CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

Conventional NDT techniques, which are based on manual, heuristic or experience-based pattern identification methods, bring about costly, lengthy and erratic analysis and thus lead to inconsistencies in results. To reduce the effect of human variability in interpretation, to get the consistency of response, and to analyze and interpret large volumes of signals, a variety of modern signal processing techniques and Artificial Intelligence (AI) tools have been adopted (Katragadda et al 1997, Ogaji and Singh 2003 and Song et al 1999). These approaches can be integrated as Automatic Ultrasonic Signal Classification (AUSC) systems. The overall approach used for an AUSC system consists of three major steps as shown in Figure 2.1.

![Figure 2.1 An illustration of an automated signal classification system](image)

In an automatic ultrasonic signal classification system, ultrasonic flaw signals acquired in a form of digitized data are pre processed and informative features are extracted using various digital signal processing techniques. The set of selected features becomes the basis of decision-making
for classification. As the relationship between ultrasonic signal characteristics and flaw classes is not straightforward, the extraction of features plays a critical role in classification accuracy and this becomes the important basis of decision-making for classification (Zhu et al 2004).

A number of previous studies have proposed various sets of ultrasonic signal features chosen from the time-domain and/or the frequency-domain. The studies investigated the feasibility of using those features for AUSC systems. Previously proposed features include time-domain waveforms which were processed through a series of preprocessing methods (Rose 1988 and Kim et al 2004), principal components of signals (Bae et al 1997 and Sophian et al 2003), moments of Fourier transform of signals (Raad and Dijkstra 1998) and other informative descriptors from combinations of time-domain and frequency-domain features (Timothy and Waag 1996, Redouane et al 2000, Matz et al 2007 and Patrick et al 2006).

Instead of using a set of extracted features from time and frequency domains, a whole signal section derived from the ultrasonic scans, employing a minimum of preprocessing using only Fast Fourier Transform (FFT) has been used directly as inputs into the classifier (Cotterill and Perceval 2001, Margrave et al 1999). More recent studies on the ultrasonic flaw classification employ Discrete Wavelet Transform (DWT) as a part of their feature extraction scheme as DWT provides considerably effective signal compression and data reduction (Obaidat et al 2001 and Simone et al 2001). Further details of the feature extraction schemes that can be applied to AUSC systems will be discussed in Chapter.

In their quest for better sets of features for AUSC, many researchers have compared these two feature extraction schemes (FFT and DWT), classifying short signals taken from plate or pipe surfaces and distinguishing corrosive from intact ones. Most comparisons between FFT
and DWT showed a superiority of DWT over FFT, for example discriminating between types of flaws (or its non-existence) (Polikar et al 1998 and Spanner et al 2000).

Discrete wavelet transform (DWT) coefficients have been suggested as useful features for input into an ultrasonic flaw classification system (Obaidat et al 2001 and Polikar et al 1998) because of their time–frequency presentation properties. The potential of using DWT for ultrasonic shaft test data analysis also has been presented by Lee and Estivill-Castro 2003.

Once the feature extraction process has been completed, a suitable decision making algorithm known as Artificial neural network is applied for classification to determine and classify the flaw type information. Among the various learning mechanisms for ultrasonic signal classification, Artificial Neural Networks have gained more popularity and are considered to outperform conventional pattern recognition algorithms (Margrave et al 1992). Many researchers use Artificial Neural Networks due to their ability to generate complex decision boundaries in the multidimensional feature space. This is attractive, especially in ultrasonic flaw classification, because the relationship between ultrasonic signal characteristics and their defect class is highly non-linear; thus, it is not straightforward (Katragadda et al 1997, Santos and Perdigao 2001).

2.2 DEFECT CLASSIFICATION USING ANN

In the application of non-destructive testing techniques for material inspection researchers have always tried to develop a decision support system for the automatic defect classification. In spite of several modern automated inspection methods, defect classification still is a difficult task. Much work published in this area is based on artificial intelligence methods using

Burch and Bealing (1986) using pulse echo method tried to classify smooth and rough cracks from more benign volumetric flaws such as porosity and slag. Qualitative physical models were developed for the interaction of ultrasound with these defects to determine three uncorrelated features (amplitude ratio, waveform kurtosis and sphericity). Weighted minimum distance pattern recognition algorithm was used for defect classification.

Baker and Windsor (1989) used the Hopfield network for classification of processed ultrasonic data from various classes of defects (cracks, rough cracks, pores and slag with in steel test welds. Classification accuracy of 80% was reported which is comparable to the conventional minimum distance classification algorithm.

Raju Damarla et al (1992) using the quasi pulse echo ultrasonic classification technique tried to distinguish between smooth edged and sharp edged geometries. To test the practicality of this approach, experiments were conducted on cylindrical cavities and surface breaking fatigue cracks. Their results showed a good consistency in the classification of smooth and sharp edged flaws. Self learning back propagation neural networks for classification of ultrasonic inspection data was performed in both time and frequency domain. It was found that most of signals with flaws could be correctly classified.

Song and Schemrr (1992) tried to classify flaws in weldments from their ultrasonic scattering signatures using probabilistic neural networks and it
was shown that such a network is simple to construct and fast to train. They reported a high classification performance than the other types of neural networks. Neural network was used to distinguish crack-like defects from volumetric defects by directly analysing the images collected from ultrasonic scan (Windsor et al 1993).

Masnata and Sunseri (1995) developed a methodology for automatic characterization of weld defects detected by a P-scan ultrasonic system. Fischer linear discrimination analysis was used to reduce the number of features from 24 to 14 uncorrelated features which were classified using a three-layered multiple layer Perceptron.

Thavasimuthu et al (1996) evolved a methodology to classify weak ultrasonic signals using artificial neural network. They explained and demonstrated the limitations of the use of peak amplitude information alone, in the detection, evaluation and classification of weak signals. The use of a multi-parameter approach has been suggested. They used the multi-layered, feed-forward, error back propagation neural network (the multi-layered perceptron, MLP). It has been found that by using a neural network classifier, even defects having an area around 0.7% of the incident beam area of cross-section could be reliably detected and classified.

Margrave et al (1999) evaluated performance of different types of neural networks inaccurate flaw detection in steel plates. The networks employed were 3 layers Multilayer Perceptron (MLP), Self Organizing maps using Kohonen learning rule and Linear vector quantization (LVQ) networks. Neural networks were trained to classify between six classes of defects; no defective, side drilled holes, slots, inclusions, porosities and cracks. Signals in time domain obtained directly from the ultrasonic scans and in frequency domain were given as inputs to the neural networks with little or no preprocessing. It was reported that the performance of MLP to be the best
among all three, the self organizing maps performed the least satisfactorily among the considered networks and performance of LVQ was faster than MLP but requires the classes to be clearly discriminated. In comparison with the time domain analysis, frequency domain analysis results in better classification. Classification rates in the range from 80 to 100 % were obtained with no form of feature extraction employed. It was also suggested that the implementation will have to move to Digital signal processing architectures in order to realize practical solution.

Santos and Perdigao (2001) using pulse-echo technique tried to discriminate between defects with three different shapes (cylindrical, spherical, planer). A total of four features were extracted from the signals, three in time domain, namely, pulse duration, pulse decay rate and peak-to-peak relative amplitude of the third cycle, frequency for maximum amplitude was extracted in the frequency domain. Classification accuracy of 100% was reported using the nearest neighbor approach.

Pagodinas (2002) used the back propagation neural networks in conjunction with finite element method to detect the existence and to identify the characteristics of damage in laminate composite beams with various imperfections.

Song et al (2002) simulated the pulse-echo method by developing numerical models using finite element method combining with boundary integral equation to investigate the effects of cracks in a medium. Back propagation neural network was utilized which gave an accuracy of 94% in classifying between three distinct classes; without cracks, surface cracks and sub-surface cracks.

Veiga et al (2005) evaluated the application of ANN for pattern recognition of ultrasonic signals in weld defects using pulse echo and TOFD
techniques. Four welding defects were classified by using supervised feed forward back propagation type neural network. It was reported that the success rate of 72.5 % for pulse echo and 77.5 % for TOFD technique, both without preprocessing.

Martin et al (2007) using pulse echo method developed artificial neural network model to classify resistance spot welds in four quality levels. Back-propagation multilayer feed forward ANN with Levenberg–Marquardt training algorithm was used for this classification. Input of the ANN is a 10-component vectors that contain the relative heights of the echoes and the distance between consecutive echoes.

2.3  DEFECT CLASSIFICATION USING ANN AND SIGNAL PROCESSING TECHNIQUES


Obaidat et al (2001) developed a methodology to detect defects obtained from ultrasonic-based NDT using the multilayer perceptrons (MLP). It was found that results obtained by using discrete wavelet transform (for feature extraction) and neural networks were superior over the classification of NDT signals using only neural networks.

Drai et al (2002) tried to distinguish between a planar and volumetric flaw based on the calculation of wavelet coefficients, time and frequency domain parameters to characterize the defects. Classification was performed using K nearest neighbor, Bayesian statistical method and artificial
neural network. Classification accuracy of 97% was reported with features from wavelet transforms associated with ANN.

Lim et al (2003) classified the artificial flaws in welding parts using the pattern recognition technology. Signal pattern recognition package using digital signal processing technique was developed. The recognition rate of 80% was obtained by using artificial neural network classifier.

Bettayeb et al (2004) used the wavelet transform successfully in experiments to suppress noise and enhance flaw location from ultrasonic signals, with a good defect localization. The obtained result was then fed to an automatic Artificial Neural Network classification and learning algorithm of defects from A-scan data.

Moura et al (2004) using the TOFD technique classified three kinds of welding defects based on signal processing techniques and artificial neural network. The Fourier transform and wavelet transform were used for preprocessing A scan signals. Linear pattern classifiers were implemented into the network. In comparison with Fourier transform, Wavelet transform results in better classification.

Francesca Cau et al (2006) developed an ANN model for fault detection in not accessible pipes. Fault classification was based on the depth and width of the faults and the signal database for the training, validation and test set were obtained using finite element simulations based on propagation of guided ultrasonic waves. A total of 46 features were extracted: 39 in time domain and 7 in frequency domain. Out of the two types of data reduction strategies employed, namely, Garson’s method and Principle component analysis, the later gave better classification accuracy. It was shown from the results that the percentage error of ANN for fault width classification to be less than 5% and less than 7% for fault depth classification. In addition to
experimental works, numerical simulations were also used to generate ultrasonic signals for flaw detection using neural networks.

Lee and Estivill-Castro (2007) developed a new technique to derive a preprocessing method for time-domain A-scans signal. This technique offers consistent extraction of a segment of the signal from long signals that occur in the non-destructive testing of shafts. Two different classifiers using artificial neural networks and support vector machines were supplied with features generated the new preprocessing method and their classification performance were compared and evaluated. It was reported experimentally that DWT coefficients can be used as a feature extraction scheme more reliably by the new preprocessing technique.

D’Orazio et al (2008) developed an automatic system for the analysis of ultrasonic data in order to detect and classify internal defects in composite materials. Two main steps for interpreting ultrasonic data were considered: the pre-processing technique necessary to normalize the signals from composite structures with different thicknesses and the classification techniques used to compare ultrasonic signals and to detect classes of similar points. The second step was carried out by using a multilevel neural approach, firstly defective areas are separated from the sound ones and then they are classified on the basis of the defect type and localization in depth.

2.4 RESEARCH GAP

From the available literature, it is evident that not much is reported in the classification of defects based on the extracted features from the ultrasonic flaw signals. The informative features extracted from the ultrasonic flaw signals (features such as mean, max. amplitude, average frequency etc.) were not considered for the classification of defects using ANN and SVM.
It is also found that classification of more than four classes of welding defect was not carried out using the above techniques.

Hence in the present study the above aspect is given due importance and an Artificial intelligence system with signal processing technique is proposed to improve the sensibility of flaw detection and to classify defects in Ultrasonic testing.

2.5 SUMMARY

In this chapter the contemporary literature within the perusal of the present study is reviewed and presented under the major topics defects classification using ANN and defects classification using ANN and signal processing technique respectively. The additional relevant literature is further cited in the oncoming chapters at the appropriate places. It is further delineated that how the present study differs from the literature cited.