

Proceeding Paper

University Laval Infrared Thermography Databases for Deep Learning Multiple Types of Defect Detections Training [†]

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Abstract: Nowadays, automatic defect detection research by deep learning algorithms plays a crucial role, especially for non-destructive evaluation with infrared thermography. In deep learning research, the databases are the Achilles' heel during the training in order to preserve optimized performance. In this work, we will present the infrared thermography sequences databases from the Université Laval Multipolar Infrared Vision Infrarouge Multipolaire (MIVIM) research group for regular and irregular defect analysis in order to provide the best data collection resources for the pretraining of convolutional neural network and feature extraction analysis with future researchers and engineers. The databases will include infrared thermography sequences from regular and irregular defects of carbon fiber-reinforced polymer (CFRP), glass fiber-reinforced polymer (GFRP), plexiglass, aluminum, and steel, which could be available online for public use and research purposes.

Keywords: non-destructive evaluation; infrared thermography; data augmentation; deep learning; defect detection analysis



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1. Introduction

Non-destructive evaluation [1] is a technology applied in the industry for quality integrity and manufacture evaluation in the field of aerospace. Infrared thermography [2] is the representative industrialized NDT technique based on measuring and mapping temperature to detect the detection and protect the integrity of the materials.

Artificial intelligence [3] has become a tendency topic in the sciences and industrial field that brings a lot of attention. Defect detection with artificial intelligence [4–7] has also become an interesting research topic. Many works have focused on advanced machine learning techniques and algorithms to evaluate their capability in achieving the automatic detection and characterization of the defects. However, there is still an Achilles' heel issue about the infrared non-destructive evaluation with the deep learning technique: the shortage of unique training thermal databanks. During the training process of the deep learning project, only enough and accurate thermal images will be beneficial to the proposed algorithms to learn the reliable interest and features. A sufficient database can provide a higher possibility for accurate detection results and boost the performance of proposed models.

For this purpose, we collected and gathered the largest thermal databases from several industrial structured samples from multiple types of representative materials (advanced composite materials, etc.). These samples, containing artificial defects of different shapes and nature (flat-bottom holes, Teflon inserts), have been tested by pulsed thermography. It could be a reference and training resource for future researchers to exploit defect detection in non-destructive evaluation via artificial intelligence.

2. Data Acquisition and Setup

Our thermal databases recording methodology was set up using optical pulsed thermography for the conduction of all thermal databases. The data acquisition pipeline is set up through thermophysical equipment: an infrared camera, two photographic flashes, a control PC unit, etc.

3. Infrared Defect Detection Experimental Databases

All databases of each subject acquired from pulsed thermography have been evaluated of their visibility and detection of geometrics defects from the samples.

3.1. Composite Materials (CFRP, GFRP) Thermal Databases

Advanced composite material is the most important part of the defect and flaw evaluation for the aircraft industry. Two represent composite materials—carbon fiber-reinforced polymer (CFRP) and glass fiber-reinforced polymer (GFRP)—are provided as a ground truth training database for deep learning defect detection in composites. Three typical CFRP and GFRP sample thermal specimens have been included.

3.2. Plexiglass Thermal Databases

This dataset contains thermal sequences from eight different samples (640×512 pixels spatial size) of plexiglass specimens (contained regular and irregular shapes of defects).

3.3. Steel Thermal Databases

This dataset contains the images (320×500 pixels) from a thermal sequence of steel samples including the regular and irregular shape of defects. The sequence from steel specimens sampled ranged from 13.4 Hz and 94 Hz typical frame rates.

3.4. Aluminum Defect Samples Thermal Databases

This dataset contains thermal sequences (620×520 pixel spatial size) from eight aluminum specimens including the regular and irregular shape of defects. In this database, the aluminum samples have the same geometrical distribution as plexiglass samples from Section 3.2 for deep learning defect detection training (the sample frame rates at (50 Hz; 88 Hz).

4. Synthetic Infrared Database for Defect Detection

The thermal database is generated from engineering software such as COMSOL Multiphysics [8] and Thermo-Calc [9]. In this section, the inexpensive thermal database could be an alternative training databank for defect detection with deep learning algorithms.

5. Segmentation Results

The segmentation results in this work include the algorithm from several types, such as the objective detection YOLO-V3, as shown in Figure 1b,c, and instance segmentation detection algorithm Mask-RCNN as indicated in Figure 1a,d. These results have shown validation results from the training of the state-of-the-art deep learning algorithms.

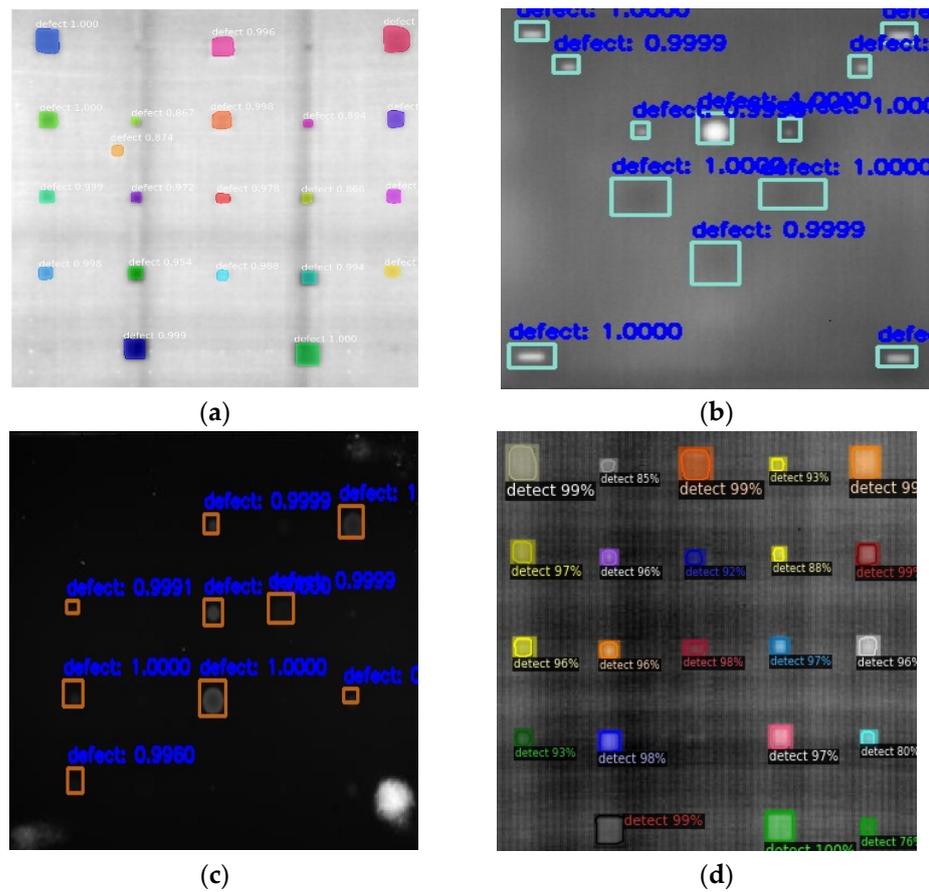


Figure 1. The detection results from the state-of-the-art deep learning algorithms; (a) instance segmentation results for a CFRP sample via Mask-RCNN [10] algorithm; (b) YOLO-V3 [11] detection results on a plexiglass sample; (c) YOLO-V3 detection results on a steel sample; (d) instance segmentation results for a GFRP sample via Mask-RCNN algorithm.

6. Annotations/Ground Truth

For the training part, the labelling process for each map based on the ground truth through the two different annotation software (Colabeler toolkit, Labelme toolkit). In Colabeler, each profile is extracted as a .xml file format. In the Labelme toolkit, each profile is extract as a json.file) as indicated in Figure 2.

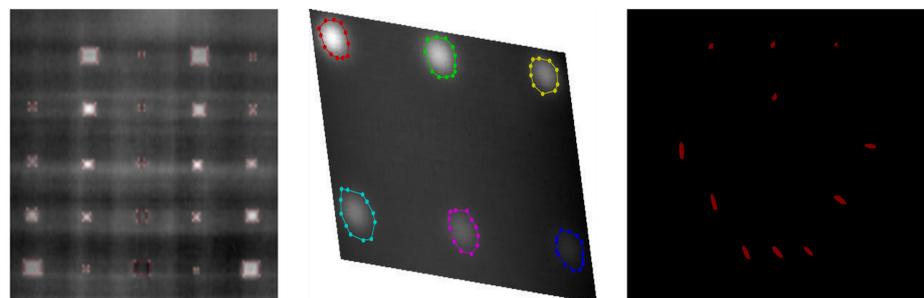


Figure 2. Processing of labeling.

7. Conclusions

In this paper, we present the Universite Laval infrared thermography databases for deep learning defect detection. The time frame sequences from different materials (Composites, etc.) gathered in the multiple kinds of materials can be adapted as the infrared databank for future deep learning non-destructive evaluation research. We not only focus

on the defect information provided from these representative samples from materials but also the state-of-the-art deep learning detection mechanism and results on these samples.

8. How to Obtain Databases and Access It

We provide the available databases for research with deep learning non-destructive evaluation, which could be accessed and downloaded from the Multipolar Infrared Vision Infrarouge Multipolaire (MIVIM) website. We also provided the implementation guidance documents for the researcher basic and the training and resource of annotation software. All the research are for public use, for research purposes only.

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

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