Non–Referenced Quality Assessment of Image Processing Methods in Infrared Non–Destructive Testing based on Higher Order Statistics

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Abstract

Infrared Non-Destructive Testing (IRNDT) inspects the defects in a material by evaluation of a thermal image sequence, acquired from the material being heated. Current image processing techniques require all images of the sequence to enhance the defect's visibility in materials, thus the best-quality image must be found exhaustively from the whole sequence. In this work, we study the appropriateness of implementation of higher order statistics as a technique for IRNDT, where a single enhanced image is produced by sequence, avoiding the best-quality image search. For validation purposes, we compare the performance of IR Thermography processing based in High-Order Statistics (IRTHOS) among the common techniques used for IRNDT. Comparison is carried out by quality assessment of processed images of considered techniques. We use a Non-Referenced (NR) measure for Image Quality Assessment (IQA), giving as a result that IRTHOS achieves a 4.68% higher quality for TSR first derivative, than the best–quality image found. However, the image processed by the considered technique exhibits singularities due to net structure and geometry of the material.

1 Introduction

Non–Destructive Testing (NDT) refers to those methods used to inspect an object, for its evaluation on either material or performance in a system. To avoid affection of the basic nature of the object or impairment of its future usefulness, Pulsed Thermography (PT) is one of the most common thermal stimulation methods used in Infra–Red NDT (IRNDT), which records the temperature decay curve after test object is briefly heated. Hence, IRNDT is a non–contact inspection tool which analyzes the heat emitted by objects for fast evaluation of wide surfaces. This tool is useful to characterize defects such as material cracks, voids and discontinuities. Diverse image processing techniques are used in IRNDT to enhance image's contrast and therefore the visibility of defects in objects. In essence; the performance of such techniques implicitly involves the Image Quality Assessment (IQA) on defects, which is commonly subjective [6]: the experts visually compare the images for each technique to determine, for some given parameters, which technique works better by counting the number of visible defects in a particular image.

SNR (Signal to Noise Ratio) is commonly used to compare image processing techniques in IRNDT [8], [9], [3]. This measure is defined as the ratio of the absolute contrast at the center of the defect to the spatial noise in a non–defective region in the inspected material sample.

SNR is considered as a reduced–referenced (RR) measure, since only partial information in the form of RR features (i.e spatial noise in a non–defective region) is taking into account in assessing the visibility of one particular defect. Nevertheless; SNR is constrained by the existence of a non–defective area. Therefore, definition of a region free of defects in a sample material remains a difficult problem when considering a real structure. In a wide sense, its location is not precisely identified since it may not be known in advance where the defects are, if present at all. Moreover, SNR is only useful to measure the detectivity of one defect in the image, but it does not provide an assessment of the overall image contrast enhancement provided by the specific technique [1], [4]. The situation previously described indicates that the benchmarking of image processing techniques in IRNDT remains difficult.

In a previous study [10] the authors use DIIVINE index as NR measure to assess a variety of IR image processing techniques, demonstrating high correlation with human perception. The validation of its outcomes is performed by means of the analysis of Power Spectral Density and statistics of marginal and joint distribution of detail wavelet coefficients at different scales and orientations. On this point, DIIVINE constitutes a plausible measure to evaluate the quality of image processing techniques for infrared thermography and resulting images of higher order statistical moments.

Information about surface defects for inspection purposes is contained in the whole thermogram sequence, analysis of a single image is rarely conducted in active approach of thermography. From the opposite position, higher order statistical moments are considered as a useful tool for defects visualization. As a result of this, IR Termography processing based in Higher–Order Statistics (IRTHOS) provide an unique image, reducing the amount of processed data, as well as IRTHOS takes into account all the information comprised in the images of target sequence [5].

This paper is composed by the following sections: Section 2 gives the details of IR processing techniques along with NR–IQA index used to assess the quality of the considered images, Section 3 delineates the "step–by–step" methodology developed in order to achieved this study, Section 4 reports the results and discusses it after apply the methodology developed, and by last, Section 5 concludes this paper and proposes a future work related to this study.

2 Methods

In this section, we describe the IRNDT techniques used to analyze sequences of temperature images acquired from pulsed thermography (PT) experiments. We compute the output images generated by these IRNDT techniques as well as images obtained by IRTHOS aiming to compare them using a NR–IQA.

2.1 Thermographic Signal Reconstruction (TSR)

This technique enhances image sequences resulting from pulsed thermography experiments, making use of the one–dimensional heat diffusion equation describing the surface temperature evolution in a semi–infinite sample after thermal stimulation by a Dirac pulse:

$$T = \frac{Q}{e\sqrt{\pi t}} \tag{1}$$

where t is the time, e is the material effusivity and Q is the energy density at the surface. This relationship can be rewritten in a double logarithmic form such that the time dependency of temperature at each pixel can be approximated with a polynomial having the following form:

$$ln[T(t)] = a_0 + a_1 ln(t) + a_2 ln^2(t) + \ldots + a_N ln^n(t) \tag{2}$$

Typically, N is set to 4 or 5 to avoid ringing artifacts and ensure a valid correspondence between fitting accuracy and signal de–noising for different IRNDT applications. The qualitative results of TSR adequately allow the detection of defects, the reduction of data for processing and filtering of high–frequency noise [11]. Time derivatives of fitted polynomial are useful for thermal analysis as well. The first derivative for the Nth degree polynomial in 2 can be expressed as:

$$dln[T(t)] = \sum_{n=1}^{N} n a_n ln^{n-1}(t) \tag{3}$$

Second time derivative can be expressed as:

$$\frac{d^2}{dt^2} ln[T(t)] = \sum_{n=2}^{N} (n-1) a_n ln^{n-2}(t) \tag{4}$$

2.2 Non–Referenced Metric

The Distortion Identification–based Image Verity and INtegrity Evaluation (DIIVINE) is a non–reference image quality metric, based in natural scene statistics of a diverse kind of images. This index is not straitened for a particular distortion type, but can predict the type of distortion of an image and provide a score according to the distortion of the evaluated image. This non–reference evaluation approach is based on the hypothesis that natural scenes possess certain statistical properties, which are altered in the presence of a distortion, making them *un–natural* [7]. DIIVINE is composed by 2 stages: first stage extracts the statistics of target image in order to classify it into the different distortion types, the second stage, uses the same set of statistics extracted in first stage to evaluate the distortion–specific quality in order to provide a quality score. DIIVINE scores values near to 1 denotes "excellent" quality images, on the other hand, DIIVIVE scores values near to 100 indicates "poor" quality images.

2.3 Higher Order Statistical Moments

It is possible to obtain an IRTHOS mapping of a given sequence of temperature images as well as the considered IRNDT techniques. By doing this an unique image is obtained instead of the totality of the images' sequence. Only the first four statistical moments have a physical interpretation, being this: mean, variance, skewness and kurtosis. Corresponding to the first, second, third and fourth statistical moments. Mean is defined as:

$$\mu = E\left[\mathbf{X}\right] = \frac{1}{P}\sum_{n=1}^{P} \mathbf{X}_n \tag{5}$$

The variance σ^2 is the second central moment of a distribution and denotes the statistical dispersion about the mean of the distribution.

$$\sigma^2 = E\left[(\mathbf{X} - E[\mathbf{X}])^2\right] \tag{6}$$

The standardized central moments M_l, where the subscript l is indicates the moments order, and it is defined as:

$$M_l = \frac{E[(\mathbf{X} - E[\mathbf{X}])^l]}{\sigma^l} \tag{7}$$

3 Experimetal Setup

In order to achieve the comparison of considered IRNDT techniques against IRTHOS by using a NR–IQA measure, a methodology was developed to carry out this task. Figure 1 depicts the *step–by–step* of involved stages which are explained subsequently.

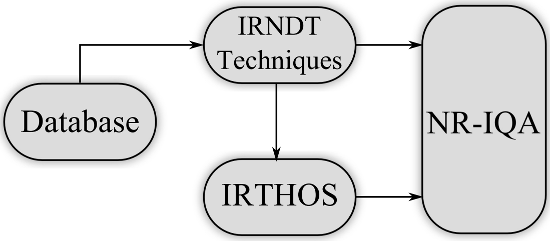


Figure 1. Methodology Scheme

3.1 Image Database Setup

The image sequences surveyed in this paper comes from the PT inspection of a Carbon Fiber Reinforced Plastic (CFRP) sample with 25 defects at different depths and sizes. Defects are simulated with Teflon inserts in the sample. For this test an infrared camera Santa Barbara Focal Plane SBF125 with sensor size 320×256, acquires images at the spectral band 3μ – 5μ with a sampling frequency of 157.3 Hz. The size of the sequence of thermograms given by captured thermal images is $292 \times 246 \times 991$. These images are thereafter processes by either TSR, TSR 1st derivative, TSR 2nd derivative, giving their respective sequence. Figure 2 shows the sample's configuration.

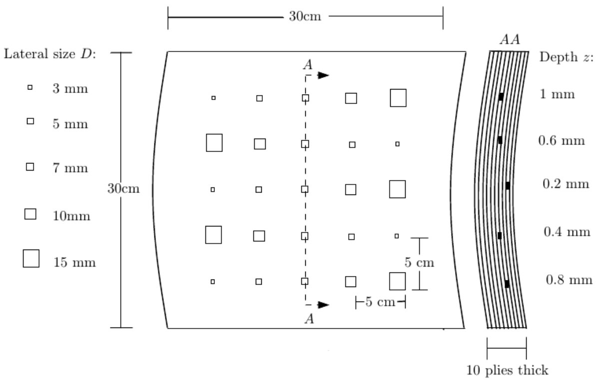


Figure 2. Geometry of the CFRP sample.

3.2 IRNDT Techniques

Considered IRNDT methods are applied to *acquired* temperature images sequence, obtaining a processed sequence per IRNDT technique. Since this work is an evaluation of the quality of the outputted images by these image processing methods, we filtered the temperature curves using the polynomial fitting proposed by previous studies [2],[4] where the authors use TSR to accomplish this task. The following are the considered IRNDT techniques: TSR, TSR first and second derivative.

3.3 IRTHOS

A previous analysis was made with the aim to define the most suitable statistical moments to conduct this experiment. Resulting higher order statistical moments were 4th and 5th. By applying this statistical moments we obtained an unique image by IRNDT technique.

3.4 NR–IQA

The main purpose of this paper is to assess a variety of image–processing techniques in the field of IRNDT. In order to carry out this objective, we use the NR–IQA metric DIIVINE, since there is no ground truth image in the same domain of the image to be analyzed. DIIVINE index extracts natural scene statistics from sequences of processed images and IRTHOS images, providing a quality score for each image.

4 Results and Analysis

Figure 3 show the resulting curves of the scores obtained by each IRNDT technique along the whole sequence.

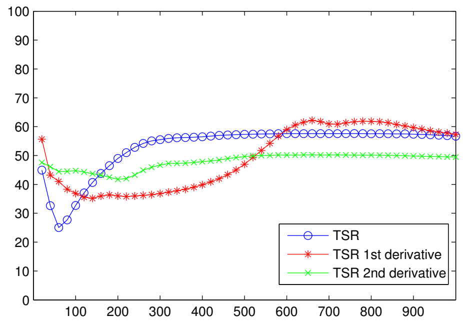


Figure 3. DIIVINE curves. Low score values denotes "good" image quality.

Smooth behavior in DIIVINE curves is evident. Moreover, minimum DIIVINE values (i.e good image quality) appear at the onset of curves in agreement with physical phenomena. The visual contrast of defects is high at early frames, since the effects of 3–D conduction in the sample are not so remarkable at these times. This is numerically demonstrated in Table 1.

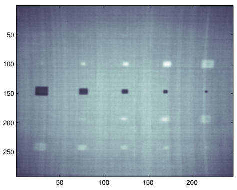
Table 1. Minimum DIIVINE scores obtained by considered IRNDT technique and its corresponding image index.

IRNDT Technique	Min DIIVINE Score	Image Index
TSR	24, 71	45
TSR 1st derivative	49, 07	132
TSR 2nd derivative	45, 20	4

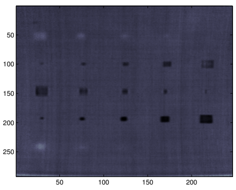
Figure 4 and 5 shows the resulting images for considered IR techniques after IRTHOS process for 4th and 5th.

DIIVINE scores obtained for 4th and 5th statistical moments are reported in Table 2.

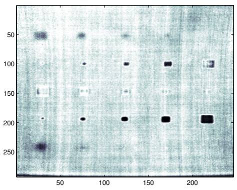
Observing scores obtained by each technique, according to Table 2 it is appreciable that, in a broadly sense, DIIVINE



(a) TSR

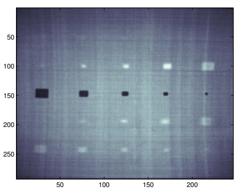


(b) TSR 1st derivative

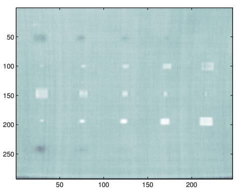


(c) TSR 2nd derivative

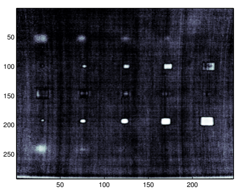
Figure 4. IRTHOS 4th statistical moment.



(a) TSR



(b) TSR 1st derivative



(c) TSR 2nd derivative

Figure 5. IRTHOS 5th statistical moment.

scores increases as the order increase, denoting low quality for 5th statistical moment. Specifically, TSR exhibit for both IRTHOS 4th and 5th order in Figures 4(a) and 5(a) heat diffusion over the surface product of heating process, an undesirable feature for fault diagnosis of components and structures.

However, it is observable that for TSR 1st derivative, DIIVINE score remains its trend, this is, for both IRTHOS (4th and 5th order) obtain similar scores. Moreover, after the transformation the heat diffusion over the sample's surface is completely removed. Furthermore, TSR reveals the net structure of CFRP sample, by–product of the sample's configuration.

Table 2. DIIVINE SCORES VALUES FOR 4TH AND 5TH STATISTICAL MOMENTS.

IR Technique	4th Order	5th Order
TSR	$22,00$	$93,86$
TSR 1st derivative	$44,38$	$44,46$
TSR 2nd derivative	$28,95$	$59,72$

5 Conclusions and Futurework

In this work it was compared different IRNDT image processing techniques with IRTHOS in order to determine if statistical central moments performs better than TSR, TSR 1st derivative and TSR 2nd derivative. Being this techniques one of the most used for IRNDT inspection scene, since TSR allows reduce the amount of processing data. With the aim to accomplish this task, DIIVINE index was used as NR measure to assess the quality of target sequences. According to Table 1 TSR DIIVINE value was $24,71$, the lowest score; denoting "good" quality. While its corresponding 4th IRTHOS obtained a score of $22,00$, exhibiting a slightly better performance.

Albeit Figure 4(a) (TSR) presents low DIIVINE score than Figure 4(b) (TSR 1st derivative), it is observable the heat diffusion over the surface of the sample, an undesirable feature in order to observe the defects. On the contrary, Figure 4(b) present no heat diffusion at all, moreover, it is appreciable the net structure of the sample due to the geometry of the CFRP sample. Also, it is observable more defects at the surface than any other IR technique. Obtained results highlights the capabilities of using IRTHOS for defects detection, reducing the amount of data to be processed and providing and unique image that contains the information of the whole sequence. Further work, can comprehend the analysis of more IRNDT processing methods for different public databases that take into account reliable industrial processes. And considering the ideas stated previously, develop a complementary NR–IQA assessment that involve more measures.

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