

Defect detection on inductive thermography images using convolutional neural networks

by K. Tout^{*}, P. Bouteille^{**}

- * Cetim Grand Est, NDT/AI Division, Mulhouse, France
- * Cetim, NDT Division, Senlis, France

Abstract

Inductive infrared thermography has been proven as an interesting solution for the inspection of surface defects. However, inductive thermography images can be noisy or present large variations in contrast and texture. Combine that with the large variability in surface defects shapes, sizes and types, the defect detection task becomes very complex. Defect detection methods based on convolutional neural network (CNN) proved their efficiency for complex detection tasks. This paper discusses two main approaches of defect detection with CNN : classification and object detection. Detection results are presented along with the advantages and weaknesses of each approach for real-time defect detection.

1. Motivation of this work

CETIM has been developing and evaluating for several years non destructive testing techniques based on inductive infrared thermography to detect defects on metallic materials such as forging laps, hardening taps, welding or grinding cracks for example. Inductive infrared thermography has been proven as an interesting alternative to penetrant testing and magnetic particle inspection which are still widely used in the industry for the inspection of surface defects [1]. It enables the same detection quality as these testing techniques while being more environmentally-friendly, more energy-efficient, and not requiring the use of any chemicals [1]. Furthermore, it gains even more interest since it is easier to fully automate compared to the other NDT techniques. However, to be able to automate the inspection with the inductive infrared thermography technique, we must automate the defect detection task, that is develop defect detection methods to efficiently detect defects in inductive infrared thermography images. In recent years, several defect detection methods based on deep learning algorithms, more precisely convolutional neural network (CNN), have been proposed and proved to be more efficient than conventional image processing methods in several tasks. In this paper, we propose to evaluate the efficiency of deep learning based methods for defect detection on inductive thermography images of wheel hubs.

2. Defect Detection using convolutional neural networks

2.1 Acquisition system

Acquisitions on the wheel hubs were performed using a FLIR X6580sc cooled infrared camera with high frequency induction excitation. To facilitate image acquisition, an inductor consisting of a coil wound around a magnetic core was used. It generates induced currents at a frequency of $61 \ kHz$. The images used for the paper are $4.5 \ Hz$ phase images obtained in the frequency domain by Fourier transform on the sequence of images acquired during induction heating $(120 \ ms)$ and part of the cooling $(100 \ ms)$. A total of 539 wheel hubs were tested to acquire a dataset of 2695 inductive thermography images, 60% of which are without defects, 30% with a type 1 defect and 10% with a type 2 defect.

2.2 Defect detection methods

The acquired images of the wheel hubs are very complex to inspect. Figure 1 shows images of both defective and non defective wheel hubs acquired with the imaging setup described above. It can be seen that the defect detection task on these images is not straightforward. This inspection complexity is due to many factors. First, even with consistent acquisition conditions, there is a large variation in contrast and texture between acquired images due to the nature of the inspected parts and the nature of the inductive infrared thermography technique. Secondly, defects can be located anywhere on the surface of the inspected wheel hub, and they vary in type, size, and shape. And most importantly, we notice that for all inspected wheel hubs whether defective or non defective, their surface may contain some irregularities and deformities that are not considered as real defects. Hence the real challenge is to design a detection method that is able to distinguish between the anomalies (non defective deformities) and the real defects.

In such a wide detection environment, conventional image processing methods all lack the necessary adaptability and robustness to the different scenarios that may occur, since they are generally tuned to deal with a specific scenario.

In recent years, several defect detection methods based on deep learning algorithms, more precisely convolutional





(a) Non defective

(b) Defective

Fig. 1. Images of both defective and non defective wheel hubs. The bounding boxes show the location of the defects. Blue boxes correspond to type 1 defects and red boxes correspond to type 2 defects.

neural network (CNN), have been proposed. These methods have achieved excellent results and proved to be more efficient than traditional defect detection methods when dealing with highly textured surfaces [2].

There are three main approaches for defect detection with CNN : classification, object detection and semantic segmentation. Only classification and object detection approaches are studied in this paper due to the shape of the defects on the inspected parts. Classification is considered as the most common task performed by CNN, where given an image, the CNN is expected to output a discrete label that simply indicates the image class. On the other hand, object detection aims to localize and classify each defect in the image. In such a case, given an image, the CNN is expected to output the coordinates of the rectangular bounding box for each defect detected in the image, along with the label of its corresponding class.

In this paper, these two detection approaches are discussed and their performance are compared in terms of detection accuracy and real-time implementation to choose the most appropriate for defect detection on inductive thermography images of wheel hubs.

References

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