Artificial Intelligence approaches as tools for auditing and improving data analysis of advanced ultrasound techniques in Non-Destructive Testing

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Scope

Advanced Non Destructive Testing (NDT) techniques rely on consistent acquisition of data and its reliable analysis. As technology advances, new challenges emerge. For instance, the amount of data produced is exceeding the qualified personnel available for data analysis; moreover, the files produced can be easily handle unethically. Our project proposes the implementation of Artificial Intelligence (AI) techniques to develop algorithms to better harness the data available, in order to enhance the quality of data analysis and better monitor ethical practices.

1. Methods

For any NDT technique, the consistency of the results and the reliability of the findings depends heavily on the personnel performing the inspections and evaluating the results. As more advanced NDT techniques are available in the areas of ultrasound, digital data becomes available opening the door for intelligent tools for analysing and handling ultrasound data. This project proposes an innovative analysis software based on Computational Intelligence (CI) techniques. The implementation of this software reduces the time needed for a single analysis and, more importantly, increases the consistency of results; it can be use as an audit tool to ensure data files have not been mishandled.

1.1. Analysing Data in 3D

Historically PAUT data has been represented and analysed by human analysts with 2D views because 3D rendering was not available or demanded computational resources only recently available. In fact, PAUT was partially created so UT data that was represented with A-Scans (Fig. 1) could be represented in 2D views (Fig. 2) and thus be easier to understand by a human analyst. But the fact remains that the data is recorded as a 3D volume (Fig. 3), so, to be more efficient, the data analysis should be done directly on the 3D volume of data. By using artificial intelligence and more specifically fully convolutional networks, it becomes possible to analyse 3D volumes instead of analysing 2D planes and stitching these analyses together to give a 3D analysis. Using Artificial Intelligence to analyse 3D volumes can be demanding as far as computing power is concerned.

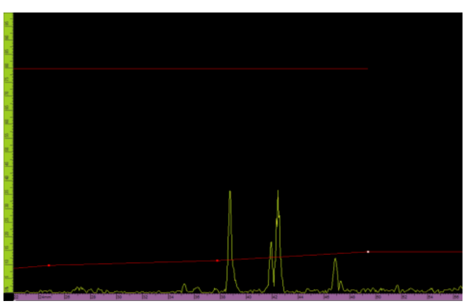
Fig. 1 1D A-Scan

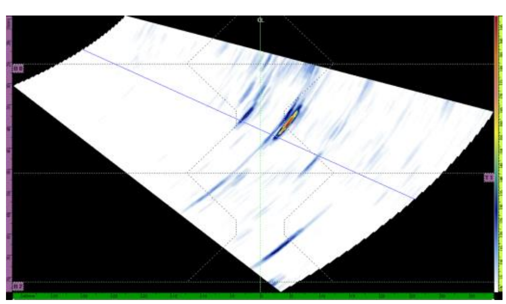
Fig. 2 2D S-Scan

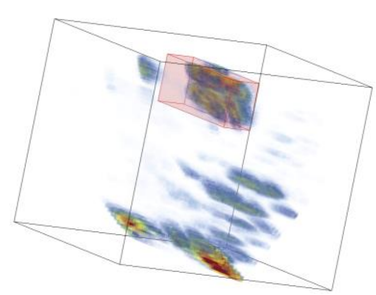
Fig. 3 3D Scan

1.2. Pattern recognition

When a human analyst is looking at a data set, he will look for the patterns representing possible defects while ignoring patterns representing geometrical indications or phantom echoes. Since the human analyst is doing his pattern recognition on 2-D views, he is probably looking at only a fraction of the patterns available in the data set.

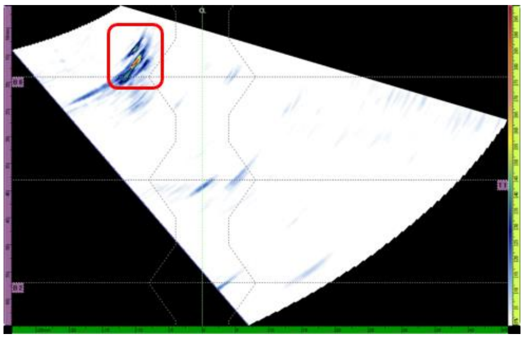

Fig. 4 Pattern of a defect

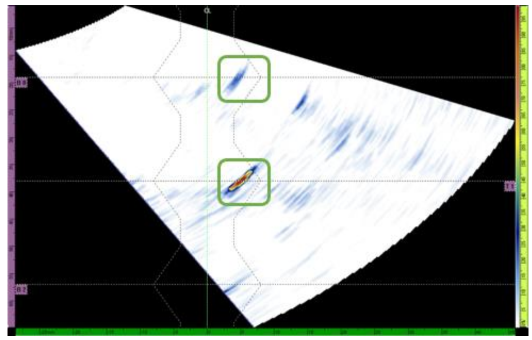

Fig. 5 Patterns of geometrical indications

Artificial intelligence or more specifically deep learning is very good at pattern recognition; hence, it can define 3D patterns that are indication specific. These patterns are probably ignored by human analysts because of their complexity and the fact that they are spanning several 2D planes. Artificial intelligence can thus enhance the abilities of the human analyst by pointing out possible defects that could have been missed by the analyst due to the ambiguity of the signal.

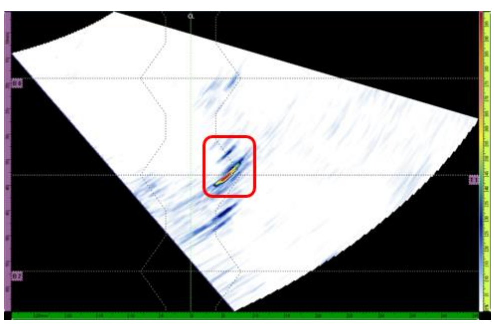

Fig. 6 Toe crack

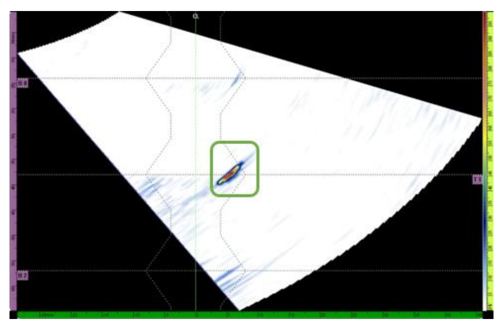

Fig. 7 Normal cap reflector

Since conventional algorithms reflect the human comprehension of the patterns in the data, they are therefore limited in their scope. Artificial intelligence offers the possibility to use pattern recognition as done by a human analyst, but also to discover hidden patterns in the data that are not necessarily detected by a human analyst. Internal reflections, mode conversions, diffractions and the 3D nature of the UT beam can all create additional patterns that can be associated with certain type of defects by the artificial intelligence but would otherwise go unnoticed by a human analyst.

1.3. Data Filtering

Artificial intelligence can be used to filter through huge amount of data to find the location of possible problems. This capacity can be used for many purposes. It can be used to look for geometry indications like the weld root, cap signals or the surface of the part. It can be used to better understand the shape of the weld itself which in-turn leads to a better characterisation of the indications found. It can be used to seep through large amount of data to find potential defects. This information can be submitted to a human analyst for further investigation and approval, limiting the time spent by the analyst on irrelevant data.

Data filtering can also be used to detect fraud. For big projects, it is nearly impossible to audit all the files produced by the NDT inspection companies. Artificial intelligence can automatically compare files to root out the ones that have been duplicated. Several methods can be use for the comparison. Direct datapoint-to-datapoint comparison is the most basic, but more importantly, the AI can be used to find similar patterns in two datasets preventing the cut and paste approach to data fraud. Although this applies to fraud, it can also be considered a quality control step as human error is always possible and probable in big projects.

1.4. Flexibility

Data produced by phased-array instruments are highly varied. Materials inspected (carbon steel, stainless, composites, plastics), weld types (V, double V, U, J), scan types (L-scan, S-Scan, FMC-TFM) are all variables that influence the characteristics of the data. Flexibility is thus needed to analyse phased-array ultrasound data. Deep learning provides the necessary flexibility through its learning capability.

If deep learning algorithms can be trained on different data sets resulting in application-specific versions of the deep learning algorithms, they can also be trained to work within a larger range of conditions. In this case, several examples of the different possible defects along with examples of geometry indications and examples of data without any defects must be provided. The main drawback is that a minimum number of data sets is needed for the training of the deep learning algorithms. The more data sets, the better the accuracy of the analysis.

1.5. Supervised learning

During supervised learning, the artificial intelligence is trained by feeding it data sets that have been analysed by a human analyst. The artificial intelligence will then learn to associate a pattern with a specific type of indication.

1.6. Un-supervised learning

When a large data pool is available, the artificial intelligence can be trained by feeding it all the data sets available and letting the artificial intelligence come-up with what it thinks are possible indications. A human analyst must then identify the different patterns discovered by the artificial intelligence.

1.7. Data augmentation

Data augmentation can be used when few data sets are available. Data augmentation is done by modifying existing data sets as to provide variants. These variations of the original data sets are fed to the artificial intelligence along with the original data sets providing the artificial intelligence with a bigger training data pool. Another aim of data augmentation is to provide the artificial intelligence with variations of the pattern of a specific indication. Providing pattern variations to the artificial intelligence while in training is important to better the chance the artificial intelligence will correctly label and measure the indications.

1.8. Data bias

Artificial intelligence can be biased if the data sets fed to it during training is too homogeneous. The result of biased data sets is a lower rate of success in recognizing defects and mischaracterisation of indications. The training data sets should be representative of the type of data that will be encountered in the real world. Artificial intelligence can be trained to give excellent results with carbon steel welds but will nonetheless give poor results for austenitic welds. The training data must be chosen to reflect the goal of the artificial intelligence.

Analyst bias. If all the analysed data sets come from one analyst, the artificial intelligence can be bias towards his way of analysing data which can lead to mischaracterisations or worse omissions. A human analyst can consistently oversize, or worst, undersize defects, he can misinterpret the signals and wrongly name the indications. During training, the artificial intelligence continuously adjusts its parameters to try to match the results the human analyst is feeding it. If the analysed data is biased, the resulting artificial intelligence will be bias.

Solution: Have a pool of experienced analysts cross analyse the data sets before feeding them to the artificial intelligence.

Artificial defects bias. If all the indications in the data sets are from artificially created defects, the artificial intelligence can be bias toward artificial defects and not be as efficient to find natural defects. Artificial defects found in test coupons are often created using techniques that have nothing to do with how real defects are created. If the patterns given by those artificial defects are close enough to the real thing for a human analyst, they can be confusing for an artificial intelligence looking for much more detailed patterns.

Solution: Have a mix of artificial, natural and simulated defects

Welding technique bias. If all the data set come from the inspection of a single type of weld and the welds have been done with one welding technique, the artificial intelligence will be very good at recognising the indications in that type of weld but not as efficient for other types of welds or weld processes.

Solution: Diversify the data pool so it contains data sets from different types of welds done with different welding techniques.

Acquisition instrument bias. If all the data set are acquired with only one type of instrument, the artificial intelligence can identify patterns that are unique to this one instrument and not relevant to the analysis thus skewing the analysis.

Solution: Use data sets coming from different types of instruments.

1.9. Data quality

As for manual data analysis, data analysis with artificial intelligence requires high quality data. Before analysing the data set, it should be run through a primary artificial intelligence algorithm used to assess the quality of the data. Checks should be made for:

- The signal to noise ratio
- The amount of missing data
- Proper coupling between the probe and part
- The type of material
- The type of weld
- The thickness of the part
- The geometry indications

1.10. Computational power

Due to the size of phased-array ultrasound data sets (10 MB to 1 GB), analysing these data sets with artificial intelligence requires enough computational power to keep the computational time to a minimum. Although most desktop computers can run an artificial intelligence, especially the ones equipped with a Graphic Processor Unit, a better solution is to rely on dedicated servers. These types of servers can be configured to handle the heavy workload generated by the analysis of data sets. The best solution is to upload the data on cloud-based servers that can be scaled-up on demand to address the need for more computational power. This setup is especially efficient for projects with thousands of data sets to be analysed.

1.11. Human/artificial intelligence interaction

The human analyst must have access to the raw data and a proper analysis software to validate each indication provided by the artificial intelligence. To facilitate data visualisation, a 3D visualisation tool including a CAD drawing of the part should be used as the information provided by the artificial intelligence is in 3D. Using a detailed list of indications provided by the artificial intelligence, the human analysts can quickly jump from indication to indication to assess and approve the decision taken by the artificial intelligence. In case of disagreement, the human analyst can override the values provided by the artificial intelligence. Both the values from the human analyst and the artificial intelligence should be part of the final report.

1.12. Feedback loop

The feedback loop is an essential part of the artificial intelligence training. Analysis results provided by a trained artificial intelligence and corrected by a human analyst are fed back to a version of the same artificial intelligence in training. The artificial intelligence in training will use the corrected data to tweak its algorithm to better reflect the reality. It is recommended that the corrected data be reviewed by other analysts before feeding it to the artificial intelligence.

2. Results

For the first stage of the proposed CI cloud-based software, the data collected by the inspector is send via internet connection to cloud-based servers. Since the data analysis must be completed within a reasonable time frame and considering the potentially large volume of data to be analysed, a cloud-based solution is the only viable option to efficiently run an AI-driven analysis software. With a cloud-based solution, the computational power can be tailored to the analysis needs simply by adding or subtracting virtual servers. These virtual servers can be tailored to the specific needs of the AI by continuously adjusting the number of Graphic Processing Units (GPU) used for the analysis according to the workload. Since cloud-based virtual servers are mainly on a pay-per-use pricing scheme, controlling in real-time the size and number of virtual servers used to power the AI keeps the analysis costs at a reasonable level. In a cloud-based environment, several types of AI can be offered depending on the type of data to be analysed. Each AI can be activated individually and when the workload on an activated

AI becomes too high, it can be cloned on virtual servers as many times as needed to temporarily multiply the analysis capacity and thus reduce the analysis time. With a cloud-based solution, it becomes possible to offer data storage and analysis solutions tailored to the needs of the user. Data can be stored and analysed within specific geographic location.

During the second stage, the data will be verified for quality. Special algorithms are looking for incorrect data file length, missing data, lack of couplant or poor coupling or unacceptable variations in the probe position in regards of the center of the weld. If any of these quality issues are encountered during the quality verification process, the software can automatically and in real-time, inform the inspector that the inspection must be redone and the resulting data resubmitted.

During the third stage, once the quality verification of the data is completed and the data approved, a preliminary data analysis is performed to root out duplicate files. Duplicates files can be a problem especially in large projects. The causes behind duplicated files can be many ranging from outright fraud to human error during the data transfer process. Whatever the cause, duplicated files can be detrimental to the overall quality of a project and can affect the safety of the equipment being inspected. Duplicated data can be difficult to root out by a human analyst since it requires a direct comparison of two files which in turns requires an analysis program being able to display several data files at the same time. In bigger projects, the sheer amount of data files to compare can make this task near impossible for a human analyst. However, an automated data analysis software is especially well suited to do this task. For example, on weld analysis, it can compare two data files down to each data point and even provide a probability of two data files coming from the same weld. The CI-based analysis tools have already been used to monitor several data files from NDT inspections using Phased Array Ultrasound (PAUT) and the results have successfully verified the authenticity of the ultrasound raw data, which is a critical verification step and evidence of any mal practices or mistakes of data handling.

During the fourth stage, once the analysis for data duplication is completed, an in-depth data analysis is then performed by CI-based algorithms. The first step of this analysis is to look for geometry indications and features. In a weld, the geometry indications can be produced by the shape of the root or the cap or by scratches on the surface of the part and are considered acceptable if within norms. Features can include the shape of the weld and the location of the surface of the part. The second step of the in-depth analysis is to look for abnormal indications. During this step, the CI-based algorithms are looking for patterns associated with known defects in the data. In this second step, both geometry indications and features are used to refine the search and qualification of abnormal indications by providing essential information about their position relative to the weld and surfaces.

For each stage, a report is produced. The reports are available for revision and approval by the supervising data analyst. The data quality reports give a listing of the quality issues with their nature, their position and a 3D image. The data duplication reports give a listing of the groups of duplicated files with an image of each data set for visual confirmation by the human analyst. The data analysis reports give a listing of indications with their size, location, characterization and a 3D image. The data associated with the report can be viewed in a 3D visualization interface. Using this interface, the human analyst can verify the indications measurements, confirm the characterization of the indications and approve the report.

When the welding process is well controlled, unwanted indications are relatively rare and thus the human analyst must go through a lot of data to find the occasional indication. This leads to visual fatigue and waning attention which in turn leads to missed indications. With the assistance of an automated data analysis software, the human analyst can concentrate his attention on the part of the data file where indications are encountered, improving his productivity.

3. Conclusion

There is a lack of reliable tools available to NDT experts that can facilitate the task of analysing data; this innovative software takes advantage of the CI techniques and expert knowledge to address this issue. Furthermore, our approach offers a high degree of consistency for identifying defects; improves the quality of the analysis and reduces the time invested in such critical NDT duty. Auditing raw data from ultrasound inspection is a challenging task; by taking advantage of CI-based analysis tools this task can be easily implemented as a reliable auditing practice.