engineering proceedings

Proceeding Paper

Thermal Data Augmentation Approach for the Detection of Corrosion in Pipes Using Deep Learning and Finite Element Modelling †

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† Presented at the 17th International Workshop on Advanced Infrared Technology and Applications, Venice, Italy, 10–13 September 2023.

Abstract: Defects in in-service pipelines, including corrosion under insulation (CUI) and thickness loss, pose significant challenges to asset integrity in the oil and gas industry. These defects are particularly hazardous as they often remain unnoticed. The automation of defect detection processes can assist inspectors in reducing analysis time, costs, and human error. However, recent attempts to adopt machine learning for automated defect detection from thermal images have been hindered by limited data availability. This paper presents a novel approach to address this issue by utilizing thermal data augmentation, generating synthetic sub-surface defects via finite element modeling. The resulting synthetic thermal images, combined with real images, are then used to train a deep learning model for the automatic detection of potential defects. Additionally, this study explores the efficacy of synthetic thermal images in enhancing the generalization of the detection model.

Keywords: thermography; deep-learning; defect detection; data augmentation; finite element

Citation: Rezayiye, R.K.; Laurent, K.; Nooralishahi, P.; Ibarra-Castanedo, C.; Maldague, X. Thermal Data Augmentation Approach for the Detection of Corrosion in Pipes Using Deep Learning and Finite Element Modelling. *Eng. Proc.* **2023**, *51*, 20. https://doi.org/10.3390/engproc2023051020

Academic Editors: Gianluca Cadelano, Giovanni Ferrarini and Davide Moroni

Published: 31 October 2023

1. Introduction

The importance of pipeline integrity for the oil and gas industry is crucial, but the detection of hidden defects like corrosion under insulation (CUI) and thickness loss is challenging due to their concealed nature [1]. Automating inspections using machine learning is limited by the lack of real-world defect data. This study addresses this issue by using a thermal data augmentation strategy that generates synthetic defects via finite element modeling and deep learning algorithms. This approach aims to enrich the training dataset, improve defect detection model performance, and compare different supervised learning networks for image segmentation. The outcomes of this research could significantly impact automated pipeline inspection in the oil and gas industry.

2. Background

Thermography, vital in subsurface defect detection, ensures the integrity of critical infrastructures such as pipelines. Significant advancements, particularly machine learning techniques, have improved accuracy in defect detection [2]. These techniques of discovering relationships between thermal data and defect features have yielded promising results across various applications [3]. However, the laborious and costly nature of data labeling remains a challenge. Unsupervised learning methods, which discover hidden patterns within input data, have emerged to address this issue. Semi-supervised learning (SSL), a compromise between supervised and unsupervised learning, uses a blend of labeled and unlabeled data, offering a cost-effective solution, especially when labeled samples are scarce [4,5].

Data augmentation techniques have been adopted to combat limited datasets. The finite element method, simulating the thermal process, creates synthetic data that resemble real-world defects. Generative adversarial networks (GANs) also enhance training datasets by generating synthetic data, thereby improving model performance [6,7]. This study focuses on the novel integration of these techniques in a thermal data augmentation approach.

3. Methodology

3.1. Data Augmentation

The scarcity of data, specifically thermal images for training, significantly challenges the effective implementation of machine learning techniques for defect detection, potentially weakening the model's predictive power and real-world applicability. In response, this study proposes a thermal data augmentation method, creating synthetic sub-surface defects using finite element modeling for a realistic representation of material properties and defect features. This approach also utilizes DeepSIM [8], a deep learning method that capitalizes on the strengths of generative adversarial networks and variational autoencoders to generate high-fidelity thermal images resembling real-world conditions. The synthetic images enrich the training dataset, enhancing the variety of defect types, sizes, and orientations, thereby improving the model's robustness and generalization capacity. The dataset size is doubled using the finite element method and further expanded using the DeepSIM method, with the outcomes subsequently compared and analyzed.

3.2. Supervised Learning for Image Segmentation

To identify and quantify defects, we utilized supervised learning techniques for image segmentation, a key step in highlighting potential defects in thermal images. Our approach incorporates various network architectures, namely UNet [9], UNet++ [10], DeeplabV3+, and FPN, each chosen for their proven prowess in image segmentation tasks and bringing unique strengths to the defect detection process. UNet and UNet++ provide a balance between localization and context aggregation, while DeeplabV3+ uses convolution and spatial pyramid pooling for precise segmentation. The FPN, on the other hand, employs a top-down architecture with lateral connections for high-quality segmentations at multiple scales.

4. Experiment

The study focused on the non-destructive inspection of steel pipes with diameters of 2, 3, and 6 inches and insulated with perlite. Infrared (IR) imaging was used to detect moisture and corrosion under insulation (CUI). A static approach was employed, leveraging a long-wave infrared (LWIR) camera, specifically the FLIR T650Sc, to observe temperature variations indicative of potential defects. This camera featured a minimum focus distance of 0.3 m, an IR resolution of 640 $\times$ 480 pixels, a thermal sensitivity of less than 20 mK at +25 °C, and a maximum frame rate of 30 Hz. Artificial defects, ranging in size from 1 to 4 in^2 and depths from 0.98 to 2.74 inches, were introduced within the insulation layer of the samples, which had different thicknesses of 3, 5, and 10 mm. These samples were then secured with aluminum claddings. A heat transfer system (HTS) was used for precise fluid temperature (150 °C) control and was equipped with multiple thermocouples for comprehensive thermal behavior monitoring. During the steady-state regime, the temperature evolution was carefully observed to ensure stability and minimal variations within the insulation and cladding. Figure 1 illustrates the defect structure and heating setup for this experiment.

(a)

(b)

Figure 1. (**a**) Artificial defects created in the insulation on the pipe; (**b**) Heat transfer system.

5. Results and Discussion

5.1. Data Augmentation and Defect Detection

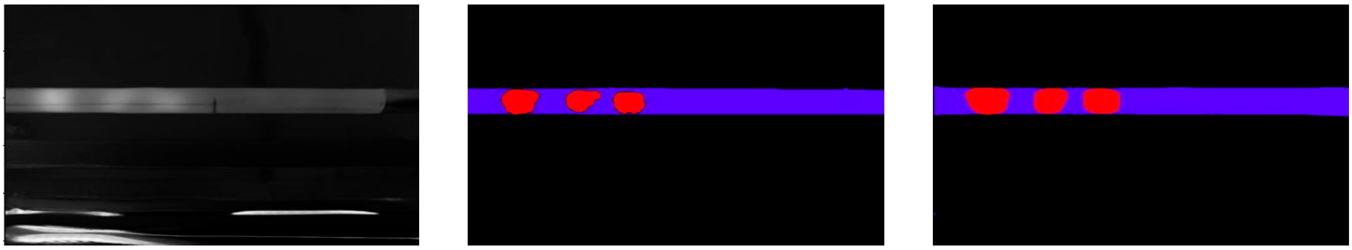
The proposed thermal data augmentation approach, combining finite element modeling and DeepSIM methods to create synthetic sub-surface defects, effectively mitigated the issue of data scarcity for defect detection in insulated piping. Following this, the acquired datasets from the experimental, finite element simulation, and DeepSIM generation stages were subjected to image segmentation through supervised learning. Using networks such as UNet, UNet++, DeeplabV3+, and FPN, thermal images were successfully segmented based on neighboring thermal patterns, providing clear demarcations of potential defects.

5.2. Evaluation Metrics

The effectiveness of our data augmentation and segmentation strategies is evidenced by the training and evaluation metrics of our supervised learning approach, including F1 score, Loss, Mean IoU, and Mean F1, as consolidated in Table 1. These metrics were evaluated on the same dataset for comparison. Our multi-tiered data augmentation approach, which combines experimental data with finite element or DeepSIM augmented data, demonstrated superior defect detection precision and recall compared to using solely experimental or augmented datasets. The proposed methodology illustrates the potential of integrating thermal data augmentation approaches with advanced image segmentation networks for accurate and efficient defect detection in insulated piping. Figure 2 shows the ability of the UNet++ network on the dataset to predict the mask for the defects. Future efforts aim to further optimize these processes and broaden their applicability across diverse industrial contexts.

Table 1. Evaluation metrics of training and validation process for the segmentation models.

Dataset	**UNet-R152**		**UNet++-R152**		**DeepLabV3+-R152**		**FPN-R152**	
Experiment	F1	0.66	F1	0.92	F1	0.91	F1	0.95
	Loss	0.48	Loss	0.46	Loss	0.35	Loss	0.08
	Mean IoU	0.49	Mean IoU	0.83	Mean IoU	0.85	Mean IoU	0.80
	Mean F1	0.65	Mean F1	0.99	Mean F1	0.92	Mean F1	0.87
Experiment + Finite Element	F1	0.77	F1	0.96	F1	0.93	F1	0.96
	Loss	0.45	Loss	0.37	Loss	0.30	Loss	0.06
	Mean IoU	0.59	Mean IoU	0.92	Mean IoU	0.85	Mean IoU	0.94
	Mean F1	0.71	Mean F1	0.96	Mean F1	0.92	Mean F1	0.96
Experiment + Deep SIM	F1	0.95	F1	0.96	F1	0.94	F1	0.65
	Loss	0.47	Loss	0.39	Loss	0.30	Loss	0.07
	Mean IoU	0.94	Mean IoU	0.93	Mean IoU	0.94	Mean IoU	0.58
	Mean F1	0.97	Mean F1	0.96	Mean F1	0.97	Mean F1	0.73



(**a**) Input image (**b**) Ground truth (**c**) Predicted mask

Figure 2. Prediction results of UNet++ network for the experimental + DeepSIM dataset. (**a**) Input image. (**b**) Ground truth. (**c**) Predicted mask.

6. Conclusions

In conclusion, this study substantiates the potency of thermal data augmentation strategies, in particular, the approach combining experimental data with DeepSIM and finite element augmented data for proficient defect detection in insulated pipelines. This novel approach has proven to be significantly effective when coupled with advanced image segmentation networks such as UNet, UNet++, DeepLabV3+, and FPN. The results, as presented in Table 1, establish that the combination of experimental data and DeepSIM augmented data outperforms the other methods, particularly in terms of precision, recall, and Mean F1 score. The UNet++ model performed exceptionally well in this context, exhibiting an F1 score of 0.96, a Loss of 0.39, a Mean IoU of 0.93, and an impressive Mean F1 of 0.96. These encouraging results, along with superior visual outputs, highlight the strength and potential of using the DeepSIM augmented approach for defect detection in insulated pipelines. This study's findings carry significant implications for the broader oil and gas industry, and future work will focus on further refining these methods and exploring their applications in diverse industrial settings.

Author Contributions: Conceptualization, P.N., X.M. and C.I.-C.; methodology, R.K.R., K.L. and P.N.; software, R.K.R. and K.L.; validation, R.K.R.; formal analysis, R.K.R. and K.L.; investigation, R.K.R., K.L. and P.N.; resources, X.M. and C.I.-C.; data curation, X.M.; writing—original draft preparation, R.K.R.; writing—review and editing, R.K.R.; visualization, R.K.R. and K.L.; supervision, X.M. and C.I.-C.; project administration, X.M.; funding acquisition, X.M. and C.I.-C. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by the Natural Sciences and Engineering Council of Canada (NSERC), CREATE oNDuTy Program (funding ref. number 496439-2017), the Canada Research Chair in Multipolar Infrared Vision (MIVIM), Department of Civil Engineering from Université Laval, and the MITACS Accelerate Program.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: All the data for this research are available in this link: https://github.com/reza7293/Thermal-Data-Augmentation-Approach-for-the-Detection-of-Corrosion-In-Pipes-Using-Deep-Learning (accessed on 26 October 2023).

Conflicts of Interest: The authors declare no conflict of interest.

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