Wavelet-based PCA defect classification and quantification for pulsed eddy current NDT

G.Y. Tian, A. Sophian, D. Taylor and J. Rudlin

Abstract: A new approach for defect classification and quantification by using pulsed eddy current sensors and integration of principal component analysis and wavelet transform for feature based signal interpretation is presented. After reviewing the limitation of current parameters of peak value and its arrival time from pulsed eddy current signals, a two-step framework for defect classification and quantification is proposed by using adopted features from principal component analysis and wavelet analysis. For defect classification and quantification, different features have been extracted from the pulsed eddy current signals. Experimental tests have been undertaken for ferrous and non-ferrous metal samples with manufactured defects. The results have illustrated the new approach has better performance than the current approaches for surface and sub-surface defect classification. The defect quantification performance, which is difficult by using current approaches, is impressive.

1 Introduction

Non-destructive testing (NDT) technologies have wide applications in the transportation, aerospace, automotive, manufacturing, petrochemical, and defence industries [1]. Particularly, eddy current NDT has been used for metal inspection for more than four decades with the distinct advantages for these particular applications. NDT requires detection, classification and quantification of defects to meet safety standards, and calculations of structural safety. Accurate characterisation of surface and sub-surface flaws still poses a major challenge [2].

One of the recent developments in eddy current NDT techniques is the emergence of pulsed eddy current (PEC) techniques [3]. These techniques, in contrast to the conventional techniques that use a single frequency excitation, use a pulsed coil excitation. The pulsed excitation is comprised of a spectrum of frequencies, which allows simultaneous inspection to different depths of the target owing to the skin effect. This enables the detection and characterisation of flaws at the surface and sub-surface. Interpretation techniques are required to translate the transient response from pulsed eddy current sensors into useful information. These techniques have the potential advantages of greater penetration, the ability to locate discontinuities from time-of-flight determinations and a ready means of multi-frequency measurement. However, the lack of interpretation techniques is one of the main reasons why PEC sensing is not widely used by the NDT community [4]. This difficulty can be overcome by using the recent advances in computing power and signal processing techniques, and already a number of different approaches on interpreting the eddy current sensor response using advanced signal processing techniques such as independent component analysis (ICA) and pattern recognition techniques have been proposed [5, 6].

The rest of the paper is organised as follows. In the following Sections, a new approach of defect classification and quantification based on principal component analysis (PCA) and wavelet transforms (WT) for our PEC system [7] is presented. Sections 2 and 3 introduce the PCA and wavelet transform for the PEC signals. Section 4 reports using the new data analysis for defect classification and quantification. Following the proposed approach, experiments and results are presented. Finally, conclusions and further work are outlined.

2 PCA

PCA is extensively used in feature extraction to reduce the dimensionality of the original data by a linear transformation. PCA extracts dominant features (principal components) from a set of multivariate data. The dominant features retain most of the information, both in the sense of maximum variance of the features and in the sense of minimum reconstruction error. PCA is widely used in face recognition [8–10]. It is also used in vehicle sound signature recognition [11], speech recognition [12], speaker recognition [13], medical applications [14–16], signal noise reduction [17], and active noise control [18], among others.

The suggested approach in this paper has been adopted from a feature extraction technique for face recognition [9]. It requires training where a data set from various testing conditions is required as input. In this case, the data will be PEC time-series signals from various different flaws, and a few signals recorded for each flaw. To obtain the principal components or eigensignals, each data set from an observation is formed into a column vector, $\boldsymbol{\Gamma_n}$, whose length $\boldsymbol{N}$ is dependent on the number of variables used. For $\boldsymbol{M}$ observations, an array matrix $\boldsymbol{\Gamma}$ with the size of $\boldsymbol{M} \times \boldsymbol{N}$ will be obtained, hence

$$\boldsymbol{\Gamma} = [\boldsymbol{\Gamma}_1, \boldsymbol{\Gamma}_2, \boldsymbol{\Gamma}_3, \ldots, \boldsymbol{\Gamma}_M] \tag{1}$$

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The average signal $\bar{\boldsymbol{\Gamma}}$ is defined by:

$$\bar{\boldsymbol{\Gamma}} = \frac{1}{\boldsymbol{M}} \cdot \sum_{n=1}^{\boldsymbol{M}} \boldsymbol{\Gamma}_n \tag{2}$$

Difference signals are computed by subtracting the average signal from each training signal:

$$\boldsymbol{\Phi}_i = \boldsymbol{\Gamma}_i - \bar{\boldsymbol{\Gamma}} \tag{3}$$

These vectors are now subjected to principal component analysis. To find the orthogonal eigensignals, the covariance matrix $\boldsymbol{C}$ should be worked out:

$$\boldsymbol{C} = \frac{1}{\boldsymbol{M}} \sum_{n=1}^{\boldsymbol{M}} \boldsymbol{\Phi}_n \cdot \boldsymbol{\Phi}_n^T = \frac{1}{\boldsymbol{M}} \boldsymbol{A} \cdot \boldsymbol{A}^{\boldsymbol{T}} \tag{4}$$

where $\boldsymbol{A} = [\boldsymbol{\Phi}_1, \boldsymbol{\Phi}_2, \ldots, \boldsymbol{\Phi}_M]$.

However, the determination of the eigenvectors for covariance matrix $\boldsymbol{C}$ will require excessive computation as the matrix $\boldsymbol{C}$ will have the size of $\boldsymbol{N} \times \boldsymbol{N}$. A better way is considered. If $\boldsymbol{v}_i$ are the eigenvectors of $\boldsymbol{A}^{\boldsymbol{T}} * \boldsymbol{A}$ and $\boldsymbol{\mu}$ are the eigenvalues:

$$\boldsymbol{A}^{\boldsymbol{T}} \boldsymbol{A} \boldsymbol{v}_i = \boldsymbol{\mu}_i \boldsymbol{v}_i \tag{5}$$

then the eigenvectors of $\boldsymbol{C}$ can be computed by:

$$\boldsymbol{u}_i = \boldsymbol{A} \boldsymbol{v}_i \tag{6}$$

where $\boldsymbol{C} = \boldsymbol{A}^{\boldsymbol{T}} * \boldsymbol{A}$. These $\boldsymbol{u}_i$ are referred to as eigensignals. Having obtained the eigensignals, the most significant $\boldsymbol{M}$ eigensignals are chosen according to the largest corresponding eigenvalues. Any signal can be identified as a linear combination of the eigensignals. The principal components for any signal $\boldsymbol{\Gamma}$ are defined by:

$$w_k = u_k^T (\boldsymbol{\Gamma} - \bar{\boldsymbol{\Gamma}}) \tag{7}$$

The value $\boldsymbol{w}_k$ represents the data mapped into the axis corresponding to the eigenvector. These values are the new features that can be used for classification and recognition purposes, and in our case, they might correlate with quantities to be measured. Signals can be presented by a linear combination of eigenvectors, where the number of eigenvectors will decide the accuracy of the signal reconstruction. To illustrate how the feature extraction can be presented by lower dimensional vectors, two main eigenvectors are chosen.

3 Wavelet transforms

Wavelet analysis is a relatively new technique in signal processing. The fundamental idea behind wavelet analysis is to analyse according to scale, therefore both coarse and fine features of a data signal can be probed [19]. The analysis is done in both time and frequency domains, while the similar and widely used Fourier analysis only provides a frequency aspect. This extra ability makes wavelet analysis suitable to analyse transient phenomena in a signal.

Wavelet analysis is presently used in various applications, including astronomy [19], classification of washing machine vibration signals [20], speech recognition [21, 22], fingerprint recognition [23], engine diagnosis [24], condition monitoring [25, 26], and medical applications [27, 28] among others.

The wavelet transform (WT) performs the decomposition of a signal onto the family of wavelet functions generated from a prototype function, called the mother wavelet, $\Psi(t)$ by dilation and translation operations [29]. The wavelet transform of a signal $f(t)$ can be computed by using the following equation:

$$c_{a,b} = \int_{-\infty}^{\infty} f(t) \Psi_{a,b}(t) dt \tag{8}$$

where a and b are scale and space parameters, respectively. The signal can be decomposed into orthogonal subspaces, each containing information about details at a given resolution. The mother wavelet is constructed from the scaling function $\phi(t)$. More details can be found in [29].

Wavelets can be used to pre-process data in order to better locate and identify significant events [30]. PCA is a statistical process for feature extraction by reducing the data dimensionality using orthogonal basis. Combining this type of data pre-processing with multivariate statistics can generate useful insights into the problem of data analysis and data interpretation. The integrative approach treats a time signal as if it were made up from numerous individual signals of limited duration (the wavelets). The wavelets occur at various times; they are characterised by their location on the time axis and by their resolution (their duration is short for a high resolution, long for low resolution). The wavelet transform is a series of coefficients indicating the amplitude of each of the wavelets. PCA will be applied to these coefficients, which is proposed for defect classification and quantification in the following Sections.

4 Defect characterisation

In the characterisation of defects, three stages have been proposed. Defect detection is the first stage where a feature threshold is set to conclude whether the part of the sample being tested has a discontinuity or not. If a discontinuity is predicted then the second stage, defect classification, is carried out. Here, the discontinuity is classified to a defect class, such as surface cracks and sub-surface cracks. This stage is important as it allows accurate defect sizing at the following stage. Subsequently, the sizing or the quantification of the defect is performed to gain information about the severity of the detected defect. Figure 1 shows the stages in defect characterisation. Following all the information, a decision is made whether the material or structure under test can still be operating safely or if repair work must be scheduled, or even if a replacement must be obtained.

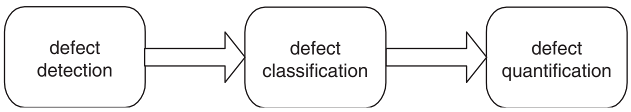

Fig. 1 *Defect characterisation stages*

In the proposed approach, in order to be able to provide both the defect type and size, hierarchical PCAs are used to analyse the PEC signals as illustrated by the block diagram shown in Fig. 2. As shown in the diagram, in general the whole process is divided into two stages; first, the class of flaw is defined, and second, the size of the flaw is defined. Each stage will comprise of similar steps, which include wavelet transforms and PCA.

The steps in each stage have been shown in the block diagram in Fig. 3. The motivation for the integration of PCA and WT is for better extraction of defect information. The wavelet transform naturally separates the high frequency noise and also allows extraction of specific frequency components relevant to the penetration of the eddy current. The differential approach improves the sensitivity of defect quantification and discriminability of

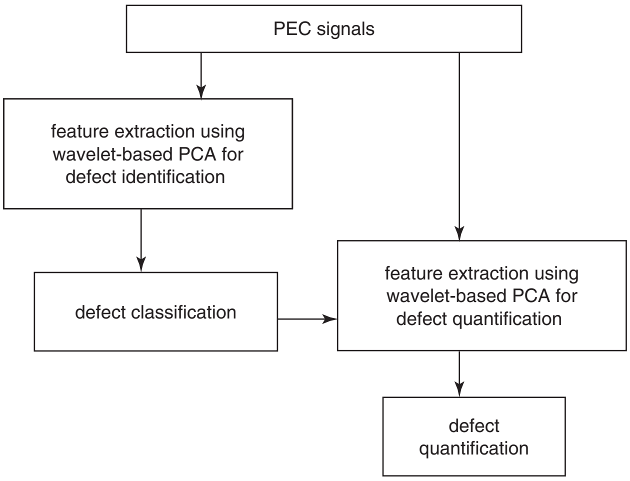

Fig. 2 *Flow diagram of the new approach*

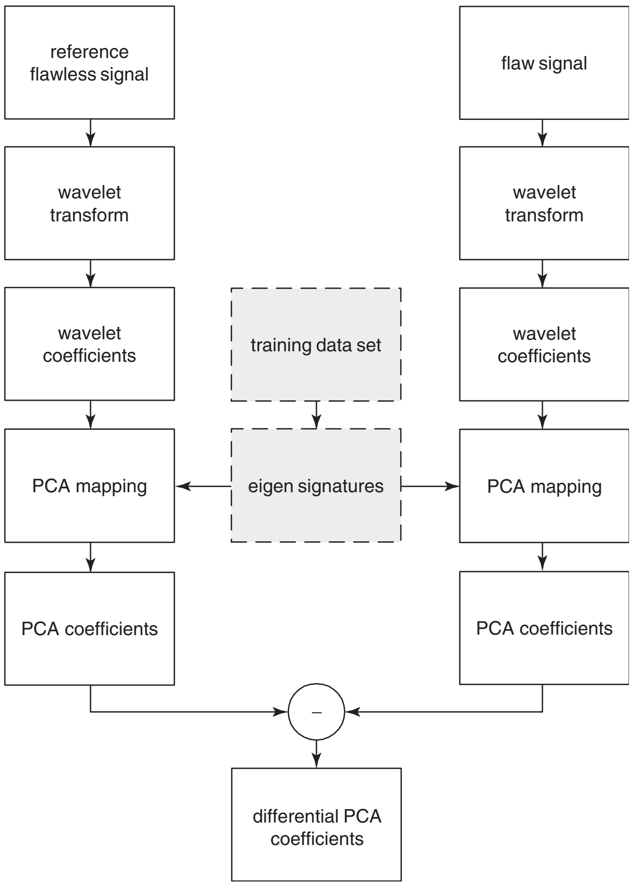

Fig. 3 *Flow diagram of the wavelet-based PCA for defect classification/quantification*

defect classification. The processes in the shaded boxes are performed off-line, while those in boxes with solid lines are performed on-line. Off-line processes are undertaken before the actual inspection is carried out. These include setting up a training data set by recording signals representing relevant flaws and a flawless part. After calculating the wavelet coefficients of the signals, using the steps described in Section 2, the eigensignals or PCA basis are generated and ready to be used in the on-line processes.

On-line processes are performed during the actual inspection of a given sample. They start with recording a reference signal from a flawless part of the sample. The wavelet transform is then applied to the signal generating wavelet coefficients at appropriate levels, which are discussed in the following two Sections. Subsequently, PCA mapping is carried out by basically summing the weighted wavelet coefficients, while the weightings are given by the pre-recorded eigensignals. This results in PCA coefficients representing the reference signal. Then, the same steps apply to the flaw signal resulting in PCA coefficients representing the flaw signal. Finally, differential PCA coefficients are worked out by finding the difference between the two sets of PCA coefficients representing the reference and flaw signals. The differences between the wavelet-based PCA for flaw classification and that for flaw quantification are described separately as follows.

4.1 Defect classification using wavelet-based PCA

At this stage, it is attempted to assign a detected flaw to a defect class. The conventional feature extraction technique for PEC is based on the peak characteristics of PEC differential signals [1] that are obtained by subtracting a defect-free signal from flaw signals. Figure 4 shows some typical examples of these signals. The peak value and time are used to classify detected defects. These two features are not sufficient for in-field inspection, the features can easily become ineffective owing to noise interference and lift-off variation. Secondly, more information is often required for quantification purposes.

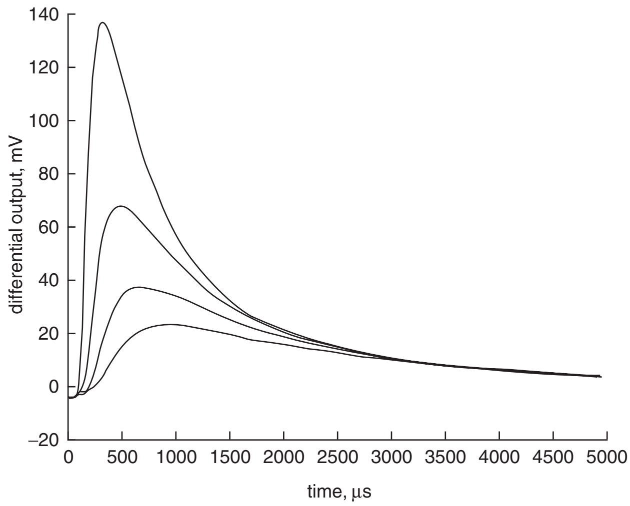

Fig. 4 *Typical PEC differential signals*

For the proposed technique using wavelet-based PCA, the training data set is comprised of signals representing flaws of different types, which may include, for example, surface defects, sub-surface defects, and metal losses. Figure 5 illustrates the first two eigensignals of test sample signals for flaw classification. The mother wavelet chosen for simplifying the implementation is the Morlet wavelet because it is known to provide better localisation, both spatial and frequency, although a redundant wavelet transform may be better for this type of work [31]. The two eigensignals are clearly unrelated. The first eigensignal's local maxima and minima points highlight the points in time where the major differences are taking place among the training signal wavelet coefficients. From the point of wavelet analysis, it is noticed that good discrimination is achieved when high levels (low resolution wavelet coefficient bands) are used. This is as

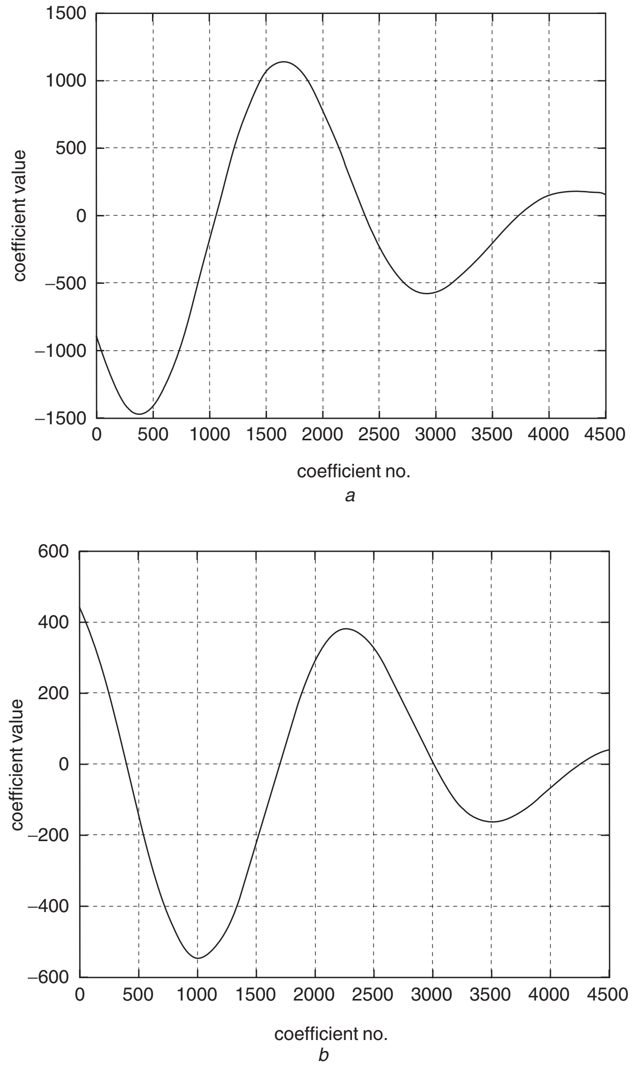

Fig. 5 *Examples of wavelet-based PCA basis for flaw classification*

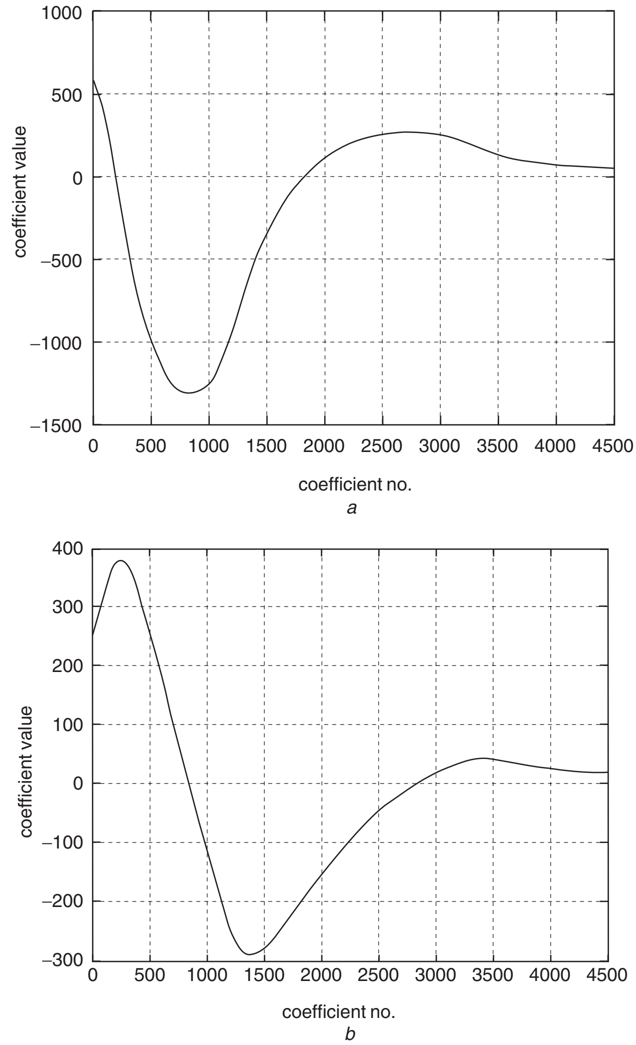

Fig. 6 *Examples of wavelet-based PCA basis for flaw quantification*

expected as these levels correspond to low frequencies that are required to achieve deep penetration.

4.2 Defect quantification using wavelet-based PCA

In contrast to the wavelet-based PCA for flaw classification, the training data set is comprised of signals representing flaws of the same type and of various sizes. Figure 6 illustrates eigensignals for flaw quantification. This stage is carried out once the type of the flaw is already identified from the defect classification. For example, this should produce estimation of the depth of the flaw for sub-surface defects or the sizes of surface defects. The levels of wavelet transform are variable depending on the flaw type and its expected range of sizes.

The eigensignals in Figs. 5 and 6 give high weightings at the beginning of the signals, i.e. coefficients numbered between 1 and 1000 approximately. The timing or locations of these high weightings seem to correspond to the peaks of the signals in time domain. The features obtained using this technique for maximising the discriminability or sensitivity for quantification may be combined with the conventional time-domain features of peak time and peak values from differential signals.

For the conventional technique, the peak arrival time mainly indicates the depth of defects.

5 Experimental setup

To evaluate the performance of the proposed technique, comparative experiments are carried out. Both techniques of the proposed wavelet-based PCA and conventional peak-value features for defect classification and quantification are used to analyse the same signals obtained from ferromagnetic and non-ferromagnetic materials in two separate experiments. For the non-ferromagnetic material, aluminium is chosen, and for the ferromagnetic, a carbon steel is chosen. For each material, two samples are prepared: one sample to simulate metal loss defects, and the other for surface and sub-surface defects. The aluminium samples are shown schematically in Fig. 7. For sub-surface slot detection, we probe the sample shown in Fig. 7*b* over its top surface, and for surface slots, we probe over the reverse side.

The steel samples have similar layouts but have different sizes of defects. Magnetisation is used during steel inspection to reduce the effective relative permeability and reduce the magnetic property variation. The setup is shown in Fig. 8.

In the experiment, both the conventional and the proposed approaches are used to classify the defects. It will also be shown how the new method performs quantification of defects having classified the detected defects. Initially, a training data set is created by recording signals from all available defects. Ten signals are recorded for each defect.

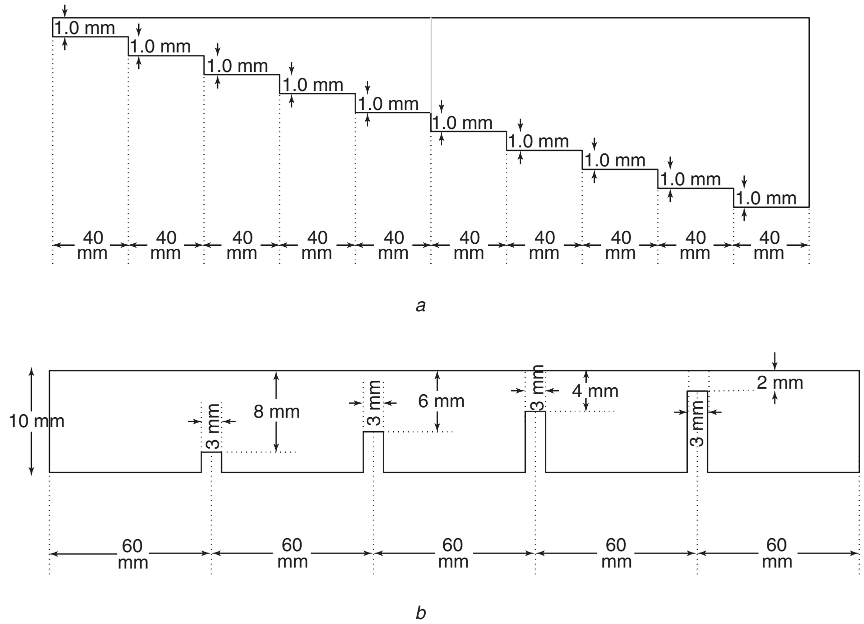

Fig. 7 *Specimens*
a Metal loss
b Surface and sub-surface slots

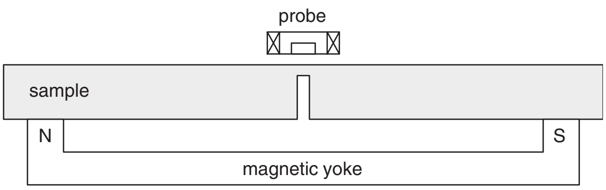

Fig. 8 *Steel magnetisation setup*

6 Results

6.1 Aluminium testing

6.1.1 Classification: Figure 9 shows how classification has been achieved using both techniques. It demonstrates how the two techniques have achieved separation of the detected defects according to their types qualitatively. Table 1 shows quantitatively the classification success rate using both techniques, where all the samples are calibrated. It can be seen that the wavelet-based PCA performs better with a higher number of correct identifications. The lower success rates of the approach using the peak values and arrival times is attributed to its higher sensitivity to noise. The rates are derived after five measurements are taken for each defect described in the preceding Section.

6.1.2 Quantification: Both techniques can be used to achieve defect sizing as illustrated in Fig. 10. The advantage of the peak value and the time at the peak value is that it allows faster processing by simple computation. However, the repeatability is poor, especially when the defect is buried deeply. In contrast, the robustness of wavelet-based PCA for the defect quantification is much better than the conventional approach; the 3-D distribution is particularly useful for defect quantification.

6.2 Steel testing

6.2.1 Classification: The classification cannot be achieved by using the conventional peak-value features as

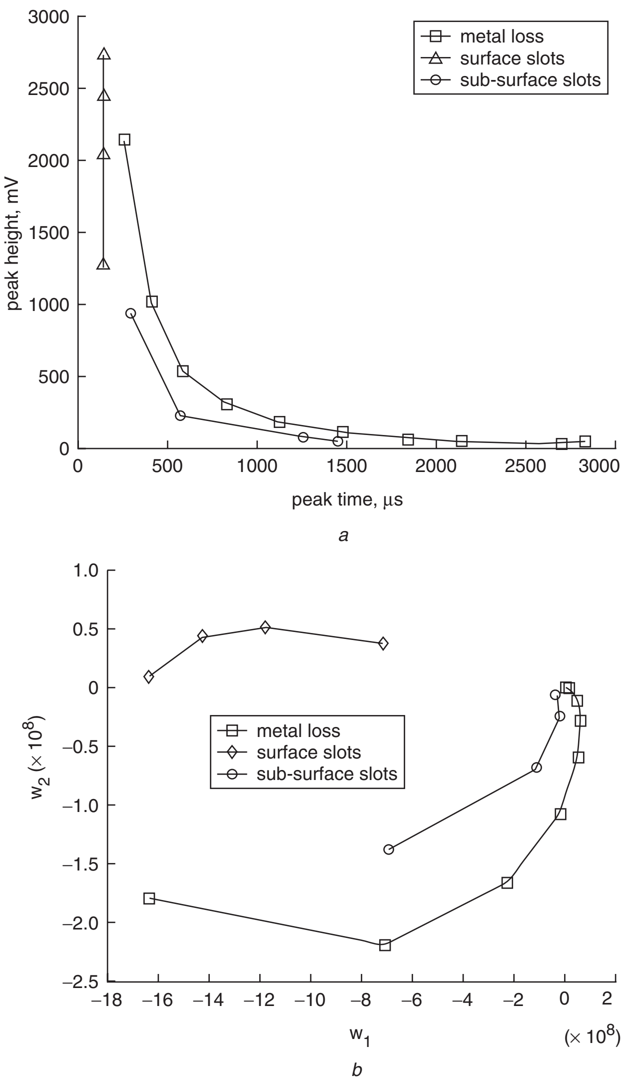

Fig. 9 *Defect classification*
a Using peak value and time
b Using wavelet-based PCA

Table 1: Classification rates using both techniques

	Correct identification rate (%)			
	Surface slot	Sub-surface Slot	Sub-surface metal loss	No defect
Wavelet-PCA	100	95.0	97.7	100
Peak value and the time	100	90.0	88.9	40.0

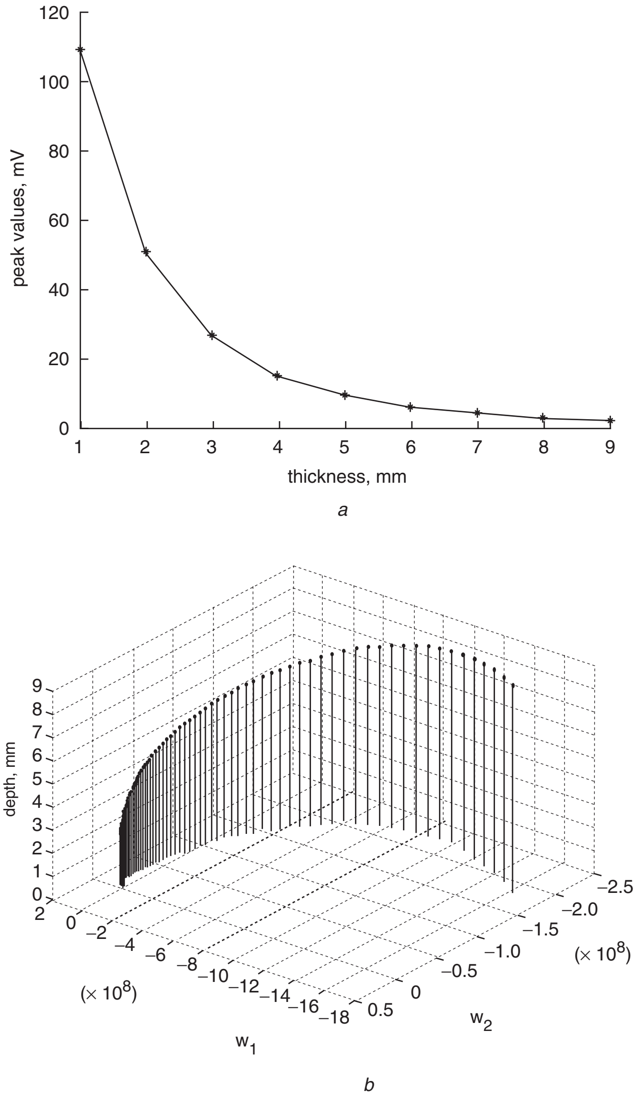

Fig. 10 *Defect sizing*
a Peak value against sample thickness
b Wavelet-based PCA coefficients against sample thickness

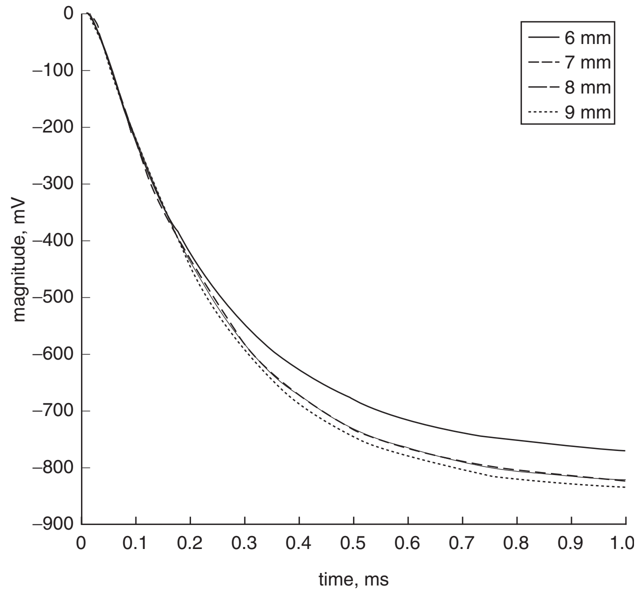

Fig. 11 *Differential signals for steel samples by using magnetisation*

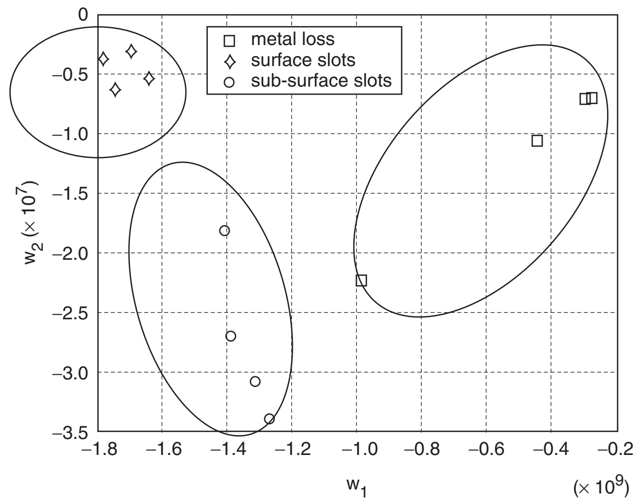

Fig. 12 *Defect classification using the wavelet-based PCA technique*

the differential signals do not have local maxima as shown in Fig. 11. The ferromagnetic steel samples amplify the magnetic field measured as they reduce the resistance of the magnetic circuits. Therefore, the presence and absence (e.g. slot) of the material alters the resistance and hence the measured magnetic field intensity. This is in contrast to the situation where the aluminium samples are used. In this case, the intensity will be constant provided the eddy current has disappeared regardless of the presence or absence of the material. The variation of the field intensity in the steel samples leads to the non-existence of the peak in the differential signals rendering the approach unusable. However, good separation can be achieved by using the proposed wavelet-based PCA as shown in Fig. 12. The defects of different types have been clustered correctly according to their type.

6.2.2 Quantification: For quantification of defects in steel samples, a new approach is proposed. The measured base signals representing the magnetic field intensity are normalised to its amplitude prior to the calculation of the differential signals. In this way, the magnetic field intensity variation owing to the variation in the resistance of the magnetic circuit is suppressed. The differential signals for steel samples under magnetisation calculated using this approach are illustrated in Fig. 13. For the classification, the peak time and value-based technique fails. The proposed technique, however, produces discernable features from negative peaks with magnitude and the time of peak value, which have correlation with the sizes of defects. Experiments have shown that the quantification of defects is strongly correlated with the calibrated data of samples.

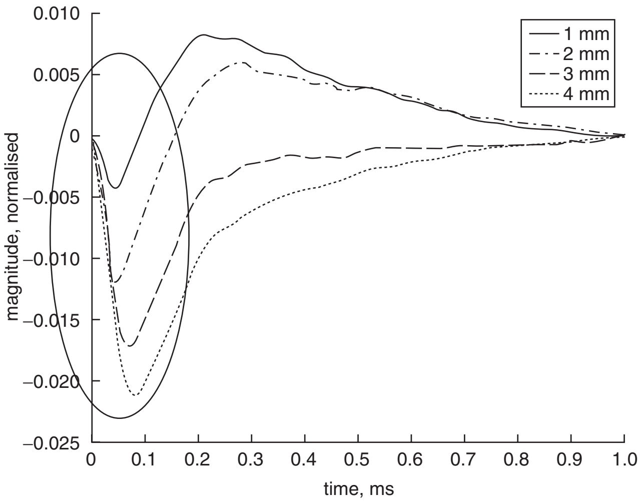

Fig. 13 *Differential signals from PEC testing magnetised steel samples*

7 Conclusions

A new approach for NDT using hierarchical wavelet-based PCA has been proposed and investigated. The results show that this approach, using a combination of wavelet and PCA, provides better results for the classification of defect types than the conventional approach. The integration approach provides a better location and identification of significant events by reducing the dimensionality. More deeply-buried flaws are identified correctly using the proposed technique. This also shows that the new technique is more robust than the technique using peak value and peak time. The proposed approach is a flexible method for defect classification and quantification by using different PCA basis. The results also demonstrate that the new wavelet-based PCA approach has a quantitative capability. In this case it provides the depths of the defects.

Following a common practice in electromagnetic NDT steel inspection the use of magnetisation with PEC has been performed for flaw detection in ferromagnetic steels. The results also show the robustness of the developed feature extraction technique that successfully achieves the classification of flaws in the ferromagnetic samples, although defect sizing has not been achieved with these samples. The conventional technique is not giving results owing to the absence of local maxima. Instead, a technique using the differential signals has been proposed and shown potentials for both defect classification and quantification. In addition to dynamic inspection of defects [32], more samples from industry will be tested by the proposed approach in the near future. Further work will use the proposed approach for reconstruction of defects by using sensor arrays [33].

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