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Abstract

Ultrasonic Time-Of-Flight Diffraction (TOFD) is a fairly recent innovation in NDT that has proved highly effective for the inspection of welds in steel structures, providing highly accurate detection, characterisation, positioning and sizing of defects with a high probability of detection. This has enabled it to gradually replace other more conventional ultrasonic testing techniques. Currently most TOFD data interpretation is done off-line manually by a trained operator and using advanced interactive processing tools in software. This processing is highly dependent on operator skill, experience, alertness and consistency and is a cumbersome, tedious and time-consuming process. Results typically suffer from inconsistency and slight inaccuracies as a result of natural human error when dealing with such large volumes of data that are commonly generated in TOFD investigations.

The recent trend in the related disciplines of remote sensing and medical imaging is to automate the data processing and interpretation process as far as possible, relieving the expert to some extent of unnecessary or repetitive tasks. In light of industrial pressure, it is anticipated that TOFD interpretation could benefit from such automation, potentially improving the interpretation procedures by adding an element of robustness, accuracy and consistency. This can be achieved by utilising computational tools that are better suited to discriminating between subtle variations in visual and spectral properties of the data. Furthermore, this would result in a saving in time, effort and cost. Although each defect category has unique characteristics and patterns but there are some similarities between these categories which make the discrimination between these categories not an easy task.

This paper presents a novel system for rapid and consistent automatic classification of detected defects in TOFD data as essential stage of a comprehensive unsupervised TOFD inspection and interpretation aid. This system is based on extracting some visual and spectral distinguishable features from A-scan and D-scan segments which represent different defect classes in TOFD data to produce the discrimination bases for the neural classifier to distinguish between these classes. This classifier was applied to a variety of TOFD data sets gathered from a variety of steel plates and tubular pipe lines with different thickness and different defect classes have been successfully discriminated with a consistency greater than that of the expert operator, but in a fraction of the time.

The results achieved are rapid, with satisfactory levels of accuracy and reliability to form a robust automatic classification of detected defects. It is hoped this will form the basis for a new paradigm in ultrasonics for fully-automatic batch processing and interpretation.

1. Introduction

Ultrasonic techniques are still the most popular non-destructive testing methods applied to problems such as the inspection of welds in steel structures. Since its early development by Silk in late 1970s, TOFD has gained popularity in the ultrasonic NDT community to the extent that it is gradually replacing other more conventional ultrasonic testing techniques. This has been to a large extent because of its ability to provide accurate characterisation, sizing and positioning of a large variety of defects (1). Use of TOFD as a rapid non-destructive inspection tool for steel plates, pipelines and vessels has grown tremendously during recent years, brining into light the challenge of developing a fast and reliable data processing and interpretation platform.

Raw TOFD data returns from the data acquisition process are in need of significant processing before being 'usable' for visual defect classification and evaluation. These processes include noise suppression, drift correction, background removal, scan alignment, and estimation of lateral wave and backwall positions. This is in addition to scale linearisation, calibration and the highlighting areas corresponding to defects (2). Despite the existence of software aids, these operations are still heavily reliant on the judgment and skill of a trained operator. Such operations would require considerable amounts of time and efforts, in additional to the increased time and cost involved with an intensively operator-dependent processing system, the very existence of the human factor at these critical process stages invariably introduces inconsistency and error into the overall interpretation results.

To overcome this bottleneck, all these processing operations have been successfully automated here (3), thereby shifting part of the interpretation burden from the trained operator to the computer, allowing the operator to make better judgments about the exact nature of the flaws in light of knowledge of the structure and geometry of the weld.

Each defect class in TOFD images has its main characteristics and patterns. The classification of these defects can be achieved by feeding some distinguishable features in addition to the main clues of characterising each defect class to an artificial intelligent system which will be able to use these main clues and distinguishable features and perform the automatic classification of detected defects (4,5). During the last decade, artificial neural networks have played a vital and effective roll regarding a vast variety of science branches. They have proven to be adaptable, efficient, rapid, and accurate in many applications. One of the most powerful applications of a neural network in which the above mentioned properties can be prominently seen is classification.

This paper presents an automatic classification system for discriminating between different defect classes in TOFD data, based on extracting features out of the A-scan signals and D-scan images segments representing the different classes of detected defects in TOFD data [6,7]. Then a backpropagation neural network classifier is applied on the extracted features to classify each segment into its relative class of defects. The classifier was applied to various TOFD scans collected from a variety of steel plates, and the obtained results were quit encouraging in all of the three aspects as it will be detailed later.

This paper is showing how classification stage would fit into a comprehensive semi-autonomous processing and interpretation system. It is expected that such an interpretation system will greatly reduce the degree of reliance on the trained operator during initial investigations.

2. TOFD

Conventional ultrasonic techniques measure the reflected pulse transit time and the signal amplitude to locate and size flaws. As the amplitude of the reflected pulse is influenced by parameters other than the dimensions of the reflector (such as the orientation of the defect, transparency and surface roughness), pulse-echo may not always provide reliable or accurate sizing information [8]. Echo strength in TOFD on the other hand, does not depend on the defect orientation, allowing defect sizes to be accurately determined (generally accurate to within ±1 mm), with a high probability of detection of approximately 95%. Defect sizing using this technique depends on the accurate measurement of arrival time of the diffracted and reflected waves at the defect extremities [9].

TOFD is based on measurement of the time-of-flight of the ultrasonic waves diffracted from the tips of discontinuities originating from defects. Two longitudinal broad beam probes are used in a transmitter-receiver arrangement, so that the entire flaw area is flooded with ultrasound and, consequently, the entire volume is inspected using a single scan pass along the inspection line, as shown in Figure 1. The collected data can be visualised in an A-scan representation or stacked together side-by-side in a raster representation called a D-scan (longitudinal) or B-scan (parallel) or as in Figure 2.

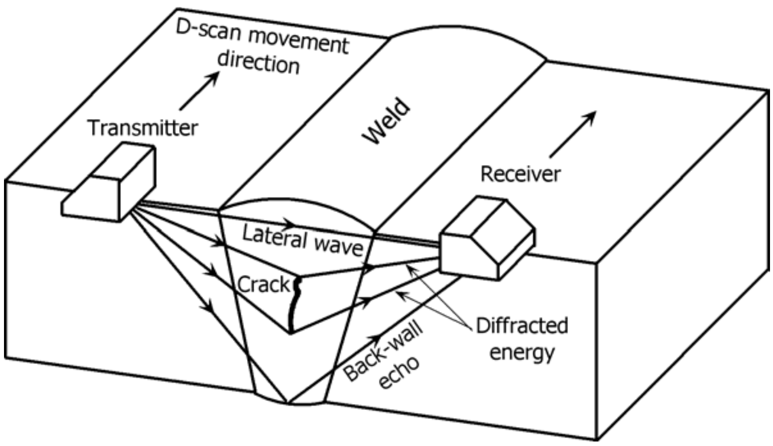

Figure 1: Illustration of TOFD operation

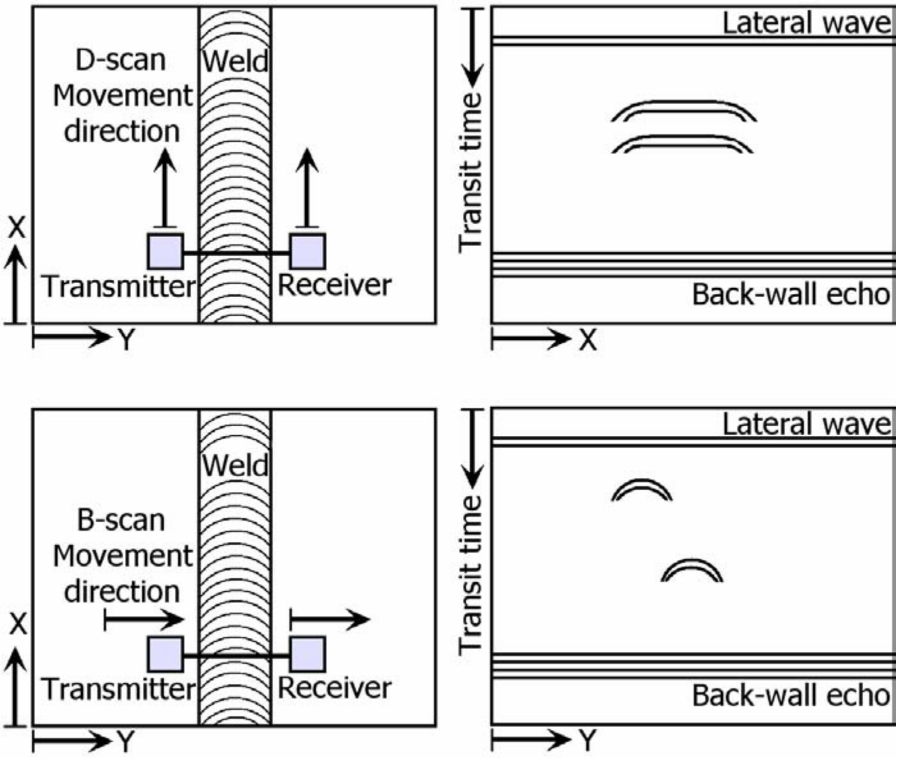

Figure 2: TOFD D-scan and B-scan representations

When an ultrasonic wave encounters a defect, it undergoes reflection, transmission and diffraction. According to Huygens's principle, each defect tip acts as a point source of diffracted energy over wider angles than what is possible under reflection and transmission. The diffracted energy originating at the extremities of the flaw is well suited for flaw detection and sizing as it is directly related to the true position and size of the defect.

In TOFD data there are generally four characteristic signals that are sought:

- **the lateral wave** which arises from the wave that travels directly from the transmitter to the receiver along the surface with the shortest time of travel and a speed close to the longitudinal wave speed in the structure,
- **the defect top tip echo** which is the wavefront diffracted by the top tip of the defect and travels at longitudinal wave speed,
- **the defect bottom tip echo** which is the wavefront diffracted by the bottom tip of the defect and also travels at longitudinal wave speed, and
- **the backwall reflection** which arises from both the mode converted and longitudinal wave reflected from the bottom surface.

Mode-converted echoes appear in the portion of the TOFD image immediately (after) below the backwall echo, and can provide an exceptional resolution of shallow flaws especially when the flaw is located closer (laterally) to one probe than the other. In all instances, due to the lower speeds of these echoes, these echoes may provide better resolution of the flaws than in the compressional wave. Although this data is often discarded to gain benefits in processing time, there are instances where examining the patterns in this portion can lead to meaningful insight into the geometry and nature of the defects.

After close scrutiny of the manner and sequence in which a trained expert processes and interprets TOFD data according to the suggested interpretation flowchart in Annex C of BS7706 [10], taking into account the functionality of the available interactive software tools, the format of the data, the visual and mental processes involved and the terms of reference employed, a streamlined and modularised interpretation system has been proposed, as shown in Figure 3.

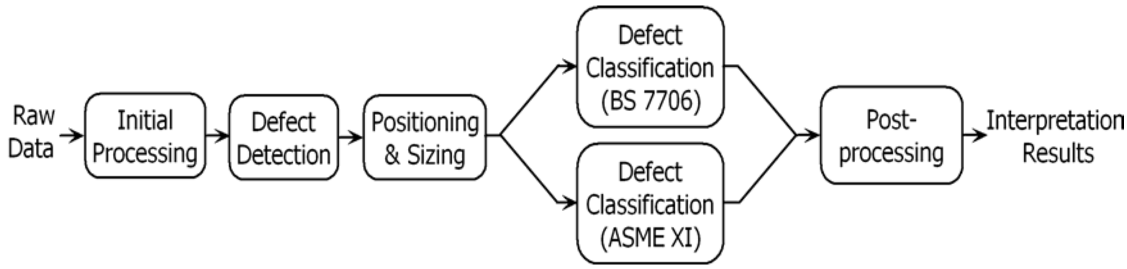

Figure 3: Block diagram of proposed semi-automatic interpretation system

Each stage consists of a number of processes which are carried out sequentially in order to correctly interface with the input of the following stage until the final interpretation result is obtained. This paper described the functionality of defect classification stage block in Figure 3.

3. Flaw characteristics

The common defects in welds can be classified into four main categories, planar flaws, volumetric flaws, thread-like flaws and point flaws [10]. Each flaw category has special characterisations and patterns but also there are some similarities between these categories. It is very important to study these characterisations and patterns carefully which may be helpful in providing an automatic interpretation system.

Planar flaws include cracks and lack of fusion. Planar flaws may be open to upper surface, breaking the lower surface or internal. The planar flaws open to the upper surface show up as an echo from the bottom edge of the flaw with higher frequency content and the phase is still as the lateral wave. The defect signature is this case is similar to a reflected moustache shape. While the planar flaws breaking the lower surface show up as an echo from the top edge usually accompanied by an increasing delay in and/or weakening of the backwall signal. The phase of the echo is still the same as the backwall echo. The defect signature is this case is similar to a moustache shape. Internal planar flaws show as two echoes with a distinct 180° phase difference between them. The phase of the upper tip echo is the same as the backwall echo. Both echoes have a similar amplitude and defect signature. The defect signature in this case is also similar to a moustache shape. Lack of fusion is very similar to the internal cracks.

Volumetric flaws include lack of penetration and large slag lines. The echoes from reflectors of this type also show the features and phases outlined for internal planar flaws but the echo from the upper surface is greater than the diffracted around the lower surface. The target signature of the large slag lines look like the straight line.

Thread-like flaws include flaws with significant length but little through wall extent such as lamellar flaws and near horizontal area lack of fusion. The reflector appears as an apparent upper edge echo in phase with backwall echo without lower edge echo. The target signature of this category looks like the thin straight line.

Point flaws category includes pores and small pieces of slag. These flaws are most common in welds and their echoes have similar pulse characteristics to the volumetric or thread like flaws but have no resolvable length. Point flaws give multiple echoes but with no other co-linear echoes. The defects of this category produce signals which look like arcs on D-scan.

4. Artificial neural networks

In order for the automatic classification process to be complete, the selected features need to be employed into a classification mechanism. One of the most successful approaches in this field is artificial neural networks. Neural network is a massively parallel distributed processor made up of simple processing units, which has a natural propensity for strong knowledge and making it available for use. It resembles the human brain in its work [11]. Neural networks have been proven to be rapid, accurate, and most importantly, adaptive in classifying and simplifying complex data. These networks have proved to be extremely effective in learning subtle differences between various classes.

In order for the neural classifier to make right decisions, it needs distinguishing bases upon which its decision would be made. These bases can be viewed as features of the signals and image segments, and are to be extracted so the classifier would build its decisions accordingly. The data set used to train and validate the network comprises a number of carefully selected features extracted from image segments and A-scans representing all defect classes from a variety of TOFD scans. Investigation of these features in the sense of their clustering capability has produced encouraging results which, in turn led to selecting them as decision making bases for the neural classifier.

The type of neural networks used in this work is supervised neural networks. The supervised neural networks presented are three-layer feed-forward neural networks that are trained using one of the supervised learning algorithms (backpropagation), which uses the data to adjust the network's weights and thresholds so as to minimise the error in its predictions on the training set. When the network is properly trained, it has then learned to model the (unknown) function which relates the input variables to the output variables, and can subsequently be used to make predictions where the output is not known.

5. Defect Classification

Most standards stipulate that a flaw characterisation process should immediately follow the flaw detection stage, to enable flaws to be evaluated, reported and documented according to the adopted reporting and acceptance criteria (such as BS 7706 (10) and ASME XI (12)) in order to distinguish between serious flaws which can grow to fail and less series flaws. While it is never possible with TOFD alone to fully characterise the flaws, they can nevertheless be broadly classified into broad categories according to their location, size and geometry. The British Standard on TOFD (10) is fairly detailed in its categorisation of flaws, recognising the following main categories of flaw, each with a number of sub-categories:

1. Planar flaws (includes upper cracks, internal cracks, lower cracks and lack of fusion)
2. Volumetric flaws (includes lack of penetration and large slag line)
3. Thread-like flaws
4. Point flaws (includes porosity and small pieces of slag)
5. Uncategorised flaws

The ASME XI codes (12) on the other hand classify only crack-like flaws, and use the following categories:

1. Open to one of the surfaces
2. Clear internal
3. Internal but approaching one of the surfaces
4. Very small surface breaking

To classify the detected defects into the five categories explained in BS 7706 (10) or the four categories in ASME XI (12) the special characterisations and patterns of each category have been studied carefully to decide which ones can be used as discriminating features between these classes. In this classifier, a novel system for rapid and consistent automatic classification of detected defects has been investigated as shown in Figure 4.

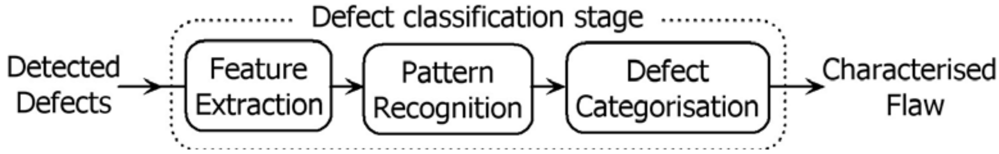

Figure 4: Block diagram of defect classification stage

This system is based on extracting some regional shape and spectral features from A-scan and D-scan segments which represent different defect classes in TOFD data to produce the discrimination bases for a supervised neural-network classifier to distinguish between these classes. A large number of features have been investigated and their individual and combined effects on the classification rate have been tested exhaustively before deciding which to retain and which to ignore. For classification based on the ASME XI code [12], the features are related to the aspect ratio of the defect height and length which have been previously obtained from the sizing and poisoning stage. The process of feature investigation, combination, selection and testing has led to a subset of features which are found to best distinguish between different defect classes, not only the main defect categories but also between the subcategories in each main category.

Depending on which standard is being adopted, the selected features are used as inputs to a three-layer feed-forward neural network that is trained using the backpropagation supervised learning algorithm, using the data to adjust the network's weights and thresholds so as to minimise the error in its predictions on the training set. The trained network can then be applied to new unseen data and possesses the ability to generalise what it has learnt in such a way as to correctly classify each detected defect. In line with the BS7706 procedures [10], the network outputs are processed in such a way as to favour a more pessimistic interpretation (i.e. reporting a more serious flaw) in cases where the network's judgement is uncertain.

6. Results

The developed procedure has been applied to the same data set consisting of 76 D-scans obtained from a variety of sample plates with thicknesses ranging from 24mm to 30mm. These scans contain a total of 174 defects: 24 upper crack flaws, 24 internal crack flaws, 11 lower crack flaws, 28 lack of fusion flaws, 14 lack of penetration flaws, 52 slag flaws, 15 porosity flaws and 6 threadlike flaws. This is equivalent to 9 cracks open to one of the surfaces, 24 clear internal cracks, 16 internal cracks approaching one of the surfaces and 10 very small surface breaking cracks.

For both standards, the achieved classification results on the data set described earlier, are very promising in terms of accuracy and processing speed and its outputs were presented in a clear form, where the classified data are illustrated to the operator by colour-coding the areas of interest on the original image data with a textual description indicating the class and dimensions of each defect.

In the case of BS 7706 [10], upper crack, internal cracks, porosity and threadlike defects are classified with a classification rate of 100%; lower cracks is classified with a classification rate of 90%, lack of fusion is classified with a classification rate 89% with slight confusion with internal cracks which are related to the same main flaw category (planar flaws); lack of penetration is classified with a classification rate 85% with confusion with slag which is related to the same main flaw category (volumetric flaws) and slag is classified with a classification rate 94% with mainly confusion with lack of penetration which is related to the same main flaw category (volumetric flaws). As shown the classification rate of cracks which considered much more serious than other flaws is approximately 100% and the classification rates of other flaws are considered good especially this classification rate not only for the main flaw categories but also is for the classes inside each main category. If the results are combined to classify the main categories the classification rate as overall will be 96.5%.

In the case of ASME XI [12] categorisation, only crack-like flaws are considered, and hence only 59 of the 174 defects are subject to this classification, with the remaining flaws reported as either “uncategorised” or “clear internal” for further investigation. Clear internal cracks are classified with a classification rate of 100%; internal cracks approaching one of the surfaces are classified with a classification rate of 93.7%; cracks open to one of the surfaces are classified with a classification rate 88.9% and very small surface breaking cracks are classified with a classification rate of 80%. If the results are combined to classify all flaws the classification rate as overall will be 93.2%. Figure 5 shows an example of classification results for different defect classes.

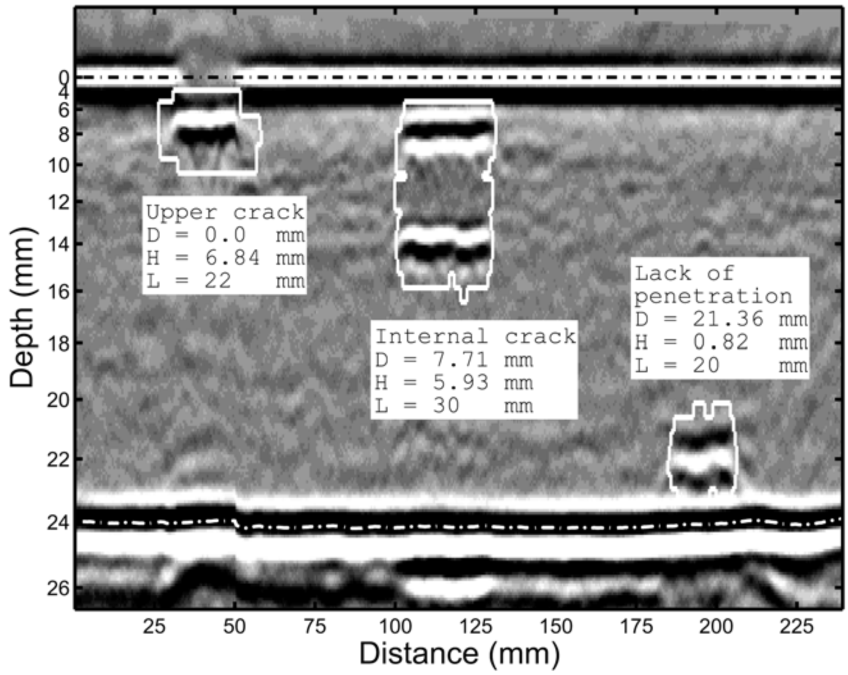

Figure 5: Final interpretation output representation indicating classified flaws

7. Conclusions

This paper has addressed the task of automatic classification of defects in ultrasonic TOFD data as part of a comprehensive automatic interpretation system being developed at the University of Liverpool. This system has been applied to a variety of TOFD data gathered from a variety of steel plates with different thickness and different defect classes have been successfully categorised with a consistency greater than that of the expert operator, but in a fraction of the time. All processes are carried out automatically, avoiding the need for any external intervention in the processing, and allowing batch file processing. Results of the application of the developed classifiers to the available data have been extremely promising in terms of speed, robustness, accuracy and reliability when dealing with highly variable data. This would make the proposed system suitable for implementation in situations requiring real-time processing and interpretation of large volumes of data. Combining semi-automatic interpretation with automatic inspection will provide the trained operator with invaluable assistance during inspections, reducing the reliance on expert judgement in the more routine and straightforward application of the standards, and thus reducing the possibility of human error due to loss of concentration and visual fatigue.

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