Improvement Possibilities for Nuclear Power Plants Inspections by Adding Deep Learning-based Assistance Algorithms Into a Classic Ultrasound NDE Acquisition and Analysis Software

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ABSTRACT

The safety of nuclear power plants has always been one of the most important security issues in the industry in general. Numerous standards, techniques, and tools have been developed to deal specifically with the safety of nuclear power plants – one has specialised probes, robotized systems, electronics, and software. Although seen as a mature (or slowly evolving) industry, this notion about nuclear safety is a bit misleading – the area is developing in many promising new directions. Some recent global events will speed up this development even more.

On the other hand, the industry is currently going through digital transformation, which brings networking of devices, equipment, computers, and humans. This fourth industrial revolution promises speed, reliability, and efficiencies not possible up until now. In the NDE sector, new production techniques and traditional manufacturing lines are getting to be lights-out operations (near-total automation). The same is most probably going to happen with the safety inspections and quality insurance. Robotics and automation are improving worker safety and reducing human error. The well-being of inspectors working in a hazardous environment is being taken care of. Most experts agree that the digitalization of NDE offers unprecedented opportunities to the world of inspection for infrastructure safety, inspector well-being, and even product design improvements. While the community tends to agree on the value proposition of digital transformation of NDE, it also recognizes the challenges associated with such a major shift in a well-established and regulated sector.

The work presented in this paper shows a part of the project that aims to develop a modular ultrasound diagnostic NDE system (consisting of exchangeable transducers, electronics, and acquisition/analysis software algorithms), for applications in hazardous environments within nuclear power plants. The paper will show how the software part of this system can reach near-total automation by implementing various deep learning algorithms as its features and, then, testing those algorithms on laboratory samples, showing encouraging results and promises of online monitoring applications. Furthermore, future general prospects of this technology are discussed, and how this

technology can affect the well-being of nuclear power plant inspectors and contribute to overall plant safety.

Keywords: *ultrasound, nuclear, safety, deep-learning, industry 4.0*

1 INTRODUCTION

Detecting a defect, e.g. a crack in the material such as a metal or a composite using an automated deep learning-based procedure, is still an underdeveloped problem. Specifically, in ultrasonic non-destructive evaluation, autonomous defect detection methods are not widely used. Most inspections are still highly dependent on human experts and their experience in analysing certain types of data. Therefore, inspections are not yet automated, are slow, and are prone to human errors.

Analysis of ultrasonic inspection data has captured a lot of researchers' attention recently. In [1] authors proposed two popular deep-learning convolutional neural networks YOLO and SSD and adapted them for the ultrasonic anomaly detection task. In [2] the same authors showed that the EfficientDet-D0 model successfully detected all defects in the material. The biggest setback in the development of deep-learning models is the data needed for training such big neural networks. Although in a single inspection a lot of data is captured, this data is often protected by different NDA agreements and cannot be used after the inspection. Furthermore, in real inspections, flaws are rather scarce. On the other hand, metal blocks with synthetically implemented flaws are expensive and difficult to produce. In [3] authors extracted a few defects and pasted them on ultrasonic scans without visible defects. This way they managed to produce a large dataset and train a classifier that successfully detected all defects. In [4] a generative adversarial network (GAN) was used to generate a large amount of novel synthetic scans. Synthetic data was then used to improve the defect detector's performance. In [5] the same synthetic data generated by a GAN was shown to be of such high quality that human experts could not distinguish them from the real ultrasonic data. In [6] authors developed a novel convolutional neural network that outperforms all current models on ultrasonic defect detection. In [7, 8] authors managed to develop a deep learning approach that utilizes only non-anomalous data for training the defect, or anomaly, detector network. In [8] they show that the proposed network successfully detects all defects and outperforms standard classification approaches when a small number of anomalous data is present.

Developing a state-of-the-art defect detector on a limited dataset of ultrasonic data is one thing, putting the developed algorithms into real-world production is another. The developed algorithms are dataset specific and should be retrained if desired to be used on a challenge other than the one they were trained on while developed. Every inspection, used probe, and manipulator leaves its own mark on the data. A slight difference in the data could ruin the performance and reliability of the algorithm. Furthermore, for each inspection challenge, a novel module should be developed. For example, separate modules and algorithms should be used for detecting defects in metal blocks and in bolts. Since there are still no official qualification protocols for deep-learning algorithms in non-destructive evaluation, developed algorithms can only be used as an assisted analysis module. These algorithms can filter out the data that the inspectors need to look at, thus making the analysis much faster and more reliable.

Reliable and functional NDE systems that can compete as solutions for the Industry NDE 4.0 cannot only rely on the software support based on the deep learning and smart defects detection algorithms. An important part of the technology is, as well, the design and creation of hardware solutions that are both compatible and functional with the software backup and with the NDE inspection environment and conditions, no matter if those conditions are significantly elevated working temperatures, humidity, presence of ionizing radiation, high pressures, mechanical tension, etc. Within this project we work on a completely modular hardware-software solution, although in this work we will mostly focus on the software component, as we consider it the most important to discuss.

2 DATA ACQUISITION

The ultrasound data acquisition for this work (and for such kind of research) is done by classic INETEC commercial multielement piezoelectric effect based phased array ultrasound transducers and an INETEC commercial pulser-receiver electronics device, instrument, used for excitation of the transducers and the data acquisition. The instrument, and the whole process, has been controlled and optimized by using a commercial INETEC acquisition and analysis software package. The smart part added to this software are the assisted analysis algorithms based on deep learning.

Figure 1: A typical instrument for excitation of ultrasound transducers and data acquisition in ultrasound NDE inspections and experiments.

During the data acquisition process, the ultrasound phased array transducer sends a multitude of ultrasound acoustic radiation beams. In the moment of the data acquisition all the ultrasound beams are fired through the material. After the acoustic wave is reflected, the results are collected using the same transducers that did the acoustic beams firing. Based on the focal laws defined for the transducer by the user and additional signal processing, the final ultrasound scans, ready for data analysis, are obtained. The data is encoded by the encoder position. This provides the analyst the information about the obtained data Cartesian coordinates in the x-y plane, while the depth of the data position (for example, when we look for defects and their depths) is calculated by using the sound velocity in the material. The data prepared in such a manner is served from the ultrasound instrument and cannot be modified further.

Figure 2: A typical phased array ultrasound transducer for data acquisition in ultrasound NDE inspections and experiments. A phased array transducer consists of many small piezoelectric acoustically active elements that are independently excited both in the process of firing ultrasound beams and in the process of collecting the ultrasound waves reflected within the tester materials and configurations.

All the software modifications and editing of the scans later are of visual nature and do not affect nor influences on the obtained acquired data. Shortly, the data acquisition and its display is relatively straightforward and mature technology.

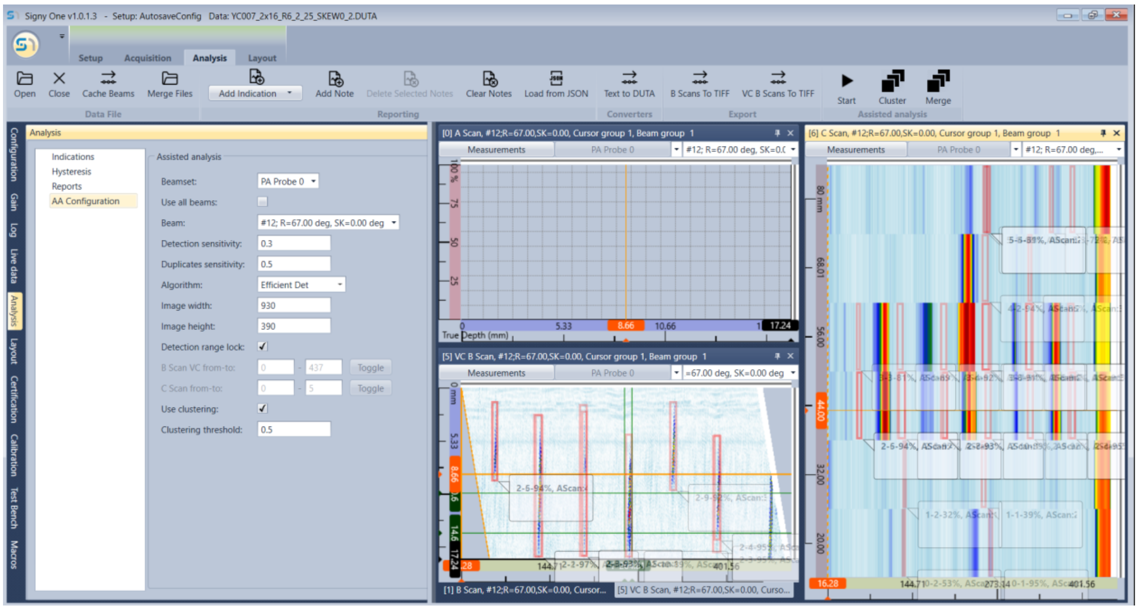

Figure 3: Typical GUI image of an ultrasound acquisition and analysis software with the addition of the implemented deep learning modules which, when applied, mark, frame and store the defects coordinates on different scans. One can notice framed and labelled defects on the scans - this is the work of the deep learning assistant analysis algorithms.

3 DATA ANALYSIS

The main part of the assisted analysis are the data processing algorithms. Since human experts inspect the data by looking at different data visualisations such as A-scans, B-scans and C-scans, we choose the computer vision approach to defect detection. While some inspections require localization and sizing of the defects, some may require only classification. Depending on the task at hand, we develop different approaches and convolutional neural networks. We developed a generative neural network for augmenting the available dataset for training the defect detection algorithms in [5]. We also developed a self-supervised anomaly detection method in [7], and a supervised learning defect detection method on B-scans in [6] and on C-scans in [9].

4 MODULAR NDE SYSTEM

Assisted analysis of ultrasonic data is a combination of inspectors' expert knowledge, data acquisition and analysis software, and various algorithms for the detection of defects. Human experts in ultrasonic data analysis usually have to pass some education and qualification prior to analysis of the non-destructive testing data. The same procedure implies to the data analysis algorithms. Each developed algorithm has to be tested on data similar to the one we expect to see in the inspection on-site. Each type of inspection is unique and significantly differs according to the ultrasonic probes being used, the material being inspected, and the geometry of the inspected component. This is why we chose the modular approach to the development of assisted analysis software. For each type of inspection, we developed a specialised algorithm that performs the best for the situation.

The performance of the developed algorithms highly depends on the quality of the data being used. Furthermore, neural network architecture and training procedure also differs according to certain inspection. The best-case scenario would be training the neural networks before each inspection on the ultrasonic data taken from the same power plant. To date, there are no certification protocols for deep-learning algorithms. Usage of the developed algorithms should always be taken with good interpretability of their internal work. In the end, even after thoroughly evaluating the performance of the developed algorithms, the final decision on the state of the inspected material should be done by a human expert.

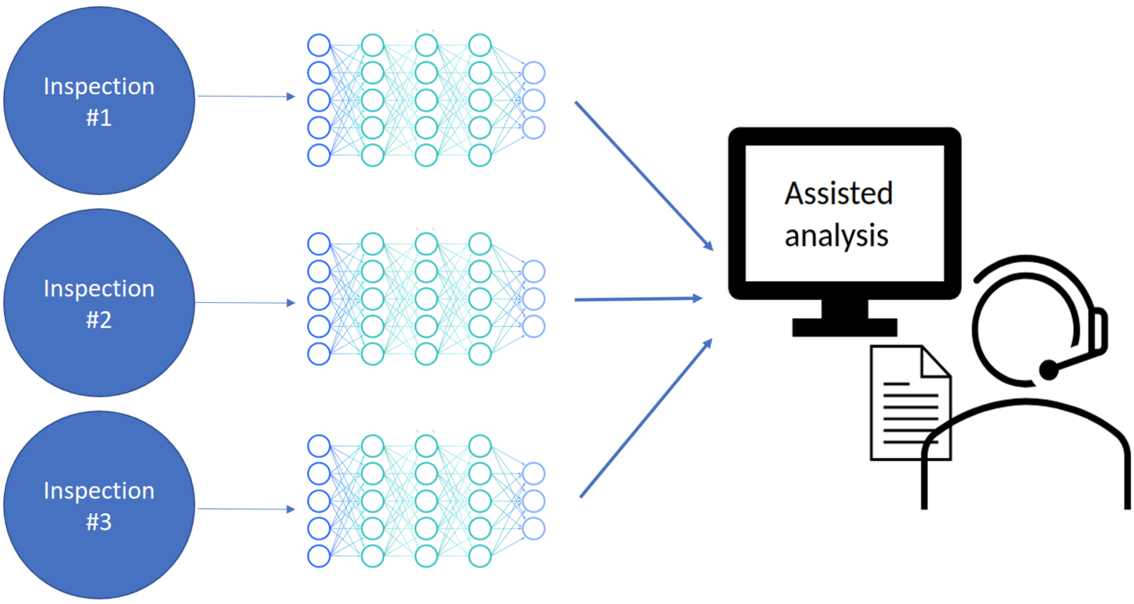

Figure 4: A modular approach to the Assisted analysis

5 FUTURE TECHNOLOGY PROSPECTS

Considering the future prospects of this technology, as a subset of the NDE 4.0 industry, the first significant goal is the digital connectivity: on the one hand, digital connectivity between the different elements of the NDE inspection system and, on the other, digital connectivity of the input/output of the inspection system with the outside world. Therefore, in the first place, it is necessary to know the characteristics of the specific NDE inspection system, analyse them, and, thus, propose where to go and how to move forward. There are several types of NDE inspections: in-line inspection (of manufactured pieces), maintenance at the workshop inspection, and maintenance in-service inspection. Each of them has a series of characteristics that determine the steps to be taken and to reach digital connectivity. In any of the inspections the information involved is the same: inspection requirements and input information, inspection procedure (including essential variables, scan plan, and calibration settings), and inspection data (data from NDE sensors and their position). The content, quantity, and complexity of the information will depend on the requirements and characteristics of the components examined. In principle, any type of inspection system can lead the way toward NDE 4.0, but first it is necessary to analyse its characteristics, the investments to be made, and the benefits to be achieved. The final balance, positive or negative, will tell us the way to go.

6 CONCLUSION

According to the recent breakthroughs in developing automated defect detection algorithms, we can be sure that the automation of non-destructive inspection is a trend you cannot avoid. Industry 4.0 will bring a lot of innovations that will revolutionize the safety inspections of nuclear power plants, oil and gas pipelines, and many more. More and more research papers show that successfully and more importantly, reliably detecting all defects in the inspected material is possible while speeding up the analysis many-fold. Therefore, the industry should prepare and start adapting the protocols toward assisted and even completely automated inspections. Implementation of such algorithms will contribute to the healthy state of the inspected power plants and reduce the downtime of such systems. Inspectors' tasks will become less tedious, and total automation will completely reduce human exposure to harsh conditions such as radiation, high temperature, and high humidity.

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