and application of the new method in combination with other types of NDT technique, such as radio frequency identification (RFID) sensor-based feature extraction [19], [20], are currently being carried out by the authors.

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