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Simple Statistics And Frame Interpolation, On The Task of Defect Enhancement, in Carbon Fiber Reinforced Plastic and Cultural Heritage.

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Abstract

This paper investigates the use of the InterQuartile Range (IQR) as a defect enhancement method for pulsed thermography thermograms. The interest of the IQR as a defect enhancement method is directly related to the frequency of the acquisition; for this reason, this paper also investigates its application in association with the frame interpolation (aka generative) algorithm. The interest of the IQA is its ability to enhance defective regions while having a computational cost lower than common dimensionality reduction methods. The method's validity is demonstrated using a test sample of Carbon Fiber Reinforced Plastic (CFRP), while a possible application to cultural heritage is also studied.

1. Introduction

Increasing the acquisition frequencies of the Long Wavelength InfraRed (LWIR) camera makes it easier to find defects in thermograms. The increase in the acquisition frequency means that the difference of heat acquired between two frames is lower. Thus, both deeper defective regions and least contrasted defective regions are easier to detect. However, with a quantity of data that increase proportionally with the frequency of acquisition of the cameras, using dimensionality reduction method such as the Principal Component Analysis (PCA) become more and more challenging. This challenge comes from the need for the cost function to iterate over a more considerable amount of data. Finding methods that enhance the evident defects without having to iterate too many times over the whole data may save computational time and save computational resources to identify deeper or more challenging defects. Data acquired with an older generation of cameras might also benefit from such methods; nonetheless, a major drawback for such data regards the frequency of acquisition. Recent works, such as the works of Liu et al. [1, 2, 3], show that frame interpolation can be used in order to increase the size of the thermograms, which, when used with dimensionality reduction method, provide improved results. This paper shows that using simple statistical methods such as the IQR, high-frequency cameras can provide comparable results as dimensionality reduction methods while being noticeably faster to compute. Such observation can also be reached from thermograms acquired with lower frequency using frame interpolation.

2. Material

The proposed approach mainly consists of computing the IQR of the thermal profile of every pixel of a thermogram. The IQR is a measure of the spread of the data. The general formulation of the IQR is:

$$IQR = Q3 - Q1 \tag{1}$$

where $Q1$ and $Q3$ are respectively the first and third quartiles. To compute the IQR from a given thermal profile, first, the values of the profile must be sorted in ascending order. The argument of the median value of the sorted thermal profile is determined. Then the sorted profile can be split into two parts; the first part contains all the values located before the argument of the median of the profile, while the second part contains all the values found after the argument of the median of the profile. The median value of the first part is the first quartile ($Q1$), and the median value of the second part is the third quartile ($Q3$).

Frame interpolation is a hot topic in research. In their works, Liu et al. used DCGAN [4], and SNGAN [5] to perform the frame interpolation, which is both Generative Adversarial Networks (GAN). GAN consists of two Artificial Neural Networks (ANN) trained simultaneously. One of the two ANN is trained to generate an output with the same dimension as the images of the dataset used to train. This ANN is often referred to as Generator. The other ANN is trained to provide a score, which assesses the quality of an image, and is often referred to as Discriminator. The Generator is trained only with a database of images, while the Discriminator is trained with the same database as the Generator, plus the output of the Generator at each iteration. In this works, the frame interpolation is made by the approach proposed by Niklaus et al. [6]. The model proposed by Niklaus et al. ; use separable filters with one-dimensional kernels rather than two-dimensional kernels to reduce the number of parameters. Additionally, their approach is not based on a GAN, making it faster to train.

3. Preliminary Experiments

The first experiment assumed that IQR applied can provide similar results as dimensionality reduction methods used on thermograms acquired at a specific frequency. Two datasets, one acquired at 145 Hz the other at 88 Hz, were selected. The very first step of our experiments consists of applying the Thermography Signal Reconstruction (TSR) [7], to reduce the level of noise in the data. Then PCT, PLST, and IQR are applied to the reconstructed data. The data processed by the PCT are then post-processed using the method proposed by Rengifo et al. [8]. The data processed by the PLST are also post-processed by computing the median value of a thermogram for a given pixel. Figure 1 shows the results of different methods for the three datasets we selected. The datasets were acquired at frequencies of 145 Hz, 120 Hz, and 88 Hz, respectively, using a standard pulse thermography protocol and a reference Carbon Fiber Reinforced Plastic (CFRP) sample. The first observation is that for every method, the higher the frequency, the higher the number of defects detected. On the first row, one can note that the IQR and PLST offer a good contrast for the shallower defects. The PCT allows detecting larger defects among the deepest depth partially. PLST also enhanced some of the largest defects located at the deepest depth with noticeably lesser contrast than the PCT. This dataset contains 287 images. The TSR on this dataset took 12.77 seconds to be computed, the PCT took 3.38 seconds to be computed, the PLST took 6.29 seconds, the IQR took 1.14 seconds. In the second row, the IQR shows most of the deepest defects and the shallowest. However, the central column has a gradient inversion (the defects appear darker than the background) compared with the other rows, which makes them barely visible. The PCT offers the best contrast enhancement; most of the shallowest defects were detected, deeper defects are visible. The PLST results also show most of the shallowest defects and the three largest defects (over five) located at the deepest (0.8 mm and 1mm from the surface). One can note that the deepest defects are barely visible. It is surprising that the IQR on this dataset, even if it does not provide the best contrast for every defect, is the method that enhanced the most defects. This dataset contains 2003 images. The TSR took 23.74 seconds to compute on this dataset, the PCT took 21.59 seconds, the PLST took 45.51 seconds, and the IQR took 10.11 seconds. In the last row, the results of the IQR offer better contrast than the results obtained in the second row. As for the second row, most defects are visible in the results (24 over 25). Similarly, the result of the PCT also shows a better contrast for the shallowest defect, and more are also enhanced. The PLST is quite close to the results obtained by the IQR regarding the number of defects visible. This dataset contains 2203 images; on this dataset, the TSR took 34.19 seconds to compute, the PCT took 21.51 seconds, the PLST took 45.12 seconds, and the IQR took 6.26 seconds. The experiments confirm that the frequency of acquisition influences the detectability of the defects. Another observation is that the IQR can provide similar results as state-of-the-art algorithms such as the PCT and the PLST for a fraction of their computational cost.

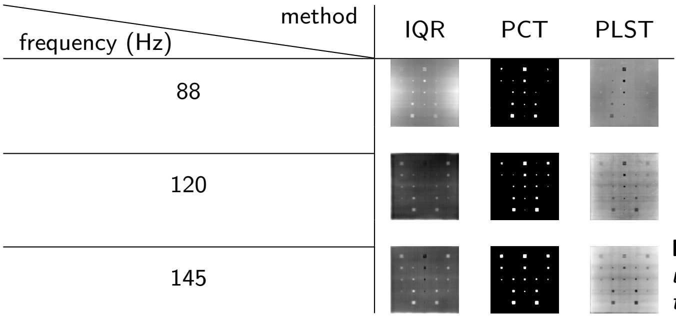

Fig. 1. *This images shows the results of three different methods all applied on data reconstructed by TSR. The data of each row were acquired at different frequency.*

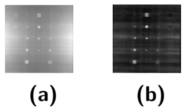

Fig. 2. *2a shows the IQR when applied directly (without using TSR) on the thermogram acquired at 88 Hz. 2b shows the result of the IQR after applying a frame interpolation on the previous dataset to simulate an acquisition at 176 Hz.*

With the assumption regarding the influence of the acquisition frequency on defect detection confirmed, another investigation of interest regards the ability to obtain similar results by using frame interpolation. As one can note in Figure 2 the contrast obtained on the results obtained after interpolating the original thermogram to a higher frequency of acquisition shows a more significant difference. The interpolation also highlights some deeper defects while making others less visible. This behaviour is likely due to a lack of pre-processing; methods such as standardization might help further improve the results.

4. Preliminary Conclusion

The IQR, when applied to material detection, shows promising results in terms of contrast enhancement of the defective area, compared with state-of-the-art methods such as PCT or PLST. This article aims to further investigate the IQR as a defect enhancement method, with and without frame interpolation. The applications targeted are defect detection in CFRP as well as cultural heritage.

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