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Toward deep learning fusion of flying spot thermography and visible inspection for surface cracks detection on metallic materials

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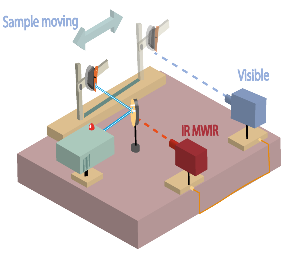
Abstract

"Flying spot" laser infrared thermography (FST) is a non destructive testing technique able to detect small defects through scanning surfaces with a laser heat source. Defects such as cracks can indeed be detected by the disturbance of heat propagation measured by an infrared camera. However this examination method is limited to small regions of interest and the measurement might be affected by heterogeneous surface properties. Moreover, visible spectrum enables the location of variations of properties on the surface and an inspection within large field of view in a single snapshot. The aim of the present work is to couple FST with visible inspection using deep learning techniques. This paper presents our preliminary work toward this fusion, from experimental bench realization, to sample examination in both spectra. A performance comparison of our dedicated convolutional defect detection neural network trained on each spectrum separately concludes the paper.

1. Introduction

In order to inspect metallic aeronautical parts, FST can be used to provide local data for a precise detection and characterization of defects like surface cracks. However performances of this inspection method can be limited for parts with heterogeneous regions and various surface properties. So the addition of a visible global examination seems useful to locate regions of interest and then plan focused infrared inspections. Besides, the estimation of surface properties in visible spectrum can help for a local thermographic inspection.In this paper we propose to use deep learning for non destructive testing(NDT) in infrared and visible spectra, highlighting the benefits of coupling these means. We first make a brief review of the state of the art for the FST, defect detection using deep learning, and the data fusion techniques. Then we present our experiments and associated preliminary results.
The FST was originally developed for cracks detection in military aircraft parts in the end of the 1960s' [1]. In [2], Krapez describes the Peclet number theory, giving a ratio between convective and conductive heat flux, and how it will influence cracks detection for constant scanning speeds. In [3] Maffren uses FST to examine cracks on AM1 superalloy samples covered with thermal barriers, revealing how difficult it can be to detect cracks on heterogeneous surfaces. Many image processing techniques dedicated to this mean have been proposed, even with deep learning experiments with complex architectures [4]). In visible deep learning for cracks detection is more developed, as in civil engineering [5]. To the best of our knowledge, data fusion between IR and visible for object detection in NDT is not much developed in the literature : there are only few papers about IR-Visible fusion, based on the creation of an intermediate image combining visible and IR images [6].

2. Experiment set-up



1	Laser heat source (λ = 532 nm)
2	Sample moving through the 3 directions of space
3a	IR-MWIR Camera (3-5µm)
3b	Visible Camera

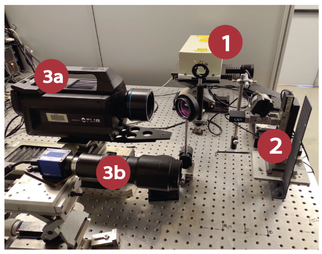


Fig. 1. *Illustration of the FST bench of ONERA*

The FST bench of ONERA as illustrated above uses a laser heat source, power varying from 0.5 to 1.5 W. The wavelength is 532 nm. A dichroic lens is added to reflect laser spot on the part and to leave IR heat flux arrive to the MW-IR camera, sensitive between 3 and 5 µm. Our samples are superalloy samples coated with a thermal barrier: 3 with cracks, and 3 without crack. The laser Spot length varies between approximately 0.5 mm and 1.5 mm. The spot covers a distance of 4.5 mm for horizontal scans, 6 mm for vertical scans, close to the defect. Scan speeds varies between 0.5 and 2.5 mm/s. An angular rotation is applied manually to part to increase the dataset. It varies from 0°(defect is vertical) to 45°. Using these settings we create a first IR-dataset containing a hundred of thermographic samples, converted into rebuilt IR scanning images as illustrated in figure 2.
For visible we set up a system with a visible camera (MVBlueFox 124C CMOS camera) to proceed to inspection shots. We produce our dataset by randomly moving the part vertically and horizontally, then adding a random rotation. Thereafter we generate patches of 227*227pixels by sampling large field images.
Patches are sorted in two balanced classes: with/without defect. This second dataset contains 6000 patches. Visible images and patches are illustrated in the next figure.

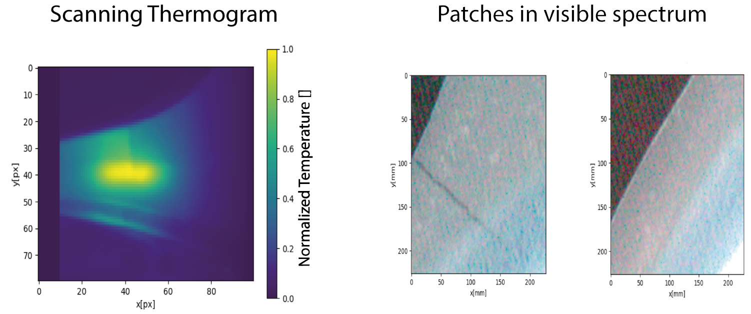


Fig. 2. *From left to right ; Synthetic IR image compiling all the images from an horizontal scan. We sum each frame from the scan movie. The crack is highlighted by the change of contrast after normalization and image processing / Example of patches we generated from the high resolution visible image*

3. Image processing

We build a first basic convolutional classifier in order to detect cracked images in each spectrum separately. The network contains 3 convolutional layers (max-pooling between each layer), and 4 fully connected layers after flattening. Dropout layer before the classification layer prevents over-fitting. The network is pretrained using a public dataset of concrete cracks [5]. Then we trained it for 30 epochs on our data. The optimizer used is ADAM. We choose a beginning learning rate of 0.001. The loss is the cross-entropy.

4. Preliminary Results

After training our network on the visible spectrum dataset, our architecture gives respectively a F1-Score, precision and recall of 0.92, 0.87 and 0.99. For the IR-Spectrum dataset it gives respectively a F1-Score, precision and recall around 0.93, 0.93 and 0.93. Note that the recall score measures the ability of the classifier to find all the samples with a defect, whereas precision gives its capability not to label as positive patches that are not cracked. F1 combines both in a synthetic score. For each 1 is equal to the perfect score.
These first results with our architecture trained on IR and visible datasets are promising for the next experiments. Our network is able to proceed to a correct defect detection in both spectra. What we still lack is a larger database of labelled IR images to build deeper architectures having a better generalization ability. This future database has to contain a wider diversity of parts and defects geometry. Working on synthetic data and setting up a more complex training process like curriculum training is possible: this method consists in a graduation of train-set features difficulty. It is adapted for unsupervised learning when lacking of labelled data as for depth estimation [7]. We are working on a comparison with traditional convolutional architectures like Dense Net. We are also building a dataset for a Region-Based neural network(R-CNN) to differentiate regions like coated or uncoated surfaces and working on a specific neural network architecture to fuse both spectra.

5. Conclusion

In this paper we presented our work towards the fusion of IR Flying Spot and visible inspection. Using an experimental bench having both modalities, two datasets have been built and we trained a defect detection neural networks for each spectrum. Detection results obtained using this preliminary work are promising for defect detection using neural network. In further works we will first increase the size of the database, especially in the IR spectrum. Hence we will be able to use more complex neural network architectures, that would for instance be able to differentiate regions like coated or uncoated surfaces on the data. Finally, fusion architecture between IR and visible data will be developed to benefit from defect information from both modalities.

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