Defect Classification in NDT Applications using Time Frequency Features, LDA, and a KNN Classifier

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ABSTRACT

In this paper, we develop a new approach for detecting defects in steel. We show that given the time varying nature of the acquired signals, we need to use nonstationary signal processing approaches. In particular, we focus on the performance of different time-frequency distributions (TFD). We show that the extraction of robust features from such TF distributions can lead to excellent classification accuracy of different defects independent of the specific classifier used. To evaluate the performance of our system, we compare our results with those obtained using the conventional 71 features traditionally used in benchmarking algorithms. Our experimental results using artificial and real defects show that the use of TF features provides an excellent characterization of defects in steel. Classification is carried used a dimension reduction technique, namely Linear Discriminant Analysis (LDA), followed by a KNN classifier. Additionally, we show that some specific TFDs can perform better than others in steel defect detection. In particular, the Gabor transform is shown to yield the best classification accuracy among the different time-frequency distributions considered in this study.

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INTRODUCTION

Studies have shown that manual ultrasonic inspection can be very accurate but is highly variable, depending upon the inspection skills, training, and even the emotional status or fatigue of the technician (Lippi and Mayer, 1987). The majority of inaccurate inspections result from faulty instrument calibrations, inaccurate probe selection, or inaccurate interpretation of the results. The human errors when combined with instrumentation errors, leads to inconsistent inspection results and more importantly inaccurate interpretation of such results.

The considerable advances made in the area of nondestructive testing (NDT) have changed the profession from a trade to an advanced area of active research with major industry involvement. This has led to new solutions to major industry problems. Pipelines, among others, can now be screened without stopping the production line using powerful tools such as pigging techniques (Dauby, 2005), guided wave ultrasound (Alleyne et al., 2001; Labbe, 2004), and others.

Moreover, the availability of powerful computing resources has led to the development of advanced NDT techniques that are less reliant on the operator. Automated ultrasonic classification (AUC) systems are becoming increasingly popular (Polikar et al., 2004; Le Gonidec et al., 2003) in industry. The rationale for using such systems comes from the need to analyze and interpret large amounts of inspection data and also trying to minimize errors due to human factors. AUC systems can be as typical pattern recognition systems. A number of supervised and unsupervised classification algorithms such as the K-means clustering algorithm, KNN, fuzzy C-means, Bayes’s and other statistical techniques, neural networks (Anastassopoulos et al., 1999), and more recently fusion of such approaches (Devi Parikh et al., 2004), have been proposed in the literature. The classification stage generally consists of a training (or learning) phase to learn the relationship between features extracted from the signals and the type of reflector (and ultimately defect), followed by a testing or deployment stage. It is worth noting that the success of all such algorithms depends heavily upon the availability of adequate and representative sets of features.

In typical NDT applications, the objective is to detect and classify defects that may exist in a given material. An ultrasonic transducer is usually used to generate a wave that is scattered by the given defect (if it exists) and is picked up by a transducer. The resulting ultrasonic defect echo consists of the reflection from the
discontinuities which manifests in the A-scans as an abrupt time localized change resulting in time varying spectral characteristics.

As such, the conventional Fourier decomposition techniques become inappropriate for analyzing these signals. A number of approaches using features from the joint time-frequency (TF) or time-scale (TS) domains have been proposed as powerful alternatives to the Fourier Transform (Chen and Cheng, 1996; Chen and Cheng, 1996). Time frequency representations have been shown to provide meaningful information for ultrasonic NDT, which is not available in conventional time, or frequency domains based features. Since TF signal analysis can provide detailed time information at a certain frequency and a detailed frequency distribution at any time indices, it should be an appropriate tool for ultrasonic signal processing. Considerable research on the application of TF analysis to ultrasonic NDT has been reported in recent years. Previous studies indicated that it was possible to obtain frequency dependent ultrasonic characteristics in a time-frequency plane rather than in a time or in a frequency domains only, and these characteristics could be applied to identify internal defects or to assess damage of crucial structure in materials. A sample of the overwhelming and rich literature of the use of TF representation in NDE can be found in (Chen and Cheng, 1996; Vijay et al., 2013).

Chen et al (1996) discussed the power of TF analysis in decomposing a pulse echo into three components: specular echo, dispersive wave, and non dispersive wave. Thus, features extracted from the joint TF plots were shown to provide much useful information for ultrasonic NDE, which was not available in conventional time or frequency domain based features. In more recent times, we have also witnessed the introduction of another transform suitable for the analysis of signals with time varying spectrum (Broughton and Bryan, 2009). In particular, the representation of A-scans signals using different Time Scale (TS) distributions has been proven to provide some important insight about the characteristic features of different defects. One such transform which gained a lot of popularity is the Discrete Wavelet Transform.

Among the different TF distributions used in the area of NDT are the Wigner-Ville distribution (WVD), the Exponential distribution (ED), the Gabor transform (GT), and the Morlet-based wavelet transform (WT). Malik et al (Kauer and Guo, 2005) investigated the performance of different TF distributions for ultrasonic NDT signals and concluded that the GT outperformed the others distributions in a Gaussian noise environment. However, for experimental ultrasonic signals, the ED is most suited when compared to the other distributions (Kauer and Guo, 2005; Solis et al., 2002).

The extraction of features from the joint TF and TS has, itself, been a very challenging topic. In (Pittner and Kamarthi, 2000), Pittner et al. showed that the energies extracted from the TS decomposition can be misleading as raw features such as the Wavelet coefficients are not directly related to the nature of the different defects. They proposed a technique for clustering the wavelets coefficients where there is more frequency-based information leading to more meaningful features for the case of defect characterization. In (Dray et al., 2002), Dray and his colleagues proposed to compensate for the deficiencies of the wavelets coefficients and the time domain features by combining the features into a single feature vector which is then used in conjunction with a Bayesian classifier to cluster the different defects. To improve the performance of wavelets in NDT, Zhang et al. in (2001) developed a new procedure for choosing the variance of the optimal Gaussian wavelet in ultrasonics. Lee et al., on the other hand (Lee et al., 2003), proposed to select certain segments from the wavelet decomposition to be used as input to either a Neural Network or a support vector machine (SVM) based classifier.

In (Qidwai and Bettayeb, 2009), the authors analyzed the TF representation as an image then extracted texture features to identify slag, porosity, cracks, and lack of fusion defects, achieving 86% classification accuracy. In (Sambath et al., 2011), the authors used features extracted from the wavelet transform together with a neural network classifier to identify 3 types of defects porosity, lack of fusion, and tungsten inclusions with an overall accuracy in correct detection of 94%. In (Nafaa et al., 2013), the authors developed a new research direction in NDT by developing an image based approach from defect retrieval from a database. The approach used texture and shape features from radiogram images. In (Vijay et al., 2013), the authors considered nine types of defects and used segmentation techniques borrowed from image processing together with a neural network classifier achieving an accuracy in classification of more than 90%. In summary, we note that the majority of the authors either used image processing techniques or used classical stationary signal processing tools. While wavelets have also been shown to provide powerful results, the problem of finding the optimal decomposition tree is still a challenging task.

In this paper, we will show that accurate classification of defects can robustly be achieved when one uses a selected set of representative features extracted from the TF domain. We will show that when the appropriate set of features is selected, the effect of the classifier becomes minor in the overall performance of the system. We will start our discussion with an overview of A-Scan signals and some of their properties, we then discuss the different TF distributions used in this work together with the features extracted from such distributions. Finally, we will present our results obtained using both artificial and real data.
**Ultrasonic Pulse Echoe Signals:**

In ultrasonic pulse echo mode, we use a flaw detector to send an ultrasonic wave into the specimen under test through a sensor (transducer). An echo is reflected back each time the ultrasonic wave encounters a discontinuity in the medium. The reflected data is acquired through an RS 232 port. The signal is represented by a symmetric envelope that is amplitude-modulated. Equation 1 defines an A-scan signal (Hlawatsch and Auger, 2008) whose wavelet envelope is a Gaussian pulse.

\[
x(t) = \exp\left(-\left(\frac{\alpha t}{\sigma}\right)^2\right) \cos(\alpha t)
\]

Thus, the signal contains several cycles whose duration should be constant. However, the reflected pulse echo envelope is usually not symmetric and the cycle duration, itself, is not constant (Figure 1). When we measured the cycle durations over several traces, we observed a maximum frequency deviation of 33% from the center frequency. Such observation prompted us to investigate further the time varying nature of reflected signals and in particular investigate the power of time-frequency distributions in analyzing such phenomena.

![Fig. 1: Snap shot of the screen (Masterscan flaw detector) showing a reflection.](image)

**Time-Frequency Signal Analysis:**

In section 2, we showed that the analysis of A-scan signals requires the use of signal processing tools that take into account both time and frequency variations. Such tools are the TF and TS signal analysis tools mentioned earlier. In this paper, we focus on finding the TF distributions most adapted for the analysis of A-scan signals. Before using such transforms in our experiments, we will describe briefly the different TF distributions considered in this work, we then discuss the issue of feature extraction from such transforms.

TF signal analysis techniques are generally classified into linear and quadratic transforms. The following flowchart (Figure 2) displays the different types of transforms under each of the above classes (Malik et al., 1996; Hlawatsch and Auger, 2008).

![Fig. 2: Classes of time frequency transforms.](image)
The first basic linear TF transform evolved from the traditional Fourier transform:

\[ S(\omega) = \int_{-\infty}^{\infty} s(t)e^{-j\omega t} dt \]  

(2)

\( S(\omega) \) is seen as the projection of time signal \( s(t) \) onto the space of non-decaying complex sinusoids \( \{e^{j\omega t}\} \). Since such a set forms an orthogonal basis, the original signal can easily be reconstructed from the projection weights.

When the above equation is used, it is assumed that the frequency content of the signal is relatively invariant with time. However, if its frequency content changes with time, the Fourier transform becomes useless. A simple way to overcome this deficiency is to evaluate the Fourier transform for a window of the signal, then move the window across time. This is what is known as the continuous-time Short Time Fourier Transform (STFT):

\[ STFT(t,\omega) = \int s(\tau)g^*(\tau-t)e^{-j\omega \tau} d\tau \]  

(3)

where the window \( g(t) \) is used to control the main lobe bandwidth, and balances time and frequency resolutions.

Fig. 3: Illustration of the STFT.

The squared magnitude of the STFT is known as the STFT spectrogram (Figure 2). The STFT spectrogram is the simplest form of a time-dependent spectrum, which depicts the signal’s energy distribution in the joint TF plane. In practice, we sample the STFT in both time and frequency to obtain the discrete-time STFT.

One special form of the STFT is the Gabor expansion. For this transform, the Gaussian window (with variance parameter \( \alpha \)) is used to achieve optimal joint TF concentration based on the uncertainty principle (Hlawatsch and Auger, 2008). The smaller the value of \( \alpha \), the narrower the frequency bandwidth (longer time duration) and vice-versa.

The Gabor Expansion \( \{C_{m,n}\} \) for discrete signals is expressed as follows:

\[ s[t] = \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} C_{m,n}W_{n}exp\left(\frac{2\pi in\tau}{N}\right) \]  

where \( N \) is the number of frequency components, and \( N/\Delta M \) is just the oversampling rate (when needed).

Instead of dealing directly with the signal in time domain, the so-called quadratic transforms have been introduced. These transforms focus on the signal’s energy distribution in the joint time-frequency domain. The most common transforms under this category are the so-called Cohen’s class of distributions. The general formula for this class is given by:

\[ S(t,\omega) = \int_{-\infty}^{\infty} e^{j\nu v} g(v,\tau)s^*(u-\frac{1}{2}v)s(u+\frac{1}{2}v)e^{-j\omega \tau} dv d\tau \]  

(5)

where \( s^*(t) \) is the complex conjugate of the signal, and \( g(v,\tau) \) is an arbitrary function called kernel. The kernel is different for each TFD (more than 20 forms for the kernel have been proposed in the literature).

The most commonly used transform from the Cohen’s class is the Wigner Ville Distribution (WVD) in which the kernel is just considered to be unity (equals 1). The WVD was originally introduced in the area of quantum mechanics. Let us first define the time-dependent autocorrelation as:

\[ R(t,\tau) = s\left[\frac{t+\tau}{2}\right]s^*\left[\frac{t-\tau}{2}\right] \]  

(6)

The WVD can easily be seen as the Fourier transform of the above time-dependant autocorrelation (with no windowing). Compared to the STFT spectrogram, the WVD exhibits better time and frequency resolutions. The main problem of the WVD is the cross-term interference i.e., (WVD of the sum of two signals is not the sum of their WVD’s). As such, when the signal is multicomponent, its WVD will exhibit several cross-terms.

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occurring between each pair of auto-terms. These cross-terms prevent the WVD from being used for real applications, though it possesses many attractive properties.

In addition to the WVD, a number of other kernel functions have been proposed to reduce the cross-term interference problem. These include the Born-Jordan transform (BJ), the Choi-Williams (CW) distribution, the cone-shaped distribution, and the adaptive kernel representation, to mention a few (Hlawatsch and Auger, 2008).

**Feature Extraction From TF Transforms:**

When NDT started gained popularity, skilled technicians and operators had to deal with the challenging task of interpreting large amounts of reflected data either as images or as one-dimensional waveforms. Over the years, good expertise is acquired by these technicians for proper interpretation of the results. With the massive deployment of computer systems and huge amount of acquired data, the need arised for developing automated tools to ease the operator subjectivity by first, “cleaning” up the collected data through pre-processing, and second, identifying (if possible) the characteristic features of a given defect signature so that appropriate remedy action is taken.

The classification of a given A-Scan signal into one of several possible defects need to be carried based on the estimation of certain characterizing features extracted from the echo-signals reflected from the defects. This is actually the essence of the feature extraction stage.

In practice, most waveform patterns are single-trace time series signals, taken from sensors or gauges through digitization. Traditionally, the features are extracted from time domain only, frequency domain only, or from time and frequency domains. In this work, and given the non stationarity of the A-scan signals, we considerer here features that are extracted from the different TF distributions. We will start by discussing the different conventional features used in NDT, then we proposed our own features extracted from the TF domain.

**Conventional Time and Frequency Features:**

Traditionally, both time and frequency domains features have been used in NDT. For comparison purposes, we have used in this work the 71 conventional features (Ma S et al., 2003), of which 35 are time domain features and the remaining 36 features are extracted from the frequency domain.

The time domain features are extracted from the waveform itself, the cumulative distribution of the waveform, and the envelope of the waveform. The features include the maximum absolute value of the amplitude, peak amplitude, maximum peak-to-peak amplitude, etc... The frequency domain features are estimated from the power spectrum of the normalized waveform and the cumulative distribution of the power spectrum. The features include the mean and standard deviation of the normalized power spectrum, the maximum value of the power spectrum and its location, the center frequency, the bandwidth, etc…

**Joint Time-Frequency Features:**

We mentioned earlier the importance of considering features extracted from TF distributions. A very important property of TF representations is that the time and frequency resolutions are not uniform over the entire time frequency domain. These resolutions vary in both time and frequency (or scale). At high frequencies, we have a better time resolution while at low frequencies, we have better frequency resolution. The wavelet transform for instance matches a long-duration signal with low oscillation and a short-duration signal with high oscillation. When using traditional time-frequency analysis techniques with NDT signals, a number of issues need to be considered (Yamani and Deriche, 2007; Wang et al. 2009). In particular, one needs to decide whether to use linear of quadratic transformations. Together with the selected transformation, a choice should be made in relation to the best time resolution and the frequency resolution to be used. Such parameters will affect the number of time-frequency bins resulting from the analysis. In our experiments, we chose to divide the joint TF plane into 20 time slots and 30 frequency bins (80% overlap is considered). As such, the energy feature vector obtained to cover the whole joint TF plane is 600x1. This of bins was found to capture all variations the joint TF plane. Moreover, once the TF bins are obtained, one needs to decide on the features to be extracted from such bins. In this work, we refer to “all features” when all the TF bins are used to compute these features. Whereas, we refer to “centered features” when only those bins centered around the main beam are used whose energy is above a certain threshold (a given percent from the maximum bin-energy).

In addition to the traditional energy signatures (above), we propose to use the following time and frequency projection signals to extract TF features (Eskandari et al., 2003). These projections signals are:

- Energy parameter (EP),
- Energy spread parameter (ESP),
- Frequency parameter (FP), and
- Frequency spread parameter (FSP).

These are defined as:
where \( M(t,w) \) is the given time-frequency distribution, and \( wM \) is the maximum frequency in the distribution. For the linear TF distributions, \( M(t,w) \) is taken as the square of the absolute value of the distribution, whereas, for the quadratic TF distributions, \( M(t,w) \) is taken as is since it inherently represents the energy components of the signal considered.

To represent the different projection signals in a compact form, we propose to extract the means and variances from each of the four signals mentioned above. Thus, for each A-scan signal, 8 time frequency projection features (TFPF) are obtained and used in the classification stage. We will discuss the performance of these features in defect classification, however, it is worth mentioning that the diversity and richness of information found in a the 2-D joint time frequency plane cannot be accurately represented by the 1-D projection signals especially when only the first second order moment are used. Hence, the 8 features above are used together with the energies from the joint time-frequency bins resulting in a feature vector of dimension 608x1.

Once the features are computed, these are fed to one of the classifiers mentioned in the results section, namely a simple Linear Discriminant Analysis (LDA) and a KNN Classifier.

**Data Acquisition and Experiment Setup:**

**Signal Acquisition:**

The data acquisition system used in this work is shown in Figure 4. We use a flaw detector to send ultrasonic waves into the material of interest through a transducer. An echo is reflected back each time the ultrasonic wave encounters a discontinuity in the propagation medium. The reflected echo is digitized and collected using an RS232 port for further processing (10 MHZ sampling rate).

To test the proposed system under different scenarios, we included in our study 3 different types of ultrasonic signals:  
1. Simulated Signals (SS)  
2. Signals from artificial defects (AD)  
3. Signals from real defects (RD)

In this paper, we use two categories of defects namely artificial and real defects. For each category, the defects have similar reflecting properties so that the resulting A-scan signals are closely similar which makes it difficult for an experienced NDT inspector to differentiate between the A-scan signals. However, we will show that when features are extracted from the TF distributions, high classification accuracy is obtained compared to its counterpart classification accuracy when conventional features are used. A brief description of the defects used in this research will be outlined next.

**Simulated Ultrasonic Signals:**

Simulated pulse echo signals can be generated as the output of a linear time-invariant system whose input is a Gaussian pulse given by:
where \( f_0 \) is the center frequency of the transducer and \( \sigma \) is a parameter that controls the number of cycles within the bell-shaped pulse. Here, a defect with a specific geometry is modeled as a linear time-invariant (LTI) system, hence the defect is characterized by its "unique" corresponding impulse response \( h(t) \). To identify a given defect, deconvolution of the pulse echo signal is performed to estimate the impulse response representing the defect (Yamani and Bettayeb, 1998). Since the focus of this paper is on using time-varying signal processing tools, we will not discuss deconvolution techniques in our experiments.

**Fig. 4:** Data acquisition system used to collect A-scan signals.

**Artificial Defects:**
To assess the performance of different tools used in defect detection and classification, we usually carry tests on artificial defects of known geometry. Flat-bottom holes, circular holes, notches are few examples of these artificial defects. In this paper, we include three types of defects commonly used in the literature: artificial flat-bottom holes (AFBH), artificial curved-top holes (ACTH) to simulate flat and curved reflecting surfaces, and artificial lamination defects (ALAM) (Figure 5).

**Fig. 5:** Position of transducer for collecting ACTH (T1), AFBH (T2), and ALAM (bottom) signals.

**Real Defects:**
These are real defects found in industrial components. They could result from fabrication (lamination defects, weld defects) or could result in service due to harsh environmental operation (corrosion, high...
temperature hydrogen attack). For the local industry, data from real defects found at different ARAMCO and SABIC installations were collected. In particular, an old pressure vessel (SLUG CATCHER 470-D-11-B) from ARAMCO located in Dhahran was used to collect high temperature hydrogen attack (HTHA) defects (see Figure 6).

![Portion of a pipeline showing HIC attack.](image)

In this work, we will consider real lamination defects (RLAM) and high temperature hydrogen attack (HTHA) defects as these were the most common defects found in our application.

**High Temperature Hydrogen Attack Defects (HTHA):**

High temperature hydrogen attack (HTHA) is a form of degradation caused when the hydrogen reacts with carbon in a high temperature environment. The resulting methane accumulates as grain boundaries and does not diffuse out of the metal. Once it accumulates, it expands and forms blisters that weaken the metal strength and initiate cracks. Steels exposed to high pressure of hydrogen at elevated temperature are particularly affected by HTHA attacks (see Figure 7) (Saleh and Aouni, 2012; Birring et al., 2005; Yamani, 2008).

![Hydrogen attack (a) dark area representing hydrogen damage. (b) Hydrogen Attack in the 18 mm thick pipe sample from a failure in a refinery de-sphurization plant in Japan.](image)

**Real Lamination Defects (RLAM):**

Real lamination defects are metal defects with separation or weakness parallel to the external surface of the metal. Laminations are planar elongations either internal or extending to the surface of an end or edge. They most often occur in rolled or forged products (Figure 8).

![A example of a real planar lamination defect.](image)
Even though we will focus, in this paper, on HTHA and RLAM defects, for the sake of completion, we will list in what follows the other types of defects commonly found in practical NDT setups:

- Corrosion / Erosion Defects (RCOR/RERO) (due to electrochemical oxidation of metals)
- Slag Defects (RSLG) (due to welding imperfections)
- Lack of Penetration Defects (RLOP) (failure of penetration of weld metal in joint roots)
- Lack of Fusion Defects (RLOF) (incomplete fusion between weld metal and parent metal)
- Porosity Defects (RPOR) (defects occurring when gases are trapped in the solidifying weld metal)

**Experimental Results:**

To test the performance of our proposed system using the different TF distributions mentioned in section 4, we carried a number of experiments on both artificial and real data. Category 1 consists of artificial defects, while category 2 contains real defects.

The experimental setup described above was used to collect many A-scan signals for each defect. The signals were collected using a compression ultrasonic wave moved above the defect until maximum echo is obtained. Then, 100 A-scan signals are collected in vicinity of maximum echo position to mimic data collected by different NDT inspectors. The experiments were repeated by changing the training/testing data. Basic preprocessing is applied to the A-scan signals. It consists of removing the DC offset, normalizing all the signals in energy, and centering the main peak of all A-scan signals. All the experiments were carried using cross validation. In particular, 90 signals are used for training and the remaining 10 signals are used in testing. The 10 test signals are circulated randomly among the 100 acquired signals (50 times). The results are averaged over the 50 runs.

For comparison purposes, we started by extracting the 71 conventional features from the different frames of the A-scan signals. Then, TF features are extracted from the joint TF transforms of the A-scan signal. In what follows, we will discuss the results under the two scenarios: simulated & artificial defects, and real defect defects.

**Linear Discriminant Analysis (LDA) and KNN Classification:**

To capture the complete structure of the joint TF plane, we have used a feature vector of over 600 in dimension. Using this high dimensional vector in classification such as in training neural networks or even Bayesian classifiers can computationally be very expensive. To reduce the complexity of the problem, we propose to use LDA to reduce the dimensionality of the feature vector without sacrificing the main characteristics of the patterns.

LDA has successfully been used in many engineering and technology applications (Andrew and Keith, 2011). Here, we use LDA to identify the different types of defects. Each defect is considered as a class. The vectors of energies are seen as the extracted feature vectors (of dimension n=608).

LDA can be seen as a simple projection of high-dimensional data onto a low dimensional space where the data achieves maximum class separability. The resulting projections using matrix W are just linear combinations of the original vectors. The optimal projection or transformation is obtained by minimizing within-class-distance as well as maximizing between-class-distance simultaneously. As such, maximum class discrimination is achieved. The matrix W is readily computed by solving a generalized eigenvalue problem. Contrary to Principal Component Analysis (PCA) which considers each observation vector as a class on its own, LDA finds the projection matrix W while preserving as much of the within-class discriminatory information as possible.

Starting with the available samples from the training data, we define two measures: (i) within-class scatter matrix, given by:

\[ s_w = \sum_{j=1}^{c} \sum (x_j - \mu_j)(x_j - \mu_j)^T \]  \hspace{1cm} (9)

where \( x_j \) (dimension nx1) is the ith sample vector of class j, \( \mu_j \) is the mean for class j, M is the total number of classes, and Ni is the number of samples in class j.

We also define the between-class scatter matrix:

\[ s_b = \sum_{j=1}^{c} (\mu_j - \mu)(\mu_j - \mu)^T \]  \hspace{1cm} (10)

where \( \mu \) is mean vector of all classes.

The goal is to find a transformation \( W \) that maximizes the between-class measure while minimizing the within-class measure. One way to achieve this is to maximize the ratio \( \text{det}(S_b)/\text{det}(S_w) \). When \( S_w \) is a non-singular matrix, then, the ratio is maximized when the column vectors of the projection matrix, \( W \), are the eigenvectors of \( S_w^{-1}S_b \) (Andrew and Keith, 2011). In this paper, we used a dimension of 15 in the reduced feature space as our initial experiments showed that 15 largest eigenvalues chosen are able to capture more than 98% of the total energy in the eigenvalues of the matrix \( S_w^{-1}S_b \).
Once all the TF feature vectors are transformed into reduced dimension feature vectors of dimension 15x1, we proceed to the classification stage. For classification, we propose to use a simple k Nearest Neighbor classifier (KNN). The KNN is one of the simplest classification (or regression) algorithms which works incredibly well in practice. It is a versatile tool and its applications range from vision to biology to communications, to mention a few.

Given N n-dimensional entries with known associated classes for each entry, with the number of classes being M, that is, \( \{x_i, y_i\}, x_i \in \mathbb{R}^n, y_i = \{c_1, \ldots, c_M\}, i = 1, \ldots, N \). For a new entry, \( \vec{V} \), which class should it belong? We need to use a distance measure to get the k closest entries of the new entry \( \vec{V} \), the final decision is simple majority vote based on the closest k neighbors. The distance metric could be Euclidean or other similar ones.

The KNN approach is a non parametric classification algorithm. The algorithm does not make any assumptions on the underlying data distribution. This is very useful, as in the real world, most of the practical data does not obey the typical theoretical assumptions made (eg Gaussian mixtures, linearly separable etc.). It assumes that the data is in a feature space. Each of the training data consists of a set of vectors and class label associated with each vector.

We are also given a single number "k". This number decides how many neighbors (where neighbors is defined based on the distance metric) influence the classification. This is usually an odd number if the number of classes is 2. If k=1, then the algorithm simply becomes the traditional nearest neighbor classifier (or just MD) (Andrew and Keith, 2011).

**Scenario 1: Simulated and artificial defects:**

First, conventional features are computed and fed to an MD classifier that produces a confusion matrix (CM). For the MD classifier, the CM in Table 1 shows the average over the 100 test signals (50 runs). It shows an overall classification accuracy (average of the diagonal of CM) of 66.7. However, when a KNN classifier is used with k=10, an overall classification accuracy of 75.1% is obtained. Hence, we observe some improvement when a better classifier is used. This scenario shows that when conventional feature are used, the type of classifier implemented can affect greatly the overall accuracy of the defect detection and classification system.

### Table 1: CM obtained with conventional features (time and frequency)

<table>
<thead>
<tr>
<th>True class</th>
<th>Classified as</th>
<th>MD classifier</th>
<th>KNN classifier</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>AFBH</td>
<td>ALAM</td>
<td>ACTH</td>
</tr>
<tr>
<td>AFBH</td>
<td>71.2</td>
<td>14.7</td>
<td>14.1</td>
</tr>
<tr>
<td>ALAM</td>
<td>15.2</td>
<td>64.3</td>
<td>20.5</td>
</tr>
<tr>
<td>ACTH</td>
<td>21.4</td>
<td>14.0</td>
<td>64.6</td>
</tr>
</tbody>
</table>

For the extraction of the TF features, we selected the following TF distributions: the GT, the WV, the CW, the BJ, and the STFT. These transforms are the most commonly used in practice. We show in figures 9 and 10 the TF spectra for two artificial sample defects using the BJ and the GT transforms. Figure 9 shows very little difference across the defects with a better discrimination results when the GT transform is used (Figure 10).

With reference to the GT of the AFBH defect signal shown in Figure 10; there exists one strong frequency component, and an additional signal from frequency that extends throughout the time trace. For ALAM defect, the second frequency component appears to consist of more than a single tone and is localized around the envelope of the time signal only.

Although the BJ TF distribution (Figure 9) appears to be unable to differentiate between the defects considered, the classification accuracies based on the extracted TF features are much higher than their counterparts obtained when 71 conventional features are used. The results are shown in Figure 11, where we see that even the 8 TFPF features (Equation 7) yield much better classification accuracy (76%) than those obtained using the 71 conventional features (66.7%). The Figure also shows that the results can be slightly improved if we only the TF bins around the central instantaneous frequency (centered features).

Next, when the TF features are estimated from GT (or GAB), BJ, and WV distributions and are fed to the MD classifier, the results, shown in Figure 12 demonstrate, that the GT (or GAB) outperforms the other TF distributions. Figure 13 shows the same results as Figure 12 but when a KNN classifier is used. Thus, it can be said that the classification accuracy is highly dependent on the features used rather than the classification type when a “good” set of features are used.

Figures 11, 12, and 13, also show the effect of thresholding the TF features (so-called centered TF features). As the centered TF features are computed from the peak of the TF distributions, their values (energy) are inherently descending. The figures show some improvement when centred features are used. The best accuracy achieved was 91.2% with GAB, Centered features, and a KNN classifier.
Fig. 9: TF magnitude plot using BJ TFR on all defects (AFBH/ALAM).

Fig. 10: TF magnitude plot using GT TF on all defects (AFBH/ALAM).
Scenario 2: Real defects:

In what follows, we will discuss the more practical case of data acquired from real defects such as HTHA and RLAM (see the discussion in section 5). In a similar way to section 6.1, A-scan signals are used to compute features for defect classification. When conventional features are used, the worst classification accuracy among the different test sets was found to be around 63% while the best classification accuracy obtained was 80% (over the 50 runs). The average accuracy over 100 tests was about 73% which is slightly lower than the accuracy obtained for artificial defects. This is due to the fact that unlike artificial defects that have controlled geometries, real defects produce signals that are affected by the complex signal-geometry interaction and thus, classification accuracy hence obtained is expected to be lower.
When TF distributions are used to process the A-scan signals of both RLAM and HTHA, the results shown in Table 2 summarize the average classification accuracy over 100 tests for each TF distribution. It can be seen, the classification accuracy obtained for centered features is much higher that that obtained when all features are used. Also, it is clearly shown that GT outperforms the other TF distributions achieved earlier. This can be attributed to the fact that the PWV exhibits cross terms that affect substantially the extraction of robust features. On the other hand, the GT provided the best results which confirms that using a kernel that matches the signal under analysis is important in finding optimal features.

Table 2: Classification accuracy using TF features (real defects) with MD and KNN classifier.

<table>
<thead>
<tr>
<th>TFR</th>
<th>All Features</th>
<th>Centered Features</th>
<th>TFR</th>
<th>All Features</th>
<th>Centered Features</th>
</tr>
</thead>
<tbody>
<tr>
<td>PWV</td>
<td>67.3</td>
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<tr>
<td>RJ</td>
<td>70.0</td>
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<tr>
<td>GAB</td>
<td>72.0</td>
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</table>

Conclusion:

In this paper, we have introduced a new approach for the detection of defect from A scan signals. We have shown that the signals are nonstationary as such time frequency tools needs to be used to accurately analyze such signals. We showed that among the different time frequency distributions the best classification results are obtained from the Gabor TFR is used. Moreover, we showed that the selection of features from the TF plane is important as focusing on the TF bins around the main IF trace provide better representation of the different defects. We showed that the classifier type plays a minor role once robust features are obtained. We obtained an accuracy of more than 90% for both simulated and real data. More efforts can be invested in defusing TF and TS distributions to obtain more robust features. Moreover, we plan to use a Bayesian approach for the classification.

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REFERENCES


