AN EXPERT-SYSTEMS APPROACH TO AUTOMATICALLY DETERMINING FLAW DEPTH WITHIN CANDU PRESSURE TUBES

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ABSTRACT

Delayed Hydride Cracking (DHC) is a crack growth mechanism that occurs in zirconium alloys, including the pressure tubes of CANDU reactors. DHC is caused by hydrogen in solution in zirconium components being diffused to any flaws present, resulting in an increased concentration of hydrogen within these flaws. An increased hydrogen concentration can lead to brittleness, followed by cracking, in high-stress regions of a pressure tube. Regular in-service ultrasonic inspection of CANDU pressure tubes aims to locate and classify any flaws that pose a potential for DHC initiation. A common approach to inspection is the use of a bespoke tool containing multiple ultrasonic transducers to ensure that each point on the pressure tube is inspected from a minimum of three angles during a scan. All flaws from within the inspected pressure tubes must be characterized prior to restarting the reactor, thus the time-consuming analysis process lies on the critical outage path. This process is manually intensive and often requires a significant amount of expert knowledge. A modular system to automatically process outage data to provide decision support to analysts has been developed. This system saves time on the critical outage path while providing repeatable and explicable measurements. Part of the analysis process requires the depth of all flaws to be measured, which is often the most time consuming stage of the analysis process. This paper describes an approach that utilizes captured analysts knowledge to perform automatic flaw depth estimation.

Key Words: Automation, Expert System, Ultrasonic NDE

1 INTRODUCTION

As a large proportion of nuclear power plants are entering the latter stages of their operational lifetimes, ensuring reliability of components within the plant becomes more necessary for both continued safety and to minimize unplanned outages. In the case of the Canada Uranium Deuterium (CANDU) reactor, planned outages are generally scheduled approximately every three years where a comprehensive inspection of the reactor components takes place. A diagram of the CANDU reactor is shown in Figure 1 [1], where the pressure tubes and the fuel bundles contained within them are annotated, along with other key components of the reactor. As part of the inspection program, a subset of the reactor's 480 pressure tubes are examined non-destructively using a series of ultrasonic measurements [2]. These measurements are manually analyzed by a team of human analysts, which is a time-consuming process that lies on the critical path to the restart of the reactor. In order to reduce the time spent during analysis, and to increase the repeatability of measurements made, a modular system called Automated Data Analysis for Pressure Tubes (ADAPT) has been developed that aims to replicate the process performed by the human analysts in order to provide decision support for manual analysis.

A key function of ADAPT is the estimation of the depth of a located defect. Accurate measurement of a defect's depth allows the tracking of defect growth over time, as well as the ability to perform informed simulations of defect behavior over time. Delayed Hydride Cracking (DHC) is a major concern within reactor designs that utilize zirconium components and is caused by increased hydride concentration coupled with the increased mechanical stresses associated with these defects as well as the heating and cooling cycles of the reactor. Aside from manufacturing flaws, the most common areas where hydride build-up takes place are surrounding defects caused by in-service operation. Defective regions are modelled in software to predict when the pressure tube is at risk of DHC [3], at which time the pressure tube will be replaced to ensure no damage can occur to the reactor, which is a possible consequence following a leak. These simulations make a conservative assessment that can be improved by knowing accurate dimensions of a defect.

This paper presents an expert-systems inspired method to measure the depth of a defect within a CANDU pressure tube. Expert systems have become common for prognostics and health management for industrial use for a number of years [4], and have been previously applied to ultrasonic NDE for the validation of simulations [5]. The use of expert systems for prognostics in nuclear applications is less common [6,7] and the use of an expert system for ultrasonic depth measurement in a nuclear application is a novel application of the approach. Results from this method are compared to measurements made by human operators where accuracy is determined by assessing the differences in depth reported by the human operator and the algorithm.

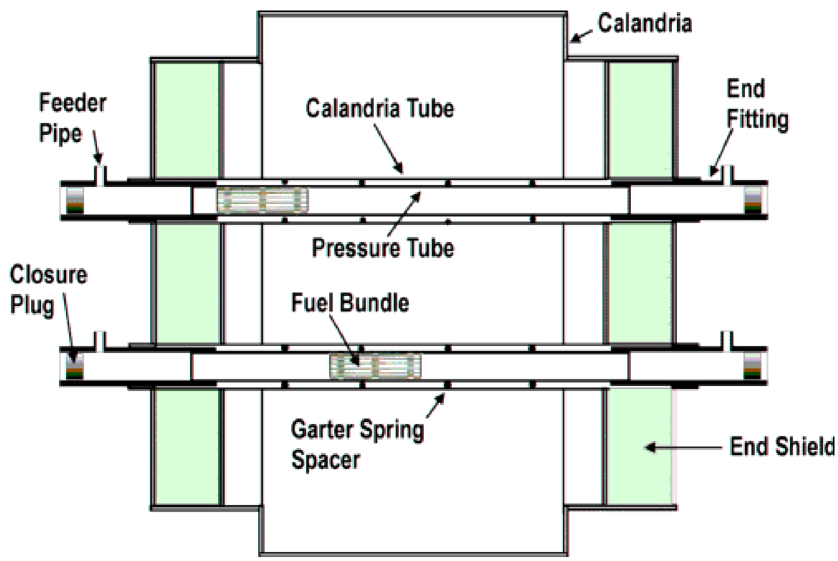

Figure 1. An illustration of the CANDU reactor, showing the pressure tubes discussed in this paper and the fuel bundles that reside within the pressure tubes. A full pressure tube contains 12 fuel bundles.

2 PRESSURE TUBE INSPECTION

Pressure tubes within CANDU reactors are inspected using a rotating tool containing multiple ultrasonic devices. The motivation behind using multiple devices on a single tool is to inspect the tube from a number of different angles to maximize the information available about potential defects [8]. The tool is moved through the pressure tube, recording its position as well as the ultrasonic signals from each device.

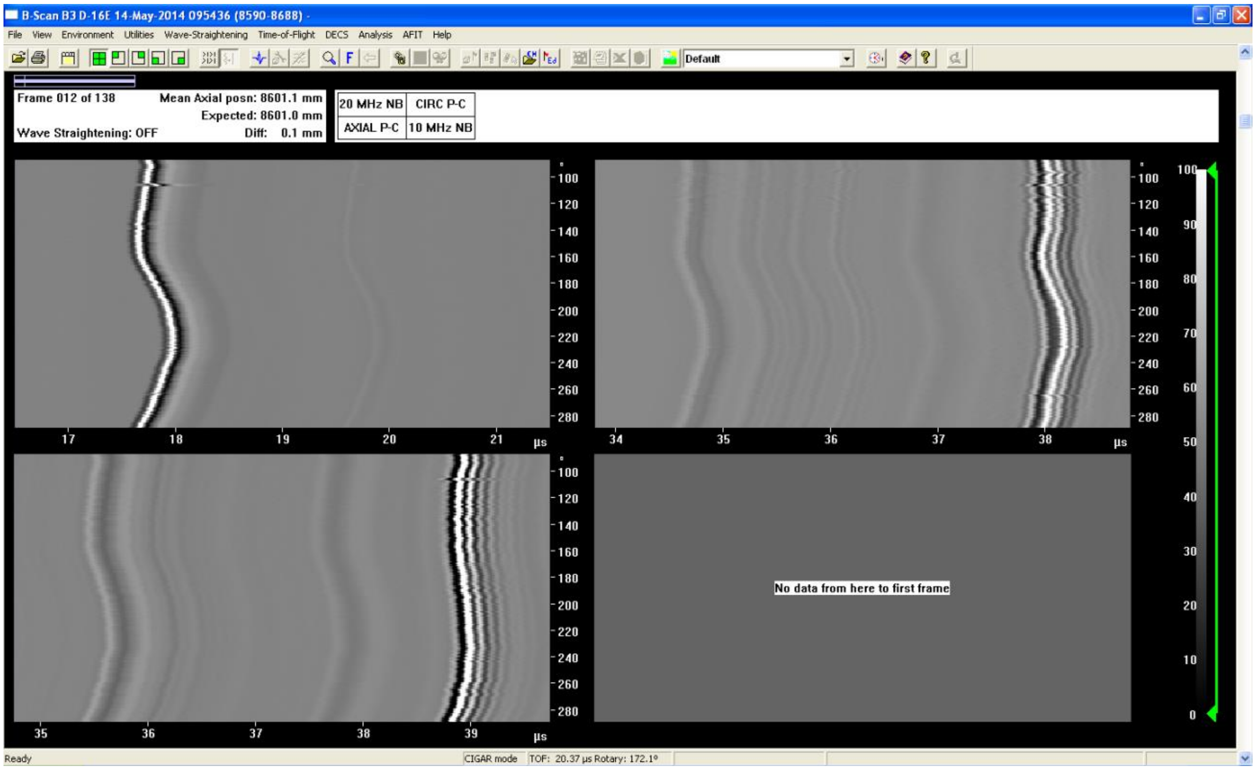

Figure 2. A screenshot from the ultrasonic analysis software. Three different B-scan datasets are available for each position and each dataset is comprised of individually focused A-scans. The backwall reflections appear to curve due to the movement of the tool as it rotates inside the pressure tube.

This data is then provided to the analysis team who review the measurements using custom software (a screenshot of which is shown in Figure 2), locating, sizing and classifying any defects found.

Once a defect has been located and the length and width measured, the depth is determined by examining B-scan datasets and locating the ultrasonic reflection from the bottom of a defect. Every B-scan dataset contains ultrasonic measurements from three sources: a 20 MHz normal incidence probe operating in pulse-echo mode (NBeam); a 10 MHz axial pitch-catch shear-wave probe in a full-skip configuration (APC); a 10 MHz circumferential pitch-catch shear-wave probe, also in a full-skip configuration (CPC). The full-skip configuration allows for inspection from below the defect, which is useful when oxide deposits within the defect make measurements from the surface difficult. A slice of data from each of these sources can be also seen in the screenshot shown in Figure 2.

The depth measurement process involves initially locating the reference back-wall reflection, which can be complicated by the fact that the distance between the probe and the internal surface of the pressure tube does not remain constant as the inspection tool rotates during the scan. Once the reference has been located, the reflection from the bottom of the target defect must be located in an A-scan. Individual A-scans can appear complex if they are subject to noise or if the bottom of the defect is rough. Each A-scan is a superposition of all of the reflections that occur within the pressure tube and complex A-scans are comprised of multiple reflections. In this case, analysts must use their knowledge and experience to select the appropriate reflection for each A-scan. The depth is then calculated by comparing the position of the backwall reference to the position of the bottom of the defect.

The confidence in the depth measurement is increased by repeating the process on each of the three data sources. If the measurements from each source agree then the analyst can be reasonably confident that the depth is accurate. If they differ, the analyst seeks an explanation and potentially seeks another measurement point within the dataset.

3 PROPOSED METHODOLOGY

In order to faithfully reproduce the process used by analysts, the CommonKADS approach to knowledge representation was adopted [9]. Knowledge Acquisition and Documentation Structuring (KADS) defines a structured approach to designing knowledge-based systems and this approach matured into the well-known CommonKADS methodology.

CommonKADS defines general guidelines for knowledge capture, knowledge representation and the implantation of knowledge systems. The process of representing a system using CommonKADS involves building a series of related models. An overall task model has been derived that defines the analysts' role in the overarching inspection process. From the task model, individual components of the analysis process have been highlighted for development in a knowledge system. The depth estimation process is one of these components and the one focused upon in this paper.

Formal knowledge elicitation was conducted with domain knowledge experts in order to build up a knowledge model. Within CommonKADS, knowledge models have three main categories: task, inference and domain knowledge. Domain knowledge specifies the domain-specific knowledge required for completion of the task. It defines the expert knowledge and allows facts about a system to be ascertained. The inference knowledge describes the reasoning that takes place within a system. The inference knowledge can be used to evaluate information made available through the domain knowledge in order to establish new facts about the system. The task category of the knowledge model represents the goals that an expert will work towards and includes a decomposition into subtasks and inferences required to complete the task.

For the specific application of depth estimation using ultrasonic data, a task model was generated with each subtask able to be represented by an inference model or an algorithm. In order to remove the requirement to revisit a dataset multiple times in a potentially iterative process, the concept of a 'depth -map' was instead introduced. Instead of a single measurement being made from each A-scan, multiple measurements

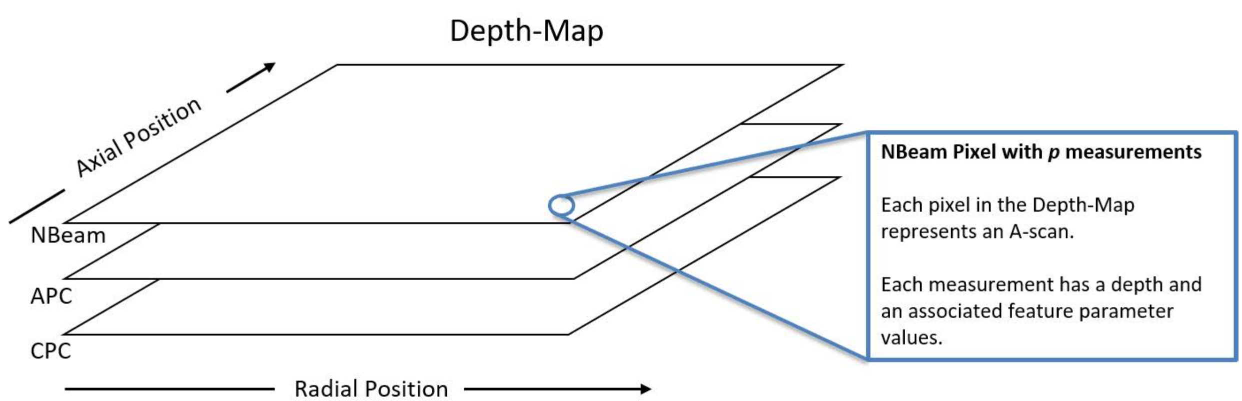

Figure 3. A visual representation of the 'depth-map' that contains multiple measurements from each A-scan.

are made with a confidence assigned to each. These measurements are stored in a dataset that can be referred to when making inferences. A visual representation of this dataset is shown in Figure 3.

A task knowledge model was generated from formal knowledge capture sessions with experts, as well as extracting information from inspection specification documentation. The task subsection of the knowledge model is represented by the image in Figure 4. The model is split into two main sections: the initial creation of the depth-map, and the selection of the most likely overall depth measurement for any given point.

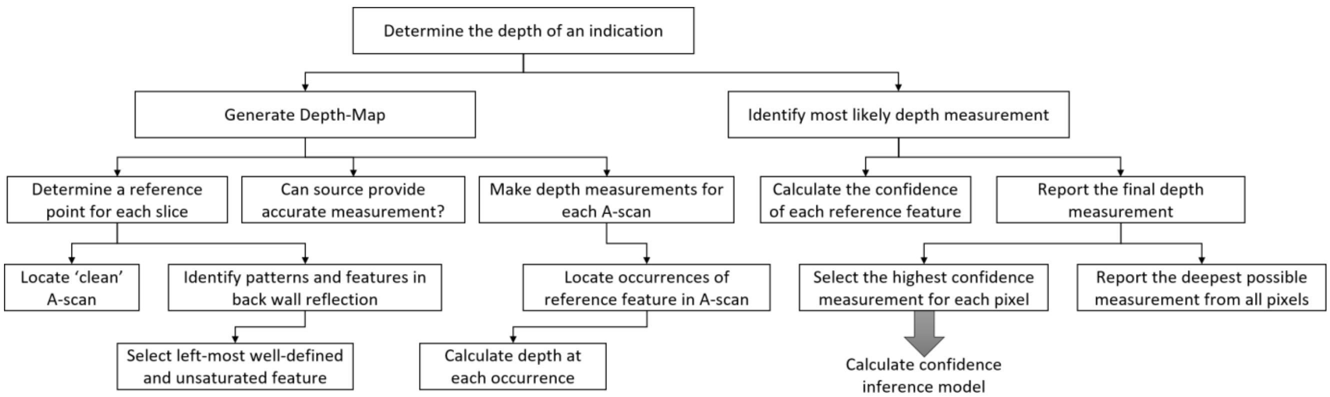

Figure 4. A portion of the task subsection of the knowledge model for measuring the depth of a defect within a CANDU pressure tube.

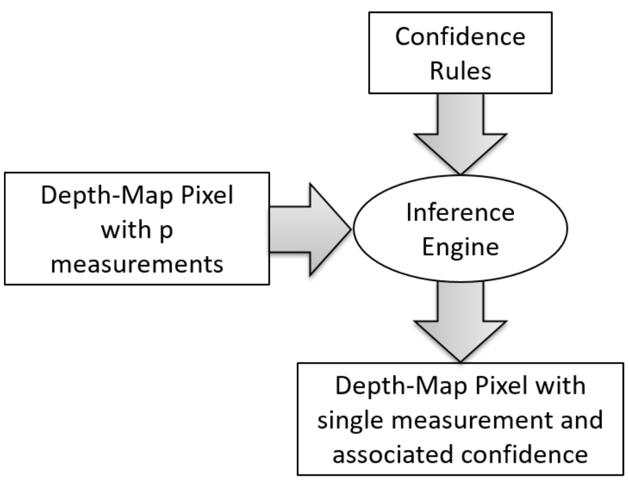

Figure 5. The inference model for used to calculate the confidence of each point in a pixel of the depth-map.

The generation of the depth-map is primarily algorithm-driven and the main goal of this section is to identify potential measurement points and establish key feature parameter values where are used as inputs to the inference model. Identification of the most likely depth measurements is achieved by applying a set of domain rules representing confidence adjustments to each element of the depth-map. This inference model is shown in Figure 5.

Once each element of the depth-map has been assigned a confidence, the highest confidence element is chosen as the best measurement for each pixel. Finally, to report a single depth, the largest depth found in the processed depth-map is returned from the system.

Figure 6 shows some example domain rules defined within the knowledge base. Each of these rules, when fired, modifies the confidence of an individual element within

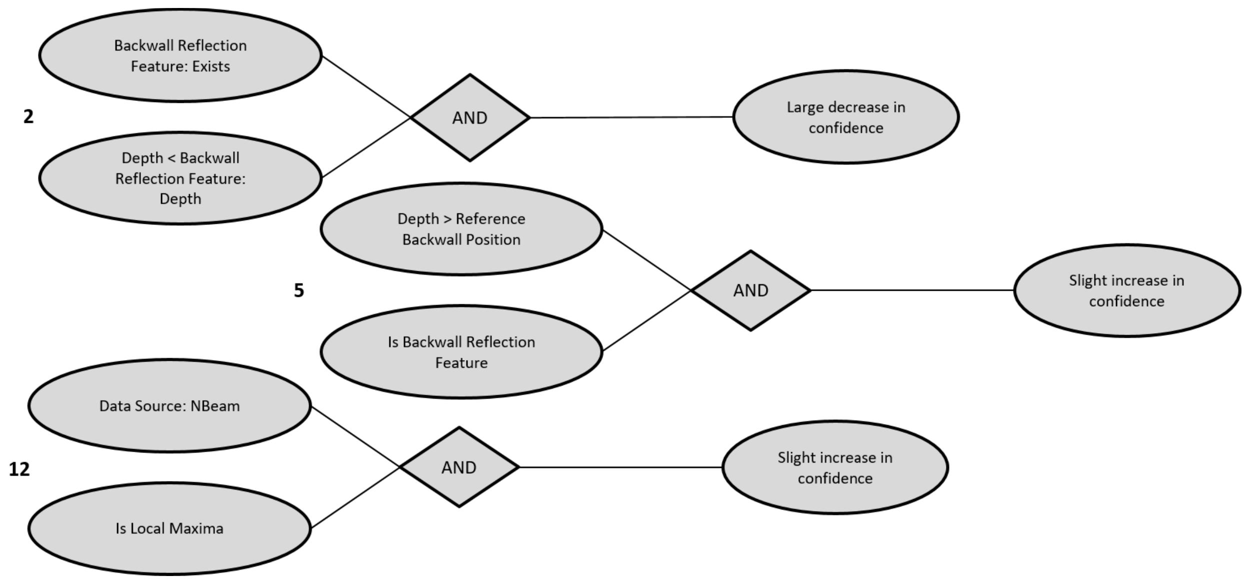

Figure 6. A representation of a subset of the confidence rules defined within our knowledge model, and used to compute the confidence of individual features within A-scans

the depth-map. These rules are assigned a unique identification number in order to facilitate tracking of the rules that have been fired for a given input. There are currently 16 rules defined within our knowledge base. These rules are run against each element within the depth map and are each rule can be run over 10,000,000 times per defect when estimating the depth over a large area.

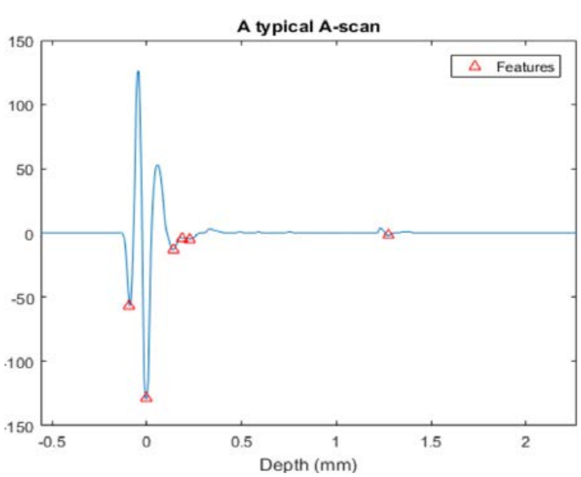

Figure 7. A typical A-scan with highlighted features

Consider a typical A-scan such as the one depicted in Figure 7 with selected features overlaid on the image. Each feature has the following key feature parameter values:

- Amplitude: the magnitude of the signal at the location of the feature.
- Backwall Reflection Feature: A Boolean value, which is true if the feature, is determined to be from the backwall reflection.
- Maximum Outside Backwall Region: A Boolean value, set to true if the feature has the largest magnitude outside of the backwall area.
- Is Local Maxima: A yes/no value that checks if the feature has the highest amplitude compared to the others for the A-scan.
- Depth: the distance from the backwall reference position that the feature is.

Each pixel within the depth-map is made up of a number of these features with the associated key feature parameter values where are referred to by rules defined within the confidence measurement inference model.

With the defined domain, inference and task categories within the knowledge model, it was possible to develop software based on the knowledge of the expert and easily validate captured knowledge using an easy-to-understand representation.

4 RESULTS

The proposed system was tested on historical data from 29 pressure tubes, with 280 defects in total. As subjectivity is often a factor among human analysts, a sensible threshold must be defined so that it is possible to fully evaluate the system. The threshold is set to 0.1 mm, and was chosen following discussions with domain experts. When comparing the results of our system to those of analysts, a form known as a verified result was used. Verified results take into account the measurements made by two independent analysts and are compiled by a third, lead analyst. These verified results will be taken as a ground truth for this system.

Within the verified result, if a depth of a defect is measured to be less than 0.1 mm, the reported depth is listed as '<0.1 mm'. Defects that are shallow pose less of a risk for DHC and therefore ascertaining an accurate depth is not critical. When making comparisons with the verified result, we assume that depths reported at a depth of '<0.1 mm' are at a depth of precisely 0.1 mm.

The depth measurements were compared to the measurements reported by analysts during the outage from which the data was recorded, known as the verified result. Figure 8. (a) shows a histogram of this comparison. It can be observed from the figure that the majority of measurements are within 0.5 mm of the verified result. There are a number of outliers in this dataset, with an error of over 2 mm.

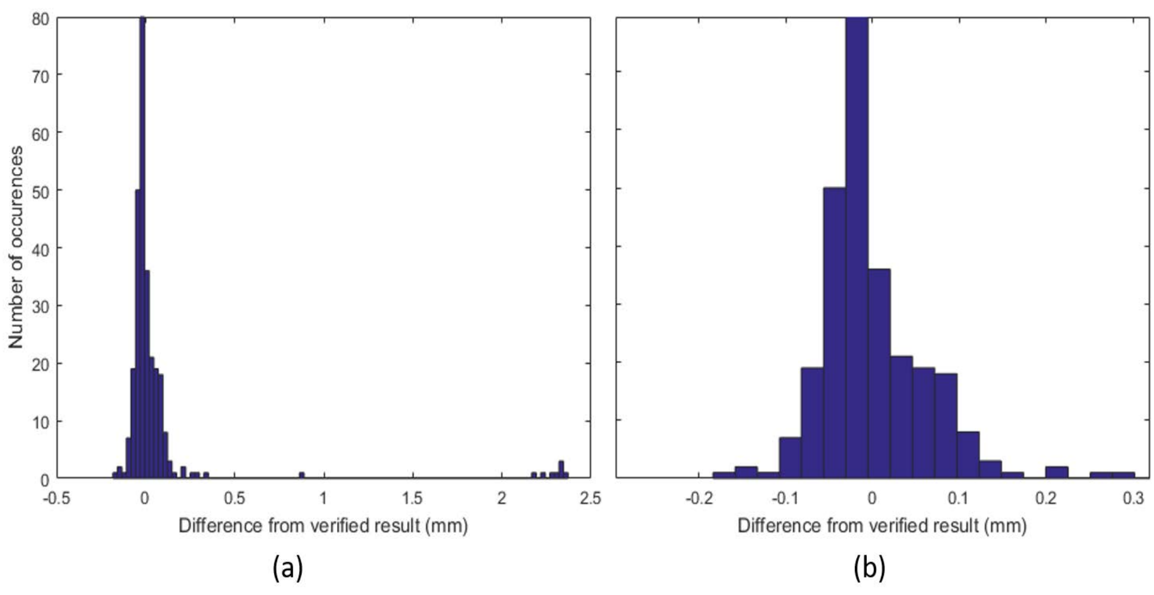

Figure 8. (a) The difference between results from the depth measurement algorithm and the analysts' verified result. (b) An enlarged region from (a), showing the region around the defined tolerance cutoff of 0.1 mm.

Figure 8. (b) takes a closer look at this histogram where the differences between the automated system and verified result are less than 0.3 mm. It appears that while most of the measurements are within the defined tolerance of 0.1 mm, there are a number of measurements outside of this region.

Analysis of the data shows that the depth of a defect has been measured to within 0.1 mm in 79% of cases and to within 0.3 mm in 85% of cases. In the cases where there are discrepancies in the depths reported by our software and the verified result, analysts can audit the measurements recorded by the system by reviewing the report of decisions made by the inference engine as it operated on the rules defined within the knowledge model. The analyst is able to view both the knowledge and the reasoning behind any decisions.

Figure 9 shows an example of the explicability within the system. The analyst may wish to query why a depth has been reported for a specific pixel within the depth-map. The analyst can view the elements of the depth-map overlaid on the A-scan from which they were extracted. Following this, the analyst can 'mouse-over' the element to view individual confidences and the reasoning behind the assignment of the confidences.

This is particularly powerful as if the expert disagrees with the outcome, then they have a set of rules to argue against (e.g. the rules are wrong and need updating, or a case in question lies outside what the rules can deal with and therefore additional rules, or refinements are required).

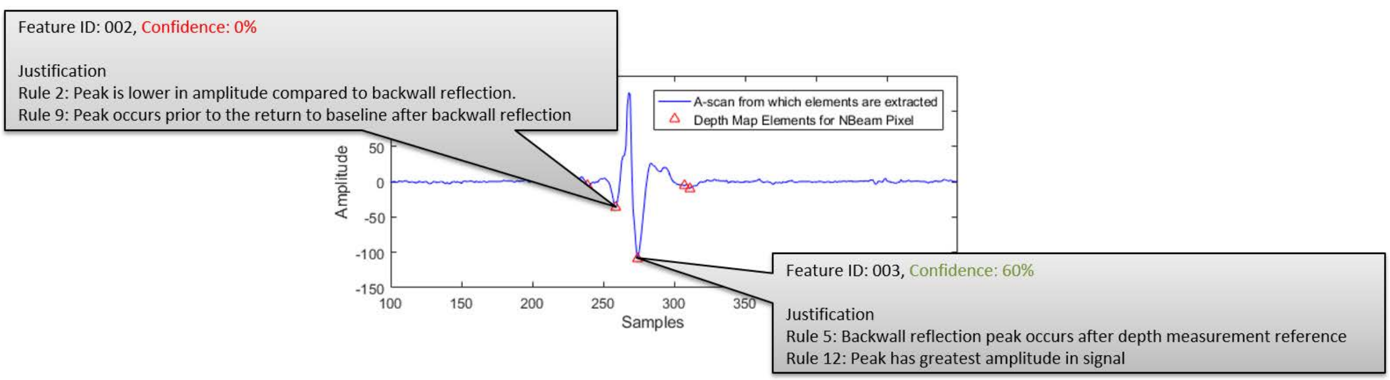

Figure 9. An example of how the measurements from the ADAPT system are auditable. The analyst has the ability to view elements of the depth-map overlaid on the A-scan from which the elements were extracted. The analyst can then 'mouse-over' elements of interest to view individual confidences and justifications for each decision.

5 DISCUSSION

From the results presented in the previous section, it is clear that an expert system can perform complex ultrasonic measurements to a reasonable degree of accuracy. An earlier implementation of the depth measurement system utilized a simple 'location of the tallest peak' algorithm that is commonly found within commercial ultrasonic systems for basic depth measurement. The basic implementation achieved approximately 30% accuracy with a 0.1 mm tolerance, compared to 79% that has been demonstrated with the expert system. The CommonKADS approach to knowledge representation has been used as both a basis for developing the system, as well as a tool used to discuss the domain expertise with analysts and facilitate knowledge exchange.

Some discrepancies between the results of our system and the verified result can be attributed to replica and historic results. Conservative guidelines state that the maximum depth recorded for a given defect must be the depth reported. As analysts review all historical measurements prior to analyzing current data, it is possible the results of a previous measurement are reported if an equal depth measurement cannot be made. The primary cause of this is due to ultrasonic data being gathered using a 0.2 mm helical scan. Introducing a 0.1 mm offset to the inspection tool leads to the scan regions being interleaved and in the case of narrow defects, such an offset can lead to a significant change in the maximum depth measured. In the cases where the depth cannot be determined ultrasonically, or where the depth measured is close to indicating a risk for DHC initiation, a replica is taken. The replica process involves creating a mold of the defect from which extremely accurate measurements can then be made. Current verified results do not indicate where measurements originate, therefore it is possible that the verified result reports a depth that cannot me made ultrasonically.

The outliers observed at an offset at approximately 2 mm in Figure 8. (a) can be attributed to a persistent feature that can often be observed in A-scans. If no other suitable candidate depth measurements can be found in a given A-scan, these features are instead reported as reflections from a defect. This represents a potential improvement that can be made to both the domain knowledge and inference components of our knowledge model so that they are excluded in future.

6 FURTHER WORK

While the initial results from this technique are promising, it is anticipated that a greater accuracy can be achieved by reviewing the knowledge base with a larger range of domain experts. The existing knowledge base has been derived from the knowledge of two analysts, which is a relatively small sample size. In the future, reviewing this data with other domain experts will ensure that the captured knowledge is robust and contains minimal subjectivity with respect to the analysis process.

In addition, a study will be conducted into the cases where this technique fails to report a depth within 0.1 mm of the verified result. Defects with different root causes appear different when inspected ultrasonically and some can be measured with more success than others. For example, if the system can measure the depth of all defects caused by fuel bundle vibration to an accuracy of 95% then additional confidences can be integrated into the system when they are measuring a particular class of defect.

7 CONCLUSION

This paper has presented a novel application of the CommonKADS knowledge engineering model, namely to apply an expert system process to ultrasonic measurements within structural components of nuclear power plants. The results presented show that the technique has promise with an accuracy approaching 80% when compared to measurements made by analysts. A program of future work has been proposed with the aim of being able to use the system with confidence during planned outages.

8 ACKNOWLEDGEMENTS

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