On the Performance of Time Frequency Distributions in A-Scan Signals Classification

Mohamed Deriche, Ahmed Yamani

KING FAHD UNIVERSITY OF PETROLEUM & MINERALS, DHAHRAN, SAUDI ARABIA, 31261

***Abstract* — In this paper we discuss the performance of different time frequency distributions in characterizing A-Scan signals in NDT applications. We then introduce a new set of time frequency features that we extract from such distributions. In particular, we propose to extract four signals representing energy and frequency parameters of A-scan signals. We show that the means and spreads extracted from such signals can be used as robust features for classification of A-scans signals. We also show the best discrimination among different classes of A-scans can be obtained using the Gabor transform.**

***Index Terms* — NDT, time-frequency distributions, A-scans, STFT, Gabor, classification.**

I. INTRODUCTION

Studies have shown that manual ultrasonic inspection can be accurate but highly variable, depending upon the inspection skills, training and emotional status or fatigue of the inspectors [1]. The majority of inaccurate inspections result from faulty instrument calibrations, inaccurate probe selection, or inaccurate interpretation of inspection results themselves. The human factor, particularly, when combined with variations in instrumentation, leads to a lack of consistency in inspection results and interpretations.

Considerable advancement in research and development in the last few decades has enabled nondestructive testing (NDT) to change from a "Black Smith" profession to an advanced multidisciplinary engineering profession. This has led to cost effective solutions of many challenging problems. Pipelines for instance, can now be screened without disturbing the production using intelligent tools such as pigging [2], guided wave ultrasound [3], phased arrays [4], etc…

In addition, the existence of cheap computing capabilities has led to the development of NDT techniques that are operator independent. These techniques rely heavily on the collection of huge measurement data that after appropriate processing will enhance operator interpretation. Automated ultrasonic detection and classification (AUDC) systems are thus becoming increasingly popular [5].

Motivation for the use of such systems arises from the need for accurate interpretation of large volumes of inspection data, and minimizing errors due to human factors. A typical AUDC system consists of three major components namely, pre-processing, features extraction, and classification. A number of supervised and unsupervised classification algorithms [6] such as K-mean clustering algorithm, fuzzy C-means, and more recently neural networks have been proposed for classifying signals. Using a suitable training algorithm, these networks can be trained to learn the correlation between features in signals and the type of reflector. However, the success of all such algorithms depends heavily on the availability of adequate and representative set of feature vectors. As NDE signals consist of reflections from discontinuities which manifest in the A-scans as abrupt time localized changes resulting in time varying spectral characteristics, the conventional Fourier decomposition technique is not therefore, an appropriate tool for analyzing these signals. Features extracted from the joint time-frequency representations (TFR) may provide us much useful information for ultrasonic NDE, which is not available in conventional time, or frequency domains based features.

The papers is organized as follows: The experimental set up and the overall system used for acquiring the data is presented in Section 1. A description of the different TFRs is given in Section 2. Section 3 introduced the new TF features used in classification followed by Section 4 on the carried experiments. Section 5 concludes the paper with a summary of the results achieved, and future directions..

II. SIGNAL ACQUISITION AND PREPROCESSING

Before discussing the different time frequency distributions used for the analysis of A-scan signals, we will describe briefly the data acquisition system used in our experiments. In particular, we start with a digital flaw detector that sends ultrasonic waves into the specimen under test through a sensor called transducer. An echo is reflected back each time the ultrasonic wave encounters a discontinuity in the propagation medium. The flaw detector then digitizes the acquired data and sends it to the PC through an RS 232 port (Figure 1).

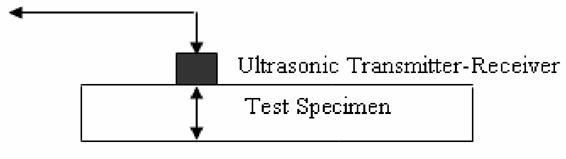

Figure 1: Pulse Echo Flaw Detector

Once the data is acquired, the signal of interest is normalized, centralized, and denoised when necessary (the wavelet transform is used for this purpose).

To evaluate the performance of the different TFR techniques in processing and classifying NDT signals, we have also generated some artificial pulse echo signals. These signals are taken as the outputs from the following convolutional model excited by an RF Gaussian pulse:

$$\text{Input:} \quad x(t) = \exp[-\left(\frac{2\pi f_0 t}{\sigma}\right)^2]\cos\left(2\pi f_0 t\right)$$

$$\text{Output:} \quad y(t) = x(t) \otimes h(t) + n(t)$$

where f_0 is the center frequency of the transducer and σ is a parameter that controls the number of cycles within the bell-shape pulse and the output, y(t), is the synthesized A-scan signal.

II. SIGNAL ANALYSIS USING TIME FREQUENCY DISTRIBUTIONS

Even though the introduction of Signal Processing tools to the area of ultrasonic NDT of materials is more than a two decades old, most researchers have focused on using either time domain or frequency domain analysis independently. The limitations of time domain or frequency domain information is well established when the analyzed signals are non-stationary. When the frequency content of a given signal of interest does not change with time, Fourier analysis is appropriate in providing an insight into the distribution of energy across different frequencies. However, since the Fourier transform uses the whole signal length to compute the energy distribution, such a transform is unable to accurately model the frequency content for signals that are non stationary.

Signals characterizing defects in materials constitute one class of signals that cannot be analyzed using simple time or frequency techniques. Ultrasonic signals typically contain reflections from discontinuities, which result in time varying spectral characteristics. Consequently, time-frequency techniques have been shown to be more appropriate for understanding the behavior of such signals. In this paper, the aim is to discuss the performance of different time-frequency techniques in the analysis of A-scan signals. The ultimate goal is to use such transforms for extracting characteristic features for accurate detection and classification of different defects (if any). We will first describe briefly the different time-frequency distributions considered in this work, we will then discuss feature extraction and classification from such transforms.

Traditionally, time frequency signal analysis techniques can be broadly classified into two classes: linear transforms and quadratic transform.

A. The Short Time Fourier Transform

The most popular linear Time-Frequency is the Short Time Fourier transform (STFT) which gives a description of both the time and frequency characteristics of the signal. The Continuous-time STFT of a signal s(t) is given as:

$$STFT(t,\omega) = \int s(\tau)\gamma^*(\tau - t)e^{-j\omega\tau}d\tau \quad (1)$$

Instead of processing the entire signal in a single frame, the STFT takes the Fourier transform on a frame-by-frame basis. Therefore, the resulting transform can be described as a signal's frequency behavior during the time period covered by the window $\gamma(t)$. The squared magnitude of the STFT is known as the STFT spectrogram.

B. The Discrete Gabor Transform

For a signal s(t) , the Gabor expansion is defined as:

$$s(t) = \sum_m \sum_n C_{m,n} h_{m,n}(t) \quad (2)$$

where $C_{m,n}$ define the Gabor coefficients. The set of elementary functions $\{h_{m,n}(t)\}$ consists of a time and frequency-shifted versions of a function h(t), i.e.

$$h_{m,n}(t) = h(t - mT)e^{jn\Omega t}$$

Recall that a function's time and frequency properties are not independent. If a function has a small frequency bandwidth, its time duration must be wide while if a function has a short time duration, its frequency bandwidth must be wide. The Gaussian window has been proven to achieve optimal joint time-frequency concentration based on the uncertainty principle. This balance of time and frequency concentrations is controlled by a certain parameter α. Because of this, the Gaussian signal is used as the window function in the Gabor expansion,.

C. The Wigner-Ville Distribution

The signal's energy distribution in the joint time-frequency domain is represented by the time-dependant power spectrum. Such distribution can be obtained using the Fourier transform of the time-dependant auto-correlation function R(t,τ), i.e.

$$P(t,\omega) = \int R(t,\tau)\, \mathrm{e}^{-j\omega\tau} d\tau \qquad (3)$$

The most popular time-dependant power spectrum is the STFT spectrogram, which is the square of the STFT. The main problem of the spectrogram is that it suffers from the window effect as the width of γ(t) controls the resulting time and frequency resolutions.

The distributions derived directly from the power spectrum are termed as quadratic time-frequency distributions. The Wigner Ville Distribution (WVD) is perhaps the popular transform under such a class:

$$WVD_s(t,\omega) = \int s\left(t+\frac{\tau}{2}\right) s^*\left(t-\frac{\tau}{2}\right) e^{-j\omega\tau} d\tau \qquad (4)$$

The WVD can be thought of as a signal's energy distribution in the joint time-frequency domain and possess a number of attractive properties, in particular, the WVD has much better time and frequency resolutions. The main problem of the WVD is cross-term interference i.e., the WVD of the sum of two signals is not the sum of their WVD's, hence, resulting in non-desirable peaks in the frequency domain. The effect of theses peaks can be reduced using the Pseudo-WVD and other smoothed TFDs such as the Choi-Williams distribution

III. FEATURE EXTRACTION FROM TIME-FREQUENCY DISTRIBUTIONS

To evaluate the performance of the different TF distributions in the case of NDT signals, we propose first to extract the following sub-signals:

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

These sub-signals are defined as follows:

$$EP(t) = \frac{\sum_{w=0}^{w=w_M} M(t,w)}{w_M}$$

$$ESP(t) = \left[\frac{\sum_{w=0}^{w=w_M} (M(t,w) - EP(t))^2}{w_M}\right]^{1/2}$$

$$FP(t) = \frac{\sum_{w=0}^{w=w_M} wM(t,w)}{\sum_{w=0}^{w=w_M} M(t,w)}$$

$$FSP(t) == \left[\frac{\sum_{w=0}^{w=w_M} (w - FP(t))^2 M(t,w)}{\sum_{w=0}^{w=w_M} M(t,w)}\right]^{1/2} \qquad (5)$$

Where *M(t,w)* is the given time-frequency distribution, and w_M is the maximum frequency in the distribution. For the linear time-frequency distributions, *M(t,w)* is taken as the square of the absolute value of the distribution, whereas, the quadratic time-frequency distributions are left as they are since they inherently represent energy components of the signal considered.

Next, time-frequency features (TFF) are computed as the mean and variance of each of the sub-signals defined above. Thus, for each signal, 8 TF Features (TFF) are obtained and used for analysis and classification purposes.

IV. EXPERIMENTAL RESULTS

In order to properly characterize the different pulse echo signals, it is important to develop robust approaches to extract such signals from the measured system response (see convolutional model mentioned above). In convolutional models, a defect with a specific geometry is modeled as a linear time-invariant (LTI) system, and hence, can be characterized by the corresponding impulse response (IR).

Advanced deconvolution techniques have been proposed to estimate *{h(t)}* from the measurements *{y(t)}*. Here, we have considered the Higher-order statistics (HOS) based deconvolution techniques developed earlier by one of the authors [7].

The performance of HOS-based approach was first evaluated using a minimum phase autoregressive moving average (ARMA) system with transfer function give by::

$$H_{MP}(z) = \frac{z+0.2}{z^3 + 0.5z^2 + 0.72z + 0.068} \qquad (6)\ 2.44)$$

Additive noise is generated using different probability density functions (PDF), namely, a Gaussian, and a uniform distribution.

The estimated defect impulse response $h_e(t)$, is compared to the actual IR signal $h_a(t)$. This comparison is quantified by computing the normalized sum-squared estimation error:

$$e_h = \frac{\|h_a - h_e\|_2^2}{\|h_a\|_2^2} \qquad (7)$$

For the simulated data, the above error can be used efficiently since the actual defect IR signal is available. However, in practice, $h_a(t)$ for real defect does not exist at hand, and thus, an alternative way to check the accuracy of the deconvolution algorithm is to compute the pulse echo signal (A-scan signal) using the estimated impulse response through a convolution. Then, compute the normalized sum-square error in terms of pulse echo:

$$e_y = \frac{\|y_a - y_e\|_2^2}{\|y_a\|_2^2} \qquad (8)$$

Where y_a is the measured pulse echo, and y_e is the estimated pulse echo using the estimated defect IR. For a Signal-to-Noise Ratio varying between 20 and 5 db, the errors are:

SNR	IR error	Output error
20 dB	$6.16*10^{-6}$	0.0099
5 dB	0.0136	0.2456

The results show increased error for the output as compared to the IR for lower SNR. This is due to the fact that y_a in Equ.(8) contains noise whereas y_e is the filtered estimated output. Figure 2 shows the actual $h_a(t)$ and the estimated $h_e(t)$ IR signals for the case of 5dB SNR. Figure 3 shows the actual $y_a(t)$ and the estimated $y_e(t)$ pulse echo for 5 dB SNR.

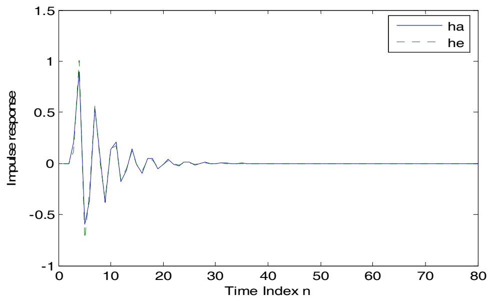

Figure 2: Actual and estimated IR signals at 5dB SNR

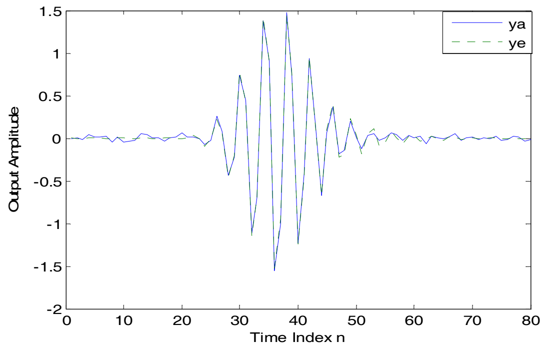

Figure 3: Actual & estimated output signals at 5 dB SNR

Next, and for the purpose of this study, five time-frequency distributions were considered: two linear time-frequency distributions (Gabor and STFT) and three quadratic time-frequency distributions (pseudo-Wiegner-Ville, Choi-Williams, and Born-Jordan).

Figures 4, 5 show the Gabor and STFT distributions for the IR signal and figure 6 shows the Gabor distribution for the output signal at 25 dB SNR (others have been omitted for lack of space). For analysis purposes, however, only the system output signals were considered to evaluate the degree of merit of each of the distributions through the computation of the TF Feature (TFF) vectors.

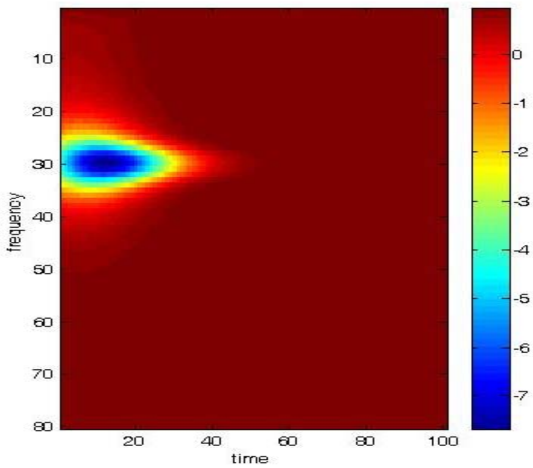

Figure 4: Gabor distribution for IR signal

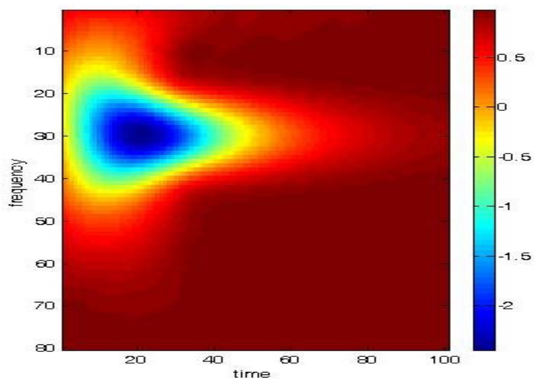

Figure 5: STFT distribution for IR signal

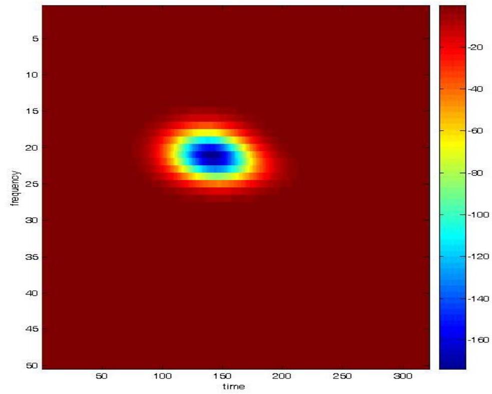

Figure 6: Gabor distribution for output signal

To quantify the degree of merit for each of the distributions, the L_2 norm of the error between elements of the TFF vectors for 20 dB and 5 dB SNR is computed.

The experimental results have shown that the Gabor distribution gave an error of 0.0129 whereas STFT resulted in an error of 0.1203 for the same class of signals. For different classes, the Gabor transform resulted in the maximum error of 0.0567 while that of the STFT was 0.0126.

We have carried extensive results all of which showed that the Gabor distribution is the best distribution for representing NDT signals. Notice that only a simple minimum distance classifier has been used in the above experiments.

DISCUSSION AND CONCLUSION

We have discussed in this paper the performance of different time frequency distributions in the analysis of NDT signals. In particular, we have shown that time or frequency domain analysis are inappropriate for extracting characteristic feature from A-scans and that joint time frequency analysis is needed. We have also shown that the Gabor transform is an optimal representation for A-scan signals and that robust classification results can be obtained using features extracted from such a transform. We have also shown that the newly introduced energy and frequency parameters (and their spreads) can be excellent features for classification of NDT signals. In current work, we are now developing a classifier for NDT signals using the principal component analysis approach (PCA) together with an Neural networks (NN).

ACKNOWLEDGEMENT

The authors wish to acknowledge the support of King Fahd University of Petroleum and Minerals, Saudi Arabia, to carry this research.

REFERENCES

[1] Lippi, A. and Mayer, W. G. (Eds.) "Ultrasonic methods in evaluation of inhomogeneous materials, NATO ASI Series, Series E: Applied Sciences, no. 126, Martinus Nijhoff Publishers, Dordrecht, 1987.

[2] Dauby, F. "Numerous lessons learned when Intelligent Pigging is attempted on 60-year-old gas pipeline" Pipeline & Gas Journal, vol. 232, no. 10, pp. 44, 48, 49-52, Oct. 2005

[3] Alleyne, D.N., Pavlakovic, B., Lowe, M.J.S., and Cawley P., "Rapid, long range inspection of chemical plant pipework using guided waves", AIP Conference Proceedings, Volume 557, pp. 180-187, April 30, 2001.

[4] Smith, R. A., Bending, J. M., Jones, L. D., Jarman, T. R. C., and Lines , D. I. A. "Rapid ultrasonic inspection of ageing aircraft", Insight- Nondestructive testing and Condition Monitoring, Vol.45, no.3, pp. 174-177, March 2003.

[5] Polikar, R.,Udpa, L., Udpa, S., and Honavar, V., "An incremental learning algorithm with confidence estimation for automated identification of NDE signals", IEEE trans. UFFC, vol. 51, no. 8, pp. 990-1001, August 2004.

[6] Anastassopoulos, A.A., Nikolaidis, V.N., and Philippidis, T.P., " A comparative study of pattern recognition algorithms for classification of ultrasonic signals", Neural Net. & Applic., Vol. 8, pp.53-66, 1999.

[7] Yamani, A., Bettayeb, M., "High Order statistics-based deconvolution of NDT Ultrasonic data," SABIC Progress Report I (EE/SABIC/96-8), June 6, 1997.