Simulation Assisted Automatic Defect Recognition (SimADR) for NDE4.0 Inspection Datasets

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Abstract

The paper highlights a new paradigm using simulation-based analysis that employs physics-based models in parallel processing using GPU for rapid generation of synthetic data sets. This paper discusses the development of a Simulation Assisted ADR (Automatic Defect Recognition) using the physics-based simulation models of the different NDE/NDT imaging modalities as well as Deep Learning (DL) and/or Machine Learning (ML) models. Our approach addresses the classic issues during the implementation of DL/ML approach to Radiography and Ultrasonics based NDE/NDT data interpretation that includes lack of sufficient apriori data as well as biases in the data sets, among others. Here, using the limited experimental/field NDE/NDT data sets that are available and by deriving critical statistical distribution parameters from this data set, the stochastics of the simulation models are determined. Thereby, the simulated data sets are generated using numerical simulations along with the variations in the different parameters during experimental/field data acquisition. This process allows the generation of simulated data sets in large quantity that augments the smaller data sets obtained experimentally. This rich data set is subsequently utilized to train the DL models and provide reliable ADR algorithms. Weld and AL casting radiography data sets from Digital X-ray Images and PAUT (with FMC/TFM) are both used to demonstrate the SimADR approach.

Keywords: *PAUT, Digital X-ray, Radiography, ADR, Simulation, Assisted*

1.0 Introduction

Digital X-ray and Phased Array Ultrasound imaging inspection technologies have been well documented in the field of industrial and medical applications. The use of digital X-ray imaging has been further enhanced by techniques such as Computed Tomography (CT) that have the capability to expand the conventional 2D imaging modalities into 3D volumetric imaging. Similarly, the Phased Array Ultrasonic Imaging technology (PAUT), particularly with the FMC/TFM mode, has vastly improved the ability to image, characterize, and size defects.

The ability of the advanced NDE imaging technology has reached very significant maturity permitting the operator to provide advanced insights into the state of the component, and more importantly, into the root cause analysis of the anomaly formations during manufacturing as well as prediction of the effect of these anomalies on performance of the components. While these advancements do represent a significant enhancement of diagnostic capabilities, the trade-off has been the large volume of data and the time consumed for processing this data set as well as the analysis of the processed data. This trade-off has led to requirement of additional well-trained manpower, faster processing instruments, and consequently its implementation in a post processing mode rather than the preferred in-line diagnostic mode.

Several researchers explored the identification of defects from radiographic images using different techniques and approaches [1-2]. Artificial intelligence and computer vision methods can be used to aid in analyzing the X-rays and provide an indication of the examined material's diagnosis. There has been a lot of effort to build and construct computational tools focused on image processing, computer vision, artificial intelligence and other related tools with the aim of encouraging radiograph analysis and thus improving the robustness, accuracy and speed of the inspection process [3-4]. Owing to the exponential increase in the capability of the processing algorithms as well as the computing power of the hardware the implementation of sophisticated image classification, object detection, and image segmentation of welds are advancing significantly.

The development of deep Convolution Neural Networks (CNN) has led to major improvements in several tasks related to image processing. Ferguson et al [4] demonstrated the defect detection system of the deep learning model Mask RCNN that uses the transfer learning technique exceeds the state-of-the-art performance on the GDXray [5] datasets of X-ray images of both casting and welds. In this work, we present the accomplishment of an automated defect recognition (ADR) system that uses deep learning algorithms to improve the effectiveness of the automated data analysis. The defect detection system used in this work is based on Mask Region-based CNN [6] that simultaneously perform object detection and image segmentation.

The application of the phased array ultrasonic testing (PAUT) has becoming common in the field of non-destructive evaluation (NDE) for faster scanning and better visibility of the scanned sample [7]. While manufacturing the welds, the weld flaws occur inherent to the structure, and some are due to the improper choice of process parameters. Inspection of welds are challenging due to the massive structures containing thousands of welds, and a few are inaccessible. The PAUT overcomes this challenge by allowing to inspect large regions from a single location, which gives an advantage to inspecting the components with limited access and complex surface geometry. The Total Focusing Method (TFM) is a sampling of PAUT [8]. The TFM is an image reconstruction technique that uses Full Matrix Capture (FMC) ultrasonic signals to construct a fully focused image [9]. This technique characterizes the weld flaws better when compared to conventional PAUT [10]. In the process of identifying defects, it is difficult to place the transducer on the weld area due to an uneven bead surface. Hence instead of using the normal ultrasonic wave beam, the angular wave beam with a multi-skip wave path is used to inspect the welds. At a given point in time, the transducer receives ultrasonic signals from different wave paths, such as direct TFM, half-skip TFM, and full-skip TFM [11]. The mode conversion takes place at the back wall and at the flaw location, and this mode converted ultrasonic signals are used to generate high-resolution TFM imaging. These reconstructed TFM images are examined by NDT experts to characterize weld flaws and qualify them. As it involves the processing of bulk images by NDT experts, there may be chances of human errors while identification of the defect and the inability to distinguish among themselves. AI, robustly identifies object detection and classification tasks through feature extraction [12].

2.0 Approach

2.1 X-ray Data Sets

The key technology in this work for X-ray based datasets is the development of advanced Simulation assisted Automated Defect Recognition (SimADR) algorithms for flaw detection, classification, and characterizations of different types of Castings and Weld Defects. These castings and weld joints are likely to develop flaws at the interfaces and inside the weld due to perturbations in the process variables and consequently its manifestation in the final products are inherent in a mass-manufacturing environment due to several reasons. Several forms of simulation software have been developed over the past few years for radiological applications [13-16]. In this work, the method is based on creating a radio-graph database with different potential defect characteristics using a simulation model based on ray casting and using this to train a deep-learning algorithm. The Sim-ADR system is proposed to enhance the detection and identification of the defects from the X-ray images of castings and welds. Fig-1 presents the Sim-ADR development flowchart. The proposed system consists of three main stages; a pre-processor, a simulation engine for X-ray images (Sim-Xray), and Artificial Neural Network based Automatic Defect Recognition (ANN-ADR). Each stage consists of a variety of processes and communicates correctly with the input of the next stage before the final identification report is obtained. In the following subsections, the functionality of each stage is described in more detail.

The Pre-processor unit prepares the radiographic image for the annotation task by enhancing the defect features in the image. The 16-bit X-ray image input first goes through a normalization step. Algorithms to enhance the images are implemented using a combination of many Image processing filters like Sharpening filters, Contrast Limited Adaptive Histogram Equalization (CLAHE), and FFT-Low Pass filters, such that the defects are clearly seen for the annotation. In the Annotation toolbox, the defects are marked using the built-in annotation features like magic-wand, contour, and circulation, and the annotated data are stored in a suitable format to train the Neural network. This is followed by automatic segmentation of defect region and annotation using the defined rules. On the successful verification of the annotations by the Radiography Expert, the annotated images are sent to the ANN-ADR module. This approach has been discussed elsewhere with more details [17]

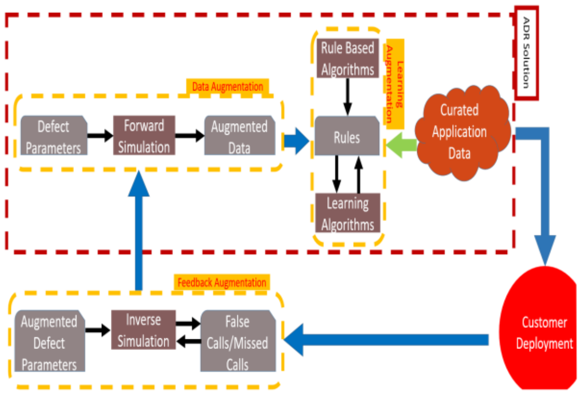

Figure 1:SimADR system Development Flowchart

2.2 PAUT with FMC/TFM Data Sets

The SimADR approach for PAUT data sets is similar to X-ray data sets, as shown in Fig. 1. However, the simulation-assisted weld TFM imaging is generated through fewer finite element (FE) simulation followed by the deployment of generative adversarial network (GAN) algorithms. These augmented images are used to train the neural network in the standard process [18-19]. The syntheses of the required high-resolution image dataset by implementing AI-based frameworks such as GANs [20]. The deep convolutional generative adversarial networks (DCGANs) [21] is a variant of GANs, which is a convolutional neural network (CNN) based framework. The DCGAN uses a complex algorithm to generate new images, which come from the training data sets distribution. However, the generated new images are similar to trained images but different in terms of varying defect patterns, clusters, and locations. In this framework, two separate CNN network architectures exist and compete with each other during the training of the networks. These neural networks are trained in an adversarial manner to generate imaging data by mimicking distribution from the real training images. Thereafter, the new imaging samples are generated from the trained AI network [22]. In this process, the AI-based model generates the training data sets several orders faster than classical FE simulations. Hence, the AI-based simulator can provide a vast volume of imaging data sets with comparatively reduced computational resources and time.

Subsequently, for ADR, we have used a convolutional neural network (CNN)-based framework, such as the YOLOv4 model [23], to detect and classify the weld flaws using the AI/FE generated simulated datasets. This algorithm scans the entire image at once to predict the outcome, which is a faster end-to-end deep learning object detection CNN-based model. The single pass image makes the YOLOv4 model faster and can be used in real-time automated defect recognition. Over a while, a series of advancements have taken place to improve the YOLO network performance [24]. The model divides the entire input image into a grid of cells and then predicts the bounding boxes and class probability of these boxes. The network generates multiple bounding boxes for a single defect. However, using the non-maximal suppression algorithm for an individual box for each defect in an image. Before training the ADR model, the AI/FE datasets need to convert to a specific YOLOv4 model acceptable format. Therefore, each defect in every training data sets image has to be annotated with a bounding box and the class of the defect. The transfer learning technique is used for YOLOv4 model training instead of random initialization of the network hyperparameters because the model has been pre-trained with various shapes in the training data sets. Although the YOLOv4 model is pre-trained, a large volume of training/testing datasets is required to teach the network of the different classes, sizes, and locations of the defects in the welds. For more details, kindly see the publication by authors elsewhere [22].

3.0 Results and Discussion

3.1 X-ray Data Sets

The x-ray radiography images were obtained on two types of test samples (a) Aluminum Cast, and (b) Steel welds. Fig. 2 shows the result obtained from using SimADR algorithm using the SimXRAY software as the modeling tool. The color represents the different categories of porosities in the casting as per ASTM 2422 standards.

The results presented in Fig. 3 shows the influence of the simulated data sets on the performance of the SimADR algorithm for the AL casting data set. In this work, the ground truth used was over 54,000 of the experimental images that were available. While this is not common for such a large number of annotated images to be available, this particular example allowed for the comparison of the pure experimental versus simulated data sets.

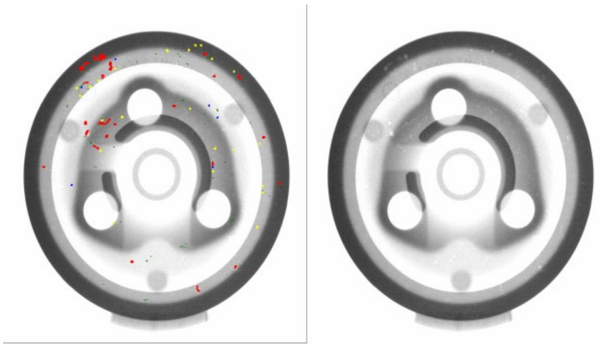

Figure 2: The SimADR result on an AL casting digital X-Ray image showing the ADR on the left from the raw data on the right.

The ratio of the number of simulated data vs experimental data was varied and evaluated. It was observed that, as expected, the POD Accuracy was improving with the number of data sets used in the training of the SimADR AI engine. Accuracy of 95% was obtained for this Al cast sample. The false positive (false-call) rate was also found to decrease significantly with an increase in the number of data sets used.

A similar approach was employed using the SimXRAY simulation software for the development of a synthetic data set for the as-welded sample. Here, the weld bead geometrical feature was captured using laser scanners, and a weld bead stochastic model was developed and used in addition to the stochastic models used for modeling the other parameters such as defect geometry, alignment, noise, etc. Fig. 4 shows the SimADR output with the defects mapped on the weld region as well as the raw radiographic image used.

3.2 PAUT with FMC/TFM Data Sets

As discussed in section 2.2, the FEM models were used to generate datasets for creating the FMC/TFM datasets for two types of volumetric defects, such as the cluster of porosity and the cluster of slag inclusions.

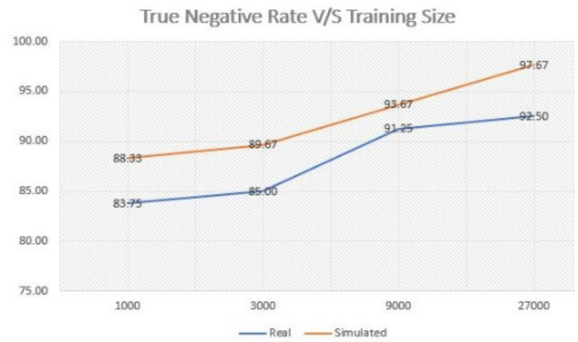

Figure 3: The plot shows the influence of levels of simulation data sets used in the SimADR for the images on the AL casting test sample shown in Fig. 2

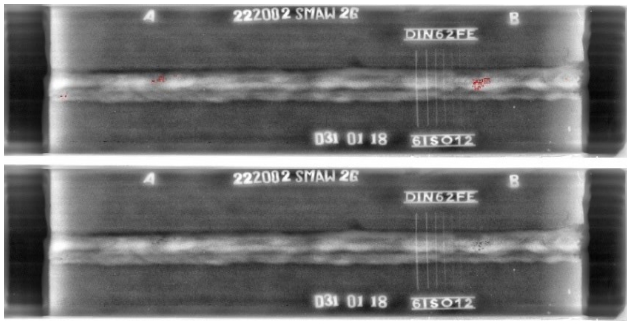

Figure 4: The SimADR result on a steel weld sample digital X-Ray image showing the ADR on the above image that was obtained from the raw data image below.

Single and multiple defect case studies were considered. A typical simulated image for slag inclusion is shown in Figure 5. The datasets used for training the SimADR engine comprised a small set of experimental data and a larger set of simulated data. The trained SimADR engine was tested on many real weld scenarios. Figure 6 illustrates an example of one such welded structure of 1 m long inspection result. Using the SimADR engine and the FMC/TFM data sets, it was feasible to not only detect the defects but also to classify and size defects.

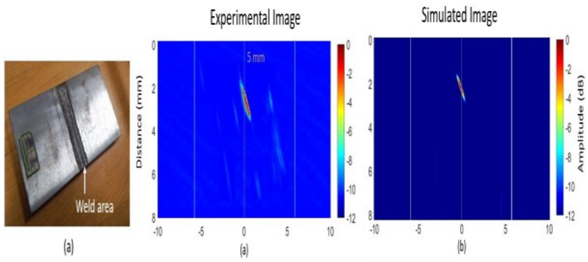

Figure 5: Simulated PAUT TFM Image of a butt-weld with a cluster of slag inclusion (a) Welded Sample, (b) Experimental image, (c) Simulated image.

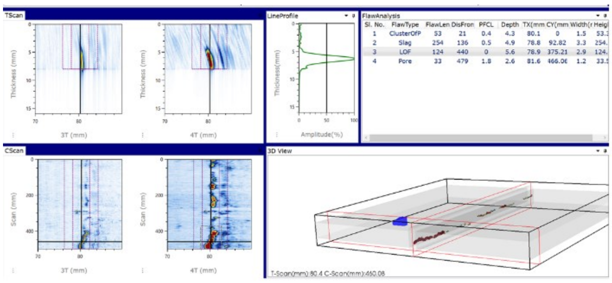

Figure 6: Screenshot of the weld data using SimADR with a B and C-scan representation on the left and the ADR result table on the right for a V-Weld with a 3D visualization plot.

4.0 Conclusions

Physics based simulations were employed for the generation of synthetic datasets for both digital radiography and Phased Array Ultrasonic Testing (PAUT) with FMC/TFM. The SimADR engine were trained and found to successfully provide automation in the interpretation of the datasets. Of the several case studies that were evaluated, Al casting and Weld inspection applications were demonstrated.

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