Advanced Neural-Fuzzy And Image Processing Techniques In The Automatic Detection and Interpretation of Weld Defects Using Ultrasonic Time-of-Diffraction

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Abstract

Ultrasonic Time-of-Flight-Diffraction (TOFD) technique has gained significant reputation in the non-destructive testing due to its ability in the accurate detection, sizing and positioning of weld flaws in steel structures. This technique is further endorsed by its reliability, portability and cost-effectiveness in the automatic scanning and data acquisition. The three key issues, due to which fully automatic TOFD interpretation system for the weld flaws, could not be achieved are classification of defects due lack of unique defect signatures in TOFD data, inconsistent detection of the near surface weld flaws and lack of standard guidelines for the data interpretation. However, a fully comprehensive automatic detection, sizing, positioning and classification TOFD system can be achieved using advanced image processing, signal processing and artificial intelligence techniques, thus reducing time, cost and errors in the interpretation of weld flaws in the steel structures.

Keywords– Ultrasonics, TOFD, Texture Segmentation, Neural Networks and Fuzzy Logic

1 Introduction

Welding is a process which allows joining of two metal pieces, often done by melting and adding a filler material to form a pool of molten material that cools to become a strong solid joint known as weld joint. However, incorrect fabrication process may lead to a failure in the weld and the structure itself. Therefore any weld joint can potentially be a weakest link in a given steel structure. Figure 1 shows cross section weld with an embedded defect.

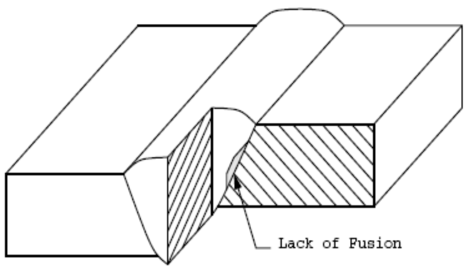


Figure 1 : Embedded Lack of Fusion Weld Defect

The ultrasonic TOFD technique uses two probes, a transmitter and a receiver, in which diffracted energy characterizes the weld defects. The TOFD technique affords high speed data collection with the available data acquisition tools using automatic robotic scanning. However, the crucial processes of data processing and interpretation are still performed off-line manually depending heavily on the skills, experience, alertness and consistency of the trained operator. Thus, interpretation results typically suffer from inconsistency and errors, particularly when dealing with large volumes of data. In the light of industrial pressure, the recent trend has been to automate the TOFD data interpretation process providing robustness, accuracy and reproducibility. This can be achieved by advanced image processing and artificial intelligence techniques to discriminate between subtle variations in visual properties of the data, reducing the overall interpretation time, effort and cost.

The TOFD research [3][4][5][7][12][14][19][20] concludes that technique is portable, fast, reliable, accurate and inexpensive in the flaw detection and sizing. Further, inspection can be semi or fully automated[3][5][15][19] for the flaw detection in metal structures. The other non-destructive testing methods such as ultrasonic pulse-echo uses recorded amplitude to characterise defects. The TOFD technique uses time of flight of the diffracted echoes to confirm the existence and location of weld defects. The D-scan image provides different texture patterns for the detected defects. The automatic texture segmentation is investigated using statistical, spectral and multi-resolution techniques improving the detection and classification of flaws in welds.

This paper presents number of advanced methods used for the automatic detection and classification of weld defects in TOFD data. The mode converted wave technique is also investigated in order to detect the near surface flaws. The prescribed[2] weld flaw types includes planar, volumetric, threadlike and point flaws, which are subdivided into different subcategories. Advanced signal and image processing techniques are used for the segmentation, classification and characterisation of weld defect types. In the classification stage three different classification techniques are employed and compared – artificial neural network-based classifier, fuzzy logic-based classifier and a hybrid neural-fuzzy classifier. A neural classifier can learn from data, but the output does not lend itself naturally to the interpretation. A fuzzy classifier on the other hand consists of interpretable linguistic rules, but they cannot learn. A neuro-fuzzy classifier is based on a 3-layer feed-forward neural network. The first layer is for input variables, the middle (hidden) layer is for fuzzy rules and the third layer is for output variables. Therefore, using a hybrid classifier is an advanced artificial intelligence approach which has advantages of both neural networks and fuzzy logic. The developed neural-fuzzy classifier exhibits high levels of accuracy, consistency and reliability within reasonable computational time and is a promising new development in the field of fully automatic weld inspection. Figure 2 shows process in achieving fully automated TOFD system.

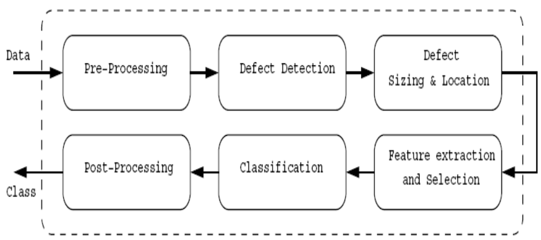
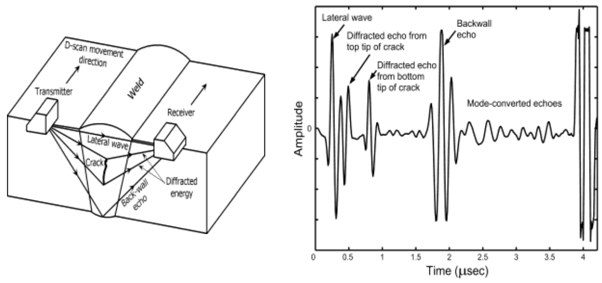


Figure 2 : TOFD Data Processing and Interpretation

2 Ultrasonic TOFD Non-Destructive Testing Method for Weld Defects

TOFD was first described by Silk[12] in the detection, sizing and location of defects. The basic TOFD system is a two-probe arrangement consisting of a separate ultrasonic transmitter and receiver as shown in figure 3.



(a) (b)

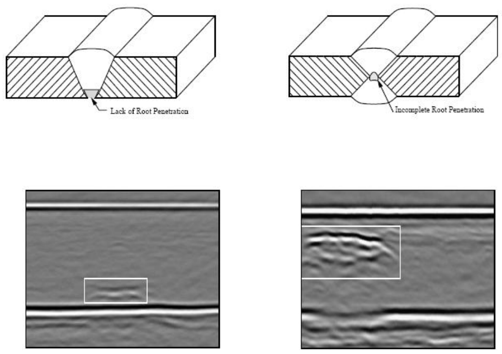
Figure 3 : (a) Two probe transmitter-receiver arrangement for Ultrasonic Time-of-Flight-Diffraction technique. (b) A-scan shows diffracted echoes.

After propagation of the compressional wave from the transmitter, the first signal to arrive at the receiver is a lateral wave through upper surface. In the absence of defects the second signal to arrive at the receiver is the back wall echo. The diffracted signal generated at the upper tip of a defect will arrive before the signal generated at the lower tip of the defect. With a time of flight of each flight path, the ultrasonic velocity and the spatial relationships of the two probes known, location and height of defects can be very accurately calculated. The widespread acceptance of TOFD is also due to the fact that it is independent of defect orientation and easy to use. Echo amplitude is not used quantitatively by this technique for the determination of flaw size[2][12]. The information acquired from the probes is investigated using A-scan, B-Scan or D-Scan. The B-scan is obtained when transducer pair moves across the flaw, perpendicular to the flaw length's direction. The D-scan is obtained when transducer pair moves in same direction as the flaw length. The B-scan provides accurate sizing where as the D-scan provides increased resolution in the detection of weld flaws. The mode converted technique[22] is investigated for the existence of surface flaws.

3 Different Types of Weld Defects and Their Characteristics.

There are numerous standards [2][14][15] which allows the characterization of weld defects using TOFD technique. These standards discriminates these flaws largely on basis such as size of flaw, location of flaw, phase relationship between defect signal and reference signal (lateral wave or back wall signal), amplitude may provide important clue to the character of a flaw. The different types of weld flaws are planar flaw, volumetric flaw, thread like flaw and porosity which can are further sub-divided into subcategories.

Lack of fusion, lack of penetration and slag lacks specific defect signatures in TOFD D-scan image due to several reasons[14]. The figure 4 shows different complexities and defect signatures for the lack of penetration flaws. The complexities involved in acceptance criteria[13] were researched. The acceptance criteria and standards must be agreed prior to an inspection and can be specific to an application. Some standards[2][14] can allow more discrete information and therefore describe cause of defects more precisely. Few European standards require acceptance criteria such that detection of defects is categorised as embedded flaws and surface flaws. However, a good standard and acceptance criteria must always give nature and cause of defect precisely which can act as a learning curve avoiding them in future welds.



(a) (b)

Figure 4 : (a) Lack of root penetration. (b) Lack of incomplete penetration.

4 TOFD Data Processing

The raw TOFD data collected needs initial processing before detection, sizing and classification of weld flaws. This involves noise suppression, drift correction, scan alignment, background removal and estimating lateral and back wall echo positions.

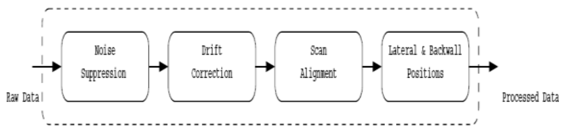


Figure 5 : Initial Processing on Ultrasonic TOFD Data.

4.1 Noise Suppression

The gain used in the amplification of diffracted energy obtained from the extreme tips of defects also amplifies the effect of noise. However, noise generally has zero-mean and SNR can be improved by averaging adjacent scans.

Drift correction

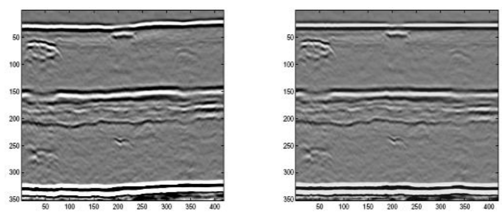
The data acquisition instrumentation generally tends to introduce a drift which often skews the histogram creating ambiguities in the processing unless removed.

Scan Alignment

When collecting the data there tends to be a misalignment of adjacent A-scans despite robotic scanning. This could occur due to several reasons such as couplant or surface irregularities, probe separation or accident probe lift-off. Using lateral and back wall signals as reference scan alignment is achieved in order to characterise weld defects accurately. Figure 6 shows scan alignment giving

Background Removal

On many occasions defect features are masked due to noise or in the lateral and back wall zone. Removing such areas improves defect characterisation.



(a) (b)

Figure 6 : (a) Before Scan Alignment. (b) After Scan Alignment.

5 Automatic Texture Segmentation for Defect Detection and Classification

Studies in psychophysics[11] investigates visual processes that allow humans to separate features in images are texture cues. A region in an image has a constant texture if a set of local statistics or other local properties of the picture function are constant or approximately periodic[17]. The texture segmentation is investigated using statistical, spectral and multi-resolution techniques. In the spectral approaches, the texture image is transformed into frequency domain by the Fourier transform. Therefore, texture features are extrapolated by analyzing power spectrum. Zahran[14] uses local variance for the detection of defects. However, to improve detection and classification of defects several textural methods[1][6][10][11][16][17][18] are investigated and implemented to greater success. The range of methods used to extrapolate texture measures were auto-correlation, first order statistics, second order statistics (spatial grey level matrix), edge frequency, primitive length, Laws energy measures and segment based texture features. Haralick's[18] co-occurrence based matrix features is widely used in calculating texture measures. A novel approach, segment based texture measure algorithm provides efficient way of discriminating defects. This method considers shape and uniformity of a detected defect in calculating features. This approach discriminates volumetric flaws such as slag and lack of penetration where discrimination is not a trivial task. This algorithm is computationally faster as first order statistics and provides more texture information as co-occurrence matrix.

Law[10] provides efficient way of calculating texture measures which is computationally faster than co-occurrence based matrix texture measures. Using small convolution kernels for a digital image and then applying non-linear windowing operation. The 2-D convolution kernels generally used for texture discrimination are generated from the following set of one-dimensional convolution kernels of length five:

$$L5 = [\ 1\ \ 4\ \ 6\ \ 4\ \ 1\ ]$$
$$E5 = [\ -1\ \ -2\ \ 0\ \ 2\ \ 1\ ]$$
$$S5 = [\ -1\ \ 0\ \ 2\ \ 0\ \ -1\ ]$$
$$W5 = [\ -1\ \ 2\ \ 0\ \ -2\ \ 1\ ]$$
$$R5 = [\ 1\ \ -4\ \ 6\ \ -4\ \ 1\ ]$$

The Level(L5), Edge(E5), Spot(S5), Wave(5) and Ripple(R5) kernels are zero-sum except Level(L5). Note that all kernels except L5 are zero-sum. In total 25 different two dimensional convolution kernels are estimated using this one-dimensional convolution kernels by convolving a vertical 1-D kernel with a horizontal 1-D kernel.The segmentation and classification was achieved by comparing each of these methods before deriving hybrid features. The texture features when combined with signal features provides very accurate and reliable automatic TOFD data interpretation system.

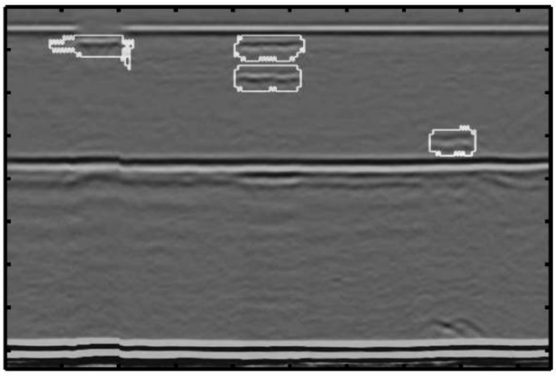


Figure 7 : Automatic Segmentation in a TOFD Data.

6 Neural Network and Fuzzy Logic Classification

In this research, three different artificial intelligence approaches were employed in classification of weld defects.

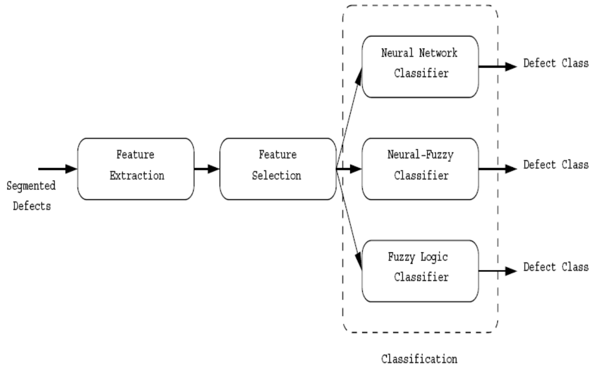


Figure 8 : Weld Defect Classification

Neural networks with their ability to derive information from complicated and imprecise data can detect and extract patterns that can be too complex for simple systems. Fuzzy logic, proposed by Prof. Zadeh[8][9], is a theory that allows the natural descriptions, in linguistic terms, of problems to be solved rather using numerical values.

Fuzzy logic classifier was simplest to design and computational speed was very less with 95% classification of defects achieved. With membership functions, if-then rules and logical operators provided robust classifier. However, tuning membership functions with large volume of features proved to be its only disadvantage. A fuzzy-neural based classifier is a hybrid classifier with advantages of both neural networks and fuzzy logic. This classifier uses three layer networks with middle layer being for fuzzy if-then rules. The hybrid classifier is computationally fast and classification achieved is better than other two classifiers. This is the classifier that learns from data and interpretable using fuzzy logic rules. Figure 8 shows a multilayer neural-fuzzy model and Figure 9 is a typical output of a classifier giving defect characteristics. The accuracy and training of fuzzy-neural classifier is reliable and reproducible.

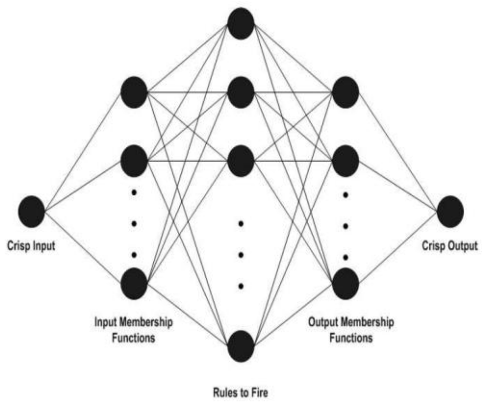


Figure 8 : Multilayer neural-fuzzy network model.

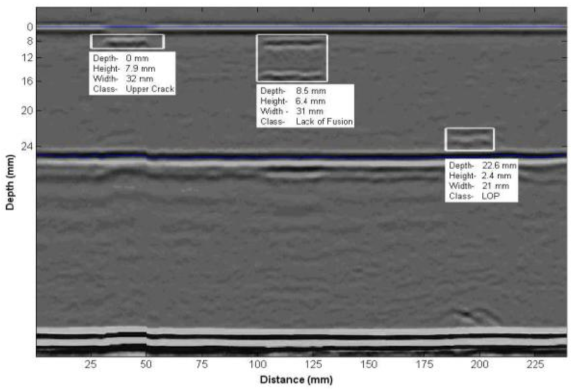


Figure 9 : Automatic detection, sizing and classification of weld defects.

7 Conclusions

The TOFD technique affords a fully automated inspection system for detection, interpretation and classification of weld defects. Mode converted technique can be used for existence of surface flaws which remains masked in the lateral or back wall signal. Using statistical, spectral and multi-resolution techniques has given improved results and has wide appeal for other NDT data such as ground penetrating radar data. The developed neural-fuzzy classifier has shown exceptional promise, with the achieved results exhibiting high levels of accuracy, consistency and reliability, within reasonable computation time. The fuzzy-neural based classifier provides better performance and combines the benefits of both neural networks and fuzzy logic. Thus, different advanced texture segmentation and classification methods can be used to set standard guidelines and characterise weld defects.

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